THOMPSON HINE LLP
Marla R. Butler, *pro hac vice*
marla.butler@thompsonhine.com
Two Alliance Center
3560 Lenox Road NE, Suite 1600
Atlanta, GA 30326
Telephone: (404) 407-3680

Jesse L. Jenike-Godshalk, *pro hac vice*
jesse.jenike-godshalk@thompsonhine.com
312 Walnut Street, Suite 2000
Cincinnati, OH 45202
Telephone: (513) 352-6702

Jeffrey C. Metzcar, *pro hac vice*
jeff.metzcar@thompsonhine.com
10050 Innovation Dr., #400
Miamisburg, OH 45342
Telephone: (937) 443-6841

Andrew Himebaugh, *pro hac vice*
andy.himebaugh@thompsonhine.com
20 N. Clark Street, Suite 3200
Chicago, IL 60602
Telephone: (312) 998-4247

TURNER BOYD SERAPHINE LLP
Jennifer Seraphine, Bar No. 245463
seraphine@turnerboyd.com
Vyson Hsu, Bar No. 322336
hsu@turnerboyd.com
155 Bovet Road, Suite 750
San Mateo, CA 94402
Telephone: (650) 521-5930
Facsimile: (650) 521-5931

Attorneys for Defendants/Counterclaim-Plaintiffs Caption Health, Inc. & GE HealthCare Technologies, Inc.

UNITED STATES DISTRICT COURT

NORTHERN DISTRICT OF CALIFORNIA

UNIVERSITY OF BRITISH COLUMBIA, Plaintiff/Counterclaim-Defendant, v. CAPTION HEALTH, INC. GE HEALTHCARE TECHNOLOGIES INC. Defendants/Counterclaim-Plaintiffs.	Case No. 3:24-cv-3200-EKL **DEFENDANTS' ANSWER, AFFIRMATIVE DEFENSES, AND COUNTERCLAIMS** **DEMAND FOR JURY TRIAL**

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CAPTION HEALTH Ex1033
Caption Health, Inc. v.
University of British Columbia
Trial IPR2025-01066

THOMPSON HINE LLP
Marla R. Butler, *pro hac vice*
marla.butler@thompsonhine.com
Two Alliance Center
3560 Lenox Road NE, Suite 1600
Atlanta, GA 30326
Telephone: (404) 407-3680

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jesse.jenike-godshalk@thompsonhine.com
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Cincinnati, OH 45202
Telephone: (513) 352-6702

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jeff.metzcar@thompsonhine.com
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andy.himebaugh@thompsonhine.com
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Chicago, IL 60602
Telephone: (312) 998-4247

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Vyson Hsu, Bar No. 322336
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For their Answer to Plaintiff University of British Columbia's ("UBC" or "Plaintiff") Complaint for Patent Infringement ("Complaint"), Defendants Caption Health, Inc. ("Caption Health") and GE HealthCare Technologies, Inc. ("GE HealthCare") (collectively "Defendants"), by and through their undersigned counsel, hereby deny each and every allegation, whether explicit or implicit, except as expressly admitted, qualified or otherwise answered herein. Moreover, to the extent that any section headings or sub-headings in Plaintiff's Complaint (which may precede any specifically enumerated paragraphs thereof) may be deemed to include any allegation(s) (whether explicit or implicit), Defendants hereby deny any such allegation(s) included therein. Defendants answer the specifically enumerated paragraphs of Plaintiff's Complaint, as follows:

ANSWER

Defendants deny the allegations in the preamble to the Complaint.

1. Defendants admit that Plaintiff purports to bring a claim against Defendants for infringement of the '591 patent under the patent laws of the United States. Defendants deny that they infringe the '591 patent, that Plaintiff has adequately stated a claim upon which relief can be granted, or that Plaintiff is entitled to the relief it seeks. Defendants deny any remaining allegations in Paragraph 1 of the Complaint.

2. Defendants admit that Plaintiff seeks judgment against Defendants. Defendants deny that they infringe the '591 patent, that Plaintiff has adequately stated a claim upon which relief can be granted, or that Plaintiff is entitled to the relief it seeks. Defendants deny any remaining allegations in Paragraph 2 of the Complaint.

3. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 3 of the Complaint, and therefore deny the same.

4. Defendants admit the allegations in Paragraph 4 of the Complaint.

5. Defendants admit that GE HealthCare is a corporation organized and existing under the laws of Delaware with a place of business at 500 West Monroe Street, Chicago, IL 60661. The cited Form 10-Q speaks for itself, and Defendants need not admit or deny Plaintiff's descriptions of the contents of the document. To the extent that a response is required, Defendants admit that GE

HealthCare acquired Caption Health in February 2023 and deny any remaining allegations in Paragraph 5 of the Complaint.

6. Paragraph 6 of the Complaint contains only jurisdictional allegations and no factual allegations that require a response. To the extent that Paragraph 6 contains factual allegations, Defendants deny them.

7. Defendants admit that Caption Health maintains a place of business within this District, has done business in the State of California and this District, and has been registered to do business in the State of California since 2013. The cited webpages speak for themselves, and Defendants need not admit or deny Plaintiff's descriptions of the contents of the webpages. To the extent that a response is required, Defendants deny the allegations in Paragraph 7 of the Complaint regarding these webpages as an incomplete description of the contents of the webpages. Defendants deny any remaining allegations in Paragraph 7 of the Complaint.

8. Defendants admit that GE HealthCare maintains a place of business within this District and has done business in the State of California and this District. The cited webpages speak for themselves, and Defendants need not admit or deny Plaintiff's descriptions of the contents of the webpages. To the extent that a response is required, Defendants deny the allegations in Paragraph 8 of the Complaint regarding these webpages as an incomplete description of the contents of the webpages. Defendants deny any remaining allegations in Paragraph 8 of the Complaint.

9. Defendants deny the allegations in Paragraph 9 of the Complaint.

10. Paragraph 10 of the Complaint contains only jurisdictional allegations and no factual allegations that require a response. To the extent that Paragraph 10 contains factual allegations, Defendants deny them.

11. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 11 of the Complaint, and therefore deny the same.

12. Defendants admit the allegations in Paragraph 12 of the Complaint.

13. Defendants admit that echocardiographic image analysis refers to the analysis of images of the heart created by ultrasound devices. Defendants admit that there are challenges to

acquiring and identifying good echocardiographic images. Defendants admit that one challenge is that operators can require years of training to expertly capture echocardiographic images. Defendants admit that changes in where an ultrasound transducer is placed, or the pressure applied when using the transducer, can result in variation in the quality and usability of an image. Defendants admit that, in many cases involving inexperienced operators, the actual quality and usability of the image can be difficult for them to ascertain. Defendants admit that operators can occasionally send inadequate or unusable images to the lab. Defendants admit that, as a result, effective echocardiographic analysis can be delayed, which can delay proper treatment. Defendants deny the remaining allegations in Paragraph 13 of the Complaint.

14. Defendants admit that echocardiography involves capturing images from multiple views. Defendants admit that echocardiography involves capturing the movement of the heart through sequences of images, known as echo cine series. Defendants deny that the '591 patent presented an improvement over the prior art and therefore deny the remaining allegations in Paragraph 14 of the Complaint.

15. Defendants deny that the inventions claimed in the '591 patent are "innovations." Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 15 of the Complaint, and therefore deny the same.

16. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 16 of the Complaint, and therefore deny the same.

17. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 17 of the Complaint, and therefore deny the same.

18. Defendants deny that application of neural networks for determining quality of echocardiographic images was not an obvious choice at the time of the purported invention. Defendants deny that the '591 patent presented an improvement over "standard modeling techniques." Defendants deny that the inventions claimed in the '591 patent are "innovations." Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 18 of the Complaint, and therefore deny the same.

19. Because the Court has not yet construed the claims of the '591 patent, Defendants lack sufficient information to admit or deny what the "various features" of the "patented system" are and therefore deny the purported description of those features in Paragraph 19 of the Complaint. Defendants admit that there are unique aspects of echocardiography that make it challenging to analyze the quality of echocardiographic images, but deny that the '591 makes echocardiography less challenging. Defendants deny that the '591 patent rectified any deficiency in echocardiography. Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 19 of the Complaint, and therefore deny the same.

20. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 20 of the Complaint, and therefore deny the same.

21. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 21 of the Complaint, and therefore deny the same.

22. Defendants admit that provisional application No. 62/325,779 was filed on April 21, 2016. Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 22 of the Complaint, and therefore deny the same.

23. Defendants deny that the United States Patent Office truly considered "over 60 references," that the Examiner "mischaracterized" the reference over which the claims were rejected, and that "the reference did not disclose the claimed features." Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 23 of the Complaint, and therefore deny the same.

24. Defendants admit that the '591 patent issued on September 28, 2021. Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 24 of the Complaint, and therefore deny the same.

25. Defendants deny that Caption Health was marketing AI-based cardiac ultrasound software that practiced the claims of the '591 patent and that was remarkably close to the prototype the inventors created. Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 25 of the Complaint, and therefore deny the same.

26. Defendants admit that UBC wrote to Caption Health. Defendants lack sufficient knowledge or information to admit or deny the remaining allegations in Paragraph 26 of the Complaint, and therefore deny the same.

27. Defendants admit that UBC's counsel sent a letter dated May 5, 2022 to Steve Cashman, President and Chief Executive Officer of Caption Health. The letter speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the letter. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 27 of the Complaint as an incomplete description of the contents of the letter.

28. Defendants deny the allegations in Paragraph 28 of the Complaint.

29. Defendants admit that UBC's counsel sent a letter dated May 24, 2022 to Mr. Cashman, enclosing the May 5, 2022 letter. The letter speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the letter. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 29 of the Complaint as an incomplete description of the contents of the letter.

30. Defendants admit that Caption Health CEO Steve Cashman sent an email dated June 13, 2022 to UBC's counsel. The email speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the email. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 30 of the Complaint as an incomplete and inaccurate description of the contents of the email.

31. Defendants admit that Mr. Cashman sent an email dated June 27, 2022 to UBC's counsel. The email speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the email. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 31 of the Complaint as an incomplete description of the contents of the email.

32. Defendants admit that UBC's counsel sent a letter dated November 11, 2022 to Mr. Cashman. The letter speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the letter. To the extent that a response is required, Defendants deny the remaining

allegations in Paragraph 32 of the Complaint as an incomplete and inaccurate description of the contents of the letter.

33. Defendants admit that Caption Health has not directly responded to the letter dated November 11, 2022. Defendants deny the remaining allegations in Paragraph 33 of the Complaint.

34. The cited webpages speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of the webpages. To the extent that a response is required, Defendants admit that GE HealthCare acquired Caption Health in February 2023. Defendants deny the remaining allegations in Paragraph 34 of the Complaint as an incomplete description of the contents of the webpages.

35. Defendants lack sufficient knowledge or information to admit or deny the allegations in Paragraph 35 of the Complaint, and therefore deny the same.

36. The '591 patent speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the patent. To the extent that a response is required, Defendants deny the allegations in Paragraph 36 of the Complaint as an incomplete description of the contents of the patent.

37. The '591 patent speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the patent. To the extent that a response is required, Defendants deny the allegations in Paragraph 37 of the Complaint as an incomplete description of the contents of the patent.

38. The '591 patent speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the patent. To the extent that a response is required, Defendants deny the allegations in Paragraph 38 of the Complaint as an incomplete description of the contents of the patent.

39. The cited webpages speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of the webpages. To the extent that a response is required, Defendants deny the allegations in Paragraph 39 of the Complaint as an incomplete description of the contents of the webpages.

40. The cited webpages speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of the webpages. To the extent that a response is required, Defendants expressly deny that their products and technology are "infringing" and deny the remaining allegations in Paragraph 40 of the Complaint as an incomplete description of the contents of the webpages.

41. The cited webpages speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of the webpages. To the extent that a response is required, Defendants deny the allegations in Paragraph 41 of the Complaint as an incomplete description of the contents of the webpages.

42. Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The '253 application speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the application. To the extent that a response is required, Defendants deny the allegations in Paragraph 42 of the Complaint.

43. Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The cited '253 application and webpage speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 43 of the Complaint as an incomplete description of the contents of the cited materials.

44. Defendants deny that the '253 application or the journal article provides a completely accurate description of the functionality of any product. The cited '253 application and journal article speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 44 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

45. Defendants deny that the '253 application, the journal article or the YouTube video provides a completely accurate description of the functionality of any product. The cited '253 application, journal article, and YouTube video speak for themselves, and Defendants need not

admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 45 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

46. Defendants deny that Caption Guidance associates captured echocardiographic images with view categories. Defendants deny that the '253 application or the YouTube video provides a completely accurate description of the functionality of any product. The cited '253 application and YouTube video speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 46 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

47. Defendants deny that Caption Guidance determines quality assessment values representing view category specific quality assessment of echocardiographic images. Defendants deny that the '253 application or the YouTube video provides a completely accurate description of the functionality of any product. The cited '253 application and YouTube video speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 47 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

48. Because Defendants deny that Caption Guidance determines quality assessment values as claimed, Defendants also deny that, once a quality assessment value is determined for an echocardiographic image, Caption Guidance automatically captures an echocardiographic image and associates the image with the determined quality assessment value. Defendants deny that the journal article or the YouTube videos provide a completely accurate description of the functionality of any product. The cited journal article and YouTube videos speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 48 of the Complaint as an incomplete description of the contents of the cited materials.

49. Defendants deny that Caption Guidance "performs the steps above." Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The '253 application speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the application. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 49 of the Complaint as an incomplete and inaccurate description of the contents of the application.

50. Defendants deny that Caption Guidance utilizes neural networks to assess the quality of captured echocardiographic images. Defendants deny that any of the documents cited in Paragraph 50 provides a completely accurate description of the functionality of any product. The cited webpage, journal article, and news release speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants expressly deny the remaining allegations in Paragraph 50 of the Complaint as an incomplete description of the contents of the cited materials.

51. Defendants deny that Caption Guidance neural networks are trained to provide quality assessment values that are specific to certain view categories. Defendants deny that the '253 application or the journal article provides a completely accurate description of the functionality of any product. The cited '253 application and journal article speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 51 of the Complaint as an incomplete description of the contents of the cited materials.

52. Defendants deny that Caption Guidance has neural networks that each have an input layer configured to receive echocardiographic images and an output layer configured to output quality assessment values. Defendants deny that the '253 application or the journal article provides a completely accurate description of the functionality of any product. The cited '253 application and journal article speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the

remaining allegations in Paragraph 52 of the Complaint as an incomplete description of the contents of the cited materials.

53. The cited webpage speaks for itself, and Defendants need not admit or deny Plaintiff's descriptions of the contents of the webpage. To the extent that a response is required, Defendants deny the allegations in Paragraph 53 of the Complaint as an incomplete description of the contents of the webpage.

54. Defendants incorporate by reference and re-allege all of the foregoing paragraphs of their Answer as if fully set forth herein.

55. Defendants deny the allegations in Paragraph 55 of the Complaint.

56. Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The cited '253 application and website speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 56 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

57. Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The cited '253 application and journal article speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 57 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

58. Defendants deny that the Accused Products perform "associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories." Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The cited '253 application speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the application. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 58 of the Complaint as an incomplete and inaccurate description of the contents of the application.

59. Defendants deny that the Accused Products perform "determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image." Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The cited '253 application speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the application. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 59 of the Complaint as an incomplete and inaccurate description of the contents of the application.

60. Defendants deny that the Accused Products perform "producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image." Defendants deny that the '253 application, the journal article, or the YouTube videos provide a completely accurate description of the functionality of any product. The cited '253 application, journal article, and YouTube videos speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 60 of the Complaint as an incomplete description of the contents of the cited materials.

61. Defendants deny that the Accused Products perform the steps described above (*see supra* ¶¶ 57-60) for multiple echocardiographic images corresponding to multiple view categories. Defendants deny that the '253 application provides a completely accurate description of the functionality of any product. The cited '253 application speaks for itself, and Defendants need not admit or deny Plaintiff's description of the contents of the application. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 61 of the Complaint as an incomplete and inaccurate description of the contents of the application.

62. Defendants deny that, in the Accused Products, "each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters," where "each of the sets of assessment parameters being a set of neural network parameters that defines a neural network having a plurality of layers including an input

layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values." Defendants deny that any of the cited articles provides a completely accurate description of the functionality of any product. The cited articles speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 62 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

63. Defendants deny that the Accused Products use neural networks that have "a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values." Defendants deny that the '253 application or the journal article provides a completely accurate description of the functionality of any product. The cited '253 application and journal article speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 63 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

64. Defendants deny that the Accused Products use neural networks that are trained to provide quality assessment values that are specific to certain view categories. Defendants deny that the '253 application or the journal article provides a completely accurate description of the functionality of any product. The cited '253 application and journal article speak for themselves, and Defendants need not admit or deny Plaintiff's description of the contents of these materials. To the extent that a response is required, Defendants deny the remaining allegations in Paragraph 64 of the Complaint as an incomplete and inaccurate description of the contents of the cited materials.

65. Defendants deny the allegations in Paragraph 65 of the Complaint.

66. The cited webpages and YouTube video speak for themselves, and Defendants need not admit or deny Plaintiff's descriptions of the contents of these materials. To the extent that a response is required, Defendants deny the allegations in Paragraph 66 of the Complaint regarding

the webpages and YouTube video as an incomplete and inaccurate description of the contents of the cited materials. Defendants deny any remaining allegations in Paragraph 66 of the Complaint.

67. Defendants deny the allegations in Paragraph 67 of the Complaint.

68. Defendants admit that UBC has not expressly authorized Defendants to make, use, offer to sell, or sell the Accused Products. Defendants deny that such authorization is or was required and deny any remaining allegations in Paragraph 68 of the Complaint.

69. Defendants deny the allegations in Paragraph 69 of the Complaint.

70. Defendants deny the allegations in Paragraph 70 of the Complaint.

71. Defendants deny the allegations in Paragraph 71 of the Complaint.

72. Defendants admit that Plaintiff purports to seek damages but deny that Plaintiff is entitled to any such damages. Defendants deny the remaining allegations in Paragraph 72 of the Complaint.

73. Defendants request a trial by jury of all issues so triable.

Defendants deny that Plaintiff is entitled to any relief requested in the "Prayer for Relief" section of the Complaint. To the extent that any statement in the "Prayer for Relief" section of the Complaint may be deemed to include any factual allegation(s) (whether explicit or implicit), Defendants hereby deny any such factual allegation(s) included therein.

Wherefore, Defendants pray that:

A. This Court grant judgment in their favor and against Plaintiff;

B. Plaintiff take nothing on its claims;

C. This Court find this to be an exceptional case pursuant to 35 U.S.C. § 285 and award Defendants their reasonable attorneys' fees; and

D. This Court grant Defendants all other and further relief that the Court deems just and proper.

AFFIRMATIVE DEFENSES

FIRST DEFENSE

74. The Complaint fails to state a claim upon which relief can be granted.

SECOND DEFENSE

75. The Complaint is barred, in whole or in part, by one or more of the equitable doctrines of estoppel, laches, waiver, acquiescence, and unclean hands.

THIRD DEFENSE

76. Plaintiff lacks standing to assert its claims.

FOURTH DEFENSE

77. The asserted claims of the '591 patent are invalid under 35 U.S.C. § 101 *et seq.*, including, but not limited to, 35 U.S.C. §§ 101, 102, 103, 111, 112, 116 and/or 256.

FIFTH DEFENSE

78. Any assertion by Plaintiff that the Accused Products infringe the asserted claims of the '591 patent is barred by the doctrine of prosecution history estoppel or otherwise by virtue of admissions, amendments, arguments, representations and/or misrepresentations made to the United States Patent and Trademark Office during the prosecution of the application(s) from which the '591 patent issued.

SIXTH DEFENSE

79. Plaintiff has failed to mitigate its damages, if in fact there are any.

SEVENTH DEFENSE

80. Plaintiff has not suffered any damages attributable to, or caused by, Defendants.

EIGHTH DEFENSE

81. Plaintiff's alleged injuries and damages (if any) were due to, and proximately caused by, in whole or in part, other events, conditions, instrumentalities, and/or acts or omissions of an individual or entity over whom or which Defendants exercised no control.

NINTH DEFENSE

82. Plaintiff's alleged damages (if any) are limited by 35 U.S.C. § 286 inasmuch as Plaintiff cannot recover for any alleged infringement committed more than six years prior to the filing of the Complaint on May 28, 2024.

TENTH DEFENSE

83. Plaintiff's alleged damages (if any) are limited by 35 U.S.C. § 287 for failure to mark patented articles.

ELEVENTH DEFENSE

84. Plaintiff is barred from recovering costs under 35 U.S.C. § 288.

TWELFTH DEFENSE

85. Defendants reserve the right to supplement or modify the defenses asserted herein.

COUNTERCLAIMS

For their counterclaims against the University of British Columbia ("UBC" or "Plaintiff"), Caption Health, Inc. ("Caption Health") and GE HealthCare Technologies, Inc. ("GE HealthCare") (collectively "Defendants") state as follows:

1. These Counterclaims for declaratory judgment are asserted against UBC by Caption Health and GE HealthCare, and arise under 28 U.S.C. §§ 2201, 2202, and 1338(a). There is an immediate, substantial, and justiciable controversy between the parties concerning infringement of United States Patent No. 11,129,591 ("the '591 patent" or "Patent-in-Suit"), a copy of which is attached as Exhibit A.

2. This Court has subject matter jurisdiction under 28 U.S.C. §§ 1331 and 1338.

3. This Court has personal jurisdiction over UBC because, among other actions, UBC has purposefully availed itself of the laws of this forum by virtue of having initiated the above-captioned lawsuit in this Court.

4. GE HealthCare is a corporation organized and existing under the laws of Delaware with its principal place of business at 500 West Monroe Street, Chicago, IL 60661.

5. Caption Health is a corporation organized and existing under the laws of Delaware with its principal place of business at 500 West Monroe Street, Chicago, IL 60661.

6. GE HealthCare acquired Caption Health in February 2023.

7. UBC alleges that it is a corporation continued under the University Act of British Columbia, with offices at 6328 Memorial Road, Room 240 Vancouver, B.C., Canada V6T 1Z2.

8. On September 28, 2021, the United States Patent and Trademark Office ("USPTO") issued the '591 patent, identifying UBC as the assignee of record.

9. UBC claims to be the owner of all rights, title, and interest in and to the '591 patent.

10. On May 28, 2024, UBC filed its Complaint against Caption Health and GE HealthCare alleging infringement of the '591 patent based on Defendants' sales of the "Venue Family" products and Vscan Air SL products that incorporate Caption Guidance or Caption AI (the "Accused Products"). UBC's Complaint, Dkt. 1 at ¶ 55.

11. UBC's claim that the Accused Products infringe the '591 patent is based, in material part, on the incorrect assumption – which is pleaded "upon information and belief" – that Caption Health's U.S. Patent Publication No. 2021/0052253 ("the '253 application") "describes the functionality of Caption Guidance." UBC's Complaint, Dkt. 1 at ¶ 42. Indeed, while comparing the asserted claims to the Accused Products, UBC's Complaint cites the '253 application no fewer than 10 times as evidence of the features of the Accused Products. *See*, *e.g.*, *id.* at ¶ 44 ("The '253 application describes that Caption Guidance is ….").

12. Caption Health's '253 application is not a description of the Accused Products.

13. The '253 application describes many features and embodiments that are not found in the Accused Products.

FIRST COUNTERCLAIM: NONINFRINGEMENT OF U.S. PATENT NO. 11,129,591

14. Defendants incorporate by reference the allegations of paragraphs 1–13 above as if set forth in their entirety here.

15. Defendants have not infringed any claim of the '591 patent in any way, either directly, contributorily, or by inducement. None of the claims of the '591 patent read on (*i.e.*, cover) the Accused Products, either as sold or as used for their intended purpose by end users. Therefore, Defendants are entitled to a judicial declaration that they have not infringed any claim of the '591 patent.

16. To directly infringe a patent claim, Caption Health or GE HealthCare must make, use, sell, or offer to sell in the United States, or import into the United States, a device that meets or performs each and every element of the claim.

17. The '591 patent includes 20 total claims, three of which are independent claims: claims 1, 11, and 15.

18. As a matter of law, if Defendants do not infringe any of the independent claims of the '591 patent, then they cannot infringe any claim of the '591 patent, including any claim that depends from the independent claims.

19. Each independent claim of the '591 patent is directed to either a system or method that evaluates the quality of echocardiographic images using a plurality of neural networks, where each respective neural network is associated with a different image "view category" and defined by different quality assessment parameters. To paraphrase the claims, after an image that is to be evaluated is identified as pertaining to a particular view category, the image is input into the respective neural network associated with that view category, and the output of the neural network is a view category specific image quality assessment value. Thus, images associated with different view categories are input into, and evaluated by, different neural networks having different quality assessment parameters.

20. The Accused Products do not infringe any claim of the '591 patent *at least because* they do not: (i) use a plurality of view category specific neural networks; (ii) determine which of a plurality of view category specific neural networks is associated with the same view category as the image to be evaluated; (iii) input an image into one of a plurality of neural networks based on the view category associated with the image; or (iv) use any neural network having an output layer that outputs an image quality assessment value. Every echocardiographic image that is evaluated by the Accused Products – regardless of the image's view category – is [redacted]

21. The three independent claims of the '591 patent, claims 1, 11, and 15, correspond to original claims 1, 13, and 17 of the application for the '591 patent, respectively.

22. As filed, original claims 1, 13, and 17 of the application for the '591 patent were all rejected by the USPTO under 35 U.S.C. § 102(a)(1) as being anticipated by U.S. Patent Publication No. 2005/0251013 ("Krishnan").

23. In the applicant's response to the Patent Office's rejection, a copy of which is attached as Exhibit B, UBC substantially amended claims 1, 13, and 17 to distinguish over Krishnan such that every claim now includes common limitations that are pertinent here, including the use of multiple view category specific neural networks. For example, UBC amended every independent claim of the '591 patent application to recite: "wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values." Exhibit B, Office Action Response at 3, 7, 9 (emphasis added). Additionally, whereas the original claims recited the step of associating a first image with a first view category, UBC amended every independent claim to also require the computer-implemented steps of "determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category" and "in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters." *Id*. at 3, 7, 9–10 (emphasis added).

24. Along with the amendments to claims 1, 13, and 17 of the '591 patent application, UBC provided the following contemporaneous remarks that explain the scope of the claims as amended:

> [A]mended claim 1 recites at least one processor configured to determine first and second quality assessment values of respective first and second echocardiographic

images utilizing respective neural networks. Amended claim 17 recites a computer-implemented method for determining first and second quality assessment values of respective first and second echocardiographic images utilizing respective neural networks. The claims include determining that a set of assessment parameters is associated with a respective view category and, in response, inputting a corresponding echocardiographic image into a respective neural network to determine the respective quality assessment value of each image. Each neural network is defined by a respective set of assessment parameters associated with one of a plurality of predetermined view categories that may characterize an echocardiographic image . . . .

The first and second images are associated with respective first and second view categories of the plurality of predetermined view categories, and it is determined that respective first and second sets of assessment parameters are associated with those view categories. To obtain quality assessment values, the first and second images are input into neural networks defined by the first and second sets of assessment parameters, respectively. The output layer of each neural network is configured to output a corresponding quality assessment value. Accordingly, a view category specific quality assessment value is obtained for each image using a neural network defined by assessment parameters associated with a view category associated with that image.

. . .

Krishnan fails to teach or suggest determining quality assessment values for each of two images using two respective neural networks corresponding to the respective view category of each image. Accordingly, Krishnan cannot and does not teach the claimed use of a first neural network defined by a first set of assessment parameters to determine a quality assessment value for a first image, and use of a second neural network defined by a second set of assessment parameters to determine

a quality assessment value for a second image, wherein the assessment parameters defining each network are associated with a view category of the associated image.

Exhibit B, Office Action Response at 13–15 (emphasis added).

25. To summarize, as described by the patent applicant during prosecution of the '591 patent, the amended claims are directed to a system/process that, at the beginning of the process, associates a first image with a first view category. Then, from a plurality of available options, a neural network is located that has distinct assessment parameters for evaluating images in the first view category, and the first image is input to that neural network. The output of the neural network is a view category specific quality assessment of the image. Finally, the process is repeated for a second image that is associated with a different view category and that is evaluated by a different neural network.

26. Following the amendments to claims 1, 13, and 17 of the '591 patent application, and in view of UBC's contemporaneous explanatory remarks, the Patent Office allowed the '591 patent.

27. As amended, issued claim 1, which for the purpose of this counterclaim is representative of the remaining independent claims, recites in pertinent part:

. . . a processor configured to:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

. . .

receive signals representing a second at least one echocardiographic image; [and]

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

> . . .
>
> *wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine [a] first quality assessment value by:*
>
> > *determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and*
> >
> > *in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters* . . . .

Exhibit A, '591 patent at 34:9–35:3 (emphasis added).

28. With respect to the required computer-implemented step of "associat[ing] the first at least one echocardiographic image with a first view category," the specification of the '591 patent explains that "associating the at least one echocardiographic image with a particular view category may assist with subsequent quality assessment of the echocardiographic images" because "different analyses may be applied to a set of echocardiographic images, depending on which view category [the] set of echocardiographic images falls within." Exhibit A, '591 patent at 8:53–65 (emphasis added).

29. Thus, both as a matter of logic, and as described in the '591 patent, the step of associating an echocardiographic image with a view category is a prerequisite to the subsequent step of evaluating the quality of the image using one of a plurality of view category specific neural networks. Without making the claimed association, the claimed system and method cannot proceed because it would not know into which neural network the image should be input.

30. An implementation of this claimed process (*i.e.*, first associating an image with a view category, and then locating an appropriate neural network associated with the same view category) is described in the '591 patent with reference to Fig. 11 as follows:

> For example, in some embodiments, block 402 may direct the analyzer processor 100 to read [view category] "AP4" from the view category identifier field 302 of the view category record 300 associated with the echocardiographic image files received at block 202. Block 402 may direct the analyzer processor 100 to read the view category specific neural network records from the location 146 of the storage memory to find a view category specific neural network record that includes the same view category identifier of "AP4" and is therefore associated with the same view category. Accordingly, block 402 may direct the analyzer processor 100 to determine that the view category specific neural network record 340 includes the view category identifier of "AP4" and is therefore associated with the same view category that is associated with the at least one echocardiographic image received at block 202.

Exhibit A, '591 patent at 14:11–26 (emphasis added).

31. The Accused Products do not – as claimed in each independent claim of the '591 patent – associate an image with a view category before that image is evaluated using a neural network. For at least this reason, neither Defendants nor any end users of the Accused Products infringe any claim of the '591 Patent.

32. The Accused Products use [redacted], referred to as the Echo GPS Algorithm, to evaluate all echocardiographic images [redacted].

33. The Echo GPS Algorithm [redacted] receives image data [redacted], processes the image, and provides the output [redacted] – all without ever receiving information that [redacted].

34. Although the Accused Products allow a user to select a view category for which to receive feedback, this selection does not affect the processing or evaluation of the image received

by the [redacted]. All input echocardiographic images – [redacted] – are processed by the Echo GPS algorithm [redacted].

35. The Accused Products do not have [redacted] as required by each independent claim of the '591 patent. For at least this additional reason, neither Defendants nor any end users of the Accused Products infringe any claims of the '591 patent.

36. The Accused Products also do not perform the claimed step of "determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category." Because the Accused Products input all images into the [redacted], it is unnecessary to perform this claimed step. Unlike the claimed system, the Accused Products input an image into a [redacted] for evaluation without [redacted]. For at least this additional reason, neither Defendants, nor any end users of the Accused Products, infringe any claim of the '591 patent.

37. The Accused Products also do not perform the required step of: "in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters." Because the Accused Products do not perform the predicate step of "determining that a first set of assessment parameters [*i.e.*, neural network] . . . is associated with the first view category," the Accused Products also do not input an image into a neural network "in response to" such determination, as claimed. Instead, the Accused Products always input images that are to be evaluated into the [redacted]. For at least this additional reason, neither Defendants, nor any end users of the Accused Products, infringe any claim of the '591 patent.

38. The primary goal of the Echo GPS Algorithm that is utilized by the Accused Products is [redacted]

[redacted]. The Echo GPS Algorithm operates by [redacted]. After comparing the [redacted] to the [redacted], the output of the Echo GPS Algorithm, [redacted], is a [redacted] – not a "quality assessment value" as claimed.

39. As described in the specification of the '591 patent, the claimed "quality assessment value" is a characterization of image quality – specifically, suitability of the image for use in subsequent quantified measurement of anatomical features and/or diagnosis. *See*, *e.g.*, Exhibit A, '591 patent at 6:17–20 ("The quality assessment value may represent an assessment of suitability of the associated set of echocardiographic images for quantified clinical measurement of anatomical features."). For example, the specification explains:

> In various embodiments, … near real-time feedback to the operator may help the operator improve their skills and/or improve image quality for subsequently captured images. For example, in some embodiments, the operator may, in response to viewing a low quality assessment value on the display 15, adjust positioning of the transducer and/or adjust image capture parameters, such as, for example, depth, focus, gain, frequency, and/or another parameter which may affect image quality in the system 10. The operator may make such adjustments until a high quality assessment value is provided on the display 15, for example, at which point the operator may be confident that the echocardiographic images captured are suitable for subsequent quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart.

Id. at 5:30–45 (emphasis added).

40. By contrast, the [redacted] output by the Echo GPS Algorithm merely represents an [redacted]

[redacted] The closer the [redacted], the lower the [redacted] value will be. The [redacted] value is not a characterization of the quality of the input image.

41. The Echo GPS Algorithm [redacted]. Thus, for every image that is processed by the Echo GPS Algorithm, the output of the [redacted] will always be [redacted] values corresponding to [redacted].

42. The calculated [redacted] that are output from the Echo GPS Algorithm [redacted] are input into a [redacted]

43. [redacted] for user feedback. This conversion is necessary because the [redacted] on its own has no meaning to a user, and because the impact of small changes in the [redacted] varies from one view category to the next.

44. As previously explained, each independent claim of the '591 patent was amended to overcome the Krishnan prior art reference by requiring: "wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values." Exhibit B, Office Action Response at 3, 7, 9 (emphasis added).

45. The focus of the [redacted] (*i.e.*, the Echo GPS Algorithm) is to [redacted]

[redacted], not an image quality assessment value, as claimed. For at least this additional reason, neither Defendants, nor any end users of the Accused Products, infringe any claim of the '591 patent.

46. Defendants are entitled to a judicial declaration pursuant to 28 U.S.C. §§ 2201 *et seq.* that they have not infringed any claim of the '591 patent, either directly or by contributing to or inducing the infringement of another.

SECOND COUNTERCLAIM: INVALIDITY OF U.S. PATENT NO. 11,129,591

47. Defendants incorporate by reference the allegations of paragraphs 1–46 above as if set forth in their entirety here.

48. UBC alleges that "Defendants infringe *at least* claims 1 and 15 of the '591 patent." UBC's Complaint, Dkt. 1 at ¶ 55 (emphasis added).

49. There is an immediate, substantial, and justiciable controversy between the parties concerning infringement – and therefore validity – of the '591 patent.

50. One or more claims of the '591 patent, including at least claims 1 and 15, are invalid for failure to comply with one or more provisions of the patent laws and regulations of the United States including, without limitation, 35 U.S.C. §§ 101, 102, 103, 111, 112, 116 and 256.

51. As originally filed, the '591 patent application contained 35 claims, including independent claim 1, which corresponds to issued claim 1.

52. By preliminary amendment dated March 15, 2019, the patent applicant cancelled claims 25 to 35 of the '591 patent application and amended the dependencies of many of the remaining 24 claims prior to substantive examination (hereinafter "the examined claims"). In pertinent part, the applicant amended claim 6 of the examined claims to depended from claim 1, and amended claim 8 of the examined claims to depended from claim 6.

53. By Office Action dated May 5, 2021, the USPTO patent Examiner rejected every one of the examined claims of the '591 patent application under 35 U.S.C. § 102(a)(1) as being

anticipated by U.S. Patent Publication No. 2005/0251013 ("Krishnan"), a copy of which is attached as Exhibit C.

54. Although the patent applicant purportedly traversed the Examiner's rejections, the applicant did not offer any substantive arguments as to why Krishnan did not anticipate each and every element of independent claim 1 of the examined claims, as found by the Examiner. Exhibit B, Office Action Response at 12–13.

55. Instead, the applicant amended independent claim 1 to incorporate the limitations of claims 6 and 8 of the examined claims. *Id*. at 3, 12–13.

56. Claim 6 of the examined claims required, in pertinent part, that "each of the plurality of predetermined echocardiographic image view categories [recited in claim 1] is associated with a respective set of assessment parameters." Claim 8 of the examined claims required, in pertinent part, that "each of the sets of assessment parameters [recited in claim 6] is a set of neural network parameters that defines a neural network."

57. In contemporaneous remarks submitted with the amendment of claim 1, the patent applicant purported to distinguish the amended claims from Krishnan by arguing that:

> Krishnan fails to teach or suggest determining a quality assessment value of an image using a neural network defined by a set of assessment parameters associated with a view category associated with that image. At best, Krishnan suggests generally at para. [0020] that "the results of anatomy and/or view identification may be used for quality assessment." This is not the same as, and cannot reasonably be interpreted to be, the claimed neural network defined by a set of assessment parameters associated with a view category corresponding to the image.
>
> Furthermore, Krishnan fails to teach or suggest determining quality assessment values for each of two images using two respective neural networks corresponding to the respective view category of each image. Accordingly, Krishnan cannot and does not teach the claimed use of a first neural network defined by a first set of assessment parameters to determine a quality assessment value for a first

> image, and use of a second neural network defined by a second set of assessment parameters to determine a quality assessment value for a second image, wherein the assessment parameters defining each network are associated with a view category of the associated image.

Exhibit B, Office Action Response at 14–15 (emphasis added).

58. The patent applicant mischaracterized the full scope of the teachings of Krishnan such that the Examiner allowed the amended claims of the '591 patent application over Krishnan in error.

59. Whereas the patent applicant argued that "Krishnan fails to teach or suggest determining a quality assessment value of an image using a neural network defined by a set of assessment parameters associated with a view category associated with that image," Krishnan teaches just that – or at least enough to render that concept obvious to a person of ordinary skill in the art.

60. Krishnan describes multiple modules that can operate together or independently, such as in a sequence, including an automatic feature analysis module 102, an automatic anatomy identification module 103, an automatic view identification module 104, and an automatic quality assessment module 105. Exhibit C, Krishnan at [0016]–[0020], Fig. 1. The automatic view identification module can feed into the quality assessment module, and Krishnan expressly teaches that "the results of . . . view identification may be used for quality assessment. *Id*. at [0020], [0029] ("The results of . . . view identification can be used to perform automatic image quality assessment . . . .").

61. Krishnan also teaches different embodiments in which the various modules for determining views and quality can implement template-based methods (*id*. at [0022], [0041]) or classifier methods that use machine learning neural networks (*id*. at [0023], [0044]).

62. As described with respect to the template-based methods, the templates, including those "used to determine . . . the quality of the acquired image," can be view specific. *Id*. at [0044].

"For example, templates could be constructed for different cardiac views: apical four chamber, apical two chamber, etc." *Id*.

63. Similarly, with respect to the classifier methods, Krishnan teaches that "a bank of classifiers could be constructed to classify the images based on the features extracted." *Id*. at [0043] (emphasis added). "These classifiers would use the set of features as an input, and classify the image as belonging to a particular anatomy, view, or level of quality." *Id*.

64. The machine-learning based "classifiers" described in Krishnan can be of various types. Specifically, Krishnan explains:

> It is to be understood that the term "classifiers" as used herein generally refers to various types of classifier frameworks, such as hierarchical classifiers, ensemble classifiers, etc. In addition, a classifier design can include a multiplicity of classifiers that attempt to partition data into two groups and organized either organized hierarchically or run in parallel and then combined to find the best classification. Further, a classifier can include ensemble classifiers wherein a large number of classifiers (referred to as a "forest of classifiers") all attempting to perform the same classification task are learned, but trained with different data/variables/parameters, and then combined to produce a final classification label. The classification methods implemented may be "black boxes" that are unable to explain their prediction to a user (which is the case if classifiers are built using neural networks, example [sic]).

Id. at [0044] (emphasis added).

65. Importantly, Krishnan also teaches that templates and classifiers may be used separately or in combination. For example, Krishnan explains: "The system (100) further comprises a database (106) of previously diagnosed/labeled medical images, a template database (107) and a classification system (108), which can be used singularly, or in combination, by one or more of the various automated decision support modules (102–105) of the data processing system (101) to perform their respective functions." *Id.* at [0021].

66. A person of ordinary skill in the art – familiar with all of the teachings in Krishnan – would understand that Krishnan's teaching to use view specific templates for image quality assessment is equally applicable to Krishnan's teaching to use a "bank of classifiers" for image quality assessment – especially since Krishnan further teaches that templates and classifiers may be used in combination. Therefore, Krishnan teaches or renders obvious the concept of using view category specific neural networks to perform image quality assessment.

67. The Examiner of the '591 patent application failed to appreciate the full scope of Krishnan's teachings and erroneously allowed at least the broadest claims of the '591 patent, including independent claims 1 and 15, over Krishnan.

68. Krishnan anticipates at least asserted claim 1 of the '591 patent under at least 35 U.S.C. § 102(a)(1) and/or renders claim 1 obvious under 35 U.S.C. § 103.

69. In addition, Krishnan in combination with at least U.S. Patent Publication No. 2016/247034 ("Lee"), a copy of which is attached as Exhibit D, renders one or more claims of the '591 patent invalid as obvious under 35 U.S.C. § 103.

70. Lee, which was filed on February 22, 2016, and published on August 15, 2016, is prior art to the '591 patent under at least 35 U.S.C. § 102(a)(2).

71. Lee was not cited during prosecution of the '591 patent and was not considered by the Examiner before allowing the '591 patent to issue over Krishnan.

72. Whereas the patent applicant argued that Krishnan does not teach respective quality assessment parameters corresponding to respective view categories, Lee supplies that teaching, including for devices like Krishnan.

73. For example, Lee discloses: "an electronic device . . . , including: a memory that stores a plurality of images and a plurality of classifiers; and a processor that is electrically connected with the memory, wherein the processor is configured to: analyze a category of an image of which an image quality evaluation is requested, and determine a classifier corresponding to the category of the image from among the plurality of classifiers; determine image quality factor scores of the

image; and evaluate the image quality of the image based on the determined image quality factor scores and the determined classifier." Exhibit D at [0009].

74. Additionally, Lee discloses that "the electronic device may include at least one of various medical devices (e.g., . . . a Magnetic Resonance Angiography (MRA), a Magnetic Resonance Imaging (MRI), a Computed Tomography (CT) machine, and an ultrasonic machine)." *Id*. at [0038] (emphasis added).

75. With reference to Figure 6 of the Lee reference, which is reproduced below, Lee teaches: "In operation 603, the controller 480 may be configured to classify an image scene category of the obtained image. For example, the controller 480 (e.g., the category classifying module 520) may be configured to analyze an image scene that the obtained image corresponds to, for example, mountain, ocean, sky, beach, streets, night view, or the like, and may be configured to classify the category of the image based on a result of the analysis." *Id*. at [0176]. Additionally, Lee teaches: "In operation 605, the controller 480 may be configured to determine a classifier corresponding to the classified image scene category. For example, the controller 480 (e.g., the classifier selecting module 530) may be configured to select a classifier corresponding to the image scene category from among various image quality classifiers stored in advance in the memory 450. For example, the controller 480 may be configured to select an image quality classifier corresponding to a night view image when the image scene category of the image is night view, and may select an image quality classifier corresponding to a sky image when the image scene category of the image is sky (cloud)." *Id*. at [0177].

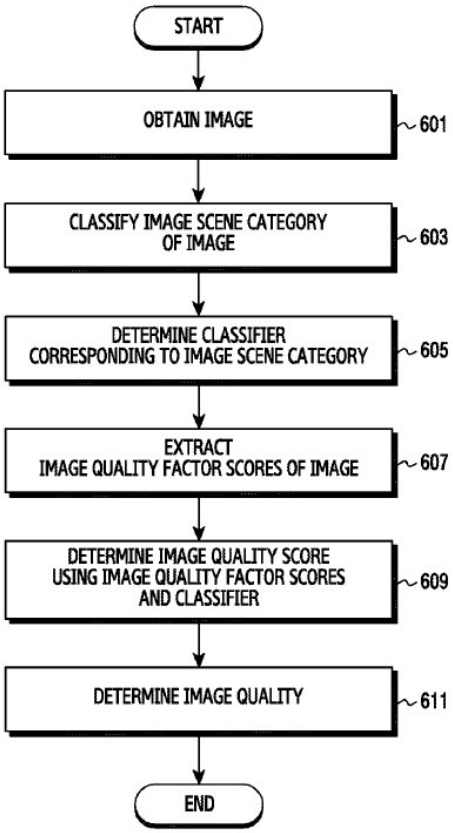


FIG.6

76. Given that Krishnan teaches the use of neural network "classifiers" to assess the quality of echocardiographic images, it would have been obvious to a person of ordinary skill in the art to also use view category specific "classifiers" with view category specific assessment parameters as taught by Lee. This is especially true since Krishnan already teaches the use of view category specific templates for the assessment of image quality.

77. When combined, Krishnan in view of the teachings in Lee, meets each and every limitation of at least asserted claim 1 of the '591 patent, thus rendering the claim obvious.

78. For at least the reasons stated above, Defendants are entitled to a judicial declaration, pursuant to 28 U.S.C. §§ 2201 *et seq.*, that one or more claims of the '591 patent are invalid under 35 U.S.C. §§ 102 and/or 103.

WHEREFORE, Defendants Caption Health and GE HealthCare pray that:

1) A judgment and order be issued in Defendants' favor and against UBC on all claims against Defendants;
2) Defendants be declared and adjudged not to have infringed any claim of U.S. Patent No. 11,129,591 directly, contributorily, or by inducement;
3) One or more claims of U.S. Patent No. 11,129,591, including at least the asserted claims, be declared invalid;
4) An order be issued dismissing UBC's Complaint in its entirety;
5) A decree be entered declaring this is an exceptional case under 35 U.S.C. § 285 in that UBC's pre-suit investigation was inadequate and UBC's allegation that U.S. Patent Publication No. 2021/0052253 describes the functionality of the Accused Products was improper and made without adequate basis;
6) Defendants be awarded their reasonable attorneys' fees, costs, and disbursements incurred in defense of this action; and
7) Defendants be awarded such other and further relief, including monetary damages, as this Court may deem just and proper.

JURY DEMAND

Pursuant to Federal Rule of Civil Procedure 38(b), Defendants request a trial by jury of all issues so triable.

THOMPSON HINE LLP

Dated: August 30, 2024

/s/ Marla R. Butler

Marla R. Butler, *pro hac* vice
marla.butler@thompsonhine.com
Two Alliance Center
3560 Lenox Road Suite 1600
Atlanta, Georgia 30326-4266
Telephone: (404) 407-3680

Jesse L. Jenike-Godshalk, *pro hac vice*
jesse.jenike-godshalk@thompsonhine.com
312 Walnut Street, Suite 2000
Cincinnati, OH 45202
Telephone: (513) 352-6702

Jeffrey C. Metzcar, *pro hac vice*
jeff.metzcar@thompsonhine.com
10050 Innovation Dr., #400
Miamisburg, OH 45342
Telephone: (937) 443-6841

Andrew Himebaugh, *pro hac vice*
andy.himebaugh@thompsonhine.com
20 N. Clark Street, Suite 3200
Chicago, IL 60602
Telephone: (312) 998-4247

Jennifer Seraphine (State Bar No. 245463)
seraphine@turnerboyd.com
Vyson Hsu (State Bar No. 322336)
hsu@turnerboyd.com
TURNER BOYD SERAPHINE LLP
155 Bovet Road, Suite 750
San Mateo, CA 94402
Telephone: (650) 521-5930

Attorneys for Defendants/Counterclaim-Plaintiffs Caption Health, Inc. & GE HealthCare Technologies Inc.

EXHIBIT A

US011129591B2

(12) **United States Patent**
Abolmaesumi et al.

(10) **Patent No.: US 11,129,591 B2**
(45) **Date of Patent: Sep. 28, 2021**

(54) **ECHOCARDIOGRAPHIC IMAGE ANALYSIS**

(71) Applicant: **THE UNIVERSITY OF BRITISH COLUMBIA**, Vancouver (CA)

(72) Inventors: **Purang Abolmaesumi**, Vancouver (CA); **Robert Rohling**, Vancouver (CA); **Amir H. Abdi**, Vancouver (CA); **Teresa S. M. Tsang**, Vancouver (CA)

(73) Assignee: **The University of British Columbia**, Vancouver (CA)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 500 days.

(21) Appl. No.: **16/095,601**

(22) PCT Filed: **Apr. 21, 2017**

(86) PCT No.: **PCT/CA2017/050496**
§ 371 (c)(1),
(2) Date: **Oct. 22, 2018**

(87) PCT Pub. No.: **WO2017/181288**
PCT Pub. Date: **Oct. 26, 2017**

(65) **Prior Publication Data**

US 2019/0125298 A1 May 2, 2019

Related U.S. Application Data

(60) Provisional application No. 62/325,779, filed on Apr. 21, 2016.

(51) **Int. Cl.**
G06K 9/00 (2006.01)
A61B 8/08 (2006.01)
(Continued)

(52) **U.S. Cl.**
CPC ***A61B 8/0883*** (2013.01); ***A61B 8/4405*** (2013.01); ***A61B 8/463*** (2013.01);
(Continued)

(58) **Field of Classification Search**
CPC A61B 8/0883; A61B 8/463; A61B 8/4405; A61B 8/5215; G06N 3/04; G06N 3/08;
(Continued)

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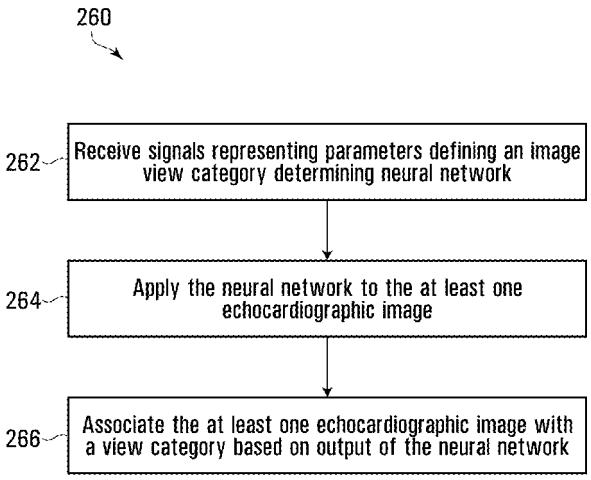
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Primary Examiner — Nan D Huynh
(74) *Attorney, Agent, or Firm* — Kolitch Romano LLP

(57) **ABSTRACT**

A computer-implemented system for facilitating echocardiographic image analysis is disclosed. The system includes at least one processor configured to receive signals representing a first at least one echocardiographic image, associate the image with a first view category of a plurality of predetermined view categories, determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, and produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image. The at least one processor may
(Continued)



also be configured to do the above steps for a second at least one echocardiographic and a second view category that is different from the first view category image. Other systems, methods, and computer-readable media are also disclosed.

20 Claims, 20 Drawing Sheets

(51) **Int. Cl.**

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G06T 7/00	(2017.01)
G06N 3/04	(2006.01)
G06N 3/08	(2006.01)

(52) **U.S. Cl.**
CPC ***G06N 3/04*** (2013.01); ***G06N 3/08*** (2013.01); ***G06T 7/0012*** (2013.01); *G06N 3/082* (2013.01); *G06T 2207/10132* (2013.01); *G06T 2207/20081* (2013.01); *G06T 2207/20084* (2013.01); *G06T 2207/30048* (2013.01); *G06T 2207/30168* (2013.01)

(58) **Field of Classification Search**
CPC G06N 3/082; G06T 7/0012; G06T 2207/10132; G06T 2207/20081; G06T 2207/20084; G06T 2207/30048; G06T 2207/30168; G16H 50/20
USPC 382/128
See application file for complete search history.

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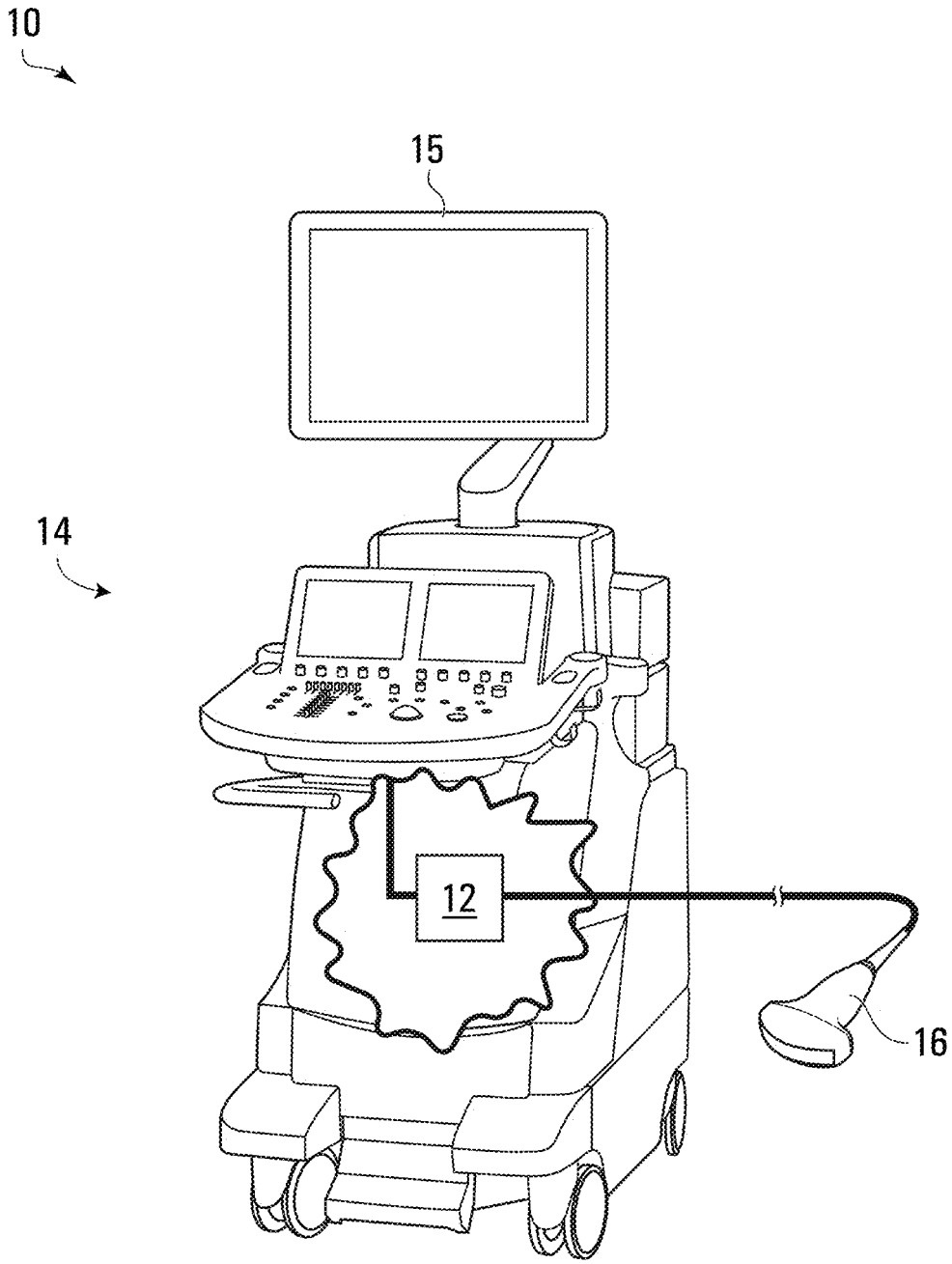


FIG. 1

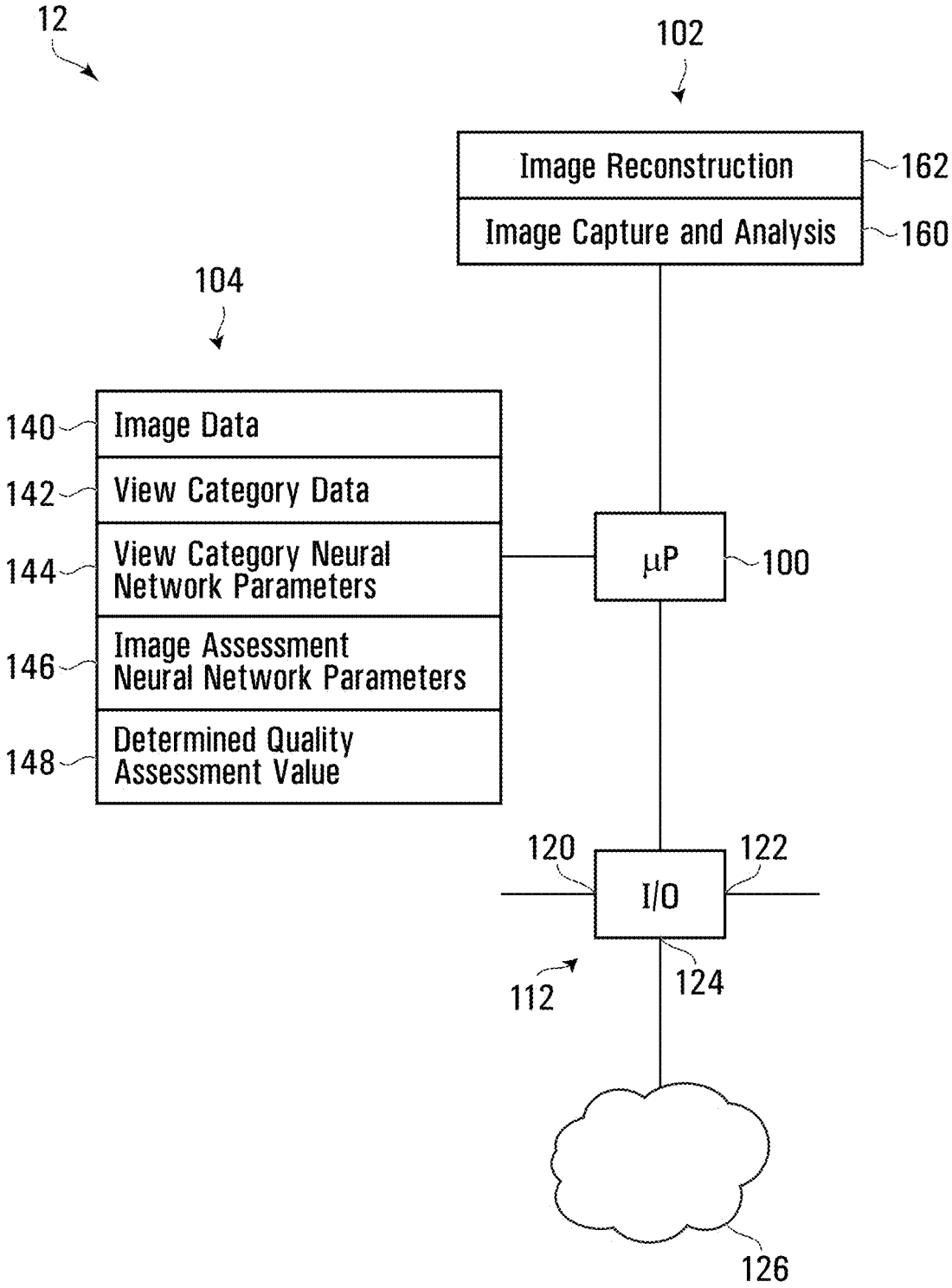

12
102
Image Reconstruction
162
Image Capture and Analysis
160
104
140
Image Data
142
View Category Data
144
View Category Neural Network Parameters
146
Image Assessment Neural Network Parameters
148
Determined Quality Assessment Value
μP
100
120
122
I/O
112
124
126

FIG. 2

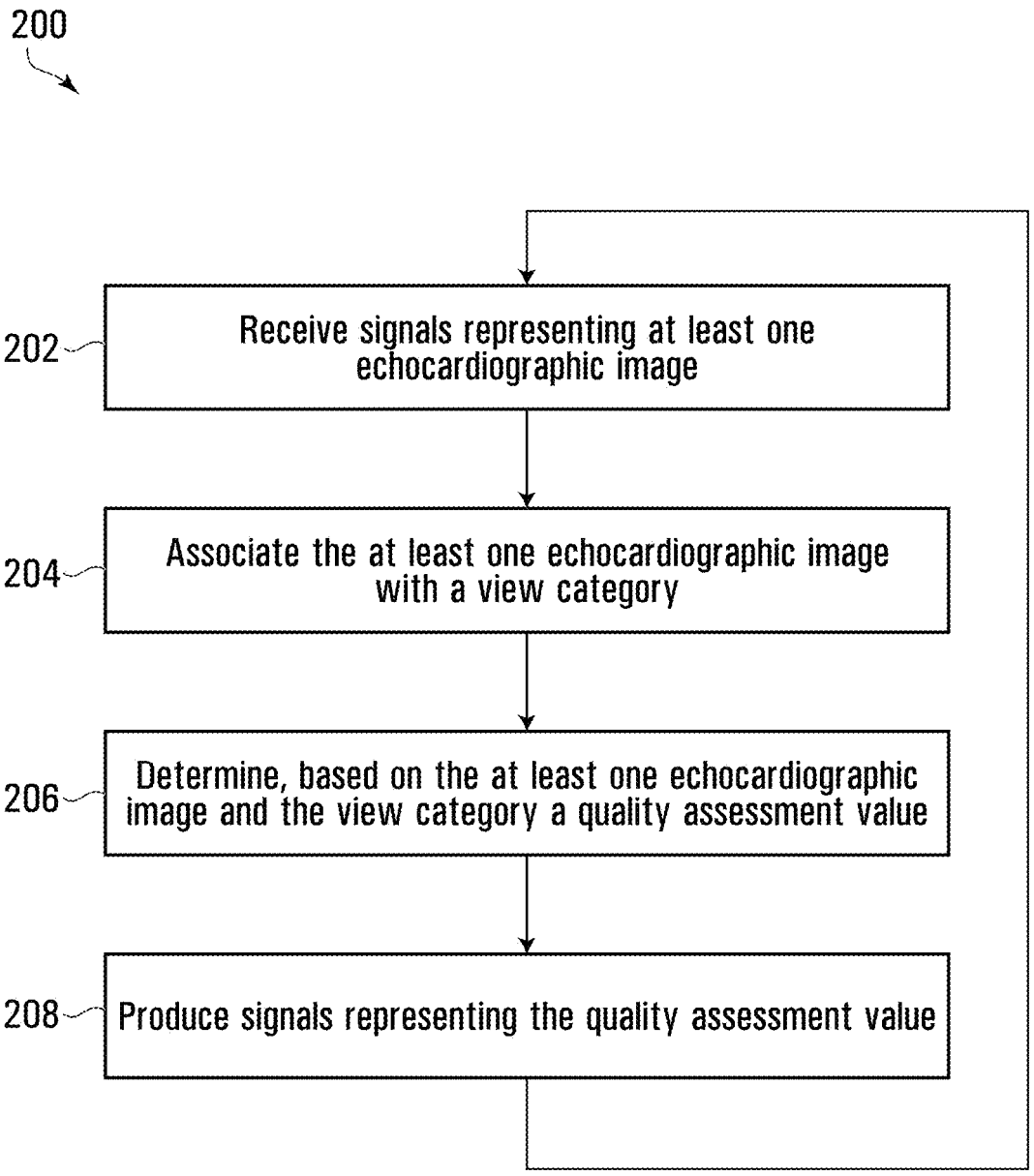

200
202
Receive signals representing at least one echocardiographic image
204
Associate the at least one echocardiographic image with a view category
206
Determine, based on the at least one echocardiographic image and the view category a quality assessment value
208
Produce signals representing the quality assessment value

FIG. 3

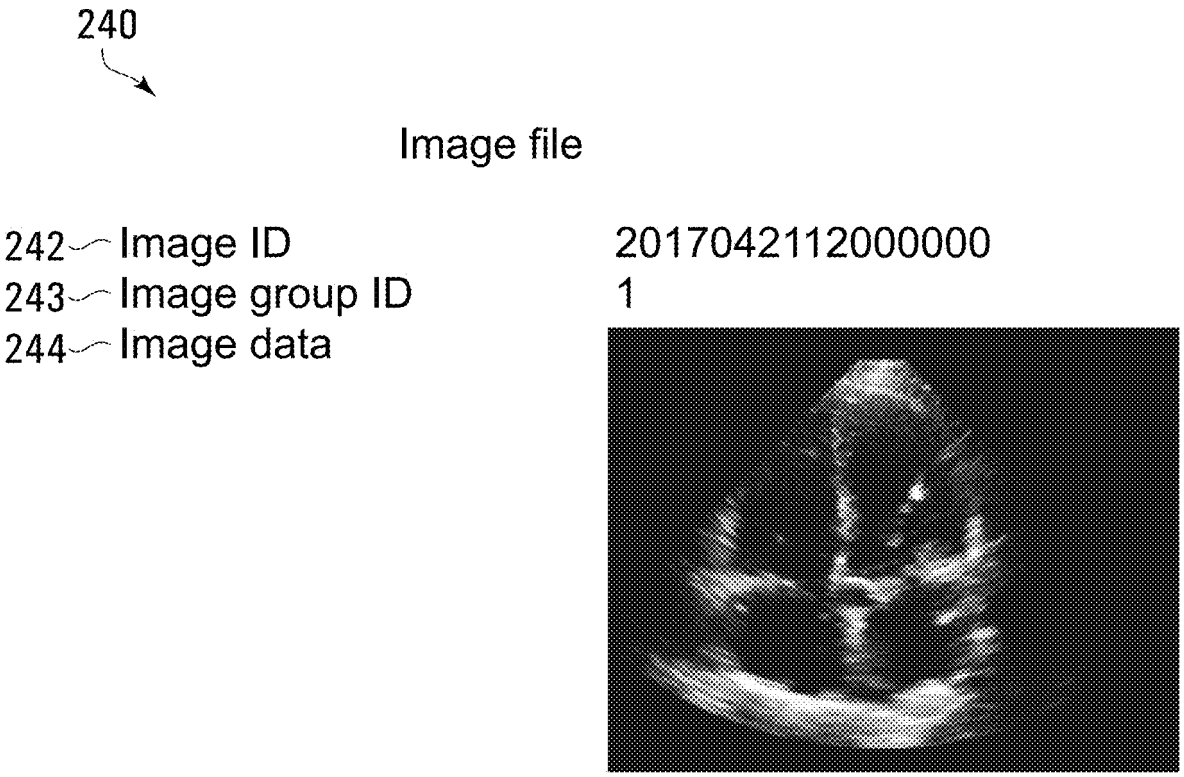

240
Image file
242 Image ID
243 Image group ID
244 Image data
20170421120000000
1

FIG. 4

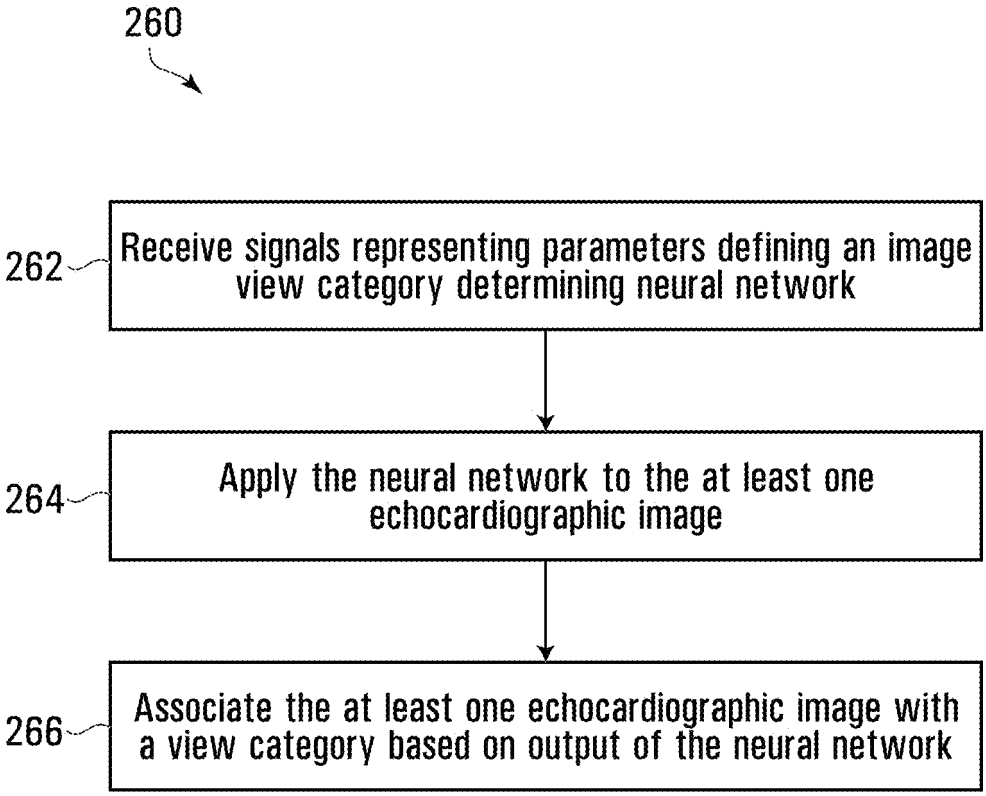

260
262
Receive signals representing parameters defining an image view category determining neural network
264
Apply the neural network to the at least one echocardiographic image
266
Associate the at least one echocardiographic image with a view category based on output of the neural network

FIG. 5

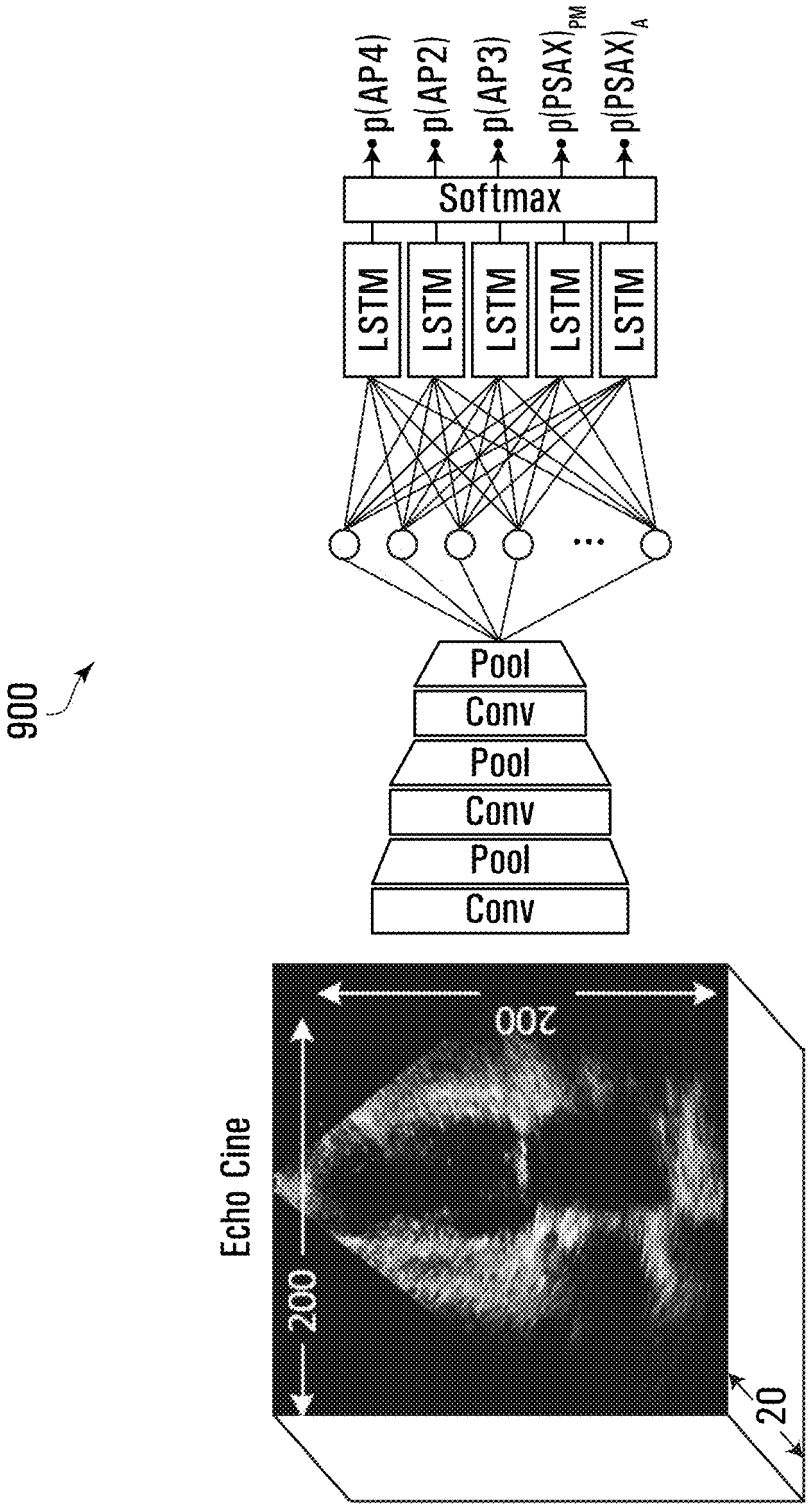

900
p(AP4)
p(AP2)
p(AP3)
p(PSAX)PM
p(PSAX)A
Softmax
LSTM
LSTM
LSTM
LSTM
LSTM
...
Pool
Conv
Pool
Conv
Pool
Conv
Echo Cine
200
200
20

FIG. 6

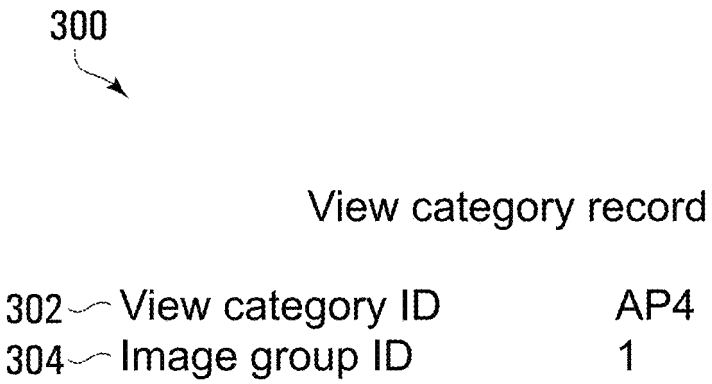

300
View category record
302 View category ID AP4
304 Image group ID 1

FIG. 7

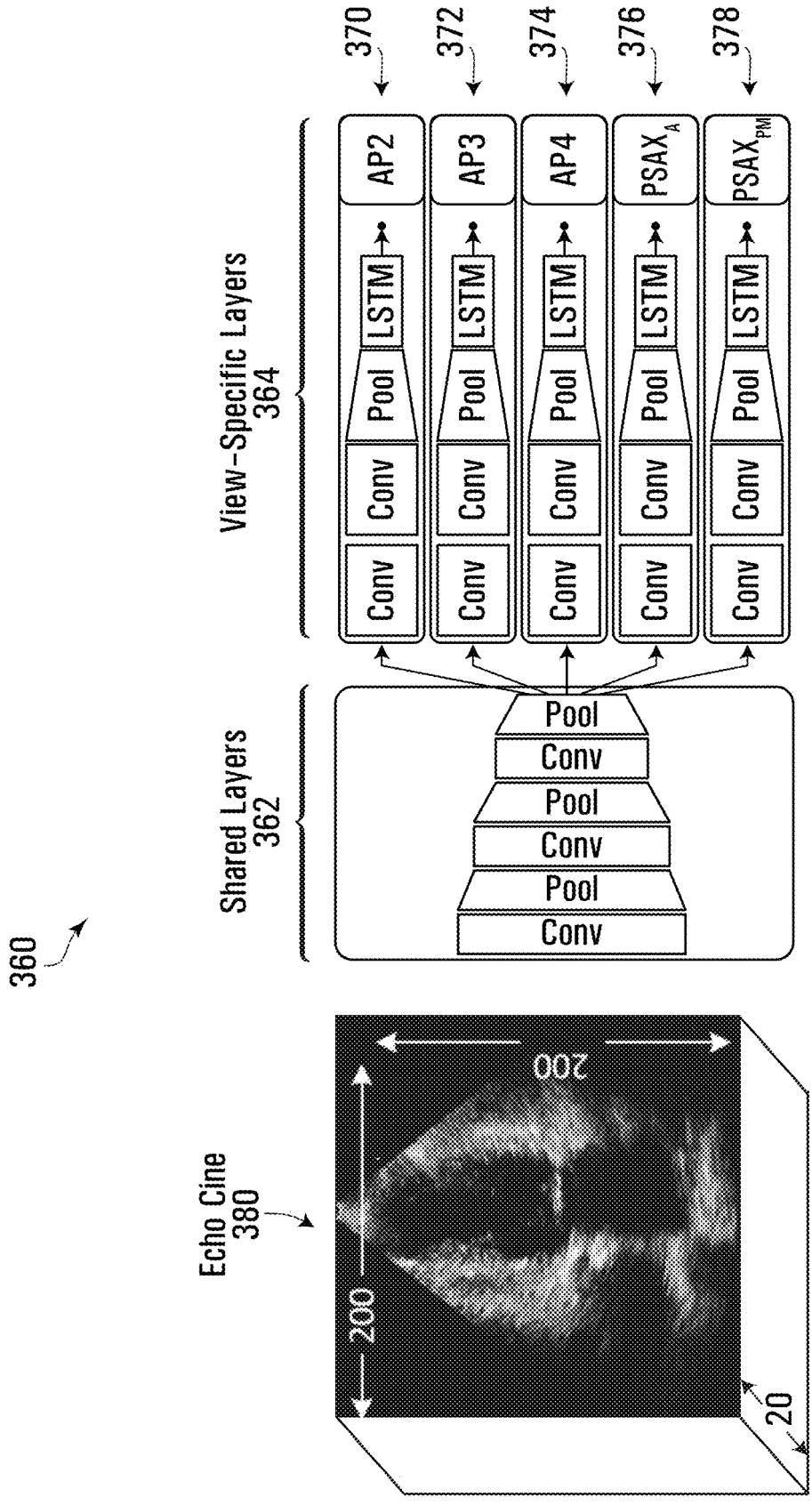

360
Shared Layers
362
Pool
Conv
Pool
Conv
Pool
Conv
View-Specific Layers
364
Conv
Conv
Pool
LSTM
AP2
370
AP3
372
AP4
374
PSAX$_A$
376
PSAX$_{PM}$
378
Echo Cine
380
200
200
20

FIG. 8



Common neural network record

324	Layer number	1
	Layer type	Convolutional
	Stride	1
	Kernel 1	[...]
	...	
	Kernel 8	[...]
326	Layer number	2
	Layer type	Max pool
	Stride	2
	Kernel size	2x2
328	Layer number	3
	Layer type	Convolutional
	Stride	1
	Kernel 1	[...]
	...	
	Kernel 16	[...]
330	Layer number	4
	Layer type	Max pool
	Stride	2
	Kernel size	2x2
332	Layer number	5
	Layer type	Convolutional
	Stride	1
	Kernel 1	[...]
	...	
	Kernel 32	[...]
334	Layer number	6
	Layer type	Max pool
	Stride	2
	Kernel size	2x2

FIG. 9

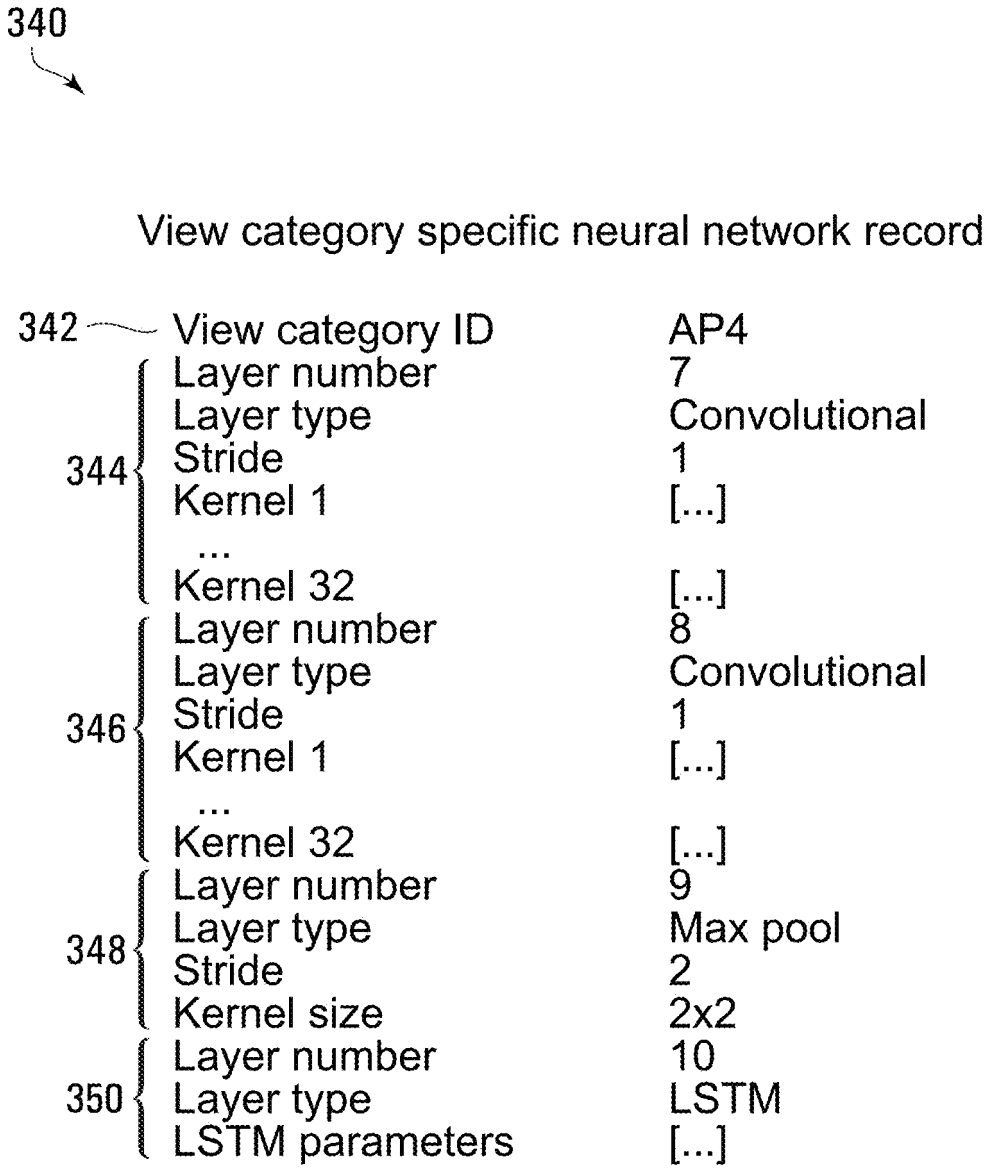

340
View category specific neural network record
342
View category ID
AP4
344
Layer number
7
Layer type
Convolutional
Stride
1
Kernel 1
[...]
...
Kernel 32
[...]
346
Layer number
8
Layer type
Convolutional
Stride
1
Kernel 1
[...]
...
Kernel 32
[...]
348
Layer number
9
Layer type
Max pool
Stride
2
Kernel size
2x2
350
Layer number
10
Layer type
LSTM
LSTM parameters
[...]

FIG. 10

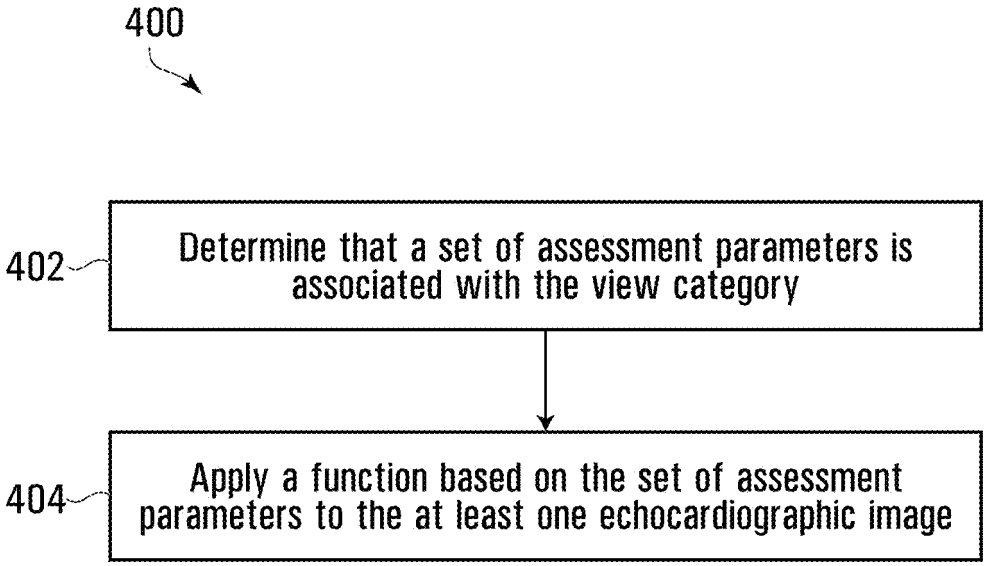

400
402
Determine that a set of assessment parameters is associated with the view category
404
Apply a function based on the set of assessment parameters to the at least one echocardiographic image

FIG. 11

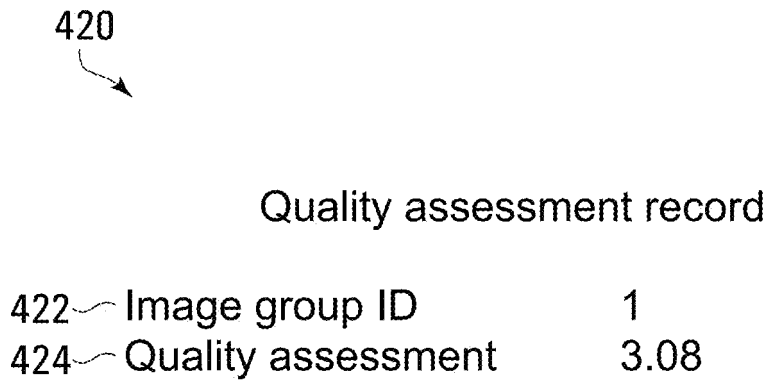

420
Quality assessment record
422 Image group ID 1
424 Quality assessment 3.08

FIG. 12

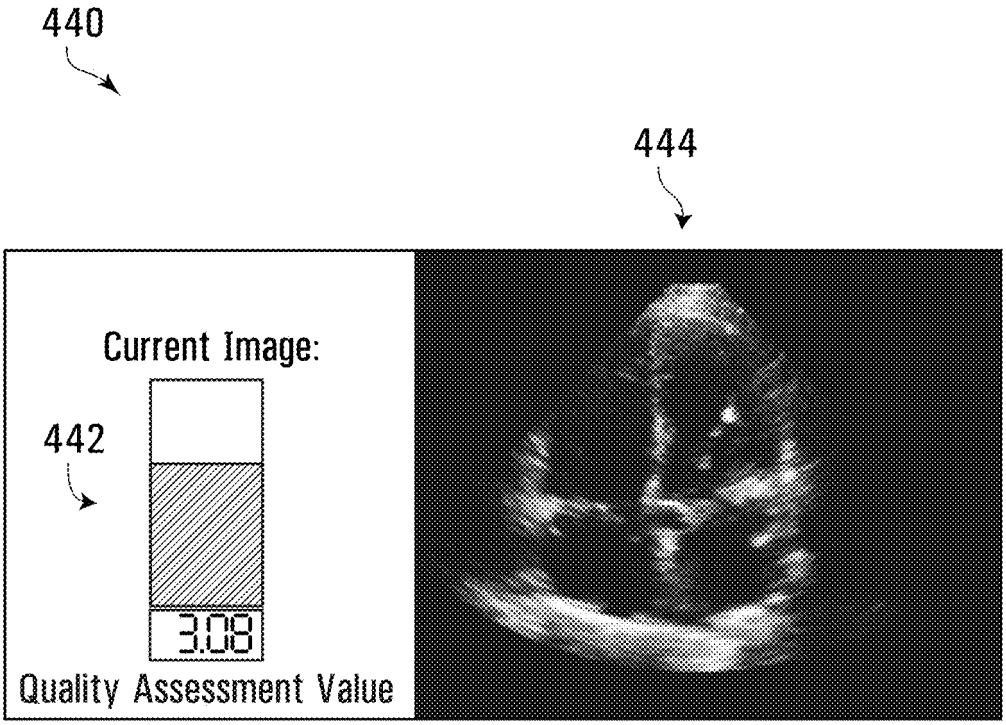


FIG. 13

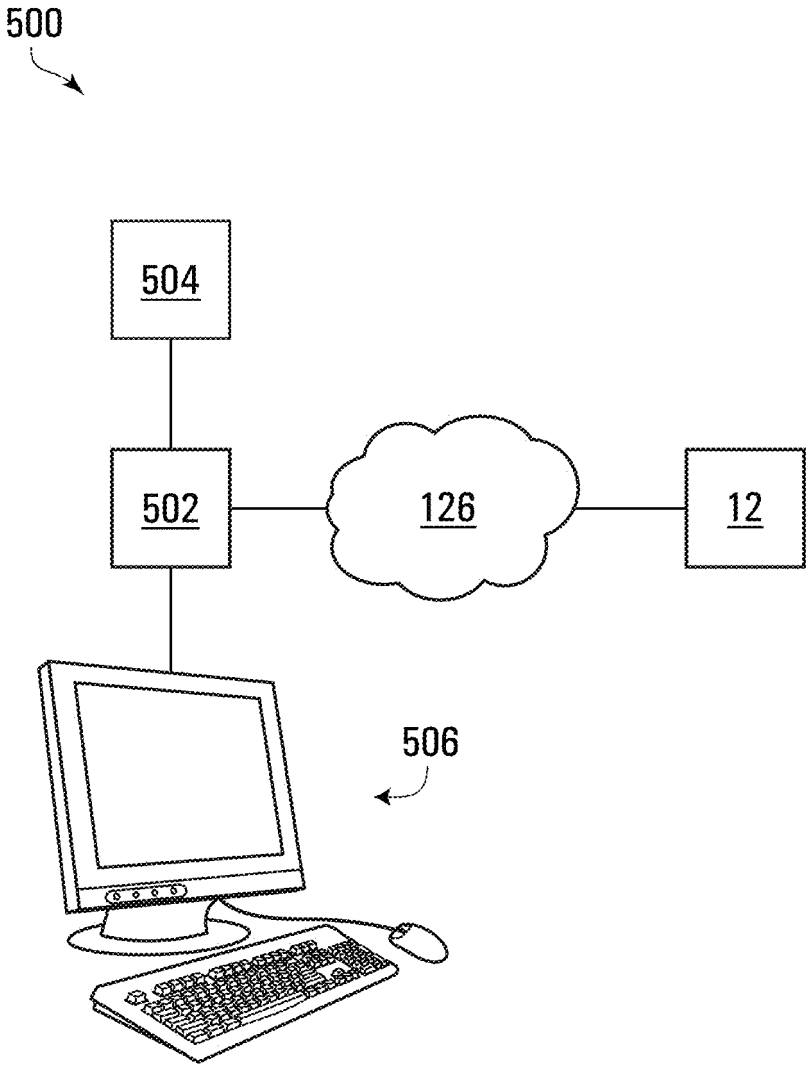


FIG. 14

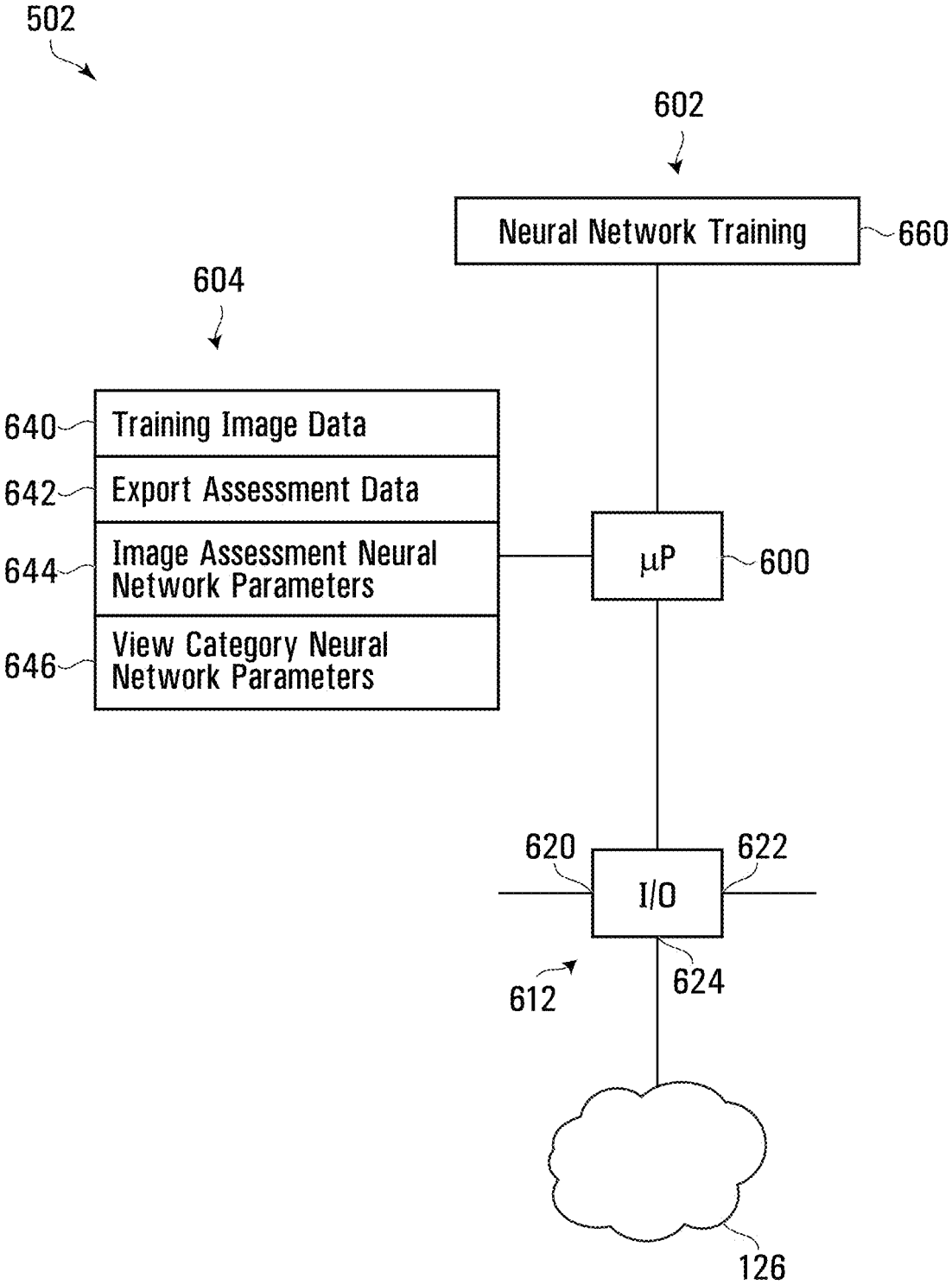

502
602
Neural Network Training
660
604
640
Training Image Data
642
Export Assessment Data
644
Image Assessment Neural Network Parameters
646
View Category Neural Network Parameters
μP
600
620
622
I/O
612
624
126

FIG. 15

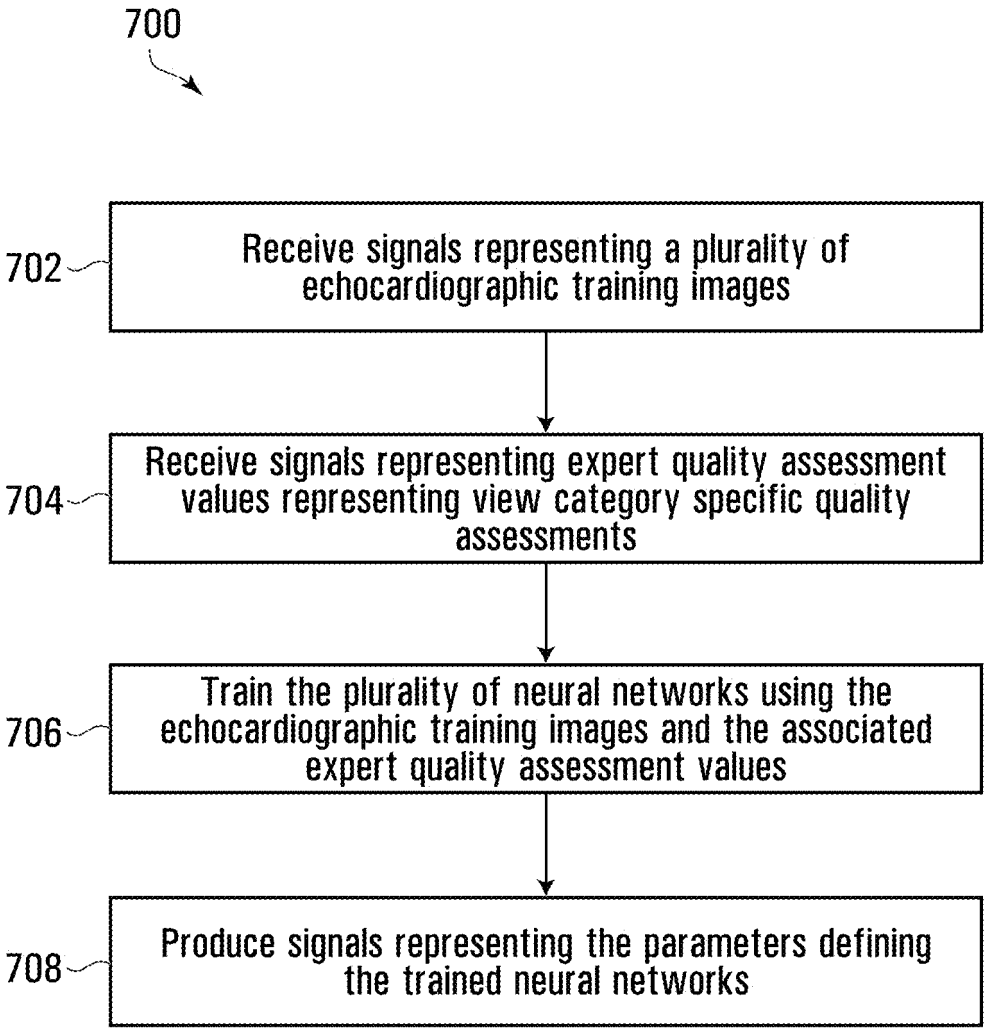

700
702
Receive signals representing a plurality of echocardiographic training images
704
Receive signals representing expert quality assessment values representing view category specific quality assessments
706
Train the plurality of neural networks using the echocardiographic training images and the associated expert quality assessment values
708
Produce signals representing the parameters defining the trained neural networks

FIG. 16

740

Training image file

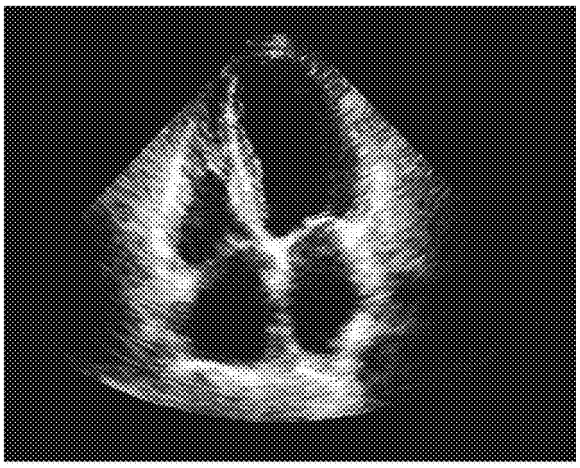
742	Image ID	20150820181200000
744	Image group ID	1
746	View category ID	AP4
748	Image data	

FIG. 17

780

Expert quality assessment record

782	Image group ID	1
784	Expert quality assessment	4

FIG. 18

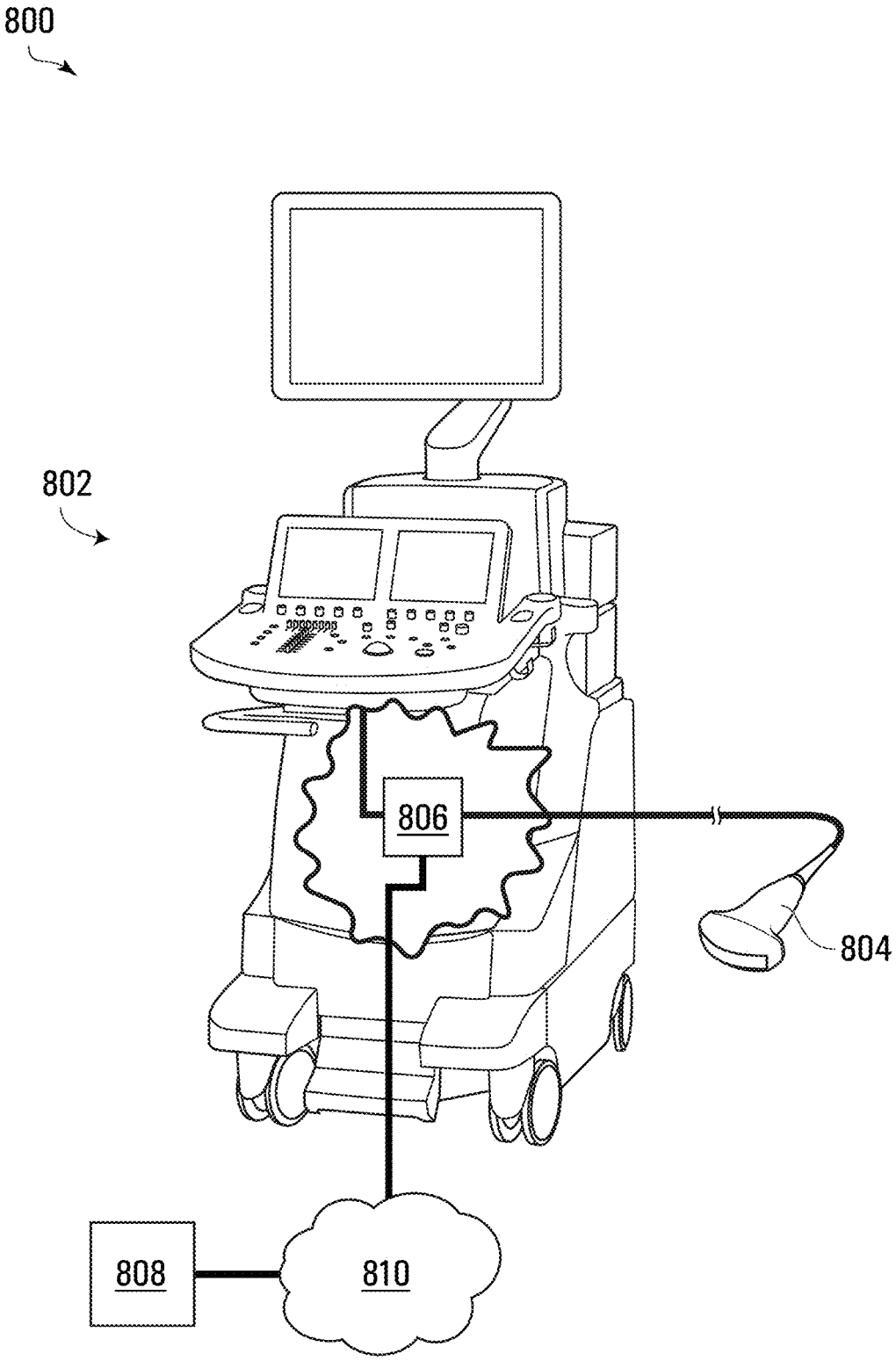


FIG. 19

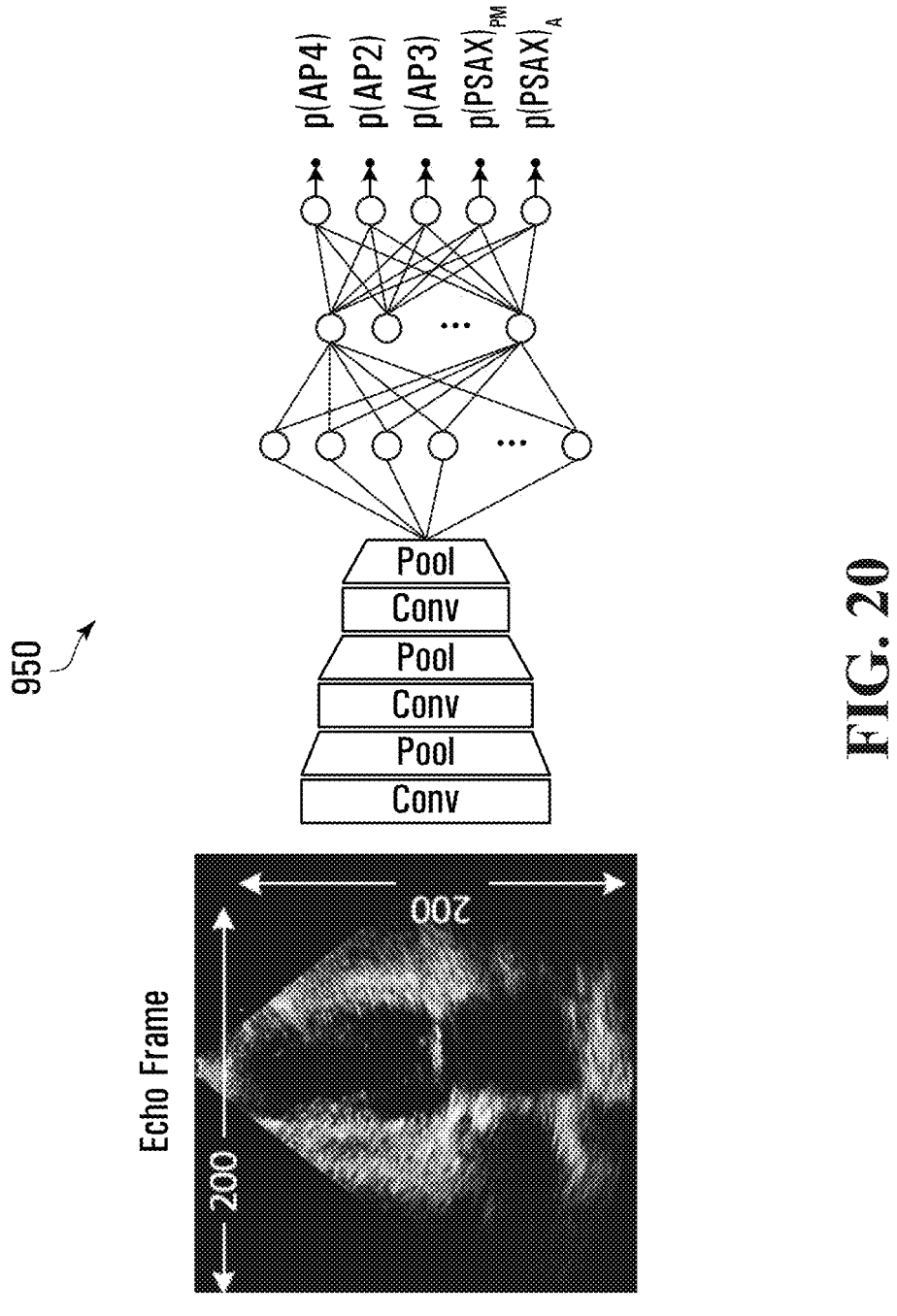

950
Echo Frame
200
200
Pool
Conv
Pool
Conv
Pool
Conv
p(AP4)
p(AP2)
p(AP3)
p(PSAX)PM
p(PSAX)A

FIG. 20

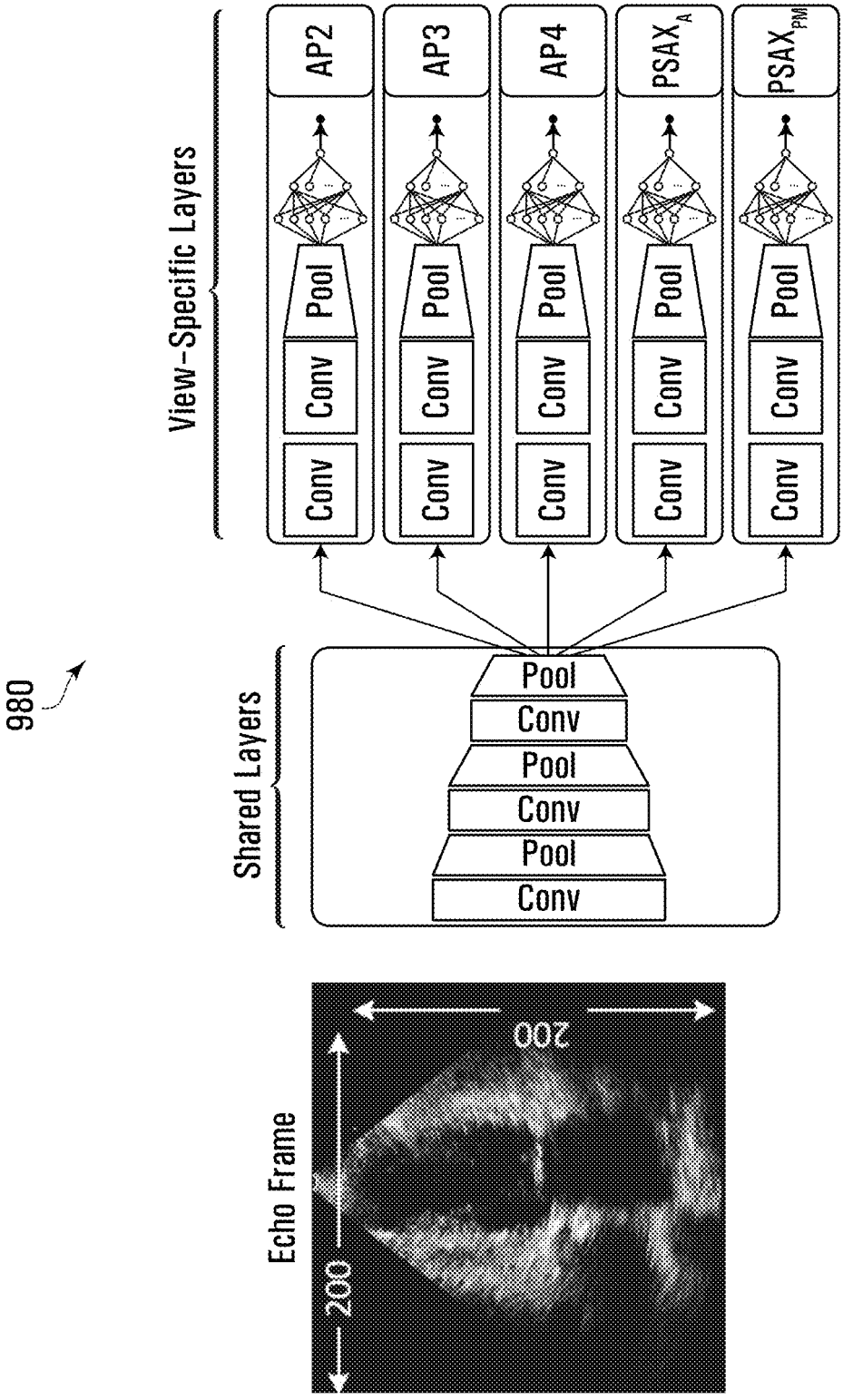

980
Shared Layers
Pool
Conv
Pool
Conv
Pool
Conv
View-Specific Layers
AP2
AP3
AP4
PSAX$_A$
PSAX$_{PM}$
Pool
Conv
Conv
Echo Frame
200
200

FIG. 21

ECHOCARDIOGRAPHIC IMAGE ANALYSIS

RELATED APPLICATION

This application claims the benefit of U.S. Provisional Application No. 62/325,779 entitled "PROCESS FOR IMAGING QUALITY ASSURANCE", filed on Apr. 21, 2016, which is hereby incorporated by reference herein in its entirety.

BACKGROUND

1. Field

Embodiments of this invention relate to echocardiographic image analysis and more particularly to echocardiographic image analysis for image quality assessment.

2. Description of Related Art

Despite advances in medicine and technology, cardiovascular disease remains the leading cause of mortality worldwide. Cardiac ultrasound, better known as echocardiography (echo), is the standard method for screening, detection, and monitoring of cardiovascular disease. This noninvasive imaging modality is widely available, cost-effective, and may be used for clinical measurement of anatomical features which may then be used for evaluation of cardiac structure and/or function. Some existing echocardiographic systems may be configured to provide feedback regarding general properties of captured images. However, this feedback may not assist echocardiographers in capturing high quality echocardiographic images for use in subsequent quantified clinical measurement of anatomical features.

SUMMARY

In accordance with one embodiment, there is provided a computer-implemented system for facilitating echocardiographic image analysis. The system includes at least one processor configured to, receive signals representing a first at least one echocardiographic image, associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories, determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image, receive signals representing a second at least one echocardiographic image, associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category, determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image, and produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

In accordance with another embodiment, there is provided a computer-implemented system for training neural networks to facilitate echocardiographic image analysis. The system includes at least one processor configured to: receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories, receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images, and train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

In accordance with another embodiment, there is provided a computer-implemented method of facilitating echocardiographic image analysis. The method includes receiving signals representing a first at least one echocardiographic image, associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories, determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image, receiving signals representing a second at least one echocardiographic image, associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category, determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image, and producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

In accordance with another embodiment, there is provided a computer-implemented method of training neural networks to facilitate echocardiographic image analysis. The method includes receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories, receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images, and training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

In accordance with another embodiment, there is provided a computer readable medium having stored thereon codes

which when executed by at least one processor cause the at least one processor to perform any of the above methods.

In accordance with another embodiment, there is provided a system for facilitating echocardiographic image analysis. The system includes means for receiving signals representing a first at least one echocardiographic image, means for associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories, means for determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image, means for producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image, means for receiving signals representing a second at least one echocardiographic image, means for associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category, means for determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image, and means for producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

In accordance with another embodiment, there is provided a system for training neural networks to facilitate echocardiographic image analysis. The system includes means for receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories, means for receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images, and means for training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories. Other aspects and features of embodiments of the invention will become apparent to those ordinarily skilled in the art upon review of the following description of specific embodiments of the invention in conjunction with the accompanying figures.

BRIEF DESCRIPTION OF THE DRAWINGS

In drawings which illustrate embodiments of the invention,

FIG. **1** is a schematic view of a system for facilitating echocardiographic image analysis in accordance with various embodiments of the invention;

FIG. **2** is a schematic view of an echocardiographic image analyzer of the system of FIG. **1** including a processor circuit in accordance with various embodiments of the invention;

FIG. **3** is a flowchart depicting blocks of code for directing the analyzer of the system of FIG. **1** to perform image analysis functions in accordance with various embodiments of the invention;

FIG. **4** is a representation of an exemplary image file that may be used in the system shown in FIG. **1**;

FIG. **5** is a flowchart depicting blocks of code that may be included in the flowchart of FIG. **3** in accordance with various embodiments of the invention;

FIG. **6** is a representation of an exemplary view category determining neural network that may be used in the system shown in FIG. **1**;

FIG. **7** is a representation of an exemplary view category record that may be used in the system shown in FIG. **1**;

FIG. **8** is a representation of an exemplary image quality assessment neural network that may be used in the system shown in FIG. **1**;

FIG. **9** is a representation of an exemplary common neural network record that may be used in the system shown in FIG. **1**;

FIG. **10** is a representation of an exemplary view category specific neural network record that may be used in the system shown in FIG. **1**;

FIG. **11** is a flowchart depicting blocks of code that may be included in the flowchart of FIG. **3** in accordance with various embodiments of the invention;

FIG. **12** is a representation of an exemplary quality assessment record that may be used in the system shown in FIG. **1**;

FIG. **13** is a representation of a display that may be presented by a display of a user interface system included in the system shown in FIG. **1** in accordance with embodiments of the invention;

FIG. **14** is a schematic view of a system for training neural networks to facilitate echocardiographic image analysis in accordance with various embodiments of the invention;

FIG. **15** is a schematic view of a neural network trainer of the system of FIG. **1** including a processor circuit in accordance with various embodiments of the invention;

FIG. **16** is a flowchart depicting blocks of code for directing the trainer of the system of FIG. **14** to perform image assessment neural network training functions in accordance with various embodiments of the invention;

FIG. **17** is a representation of an exemplary training image file that may be used in the system shown in FIG. **1**;

FIG. **18** is a representation of an exemplary expert quality assessment record that may be used in the system shown in FIG. **1**;

FIG. **19** is a schematic view of a system for facilitating echocardiographic image analysis in accordance with various embodiments of the invention;

FIG. **20** is a representation of an exemplary view category determining neural network that may be used in the system shown in FIG. **1**; and

FIG. **21** is a representation of an exemplary image quality assessment neural network that may be used in the system shown in FIG. **1**.

DETAILED DESCRIPTION

Referring to FIG. **1**, according to one embodiment of the invention, there is provided a system **10** for facilitating echocardiographic image analysis. The system **10** includes a computer-implemented echocardiographic image analyzer **12** in communication with a user interface system **14** and a transducer **16**. In the embodiment shown, the analyzer **12** is also in communication with a network **126** and the user

interface system **14** includes a display **15**. In various embodiments, the system **10** may be incorporated within an ultrasound machine or scanner. For example, in various embodiments, the system **10** may be included in an ultrasound machine generally similar to a Philips™ IE33 Ultrasound machine or a mobile ultrasound machine made by Clarius™.

In operation, an operator of the system **10**, who may be for example, an echocardiographer, technician, or sonographer, may manipulate the transducer **16** on or around a patient, and the analyzer **12** may communicate with the transducer **16** and receive signals representing echocardiographic images of the patient. The analyzer **12** may store representations of the echocardiographic images in memory and/or output representations of the images on the display **15**. The analyzer **12** may determine a quality assessment value representing a quality assessment of at least one echocardiographic image and produce signals for causing the quality assessment value to be associated with the at least one echocardiographic image. For example, the analyzer **12** may be configured to produce signals for causing the display **15** to display a sequence of echocardiographic images captured by the analyzer **12** in near real-time, in association with the determined quality assessment value for the images. In some embodiments, the quality assessment value may be determined for a single image. In some embodiments, the quality assessment value may be determined for a sequence of images or video, which may be referred to herein as an echo cine.

In various embodiments, this near real-time feedback to the operator may help the operator improve their skills and/or improve image quality for subsequently captured images. For example, in some embodiments, the operator may, in response to viewing a low quality assessment value on the display **15**, adjust positioning of the transducer and/or adjust image capture parameters, such as, for example, depth, focus, gain, frequency, and/or another parameter which may affect image quality in the system **10**. The operator may make such adjustments until a high quality assessment value is provided on the display **15**, for example, at which point the operator may be confident that the echocardiographic images captured are suitable for subsequent quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart.

In various embodiments, the operator may wish to capture echocardiographic images for various views or anatomical planes since multiple views may be required in order to perform certain quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart. In some embodiments, the views required for certain measurements or diagnoses may be chosen from standard 2D echocardiographic views. For example, the operator may wish to capture echocardiographic images of multiple standard 2D echocardiographic views to facilitate image analysis to determine ejection fraction for the patient's heart. For example, in some embodiments, a 2D Method of Simpson may be used to determine ejection fraction, which requires images from AP2 (apical 2-chamber view) and AP4 (apical 4-chamber view).

In various embodiments, some of the desirable characteristics for each of the different views may differ and so it may be desirable to determine quality assessment values for the echocardiographic images in different ways, depending on what view the echocardiographic images are meant to represent. Accordingly, the analyzer **12** may be configured to associate each set of echocardiographic images with a view category of a plurality of predetermined echocardiographic image view categories and to select and apply a function to the set of images to determine the quality assessment value wherein the function selected depends on the view category associated with the set of images. In some embodiments, the analyzer **12** may be configured to automatically determine the view category to associate with the set of images by analyzing the set of images. In some embodiments, the analyzer **12** may be configured to receive operator input (via the user interface system **14**, for example), which sets the view category with which to associate the image.

Applying the function to a set of images may involve inputting the set of images into a view category specific image assessment neural network which is configured to output a view category specific quality assessment value. The quality assessment value may represent an assessment of suitability of the associated set of echocardiographic images for quantified clinical measurement of anatomical features.

Image Analyzer—Processor Circuit

Referring now to FIG. **2**, a schematic view of the analyzer **12** of the system **10** shown in FIG. **1** according to an embodiment is shown. As discussed above, in various embodiments, the analyzer **12** may be included in an ultrasound machine, for example.

Referring to FIG. **2**, the analyzer **12** includes a processor circuit including an analyzer processor **100** and a program memory **102**, a storage memory **104**, and an input/output (I/O) interface **112**, all of which are in communication with the analyzer processor **100**. In various embodiments, the analyzer processor **100** may include one or more processing units, such as for example, a central processing unit (CPU), a graphical processing unit (GPU), and/or a field programmable gate arrays (FPGA). In some embodiments, any or all of the functionality of the analyzer **12** described herein may be implemented using one or more FPGAs.

The I/O interface **112** includes an interface **120** for communicating with the transducer **16** and an interface **122** for communicating with the user interface system **14** shown in FIG. **1**. In some embodiments, the I/O interface **112** may also include an interface **124** for facilitating networked communication through the network **126**. In some embodiments, any or all of the interfaces **120**, **122**, or **124** may facilitate a wireless or wired communication.

In some embodiments, the I/O interface **112** may include a network interface device or card with an input/output for connecting to the network **126**, through which communications may be conducted with devices connected to the network **126**, such as the neural network trainer (as shown at **502** in FIG. **14**), for example.

In some embodiments, each of the interfaces shown in FIG. **2** may include one or more interfaces and/or some or all of the interfaces included in the I/O interface **112** may be implemented as combined interfaces or a single interface.

In some embodiments, where a device is described herein as receiving or sending information, it may be understood that the device receives signals representing the information via an interface of the device or produces signals representing the information and transmits the signals to the other device via an interface of the device.

Processor-executable program codes for directing the analyzer processor **100** to carry out various functions are stored in the program memory **102**. Referring to FIG. **2**, the program memory **102** includes a block of codes **160** for directing the analyzer **12** to perform image capture functions and analysis functions and a block of codes **162** for directing

the analyzer processor **100** to perform image reconstruction functions. In this specification, it may be stated that certain encoded entities such as applications or modules perform certain functions. Herein, when an application, module or encoded entity is described as taking an action, as part of, for example, a function or a method, it will be understood that at least one processor (e.g. the analyzer processor **100**) is directed to take the action by way of programmable codes or processor-executable codes or instructions defining or forming part of the application.

The storage memory **104** includes a plurality of storage locations including location **140** for storing image data, location **142** for storing view category data, location **144** for storing view category neural network parameter data, location **146** for storing image assessment neural network parameter data, and location **148** for storing determined quality assessment value data. In various embodiments, the plurality of storage locations may be stored in a database in the storage memory **104**.

In various embodiments, the blocks of codes **160** and **162** may be integrated into a single block of codes and/or each of the blocks of code **160** and **162** may include one or more blocks of code stored in one or more separate locations in program memory **102**. In various embodiments, any or all of the locations **140**, **142**, **144**, and **146** may be integrated and/or each may include one or more separate locations in the storage memory **104**.

Each of the program memory **102** and storage memory **104** may be implemented as one or more storage devices including random access memory (RAM), a hard disk drive (HDD), a solid-state drive (SSD), a network drive, flash memory, a memory stick or card, any other form of non-transitory computer-readable memory or storage medium, and/or a combination thereof. In some embodiments, the program memory **102**, the storage memory **104**, and/or any portion thereof may be included in a device separate from the analyzer **12** and in communication with the analyzer **12** via the I/O interface **112**, for example.

In various embodiments, other device components described herein, such as memory, program memory, blocks of code, storage memory, locations in memory, and/or I/O interfaces, may be implemented generally similarly to as described above for the analyzer **12**.

Image Analysis

Referring now to FIG. **3**, a flowchart depicting blocks of code for directing the analyzer processor **100** shown in FIG. **2** to perform image analysis functions in accordance with one embodiment is shown generally at **200**. The blocks of code included in the flowchart **200** may be encoded in the block of codes **160** of the program memory **102** shown in FIG. **2** for example.

Referring to FIG. **3**, the flowchart **200** begins with block **202** which directs the analyzer processor **100** shown in FIG. **2** to receive signals representing at least one echocardiographic image. In various embodiments, block **202** may direct the analyzer processor **100** to obtain image data via the transducer **16**. For example, block **202** may direct the analyzer processor **100** to execute blocks included in the block of codes **162** of the program memory **102**, to cause the analyzer processor **100** to receive signals representing at least one echocardiographic image from the transducer **16** shown in FIG. **1** via the interface **120** of the I/O interface. The blocks in the block of codes **162** of the program memory **102** may direct the analyzer processor **100** to interpret raw ultrasound echo waveforms received from the transducer **16** into fully formed images. The block of codes **162** may direct the analyzer processor **100** to use an image reconstruction algorithm to filter the waveforms, amplify the waveforms, time delay and sum the waveforms, demodulate the summed waveforms, and/or compress amplitudes of the summed waveforms. The block of codes **162** may direct the analyzer processor **100** to finally perform a scan-conversion of the waveforms to derive an image in Cartesian coordinates with pixels of known size in millimeters.

Block **202** may direct the analyzer processor **100** to store a representation of the received at least one echocardiographic image in the location **140** of the storage memory **104**.

In some embodiments, the analyzer **12** may be configured to receive and analyze respective sequences of echocardiographic images (echo cines). Accordingly, block **202** may direct the analyzer processor **100** to receive a sequence of images. Block **202** may direct the analyzer processor **100** to store a set of image files representing the sequence of images in the location **140** of the storage memory **104**. An exemplary image file which may be included in the set of image files received at block **202** is shown at **240** in FIG. **4**.

Referring to FIG. **4**, the image file **240** includes an image identifier field **242** for storing a unique identifier for identifying the image data stored in the image file **240**, an image group identifier field **243** for storing an identifier common to a set of image files which are to be analyzed together (e.g. frames of an echo cine), and an image data field **244** for storing information representing an image. In some embodiments, for example, the image file **240** may store a PNG file type representation of the echocardiographic image.

In some embodiments, block **202** may direct the analyzer processor **100** to receive and store a plurality of image files generally similar to the image file **240** shown in FIG. **4** in the location **140** of storage memory **104** for analysis together during execution of block **206** of the flowchart **200** shown in FIG. **3**. For example, in some embodiments, the analyzer **12** may be configured to analyze a sequence of 20 images during execution of block **206** of the flowchart **200** and so block **202** may direct the analyzer processor **100** to store the received images as groups of 20 image files, each generally similar in format to the image file **240** shown in FIG. **4** and sharing a common value in their image group identifier fields.

Referring back to FIG. **4**, block **204** then directs the analyzer processor **100** to associate the at least one echocardiographic image received at block **202** with a view category of a plurality of predetermined echocardiographic image view categories. In some embodiments, block **204** may direct the analyzer processor **100** to associate the at least one echocardiographic image with the view category by storing in the location **142** of the storage memory **104** a view category record that associates the view category with the received at least one echocardiographic image.

In various embodiments, associating the at least one echocardiographic image with a particular view category may assist with subsequent quality assessment of the echocardiographic images which may be performed at block **206** of the flowchart **200** shown in FIG. **3**. In some embodiments, the view category that is associated with the at least one echocardiographic image may be associated with a function which can be applied to the at least one echocardiographic image to assess the quality of the at least one echocardiographic image. For example, in some embodiments, different analyses may be applied to a set of echocardiographic images, depending on which view category set of echocardiographic images falls within.

In some embodiments, the view categories with which the echocardiographic images may be associated may be chosen

from a plurality of standard view categories. For example, the standard view categories may include the following 2D echocardiographic imaging plane views: AP2 (apical 2-chamber view), AP3 (apical 3-chamber view), AP4 (apical 4-chamber view), $PSAX_A$ (parasternal short axis at aortic valve level view) and $PSAX_{PM}$ (parasternal short axis at papillary muscle level view). In various embodiments, the standard view categories may include further or alternative view categories, such as, for example, any or all of the following 2D echocardiographic imaging plane view categories: parasternal long axis (PLAX), apical 5 chamber (AP5), subcostal view, aortic arch, or right parasternal. In various embodiments, with any of these views, an operator may switch the system **10** to Doppler and obtain 2D Color Doppler or Power Doppler, Continuous Wave Doppler and Duplex Doppler. In various embodiments, each view category may be associated with a different function for assessing quality of images.

In some embodiments, the block **204** may direct the analyzer processor **100** to determine which of the plurality of predetermined view categories the at least one echocardiographic image falls within before associating the image with the view category.

For example, in some embodiments, this determination may be made automatically, such as by applying a function to the received at least one echocardiographic image. Referring to FIG. **5**, there is shown at **260** a flowchart representing blocks of codes which may be included in the block **204** of the flowchart **200** shown in FIG. **3**, in accordance with various embodiments. The blocks of codes included in the flowchart **260** may direct the analyzer processor **100** to apply one or more view categorization functions to the at least one echocardiographic image received at block **202** to determine which of a plurality of predetermined view categories the at least one echocardiographic image falls within.

Referring to FIG. **5**, the flowchart **260** begins with block **262** which directs the analyzer processor **100** to receive signals representing parameters defining an image view category determining neural network. The image view category determining neural network may be configured to take the at least one echocardiographic images received at block **202** as an input and to output an indication of what image view category should be associated with the input at least one echocardiographic image.

Block **262** may direct the analyzer processor **100** to receive parameters defining the image view category determining neural network from the location **144** of the storage memory shown in FIG. **2**, for example. The parameters defining the view category determining neural network may have been previously determined during training of the neural network and stored in the location **144** of the storage memory **104**.

In some embodiments, a neural network trainer (for example, as shown at **502** in FIG. **14**) may have previously determined architecture and weight and bias values for the view category determining neural network. Blocks of code included in the block of codes **160** of the program memory **102** may have previously directed the analyzer processor **100** to receive signals representing the architecture and weight and bias values via the interface **124** of the I/O interface **112** and to store a view category neural network record representing the architecture and the weight and the bias values in the location **144** of the storage memory **104**.

In some embodiments, the view category neural network record stored in the location **144** of the storage memory may represent a neural network having convolutional layers, max-pooling layers, one or more fully connected layers, one or more Long Short Term Memory (LSTM) layers, and a softmax layer acting as an output layer and having outputs which represent a likelihood that an input set of echocardiographic images falls within a particular view category. In some embodiments, the softmax outputs may indicate whether a set of echocardiographic images falls within one of the following standard 2D echocardiographic views, for example: AP2, AP3, AP4, $PSAX_A$, or $PSAX_{PM}$. An exemplary view category determining neural network that may be represented by the view category neural network record stored in the location **144** of the storage memory, in accordance with some embodiments, is shown at **900** in FIG. **6**. The view category determining neural network takes as input, a sequence of 20 echocardiographic images, and outputs respective indicators that represent respective likelihoods that an input sequence of 20 echocardiographic images fall within a particular view category.

Referring back to FIG. **5**, block **264** of the flowchart **260** then directs the analyzer processor **100** to apply the view category determining neural network defined by the parameters received at block **262** to the at least one echocardiographic image received at block **202** of the flowchart **200** shown in FIG. **3**. Block **264** may direct the analyzer processor **100** to use the image data fields **244** of the 20 image files stored in the location **140** of the storage memory **104** at block **202** as input data for the view category determining neural network defined by the view category neural network record taken from the location **144** of the storage memory **104**.

In some embodiments, the output of the neural network may be a softmax output which provides respective indicator values representing whether the set of images received at block **202** are AP2, AP3, AP4, PSAXA, and PSAXPM. In one embodiment, these indicator values may be 0.11, 0.05, 0.7, 0.11, 0.03, respectively, for example. In various embodiments, although the indicator values sum to 1.00, these values may not represent true probabilities that the at least one image received is of a particular view, as there may be a possibility that the at least one image is none of the views.

In some embodiments, block **264** of the flowchart **260** shown in FIG. **5** may direct the analyzer processor **100** to use a GPU included in the analyzer processor **100** to perform the neural network calculations. In some embodiments, use of the GPU instead of a general CPU may reduce the execution time for block **264**.

Referring to FIG. **5**, block **266** of the flowchart **260** then directs the analyzer processor **100** to associate the at least one echocardiographic image received at block **202** of the flowchart **200** shown in FIG. **3** with a view category based on the output of the neural network. In some embodiments, block **266** may direct the analyzer processor **100** to associate the at least one echocardiographic image with a view category that corresponds to the highest softmax output determined at block **264** of the flowchart **260** shown in FIG. **5**. For example, with a softmax output which provides respective indicators for AP2, AP3, AP4, $PSAX_A$, and $PSAX_{PM}$ of 0.11, 0.05, 0.7, 0.11, 0.03, block **266** may direct the analyzer processor **100** to determine which output is the largest (i.e., the AP4 view category output) and to associate the images with that output.

Block **266** may direct the analyzer processor **100** to associate the at least one echocardiographic image received at block **202** of the flowchart **200** shown in FIG. **3** with the AP4 view category by generating a view category record **300** as shown in FIG. **7** and storing the view category record **300** in the location **142** of the storage memory **104**. Refer-

ring to FIG. **7**, the view category record **300** includes a view category identifier field **302** for storing an identifier for identifying the view category to be associated with the echocardiographic images and an image group identifier field **304** for storing an identifier for identifying the images with which the view category is to be associated.

In some embodiments, block **204** of the flowchart **200** shown in FIG. **3** may not include the blocks depicted in the flowchart **260**, but rather an operator of the system **10** shown in FIG. **1** may input a view category by which the operator wishes to have the received echocardiographic images assessed. For example, in some embodiments, the operator may input a desired view category using an input device such as a keyboard and/or pointer or mouse of the user interface system **14**. In such embodiments, block **204** may direct the analyzer processor **100** to receive operator input representing the view category via the interface **122** of the I/O interface **112** shown in FIG. **2**. Block **204** may direct the analyzer processor **100** to, in response to receiving the input, generate and store a view category record in the location **142** of the storage memory **104** associating the received at least one echocardiographic image with the view category that the operator provided as input.

Referring back to FIG. **3**, after block **204** has been executed, the at least one echocardiographic image received at block **202** may now be associated with a view category.

The flowchart **200** continues at block **206**, which directs the analyzer processor **100** to determine, based on the at least one echocardiographic image received at block **202** and the view category associated with the echocardiographic image, a quality assessment value representing a view category specific quality assessment of the at least one echocardiographic image.

In some embodiments, each of the view categories may be associated with a function which can be applied by the analyzer to the received at least one echocardiographic image to generate the quality assessment value. In some embodiments, block **206** may direct the analyzer processor **100** to select a function to apply to the at least one echocardiographic image based on the view category associated with the received at least one echocardiographic image.

In various embodiments, applying the function may involve applying a neural network to the at least one echocardiographic image. A neural network is a non-linear model and so, in some embodiments, by using a neural network to analyze the echocardiographic images, the analyzer **12** may facilitate better functioning, for example, when there is variability in the echocardiographic image data than may be possible when analysis of the echocardiographic image relies on an average template or atlas with average shape.

Referring to FIG. **2**, in various embodiments, a plurality of sets of parameters, each set defining a neural network, may be stored in the location **146** of the storage memory **104** shown in FIG. **2** and each of the sets of parameters may be associated with a view category to indicate that the set of parameters defines a neural network that is to be applied to echocardiographic images which are associated with that view category.

In some embodiments, the parameters may define neural network architectures and may include weight and bias values for the neural networks. A neural network trainer (for example, as shown at **502** in FIG. **14**) may have previously determined the neural network architecture and/or the weight and bias values for each of the neural networks and provided these values to the analyzer **12**. Blocks of code included in the block of codes **160** of the program memory **102** may have previously directed the analyzer processor **100** to receive signals representing the neural network architecture and the weight and bias values via the interface **124** of the I/O interface **112**, for example, and to store this information in image assessment neural network records in the location **146** of the storage memory **104**.

For example, in some embodiments, the image assessment neural network records stored in the location **146** of the storage memory **104** may represent the neural network shown at **360** in FIG. **8**. Referring to FIG. **8**, the neural network **360** includes 5 image quality assessment neural networks, each including the same shared layers **362** but including a different set of view category specific layers **370**, **372**, **374**, **376**, and **378**. In various embodiments, the shared layers **362** and the view category specific layers **370**, **372**, **374**, **376**, and **378** may each be considered neural networks and it will be understood that a neural network may include more than one neural network within. Each of the 5 image quality assessment neural networks takes as an input a sequence of 20 echocardiographic images **380** and outputs a view category specific quality assessment value.

The neural network **360** shown in FIG. **8** is a deep neural network and a regression model, consisting of convolutional (cony), pooling (pool), and Long Short Term Memory (LSTM) layers, and in various embodiments, may be simultaneously trained to estimate the quality of a sequence of 20 echocardiographic images for any of five standard 2D echocardiographic views, AP2, AP3, AP4, $PSAX_A$, and $PSAX_{PM}$ by generating respective view category specific quality assessment values.

The neural network architecture, depicted in FIG. **8**, represents a multi-stream network, i.e., five regression models that share weights across the first few common shared layers **362**. Each stream of the network has its own view-specific layer **370**, **372**, **374**, **376**, and **378** and has been trained based on the mean absolute error loss function, via a stochastic gradient-based optimization algorithm, to minimize the absolute difference between normalized quality assessment values assigned by a trained echocardiographer to training images, as discussed further below, and the generated quality assessment values.

In the embodiment shown, all cony layers have kernels with the size of 3×3, which may, for example, follow the VGG architecture discussed in Simonyan, K., Zisserman, A.: Very Deep Convolutional Networks for Large-Scale Image Recognition. International Conference on Learning Representations (ICRL) pp. 1-14 (2015), with the number of kernels doubling for deeper cony layers, i.e., from 8 to 32 kernels. In some embodiments, the cony layers may extract hierarchical features in the image, with the first three shared layers **362** modeling high level spatial correlations, and the next two cony layers of the view category specific layers **364** focusing on view-specific quality features. In some embodiments, activation functions of the cony layers may be Rectified Linear Units (ReLUs).

Referring still to FIG. **8**, in various embodiments, the pool layers of the neural network **360** may be 2×2 max-pooling with a stride of 2 to facilitate selection of superior invariant features and divide the input feature-map size in half in both dimensions to reduce feature variance and train more generalized models. The cony and pool layers are applied to each image of an input echo cine, independently.

The output feature map of the last pool layer is flattened and sent to an LSTM unit, a type of Recurrent Neural Networks (RNN) that uses a gated technique to selectively add or remove information from the cell state. Each set of view category specific layers **370**, **372**, **374**, **376**, and **378** in

the neural network **360** shown in FIG. **8** uses a single LSTM cell to analyze 20 feature-sets corresponding to the 20 consecutive input images. The LSTM layer uses hard sigmoid functions for inner and output activations.

In some embodiments, the image assessment neural network records stored in the location **146** of the storage memory **104** which represent the neural network **360** may include a common neural network record representing the shared layers **362** and a plurality of different view category specific neural network records representing the sets of view category specific layers **370**, **372**, **374**, **376**, and **378**.

A representation of a portion of an exemplary common neural network record for storing a set of parameters defining the shared layers **362** of the neural network **360** shown in FIG. **8**, is shown at **320** in FIG. **9**. Referring to FIG. **9**, the common neural network record **320** includes first, second, third, fourth, fifth and sixth sets of fields **324**, **326**, **328**, **330**, **332**, and **334** defining the parameters for the six layers of the shared layers **362** of the neural network **360** shown in FIG. **8**. For ease of reference, not all kernel fields of the common neural network record **320** are shown in FIG. **9** and the content of the kernels is shown as [. . .], though it will be understood that there are 8 kernels in layer **1**, 16 kernels in layer **3** and 32 kernels in layer **5** and that each kernel field stores a 3×3 matrix of values.

A representation of a portion of an exemplary view category specific neural network record for storing a set of parameters defining the set of view category specific layers **374** of the neural network **360** shown in FIG. **8**, is shown at **340** in FIG. **10**. Referring to FIG. **10**, the view category specific neural network record **340** includes a view category identifier field **342** for storing a view category identifier identifying which view category the record is associated with and seventh, eighth, ninth, and tenth sets of fields **344**, **346**, **348**, and **350** for storing parameters defining the set of view category specific layers **374** of the neural network **360** shown in FIG. **8**. For ease of reference, not all kernel fields are shown in FIG. **10** and the content of the kernels and LSTM parameters are shown as [. . .], though it will be understood that there are 32 kernels in layer **7** and 32 kernels in layer **9** and that each kernel field stores a 3×3 matrix of values and the LSTM parameter fields store values defining the parameters of the LSTM.

Additional neural network records representing the sets of shared layers **370**, **372**, **376** and **378** having generally the same format as the view category specific neural network record **340** shown in FIG. **10** may also be stored in the location **146** of the storage memory **104**. Thus, each of the image view categories AP2, AP3, AP4, $PSAX_A$, and $PSAX_{PM}$ may be associated with a view category specific neural network record stored in the location **146** of the storage memory **104**.

In various embodiments, splitting the neural network **360** into a common portion and view category specific portions may facilitate more efficient training of the neural networks. In some embodiments, splitting the neural network **360** into a common portion and view category specific portions may result in requiring fewer learning parameters than would be required if using fully separate neural networks, which may help facilitate easier transferring of a neural network to a new machine, and/or may reduce memory usage.

Referring now to FIG. **11**, there is shown at **400** a flowchart representing blocks of codes which may be included in the block **206** of the flowchart **200** shown in FIG. **3**, in accordance with various embodiments. The blocks included in the flowchart **400** may direct the analyzer processor **100** to determine which of the sets of quality assessment parameters is associated with the same view category as the at least one echocardiographic image received at block **202** and to apply a function based on that set of quality assessment parameters.

The flowchart **400** begins with block **402** which directs the analyzer processor **100** to determine that a set of assessment parameters of the sets of assessment parameters stored in the location **146** is associated with the same view category that is associated with the at least one echocardiographic image received at block **202**.

For example, in some embodiments, block **402** may direct the analyzer processor **100** to read "AP4" from the view category identifier field **302** of the view category record **300** associated with the echocardiographic image files received at block **202**. Block **402** may direct the analyzer processor **100** to read the view category specific neural network records from the location **146** of the storage memory to find a view category specific neural network record that includes the same view category identifier of "AP4" and is therefore associated with the same view category. Accordingly, block **402** may direct the analyzer processor **100** to determine that the view category specific neural network record **340** includes the view category identifier of "AP4" and is therefore associated with the same view category that is associated with the at least one echocardiographic image received at block **202**.

Block **404** then directs the analyzer processor **100** to, in response to determining that the set of assessment parameters is associated with the same view category, apply a function based on the set of assessment parameters to the at least one echocardiographic image received at block **202**. In some embodiments, block **404** may direct the analyzer processor **100** to apply the neural network defined by the parameters included in the common neural network record **320** and the view category specific neural network record **340** to the image data in the image files received at block **202**.

Block **404** may direct the analyzer processor **100** to read the image files received at block **202** from the location **140** of the storage memory **104** and to read the common neural network record **320** and the view category specific neural network record **340** from the location **146** of the storage memory, and to input the image data from the image files into a neural network that includes the shared layers **362** and the view category specific layers **374** shown in FIG. **8**, which are defined by the common neural network record **320** and the view category specific neural network record **340**, to generate or determine a view category specific quality assessment value as an output of the neural network.

In some embodiments, the quality assessment value may represent a suitability for a quantified clinical measurement. In some embodiments, the quality assessment value may represent an estimate of an expected score which would be provided by an expert to the input at least one echocardiographic image. The estimate may be based on the training of the neural network wherein an expert provided quality assessment values for various echocardiographic images.

In some embodiments, the quality assessment value may be a score with criteria and/or a range that varies depending on the view category with which the neural network is associated. In some embodiments, the expert which provided the quality assessment values with which the neural network was trained may have determined the quality assessment values as an aggregation of scores derived using semi-quantitative evaluation of component structures and parameter optimization features such as centering, depth, gain, axis, focus, frequency or another parameter optimiza-

tion feature or image capture parameter. Accordingly, in various embodiments, the quality assessment value may represent an estimate of an expected aggregation of scores derived using semi-quantitative evaluation of component structures and parameter optimization features such as centering, depth, gain, axis, focus, frequency or another parameter optimization feature or image capture parameter.

For example, in some embodiments, an expert may have, for each at least one echocardiographic image that they assessed, determined for each component in the at least one echocardiographic image, a component quality score of up to 2 points based on the following observations: 0 points) the structure was not imaged or was inadequate for assessment; 1 point) the structure was adequately viewed; 2 points) the view was optimized for the structure. In some embodiments, the component score may act as a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features. The expert may have, for each at least one echocardiographic image that they assessed, determined parameter optimization scores as follows: appropriate centering (1 point), correct depth setting (0.5 points), proper gain (0.5 points), correct axis (1 point), and correct depth of focus (0.5 points). In various embodiments, the quality assessment value may represent a sum of the above-noted scores.

As discussed above, in some embodiments, images for the different view categories may include a different set of components and quality assessment values may be determined using different criteria. For example, for the AP2 view category, the left ventricle (LV), left atrium (LA), and mitral valve (MV) may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the AP3 view category, the aortic valve (AV), MV, LA, LV, and septum may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the AP4 view category, the LV, right ventricle (RV), LA, right atrium (RA), MV, and TV may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the $PSAX_A$ view category, the AV and leaflets may each be assigned a component quality score, which may be summed with scores for centering, depth, and gain to determine the quality assessment value. For the $PLAX_{PM}$ the papillary muscles may be assigned a component quality score, which may be summed with scores for centering, depth, gain, and axis to determine the quality assessment value.

In some embodiments, the quality assessment values for all views may be normalized to the same scale, which may be, for example, between 0 and 1 or between 0 and 5.

Referring back to FIG. **11**, in some embodiments, block **404** of the flowchart **400** may direct the analyzer processor **100** to apply the neural network such that the quality assessment value and associated at least one echocardiographic image may be viewed in real-time or near-real time for the operator. For example, in some embodiments, block **404** may direct the analyzer processor **100** to apply the neural network and determine a quality assessment value in less than about 3 seconds. In some embodiments, block **404** may direct the analyzer processor **100** to apply the neural network and determine a quality assessment value in less than about 1 second. In some embodiments, block **404** may direct the analyzer processor **100** to apply the neural network and determine a quality assessment value in less than about 0.33 ms. In some embodiments, for an input echo cine of 20 images of 200×200 pixels, a quality assessment value may be determined in about 10 ms, which may be suitable for real-time or near real-time deployment. In some embodiments, block **404** may direct the analyzer processor **100** to use a GPU included in the analyzer processor **100** to apply the neural network. In some embodiments, use of the GPU instead of just a general CPU may reduce the time it takes to execute the block **404** and may thus facilitate real-time or near-real time image analysis.

Referring back to FIG. **3**, the flowchart **200** continues at block **208** which directs the analyzer processor **100** to produce signals representing the quality assessment value determined at block **206**, for causing the quality assessment value to be associated with the at least one echocardiographic image received at block **202**.

In some embodiments, block **208** may direct the analyzer processor **100** to produce signals for causing the quality assessment value to be stored in the location **148** of the storage memory **104**. For example, in some embodiments, block **208** may direct the analyzer processor **100** to store a quality assessment record **420** as shown in FIG. **12** in the location **148** of the storage memory **104**, wherein the quality assessment record **420** includes an image group identifier field **422** for storing the group identifier which identifies the group of images for which the quality assessment was made and a quality assessment value field **424** for storing the quality assessment that was generated at block **404** of the flowchart **400**.

In some embodiments, block **208** may direct the analyzer processor **100** to produce signals for causing a representation of the quality assessment value to be transmitted to the display **15** of the user interface system **14** for causing the display to display the quality assessment value in association with the received at least one echocardiographic image. In some embodiments, this may assist one or more operators of the system **10** in capturing subsequent echocardiographic images. For example, in some embodiments, block **208** may direct the analyzer processor **100** to communicate with the user interface system **14** of the system **10** shown in FIG. **1** via the interface **122** of the I/O interface **112** shown in FIG. **2** to cause a display **440** as shown in FIG. **13** to be presented on the display **15** of the user interface system **14**.

Referring to FIG. **13**, the display **440** includes a representation **442** of the quality assessment value determined at block **206** shown in association with a representation **444** of the at least one echocardiographic image received at block **202**.

In some embodiments, block **208** may direct the analyzer processor **100** to transmit the quality assessment value and associated at least one echocardiographic image to another device for storage and/or further analysis. For example, in various embodiments, block **208** may direct the analyzer processor **100** to transmit a representation of the image files stored at block **202** and the quality assessment record generated at block **208** to an archive device in a picture archiving and communication system (PACS) via the interface **124** and the network **126**, for example.

In various embodiments, once block **208** has been executed, the analyzer processor **100** may be directed to return to block **202** to receive further echocardiographic images. In some embodiments, the flowchart **200** may be executed continuously such that the display **440** shown in FIG. **13** is updated with near real-time updates of images or image sequences and associated quality assessment values. In some embodiments, an operator may adjust image capture

parameters of the system **10** and/or adjust positioning of the transducer until the operator sees a desired quality assessment value.

In some embodiments, the operator may make adjustments until a quality assessment value of greater than a predetermined threshold value is achieved. In some embodiments, for example, where the quality assessment value has been normalized to a possible range of 0-5 the threshold value may be about 3.0.

In some embodiments, there may be a maximum achievable quality assessment value for a given patient and the maximum achievable quality assessment value may be dependent on the patient, given their anatomy and/or echogenicity, for example. For example, in some embodiments where the quality assessment value has been normalized to a possible range of 0-5, for many patients, the maximum achievable quality assessment value for a given view category may be about 3.0. In some embodiments, the operator may make various adjustments until a near maximum achievable quality assessment value on a given patient has been achieved.

In some embodiments, after capturing images associated with a desired quality assessment value for a first view category, the operator of the system **10** may wish to capture images for a different view category and so reposition the transducer and/or reconfigure the system **10**. For example, in some embodiments, the operator may, after capturing images of the AP4 view category, wish to capture images of one or more of the AP2, AP3, $PSAX_A$, and $PSAX_{PM}$ view categories to facilitate quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart. For example, in some embodiments, the operator may, after capturing at least one image of the AP4 view category, wish to capture at least one image of the AP2 view category to facilitate quantified clinical measurement of anatomical features for determining an ejection fraction.

Accordingly, the operator may reposition the transducer **16** shown in FIG. **1** and/or adjust image receiving parameters to cause the flowchart **200** to be executed one or more further times, but with echocardiographic images which are of different view categories and are to be analyzed using different parameters. In various embodiments, the analyzer **12** being configured as described above to switch between analyses of varying view categories may facilitate ease of use and/or efficient capture of subsequent high quality images of different view categories.

Neural Network Trainer

As discussed above, in various embodiments, a neural network trainer may first train neural networks to determine the architecture and/or parameters to be used by the neural networks at block **204** and/or block **206** of the flowchart **200** shown in FIG. **3**. Referring to FIG. **14**, there is shown a system **500** for facilitating training of neural networks. The system includes a neural network trainer **502** in communication with a training image source **504** and a user interface system **506**. In some embodiments, the neural network trainer **502** may also be in communication with the analyzer **12** via the network **126**.

The training image source **504** stores echocardiographic images and associated view category information which indicates what view category each of the images falls within. For example, in some embodiments, the training image source **504** may include a server computer for storing and archiving medical electronic images, such as, for example, an archive device from a picture archiving and communication system (PACS).

The neural network trainer **502** may be configured to retrieve and/or receive the echocardiographic images, which may act as echocardiographic training images, from the training image source **504**. In some embodiments, the neural network trainer **502** may, after receiving the training images, produce signals representing the echocardiographic training images and associated view categories to cause the user interface system **506** to present the echocardiographic images and the view categories to one or more experts, such as, echocardiographers or physicians trained in echocardiography.

The experts may then provide respective quality assessment values for each of the echocardiographic images. For example, in some embodiments, the neural network trainer may be configured to produce signals for causing the user interface system **506** to present the experts with a set of echocardiographic training images and an indication of what view category the set of echocardiographic training images is to be assessed as. An echocardiographer may assess the set of echocardiographic training images and provide a quality assessment value representing a suitability of the set of images for a quantified clinical measurement. The neural network trainer **502** may store the quality assessment value in memory in association with the assessed set of echocardiographic training images.

After quality assessment values have been received and associated with each set of echocardiographic training images, the neural network trainer **502** may train neural networks using the echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine sets of neural network parameters defining the neural networks, wherein at least a portion of each of the neural networks is associated with one of the image view categories.

In some embodiments, the neural network trainer **502** may also train a view category determining neural network to determine sets of neural network parameters defining the view category determining neural network. The view category determining neural network may be generally as described above with reference to block **262** of the flowchart **260** shown in FIG. **5**, configured to receive one or more echocardiographic images as an input, and having a softmax layer as an output layer having outputs which represent whether the input echocardiographic images fall within a particular view category.

In some embodiments, the neural network trainer **502** may produce signals representing the parameters defining the trained neural networks for causing the parameters to be provided to a system or device configured to apply the neural networks. For example, in some embodiments, the neural network trainer **502** may transmit the neural network parameters to the analyzer **12** via the network **126** shown in FIG. **14**. Alternatively, in some embodiments, the neural network trainer **502** may produce signals for causing the sets of neural network parameters to be stored in removable memory which may be provided to the analyzer **12**.

The analyzer **12** may use the sets of neural network parameters to facilitate analysis of echocardiographic images, generally as described above with reference to the flowchart **200** shown in FIG. **3**.

Neural Network Trainer—Processor Circuit

Referring now to FIG. **15**, a schematic view of the neural network trainer **502** of the system **500** shown in FIG. **14** according to an embodiment is shown. In various embodiments, the neural network trainer **502** may be incorporated in one or more computers, for example.

Referring to FIG. **15**, the neural network trainer **502** includes a processor circuit including a trainer processor **600** and a program memory **602**, a storage memory **604**, and an I/O interface **612**, all of which are in communication with the trainer processor **600**.

The I/O interface **612** includes an interface **620** for communicating with the training image source **504** and an interface **622** for communicating with the user interface system **506** shown in FIG. **14**. In some embodiments, the I/O interface **612** also includes an interface **624** for facilitating networked communication with the analyzer **12** through the network **126**.

Processor-executable program codes for directing the trainer processor **600** to carry out various functions are stored in the program memory **602**. The program memory **602** includes a block of codes **660** for directing the neural network trainer **502** to perform neural network training functions.

The storage memory **604** includes a plurality of storage locations including location **640** for storing training image data, location **642** for storing expert assessment data, location **644** for storing image assessment neural network parameter data and location **646** for storing view category neural network parameter data.

Training the Neural Networks

Referring now to FIG. **16**, a flowchart depicting blocks of code for directing the trainer processor **600** shown in FIG. **15** to perform image assessment neural network training functions in accordance with one embodiment is shown generally at **700**. The blocks of code included in the flowchart **700** may be encoded in the block of codes **660** of the program memory **602** shown in FIG. **15** for example.

Referring to FIG. **16**, the flowchart **700** begins with block **702** which directs the trainer processor **600** shown in FIG. **15** to receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories. In some embodiments, block **702** may direct the trainer processor **600** to receive echocardiographic training images from the training image source **504** shown in FIG. **14**. For example, in some embodiments, block **702** may direct the trainer processor **600** to receive sets of associated image files, which may represent respective sequences of images or videos and include common image group identifiers, from the training image source **504**. Each set of image files may make up an echo cine, which is associated with a view category.

An exemplary training image file that may be received at block **702** is shown at **740** in FIG. **17**. The training image file **740** includes an image identifier field **742** for storing a unique identifier for identifying an image included in the file, an image group identifier field **744** for storing an identifier common to a set of image files which include images that are to be analyzed together, a view category identifier field **746** for storing an identifier for identifying the view category within which the image falls and by which the image should be analyzed, and an image data field **748** for storing information representing the image.

Block **702** may direct the trainer processor **600** to store the training image files received at block **702** in the location **640** of the storage memory **604**.

After block **702** of the flowchart **700** shown in FIG. **16** has been executed, the location **640** of the storage memory **604** shown in FIG. **17** may store a large number of image files, each having generally similar format to the training image file **740** shown in FIG. **17**. For example, in some embodiments, about 2,500 echo cines of about 40 images each (about 500 echo cines of each view category) may be stored in the location **640** of the storage memory **604** and therefore about 100,000 training image files generally similar to the training image file **740** shown in FIG. **17** may be stored in the location **640** of the storage memory **104**.

Referring back to FIG. **16**, block **704** directs the trainer processor **600** to receive signals representing expert quality assessment values representing view category specific quality assessments of the echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the received sets of echocardiographic training images.

In some embodiments, the neural network trainer **502** may cause the echocardiographic training images to be presented to an expert and the expert may provide the expert quality assessment values. For example, block **704** may direct the trainer processor **600** to transmit the training image files to the user interface system **506** via the interface **622** of the I/O interface **612** shown in FIG. **15** to cause a display of the user interface system **506** to present one or more experts with the echocardiographic images and an indication of what view category the images are to be assessed as.

In some embodiments, the echocardiographers may be directed to provide a quality assessment value representing a suitability of the images for a quantified clinical measurement. For example, the echocardiographers may be directed to provide a quality assessment value, which represents an aggregation of scores derived using semi-quantitative evaluation of component structures and parameter optimization features such as centering, depth, gain, axis, focus, frequency or another parameter optimization feature or image capture parameter, generally as described above, with reference to flowchart **400** shown in FIG. **11**.

Block **704** may direct the trainer processor **600** to receive signals representing the expert quality assessment values and to store representations of the received expert quality assessment values in the location **642** of the storage memory **604**. For example, in some embodiments, block **704** may direct the trainer processor **600** to receive representations of expert quality assessment records from the user interface system **506** and to store the expert quality assessment records in the location **642** of the storage memory. An exemplary expert quality assessment record that may be received at block **704** and stored in the location **642** of the storage memory **604** is shown at **780** in FIG. **18**.

Referring to FIG. **18**, the expert quality assessment record **780** includes an image group identifier field **782** for storing the group identifier which identifies the set of images for which the expert quality assessment was made and an expert quality assessment value field **784** for storing the view category specific expert quality assessment value provided by the expert.

Referring back to FIG. **16**, the flowchart **700** continues at block **706** which directs the trainer processor **600** shown in FIG. **15** to train neural networks using the echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

In some embodiments, block **706** may direct the trainer processor **600** to train the neural network **360** shown in FIG. **8** to determine values to be included in a common neural network record and view category specific neural network

records stored in the location **644** of the storage memory **104**. In various embodiments, the common neural network record stored in the location **644** may have a generally similar format to that of the common neural network record **320** shown in FIG. **9** and each of the view category specific neural network records stored in the location **644** of the storage memory **604** may have a generally similar format to that of the view category specific neural network record **340** shown in FIG. **10**.

In some embodiments, the sequences of images received at block **702** may include a different number of images than can be analyzed by the neural network to be applied. For example, in some embodiments, the neural network **360** shown in FIG. **8** may be configured to take as an input 20 images and the sequences of images received at block **702** may include more than 40 images each. Accordingly, in some embodiments, before training the neural networks, block **706** may direct the trainer processor **600** to split one or more groups of echocardiographic images received at block **702** into subsets.

For example, block **706** may direct the trainer processor **600** to split each sequence of images into one or more groups of 20 image files each. In order to do this, block **706** may direct the trainer processor **600** to change the value stored in the image group identifier field for each file. Block **706** may further direct the trainer processor **600** to generate and store further expert quality assessment records as necessary such that each of the new groups of images is associated with the same quality assessment value as the original sequence of images.

Due to the storage length of heart cycles and different frame acquisition rates, number of images per cardiac cycle may vary for different image sequences. Accordingly, in some embodiments the neural network may be defined to take as input a static sequence size of nearly half the average heart cycle in the echocardiographic images received at block **702** (for example, in some embodiments 20 images), to capture the quality distribution of the echo imaging view categories. In various embodiments, by choosing a static sequence size of about half the average heart cycle, images in each sequence may not be synced with the heart cycle and this may, in some embodiments, help to ensure that the estimated quality assessment value provided after training for a given input sequence may be independent of the starting phase of the cardiac data.

Block **706** may direct the trainer processor **600** to, for each 20 image sequence of images having a common group identifier value, select a set of layers of the neural network **360** shown in FIG. **8** to train, and to train those layers. For example, for a 20 image sequence associated with the AP4 view category, block **706** may direct the trainer processor **600** to train the neural network including the shared layers **362** and the AP4 view category specific layers **374**. Block **706** may direct the trainer processor **600** to use the 20 images as inputs and to use the expert quality assessment value from an associated expert quality assessment record stored in the location **642** of the storage memory **604** as the desired output.

In some embodiments, block **706** may direct the trainer processor **600** work towards optimizing network hyper-parameters by cross-validation to try to ensure that the network can sufficiently learn the distribution of all view categories without overfitting to the training data. In some embodiments, after finalizing the network architecture, the network may be trained on all of the images stored in the location **640** of the storage memory **604**.

In various embodiments, the shared layer **362** and the view category specific layers **370**, **372**, **374**, **376**, and **378** may be trained simultaneously. In some embodiments, batch training may be used and each batch may consist of eight sequences (or groups of images) from each view, for example, wherein each sequence is a set of 20 consecutive gray-scale images of 200×200 pixels, with no preprocessing applied to the images.

In some embodiments, the neural networks may be trained using the adam optimizer with hyper-parameters as suggested by Kingma, D. P., Ba, J. L.: Adam: a Method for Stochastic Optimization, International Conference on Learning Representations 2015 pp. 1-15 (2015). The weight of the cony layers may be initialized randomly from a zero-mean Gaussian distribution. To try to prevent the neural network from overfitting on the training data, l_2 norm regularization may be added to the weights of the cony kernels. In some embodiments, Keras deep learning library with TensorFlow™ backend, may be used to train and test the models.

In some embodiments, to prevent co-adaptation of features and overfitting on the training data, a dropout layer with the dropout probability of 0.5 may be used after the third pooling layer.

After training has been completed, the sets of parameters stored in the location **646** of the storage memory **104** may represent a trained echocardiographic image quality assessment neural network that includes shared layers and a plurality of view category specific layers.

Referring back to FIG. **16**, in some embodiments, the flowchart **700** may include a further block **708** which directs the trainer processor **600** to produce signals representing the parameters defining the trained neural networks for causing the parameters to be provided to a system or device configured to apply the neural networks. In some embodiments, for example, block **708** may direct the trainer processor **600** to retrieve the neural network records from the location **644** and to produce signals representing the records for causing the records to be provided to the analyzer **12**.

For example, in some embodiments, block **708** may direct the trainer processor **600** to retrieve the common neural network record and the view category specific neural network records stored in the location **644** and transmit signals representing the records to the analyzer **12** via the interface **624** and the network **126**. Alternatively, in some embodiments, block **708** may direct the trainer processor **600** to cause the records to be stored in removable memory which may be provided to the analyzer **12**.

The analyzer **12** may be configured as described above to receive the neural network records and to perform image assessment by applying the neural networks represented thereby.

In some embodiments, the block of codes **660** of the program memory **602** shown in FIG. **16** may include a block that directs the trainer processor **600** to train a view category determining neural network that is configured to take as an input at least one echocardiographic image and to output an indication of what view category should be associated with the input at least one echocardiographic image. The block may use the image data from the training image files stored in the location **640** of the storage memory **104** as inputs and indications of the associated view categories (as determined by the view category identifiers included in the image files) as desired outputs.

The neural network may include convolutional layers, max-pooling layers, and fully connected layers, the fully connected layers including a softmax layer as an output

layer having outputs which represent respective determinations that an input set of echocardiographic images fall within a particular view category. In some embodiments, the block may direct the trainer processor **600** to store parameters defining the trained neural network in a view category determining neural network record in the location **648** of the storage memory **604**.

Embodiments Using Distributed Processing and/or Separate Devices

In some embodiments, separation of the neural network trainer **502**, the training image source **504**, and the analyzer **12** into different computers or systems may facilitate control of and access to information. This may be particularly desirable with the systems described herein where personal and/or confidential information may be managed. Further, in some embodiments, separation of the neural network training from the analysis, for example, may allow different or faster computers to train the neural network.

In some embodiments, the functionality of aspects of the system **10** and/or the system **500** may be further modularized and/or distributed between different devices. For example, in some embodiments, a system **800** as shown in FIG. **19** may perform generally similar functions to the system **10** shown in FIG. **1**. The system **800** includes a user interface system **802** generally similar to the user interface system **14** shown in FIG. **1**, and a transducer **804** generally similar to the transducer **16** shown in FIG. **1**. The system **800** also includes a scanner **806** and an image analyzer **808** which are in communication with one another via a network **810** and configured to together perform generally similar functions to the analyzer **12** described above. The scanner **806** may be configured to receive signals from the transducer and generate and store echocardiographic images in memory generally as described above. The scanner **806** may be configured to send the echocardiographic images to the image analyzer **808** which is configured to receive the images from the scanner **806** and generally perform image analysis steps as described above with reference to the flowchart **200** shown in FIG. **3**. The image analyzer **808** may be configured to send signals to the scanner **806** for causing the scanner **806** to cause representations of the echocardiographic images and associated quality assessment values to be displayed on the display of the user interface system **802**.

In some embodiments, the functionality of any or all of the devices included in the systems **10**, **500**, and/or **800** as shown in FIGS. **1**, **13**, and **18** may be performed by multiple devices which are in communication with one another via a network. In such embodiments, the devices may be distributed in a cloud computing context, for example. For example, in some embodiments, a system that functions generally similar to the system **800** shown in FIG. **19** may include a mobile device, such as a smart phone, acting similar to the user interface system **802**, in communication with a scanner generally similar to the scanner **806**, via a wireless connection, for example. An image analyzer acting as the image analyzer **808** may be remotely located in comparison to the scanner and the mobile device and may be in communication with the scanner **806** and/or the mobile device via a network connection, for example, over the Internet. In some embodiments, allowing the image analyzer **808** to be remotely located and accessible via a network, may facilitate the use of low cost or fast computing resources to carry the load of intensive processing during training and/or application of the neural networks.

In some embodiments, execution of block **206** may be performed by more than one analyzer device. For example, in some embodiments a first analyzer may apply the shared layers of an image quality assessment neural network to the received at least one echocardiographic image and then send the output of the shared layers to a second analyzer, which may apply one of the view specific layers to the received output. In such embodiments, the shared layers may act as a small neural network. In some embodiments, the shared layers may facilitate data compression. In some embodiments, the first analyzer may be in communication with the second analyzer via a network connection, such as, for example, an Internet connection. In some embodiments, the first analyzer may be implemented on a mobile device and the second analyzer may be in the cloud. In various embodiments, using a neural network with common shared layers may facilitate compressing the echocardiographic image data before sending the data to the second analyzer and may reduce the bandwidth needed to transfer data to the second analyzer.

In some embodiments, the first analyzer may use the shared layers of a neural network to generate a coarse quality score, and a finer quality score may be calculated by a larger architecture which is deployed in the cloud, for example, and uses the output of the shared layers.

Stored Image Analysis

In some embodiments, the analyzer **12** may be used to analyze stored images, rather than echocardiographic images received in real-time or near real-time. For example, in some embodiments, the analyzer **12** may be in communication with an image source, which may, for example, be implemented as a PACS. In some embodiments, the analyzer **12** may be in communication with the image source via a network, such as, the Internet, for example. In some embodiments, the analyzer **12** may be integrated with the image source as a single device.

In some embodiments where the analyzer **12** is used to analyze stored images from an image source, block **202** may direct the analyzer processor **100** to receive at least one echocardiographic image from the image source. Blocks **204** and **206** may direct the analyzer processor **100** to perform functions generally as described above. In some embodiments, block **208** may direct the analyzer processor **100** to produce signals for causing the quality assessment value to be stored in association with the at least one echocardiographic image at the image source. In some embodiments, using the analyzer **12** to analyze stored echocardiographic images from an image source may facilitate use of the previously captured echocardiographic images for later quantified clinical measurement of anatomical features and/or to assist in diagnosing a medical condition or a characteristic of the heart.

Embodiments Using Integrated Devices

In some embodiments, the functionality of some or all of the neural network trainer **502**, the training image source **504** and/or the analyzer **12** of the systems **500** and **10** may be provided by a single integrated device or system, for example. By way of example, in various embodiments, aspects of the neural network trainer **502** and the analyzer **12** may be integrated, such that a single device performs the neural network training and the analysis. In some embodiments, some of the blocks of code may be altered and/or omitted to facilitate the execution of the functionality of the processes described herein by one or more integrated device or system. In some embodiments, a system including such

integrated devices may provide advantages such as, for example, reduction in implementation and/or operating costs.

3D Representations

In some embodiments, block **202** may direct the analyzer processor **100** to receive or derive one or more 3D model representations of the patient's heart from the signals received from the scanner **16**. In such embodiments, each of the 3D model representations may represent one or more echocardiographic images which may be derived or extracted from the 3D model representation by taking slices or planar sections from the 3D model, for example. In such embodiments, the flowchart **200** may be executed to analyze echocardiographic images derived or extracted from the 3D model representation.

Various Embodiments

In some embodiments, echocardiographers may have previously provided the expert quality assessment values, and the training image source **504** may store respective expert quality assessment values in association with each of the images. In such embodiments, block **704** may direct the trainer processor **600** to receive the expert quality assessment values from the training image source **504**.

Certain embodiments of the systems **10**, **500**, and **800** have been described above, wherein a plurality of images, in some embodiments a sequence of 20 images, for example, are analyzed together to generate a single quality assessment value. In various embodiments, analyzing more than one image together may facilitate determining accurate and contextualized quality assessment values.

However, in some embodiments, the systems **10**, **500**, or **800** may be configured to analyze a single image at a time. In such embodiments, the flowchart **200** shown in FIG. **3**, or a generally similar flowchart, may be executed to determine a quality assessment value for a single image received at block **202** of the flowchart **200**. In various embodiments, analyzing a single image at a time may facilitate fast processing of the flowchart **200** and/or real-time or near real-time feedback for the operator. In embodiments where a single image is analyzed at a time, the systems **10**, **500**, and/or **800** may be configured to train and/or apply functions or neural networks to the single image to determine quality assessment values of each image. In such embodiments, different neural networks from those shown in FIGS. **6** and **8**, as defined by different neural network records, may be trained and applied.

For example, an exemplary view category determining neural network that may be trained and/or applied to a single echocardiographic image to determine a view category to be associated with the echocardiographic image, in accordance with some embodiments, is shown at **950** in FIG. **20**. In some embodiments, the neural network **950** may be configured to take as input an image having a size of 200×200 pixels, and may include one convolutional layer with 12 kernels of each 11×11 pixels, one pooling layer with a kernel of 3×3 and stride of 2, one convolutional layer with 24 kernels of each 7×7 pixels, one pooling layer with a kernel of 3×3 and stride of 2, one convolutional layer with 48 kernels of each 3×3 pixels, one pooling layer with a kernel of 3×3 and stride of 2, a fully connected layer with 2048 outputs, a fully connected layer with 1024 outputs, and a fully connected layer with 5 outputs.

An exemplary image assessment neural network that may be trained and/or applied to a single echocardiographic image to determine a quality assessment value for the echocardiographic image, in accordance with some embodiments, is shown at **980** in FIG. **21**.

While specific embodiments of the invention have been described and illustrated, such embodiments should be considered illustrative of the invention only and not as limiting the invention as construed in accordance with the accompanying claims.

The series of paragraphs below recites various illustrative combinations of features of the present disclosure. These paragraphs are intended to represent a non-limiting presentation of suitable combinations, and are alphanumerically designated for clarity and efficiency:

A0. A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

A1. The system of paragraph A0 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

A2. The system of paragraph A0 or A1 wherein the at least one processor is configured to:

produce signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

produce signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic

image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

A3. The system of any one of paragraphs A0 to A2 wherein the at least one processor is configured to:

apply one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

apply one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

A4. The system of any one of paragraphs A0 to A3 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

A5. The system of any one of paragraphs A0 to A4 wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters and wherein the at least one processor is configured to:

determine that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category;

in response to determining that the first set of assessment parameters is associated with the first view category, apply a first function based on the first set of assessment parameters to the first at least one echocardiographic image;

determine that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, apply a second function based on the second set of assessment parameters to the second at least one echocardiographic image.

A6. The system of paragraph A5 wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and

a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

A7. The system of paragraph A5 or A6 wherein each of the sets of assessment parameters is a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein the at least one processor is configured to:

apply the first function based on the first set of assessment parameters to the first at least one echocardiographic image by inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

apply the second function based on the second set of assessment parameters to the second at least one echocardiographic image by inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

A8. The system of paragraph A7 wherein the at least one processor is configured to train the neural networks by:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.

A9. The system of paragraph A8 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

A10. The system of paragraph A8 or A9 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

A11. The system of any one of paragraphs A8 to A10 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

B0. A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

B1. The system of paragraph B0 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

B2. The system of paragraph B0 or B1 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

B3. The system of any one of paragraphs B0 to B2 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

C0. A computer-implemented method of facilitating echocardiographic image analysis, the method comprising:

receiving signals representing a first at least one echocardiographic image;

associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receiving signals representing a second at least one echocardiographic image;

associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

C1. The method of paragraph C0 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

C2. The method of paragraph C0 or C1 wherein:

producing the signals representing the first quality assessment value comprises producing signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

producing the signals representing the second quality assessment value comprises producing signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

C3. The method of any one of paragraphs C0 to C2 wherein:

associating the first at least one echocardiographic image with the first view category comprises applying one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

associating the second at least one echocardiographic image with the second view category comprises applying one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

C4. The method of any one of paragraphs C0 to C3 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein determining the first quality assessment value comprises determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

C5. The method of any one of paragraphs C0 to C4 wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters and wherein:

determining the first quality assessment value comprises:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, applying a first function based on the first set of assessment parameters to the first at least one echocardiographic image; and

determining the second quality assessment value comprises:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, applying a second function based on the second set of assessment parameters to the second at least one echocardiographic image.

C6. The method of paragraph C5 wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and

a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

C7. The method of paragraph C5 or C6 wherein each of the sets of assessment parameters is a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein:

applying the first function based on the first set of assessment parameters to the first at least one echocardiographic image comprises inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and applying the second function based on the second set of assessment parameters to the second at least one echocardiographic image comprises inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

C8. The method of paragraph C7 further comprising training the neural networks, said training comprising:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.

C9. The method of paragraph C8 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

C10. The method of paragraph C8 or C9 further comprising deriving each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

C11. The method of any one of paragraphs C8 to C10 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values comprises, for each echocardiographic training image:

selecting one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, training a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

D0. A computer-implemented method of training neural networks to facilitate echocardiographic image analysis, the method comprising:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

D1. The method of paragraph D0 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

D2. The method of paragraph D0 or D1 further comprising deriving each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

D3. The method of any one of paragraphs D0 to D2 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values comprises, for each echocardiographic training image:

selecting one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, training a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

D4. A computer readable medium having stored thereon codes which when executed by at least one processor cause the at least one processor to perform the method of any one of paragraphs C0 to D3.

E0. A system for facilitating echocardiographic image analysis, the system comprising:

means for receiving signals representing a first at least one echocardiographic image;

means for associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

means for determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

means for producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

means for receiving signals representing a second at least one echocardiographic image;

means for associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

means for determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

means for producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image.

F0. A system for training neural networks to facilitate echocardiographic image analysis, the system comprising:

means for receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

means for receiving signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

means for training the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories.

The invention claimed is:

1. A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

wherein the at least one processor is configured to determine the second quality assessment value by:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second

view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

2. The system of claim **1** wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

3. The system of claim **1** wherein the at least one processor is configured to:

produce signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

produce signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

4. The system of claim **1** wherein the at least one processor is configured to:

apply one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

apply one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

5. The system of claim **1** wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

6. The system of claim **1** wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and

a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

7. The system of claim **1** wherein the at least one processor is configured to train the neural networks by:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.

8. The system of claim **7** wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

9. The system of claim **7** wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

10. The system of claim **7** wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

11. A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories;

wherein the at least one processor is further configured to, once the neural networks are trained:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view cat-

egory specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

wherein the at least one processor is configured to determine the second quality assessment value by:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

12. The system of claim **11** wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

13. The system of claim **11** wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

14. The system of claim **11** wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

15. A computer-implemented method of facilitating echocardiographic image analysis, the method comprising:

receiving signals representing a first at least one echocardiographic image;

associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receiving signals representing a second at least one echocardiographic image;

associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein:

determining the first quality assessment value comprises:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters applying a first function based on the first set of assessment parameters to the first at least one echocardiographic image; and

determining the second quality assessment value comprises:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

16. The method of claim **15** wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

17. The method of claim **15** wherein:

producing the signals representing the first quality assessment value comprises producing signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

producing the signals representing the second quality assessment value comprises producing signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

18. The method of claim **15** wherein:

associating the first at least one echocardiographic image with the first view category comprises applying one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

associating the second at least one echocardiographic image with the second view category comprises applying one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

19. The method of claim **15** wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein determining the first quality assessment value comprises determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

20. The method of claim **15** wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and

a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

* * * * *

EXHIBIT B

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

Inventor:	Purang ABOLMAESUMI	Dated:	August 5, 2021
Applicant:	THE UNIVERSITY OF BRITISH COLUMBIA	Attorney Docket:	CRB313
Filing/371:	October 22, 2018	Group Art Unit:	2665
Serial No.:	16/095,601	Examiner:	VAN D. HUYNH

For: **ECHOCARDIOGRAPHIC IMAGE ANALYSIS**

Mail Stop **Amendment**
Commissioner for Patents
P.O. Box 1450
Alexandria, Virginia 22313-1450

Commissioner:

AMENDMENT AND RESPONSE TO OFFICE ACTION

Please consider the following, which is filed in response to the non-final Office action dated May 5, 2021:

Listing of Claims begin on page 2 of this paper.

Remarks begin on page 12 of this paper.

LISTING OF CLAIMS

This listing of claims replaces all prior versions, and listings, of claims in the application. Material to be inserted is in **bold and underline**, and material to be deleted is in ~~strikeout~~ or (if the deletion is of five or fewer consecutive characters or would be difficult to see) in double brackets [[ ]].

1. (Currently Amended) A computer-implemented system for facilitating echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

wherein the at least one processor is configured to determine the second quality assessment value by:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

2. (Original) The system of claim 1 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

3. (Previously presented) The system of claim 1 wherein the at least one processor is configured to:

produce signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators

of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

produce signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

4. (Previously presented) The system of claim 1 wherein the at least one processor is configured to:

apply one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

apply one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

5. (Previously presented) The system of claim 1 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein the at least one processor is configured to determine the first quality assessment value by determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

6. (Canceled)

7. (Currently Amended) The system of claim **1**[[6]] wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and

a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

8. (Canceled)

9. (Currently Amended) The system of claim **1**[[8]] wherein the at least one processor is configured to train the neural networks by:

receiving signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images

associated with one of the plurality of predetermined echocardiographic image view categories;

receiving signals representing respective expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

training the neural networks using the plurality of echocardiographic training images as inputs and the associated expert quality assessment values as desired outputs to determine the sets of neural network parameters defining the neural networks.

10. (Original) The system of claim 9 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

11. (Previously presented) The system of claim 9 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for quantified clinical measurement of anatomical features.

12. (Previously presented) The system of claim 9 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment values as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to

update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

13. (Currently Amended) A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:

receive signals representing a plurality of echocardiographic training images, each of the plurality of echocardiographic training images associated with one of a plurality of predetermined echocardiographic image view categories;

receive signals representing expert quality assessment values representing view category specific quality assessments of the plurality of echocardiographic training images, each of the expert quality assessment values provided by an expert echocardiographer and associated with one of the plurality of echocardiographic training images; and

train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories**;**[[.]]

wherein the at least one processor is further configured to, once the neural networks are trained:

receive signals representing a first at least one echocardiographic image;

associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receive signals representing a second at least one echocardiographic image;

associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

wherein the at least one processor is configured to determine the second quality assessment value by:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second

view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

14. (Original) The system of claim 13 wherein each of the expert quality assessment values represents an assessment of suitability of the associated echocardiographic image for quantified clinical measurement of anatomical features.

15. (Previously presented) The system of claim 13 wherein the at least one processor is configured to derive each of the expert quality assessment values at least in part from a clinical plane assessment value representing an expert opinion whether the associated echocardiographic training image was taken in an anatomical plane suitable for a quantified clinical measurement of anatomical features.

16. (Previously presented) The system of claim 13 wherein each of the sets of neural network parameters includes:

a set of common neural network parameters, which are common to each of the sets of neural network parameters; and

a set of view category specific neural network parameters, which are unique to the set of neural network parameters; and

wherein the at least one processor is configured to, for each echocardiographic training image:

select one of the sets of view category specific neural network parameters based on the predetermined echocardiographic image view category associated with the echocardiographic training image; and

using the echocardiographic training image as an input and the associated expert quality assessment value as a desired output, train a neural network defined by the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters to update the set of common neural network parameters and the selected one of the sets of view category specific neural network parameters.

17. (Currently Amended) A computer-implemented method of facilitating echocardiographic image analysis, the method comprising:

receiving signals representing a first at least one echocardiographic image;

associating the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;

determining, based on the first at least one echocardiographic image and the first view category, a first quality assessment value representing a view category specific quality assessment of the first at least one echocardiographic image;

producing signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;

receiving signals representing a second at least one echocardiographic image;

associating the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;

determining, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and

producing signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;

wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that defines a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values and wherein:

determining the first quality assessment value comprises:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters applying a first function based on the first set of assessment parameters to the first at least one echocardiographic image; and

determining the second quality assessment value comprises:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

18. (Original) The method of claim 17 wherein the first quality assessment value represents an assessment of suitability of the first at least one echocardiographic image for quantified clinical measurement of anatomical features and wherein the second quality assessment value represents an assessment of suitability of the second at least one echocardiographic image for quantified measurement of anatomical features.

19. (Previously presented) The method of claim 17 wherein:

producing the signals representing the first quality assessment value comprises producing signals for causing a representation of the first quality assessment value to be transmitted to at least one display for causing the at least one display to display the first quality assessment value in association with the first at least one echocardiographic image, to assist one or more operators of an echocardiographic device in capturing at least one subsequent echocardiographic image; and

producing the signals representing the second quality assessment value comprises producing signals for causing a representation of the second quality assessment value to be transmitted to the at least one display for causing the at least one display to display the second quality assessment value in association with the second at least one echocardiographic image, to assist the one or more operators in capturing at least one subsequent echocardiographic image.

20. (Previously presented) The method of claim 17 wherein:

associating the first at least one echocardiographic image with the first view category comprises applying one or more view categorization functions to the first at least one echocardiographic image to determine that the first at least one echocardiographic image falls within the first view category; and

associating the second at least one echocardiographic image with the second view category comprises applying one or more view categorization functions to the second at least one echocardiographic image to determine that the second at least one echocardiographic image falls within the second view category.

21. (Previously presented) The method of claim 17 wherein the first at least one echocardiographic image comprises a plurality of echocardiographic images and wherein determining the first quality assessment value comprises determining a single quality assessment value representing a view category specific assessment of the plurality of echocardiographic images.

22. (Canceled)

23. (Currently Amended) The method of claim **17** [[22]] wherein each of the sets of assessment parameters includes:

a set of common assessment parameters, which are common to each of the sets of assessment parameters; and

a set of view category specific assessment parameters, which are unique to the set of assessment parameters.

24. (Canceled)

25-35. (Previously Canceled)

REMARKS

These remarks are responsive to the non-final Office action dated May 5, 2021. Prior to entry of this response, claims 1-24 were pending in the application. By way of this response, claims 1, 13, and 17 are amended and claims 6, 8, 22, and 24 are canceled without prejudice or disclaimer. No new subject matter has been introduced. Accordingly, claims 1 through 23 are pending and before the Examiner for consideration, with claims 1, 13, and 17 being independent. Applicant respectfully requests reconsideration of the application and allowance of the pending claims.

With respect to the remarks below, Applicant does not concede that previously pending claims are unpatentable over the cited reference. Applicant reserves the right to pursue in the future any claims that capture any subject matter supported by the present disclosure.

Support for any new claims and substantive claim amendments may be found at least in the following locations:

Claim	Support
1	Original claims 6 and 8, [0038], [0060]-[0079], [0090]-[0094], Figs. 3 & 11
13	Original claims 1, 6, and 8, [0038], [0060]-[0079], [0090]-[0094], Figs. 3 & 11
17	Original claims 22 and 24, [0009], [0038], [0060]-[0079], [0090]-[0094], Figs. 3 & 11

Claim Rejections – 35 U.S.C. § 102

All claims stand rejected under 35 U.S.C. § 102 as follows:

- Claims 1-24 as anticipated by Krishnan et al, US 2005/0251013

Applicant respectfully traverses these rejections, but nevertheless has amended independent claims 1, 13, and 17 to clarify further the claimed features over the cited art. Based on these amendments, and the remarks below, Applicant requests that all rejections be withdrawn.

Regarding anticipation under § 102, it is an established legal principle that "unless a reference discloses within the four corners of the document not only all of the limitations claimed but also all of the limitations arranged or combined in the same way as recited in

the claim, it cannot be said to prove prior invention of the thing claimed, and, thus, cannot anticipate under 35 U.S.C. §102." *Net MoneyIN, Inc. v. Verisign, Inc.*, 545 F.3d 1359, 1371 (Fed. Cir. 2008). Here, the cited reference fails to teach or suggest each of the limitations of the present claims.

Claim 1 is amended to recite, in part, the following:

> …
> wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:
>
> determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and
> in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and
>
> wherein the at least one processor is configured to determine the second quality assessment value by:
>
> determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and
> in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

Claim 17 is similarly amended. Claims 1 and 17 have been amended to include subject matter previously recited in now-canceled claims 6 and 8. Accordingly, amended claim 1 recites at least one processor configured to determine first and second quality assessment values of respective first and second echocardiographic images utilizing respective neural networks. Amended claim 17 recites a computer-implemented method for determining first and second quality assessment values of respective first and second echocardiographic images utilizing respective neural networks. The claims include determining that a set of assessment parameters is associated with a respective view category and, in response, inputting a corresponding echocardiographic image into a respective neural network to determine the respective quality assessment value of each image. Each neural network is defined by a respective set of assessment parameters

associated with one of a plurality of predetermined view categories that may characterize an echocardiographic image (e.g., AP2, AP3, AP4, AP5, $PSAX_A$, $PSAX_{PM}$, PLAX - see para. [0060]).

The first and second images are associated with respective first and second view categories of the plurality of predetermined view categories, and it is determined that respective first and second sets of assessment parameters are associated with those view categories. To obtain quality assessment values, the first and second images are input into neural networks defined by the first and second sets of assessment parameters, respectively. The output layer of each neural network is configured to output a corresponding quality assessment value. Accordingly, a view category specific quality assessment value is obtained for each image using a neural network defined by assessment parameters associated with a view category associated with that image.

In contrast, Krishnan teaches systems and methods for processing a medical image to automatically identify anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image [0002]. Krishnan teaches that the anatomy, view, and/or diagnostic quality may be identified and/or assessed by a classification module and/or a bank of classifiers configured to classify the images based on features extracted (see Krishnan at steps 201, 202 of Fig.2 below, steps 500, 502 of Fig. 5 below, para. [0043]).

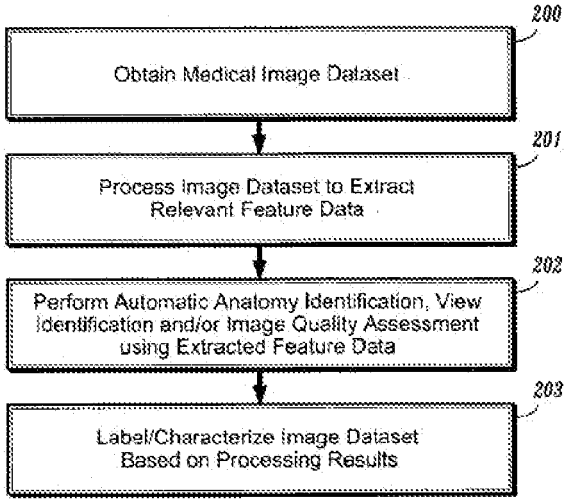


FIG. 2

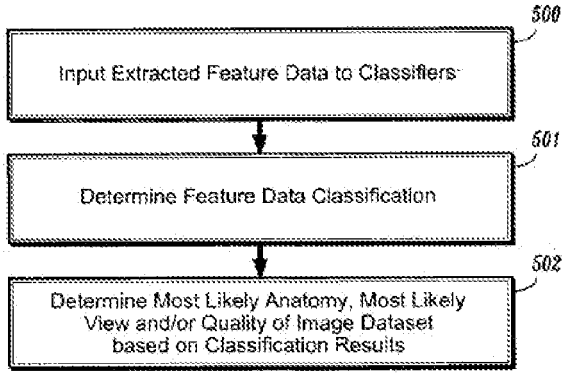


FIG. 5

The Office action at pp. 3-4 appears to interpret Krishnan's quality assessment module, which is configured to assess the diagnostic quality of the image, as reading on

the presently claimed determination of first and second quality assessment values. However, even assuming (without admitting) that this interpretation is reasonable, Krishnan fails to teach or suggest determining a quality assessment value of an image using a neural network defined by a set of assessment parameters associated with a view category associated with that image. At best, Krishnan suggests generally at para. [0020] that "the results of anatomy and/or view identification may be used for quality assessment." This is not the same as, and cannot reasonably be interpreted to be, the claimed neural network defined by a set of assessment parameters associated with a view category corresponding to the image.

Furthermore, Krishnan fails to teach or suggest determining quality assessment values for each of two images using two respective neural networks corresponding to the respective view category of each image. Accordingly, Krishnan cannot and does not teach the claimed use of a first neural network defined by a first set of assessment parameters to determine a quality assessment value for a first image, and use of a second neural network defined by a second set of assessment parameters to determine a quality assessment value for a second image, wherein the assessment parameters defining each network are associated with a view category of the associated image.

For at least these reasons, Krishnan fails to teach all of the features of claims 1 and 17. Claims 1 and 17 therefore are not anticipated by Krishnan.

Claim 13 is amended to recite, in part, the following:

> A computer-implemented system for training neural networks to facilitate echocardiographic image analysis, the system comprising at least one processor configured to:
> …
> train the neural networks using the plurality of echocardiographic training images and the associated expert quality assessment values to determine sets of neural network parameters defining the neural networks, at least a portion of each of said neural networks associated with one of the plurality of predetermined echocardiographic image view categories;
> wherein the at least one processor is further configured to, once the neural networks are trained:
> receive signals representing a first at least one echocardiographic image;
> associate the first at least one echocardiographic image with a first view category of a plurality of predetermined echocardiographic image view categories;
> determine, based on the first at least one echocardiographic image and the first view category, a first quality assessment value

representing a view category specific quality assessment of the first at least one echocardiographic image;
produce signals representing the first quality assessment value for causing the first quality assessment value to be associated with the first at least one echocardiographic image;
receive signals representing a second at least one echocardiographic image;
associate the second at least one echocardiographic image with a second view category of the plurality of predetermined echocardiographic image view categories, said second view category being different from the first view category;
determine, based on the second at least one echocardiographic image and the second view category, a second quality assessment value representing a view category specific quality assessment of the second at least one echocardiographic image; and
produce signals representing the second quality assessment value for causing the second quality assessment value to be associated with the second at least one echocardiographic image;
wherein each of the plurality of predetermined echocardiographic image view categories is associated with a respective set of assessment parameters, each of the sets of assessment parameters being a set of neural network parameters that define a neural network having a plurality of layers including an input layer configured to receive one or more echocardiographic images and an output layer configured to output one or more quality assessment values, and wherein the at least one processor is configured to determine the first quality assessment value by:

determining that a first set of assessment parameters of the sets of assessment parameters is associated with the first view category; and

in response to determining that the first set of assessment parameters is associated with the first view category, inputting the first at least one echocardiographic image into the neural network defined by the first set of assessment parameters; and

wherein the at least one processor is configured to determine the second quality assessment value by:

determining that a second set of assessment parameters of the sets of assessment parameters is associated with the second view category; and

in response to determining that the second set of assessment parameters is associated with the second view category, inputting the second at least one echocardiographic image into the neural network defined by the second set of assessment parameters.

Accordingly, amended claim 13 recites a computer-implemented system comprising at least one processor configured to both train and utilize neural networks to facilitate echocardiographic image analysis. The system includes at least one processor

configured to determine first and second quality assessment values of respective first and second echocardiographic images utilizing respective neural networks. Each neural network is defined by a respective set of assessment parameters associated with one of a plurality of predetermined view categories that may characterize an echocardiographic image.

As described above with reference to claims 1 and 17, Krishnan fails to teach or suggest the above-recited features. Furthermore, Krishnan fails to teach or suggest training neural networks using a plurality of echocardiographic training images and associated expert quality assessment values, such that at least a portion of each neural network is associated with one of a plurality of predetermined echocardiographic image view categories, as recited in amended claim 13. Amended independent claim 13 therefore is not anticipated by Krishnan.

Accordingly, amended claims 1, 13, and 17 recite features not found in Krishnan, and are therefore not anticipated by Krishnan. For at least these reasons, amended claims 1, 13, and 17 and their dependent claims are distinguishable and allowable over the cited reference, and Applicant respectfully requests the withdrawal of all rejections under 35 U.S.C. § 102.

CONCLUSION

In view of the above amendments and remarks, Applicant believes that this application is now in condition for allowance. Accordingly, Applicant respectfully requests that the Examiner issue a Notice of Allowance covering all of the claims. If the Examiner has any questions, or if a telephone interview would in any way advance prosecution of the application, please contact the undersigned practitioner of record at (503) 994-1650. The Commissioner is hereby authorized to charge or credit any deficiencies or over-payments to Deposit Account No. 602562 which may be required in connection with this filing.

CERTIFICATE OF EFS-WEB TRANSMISSION

I hereby certify that this correspondence is being transmitted via the U.S. Patent and Trademark Office electronic filing system (EFS-Web) to the USPTO on August 5, 2021.

/Lukas McNett/
Lukas MCNETT

Respectfully submitted,

/David C. Bourgeau/
David C. BOURGEAU III
Registration No. 72,711
Kolitch Romano LLP
520 SW Yamhill Street, Ste. 200
Portland, Oregon 97204
Telephone: (503) 994-1650

EXHIBIT C

US 20050251013A1

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(54) SYSTEMS AND METHODS PROVIDING AUTOMATED DECISION SUPPORT FOR MEDICAL IMAGING

(76) Inventors: **Sriram Krishnan**, Exton, PA (US); **Dorin Comaniciu**, Princeton Jct., NJ (US); **Xiang Sean Zhou**, Plainsboro, NJ (US); **Michael G. Cannon**, Haverford, PA (US); **Allen Dutton**, Exton, PA (US)

Correspondence Address:
Siemens Corporation
Intellectual Property Department
170 Wood Avenue South
Iselin, NJ 08830 (US)

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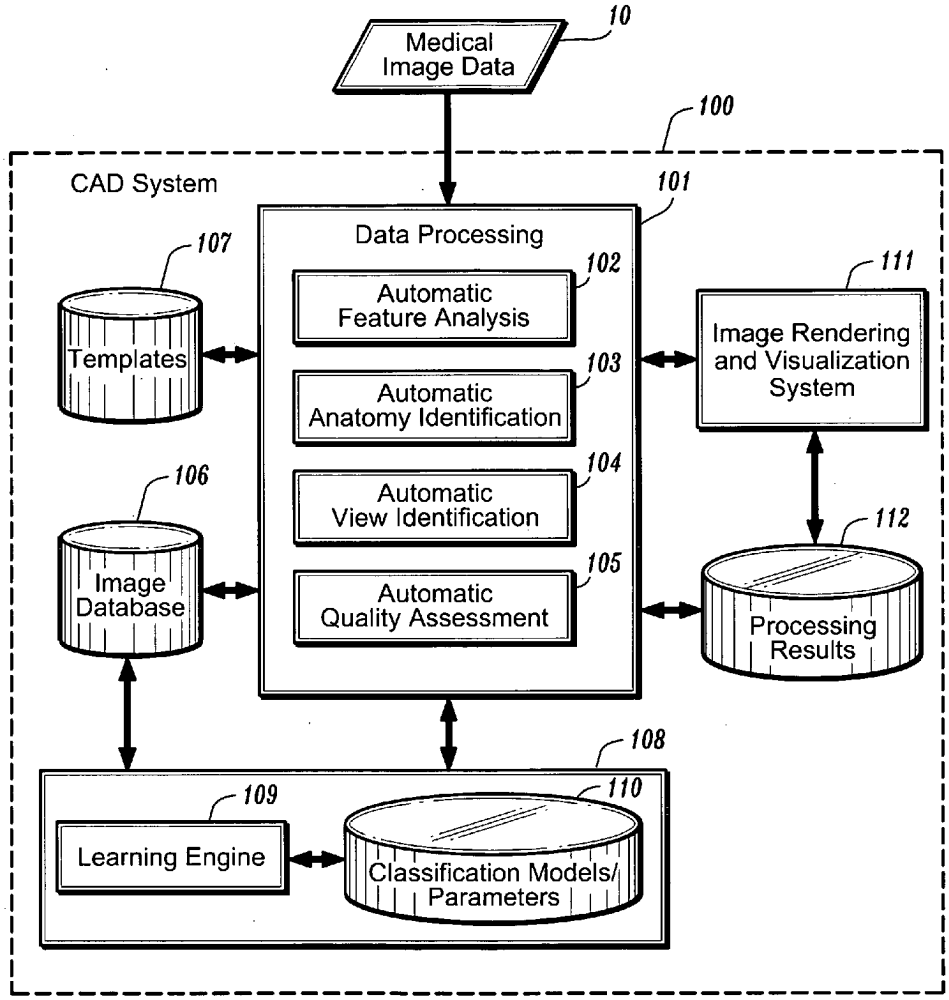
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(57) **ABSTRACT**

Systems and methods are provided for processing a medical image to automatically identify the anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image. In one aspect a method for automated decision support for medical imaging includes obtaining image data, extracting feature data from the image data, and automatically performing anatomy identification, view identification and/or determining a diagnostic quality of the image data, using the extracted feature data.



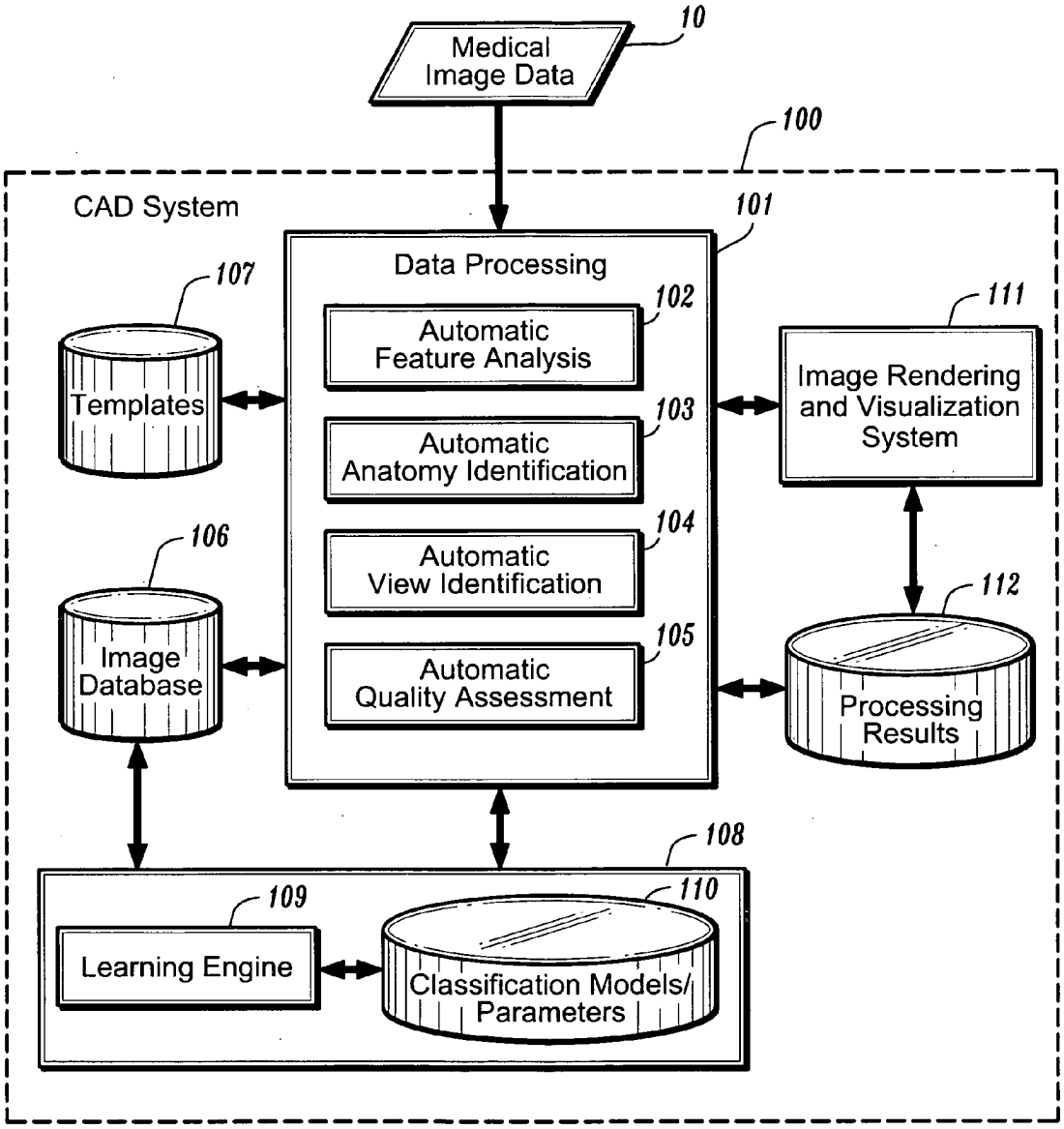

Medical Image Data
10
100
CAD System
101
Data Processing
107
Templates
102
Automatic Feature Analysis
103
Automatic Anatomy Identification
104
Automatic View Identification
105
Automatic Quality Assessment
111
Image Rendering and Visualization System
106
Image Database
112
Processing Results
108
109
Learning Engine
110
Classification Models/ Parameters

FIG. 1

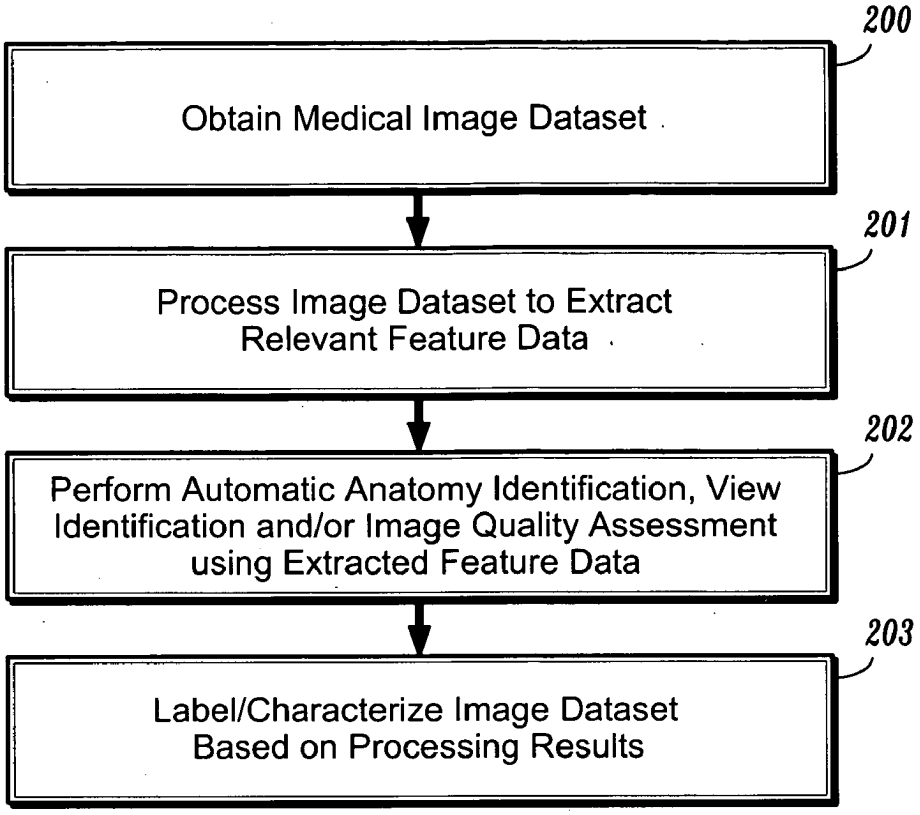

200
Obtain Medical Image Dataset
201
Process Image Dataset to Extract Relevant Feature Data
202
Perform Automatic Anatomy Identification, View Identification and/or Image Quality Assessment using Extracted Feature Data
203
Label/Characterize Image Dataset Based on Processing Results

FIG. 2

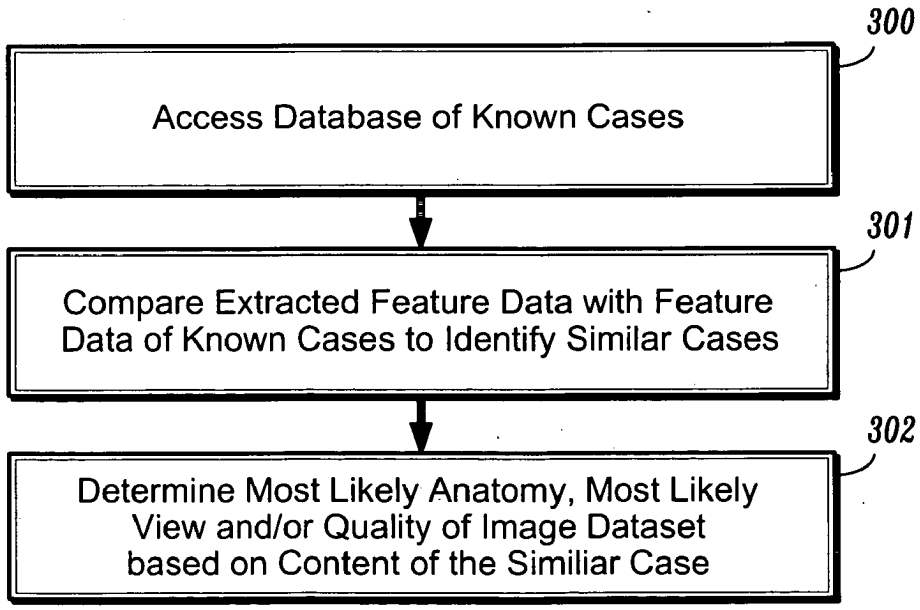

300
Access Database of Known Cases
301
Compare Extracted Feature Data with Feature Data of Known Cases to Identify Similar Cases
302
Determine Most Likely Anatomy, Most Likely View and/or Quality of Image Dataset based on Content of the Similiar Case

FIG. 3

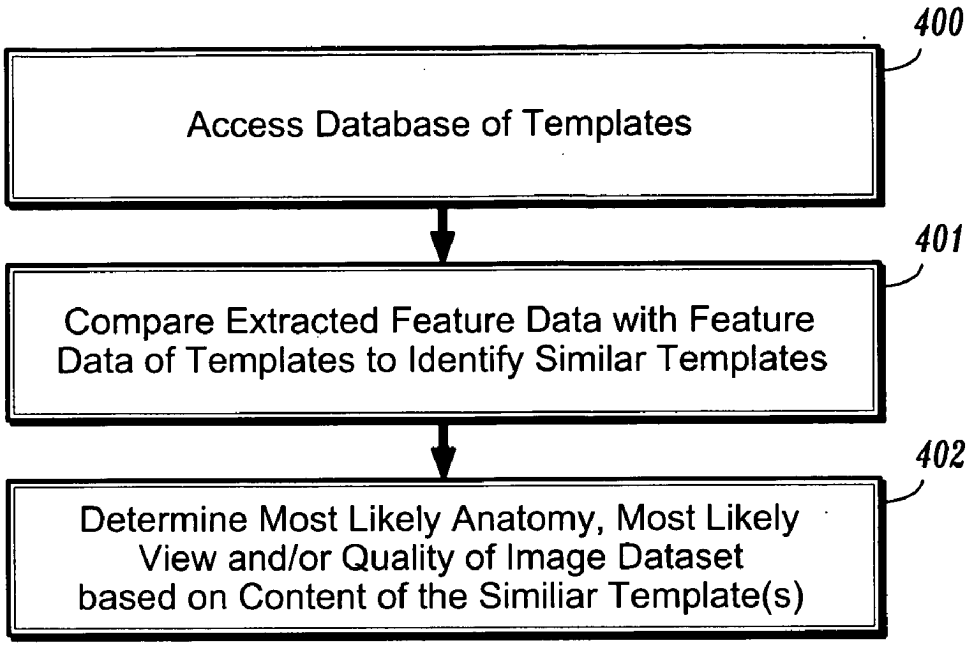

400
Access Database of Templates
401
Compare Extracted Feature Data with Feature Data of Templates to Identify Similar Templates
402
Determine Most Likely Anatomy, Most Likely View and/or Quality of Image Dataset based on Content of the Similiar Template(s)

FIG. 4

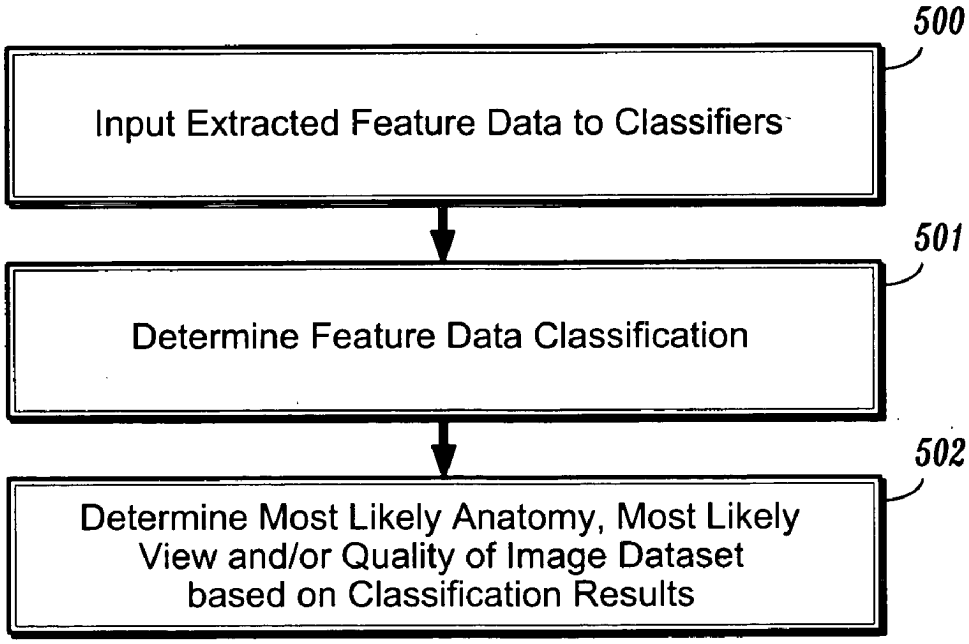

500
Input Extracted Feature Data to Classifiers
501
Determine Feature Data Classification
502
Determine Most Likely Anatomy, Most Likely View and/or Quality of Image Dataset based on Classification Results

FIG. 5

SYSTEMS AND METHODS PROVIDING AUTOMATED DECISION SUPPORT FOR MEDICAL IMAGING

CROSS-REFERENCE TO RELATED APPLICATION

[0001] This application claims priority to U.S. Provisional Application Ser. No. 60/555,620, filed on Mar. 23, 2004, which is fully incorporated herein by reference.

TECHNICAL FIELD OF THE INVENTION

[0002] The present invention relates generally to systems and methods for providing automated decision support for medical imaging. More specifically, the present invention relates to systems and methods for processing a medical image to automatically identify the anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image.

BACKGROUND

[0003] In the field of medical imaging, various imaging modalities and systems are used for generating medical images of anatomical structures of individuals for screening and evaluating medical conditions. These imaging systems include, for example, CT (computed tomography) imaging, MRI (magnetic resonance imaging), NM (nuclear magnetic) resonance imaging, X-ray systems, US (ultrasound) systems, PET (positron emission tomography) systems, etc. For each of these modalities, a specific part of the human body is targeted for imaging, which can be performed in various ways. With ultrasound, sound waves from a transducer are directed towards a specific part of the body (the heart, for example). In MRI, gradient coils are used to "select" a part of the body where nuclear resonance is recorded. The part of the body targeted by the imaging modality usually corresponds to the area that the physician is interested in exploring. Each imaging modality may provide unique advantages over other modalities for screening and evaluating certain types of diseases, medical conditions or anatomical abnormalities, including, for example, cardiomyopathy, colonic polyps, aneurisms, lung nodules, calcification on heart or artery tissue, cancer micro calcifications or masses in breast tissue, and various other lesions or abnormalities.

[0004] Typically, physicians, clinicians, radiologists, etc, will manually review and evaluate medical images (X-ray films, prints, photographs, etc) reconstructed from an acquired image dataset, to discern characteristic features of interest and detect, diagnose or otherwise identify potential medical conditions. For example, CT image data that is acquired during a CT examination can be used to produce a set of 2D medical images (X-ray films) that can be viewed to identify potential abnormal anatomical structures or lesions, for example. Depending on the skill and knowledge of the reviewing physician, clinician, radiologist, etc., however, manual evaluation of medical images can result in misdiagnosed medical conditions due to simple human error. Furthermore, when the acquired medical images are of low diagnostic quality, it can be difficult for even a highly skilled reviewer to effectively evaluate such medical images and identify potential medical conditions.

SUMMARY OF THE INVENTION

[0005] In general, exemplary embodiments of the invention include systems and methods for processing a medical image to automatically identify the anatomy and view (or pose) from the medical image and automatically assess the diagnostic quality of the medical image. For example, in one exemplary embodiment, a method for automated decision support for medical imaging includes obtaining image data, extracting feature data from the image data, and automatically performing anatomy identification, view identification and/or determining a diagnostic quality of the image data, using the extracted feature data.

[0006] In another exemplary embodiment of the invention, automated anatomy identification, view identification and/or image quality assessment are performed using associated classifiers that process the extracted feature data. The classifiers can be implemented using machine learning methods, model-based methods, or any combination of machine learning and model-based methods.

[0007] In another exemplary embodiment of the invention, automated anatomy identification, view identification and/or image quality assessment can be performed by using the extracted feature data to query a database of known cases to identify similar cases and use information associated with the identified similar cases to perform the respective functions. Training data extracted from the database of know cases can be used to train classifiers for performing such functions.

[0008] In another exemplary embodiment of the invention, automated anatomy identification, view identification and image quality assessment are performed by using the extracted feature data to query a database of templates derived from information of known cases to identify similar templates and use information associated with the identified similar templates to perform the respective functions.

[0009] In yet another exemplary embodiment of the invention, feature extraction, automated anatomy identification, view identification and image quality assessment are performed in real-time during image acquisition, wherein the results of image quality assessment are presented to a user in real-time during image acquisition. For imaging modalities, such as ultrasound imaging (e.g., 2-D echocardiography) for heart imaging, a sonographer has very limited time to acquire images during a stress stage. By providing a real-time quality assessment of the image acquisition, the sonographer can determine whether the acquired images are of sufficient diagnostic quality, thereby allowing for changes in image acquisition, if necessary.

[0010] These and other exemplary embodiments, features and advantages of the present invention will be described or become apparent from the following detailed description of exemplary embodiments, which is to be read in connection with the accompanying drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0011] **FIG. 1** is a block diagram of a system for providing automated decision support for medical imaging according to an exemplary embodiment of the invention.

[0012] **FIG. 2** is a flow diagram illustrating methods for automated decision support for medical imaging according to exemplary embodiments of the invention.

[0013] **FIG. 3** is a flow diagram illustrating methods for implementing automated decision support for medical imag-

ing using database query methods according to exemplary embodiments of the invention.

[0014] **FIG. 4** is a flow diagram illustrating methods for implementing automated decision support for medical imaging using template-based methods according to exemplary embodiments of the invention.

[0015] **FIG. 5** is a flow diagram illustrating methods for implementing automated decision support for medical imaging using classification according to exemplary embodiments of the invention.

DETAILED DESCRIPTION OF EXEMPLARY EMBODIMENTS

[0016] **FIG. 1** illustrates a high-level block diagram of a system (**100**) for providing automated decision support for medical imaging, according to an exemplary embodiment of the invention. In general, the exemplary system (**100**) comprises a data processing module (**101**) that implements various methods for analyzing medical image data (**10**) in one or more imaging modalities (e.g., ultrasound image data, MRI data, nuclear medicine data, etc.) to automatically extract and process relevant information from the medical image data to provide various decision support function(s) for evaluating the medical images. In the exemplary embodiment, the data processing module (**101**) comprises an automatic feature analysis module (**102**), an anatomy identification module (**103**), a view identification module (**104**) and an image quality assessment module (**105**).

[0017] In general, the feature analysis module (**102**) implements methods for automatically extracting one or more types of features/parameters from input medical image data and combining the extracted features/parameters in a manner that is suitable for processing by the decision support modules (**103**, **104** and/or **105**). The system (**100**) can process digital image data (**10**) in the form of raw image data, 2D-reconstructed data (e.g., axial slices), or 3D-reconstructed data (volumetric image data or multiplanar reformats), 4D-reconstructed data, or other image modalities/formats. It is to be understood that methods implemented by the feature extraction module (**102**) will vary depending on the imaging modalities and/or automated decision support methods that are supported by the CAD system (**100**), as well as the type(s) of anatomical structures under consideration.

[0018] The anatomy identification module (**102**) implements methods for using the extracted features/parameters to automatically identify anatomical objects (heart chambers, kidneys, etc) in the image dataset and label the image(s) with the appropriate anatomy identification. In another exemplary embodiment, the anatomy identification module (**102**) implements methods for determining (for each anatomy/view ID label) a confidence or likelihood measure that the identified anatomy/view is properly labeled. The results of anatomy identification for a medical image can be used by other automated methods such as the view identification and quality assessment methods, or other application that provide automated diagnosis, therapy planning, etc.

[0019] The view identification module (**103**) implements methods for using the extracted features/parameters to automatically identify the view of an acquired image. In other words, the view identification module (**104**) implements methods for pose estimation and label a medical image with respect to what view of the anatomy the medical image contains. By way of example, for cardiac ultrasound imaging, the American Society of Echocardiography (ASE) recommends using standard ultrasound views in B-mode to obtain sufficient cardiac image data—the apical two-chamber view (A2C), the apical four-chamber view (A4C), the apical long axis view (ALAX), the parasternal long axis view (PLAX), the parasternal short axis view (PSAX). Ultrasound images of the heart can be taken from various angles, but efficient analysis of cardiac ultrasound images requires recognizing the position of the imaged heart (view) to enable identification of important cardiac structures. In accordance with an exemplary embodiment of the invention, view identification module (**103**) implements methods for identifying an unknown cardiac image as one of the standard views. In addition, the view identification module (**103**) may implements methods for determining (for each view label) a confidence or likelihood measure that the identified view is properly labeled.

[0020] The quality assessment module (**105**) implements methods for using the extracted features/parameters to assess a level of diagnostic quality of an acquired image data set and determine whether errors occurred in the image acquisition process. In other exemplary embodiments of the invention, the results of anatomy and/or view identification may be used for quality assessment. Moreover, methods can be implemented for providing real-time feedback during image acquisition regarding the diagnostic quality of the acquired images, allowing for changes in the image acquisition. In addition, methods can be implemented for determining a quality measure within a predefined range of values to provide an indication as the quality level of the acquired images based on some specified criteria

[0021] The system (**100**) further comprises a database (**106**) of previously diagnosed/labeled medical images, a template database (**107**) and a classification system (**108**), which can be used singularly, or in combination, by one or more of the various automated decision support modules (**102~105**) of the data processing system (**101**) to perform their respective functions. For example, in one exemplary embodiment, the various modules (**103**), (**104**) and (**105**) implement database querying methods to use extracted feature data to search for similar labeled cases in the database (**106**). The database (**106**) may comprise a plurality of labeled/diagnosed medical images for various clinical domains, which are indexed using a multi-dimensional indexing scheme based on relevant features/parameters. In such instance, the features/parameters extracted from an image dataset under consideration can be compared to the feature data of known cases in the database (**106**) according to some metrics or criteria identify the particular anatomy or view, or help identify the quality of the image extracted.

[0022] In another exemplary embodiment, the various modules (**103**), (**104**) and (**105**) can implement template-based methods to use extracted feature data to search for similar templates in template database (**107**). In particular, various templates can be constructed using information obtained from the database of cases (**106**). For example, feature data over a plurality of known cases for a given identity and view can be processed using statistical techniques to derive feature data for a template representative over the set of related cases. In this instance, the features/

parameters extracted from an image dataset under consideration can be compared to the feature data for templates in the database (**107**) according to some metrics or criteria identify the particular anatomy or view, or help identify the quality of the image extracted.

[**0023**] In another exemplary embodiment, the various modules (**103**), (**104**) and (**105**) can implement classification methods that utilize the classification module (**108**) to process extracted feature data to classify the image dataset under consideration. In the exemplary embodiment of **FIG. 1**, the classification module (**108**) comprises a learning engine (**109**) and knowledge base (**110**) to implement a principle (machine) learning classification system. The learning engine (**109**) includes methods for training/building one or more classifiers using training data that is learned from the database (**106**) of previously diagnosed/labeled cases. The classifiers are implemented by the various decision support modules (**102**~**105**) for performing their respective functions.

[**0024**] The processing results generated by the various modules of the data processing module (**101**) can be persistently stored in a repository (**112**) in association with the corresponding image dataset. The processing results may comprise meta information for superposition of markers, segmentation, color or intensity variations, and so forth, which can be rendered as overlays on the associated image data.

[**0025**] The system (**100**) further comprises an image rendering and visualization system (**111**) to process digital image data (**10**) of an acquired image dataset (or a portion thereof) and generate and display 2D and/or 3D images on a computer monitor. More specifically, the imaging system (**111**) may be any application that provides 3D/2D rendering and visualization of image data (**10**), and which executes on general purpose or specific computer workstation having a monitor. Moreover, the imaging system (**111**) comprises a GUI (graphical user interface), for example, which enables a user to navigate through a 3D image or a plurality of 2D slices.

[**0026**] The data processing system (**101**) and image rendering and visualization system (**111**) may be implemented as a single application that executes in a computing system (e.g., workstation). Alternatively, the systems (**101**) and (**111**) may be independent tools that are distributed over a computer network, wherein known communication protocols such as DICOM, PACS, etc. are used for communicating between the systems and transmitting image data over the network.

[**0027**] It is to be appreciated that exemplary methods for automatic anatomy and view identification and image quality assessment are powerful tools that provide substantial assistance and decision support in medical imaging acquisition and evaluation. Indeed, when medical images are acquired, it is important to properly label the images with proper anatomy and view so that a physician can perform a proper diagnosis. Currently, labeling is done manually, either by a technologist acquiring the scan, or by the physician. With exemplary labeling methods described herein, the system automatically identifies the anatomy and view being imaged, which provide various advantages. For instance, automated anatomy identification improves physician workflow by eliminated manual labeling. Moreover, automated anatomy identification facilitates automated quality control, and other automated computer applications that aid in diagnosis, therapy planning, or other applications.

[**0028**] Further, automated view identification methods according to the invention could provide significant workflow enhancement for medical imaging applications, such as 2-D echocardiography, and specifically stress-echo. In stress-echo, the sonographer has a very limited time (90 seconds or so for exercise stress) to acquire images from four different views. To save time, the sonographer often just records for a significant portion of the 90 seconds, and then proceed to label the views after imaging is done. This is a cumbersome process, and could be improved by automatically identifying the views.

[**0029**] The results of anatomy identification and/or view identification can be used to perform automatic image quality assessment process according to an exemplary embodiment of the invention. The quality check would assess the quality of the acquired images, and also whether there are any errors in how the image was acquired. For example, in 2-D echocardiography, it is difficult to properly image the apex from the apical window. Typically, images will be acquired with the apex foreshortened, that is, the transducer is angled so that the apex appears thicker than it actually is, which gives an impression of a thicker myocardium at the apex. However, other clues in the image may suggest that the apex was indeed foreshortened.

[**0030**] For example, foreshortening can be identified by measuring the distance on the ultrasound image from the base of the left ventricle to the apex, and the thickness of the myocardium at the apex. This distance can be compared to the distance acquired in previous exams, or with typical values associated with hearts of the same size of the patient, and than assessed to determine the existence, if any, of foreshortening. In addition, the thickness of the myocardium at the apex is another metric that can be evaluated to identify potential foreshortening. If the apical myocardium is significantly thicker than the rest of the heart, then it can be concluded that the view may have been foreshortened. Another approach would be to have a set of images which are foreshortened, and another set of correctly acquired images with no foreshortening, which are stored in a database. Using a similarity metric, the database can be searched to determine whether a current image is more similar to the set of foreshortened images or correctly acquired images.

[**0031**] Another problem could be identification of motion artifacts in MRI. Because MRI are acquired in “k-space”, and not real space, motion during image acquisition can result in strange results. By analyzing the quality of the images, motion artifacts can be identified.

[**0032**] In addition to searching for problems, the automatic image quality assessment can be implemented to provide general feedback on the diagnostic quality of an image. For example, with 2-D echocardiography, particularly stress-echo, the sonographer has very limited time to acquire images during a stress stage. It is important for the sonographer to acquire, as quickly as possible, diagnostic quality images at multiple views. Many times, because of the time pressure of a stress-echo, diagnostic quality images are not obtained, and the images are useless. By providing a quality check, the sonographer can be assured that images are being acquired of diagnostic quality. The advantage of

doing such a quality check is that feedback can be provided back to the operator of the imaging device in real time, allowing for changes in acquisition. This could be very important in a medical situation. If the feedback is provided quickly, there may be an opportunity to re-image the patient before he is sent home or discharged. In addition, there may be other advantages. For example, again in stress-echo, another application would be to automatically select the images of highest quality for the cardiologist to review. Often in stress-echo, the sonographer acquires up to four (and sometimes more) loops of data for each view, where each loop represents a heart cycle, or at least the systole portion of the heart cycle. Typically, either the sonographer or cardiologist selects which of the loops provides the best images from a diagnostic standpoint, and uses them. By providing a quality check, this could be done automatically.

[**0033**] Referring now to **FIG. 2**, a flow diagram illustrates methods for providing automated decision support for medical imaging, according to exemplary embodiments of the invention. For purposes of illustration, exemplary methods for automated decision support will be described with reference to the exemplary system of **FIG. 1**. Initially, a physician, clinician, radiologist, etc., will obtain a medical image dataset comprising one or more medical images of a region of interest of a subject patient (step **200**). The image dataset may be obtained using a medical imaging system for real-time acquisition and processing of raw image data, such as raw CT data (radon data) which is acquired during a CT scan or raw data that is acquired using other imaging modalities. Alternatively, the image dataset may be obtained by accessing a previously acquired, and persistently stored image dataset. The digital image data (**10**) may comprise one or more 2D slices or three-dimensional volumetric images, which are reconstructed from the raw image data and persistently stored. As noted above, an exemplary CAD process can support one or more imaging modalities such as MRI, PET, etc. Image data can be 2D (e.g. X-ray Mammography images), 3D (e.g. CT, MRI, PET), 4D (Dynamic 3D MRI, multiple views of a beating heart acquired with a 3D Ultrasound probe), etc.

[**0034**] Next, the image dataset will be processed to determine or otherwise extract relevant feature data from the image dataset (step **201**) which is utilized to perform one or more decision support functions such as automatic anatomy identification, view identification and/or image quality assessment (step **202**). As noted above, the relevant features/parameters that are extracted/determined from the image dataset will vary depending on the imaging modality, the supported clinical domains, and the methods implemented for providing automated decision support, and one of ordinary skill in the art can readily envision various types of feature data or parameters that can be extracted or determined from medical image data for use with automated anatomy and view identification methods and image quality assessment methods according to exemplary embodiments of the invention. For example, various parameters related to optical density and contrast can be extracted Feature extraction can implement known segmentation and/or filtering methods for segmenting features or anatomies of interest by reference to known or anticipated image characteristics, such as edges, identifiable structures, boundaries, changes or transitions in colors or intensities, changes or transitions in spectrographic information, etc, using known methods. These features could include any kind of characteristic that could be extracted from the image, such as a particular shape or texture. Further, various types of feature data can be obtained across images, such as motion of a particular point, or the change in a particular feature across images. In other embodiments, feature data may include gradient feature data that is computed from image data along various axes (x, y, z), distributions of pixel intensities, or other statistical features, or combinations of different features.

[**0035**] Methods for automatic anatomy identification, automatic view identification and image quality assessment (step **202**) according to exemplary embodiments of the invention can be implemented using one or more techniques including a database query approach (e.g., **FIG. 3**), a template processing approach (e.g., **FIG. 4**) and/or classification (e.g., **FIG. 5**) that utilize the extracted features to provide automated decision support functions.

[**0036**] The image dataset will be labeled or otherwise classified based on the processing results obtained (step **203**). For instance, for anatomy and view identification, a medical image will be labeled with the appropriate anatomy and view identification. In addition, for each anatomy/view ID label, a confidence or likelihood measure that the identified anatomy/view is properly labeled. Moreover, for image quality assessment, the medical images may include a quality score (within a predefined range) that provides an indication a diagnostic quality level of the medical images.

[**0037**] **FIG. 3** is a flow diagram illustrating methods for implementing automated decision support for medical images using database query methods according to exemplary embodiments of the invention. The methods of **FIG. 3** may be implemented by the modules (**103**), (**104**) and/or (**105**) of **FIG. 1** and in step **202** of **FIG. 2**. In one exemplary embodiment, a query can be formulated using the feature data extracted from the image dataset and the database of known cases would be accessed (step **300**) and searched using the query. The extracted feature data comprising the query would be compared to features of known cases to identify similar cases (step **301**). The content of the identified cases would then be used to determine the most likely anatomy or view for the subject image, or to determine the quality of the acquired image (step **302**).

[**0038**] For example, consider the problem of identifying the apical four-chamber view in echocardiography. A set of typical apical four chamber views would reveal a number of features, such as the presence of four chambers, and a general shape for the heart. It is also described by the lack of other features, such as the absence of the aortic outflow track (which would lend itself to the so-called apical five chamber view). These features could be extracted from a test image, and compared to a set of features from the known view.

[**0039**] The same concept would be used in anatomy identification. For example, consider an ultrasound image of a kidney. Features would be extracted and compared with a database of cases representing all kinds of anatomy, including liver, gall bladder, kidney, etc. One could even have right and left kidneys in the database. Based on a comparison with these known cases, and the most likely anatomy would be reported.

[**0040**] Methods for indexing a database of images, and using low-level features to search the database can be

implemented using the techniques disclosed in commonly assigned U.S. patent application Ser. No. 10/703,024, filed on Nov. 6, 2003, entitled "System and Method for Performing Probabilistic Classification and Decision Support Using Multidimensional Medical Image Databases", which is incorporated herein by reference. In one embodiment, the database could be constructed with either the images, or with just the feature representations of the images. The system could identify similar images, and then determine anatomy, view and/or quality based on the content of the similar images.

[0041] **FIG. 4** is a flow diagram illustrating methods for implementing automated decision support for medical images using template-based methods according to exemplary embodiments of the invention. In one exemplary embodiment, a query can be formulated using the feature data extracted from the image dataset and the database of templates would be accessed (step **400**) and searched using the query. The extracted feature data comprising the query would be compared to features of the templates to identify similar templates (step **401**). The content of the identified templates would then be used to determine the most likely anatomy or view for the subject image, or to determine the quality of the acquired image (step **402**). As noted above, the database of known cases could be used to construct templates. For example, templates could be constructed for different cardiac views: apical four chamber, apical two chamber, etc. The system could then assess similarity to each of these templates, which provides a simpler operational approach then searching a database.

[0042] **FIG. 5** is a flow diagram illustrating methods for implementing automated decision support for medical images using classification according to exemplary embodiments of the invention. In this exemplary embodiment, the feature data extracted from the image dataset would be input to classifiers (step **500**) that are trained or designed to process the feature data to classify the image data (step **501**). The classification results would be used to determine the most likely anatomy or view, or assess image quality (step **502**).

[0043] For example, a bank of classifiers could be constructed to classify the images based on the features extracted. That is, a set of classifiers would be "learned" based on a database of cases. These classifiers would use the set of features as an input, and classify the image as belonging to a particular anatomy, view, or level of quality. In the exemplary embodiment of **FIG. 1**, the classification system (**108**) includes the knowledge base (**110**) that is used to process the extracted features/parameters and classify the images. The knowledge base (**110**) maintains one or more trained classification models, parameters, and/or other data structures of learned knowledge, etc.

[0044] It is to be understood that the term "classifiers" as used herein generally refers to various types of classifier frameworks, such as hierarchical classifiers, ensemble classifiers, etc. In addition, a classifier design can include a multiplicity of classifiers that attempt to partition data into two groups and organized either organized hierarchically or run in parallel and then combined to find the best classification. Further, a classifier can include ensemble classifiers wherein a large number of classifiers (referred to as a "forest of classifiers") all attempting to perform the same classification task are learned, but trained with different data/variables/parameters, and then combined to produce a final classification label. The classification methods implemented may be "black boxes" that are unable to explain their prediction to a user (which is the case if classifiers are built using neural networks, example). The classification methods may be "white boxes" that are in a human readable form (which is the case if classifiers are built using decision trees, for example). In other embodiments, the classification models may be "gray boxes" that can partially explain how solutions are derived (e.g., a combination of "white box" and "black box" type classifiers).

[0045] It is to be understood that the systems and methods described herein in accordance with the present invention may be implemented in various forms of hardware, software, firmware, special purpose processors, or a combination thereof. For example, the systems and methods described herein can be implemented in software as an application comprising program instructions that are tangibly embodied on one or more program storage devices (e.g., hard disk, magnetic floppy disk, RAM, CD Rom, DVD, ROM and flash memory), and executable by any device or machine comprising suitable architecture. In addition, because the constituent system modules and method steps depicted in the accompanying Figures can be implemented in software, the actual connections between the system components (or the flow of the process steps) may differ depending upon the manner in which the application is programmed. Given the teachings herein, one of ordinary skill in the related art will be able to contemplate these and similar implementations or configurations of the present invention.

[0046] It is to be further understood that systems and methods according to the present invention may be implemented as extensions to conventional CAD methods or other automated diagnostic methods for processing image data. Further, it is to be appreciated that the exemplary systems and methods described herein can be readily implemented with 3D medical imaging and CAD systems or applications that are adapted for a wide range of imaging modalities (CT, MRI, etc.) for diagnosis and evaluation. In this regard, although exemplary embodiments may be described herein with reference to particular imaging modalities or particular anatomical features, nothing should be construed as limiting the scope of the invention.

[0047] Although illustrative embodiments of the present invention have been described herein with reference to the accompanying drawings, it is to be understood that the invention is not limited to those precise embodiments, and that various other changes and modifications may be affected therein by one skilled in the art without departing from the scope or spirit of the invention. All such changes and modifications are intended to be included within the scope of the invention as defined by the appended claims.

What is claimed is:

1. A method for providing automated decision support for medical imaging, comprising:

obtaining image data;

extracting feature data from the image data; and

automatically determining a diagnostic quality of the image data using the extracted feature data.

2. The method of claim 1, wherein the image data comprises cardiac ultrasound image data.

3. The method of claim 1, further comprising automatically determining a metric that indicates a level of diagnostic quality.

4. The method of claim 1, wherein automatically determining the diagnostic quality is performed by processing the extracted feature data using a classifier to determine the diagnostic quality.

5. The method of claim 4, wherein the classifier is implemented using a machine learning method, a model-based method, or any combination of machine learning and model-based methods.

6. The method of claim 1, wherein automatically determining the diagnostic quality is performed by using the extracted feature data to query a database of known cases to identify similar cases and use information associated with the identified similar cases to determine the diagnostic quality.

7. The method of claim 1, wherein automatically determining the diagnostic quality is performed by using the extracted feature data to query a database of templates derived from information of known cases to identify similar templates and use information associated with the identified similar templates to determine the diagnostic quality.

8. The method of claim 1, further comprising automatically identifying and labeling an anatomical object of the image data using the extracted feature data.

9. The method of claim 7, wherein automatically determining a diagnostic quality of the image data further comprises using results of automatic anatomy identification.

10. The method of claim 1, further comprising automatically identifying and labeling a view of the image data using the extracted feature data.

11. The method of claim 10, wherein automatically determining a diagnostic quality of the image data further comprises using results of automatic view identification.

12. The method of claim 10, wherein the view is a standard view for a clinical domain of interest.

13. The method of claim 1, wherein automatically determining a diagnostic quality of the image data using the extracted feature data is performed in real-time during image acquisition.

14. The method of claim 13, further comprising presenting diagnostic quality determination results to a user in real-time during image acquisition.

15. A method for providing automated decision support for medical imaging, comprising:

obtaining image data;

extracting feature data from the image data; and

performing an automatic anatomy identification process using the extracted feature data to label an identified anatomical object in the image data.

16. The method of claim 15, further comprising performing an automatic view identification process using the extracted feature data and results of anatomy identification to label a view of the image data.

17. The method of claim 16, further comprising performing an automated image quality assessment process using the extracted feature data and results of anatomy and view identification to determine a level of diagnostic quality of the image data.

18. The method of claim 17, wherein automated anatomy identification, view identification and image quality assessment are performed in real-time during image acquisition.

19. The method of claim 18, further comprising presenting results of the automated anatomy identification, view identification and image quality assessment processes to a user in real-time during image acquisition.

20. The method of claim 17, wherein automated anatomy identification, view identification and image quality assessment are performed using associated classifiers that process the extracted feature data.

21. The method of claim 20, wherein the classifiers are implemented using a machine learning method, a model-based method, or any combination of machine learning and model-based methods.

22. The method of claim 17, wherein automated anatomy identification, view identification and image quality assessment are performed are performed by using the extracted feature data to query a database of known cases to identify similar cases and use information associated with the identified similar cases to perform the respective functions.

23. The method of claim 17, wherein automated anatomy identification, view identification and image quality assessment are performed are performed by using the extracted feature data to query a database of templates derived from information of known cases to identify similar templates and use information associated with the identified similar templates to perform the respective functions.

24. A method for providing automated decision support for medical imaging, comprising:

obtaining image data;

extracting feature data from the image data; and

performing an automatic view identification process using the extracted feature data to identify a view of the image data.

25. The method of claim 24, wherein the image data comprises image data of a heart acquired using ultrasound imaging.

26. The method of claim 25, wherein a view is identified as an apical two-chamber view (A2C), an apical four-chamber view (A4C), an apical long axis view (ALAX), the parasternal long axis view (PLAX), or a parasternal short axis view (PSAX).

27. The method of claim 25, further comprising performing an automated image quality assessment process using the extracted feature data and results of view identification to determine a level of diagnostic quality of the image data.

28. The method of claim 27, wherein the automated image quality assessment process is performed by determining and evaluation a metric that provide an indication as to wherein an acquired cardiac image contains a view with a foreshortened apex.

29. The method of claim 28, wherein automatically determining a diagnostic quality of the image data using the extracted feature data is performed in real-time during image acquisition.

30. The method of claim 29, further comprising presenting diagnostic quality determination results to a user in real-time during image acquisition.

* * * * *

EXHIBIT D

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(54) **METHOD AND APPARATUS FOR MEASURING THE QUALITY OF AN IMAGE**

(71) Applicant: **SAMSUNG ELECTRONICS CO., LTD.**, Suwon-si (KR)

(72) Inventors: **Heekuk LEE**, Suwon-si (KR); **Dae-Kyu SHIN**, Suwon-si (KR); **Yumin JUNG**, Suwon-si (KR)

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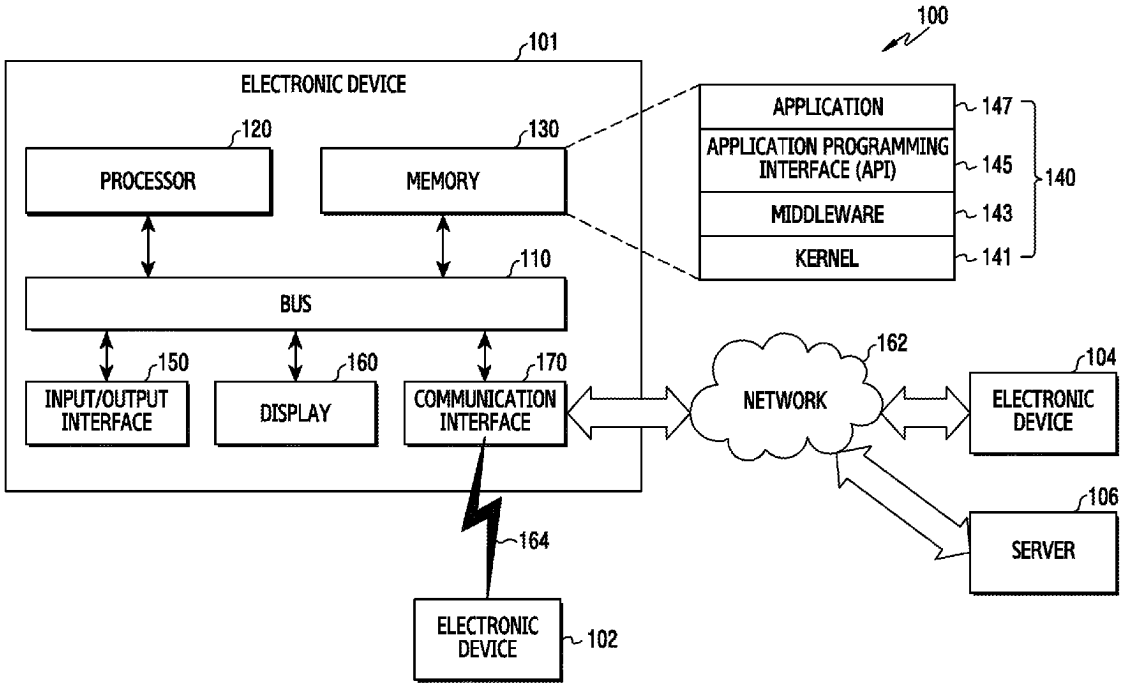
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G06K 9/66	(2006.01)
G06K 9/62	(2006.01)

(52) **U.S. Cl.**

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(57) **ABSTRACT**

An electronic device that includes an image quality measuring function and an operation method thereof are disclosed. An image quality measuring method includes: obtaining an image; classifying an image scene category of the image; determining a classifier corresponding to the classified image scene category; determining image quality factor scores with respect to the image; and evaluating image quality with respect to the image by using the determined image quality factor scores and the determined classifier.



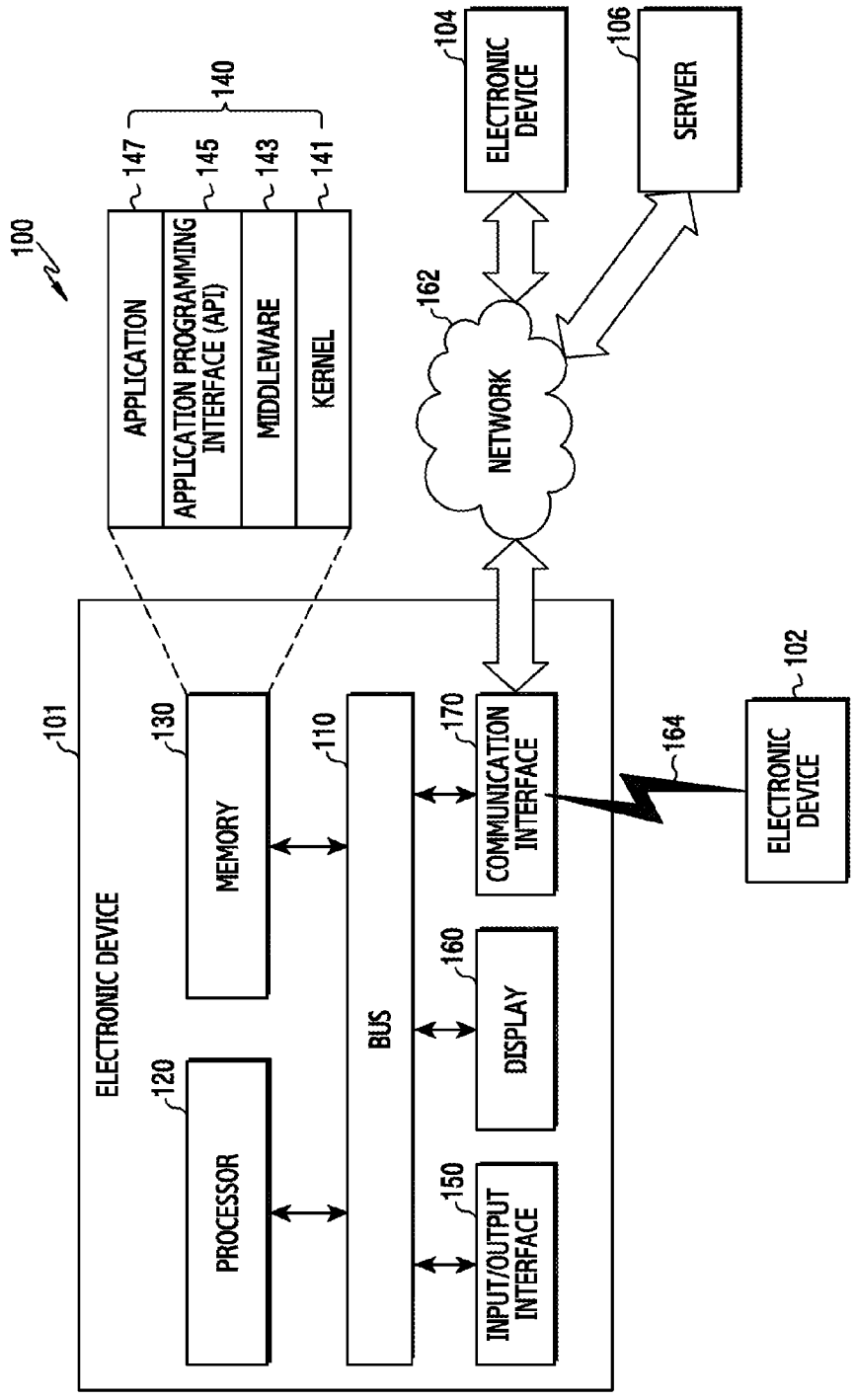

100
APPLICATION
APPLICATION PROGRAMMING INTERFACE (API)
MIDDLEWARE
KERNEL
147
145
143
141
140
ELECTRONIC DEVICE
104
SERVER
106
NETWORK
162
101
ELECTRONIC DEVICE
MEMORY
130
BUS
110
COMMUNICATION INTERFACE
170
164
ELECTRONIC DEVICE
102
PROCESSOR
120
DISPLAY
160
INPUT/OUTPUT INTERFACE
150

FIG. 1

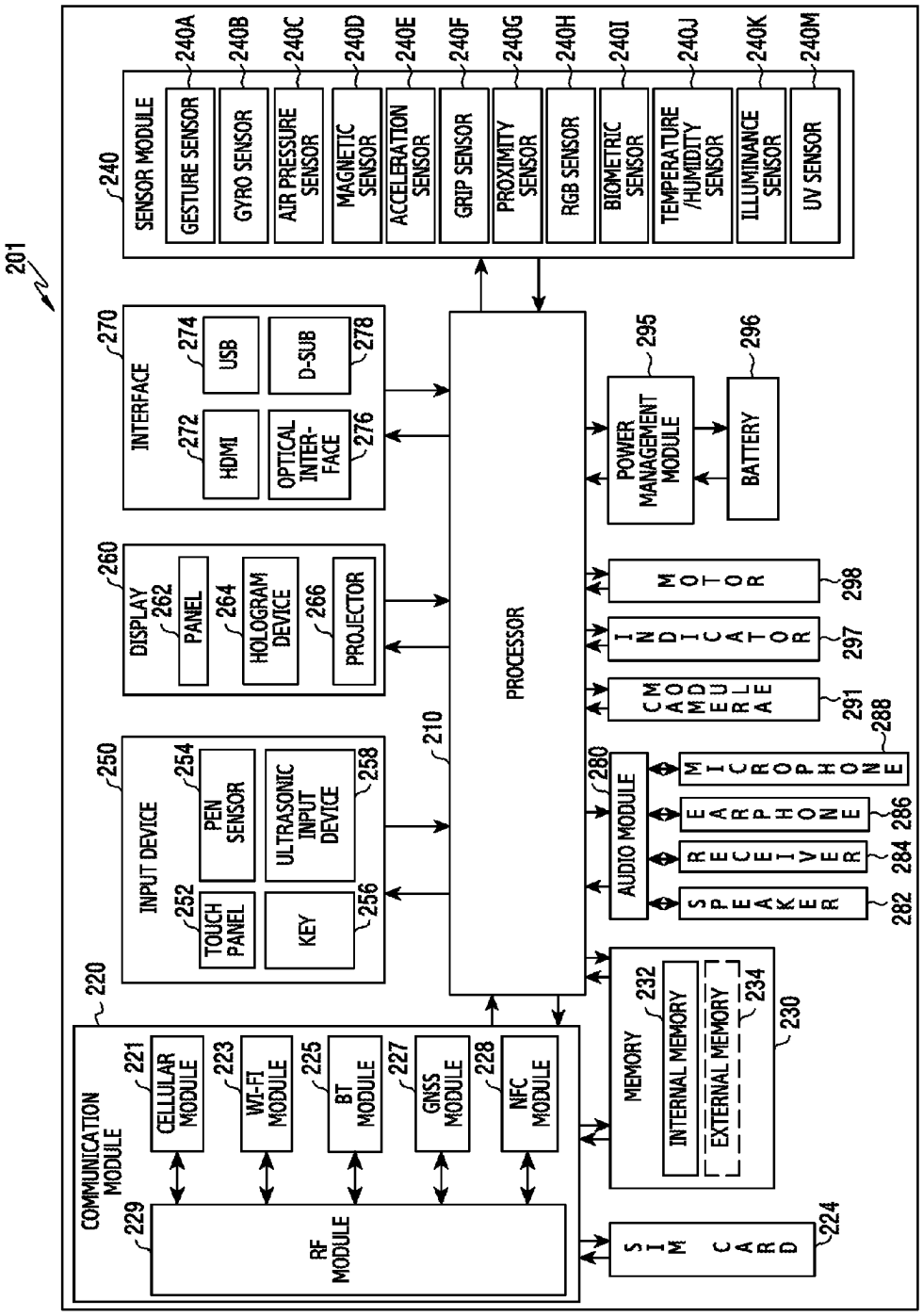

201
240
SENSOR MODULE
240A GESTURE SENSOR
240B GYRO SENSOR
240C AIR PRESSURE SENSOR
240D MAGNETIC SENSOR
240E ACCELERATION SENSOR
240F GRIP SENSOR
240G PROXIMITY SENSOR
240H RGB SENSOR
240I BIOMETRIC SENSOR
240J TEMPERATURE /HUMIDITY SENSOR
240K ILLUMINANCE SENSOR
240M UV SENSOR
270
INTERFACE
272 HDMI
274 USB
276 OPTICAL INTER-FACE
278 D-SUB
260
DISPLAY
262 PANEL
264 HOLOGRAM DEVICE
266 PROJECTOR
250
INPUT DEVICE
252 TOUCH PANEL
254 PEN SENSOR
256 KEY
258 ULTRASONIC INPUT DEVICE
210
PROCESSOR
295
POWER MANAGEMENT MODULE
296
BATTERY
298 MOTOR
297 INDICATOR
291 CAMERA MODULE
288 MICROPHONE
280
AUDIO MODULE
282 SPEAKER
284 RECEIVER
286 EARPHONE
220
COMMUNICATION MODULE
221 CELLULAR MODULE
223 WI-FI MODULE
225 BT MODULE
227 GNSS MODULE
228 NFC MODULE
229 RF MODULE
MEMORY 232
INTERNAL MEMORY
EXTERNAL MEMORY 234
230
SIM CARD 224

FIG.2

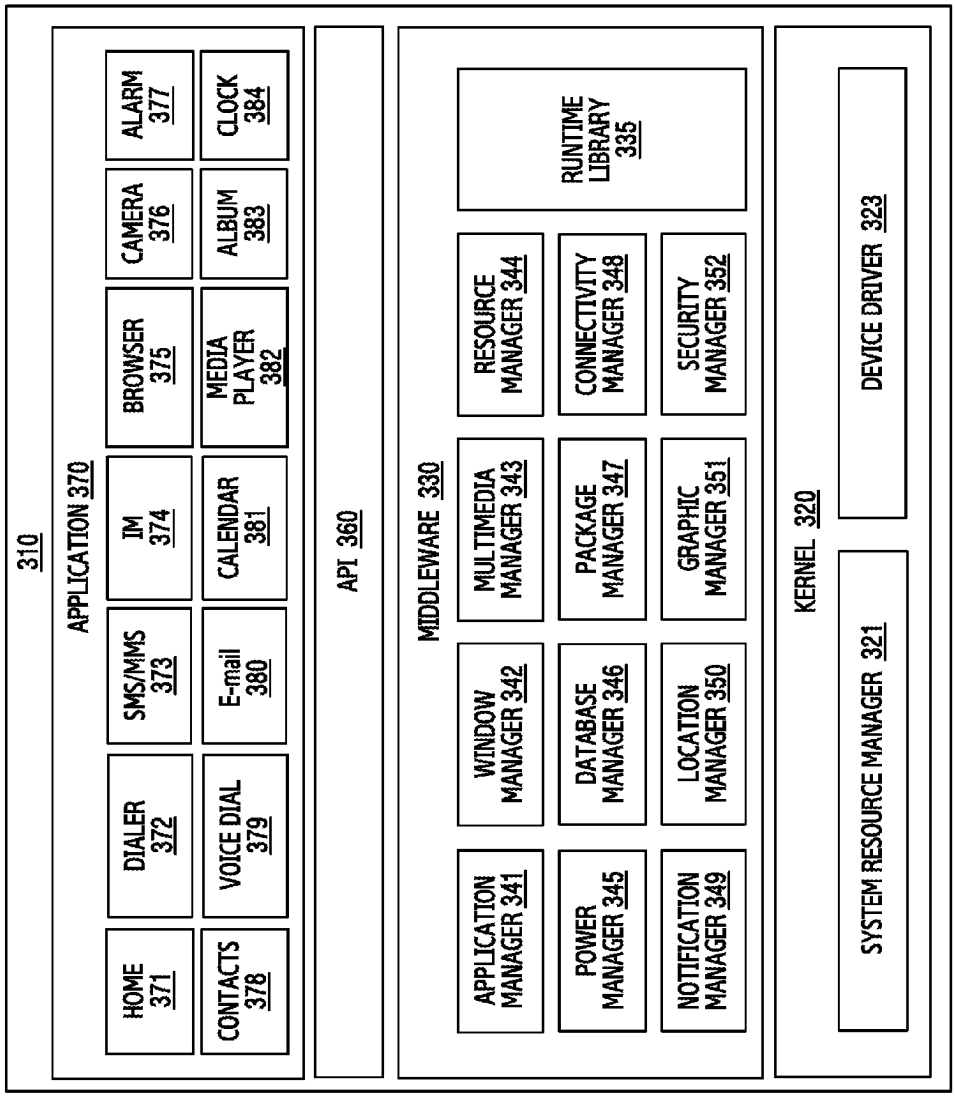

310
APPLICATION 370
HOME 371
DIALER 372
SMS/MMS 373
IM 374
BROWSER 375
CAMERA 376
ALARM 377
CONTACTS 378
VOICE DIAL 379
E-mail 380
CALENDAR 381
MEDIA PLAYER 382
ALBUM 383
CLOCK 384
API 360
MIDDLEWARE 330
APPLICATION MANAGER 341
WINDOW MANAGER 342
MULTIMEDIA MANAGER 343
RESOURCE MANAGER 344
RUNTIME LIBRARY 335
POWER MANAGER 345
DATABASE MANAGER 346
PACKAGE MANAGER 347
CONNECTIVITY MANAGER 348
NOTIFICATION MANAGER 349
LOCATION MANAGER 350
GRAPHIC MANAGER 351
SECURITY MANAGER 352
KERNEL 320
SYSTEM RESOURCE MANAGER 321
DEVICE DRIVER 323

FIG.3

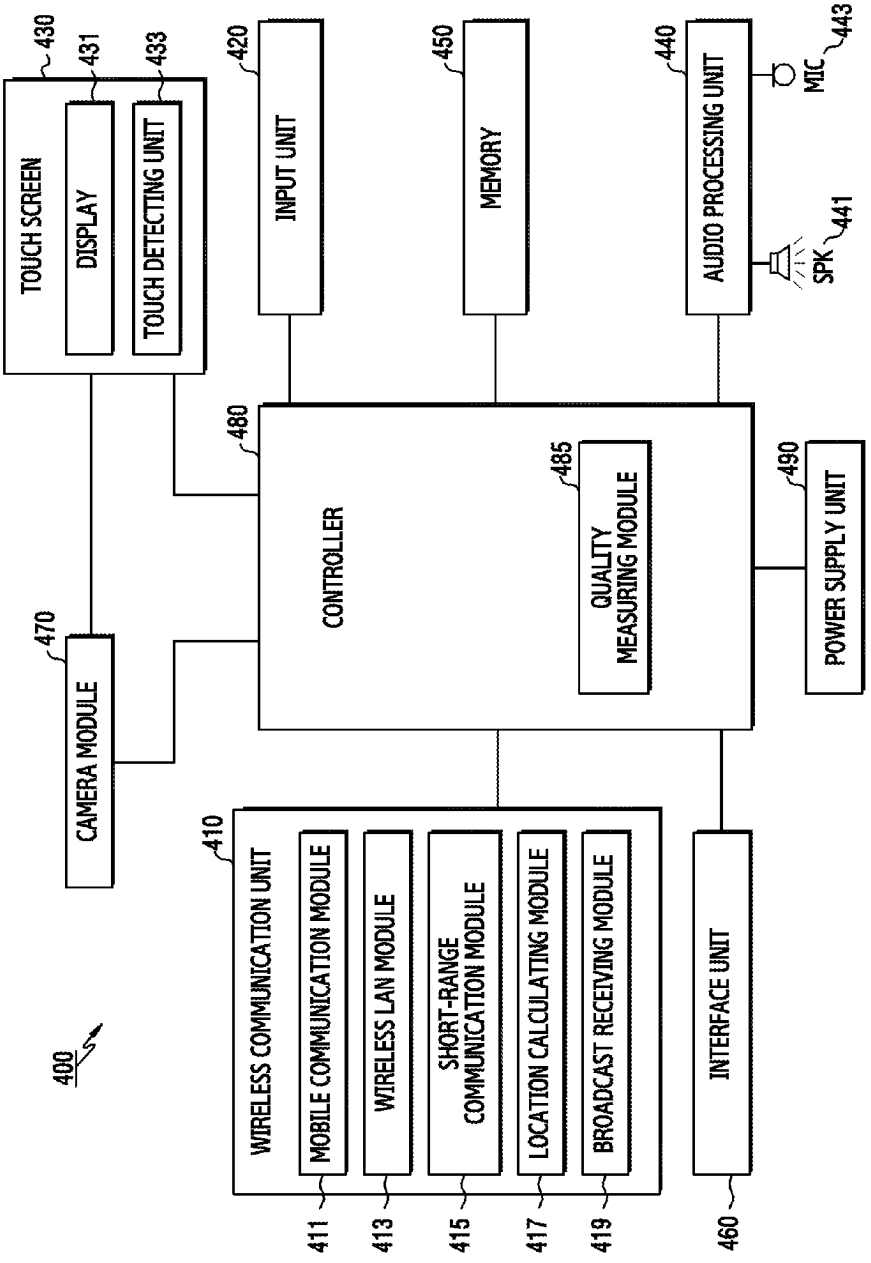

400
TOUCH SCREEN
430
DISPLAY
431
TOUCH DETECTING UNIT
433
INPUT UNIT
420
MEMORY
450
AUDIO PROCESSING UNIT
440
MIC
443
SPK
441
CONTROLLER
480
QUALITY MEASURING MODULE
485
POWER SUPPLY UNIT
490
CAMERA MODULE
470
WIRELESS COMMUNICATION UNIT
410
MOBILE COMMUNICATION MODULE
411
WIRELESS LAN MODULE
413
SHORT-RANGE COMMUNICATION MODULE
415
LOCATION CALCULATING MODULE
417
BROADCAST RECEIVING MODULE
419
INTERFACE UNIT
460

FIG.4

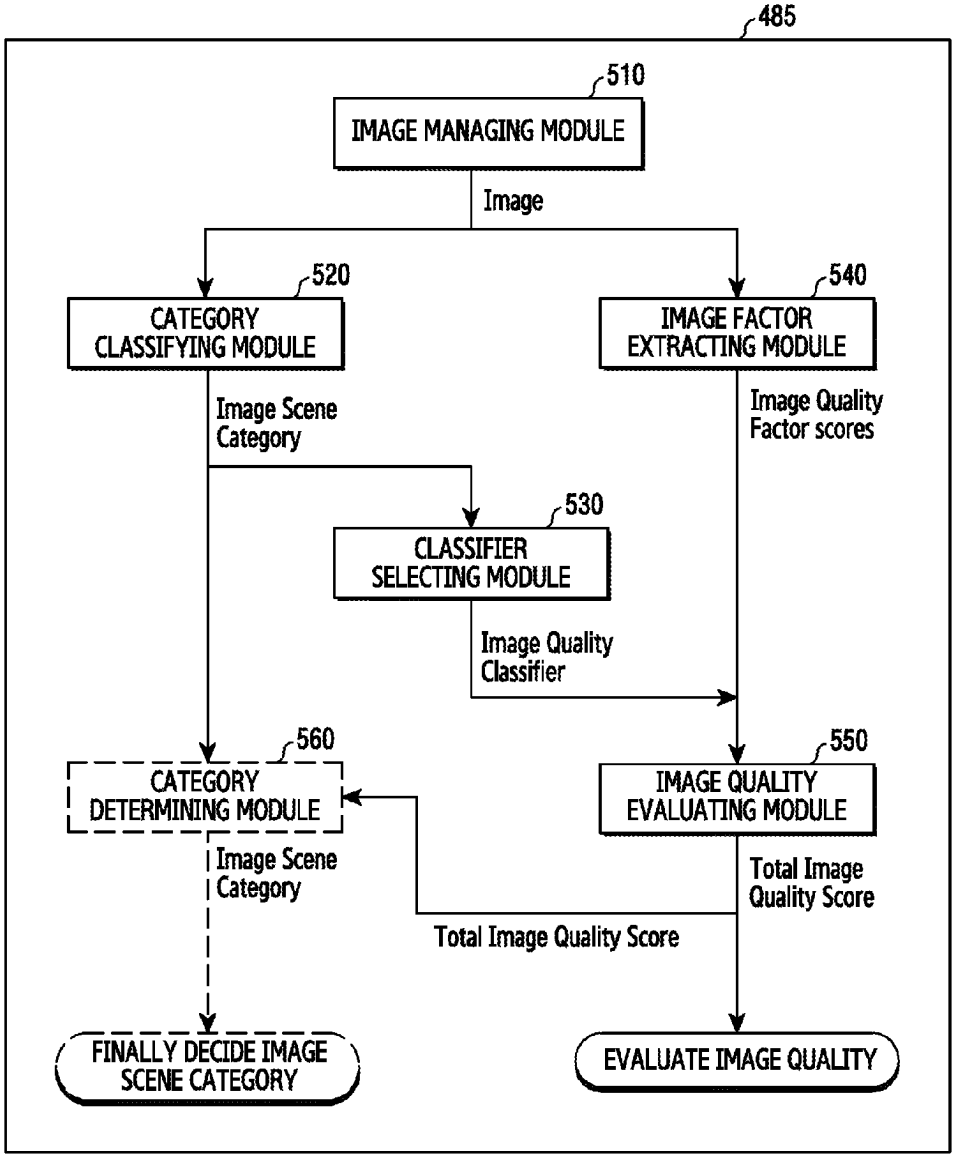

485
510
IMAGE MANAGING MODULE
Image
520
CATEGORY CLASSIFYING MODULE
540
IMAGE FACTOR EXTRACTING MODULE
Image Scene Category
Image Quality Factor scores
530
CLASSIFIER SELECTING MODULE
Image Quality Classifier
560
CATEGORY DETERMINING MODULE
550
IMAGE QUALITY EVALUATING MODULE
Image Scene Category
Total Image Quality Score
Total Image Quality Score
FINALLY DECIDE IMAGE SCENE CATEGORY
EVALUATE IMAGE QUALITY

FIG.5

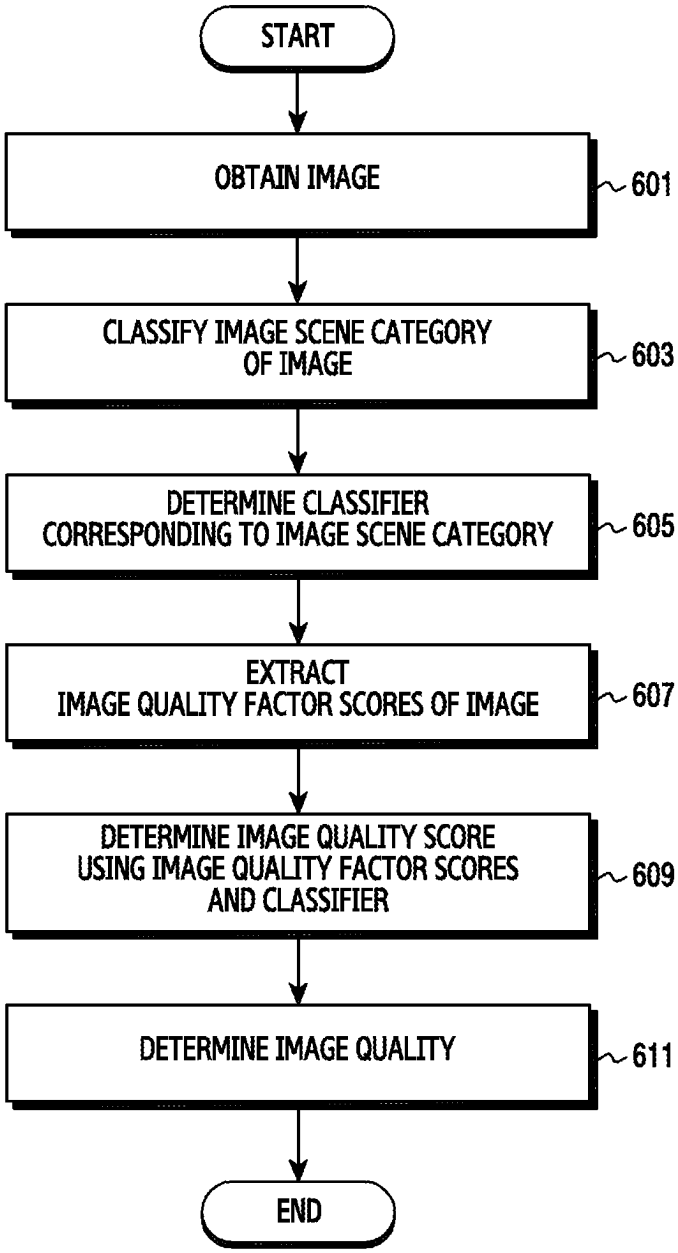

START
OBTAIN IMAGE
601
CLASSIFY IMAGE SCENE CATEGORY OF IMAGE
603
DETERMINE CLASSIFIER CORRESPONDING TO IMAGE SCENE CATEGORY
605
EXTRACT IMAGE QUALITY FACTOR SCORES OF IMAGE
607
DETERMINE IMAGE QUALITY SCORE USING IMAGE QUALITY FACTOR SCORES AND CLASSIFIER
609
DETERMINE IMAGE QUALITY
611
END

FIG.6

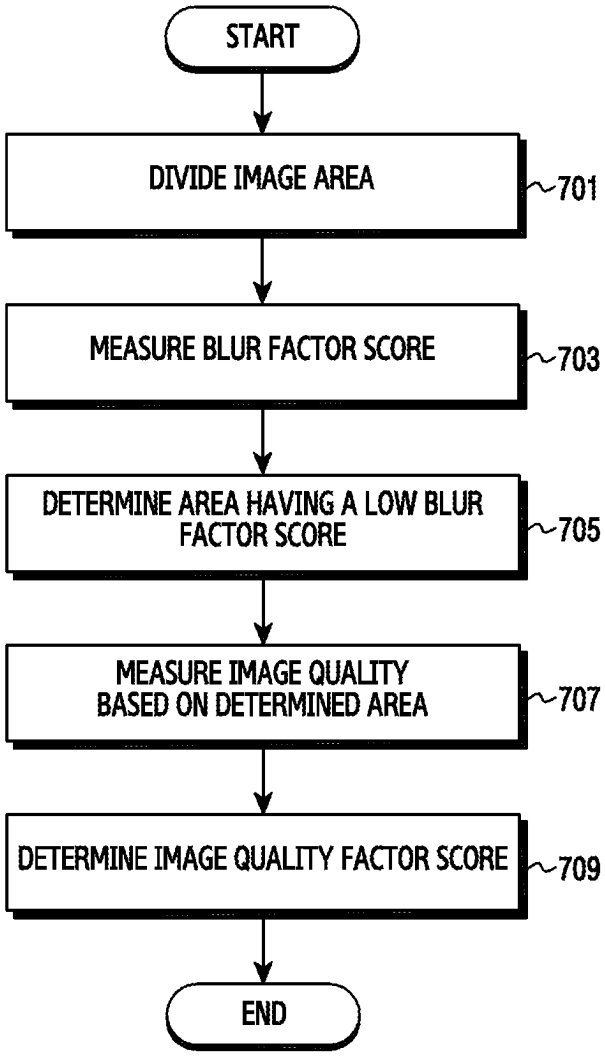

START
DIVIDE IMAGE AREA
701
MEASURE BLUR FACTOR SCORE
703
DETERMINE AREA HAVING A LOW BLUR FACTOR SCORE
705
MEASURE IMAGE QUALITY BASED ON DETERMINED AREA
707
DETERMINE IMAGE QUALITY FACTOR SCORE
709
END

FIG.7

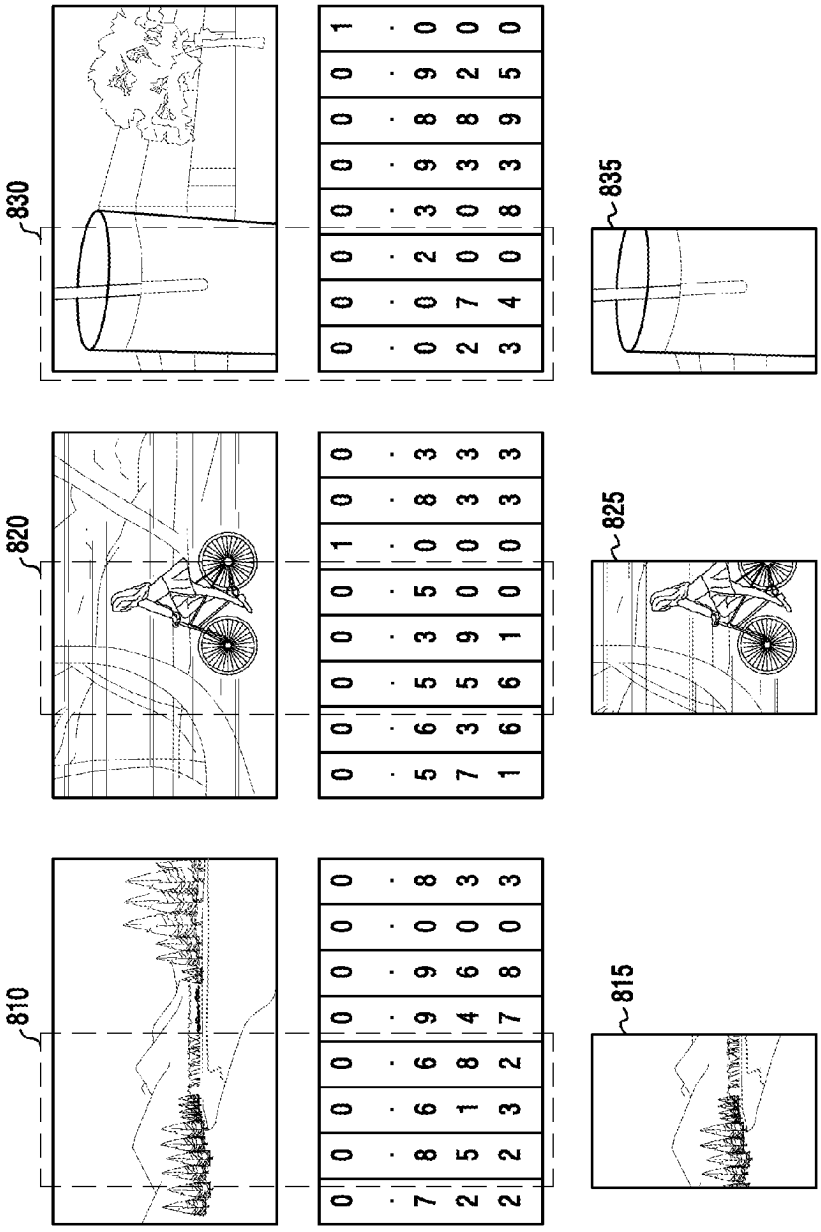


FIG.8A

FIG.8B

FIG.8C

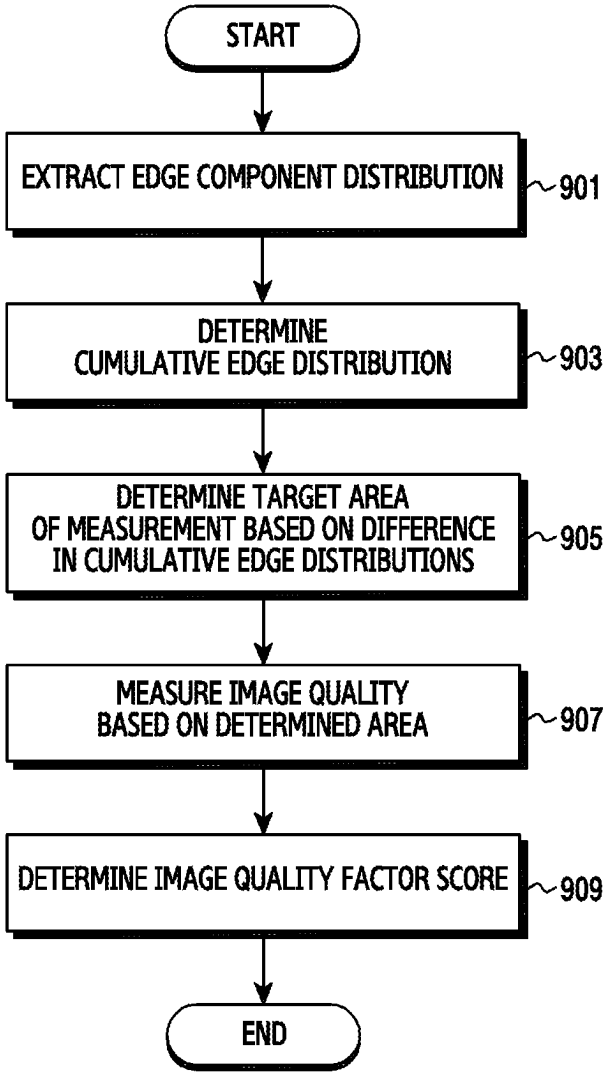

START
EXTRACT EDGE COMPONENT DISTRIBUTION
901
DETERMINE CUMULATIVE EDGE DISTRIBUTION
903
DETERMINE TARGET AREA OF MEASUREMENT BASED ON DIFFERENCE IN CUMULATIVE EDGE DISTRIBUTIONS
905
MEASURE IMAGE QUALITY BASED ON DETERMINED AREA
907
DETERMINE IMAGE QUALITY FACTOR SCORE
909
END

FIG.9

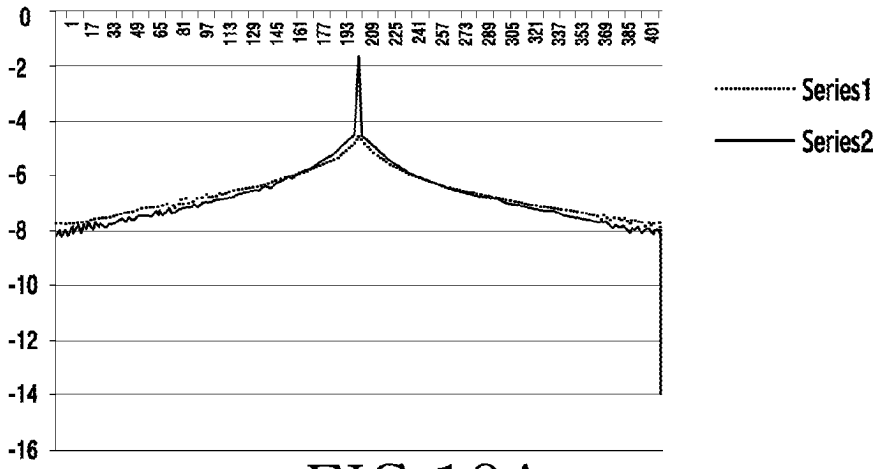


FIG.10A

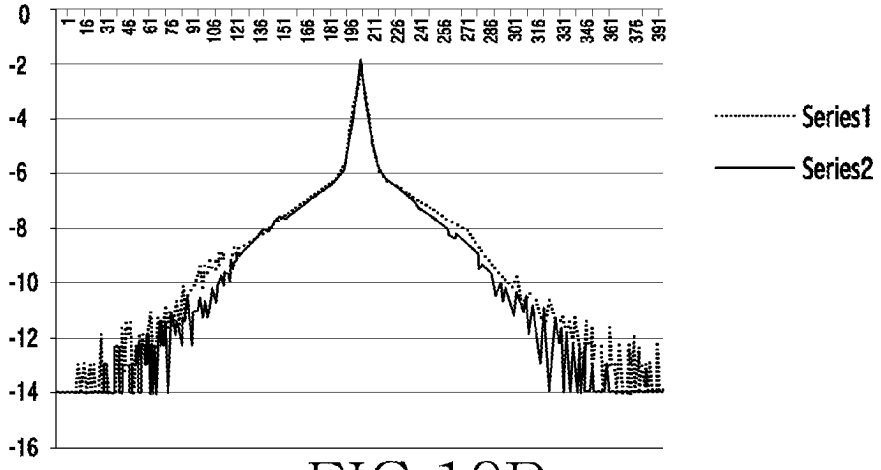


FIG.10B

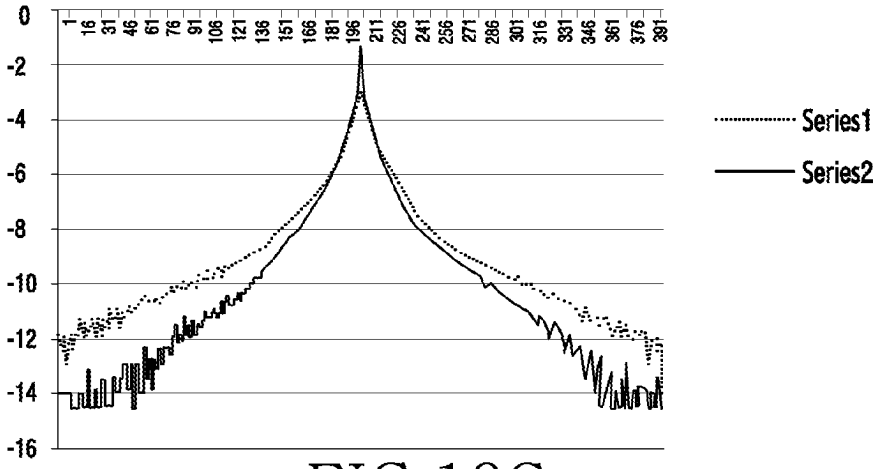


FIG.10C

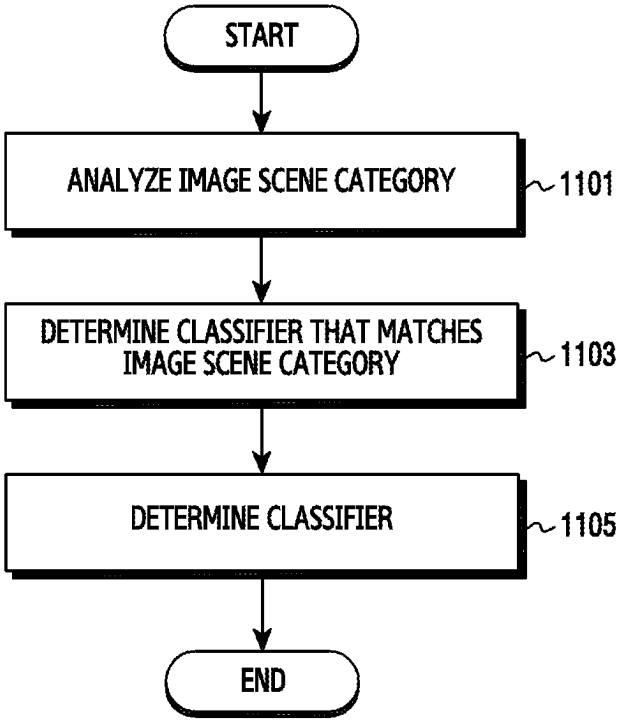

START
ANALYZE IMAGE SCENE CATEGORY
1101
DETERMINE CLASSIFIER THAT MATCHES IMAGE SCENE CATEGORY
1103
DETERMINE CLASSIFIER
1105
END

FIG.11

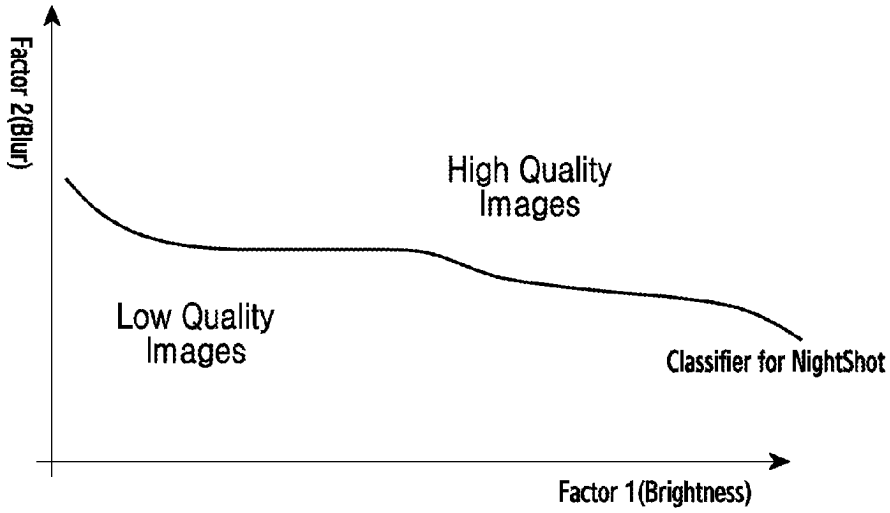


FIG.12A

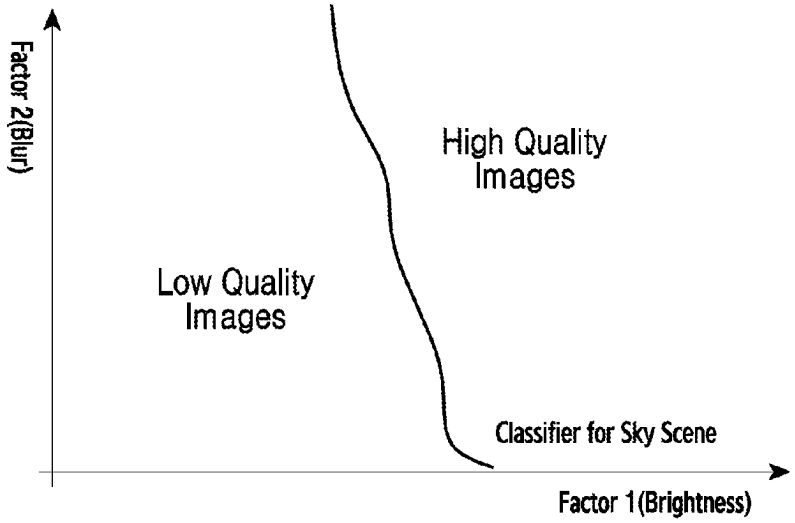


FIG.12B

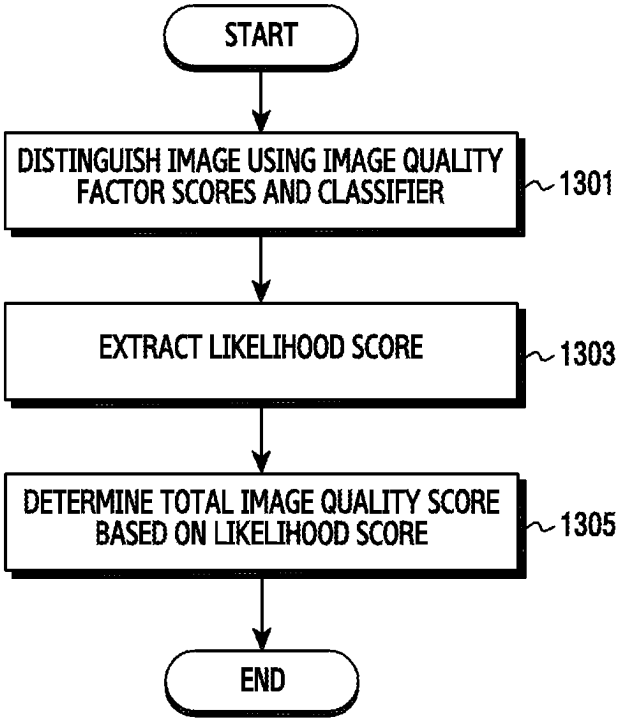

START
DISTINGUISH IMAGE USING IMAGE QUALITY FACTOR SCORES AND CLASSIFIER
1301
EXTRACT LIKELIHOOD SCORE
1303
DETERMINE TOTAL IMAGE QUALITY SCORE BASED ON LIKELIHOOD SCORE
1305
END

FIG.13

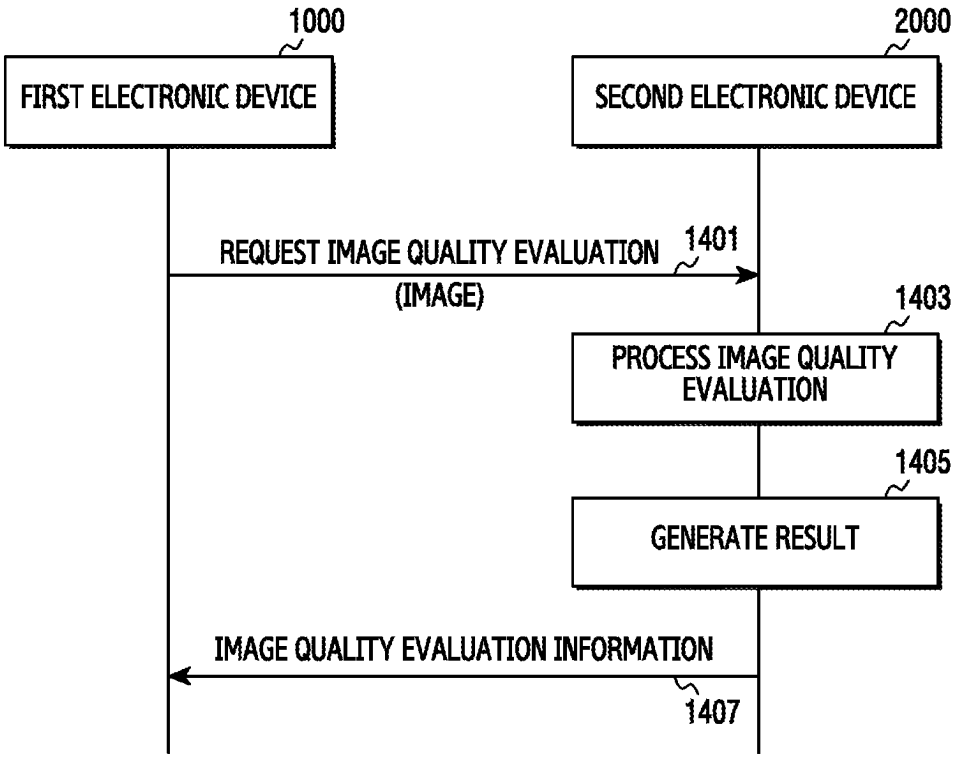

1000
FIRST ELECTRONIC DEVICE
2000
SECOND ELECTRONIC DEVICE
REQUEST IMAGE QUALITY EVALUATION (IMAGE)
1401
1403
PROCESS IMAGE QUALITY EVALUATION
1405
GENERATE RESULT
IMAGE QUALITY EVALUATION INFORMATION
1407

FIG.14

METHOD AND APPARATUS FOR MEASURING THE QUALITY OF AN IMAGE

CROSS-REFERENCE TO RELATED APPLICATION

[0001] This application is based on and claims priority under 35 U.S.C. §119 to Korean Application Serial No. 10-2015-0025854, which was filed in the Korean Intellectual Property Office on Feb. 24, 2015, the disclosure of which is incorporated by reference herein in its entirety.

TECHNICAL FIELD

[0002] The present disclosure relates to an electronic device that improves detectability in association with a measurement of the quality of an image, and a method of operating the same.

BACKGROUND

[0003] As digital technologies have developed, various types of electronic devices are widely utilized, such as a terminal, a smart phone, a tablet Personal Computer (PC), a Personal Digital Assistant (PDA), an electronic organizer, a notebook, a wearable device, or the like. The electronic devices have reached a level of mobile convergence that includes the functions of other devices. For example, the electronic devices may provide: a communication function, such as a voice call, a video call, and the like; a message transmission/reception function, such as a Short Message Service (SMS)/Multimedia Message Service (MMS), an e-mail, and the like; an electronic organizer function; a photographing function; a broadcasting program playback function; a video playback function; a music playback function; an Internet function; a messenger function; a game function; a Social Networking Service (SNS) function; or the like.

[0004] An electronic device provides a function of measuring the quality of an image. A conventional image quality measurement scheme evaluates the quality by measuring an image quality factor, such as sharpness, noise, contrast, color accuracy, distortion, blur, and the like, or evaluates the total image quality by normalizing scores of image quality factors to be different or by applying different weights to image quality factors.

SUMMARY

[0005] When an existing electronic device measures a blur from among image quality factors, various blur detection algorithms may be used. For example, a value (e.g., blur-per value) indicating a degree of a sharp area in an image and a value (e.g., blur-extent value) indicating a degree of a blur area may be used. However, the simple arithmetic combination, such as the blur measurement scheme, may have a low detectability in association with a motion blur. To improve the detectability in association with the motion blur, a detection method that uses kernel estimation may be used. However, this proceeds slowly, and may be difficult to be implemented in an electronic device. Also, the conventional image quality measurement may have a low distinction in association with an out-of-focus background image (e.g., a blurred background image), which is a drawback.

[0006] Also, according to the existing method used for an electronic device to evaluate the total image quality using an image quality factor, the total image quality may be calculated by applying a different weight to each image quality factor, or using a classifier (e.g., a Support Vector Machine (SVM) classifier or a naive bayes classifier) through learning. According to the method, the total image quality is evaluated to be good but the performance of the single classifier may become deteriorated.

[0007] According to various example embodiments of the present disclosure, a method and apparatus for supporting the improvement of the detectability in association with an image quality measurement are provided.

[0008] According to various example embodiments of the present disclosure, an image quality measuring method and apparatus are provided that may improve the detectability in association with an out-of-focus background image, the detectability in association with a motion blur, and the performance in association with a total image quality evaluation when the quality of an image is measured.

[0009] According to various example embodiments of the present disclosure, an electronic device is provided, including: a memory that stores a plurality of images and a plurality of classifiers; and a processor that is electrically connected with the memory, wherein the processor is configured to: analyze a category of an image of which an image quality evaluation is requested, and determine a classifier corresponding to the category of the image from among the plurality of classifiers; determine image quality factor scores of the image; and evaluate the image quality of the image based on the determined image quality factor scores and the determined classifier.

[0010] According to various example embodiments of the present disclosure, a system that supports measuring the quality of an image is provided, the system including: a first electronic device configured to request an image quality evaluation of an image; and a second electronic device that is connected to the first electronic device, wherein the second electronic device is configured to: obtain the image from the first electronic device; analyze a category of the image, and determine a classifier corresponding to the category of the image; determine image quality factor scores of the image; and evaluate image quality of the image based on the determined image quality factor scores and the determined classifier, and provide the first electronic device with a result of the image quality evaluation.

[0011] According to various example embodiments of the present disclosure, a method of measuring the quality of an image is provided, the method including: obtaining an image; classifying an image scene category of the image; determining a classifier corresponding to the classified image scene category; determining image quality factor scores with respect to the image; and evaluating image quality with respect to the image using the determined image quality factor scores and the determined classifier.

[0012] To overcome the above described drawbacks of the prior art, various example embodiments of the present disclosure may include a computer readable recording medium in which programs for implementing the method in a processor are recorded.

[0013] According to various example embodiments of the present disclosure, there is provided a computer readable recording medium that stores a program, which when executed, causes an electronic device to be configured to: classify an image scene category of an image and determine a classifier corresponding to the classified image scene category; determine image quality factor scores with respect to

the image; and evaluate image quality with respect to the image using the determined image quality factor scores and the determined classifier.

BRIEF DESCRIPTION OF THE DRAWINGS

[0014] The above and other aspects, features, and advantages of the present disclosure will be more apparent from the following detailed description, taken in conjunction with the accompanying drawings, in which like reference numerals refer to like elements, and wherein:

[0015] FIG. **1** is a diagram illustrating an example network environment including an electronic device;

[0016] FIG. **2** is a block diagram illustrating an example electronic device;

[0017] FIG. **3** is a block diagram illustrating an example program module;

[0018] FIG. **4** is a block diagram schematically illustrating an example configuration of an electronic device;

[0019] FIG. **5** is a diagram illustrating an example configuration for measuring the quality of an image in an electronic device;

[0020] FIG. **6** is a flowchart illustrating an example method of measuring the quality of an image in an electronic device;

[0021] FIG. **7** is a flowchart illustrating an example of measuring an image quality factor of a special image in an electronic device;

[0022] FIGS. **8**A to **8**C are diagrams illustrating examples of an operation of extracting a quality factor of an out-of-focus image in an electronic device;

[0023] FIG. **9** is a flowchart illustrating an example of an operation of measuring an image quality factor of a special image in an electronic device;

[0024] FIGS. **10**A to **10**C are diagrams illustrating examples of an operation of extracting a quality factor of a motion blur image in an electronic device;

[0025] FIG. **11** is a flowchart illustrating an example of an operation of determining an image quality classifier in an electronic device;

[0026] FIGS. **12**A and **12**B are diagrams illustrating examples of an image quality classifier in an electronic device;

[0027] FIG. **13** is a flowchart illustrating an example method of measuring the quality of an image in an electronic device; and

[0028] FIG. **14** is a sequence diagram illustrating an example of a method of measuring the quality of an image.

DETAILED DESCRIPTION

[0029] Hereinafter, various example embodiments of the present disclosure will be described with reference to the accompanying drawings. However, it should be understood that there is no intent to limit the present disclosure to the particular forms disclosed herein; rather, the present disclosure should be construed to cover various modifications, equivalents, and/or alternatives of embodiments of the present disclosure. In describing the drawings, similar reference numerals may be used to designate similar constituent elements.

[0030] As used herein, the expression "have", "may have", "include", or "may include" refers to the existence of a corresponding feature (e.g., numeral, function, operation, or constituent element such as component), and does not exclude one or more additional features.

[0031] In the present disclosure, the expression "A or B", "at least one of A or/and B", or "one or more of A or/and B" may include all possible combinations of the items listed. For example, the expression "A or B", "at least one of A and B", or "at least one of A or B" refers to all of (1) including at least one A, (2) including at least one B, or (3) including all of at least one A and at least one B.

[0032] The expression "a first", "a second", "the first", or "the second" used in various example embodiments of the present disclosure may modify various components regardless of the order and/or the importance but does not limit the corresponding components. For example, a first user device and a second user device indicate different user devices although both of them are user devices. For example, a first element may be termed a second element, and similarly, a second element may be termed a first element without departing from the scope of the present disclosure.

[0033] It should be understood that when an element (e.g., first element) is referred to as being (operatively or communicatively) "connected," or "coupled," to another element (e.g., second element), it may be directly connected or coupled directly to the other element or any other element (e.g., third element) may be interposed between them. On the other hand, it may be understood that when an element (e.g., first element) is referred to as being "directly connected," or "directly coupled" to another element (second element), there is no element (e.g., third element) interposed between them.

[0034] The expression "configured to" used in the present disclosure may be exchanged with, for example, "suitable for", "having the capacity to", "designed to", "adapted to", "made to", or "capable of" according to the situation. The term "configured to" may not necessarily imply "specifically designed to" in hardware. In some situations, the expression "device configured to" may refer to the device, together with other devices or components, "is able to". For example, the phrase "processor adapted (or configured) to perform A, B, and C" may refer to a dedicated processor (e.g. embedded processor) only for performing the corresponding operations or a general-purpose processor (e.g., central processing unit (CPU) or application processor (AP)) or processing circuitry that can perform the corresponding operations by executing one or more software programs stored in a memory device.

[0035] The terms used in the present disclosure are used to describe various example embodiments, and are not intended to limit the present disclosure. As used herein, singular forms may include plural forms as well unless the context clearly indicates otherwise. Unless defined otherwise, all terms used herein, including technical and scientific terms, have the same meaning as those commonly understood by a person skilled in the art to which the present disclosure pertains. Such terms as those defined in a generally used dictionary may be interpreted to have the meanings equal to the contextual meanings in the relevant field of art, and are not to be interpreted to have ideal or excessively formal meanings unless clearly defined in the present disclosure. Even where a term is defined in the present disclosure, it should not be interpreted to exclude embodiments of the present disclosure.

[0036] An electronic device according to various example embodiments of the present disclosure may include at least one of, for example, a smart phone, a tablet Personal Computer (PC), a mobile phone, a video phone, an electronic book reader (e-book reader), a desktop PC, a laptop PC, a netbook computer, a workstation, a server, a Personal Digital Assistant (PDA), a Portable Multimedia Player (PMP), a MPEG-1

audio layer-3 (MP3) player, a mobile medical device, a camera, and a wearable device, or the like. According to various example embodiments, the wearable device may include at least one of an accessory type (e.g., a watch, a ring, a bracelet, an anklet, a necklace, a glasses, a contact lens, or a Head-Mounted Device (HMD)), a fabric or clothing integrated type (e.g., an electronic clothing), a body-mounted type (e.g., a skin pad, or tattoo), and a bio-implantable type (e.g., an implantable circuit), or the like.

[0037] According to some example embodiments, the electronic device may be a home appliance. The home appliance may include at least one of, for example, a television, a Digital Video Disk (DVD) player, an audio, a refrigerator, an air conditioner, a vacuum cleaner, an oven, a microwave oven, a washing machine, an air cleaner, a set-top box, a home automation control panel, a security control panel, a TV box (e.g., Samsung HomeSync™, Apple TV™, or Google TV™), a game console (e.g., Xbox™ and PlayStation™), an electronic dictionary, an electronic key, a camcorder, and an electronic photo frame, or the like.

[0038] According to another example embodiment, the electronic device may include at least one of various medical devices (e.g., various portable medical measuring devices (a blood glucose monitoring device, a heart rate monitoring device, a blood pressure measuring device, a body temperature measuring device, etc.), a Magnetic Resonance Angiography (MRA), a Magnetic Resonance Imaging (MRI), a Computed Tomography (CT) machine, and an ultrasonic machine), a navigation device, a Global Positioning System (GPS) receiver, an Event Data Recorder (EDR), a Flight Data Recorder (FDR), a Vehicle Infotainment Devices, an electronic devices for a ship (e.g., a navigation device for a ship, and a gyro-compass), avionics, security devices, an automotive head unit, a robot for home or industry, an automatic teller's machine (ATM) in banks, point of sales (POS) in a shop, or internet device of things (e.g., a light bulb, various sensors, electric or gas meter, a sprinkler device, a fire alarm, a thermostat, a streetlamp, a toaster, a sporting goods, a hot water tank, a heater, a boiler, etc.), or the like.

[0039] According to some example embodiments, the electronic device may include at least one of a part of furniture or a building/structure, an electronic board, an electronic signature receiving device, a projector, and various kinds of measuring instruments (e.g., a water meter, an electric meter, a gas meter, and a radio wave meter), or the like. The electronic device according to various example embodiments of the present disclosure may be a combination of one or more of the aforementioned various devices. The electronic device according to some example embodiments of the present disclosure may be a flexible device. Further, the electronic device according to an example embodiment of the present disclosure is not limited to the aforementioned devices, and may include a new electronic device according to the development of technology.

[0040] Hereinafter, an electronic device according to various example embodiments will be described with reference to the accompanying drawings. As used herein, the term "user" may indicate a person who uses an electronic device or a device (e.g., an artificial intelligence electronic device) that uses an electronic device.

[0041] FIG. **1** is a diagram illustrating an example network environment including an electronic device.

[0042] An electronic device **101** within a network environment **100**, according to various example embodiments, will be described with reference to FIG. **1**. The electronic device **101** may include a bus **110**, a processor (e.g., including processing circuitry) **120**, a memory **130**, an input/output interface (e.g., including input/output circuitry) **150**, a display (e.g., including a display panel and display circuitry) **160**, and a communication interface (e.g., including communication circuitry) **170**. According to an example embodiment of the present disclosure, the electronic device **101** may omit at least one of the above components or may further include other components.

[0043] The bus **110** may include, for example, a circuit which interconnects the components **110** to **170** and delivers a communication signal (e.g., a control message and/or data) between the components **110** to **170**.

[0044] The processor **120** may include, for example, processing circuitry including, for example, one or more of a Central Processing Unit (CPU), an Application Processor (AP), and a Communication Processor (CP). The processor **120** may be configured to carry out, for example, calculation or data processing relating to control and/or communication of at least one other component of the electronic device **101**.

[0045] The memory **130** may include a volatile memory and/or a non-volatile memory. The memory **130** may store, for example, commands or data relevant to at least one other component of the electronic device **101**. According to an example embodiment of the present disclosure, the memory **130** may store software and/or a program **140**. The program **140** may include, for example, a kernel **141**, middleware **143**, an Application Programming Interface (API) **145**, and/or application programs (or "applications") **147**. At least some of the kernel **141**, the middleware **143**, and the API **145** may be referred to as an Operating System (OS).

[0046] The kernel **141** may control or manage system resources (e.g., the bus **110**, the processor **120**, or the memory **130**) used for performing an operation or function implemented in the other programs (e.g., the middleware **143**, the API **145**, or the application programs **147**). Furthermore, the kernel **141** may provide an interface through which the middleware **143**, the API **145**, or the application programs **147** may access the individual components of the electronic device **101** to control or manage the system resources.

[0047] The middleware **143**, for example, may serve as an intermediary for allowing the API **145** or the application programs **147** to communicate with the kernel **141** to exchange data.

[0048] Also, the middleware **143** may process one or more task requests received from the application programs **147** according to priorities thereof. For example, the middleware **143** may assign priorities for using the system resources (e.g., the bus **110**, the processor **120**, the memory **130**, or the like) of the electronic device **101**, to at least one of the application programs **147**. For example, the middleware **143** may perform scheduling or loading balancing on the one or more task requests by processing the one or more task requests according to the priorities assigned thereto.

[0049] The API **145** is an interface through which the applications **147** control functions provided from the kernel **141** or the middleware **143**, and may include, for example, at least one interface or function (e.g., instruction) for file control, window control, image processing, character control, and the like.

[0050] The input/output interface **150**, for example, may function as an interface that may transfer commands or data input from a user or another external device to the other

element(s) of the electronic device **101**. Furthermore, the input/output interface **150** may output the commands or data received from the other element(s) of the electronic device **101** to the user or another external device.

[0051] Examples of the display **160** may include a Liquid Crystal Display (LCD), a Light-Emitting Diode (LED) display, an Organic Light-Emitting Diode (OLED) display, a MicroElectroMechanical Systems (MEMS) display, and an electronic paper display, or the like. The display **160** may display, for example, various types of contents (e.g., text, images, videos, icons, or symbols) to users. The display **160** may include a touch screen, and may receive, for example, a touch, gesture, proximity, or hovering input using an electronic pen or a user's body part, or the like.

[0052] The communication interface **170** may establish communication, for example, between the electronic device **101** and an external device (e.g., a first external electronic device **102**, a second external electronic device **104**, or a server **106**). For example, the communication interface **170** may be connected to a network **162** through wireless or wired communication, and may communicate with an external device (e.g., the second external electronic device **104** or the server **106**). The wireless communication may use at least one of, for example, Long Term Evolution (LTE), LTE-Advance (LTE-A), Code Division Multiple Access (CDMA), Wideband CDMA (WCDMA), Universal Mobile Telecommunications System (UMTS), Wireless Broadband (WiBro), and Global System for Mobile Communications (GSM), or the like, as a cellular communication protocol. In addition, the wireless communication may include, for example, short range communication **164**. The short-range communication **164** may include at least one of, for example, Wi-Fi, Bluetooth, Near Field Communication (NFC), and Global Navigation Satellite System (GNSS), or the like. GNSS may include, for example, at least one of global positioning system (GPS), global navigation satellite system (Glonass), Beidou Navigation satellite system (Beidou) or Galileo, and the European global satellite-based navigation system, based on a location, a bandwidth, or the like. Hereinafter, in the present disclosure, the "GPS" may be interchangeably used with the "GNSS". The wired communication may include, for example, at least one of a Universal Serial Bus (USB), a High Definition Multimedia Interface (HDMI), Recommended Standard 232 (RS-232), and a Plain Old Telephone Service (POTS), or the like. The network **162** may include at least one of a telecommunication network such as a computer network (e.g., a LAN or a WAN), the Internet, and a telephone network, or the like.

[0053] Each of the first and second external electronic devices **102** and **104** may be of a type similar to or different from that of the electronic device **101**. According to an example embodiment of the present disclosure, the server **106** may include a group of one or more servers. According to various example embodiments of the present disclosure, all or some of the operations performed in the electronic device **101** may be executed in another electronic device or a plurality of electronic devices (e.g., the electronic devices **102** and **104** or the server **106**). According to an example embodiment of the present disclosure, when the electronic device **101** has to perform some functions or services automatically or in response to a request, the electronic device **101** may request another device (e.g., the electronic device **102** or **104** or the server **106**) to execute at least some functions relating thereto instead of or in addition to autonomously performing the functions or services. Another electronic device (e.g., the electronic device **102** or **104**, or the server **106**) may execute the requested functions or the additional functions, and may deliver a result of the execution to the electronic device **101**. The electronic device **101** may process the received result as it is or additionally, and may provide the requested functions or services. To this end, for example, cloud computing, distributed computing, or client-server computing technologies, or the like, may be used.

[0054] FIG. **2** is a block diagram illustrating an example electronic device.

[0055] The electronic device **201** may include, for example, all or a part of the electronic device **101** shown in FIG. **1**. The electronic device **201** may include one or more processors (e.g., including processing circuitry) **210** (e.g., Application Processors (AP)), a communication module (e.g., including communication circuitry) **220**, a Subscriber Identification Module (SIM) **224**, a memory **230**, a sensor module (e.g., including at least one sensor including sensor circuitry) **240**, an input device (e.g., including input circuitry) **250**, a display **260**, an interface (e.g., including interface circuitry) **270**, an audio module (e.g., including audio processing circuitry) **280**, a camera module **291**, a power management module **295**, a battery **296**, an indicator **297**, and a motor **298**.

[0056] The processor **210** may be configured to control a plurality of hardware or software components connected to the processor **210** by driving an operating system or an application program, and perform processing of various pieces of data and calculations. The processor **210** may, for example, be embodied as, for example, processing circuitry included on a System on Chip (SoC). According to an example embodiment of the present disclosure, the processor **210** may further include a Graphic Processing Unit (GPU) and/or an image signal processor. The processor **210** may include at least some (for example, a cellular module **221**) of the components illustrated in FIG. **2**. The processor **210** may load, into a volatile memory, commands or data received from at least one (e.g., a non-volatile memory) of the other components and may process the loaded commands or data, and may store various data in a non-volatile memory.

[0057] The communication module **220** may have a configuration equal or similar to that of the communication interface **170** of FIG. **1**. The communication module **220** may include, for example, a cellular module **221**, a Wi-Fi module **223**, a BT module **225**, a GNSS module **227** (e.g., a GPS module **227**, a Glonass module, a Beidou module, or a Galileo module), an NFC module **228**, and a Radio Frequency (RF) module **229**.

[0058] The cellular module **221**, for example, may provide a voice call, a video call, a text message service, or an Internet service through a communication network. According to an example embodiment of the present disclosure, the cellular module **221** may distinguish and authenticate the electronic device **201** in a communication network using the subscriber identification module **224** (for example, the SIM card). According to an example embodiment of the present disclosure, the cellular module **221** may perform at least some of the functions that the AP **210** may provide. According to an example embodiment of the present disclosure, the cellular module **221** may include a communication processor (CP).

[0059] For example, each of the Wi-Fi module **223**, the BT module **225**, the GNSS module **227**, and the NFC module **228** may include a processor for processing data transmitted/received through a corresponding module. According to an

example embodiment of the present disclosure, at least some (e.g., two or more) of the cellular module **221**, the Wi-Fi module **223**, the BT module **225**, the GNSS module **227**, and the NFC module **228** may be included in one Integrated Chip (IC) or IC package.

[0060] The RF module **229**, for example, may transmit/receive a communication signal (e.g., an RF signal). The RF module **229** may include, for example, a transceiver, a Power Amplifier Module (PAM), a frequency filter, a Low Noise Amplifier (LNA), and an antenna. According to another example embodiment of the present disclosure, at least one of the cellular module **221**, the WIFI module **223**, the BT module **225**, the GNSS module **227**, and the NFC module **228** may transmit/receive an RF signal through a separate RF module.

[0061] The subscriber identification module **224** may include, for example, a card including a subscriber identity module and/or an embedded SIM, and may contain unique identification information (e.g., an Integrated Circuit Card Identifier (ICCID)) or subscriber information (e.g., an International Mobile Subscriber Identity (IMSI)).

[0062] The memory **230** (e.g., the memory **130**) may include, for example, an embedded memory **232** or an external memory **234**. The embedded memory **232** may include at least one of a volatile memory (e.g., a Dynamic Random Access Memory (DRAM), a Static RAM (SRAM), a Synchronous Dynamic RAM (SDRAM), and the like) and a non-volatile memory (e.g., a One Time Programmable Read Only Memory (OTPROM), a Programmable ROM (PROM), an Erasable and Programmable ROM (EPROM), an Electrically Erasable and Programmable ROM (EEPROM), a mask ROM, a flash ROM, a flash memory (e.g., a NAND flash memory or a NOR flash memory), a hard disc drive, a Solid State Drive (SSD), and the like), or the like.

[0063] The external memory **234** may further include a flash drive, for example, a Compact Flash (CF), a Secure Digital (SD), a Micro Secure Digital (Micro-SD), a Mini Secure Digital (Mini-SD), an eXtreme Digital (xD), a Multi-MediaCard (MMC), a memory stick, or the like. The external memory **234** may be functionally and/or physically connected to the electronic device **201** through various interfaces.

[0064] The sensor module **240**, for example, may measure a physical quantity or detect an operation state of the electronic device **201**, and may convert the measured or detected information into an electrical signal. The sensor module **240** may include, for example, at least one of a gesture sensor **240**A, a gyro sensor **240**B, an atmospheric pressure sensor (barometer) **240**C, a magnetic sensor **240**D, an acceleration sensor **240**E, a grip sensor **240**F, a proximity sensor **240**G, a color sensor **240**H (e.g., red, green, and blue (RGB) sensor), a biometric sensor (medical sensor) **2401**, a temperature/humidity sensor **240**J, an illuminance sensor **240**K, and a Ultra Violet (UV) sensor **240**M. Additionally or alternatively, the sensor module **240** may include, for example, an E-nose sensor, an electromyography (EMG) sensor, an electroencephalogram (EEG) sensor, an electrocardiogram (ECG) sensor, an Infrared (IR) sensor, an iris scan sensor, and/or a finger scan sensor, or the like. The sensor module **240** may further include a control circuit for controlling one or more sensors included therein. According to an example embodiment of the present disclosure, the electronic device **201** may further include a processor configured to control the sensor module **240**, as a part of the processor **210** or separately from the processor **210**, and may control the sensor module **240** while the processor **210** is in a sleep state.

[0065] The input device **250** may include, for example, a touch panel **252**, a (digital) pen sensor **254**, a key **256**, or an ultrasonic input device **258**. The touch panel **252** may use, for example, at least one of a capacitive type, a resistive type, an infrared type, and an ultrasonic type. The touch panel **252** may further include a control circuit. The touch panel **252** may further include a tactile layer, and provide a tactile reaction to the user.

[0066] The (digital) pen sensor **254** may include, for example, a recognition sheet which is a part of the touch panel or is separated from the touch panel. The key **256** may include, for example, a physical button, an optical key or a keypad. The ultrasonic input device **258** may detect, through a microphone (e.g., the microphone **288**), ultrasonic waves generated by an input tool, and identify data corresponding to the detected ultrasonic waves.

[0067] The display **260** (e.g., the display **160**) may include a panel **262**, a hologram device **264**, or a projector **266**. The panel **262** may include a configuration identical or similar to the display **160** illustrated in FIG. **1**. The panel **262** may be implemented to be, for example, flexible, transparent, or wearable. The panel **262** may be embodied as a single module with the touch panel **252**. The hologram device **264** may show a three dimensional (3D) image in the air using an interference of light. The projector **266** may project light onto a screen to display an image. The screen may be located, for example, in the interior of or on the exterior of the electronic device **201**. According to an example embodiment of the present disclosure, the display **260** may further include a control circuit for controlling the panel **262**, the hologram device **264**, or the projector **266**.

[0068] The interface **270** may include, for example, a High-Definition Multimedia Interface (HDMI) **272**, a Universal Serial Bus (USB) **274**, an optical interface **276**, or a D-sub-miniature (D-sub) **278**. The interface **270** may be included in, for example, the communication interface **170** illustrated in FIG. **1**. Additionally or alternatively, the interface **270** may include, for example, a Mobile High-definition Link (MHL) interface, a Secure Digital (SD) card/Multi-Media Card (MMC) interface, or an Infrared Data Association (IrDA) standard interface, or the like.

[0069] The audio module **280**, for example, may bilaterally convert a sound and an electrical signal. At least some components of the audio module **280** may be included in, for example, the input/output interface **150** illustrated in FIG. **1**. The audio module **280** may process voice information input or output through, for example, a speaker **282**, a receiver **284**, earphones **286**, or the microphone **288**.

[0070] The camera module **291** is, for example, a device which may photograph a still image and a video. According to an example embodiment of the present disclosure, the camera module **291** may include one or more image sensors (e.g., a front sensor or a back sensor), a lens, an Image Signal Processor (ISP) or a flash (e.g., LED or xenon lamp).

[0071] The power management module **295** may manage, for example, power of the electronic device **201**. According to an example embodiment of the present disclosure, the power management module **295** may include a Power Management Integrated Circuit (PMIC), a charger Integrated Circuit (IC), or a battery or fuel gauge. The PMIC may use a wired and/or wireless charging method. Examples of the wireless charging method may include, for example, a magnetic resonance method, a magnetic induction method, an electromagnetic wave method, and the like. Additional circuits (e.g., a coil

loop, a resonance circuit, a rectifier, etc.) for wireless charging may be further included. The battery gauge may measure, for example, a residual quantity of the battery **296**, and a voltage, a current, or a temperature while charging. The battery **296** may include, for example, a rechargeable battery and/or a solar battery.

[0072] The indicator **297** may display a particular state (e.g., a booting state, a message state, a charging state, or the like) of the electronic device **201** or a part (e.g., the processor **210**) of the electronic device **201**. The motor **298** may convert an electrical signal into a mechanical vibration, and may generate a vibration, a haptic effect, or the like. Although not illustrated, the electronic device **201** may include a processing device (e.g., a GPU) for supporting a mobile TV. The processing device for supporting a mobile TV may process, for example, media data according to a certain standard such as Digital Multimedia Broadcasting (DMB), Digital Video Broadcasting (DVB), or mediaFLO™.

[0073] Each of the above-described component elements of hardware according to the present disclosure may be configured with one or more components, and the names of the corresponding component elements may vary based on the type of electronic device. In various example embodiments, the electronic device may include at least one of the above-described elements. Some of the above-described elements may be omitted from the electronic device, or the electronic device may further include additional elements. Also, some of the hardware components according to various example embodiments may be combined into one entity, which may perform functions identical to those of the relevant components before the combination.

[0074] FIG. **3** is a block diagram illustrating an example program module.

[0075] According to an example embodiment of the present disclosure, the program module **310** (e.g., the program **140**) may include an Operating System (OS) for controlling resources related to the electronic device (e.g., the electronic device **101**) and/or various applications (e.g., the application programs **147**) executed in the operating system. The operating system may be, for example, Android, iOS, Windows, Symbian, Tizen, Bada, or the like.

[0076] The program module **310** may include a kernel **320**, middleware **330**, an API **360**, and/or applications **370**. At least some of the program module **310** may be preloaded on an electronic device, or may be downloaded from an external electronic device (e.g., the electronic device **102** or **104**, or the server **106**).

[0077] The kernel **320** (e.g., the kernel **141**) may include, for example, a system resource manager **321** and/or a device driver **323**. The system resource manager **321** may control, allocate, or collect system resources. According to an example embodiment of the present disclosure, the system resource manager **321** may include a process management unit, a memory management unit, a file system management unit, and the like. The device driver **323** may include, for example, a display driver, a camera driver, a Bluetooth driver, a shared memory driver, a USB driver, a keypad driver, a Wi-Fi driver, an audio driver, or an Inter-Process Communication (IPC) driver.

[0078] For example, the middleware **330** may provide a function required in common by the applications **370**, or may provide various functions to the applications **370** through the API **360** to enable the applications **370** to efficiently use the limited system resources in the electronic device. According to an example embodiment of the present disclosure, the middleware **330** (e.g., the middleware **143**) may include at least one of a run time library **335**, an application manager **341**, a window manager **342**, a multimedia manager **343**, a resource manager **344**, a power manager **345**, a database manager **346**, a package manager **347**, a connectivity manager **348**, a notification manager **349**, a location manager **350**, a graphic manager **351**, and a security manager **352**.

[0079] The runtime library **335** may include a library module that a compiler uses in order to add a new function through a programming language while an application **370** is being executed. The runtime library **335** may perform input/output management, memory management, the functionality for an arithmetic function, or the like.

[0080] The application manager **341** may manage, for example, a life cycle of at least one of the applications **370**. The window manager **342** may manage Graphical User Interface (GUI) resources used by a screen. The multimedia manager **343** may recognize a format required for reproduction of various media files, and may perform encoding or decoding of a media file by using a codec suitable for the corresponding format. The resource manager **344** may manage resources of a source code, a memory, and a storage space of at least one of the applications **370**.

[0081] The power manager **345** may operate together with, for example, a Basic Input/Output System (BIOS) or the like to manage a battery or power source and may provide power information or the like required for the operations of the electronic device. The database manager **346** may generate, search for, and/or change a database to be used by at least one of the applications **370**. The package manager **347** may manage installation or an update of an application distributed in a form of a package file.

[0082] For example, the connectivity manager **348** may manage wireless connectivity such as Wi-Fi or Bluetooth. The notification manager **349** may display or notify of an event such as an arrival message, promise, proximity notification, and the like in such a way that does not disturb a user. The location manager **350** may manage location information of an electronic device. The graphic manager **351** may manage a graphic effect which will be provided to a user, or a user interface related to the graphic effect. The security manager **352** may provide all security functions required for system security, user authentication, or the like. According to an example embodiment of the present disclosure, when the electronic device (e.g., the electronic device **101**) has a telephone call function, the middleware **330** may further include a telephony manager for managing a voice call function or a video call function of the electronic device.

[0083] The middleware **330** may include a middleware module that forms a combination of various functions of the above-described components. The middleware **330** may provide a module specialized for each type of OS in order to provide a differentiated function. Further, the middleware **330** may dynamically remove some of the existing components or add new components.

[0084] The API **360** (e.g., the API **145**) is, for example, a set of API programming functions, and may be provided with a different configuration according to an OS. For example, in the case of Android or iOS, one API set may be provided for each platform. In the case of Tizen, two or more API sets may be provided for each platform.

[0085] The applications **370** (e.g., the application programs **147**) may include, for example, one or more applications

which may provide functions such as a home **371**, a dialer **372**, an SMS/MMS **373**, an Instant Message (IM) **374**, a browser **375**, a camera **376**, an alarm **377**, contacts **378**, a voice dial **379**, an email **380**, a calendar **381**, a media player **382**, an album **383**, a clock **384**, health care (e.g., measuring exercise quantity or blood sugar), or environment information (e.g., providing atmospheric pressure, humidity, or temperature information).

[0086] According to an example embodiment of the present disclosure, the applications **370** may include an application (hereinafter, referred to as an "information exchange application" for convenience of description) that supports exchanging information between the electronic device (e.g., the electronic device **101**) and an external electronic device (e.g., the electronic device **102** or **104**). The information exchange application may include, for example, a notification relay application for transferring specific information to an external electronic device or a device management application for managing an external electronic device.

[0087] For example, the notification relay application may include a function of transferring, to the external electronic device (e.g., the electronic device **102** or **104**), notification information generated from other applications of the electronic device **101** (e.g., an SMS/MMS application, an e-mail application, a health management application, or an environmental information application). Further, the notification relay application may receive notification information from, for example, an external electronic device and provide the received notification information to a user.

[0088] The device management application may manage (e.g., install, delete, or update), for example, at least one function of an external electronic device (e.g., the electronic device **102** or **104**) communicating with the electronic device (e.g., a function of turning on/off the external electronic device itself (or some components) or a function of adjusting the brightness (or a resolution) of the display), applications operating in the external electronic device, and services provided by the external electronic device (e.g., a call service or a message service).

[0089] According to an example embodiment of the present disclosure, the applications **370** may include applications (e.g., a health care application of a mobile medical appliance or the like) designated according to an external electronic device (e.g., attributes of the electronic device **102** or **104**). According to an example embodiment of the present disclosure, the applications **370** may include an application received from an external electronic device (e.g., the server **106**, or the electronic device **102** or **104**). According to an example embodiment of the present disclosure, the applications **370** may include a preloaded application or a third party application that may be downloaded from a server. The names of the components of the program module **310** of the illustrated embodiment of the present disclosure may change according to the type of operating system.

[0090] According to various example embodiments, at least a part of the programming module **310** may be implemented in software, firmware, hardware, or a combination of two or more thereof. At least some of the program module **310** may be implemented (e.g., executed) by, for example, the processor (e.g., the processor **210**). At least some of the program module **310** may include, for example, a module, a program, a routine, a set of instructions, and/or a process for performing one or more functions.

[0091] The term "module" as used herein may, for example, mean a unit including one of hardware (e.g., circuitry), software, and firmware or a combination of two or more of them. The "module" may be interchangeably used with, for example, the term "unit", "logic", "logical block", "component", or "circuit". The "module" may be a minimum unit of an integrated component element or a part thereof. The "module" may be a minimum unit for performing one or more functions or a part thereof. The "module" may be mechanically or electronically implemented. For example, the "module" according to the present disclosure may include at least one of processing circuitry, an Application-Specific Integrated Circuit (ASIC) chip, a Field-Programmable Gate Arrays (FPGA), and a programmable-logic device for performing operations which has been known or are to be developed hereinafter.

[0092] According to various example embodiments, at least some of the devices (for example, modules or functions thereof) or the method (for example, operations) according to the present disclosure may be implemented by a command stored in a computer-readable storage medium in a programming module form. The instruction, when executed by a processor (e.g., the processor **120**), may cause the one or more processors to execute the function corresponding to the instruction. The computer-readable recoding media may be, for example, the memory **130**.

[0093] The computer readable recoding medium may include a hard disk, a floppy disk, magnetic media (e.g., a magnetic tape), optical media (e.g., a Compact Disc Read Only Memory (CD-ROM) and a Digital Versatile Disc (DVD)), magneto-optical media (e.g., a floptical disk), a hardware device (e.g., a Read Only Memory (ROM), a Random Access Memory (RAM), a flash memory), and the like. In addition, the program instructions may include high level language codes, which can be executed in a computer using an interpreter, as well as machine codes made by a compiler. The aforementioned hardware device may be configured to operate as one or more software modules in order to perform the operation of the present disclosure, and vice versa.

[0094] Any of the modules or programming modules according to various example embodiments of the present disclosure may include at least one of the above described elements, exclude some of the elements, or further include other additional elements. The operations performed by the modules, programming module, or other elements according to various example embodiments of the present disclosure may be executed in a sequential, parallel, repetitive, or heuristic manner. Further, some operations may be executed according to another order or may be omitted, or other operations may be added. Various example embodiments disclosed herein are provided merely to easily describe technical details of the present disclosure and to aid in the understanding of the present disclosure, and are not intended to limit the scope of the present disclosure. Therefore, it should be construed that all modifications and changes or modified and changed forms based on the technical idea of the present disclosure fall within the scope of the present disclosure.

[0095] Various example embodiments of the present disclosure provided below are related to an electronic device that includes an image quality measuring function, and a method of operating the same. According to various example embodiments of the present disclosure, detectability may be improved in association with an image (e.g., an out-of-focus background image, a motion blur image, or the like) to which

special effects (e.g., out-of-focus, a motion blur, or the like) are applied when an image is generated (photographed), when an electronic device determines an image quality score in association with the measurement of the quality of an image. According to various example embodiments of the present disclosure, an electronic device may improve the performance (e.g., accuracy) in association with a total image quality evaluation through improving the detectability with respect to an out-of-focus background image or a motion-blur image.

[0096] According to various example embodiments of the present disclosure, an electronic device may measure an image quality by distinguishing each property of an image (e.g., an out-of-focus background image, a motion blur image, or the like). According to various example embodiments of the present disclosure, an electronic device may classify an image based on an image scene category (e.g., mountain, ocean, sky, beach, streets, night view, or the like) when measuring the quality of the image, and may determine an image scene classifier corresponding to the corresponding image scene category. According to various example embodiments of the present disclosure, the image quality may be determined by applying, to the image, a different weight based on the determined image scene classifier.

[0097] According to various example embodiments of the present disclosure, when an electronic device is configured to perform total image quality evaluation, the image quality may be determined based on the property of an image and an image scene category. Therefore, according to various example embodiments of the present disclosure, the detectability, with respect to an image in association with the total image quality evaluation, and the accuracy of a quality determination result may be improved.

[0098] According to various example embodiments of the present disclosure, an electronic device operates in various electronic devices that contain an image quality measuring function. For example, an electronic device, according to various example embodiments of the present disclosure, may include all devices that use one or more processors from among various processors (e.g., the processors **120** and **210**), such as, an application processor (AP), a communication processor (CP), a graphic processing unit (GPU), a central processing unit (CPU), and the like, for example, all information communication devices that support a function according to various example embodiments (e.g., an image quality measuring function), multimedia devices, wearable devices, and application devices thereof.

[0099] Hereinafter, a method and apparatus for performing an image quality measuring function, using an electronic device according to various example embodiments of the present disclosure, will be described. However, various example embodiments of the present disclosure may not be limited to the descriptions provided below and thus, it should be understood that the present disclosure may be applied to various example embodiments based on the example embodiments provided below. Also, various example embodiments of the present disclosure will be provided from the perspective of hardware. However, various example embodiments of the present disclosure include a technology that uses both hardware and software, and thus, the various example embodiments of the present disclosure may not exclude the perspective of software.

[0100] FIG. **4** is a block diagram schematically illustrating an example configuration of an electronic device.

[0101] Referring to FIG. **4**, an electronic device **400**, according to various example embodiments of the present disclosure, may include a wireless communication unit (e.g., including wireless communication circuitry) **410**, an input unit (e.g., including input circuitry) **420**, a touch screen **430**, an audio processing unit (e.g., including audio processing circuitry) **440**, a memory **450**, an interface unit (e.g., including interface circuitry) **460**, a camera module **470**, a controller (e.g., including processing circuitry) **480**, and a power supply unit **490**. According to various example embodiments of the present disclosure, the electronic device **400** may include fewer or more component elements when compared to the component elements of FIG. **4**, since the component elements of FIG. **4** are not essential.

[0102] The wireless communication unit **410** may include a configuration that is identical or similar to the communication module **220** of FIG. **2**. The wireless communication unit **410** may include one or more modules that enable wireless communication between the electronic device **400** and a wireless communication system or between the electronic device **400** and another electronic device (e.g., the electronic device **102** or **104**, or the server **160**). For example, the wireless communication unit **410** may be configured to include a mobile communication module **411**, a wireless local area network (WLAN) module **413**, a short-range communication module **415**, a location calculating module **417**, a broadcast receiving module **419**, and the like. According to various example embodiments of the present disclosure, the wireless communication unit **410** may execute wireless communication with an external electronic device (e.g., the electronic device **102** or **104**, or the server **106**) based on at least some of various set communication schemes, and may receive various images based on wireless communication.

[0103] The mobile communication module **411** may transmit/receive a wireless signal to/from at least one of a base station, an external electronic device (e.g., the electronic device **104**), and various servers (e.g., an integration server, a provider server, a content server, an Internet server, a cloud server, or the like) on a mobile communication network. The wireless signal may include a voice call signal, a video call signal, and data in various forms according to the transmission and reception of text/multimedia messages.

[0104] The mobile communication module **411** may receive one or more data (e.g., contents, a message, a mail, an image, a video, weather information, location information, time information, and the like). According to an example embodiment of the present disclosure, the mobile communication module **411** may obtain (receive) various pieces of data by being connected with at least one of other devices (e.g., the electronic device **104** or the server **106**), which are connected with the electronic device **400** over a network (e.g., the mobile communication network). The mobile communication module **411** may transmit various pieces of data required for the operations of the electronic device **400**, to an external device (e.g., the server **104**, another electronic device **104**, or the like), in response to a user's request.

[0105] The mobile communication module **411** may execute a communication function. For example, the mobile communication module **411** may convert a radio frequency (RF) signal into a baseband signal and transmit the same to the controller **480** under the control of the controller **480**, or may convert the base band signal from the controller **480** into an RF signal and transmit the same. For example, the controller **480** may be configured to process a baseband signal based

on various communication schemes. For example, the communication scheme may include an Long-Term Evolution (LTE) communication scheme, an LTE advance (LTE-A) communication scheme, Global System for Mobile Communication (GSM) communication scheme, Enhanced Data GSM Environment (EDGE) communication scheme, Code Division Multiple Access (CDMA) communication scheme, W-Code Division Multiple Access (W-CDMA) communication scheme, or Orthogonal Frequency Division Multiple Access (OFDMA) communication scheme, or the like, but the communication scheme may not be limited thereto.

[0106] The wireless LAN module **413** may include a module for establishing a wireless Internet access and a wireless LAN link with another electronic device (e.g., the electronic device **102** or the server **106**). The wireless LAN module **413** may be embedded in the electronic device **400** or may separately exist outside the electronic device **400**. Wireless Internet technology may include wireless fidelity (WiFi), wireless broadband (Wibro), world interoperability for microwave access (WiMax), high speed downlink packet access (HSDPA), millimeter wave (mmWave), or the like.

[0107] The wireless LAN module **413** may transmit or receive one or more pieces of data selected by a user to/from the outside. According to an example embodiment of the present disclosure, the wireless LAN module **413** works together with at least one of external devices (e.g., another electronic device or a server), which are connected with the electronic device **400** over a network (e.g., a wireless Internet network), and transmits or receives various data of the electronic device **400** to/from the external device. The wireless LAN module **413** may always maintain the ON-state, or may be turned on based on settings of the electronic device **400** or a user input.

[0108] The short-range communication module **415** may be a module for performing short-range communication. The short-range communication technology may include Bluetooth, Bluetooth low energy (BLE), a radio frequency identification (RFID), infrared data association (IrDA), ultra wideband (UWB), Zigbee, Near Field Communication (NFC), and the like.

[0109] The short-range communication module **415** may receive one or more pieces of data. According to an example embodiment of the present disclosure, the short-range communication module **415** works together with an external device (e.g., another electronic device) that is connected with the electronic device **400** over a network (e.g., a short-range communication network), and transmits or receives various data of the electronic device **400** to/from the external device. The short-range communication module **415** may always maintain the ON-state, or may be turned on based on settings of the electronic device **400** or a user input.

[0110] The location calculating module **417** may be a module for obtaining the location of the electronic device **400**, and may include a global position system (GPS) module as a representative example. The location calculating module **415** may measure the location of the electronic device **4100** based on the principals of triangulation. The location calculation module **417** may calculate three dimensional information on a current location according to a latitude, a longitude, and an altitude, by calculating distance information associated with a distance away from three or more base stations and time information, and then applying triangulation to the calculated information. Furthermore, the location calculating module **417** may calculate location information by continuously receiving location information of the electronic device **400** from three or more satellites in real time. The location information of the electronic device **400** may be obtained by various methods.

[0111] The broadcast receiving module **419** may receive a broadcast signal (e.g., a TV broadcast signal, a radio broadcast signal, a data broadcast signal, and the like) and/or broadcast related information (e.g., information associated with a broadcast channel, a broadcast program, or a broadcast service provider) from an external broadcast management server through a broadcast channel (e.g., a satellite broadcast channel, a terrestrial broadcast channel, or the like).

[0112] The input unit **420** may generate input data for controlling the operations of the electronic device **400**, in response to, for example, a user input. The input unit **420** may include at least one input device for detecting various inputs of the user. For example, the input unit **420** may include a key pad, a dome switch, a physical button, a touch pad (resistive/capacitive type), jog & shuttle, a sensor (e.g., the sensor module **240**), or the like.

[0113] A part of the input unit **420** may be embodied outside the electronic device **400** in the form of a button, or a part or the whole of the user input unit **420** may be embodied as a touch panel. The input unit **420** may receive a user input for initiating the operations of the electronic device **400** according to various example embodiments of the present disclosure, or may generate an input signal based on a user input. For example, the input unit **420** may receive various user inputs for measuring an image quality, photographing an image, executing an application, inputting (writing or inserting) data, changing the position of the electronic device **400**, displaying contents, transmitting or receiving data, or the like, and may generate an input signal based on the user input.

[0114] The touch screen **430** may include an input/output means that simultaneously executes an input function and a display function, and may include a display **431** (e.g., the display **160** or **260**), and a touch sensing unit **433**. The touch screen **430** may provide an input/output interface between the electronic device **400** and the user, may transfer a touch input of the user to the electronic device **400**, and may serve as a medium that shows an output from the electronic device **400** to the user. The touch screen **430** may show a visual output to the user. The visual output may be shown in the form of a combination of text, graphics, and videos. For example, according to example embodiments of the present disclosure, the touch screen **430** may display various screens associated with operations of the electronic device **400**, through the display **431**. The various screens may include various User Interface (UI)-based screens that may be displayed to correspond to an executed application, for example, an image screen, an image quality measurement result screen, a messenger screen, a call screen, a game screen, a video reproduction screen, a gallery screen, a webpage screen, a home screen, a network connection screen, or the like.

[0115] The touch screen **430** may detect an event based on at least one of a touch, a hovering, and an air gesture (e.g., a touch event, a hovering event, an air gesture event), which are provided from a user, through the touch detecting unit **433**, while displaying a predetermined screen through the display **431**, and may transfer an input signal associated with the event to the controller **480**. The controller **480** may distinguish a transferred event, and may control executing an operation based on the distinguished event.

[0116] According to various example embodiments of the present disclosure, the display **431** may display (output) various information processed in the electronic device **400**. For example, the display **431** may display a User Interface (UI) or a graphic UI (GUI) associated with image quality measurement when the electronic device **400** measures the quality of an image. The display **431** may display a UI or a GUI associated with calling when the electronic device **400** operates in a call mode. Also, the display **431** may display a photographed or/and received image and a UI or GUI associated with operating a corresponding mode, when the electronic device **400** is in a video call mode or a photographing mode. The display **431** may display data associated with the use of the electronic device **400**, contents, or information associated with an external device that is connected with a network. The display **431** may display various application execution screens corresponding to an executed application.

[0117] The display **431** may support displaying a screen based on a landscape mode, displaying a screen based on a portrait mode, or displaying a screen based on a change between the landscape mode and the portrait mode, according to a rotation direction (or an orientation) of the electronic device **400**. The display **431** may use various displays (e.g., the display **160**). A few displays may be embodied as a transparent display formed in a transparent type or an optical transparent type.

[0118] The touch detecting unit **433** may be mounted on the display **431**, and may detect a user input that is in contact with, or in proximity to, the surface of the touch screen **430**. The user input may include a touch event or a proximity event that is input based on at least one of a single-touch, a multi-touch, a hovering, and an air gesture. For example, the user input may be input by a tap, a drag, a sweep, a flick, a drag & drop, or a drawing gesture (e.g., writing) or the like. The touch detecting unit **433** may detect a user input (e.g., a touch event or a proximity event) on the surface of the touch screen **430**, generate a signal corresponding to the detected user input, and transfer the same to the controller **480**. The controller **480** may control the execution of a function corresponding to an area where the user input (e.g., a touch event or a proximity event) is generated by the signal transferred from the touch detecting unit **433**.

[0119] The touch detecting unit **433** may receive a user input for initiating the operations of the electronic device **400** according to various example embodiments of the present disclosure, or may generate an input signal based on a user input. The touch detecting unit **433** may be configured to convert a pressure applied to a predetermined part of the display **431** or a change in a capacitance generated from a predetermined part of the display **431**, into an electrical input signal. The touch detecting unit **433** may detect a location and an area where an input means (e.g., a user's finger, an electronic pen, or the like) touches or approaches the surface of the display **431**. Also, the touch detecting unit **433** may be configured to detect even a pressure when a touch is given, based on an applied touching scheme. When a touch or proximity input with respect to the touch detecting unit **433** exists, a signal(s) corresponding thereto may be transferred to a touch screen controller (not illustrated). The touch screen controller (not illustrated) may process the signal(s), and may transfer the corresponding data to the controller **480**. Accordingly, the controller **480** may be configured to determine an area of the touch screen **430** where a touch or proximity input is given, and may process the execution of a function corresponding thereto.

[0120] The audio processing unit **440** may include a configuration that is identical or similar to the audio module **280** of FIG. **2**. The audio processing unit **440** may transmit an audio signal received from the controller **480** to a speaker (SPK) **441**, and may transfer, to the controller **480**, an audio signal such as a voice or the like, which is input from a microphone (MIC) **443**. The audio processing unit **440** may convert voice/sound data into audible sound through the speaker **441** under the control of the controller **480** and may output the audible sound, and may convert an audio signal, such as a voice or the like, which is received from the microphone **443** into a digital signal and may transfer the digital signal to the controller **480**. The audio processing unit **440** may output an audio signal that responds to a user input, based on audio processing information (e.g., sound effect, music file, or the like) included in data.

[0121] The speaker **441** may output audio data that is received from the wireless communication unit **410** or stored in the memory **450**. The speaker **441** may output a sound signal associated with various operations (functions) executed by the electronic device **400**. The speaker **441** may be in charge of outputting an audio stream, such as a voice recognition function, a digital recording function, a phone call function and the like. Although not illustrated in various example embodiments of the present disclosure, the speaker **441** may include an attachable and detachable ear phone, a head phone, or a head set, and they may be connected with the electronic device **400** through an external port.

[0122] The microphone **443** may receive an external sound signal and process the same as electrical voice data. The voice data that is processed through the microphone **443** may be output by being converted into a form that is transmittable to the outside through the mobile communication module **411** when the electronic device **400** is in a call mode. Various noise reduction algorithms may be implemented in the microphone **443** to remove noise generated in the process of receiving an external sound signal. The microphone **443** may be in charge of inputting an audio stream, such as a voice command (e.g., a voice command for initiating an image quality measuring operation of the electronic device **400**), voice recognition, digital recording, phone call, and the like. For example, the microphone **443** may convert a voice signal into an electrical signal. According to various example embodiments of the present disclosure, the microphone **443** may include an embedded microphone that is contained in the electronic device **400** and an external microphone that is connected to the electronic device **400**.

[0123] The memory **450** (e.g., the memory **130** and **230**) may store one or more programs that are executed by the controller **480**, and may execute a function for temporarily storing input/output data. The input/output data may include, for example, contents, messenger data (e.g., conversation data), contact information (e.g., wired or wireless phone number or the like), a message, a media file (e.g., an audio file, a video file, an image file, or the like), or the like. According to various example embodiments of the present disclosure, the memory **450** may store one or more images that are the target of an image quality evaluation and a plurality of classifiers that may be used for the image quality evaluation of the one or more images.

[0124] The memory **450** may store one or more programs and data in association with the execution of an image quality measuring function. For example, the memory **450** may store one or more programs that process an operation of obtaining an image, an operation of analyzing (recognizing) an image, an operation of classifying an image scene category, an operation of extracting image quality factor scores, an operation of selecting an image quality classifier corresponding to an image scene category, an operation of extracting a total image quality score using image quality factor scores and an image quality classifier, an operation of determining a total image scene category using an image scene category and a total image quality score, and the like, and may store data that is processed accordingly.

[0125] The memory **450** may store a frequency of the use (e.g., a frequency of the use of an image scene classifier, a frequency of the use of an image, a frequency of the use of an application, a frequency of the use of contents, and the like) in association with the operations of the electronic device **400**, importance, and priority, together. The memory **450** may store data that is associated with vibrations and sounds of various patterns that are output in response to a touch input or a proximity input made on the touch screen **430**. The memory **450** may continuously or temporarily store an Operating System (OS) of the electronic device **400**, a program that is associated with controlling inputting and displaying through the touch screen **430**, a program associated with controlling various operations (functions) of the electronic device **400**, and various data generated by the operations of each program, and the like.

[0126] The memory **450** (e.g., the memories **130** and **230**) may include an external memory (e.g., the external memory **234**) or an embedded memory (e.g., the embedded memory **232**). The electronic device **400** may also operate in relation to a web storage performing a storage function of the memory **450** on the Internet.

[0127] The memory **450** may store various software. For example, the component elements of software may include, an operating system software module, a communication software module, a graphic software module, a user interface software module, a Moving Picture Experts Group (MPEG) module, a camera software mode, or one or more application software modules, and the like. Further, since a module, which is a component element of software, may be expressed as a set of instructions, the module is also expressed as an instruction set. The module is also expressed as a program. According to various example embodiments of the present disclosure, the memory **450** may include an additional module (instructions) in addition to the above described modules. Alternatively, the memories may not use some modules (instructions) when necessary.

[0128] The operating system software module may include various software component elements that control a general system operation. The control of such general system operations refers to, for example, memory management and control, storage hardware (device) management and control, power management and control, and the like. Also, the operating system software module may execute a function that supports smooth communication between various hardware (devices) and software component elements (modules).

[0129] The communication software module may enable communication with another electronic device, such as a wearable device, a device, a computer, a server, a portable terminal, or the like, through the wireless communication unit **410** or the interface unit **460**. The communication software module may be formed in a protocol structure corresponding to a corresponding communication scheme.

[0130] The graphic software module may include various software component elements for providing and displaying graphics on the touch screen **430**. The term "graphics" may include, for example, text, a webpage, an icon, a digital image, a video, animation, and the like.

[0131] The user interface software module may include various software component elements associated with a user interface (UI). For example, the user interface software module may include the contents associated with how the state of the UI changes, a condition where a change of the state of the UI is made, or the like.

[0132] The MPEG module may include a software component element that enables processes and functions (e.g., generating, reproducing, distributing, and transmitting a content, or the like) that are associated with a digital content (e.g., video or audio).

[0133] The camera software module may include a camera software component element that enables camera related processes and functions.

[0134] The application module may include a web browser including a rendering engine, an email, an instant message, word processing, keyboard emulation, an address book, a touch list, a widget, digital right management (DRM), voice recognition, a position determining function, a location based service, and the like. According to various example embodiments of the present disclosure, the application module may include instructions for executing image quality measurement. For example, the application module may process an operation (function) that executes analyzing an input (obtained or photographed) image, classifying an image scene category of the analyzed image, extracting image quality factor scores, determining an image quality classifier corresponding to the classified image scene category, and determining a total image quality score using the image quality factor scores and the image quality classifier.

[0135] The interface unit **460** may include a configuration identical or similar to the interface **270** of FIG. **2**. The interface unit **460** may serve as an interface with all external devices that are connected to the electronic device **400**. The interface unit **460** may receive data or power from an external device and transmit the same to each component element of the electronic device **400**, or may enable data inside the electronic device **400** to be transmitted to an external device. For example, the interface unit **460** may include a wired/wireless headset port, an external charger port, a wired/wireless data port, a memory card port, a port for connecting a device provided with an identification module, an audio input/output port, a video input/output port, an earphone port, and the like. According to various example embodiments of the present disclosure, the interface unit **460** may communicate with a device in a connected state that enables the electronic device **400** and the device to execute communication, so as to exchange various data (e.g., a control signal by a device, a response signal by the electronic device **400**, an image signal, an audio signal, a file, and the like).

[0136] The camera module **470** (e.g., the camera module **291**) may include a configuration that supports a photographing function of the electronic device **400**. The camera module **470** may support photographing an image (a still image or a moving image) of a subject. The camera module **470** may photograph a subject under the control of the controller **480**,

and may transfer the photograph data to the display **431** and the controller **480**. The camera module **470** may be configured to include an image sensor (or a camera sensor) (not illustrated) for converting an input optical signal into an electric signal, and an image signal processing unit (not illustrated) for converting the electric signal input from the image sensor into digital image data.

[0137] The image sensor may include a sensor using a Charge-Coupled Device (CCD) or a Complementary Metal-Oxide-Semiconductor (CMOS), or the like. Additionally or alternatively, the camera module **470** may include, for example, a color sensor for distinguishing colors by sensing a wavelength of light that an object radiates or reflects. The camera module **470** may support an image processing function that supports photographing according to various photographing options (e.g., out-of-focus, motion blur, zooming, a screen ratio, and effects (e.g., sketch, mono, sepia, vintage, mosaic, a picture frame, and the like)) based on the user's settings.

[0138] The controller **480** may be configured to control the general operations of the electronic device **400**. For example, the controller **480** may be configured to execute a control associated with a voice communication, a data communication, a video communication, or the like. The controller **480** may include processing circuitry including one or more processors (e.g., the processor **210**), or the controller **480** may be referred to as a processor. For example, the controller **480** may include a Communication Processor (CP), an Application Processor (AP), an interface (e.g., General Purpose Input/Output (GPIO)), an embedded memory, or the liker as separate component elements, or may integrate the above component elements as one or more integrated circuits. The application processor may execute various software programs and perform various functions for the electronic device **400**, and the communication processor may execute a process and a control for the voice communication and data communication. Also, the controller **480** may execute a predetermined software module (instruction set) stored in the storage unit **450**, and may execute various predetermined functions corresponding to the module.

[0139] According to various example embodiments of the present disclosure, the controller **480** may be configured to control an operation associated with executing an image quality measuring function. For example, the controller **480** may be configured to distinguish an image (e.g., an out-of-focus background image, a motion blur image, or the like) to which a special effect (e.g., out-of-focus, motion blur, or the like) is applied when an electronic device determines an image quality score in association with the image quality measurement. The controller **480** may be configured to measure an image quality by distinguishing each property of an image (e.g., an out-of-focus background image, a motion blur image, and the like), as described above. The controller **480** may be configured to classify the image based on an image scene category (e.g., mountain, ocean, sky, beach, streets, night view, or the like) and to determine an image scene classifier corresponding to the corresponding image scene category, in the image quality measurement. The controller **480** may be configured to determine an image quality by applying, to the image, a different weight based on the determined image scene classifier. According to various example embodiments of the present disclosure, when the controller **480** executes total image quality evaluation, the controller **480** may be configured to determine an image quality (e.g., may determine an image quality score) based on an image quality factor score determined based on the property of the image and an image scene category classifier. The operations of the controller **480**, according to various example embodiments of the present disclosure, will be described with reference to the following drawings.

[0140] According to various example embodiments of the present disclosure, the controller **480** may be configured to work together with software modules stored in the memory **450**, and may be configured to execute an image quality measuring function of the electronic device **400** according to various example embodiments of the present disclosure. According to various example embodiments of the present disclosure, the controller **480** may be embodied as one or more modules that are capable of processing the above described image quality measuring function. According to various example embodiments of the present disclosure, the controller **480** may be embodied as one or more processors that controls an operation (e.g., an operation of executing an image quality measuring function) of the electronic device **400**, according to various example embodiments of the present disclosure, by executing one or more programs stored in the memory **450**. For example, the controller **480** may be embodied to include a quality measuring module **485**. According to various example embodiments of the present disclosure, the quality measuring module **485** may be embodied to include an image managing module, a category classifying module, an image factor extracting module, a classifier selecting module, an image quality evaluating module, and the like.

[0141] According to various example embodiments of the present disclosure, the quality measuring module **485** may be configured to measure the quality of an image. According to various example embodiments of the present disclosure, the controller **480** may be configured to control the execution of various operations by distinguishing a good image or a bad image in association with an image, based on the image quality evaluation by the quality measuring module **485**. For example, the controller **480** may be configured to extract and remove a bad image from images stored in the electronic device **400** or an external device (e.g., another electronic device or a server), may be configured to provide the management of a memory by informing a user of an unnecessary image stored in the memory **450**, and may be configured to propose candidate images (e.g., propose candidate images based on a good image) for image summarization. Detailed example configurations of the quality measuring module **485** and controlling operations thereof, according to various example embodiments of the present disclosure, will be described with reference to the following drawings.

[0142] The controller **480** according to various example embodiments of the present disclosure may be configured to control various operations associated with normal functions of the electronic device **400**, in addition to the above described functions. For example, when a predetermined application is executed, the controller **480** may be configured to control an operation and displaying of a screen for the predetermined application. Also, the controller **480** may be configured to receive input signals corresponding to various touch event inputs or proximity event inputs that are supported by a touch-based or proximity-based input interface (e.g., the touch screen **430**), and control operating functions corresponding thereto. Moreover, the controller **480** may also

be configured to control data transmission/reception based on wired communication or wireless communication.

[0143] The power supply unit **490** may receive an external power or an internal power under the control of the controller **480**, and may supply power that is required for the operation of each component element. According to various example embodiments of the present disclosure, the power supply unit **490** may turn on or off the power supplied to one or more processors of the controller **480**, the display **431**, the wireless communication unit **410**, and the like, under the control of the controller **480**.

[0144] Various example embodiments described in the present disclosure may be implemented in a computer (or similar device)-readable recording medium using software, hardware or a combination thereof. According to the hardware implementation, the various example embodiments of the present disclosure may be implemented using at least one of hardware circuitry, Application Specific Integrated Circuits (ASICs), Digital Signal Processors (DSPs), Digital Signal Processing Devices (DSPDs), Programmable Logic Devices (PLDs), Field Programmable Gate Arrays (FPGAs), processors, controllers, micro-controllers, micro-processors, and electrical units for performing other functions.

[0145] According to various example embodiments of the present disclosure, the recording medium may include a computer readable recording medium that stores a program for implementing an operation of classifying an image scene category of an image and determining a classifier corresponding to the classified image scene category, an operation of determining image quality factor scores of the image, an operation of executing image quality evaluation of the image using the image quality factor scores and the classifier.

[0146] In some examples, the embodiments described in the present specification may be implemented by the controller **480** itself. Furthermore, according to the software implementation, the example embodiments such as procedures and functions described in the present specification may also be implemented as separate software modules. The software modules may perform one or more functions and operations described in the present disclosure.

[0147] According to various example embodiments of the present disclosure, at least some of the functions executed by the electronic device **400** may be executed by an external device (e.g., the server **106**) thereof. For example, the server **106** may include a processing module corresponding to the controller **480**, may process, using the processing module, at least some of the functions associated with measuring the quality of an image of the electronic device **400** and controlling the execution of the function, based on at least some of the information transferred from the electronic device **400**, and transmits a result of processing to the electronic device **400**.

[0148] FIG. **5** is a diagram illustrating an example configuration for measuring the quality of an image in an electronic device.

[0149] Referring to FIG. **5**, FIG. **5** schematically illustrates an example configuration of the quality measuring module **480** of the controller **480** as illustrated in FIG. **4**. The quality measuring module **485**, according to various example embodiments of the present disclosure, may include an image managing module **510** (e.g., a camera manager or an image manager), a category classifying module **520**, a classifier selecting module **530**, an image factor extracting module **540**, and an image quality evaluating module **550**. In various example embodiments of the present disclosure, the quality measuring module **485** may selectively further include a category determining module **560** or may omit the same. For example, in various example embodiments of the present disclosure, the quality measuring module **485** may include fewer or more component elements when compared to the component elements of FIG. **5**, since the component elements of FIG. **5** are not prerequisite.

[0150] The image managing module **510** may obtain an image photographed through the camera module **470**, an image stored in the memory **450**, or an image received from an external device (e.g., another electronic device or a server). The image managing module **510** may recognize image information (e.g., an image file format) from an image obtained for measuring the quality of an image. The image managing module **510** may transfer at least some of the recognized image information or the image to the category classifying module **520** and the image factor extracting module **540**. According to various example embodiments of the present disclosure, the image information may include, for example, Exchangeable Image File Format (EXIF) information, and may include, for example, various information, such as information associated with a date when an image is generated (photographed), size information, exposure time (shutter speed) information, location information, effects (e.g., out-of-focus, blur, motion blur, or the like) information, scene information, and the like.

[0151] The category classifying module **520** may classify an image scene category of the image based on at least some of the image or the image information transferred from the image managing module **510**. For example, the category classifying module **520** may classify the category of the image by analyzing a type of scene that the image corresponds to, for example, mountain, ocean, sky, beach, streets, night view, or the like. According to an example embodiment of the present disclosure, the category classifying module **520** may define a type of scene (e.g., a category or a class) of an image through an image classifying method that classifies an image by quantizing feature vectors of an image or an image classifying method that classifies an image using deep learning An image classifying method that quantizes a feature vector of the image may, for example, extract a feature vector (e.g., a feature point of a corner, a color, letters, a sentence, a specific shape, a behavior pattern, statistics, or the like), quantizes the feature vector, and measures likeness to a predetermined scene category that is stored in advance, using the similarity of a cumulative histogram of the feature vector. The image classifying method using deep learning may define a class of an image by attempting, for example, a high level abstraction (which abstracts main contents or functions from a large amount of data or complex materials) through the combination of various non-linear conversion schemes. The category classifying module **520** may transfer the classified image scene category of the image to the classifier selecting module **530**.

[0152] The classifier selecting module **530** may select (determine) a classifier (e.g., an image quality classifier) corresponding to the image scene category that is transferred from the category classifying module **520**. For example, the classifier selecting module **530** may select a classifier corresponding to the transferred image scene category of the image (e.g., mountain, ocean, sky, beach, streets, night view, or the like), out of image quality classifiers stored in advance. According to various example embodiments of the present

disclosure, the classifier may indicate a reference value that is used for differentially measuring quality based on an image scene category of a corresponding image when the classifier measures the quality of the image.

[0153] According to an example embodiment of the present disclosure, in a case of a night view image (e.g., image scene category=night view), although the image (picture) has a good quality, the image may have the features of low brightness and low exposure. Also, in a case of a cloud image (e.g., an image scene category=cloud), although the image (picture) has a good quality, a blur factor score may be low due to a unique frequency feature of the cloud. Therefore, when the quality of an image is measured, the quality may be measured from a different perspective view based on an image scene category. Accordingly, in various example embodiments of the present disclosure, the classifier selecting module **530** may change an image quality classifier to correspond to an image scene category, and thereby changing a perspective of measurement. For example, the classifier selecting module **530** may select and provide an image quality classifier that is appropriate for a night view image in a case of a night view image, and may select and provide an image quality classifier that is appropriate for a sky (cloud) image. The classifier selecting module **530** may transfer, to the image quality evaluating module **550**, an image quality classifier that is determined for the image.

[0154] The image factor extracting module **540** may extract image quality factor scores with respect to the image based on at least some of an image or image information that is transferred from the image managing module **510**. For example, the image factor extracting module **540** may extract an image quality factor such as sharpness, noise, contrast, color accuracy, distortion, blur, or the like of the image, measure the extracted image quality factor, and determine a score of each image quality factor. The image factor extracting module **540** may transfer, to the image quality evaluating module **550**, the image quality factor scores that are determined for the image.

[0155] According to various example embodiments of the present disclosure, when the image includes special effects (e.g., out-of-focus, motion blur, or the like), the quality of the image may be measured from a different perspective.

[0156] According to an example embodiment of the present disclosure, in a case of an out-of-focus background image, although the image has a good quality, an area that is in focus may be insufficient. In this example, a blur factor score may increase. Therefore, according to various example embodiments of the present disclosure, the image factor extracting module **540** may divide an image into a plurality areas, and measures a blur factor score for each divided area. The image factor extracting module **540** may measure a blur factor score with respect to the sharpest area (or the sharpest group of a predetermined areas) from among blur factor scores of the areas. According to an example embodiment of the present disclosure, the image factor extracting module **540** may determine at least some areas (e.g., the sharpest area) out of the areas based on a result of measuring a blur factor score for each area, and may determine a blur factor score for evaluating the quality of an image based on the at least some area.

[0157] Also, in a case of a blur image, the corresponding score may be low. In a case of an image of which the entire area is sharp, or an out-of-focus background image, the corresponding score may be relatively high. Therefore, in a case of the sharp image, the blur image, or the out-of-focus image, this may be used as an image factor that has a high differentiation.

[0158] Conversely, in a case of the motion blur image, a sharp area in the image is low, and thus, a blur factor score may have a low differentiation with respect to the motion blur image. In a case of the motion blur image, an edge component does not exist in a motion direction in the image, and most edge components exist in a direction that is perpendicular to the motion direction. Therefore, a distribution of edge components for each motion direction (e.g., a distribution of vertical edge components and a distribution of vertical edge components) is extracted, and when a difference in cumulative edge distributions between orthogonal directions is larger, it is determined that a corresponding area belongs to a blur area by a motion blur.

[0159] According to various example embodiments of the present disclosure, the image factor extracting module **540** may extract a distribution of vertical edge components and a distribution of horizontal edge components, and may measure a blur factor score based on an area in which a difference in cumulative edge distributions between orthogonal directions is high. For example, in various example embodiments of the present disclosure, the image factor extracting module **540** may determine a target area of measurement for measuring a blur factor score, based on a difference in cumulative edge distributions between orthogonal directions (e.g., a difference between cumulative edge distributions of vertical edge components and horizontal edge components that are perpendicular thereto, or a difference between cumulative edge distributions of horizontal edge components and vertical edge components that are perpendicular thereto). For example, the image factor extracting module **540** extracts a distribution of edge components for each direction from the image, and determines the target area of measurement for measuring a blur factor score for evaluating the quality of the image based on an area having a large difference in cumulative edge distributions from among areas where a horizontal edge component and a vertical edge component are perpendicular to each other. According to an example embodiment of the present disclosure, as a difference in cumulative edge distributions between orthogonal directions is low, an image corresponds to an image where blur does not exist. As a difference in cumulative edge distributions between orthogonal directions is high, an image corresponds to an image where a motion blur exists.

[0160] The image quality evaluating module **550** (e.g., a total image quality evaluator) may extract a total image quality score with respect to the image using the image quality factor scores transferred from the image factor extracting module **540** and the image quality classifier transferred from the classifier selecting module **530**. For example, the image quality evaluating module **550** may extract a likelihood score between a low quality image class and a high quality image class, using the image quality classifier based on the image quality factor scores. According to various example embodiments of the present disclosure, the extraction of the likelihood score may be an example of a score-based determination scheme that does not overestimate or underestimate reliability with respect to the image, but executes accurate determination. According to an example embodiment of the present disclosure, the image quality evaluating module **550** may compare learning data stored in advance and the image that is the target of image quality evaluation, and may determine a

similarity (reliability) between the image and the learning data. According to various example embodiments of the present disclosure, the learning data may include sample data corresponding to a high-quality image and a low-quality image, which are stored by learning various images in advance.

[0161] According to various example embodiments of the present disclosure, the learning data used by the image quality evaluation module **550** may be learning data of images included in an image scene category that is classified by the category classifying module **520**, and the images included in the image scene category may be classified into a high-quality image and a low-quality image based on an image quality classifier selected by the classifier selecting module **530**. According to various example embodiments of the present disclosure, the image quality evaluating module **550** may compare the image and the images of the learning data, and may extract a likelihood score of the image based on learning data having a high reliability. For example, the image quality evaluating module **550** may estimate the likelihood score of the image based on the learning data that is distinguished based on the image quality factor scores and the determined classifier.

[0162] The image quality evaluating module **550** may determine a total image quality score with respect to the image, based on the extracted likelihood score. The image quality evaluating module **550** may manage an image quality score of the image, based on the determined total image quality score. For example, the image quality evaluating module **550** may provide the image quality score to a function (application) executed in the electronic device **400** using the evaluation of an image (e.g., removing a bad image, managing a memory, proposing candidate images for abstracting an image, or the like).

[0163] The category determining module **560** may determine (decide) an image scene category of the image using the image scene category transferred from the category classifying module **520** and the total image quality score transferred from the image quality evaluating module **550**. For example, when the quality of an original image is bad, it is better to not classify the image to a predetermined category from the perspective of precision. Therefore, the category determining module **560** may finally determine the image scene category of the image, based on the total image quality score.

[0164] According to various example embodiments of the present disclosure, the image scene category classified in association with the image in the category classifying module **520** and the image scene category finally decided in the category determining module **560** may be determined to be an identical image scene category based on the total image quality score, or may be determined as a detailed image scene category. For example, it is assumed that the category classifying module **520** classifies the image scene category as a "sky" category, the category determining module **560** may finally decide the image scene category of the image as the "sky" category when the total image quality score is determined to be within a predetermined range of a predetermined reference value. Also, when the total image quality score is determined to be higher than the predetermined range of the predetermined reference value, the category determining module **560** may finally determine the image to be a "clear sky" category. When the total image quality score is determined to be lower than the predetermined range of the predetermined reference value, the category determining module **560** may classify the image as a "cloudy sky" category. As described above, the category determining module **560** may classify the image scene category as a detailed category. The category determining module **560** may update the image scene category of the image based on the finally decided image scene category, when the image scene category is finally decided. Subsequently, in a process of evaluating the quality of an image, the image scene category of the image may be classified to correspond to the finally decided image scene category.

[0165] According to various example embodiments of the present disclosure, the configuration of the category determining module **560** may be excluded.

[0166] As described above, the electronic device **400** may include the memory **450** that stores a plurality of images and a plurality of classifiers; and a processor (e.g., the controller **480**) that is electrically connected with the memory **450**, wherein the processor is configured to: analyze a category of an image of which image quality evaluation is requested, and determine a classifier corresponding to the category of the image from among the plurality of classifiers; determine image quality factor scores of the image; and evaluate the image quality of the image based on the determined image quality factor scores and the determined classifier.

[0167] In various example embodiments of the present disclosure, the processor (e.g., the controller **480**) may include: the image factor extracting module **540** that measures the quality for each image quality factor of the image; the category classifying module **520** that classifies an image scene category of the image; the classifier selecting module **530** that selects an image quality classifier corresponding to the image scene category; and the image quality evaluating module **550** that determines the total image quality score of the image based on results from the image factor extracting module **540** and the classifier selecting module **530**.

[0168] The category classifying module **520** may analyze the image scene category based on a scheme that classifies an image using feature vectors of the image or a scheme that classifies an image using deep learning.

[0169] The classifier selecting module **530** may select a classifier corresponding to the image scene category from among image quality classifiers stored in advance in the memory **450**.

[0170] According to various example embodiments of the present disclosure, the image factor extracting module **540** divides the image into a plurality of areas, and measures a blur factor score for each divided area, and measures a blur factor score for evaluating an image quality in at least one of the areas based on a result of measuring the blur factor score for each area. The image factor extracting module **540** performs: measuring a blur factor score for each of the divided areas of the image, and determining, as a target area of measurement, one or more areas that have a high sharpness out of the divided areas, wherein the target area of measurement includes a predetermined area or a group of a predetermined number of adjacent areas, which has a low blur factor score out of the divided areas.

[0171] According to various example embodiments of the present disclosure, the image factor extracting module **540** extracts, from the image, a distribution of edge components for each direction, and measures a blur factor score for image quality evaluation based on an area that has a large difference in cumulative edge distributions from among areas where a

horizontal edge component and a vertical edge component are perpendicular to each other.

[0172] The image quality evaluating module **550** extracts a likelihood score corresponding to the image, using image quality factor scores that are transferred from the image factor extracting module **540** and the image quality classifier transferred from the classifier selecting module **530**, and determines a total image quality score with respect to the image based on the extracted likelihood score.

[0173] According to various example embodiments of the present disclosure, the processor (e.g., the controller **480**) may include the image managing module **510** that obtains the image from the inside or the outside, and recognizes image information for measuring the quality of the image. According to various example embodiments of the present disclosure, the processor (e.g., the controller **480**) may include the category determining module **560** that finally decides the image scene category with respect to the image, using the image scene category transferred from the category classifying module **520** and the total image quality score transferred from the image quality evaluating module **550**.

[0174] FIG. **6** is a flowchart illustrating an example image quality measuring method in an electronic device.

[0175] Referring to FIG. **6**, in operation **601**, the controller **480** is configured to obtain an image. For example the controller **480** (e.g., the image managing module **510**) may obtain an image photographed using the camera module **470**, an image stored in the memory **450**, an image received from an external device (e.g., another electronic device or a server), or the like, in response to a user's request.

[0176] In operation **603**, the controller **480** may be configured to classify an image scene category of the obtained image. For example, the controller **480** (e.g., the category classifying module **520**) may be configured to analyze an image scene that the obtained image corresponds to, for example, mountain, ocean, sky, beach, streets, night view, or the like, and may be configured to classify the category of the image based on a result of the analysis. According to various example embodiments of the present disclosure, the controller **480** may be configured to classify the image through various algorithms, such as an image classifying scheme that quantizes a feature vector of an image, an image classifying scheme that uses deep learning, or the like.

[0177] In operation **605**, the controller **480** may be configured to determine a classifier corresponding to the classified image scene category. For example, the controller **480** (e.g., the classifier selecting module **530**) may be configured to select a classifier corresponding to the image scene category from among various image quality classifiers stored in advance in the memory **450**. For example, the controller **480** may be configured to select an image quality classifier corresponding to a night view image when the image scene category of the image is night view, and may select an image quality classifier corresponding to a sky image when the image scene category of the image is sky (cloud).

[0178] In operation **607**, the controller **480** may be configured to extract image quality factor scores of the obtained image. For example, the image may include various image quality factors, such as sharpness, noise, contrast, color accuracy, distortion, blur, or the like, and the controller **480** (e.g., the image factor extracting module **540**) may be configured to extract the various image quality factors from the image. The controller **480** (e.g., the image factor extracting module **540**) may be configured to measure the extracted image quality factors so as to determine scores of each image quality factor.

[0179] According to various example embodiments of the present disclosure, the controller **480** (e.g., the image factor extracting module **540**) may be configured to determine the scores of image quality factors, with respect to a special image to which special effects are applied by user's intention, such as an out-of-focus image, a motion blur image, or the like, and the scores may be determined by applying a weight to the corresponding image, as opposed to using the score determination based on a general blur factor. According to various example embodiments of the present disclosure, an operation of measuring a blur factor of the corresponding image by distinguishing the out-of-focus image or the motion blur image will be described.

[0180] In various example embodiments of the present disclosure, although it has been described that the image scene category classifying operation of operation **603** is executed before the image quality factor score extracting operation of operation **607**, this is merely for ease of description, the operations may not always be executed in this order. For example, according to various example embodiments of the present disclosure, operation **607** may be executed before operation **603**, or operation **603** and operation **607** may be executed in parallel.

[0181] In operation **609**, the controller **480** may determine image quality scores of the image. For example, the controller **480** (e.g., the image quality evaluating module **550**) may be configured to determine an image quality score of the image using the scores of the image quality factors of the image and the classifier selected for the image. According to various example embodiments of the present disclosure, the operation of determining the image quality scores will be described with reference to the drawing to be described below.

[0182] In operation **611**, the controller **480** determines and provides the quality of the image based on the image quality scores.

[0183] FIG. **7** is a flowchart illustrating an example of measuring an image quality factor of a special image in an electronic device. FIGS. **8**A to **8**C are diagrams illustrating examples of an operation of extracting a quality factor of an out-of-focus image in an electronic device.

[0184] FIG. **7** is a flowchart illustrating an example of an operation of extracting, from a special image, an area (e.g., a sharp area to which out-of-focus is not applied (an area being in focus)) remaining after excluding an out-of-focus background, and measuring the quality when the special image is an out-of-focus image.

[0185] In operation **701**, the controller **480** is configured to divide an image area. For example, the controller **480** (e.g., the image factor extracting module **540**) may be configured to divide the image into a plurality of areas based on a number that is adaptively determined to correspond to a set number or the size of an image. According to various example embodiments of the present disclosure, the image division may be vertical division, horizontal division, or vertical and horizontal division (lattice form). The example is illustrated in FIG. **8**.

[0186] FIG. **8** is a diagram illustrating an example of extracting an out-of-focus background factor, in an operation of measuring an image quality factor with respect to an out-of-focus image. As illustrated in FIGS. **8**A, **8**B, and **8**C, FIGS. **8**A to **8**C illustrate examples of vertically dividing an image into 8 areas. According to various example embodiments of the present disclosure, the division is virtual division for

extracting a target area for measuring the quality, but does not change the properties of the image itself.

[0187] Referring again to FIG. **7**, in operation **703**, the controller **480** may be configured to measure a blur factor score based on a plurality of divided areas. For example, the controller **480** (e.g., the image factor extracting module **540**) may be configured to measure a score of a blur factor out of the image quality factors for each of the divided areas. For example, as illustrated in FIGS. **8**A, **8**B, and **8**C, a blur factor score may be measured for each of 8 divided areas. According to an example embodiment of the present disclosure, FIG. **8**A illustrates an example in which a blur factor score of a first divided area is measured as 0.722, a blur factor score of a second divided area is measured as 0.852, a blur factor score of a third divided area is measured as 0.613, a blur factor score of a fourth divided area is measured as 0.682, a blur factor score of a fifth divided area is measured as 0.947, a blur factor score of a sixth divided area is measured as 0.968, and a blur factor score of a seventh divided area is measured as 1.000, and a blur factor score of an eighth divided area is measured as 0.833.

[0188] In operation **705**, the controller **480** may be configured to determine an area having a low blur factor score. For example, the controller **480** (e.g., the image factor extracting module **540**) may be configured to determine an area having the lowest blur factor score, based on a result of the blur factor score measurement executed for each of the 8 divided areas. In a case of an out-of-focus image, the image is photographed by intending to be out-of-focus, and thus, an out-of-focus background corresponding to a blur area may be included. Therefore, in the case of the out-of-focus image, the image has a high quality, an area that is in focus may be insufficient. In this instance, a blur factor score may increase. Therefore, according to various example embodiments of the present disclosure, the out-of-focus image is divided, and a blur factor score may be determined based on one or more areas (e.g., an area being in focus) having a high sharpness.

[0189] According to various example embodiments of the present disclosure, a target area of measurement for measuring a blur factor score may be determined, and the target area of measurement may be determined based on an area having the lowest blur factor score out of the divided areas, a predetermined number of adjacent areas (hereinafter, a group area) having the lowest sum of blur factor scores, or the like. For example, according to various example embodiments of the present disclosure, the target area of measurement may be determined based on a group of 3 divided areas out of the 8 divided areas, for example, the first through eighth divided areas. According to an example embodiment of the present disclosure, as illustrated in FIG. **8**, the controller **480** may be configured to determine a blur factor score of a first group area (e.g., the first divided area, the second divided area, and the third divided area) by, for example, adding blur factor scores of the first divided area and consecutive two other divided areas (e.g., the second divided area and the third divided area), and may determine a blur factor score of a second group area (e.g., the second divided area, the third divided area, and the fourth divided area) by, for example, adding blur factor scores of the second divided area and consecutive two other divided areas (e.g., the third divided area and the fourth divided area). The controller **480** may be configured to determine a group-based (e.g., a total of 6 groups) blur factor score with respect to all of the divided areas.

[0190] According to various example embodiments of the present disclosure, the controller **480** may be configured to determine a group-based blur factor score as described above, and may be configured to determine, as a target area of measurement, the areas of a group having the lowest blur factor score (e.g., as a blur factor score becomes lower, sharpness becomes higher, and as a blur factor score becomes higher, sharpness becomes lower and an area corresponds to a blur image). For example, in a case of FIG. **8**A, a blur factor score of a group area **810** of a second divided area (0.852), a third divided area (0.613), and a fourth divided area (0.682) has the lowest blur factor score. In a case of FIG. **8**B, a blur factor score of a group area **820** of a third divided area (0.556), a fourth divided area (0.391), and a fifth divided area (0.500) has the lowest blur factor score. In a case of FIG. **8**C, a blur factor score of a group area **830** of a first divided area (0.023), a second divided area (0.023), and a third divided area (0.200) has the lowest blur factor score.

[0191] In operation **707**, the controller **480** may be configured to re-measure an image quality (e.g., measuring a blur factor score), based on an area (or group area) determined in operation **705**. For example, the controller **480** may be configured to measure the image quality, based on the target area of measurement, which is determined in operation **705**, as opposed to based on all of the areas of the image. According to an example embodiment of the present disclosure, the controller **480** (e.g., the image factor extracting module **540**) may be configured to measure an image quality with respect to an image part **815** included in the group area **810** of an image in FIG. **8**A. In FIG. **8**B, the controller **480** may be configured to measure an image quality with respect to an image part **825** included in the group area **820** of an image. In FIG. **8**C, the controller **480** may be configured to measure an image quality with respect to an image part **835** included in the group area **830** of an image. For example, according to various example embodiments of the present disclosure, a target area of measurement having a high sharpness may be distinguished by dividing the out-of-focus image into areas, and a blur factor score may be re-measured based on the distinguished target area of measurement.

[0192] In operation **709**, the controller **480** may be configured to determine and provide an image quality factor score (e.g., a blur factor score) of the image, based on the measurement of an image quality with respect to the target area of measurement.

[0193] FIG. **9** is a flowchart illustrating an example of an operation of measuring an image quality factor of a special image in an electronic device. FIGS. **10**A to **10**C are diagrams illustrating examples of an operation of extracting a quality factor of a motion blur image in an electronic device.

[0194] Referring to FIG. **9**, FIG. **9** is a flowchart illustrating an example of an operation of measuring quality by extracting a motion blur area from a special image when the special image is a motion blur image.

[0195] In operation **901**, the controller **480** is configured to extract an edge component distribution from an image. For example, in a case of the motion blur image, a sharp area in the image is low, and thus, a blur factor score may have a low differentiation with respect to the motion blur image. According to an example embodiment of the present disclosure, in a case of the motion blur image, an edge component does not exist in a motion direction in the image, and most edge components exist in a direction that is perpendicular to the motion direction. According to various example embodiments of the

present disclosure, the controller **480** (e.g., the image factor extracting module **540**) may be configured to extract an edge component distribution for each direction (e.g., vertical direction and horizontal direction).

[0196] In operation **903**, the controller **480** may be configured to determine a cumulative edge distribution based on the edge component distribution extracted for each direction. For example, the controller **480** (e.g., the image factor extracting module **540**) may be configured to determine an area (hereinafter, a target area of decision) that includes the largest edge components in the image.

[0197] In operation **905**, the controller **480** may be configured to determine a target area of measurement, based on a difference in cumulative edge distributions. For example, the controller **480** (e.g., the image factor extracting module **540**) may be configured to determine a target area of measurement out of the target area of decision, based on a difference in cumulative edge distributions between orthogonal directions (e.g., a difference between cumulative edge distributions of vertical edge components and horizontal edge components that are perpendicular thereto, or a difference between cumulative edge distributions of horizontal edge components and vertical edge components that are perpendicular thereto). For example, the controller **480** may be configured to extract a distribution of edge components for each direction from the image, and to determine the target area of measurement for measuring a blur factor score for evaluating an image quality based on an area having a large difference in cumulative edge distributions from among areas where a horizontal edge component and a vertical edge component are perpendicular to each other. According to an example embodiment of the present disclosure, as a difference in cumulative edge distributions between orthogonal directions is low, an image corresponds to an image where blur does not exist. As a difference in cumulative edge distributions between orthogonal directions is high, an image corresponds to an image where a motion blur exists. The example is illustrated in FIG. **10**.

[0198] FIG. **10** is a diagram illustrating an example of a motion gradient histogram of an image. FIG. **10**A illustrates an example of a gradient histogram corresponding to a non-blurred image. FIG. **10**B illustrates an example of a gradient histogram corresponding to a blurred image. FIG. **10**C illustrates an example of a gradient histogram corresponding to a motion-blurred image.

[0199] As illustrated in the gradient histogram of FIG. **10**A, in a case of a non-blurred image, a difference between a vertical edge component (e.g., series **1**) and a horizontal edge component (e.g., series **2**) is little. As illustrated in the gradient histogram of FIG. **10**B, in a case of a blurred image, a difference between a vertical edge component (e.g., series **1**) and a horizontal edge component (e.g., series **2**) is greater than the case A. As illustrated in the gradient histogram of FIG. **10**C, in a case of a motion-blurred image, a difference between a vertical edge component (e.g., series **1**) and a horizontal edge component (e.g., series **2**) is greater than the case B. According to various example embodiments of the present disclosure, the electronic device **400** (e.g., the image factor extracting module **540**) extracts a distribution of edge components for each motion direction (e.g., a distribution of vertical edge components and a distribution of vertical edge components), and determines that a corresponding area belongs to a blurred area by a motion blur when a difference in cumulative edge distributions between orthogonal directions is large.

[0200] Referring again to FIG. **9**, in operation **907**, the controller **480** may be configured to measure an image quality based on the area (target area of measurement) determined in operation **905**. For example, the controller **480** (e.g., the image factor extracting module **540**) may be configured to determine an image for each of FIGS. **10**A, **10**B, and **10**C, and may be configured to measure the image quality based on the target area of measurement when it is determined that the determined image corresponds to a motion blur image. According to an example embodiment of the present disclosure, the controller **480** (e.g., the image factor extracting module **540**) may be configured to measure the image quality based on the target area of measurement (e.g., an area having a large difference in cumulative edge distributions between orthogonal directions), which is determined in operation **905**, as opposed to all of the areas of the image. For example, according to various example embodiments of the present disclosure, the target area of measurement may be distinguished out of the motion blur image, and a blur factor score may be re-measured based on the distinguished target area of measurement.

[0201] In operation **909**, the controller **480** may be configured to determine an image quality factor score (e.g., a blur factor score) of the image, based on the measurement of an image quality with respect to the target area of measurement.

[0202] FIG. **11** is a flowchart illustrating an example of an operation of determining an image quality classifier in an electronic device. FIGS. **12**A and **12**B are diagrams illustrating examples of an image quality classifier in an electronic device.

[0203] Referring to FIG. **11**, the controller **480** may be configured to analyze an image scene category in operation **1101**, and to determine a classifier that matches the image scene category in operation **1103**. For example, in a case of a night view image, the image may have a feature of a low brightness and a low exposure irrespective of whether the image has a good quality. Also, in a case of a sky (cloud) image, a blur factor score may be measured to be low due to a unique frequency feature of cloud, irrespective of whether the image has a good quality. Therefore, according to various example embodiments of the present disclosure, the controller **480** (e.g., the classifier selecting module **530**) may be configured to analyze an image scene category of the image, and may be configured to measure an image quality by taking into consideration the image scene category. According to various example embodiments of the present disclosure, an image quality classifier corresponding to an image scene category may be defined in advance. The example is illustrated in FIG. **12**.

[0204] FIG. **12**A illustrates an example of a classifier that is applied when the image scene category is classified as a night view. FIG. **12**B illustrates an example of a classifier that is applied when the image scene category is classified as sky.

[0205] According to an example embodiment of the present disclosure, in a case of a night view image, the image has a feature of a low brightness and a low exposure, irrespective of the quality, and thus, a brightness factor (or an exposure factor) score may be measured to be low, and also may be greatly affected by a blur factor. Therefore, according to various example embodiments of the present disclosure, as illustrated in FIG. **12**A, a classifier that distinguishes an image quality based on a blur factor rather than a brightness (exposure) factor, may be provided for the night view image. For example, images corresponding to the part over the clas-

sifier (e.g., Classifier for NightShot in FIG. **12**A) may be determined to be high quality images, and images corresponding the part under the classifier may be determined to be low quality images.

[0206] According to an example embodiment of the present disclosure, in a case of a sky image, due to a unique frequency feature, a blur factor score may be measured to be low and may be greatly affected by a brightness factor. Therefore, according to various example embodiments of the present disclosure, as illustrated in FIG. **12**B, a classifier that may distinguish an image quality based on a brightness factor rather than a blur factor, may be provided for the sky image. For example, images corresponding to the part on the left of the classifier (e.g., Classifier for Sky Scene in FIG. **12**B) may be determined to be low quality images, and images corresponding to the part on the right of the classifier may be determined to be high quality images.

[0207] Referring again to FIG. **11**, in operation **1105**, the controller **480** may be configured to determine a classifier that is appropriate for measuring the image quality. For example, the controller **480** (e.g., the classifier selecting module **530**) may be configured to determine an image quality classifier to be different for each image scene category, as described above. For example, a classifier for a night view image and a classifier for a sky image may be provided to be different.

[0208] FIG. **13** is a flowchart illustrating an example method of measuring the quality of an image in an electronic device.

[0209] Referring to FIG. **13**, in operation **1301**, the controller **480** may be configured to distinguish an image using image quality factor scores and a classifier. For example, the controller **480** (e.g., the image quality evaluating module **550**) may be configured to use an image quality classifier based on the image quality factor scores, and thus, may distinguish a high quality image class and a low quality image class, as illustrated in FIG. **12**.

[0210] In operation **1303**, the controller **480** may be configured to extract a likelihood score between a low quality image and a high quality image, based on distinguishing an image. According to various example embodiments of the present disclosure, the extraction of the likelihood score may be an example of a score-based determination scheme that does not overestimate or underestimate reliability with respect to the image, but executes accurate determination. For example, the controller **480** may be configured to compare learning data stored in advance and the image that is a target of image quality evaluation, and may determine a similarity (reliability) between the image and the learning data.

[0211] According to various example embodiments of the present disclosure, the learning data may include sample data corresponding to a high-quality image and a low-quality image, which are stored by learning various images in advance. According to various example embodiments of the present disclosure, the learning data used by the image quality evaluating module **550** may be learning data of images included in an image scene category that is classified by the category classifying module **520**, and the images included in the image scene category may be classified as a high-quality image or a low-quality image based on an image quality classifier selected by the classifier selecting module **530**.

[0212] According to various example embodiments of the present disclosure, the controller **480** may be configured to compare the image and the images of the learning data, and may extract a likelihood score of the image based on learning data having a high reliability. For example, the controller **480** may be configured to estimate the likelihood score of the image based on the learning data that is distinguished based on the image quality factor scores and the determined classifier.

[0213] In operation **1305**, the controller **480** may be configured to determine a total image quality score with respect to the image, based on the extracted likelihood score.

[0214] As described above, an image quality evaluating method of the electronic device **400**, according to various example embodiments of the present disclosure, may include: obtaining an image; classifying an image scene category of the image; determining a classifier corresponding to the classified image scene category; determining image quality factor scores with respect to the image; and executing image quality evaluation with respect to the image, using the determined image quality factor scores and the determined classifier.

[0215] According to various example embodiments of the present disclosure, the determining of the image quality factor scores includes: dividing the image into a plurality of areas; measuring a blur factor score for each of the plurality of divided areas; determining an area that has a low blur factor score; and executing image quality measurement based on the determined area. According to various example embodiments of the present disclosure, the determining of an area having a low blur factor score includes: determining, as a target area of measurement, one or more areas having a high sharpness out of the divided areas of the image, wherein the target area of measurement includes a predetermined area or a group of a predetermined number of adjacent areas, which has a low blur factor score out of the divided areas.

[0216] According to various example embodiments of the present disclosure, the determining of the image quality factor scores includes: extracting, from the image, a distribution of edge components for each direction; determining a cumulative edge distribution based on the extracted distribution of edge components for each direction; determining a target area of decision that includes the largest number of edge components; determining, from the target area of decision, a target area of measurement based on a difference in cumulative edge distributions; and executing image quality measurement based on the target area of measurement. According to various example embodiments of the present disclosure, the determining of the target area of measurement includes determining the target area of measurement based on a difference in cumulative edge distributions between orthogonal directions in the target area of decision.

[0217] FIG. **14** is a sequence diagram illustrating an example of a method of measuring the quality of an image.

[0218] Referring to FIG. **14**, FIG. **14** illustrates a sequence diagram illustrating an example in which a second electronic device **2000** (e.g., another electronic device or the server **106**) processes an image quality measuring operation according to various example embodiments of the present disclosure. In FIG. **14**, a first electronic device **1000** may be an electronic device that requests a measurement of the quality of an image, and the second electronic device **2000** may include a configuration identical or similar to that of the electronic device **400** as described above, and may include a processing module corresponding to the controller **480** of the electronic device **400**. The second electronic device **2000** may process at least some (e.g., measurement of the quality of an image and the execution of related functions) of the functions executed by

the electronic device **400**, and may transmit a result thereof to the first electronic device **1000**.

[0219] In operation **1401**, the first electronic device **1000** transmits an image quality evaluation request to the second electronic device **2000**. The first electronic device **1000** may request image quality evaluation with respect to an image stored in the second electronic device **2000**, or may request image quality evaluation with respect to an image stored in the first electronic device **1000**. When the first electronic device **1000** requests image quality evaluation with respect to an image stored in itself, the first electronic device **1000** may provide the stored image to the second electronic device **2000**.

[0220] In operation **1403**, the second electronic device **2000** processes the image quality evaluation with respect to the image obtained in response to the request of the first electronic device **1000**. For example, the second electronic device **200** may execute an operation corresponding to the image quality evaluation processing operation of the electronic device **400**, as described above. According to an example embodiment of the present disclosure, the second electronic device **2000** may receive an image from the first electronic device **1000**, may analyze a category of the image, and may determine a classifier corresponding to the category of the image. Also, the second electronic device **2000** may determine image quality factor scores of the image. The second electronic device **2000** may execute an image quality evaluation of the image based on the determined image quality factor scores and the determined classifier.

[0221] In operation **1405**, the second electronic device **2000** may generate a result of processing the image quality evaluation. For example, the second electronic device **2000** may generate image quality evaluation information (e.g., a total image quality score) with respect to the image based on the processing of the image quality evaluation.

[0222] In operation **1407**, the second electronic device **2000** transmits the image quality evaluation information to the first electronic device **1000**.

[0223] According to various example embodiments of the present disclosure, the image quality measurement may be executed by the electronic device **400**, or by an external device (e.g., the server **106** or another electronic device) that is connected with the electronic device **400**.

[0224] According to various example embodiments of the present disclosure, a system that supports measuring the quality of an image may include the first electronic device **1000** that requests image quality evaluation of an image; and the second electronic device **2000** that is connected (e.g., in communication with, including wired and/or wireless communication) with the first electronic device **1000**, wherein the second electronic device **2000** performs: obtaining the image from the first electronic device; analyzing a category of the image, and determining a classifier corresponding to the category of the image; determining image quality factor scores of the image; and executing an image quality evaluation of the image based on the determined image quality factor scores and the determined classifier, and providing the first electronic device **1000** with a result of the image quality evaluation.

[0225] An electronic device, according to various example embodiments of the present disclosure, and an operation method thereof may improve detectability in association with image quality measurement. According to various example embodiments of the present disclosure, the detectability with respect to an out-of-focus background image, the detectability with respect to a motion blur, and the performance with respect to total image quality evaluation may be increased when image quality measurement is executed.

[0226] According to various example embodiments of the present disclosure, a good image or a bad image are clearly distinguished in association with an image, and various functions corresponding thereto may be provided. For example, according to various example embodiments of the present disclosure, a bad image may be extracted and readily removed from images stored in an electronic device or an external device (e.g., another electronic device or a server). Management of a memory may be provided by informing a user of an unnecessary image (e.g., a bad image) stored in a memory. Candidate images for image summarization may be proposed based on a good image.

[0227] According to various example embodiments of the present disclosure, an electronic device for executing an image quality evaluation may be provided so that user's convenience may be improved, and the usability, convenience, accessibility, and competitiveness of the electronic device may be improved.

[0228] The example embodiments of the present disclosure disclosed herein and illustrated in the drawings are merely examples presented in order to easily describe technical details of the present disclosure and to aid in the understanding of the present disclosure, and are not intended to limit the scope of the present disclosure. Therefore, it should be understood that, in addition to the example embodiments disclosed herein, all modifications and changes or modified and changed forms derived from the technical idea of the present disclosure fall within the scope of the present disclosure.

What is claimed is:

1. An electronic device, comprising:

a memory that stores a plurality of images and a plurality of classifiers; and

a processor electrically connected to the memory,

wherein the processor is configured to at least:

analyze a category of an image of which an image quality evaluation is requested, and determine a classifier corresponding to the category of the image from among the plurality of classifiers;

determine image quality factor scores of the image; and

evaluate the image quality of the image based on the determined image quality factor scores and the determined classifier.

2. The electronic device of claim **1**, wherein the processor comprises:

an image factor extracting module configured to measure a quality for each image quality factor of the image;

a category classifying module configured to classify an image scene category of the image;

a classifier selecting module configured to select an image quality classifier corresponding to the image scene category; and

an image quality evaluating module configured to determine a total image quality score of the image based on results from the image factor extracting module and the classifier selecting module.

3. The electronic device of claim **2**, wherein the category classifying module is configured to analyze the image scene category based on a scheme that classifies an image using feature vectors of the image or a scheme that classifies an image using learning.

4. The electronic device of claim **2**, wherein the classifier selecting module is configured to select a classifier corresponding to the image scene category from among image quality classifiers stored in advance in the memory.

5. The electronic device of claim **2**, wherein the image factor extracting module is configured to divide the image into a plurality of areas, and to measure a blur factor score for each divided area.

6. The electronic device of claim **5**, wherein the image factor extracting module is configured to:

measure a blur factor score for each of the divided areas of the image, and determine, as a target area of measurement, one or more areas that have a high sharpness out of the divided areas,

wherein the target area of measurement includes a predetermined area or a group of a predetermined number of adjacent areas of the divided areas, having a low blur factor score.

7. The electronic device of claim **2**, wherein the image factor extracting module is configured to extract, from the image, a distribution of edge components for each direction, and to measure a blur factor score for image quality evaluation based on an area that has a large difference in cumulative edge distributions from among areas where a horizontal edge component and a vertical edge component are perpendicular to each other.

8. The electronic device of claim **2**, wherein the image quality evaluating module is configured to extract a likelihood score corresponding to the image, using image quality factor scores that are transferred from the image factor extracting module and the image quality classifier transferred from the classifier selecting module, and to determine a total image quality score with respect to the image based on the extracted likelihood score.

9. The electronic device of claim **2**, wherein the processor comprises:

an image managing module configured to obtain the image from the inside or the outside, and to recognize image information for measuring the quality of the image.

10. The electronic device of claim **2**, wherein the processor comprises:

a category determining module including processing circuitry, the category determining module configured to determine the image scene category with respect to the image, using the image scene category transferred from the category classifying module and the total image quality score transferred from the image quality evaluating module.

11. A system for measuring a quality of an image, the system comprising:

a first electronic device configured to request image quality evaluation of an image; and

a second electronic device operatively connected to the first electronic device,

wherein the second electronic device is configured to at least:

obtain the image from the first electronic device;

analyze a category of the image, and determine a classifier corresponding to the category of the image;

determine image quality factor scores of the image; and

evaluate an image quality of the image based on the determined image quality factor scores and the determined classifier, and provide the first electronic device with a result of the image quality evaluation.

12. A method of measuring a quality of an image, comprising:

obtaining an image;

classifying an image scene category of the image;

determining a classifier corresponding to the classified image scene category;

determining image quality factor scores with respect to the image; and

evaluating an image quality with respect to the image, using the determined image quality factor scores and the determined classifier.

13. The method of claim **12**, wherein the classifying comprises:

analyzing the image scene category based on a scheme that classifies an image using feature vectors of the image and a scheme that classifies an image using learning.

14. The method of claim **12**, wherein the determining of the classifier comprises:

selecting a classifier corresponding to the image scene category from among various image quality classifiers stored in advance.

15. The method of claim **12**, wherein the determining of the image quality factor scores comprises:

dividing the image into a plurality of areas;

measuring a blur factor score for each of the plurality of divided areas;

determining an area that has a low blur factor score; and

measuring an image quality based on the determined area.

16. The method of claim **15**, wherein the determining of an area having a low blur factor score comprises:

determining, as a target area of measurement, one or more areas of the divided areas of the image having a high sharpness,

wherein the target area of measurement includes a predetermined area or a group of a predetermined number of adjacent areas of the divided areas, which has a low blur factor score.

17. The method of claim **12**, wherein the determining of the image quality factor scores comprises:

extracting, from the image, a distribution of edge components for each direction;

determining a cumulative edge distribution based on the extracted distribution of edge components for each direction;

determining a target area of decision that includes the largest number of edge components;

determining, from the target area of decision, a target area of measurement based on a difference in cumulative edge distributions; and

measuring an image quality based on the target area of measurement.

18. The method of claim **17**, wherein the determining of the target area of measurement comprises:

determining the target area of measurement based on a difference in cumulative edge distributions from among areas where a horizontal edge component and a vertical edge component are perpendicular in the target area of decision.

19. The method of claim **12**, wherein the determining of the image quality score comprises:

classifying an image as a high quality image class or a low quality image class using the image quality factor scores and the classifier;

extracting a likelihood score corresponding to the image; and

determining a total image quality score with respect to the image, based on the extracted likelihood score.

20. A computer readable recording medium that stores a program which, when executed in an electronic device, causes the electronic device to perform operations comprising:

classifying an image scene category of an image and determining a classifier corresponding to the classified image scene category;

determining image quality factor scores with respect to the image; and

evaluating an image quality with respect to the image, using the determined image quality factor scores and the determined classifier.

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