

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

AXON ENTERPRISE, INC., DEDRONE HOLDINGS, INC., AND
SKYDIO, INC.
Petitioners

v.

AIRSPACE DEFENSE, INC.
Patent Owner

Case No. IPR2025-00629
Patent 10,514,711

**DECLARATION OF DR. WILLIAM SINGHOSE IN SUPPORT OF
PETITIONERS' OPPOSITION TO PATENT OWNER'S CONTINGENT-
IN-PART AND NON-CONTINGENT-IN-PART REVISED MOTION TO
AMEND**

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Third Declaration of Dr. William Singhose

I. INTRODUCTION

1. My name is Dr. William Singhose. I make this declaration based upon my own personal knowledge and, if called upon to testify, would testify competently to the matters contained herein.

2. I previously authored a declaration on February 23, 2025, which I understand was submitted as Exhibit 1003 to the Patent Trial and Appeal Board (“PTAB”) of the United States Patent and Trademark Office in case number IPR2025-00629. I may alternatively refer to the February 23, 2025, declaration as “Exhibit 1003” or “Original Declaration.”

3. I also previously authored a declaration on March 9, 2026, which I understand was submitted as Exhibit 1030 to the PTAB in case number IPR2025-00629. I may alternatively refer to the March 9, 2026, declaration as “Exhibit 1030” or “Second Declaration.”

4. In this Third Declaration, I incorporate the facts and opinions provided in my Original Declaration and in my Second Declaration.

II. TASK SUMMARY AND MATERIALS REVIEWED

5. My Original Declaration and Second Declaration addressed U.S. Patent No. 10,514,711 (EX1001, “’711 Patent”).

6. I have been informed that Airspace Defense, Inc. (“Patent Owner” or “PO”) filed a Contingent-in-Part and Non-Contingent-In-Part Revised Motion to

Amend for the '711 Patent (Paper 37, "Revised Motion to Amend" or "RMTA"). I have been informed that the RMTA is non-contingent with respect original claims 1-4, 8-11, and 13-20, and contingent with respect to original claim 12, and replaces these claims with new claims 21-37 ("Substitute Claims" or "SCs"). The RMTA requests cancelation of original claims 5-7, so I will not address them further.

7. Counsel for Petitioner has informed me that because the Revised Motion to Amend was filed as "non-contingent" with respect to original claims 1-4, 8-11, and 13-20, the Board will issue a final decision on the patentability of Substitute Claims 21-28 and 30-37 rather than determining the patentability of the corresponding Original Claims. Counsel has also informed me that because the Motion to Amend was filed as "contingent" with respect to original claim 12, the Board will issue a final decision on the patentability of original claim 12, and if this claim is found unpatentable, then the Board will issue a final decision on the patentability of Substitute Claim 29.

8. I have been asked to review the RMTA filed by Patent Owner regarding the '711 Patent, the proposed Substitute Claims, and the exhibits cited by PO. I have been asked to provide an understanding of the technology relevant to the RMTA, to review certain prior-art references, and analyze whether or not those references disclose or teach limitations of the proposed Substitute Claims. Finally, I have been asked to assess the validity of the amended claims in view of Section 112

requirements such as written description, enablement, and definiteness. The opinions stated in this declaration are from the perspective of a person of ordinary skill in the art (“POSITA”).

III. EXPERIENCE AND QUALIFICATIONS

9. My experience, qualifications, CV, and consulting fee are outlined in my Original Declaration and Second Declaration. However, the RMTA has introduced new claim limitations that relate to machine learning and image processing. Therefore, I briefly review some of my relevant experience with those topics.

10. One of the primary types of machine learning algorithms covered in the amended claims are neural networks. I started working with neural networks in the mid 1990's for the purpose of controlling flexible spacecraft. I created and trained neural networks to generate commands to move flexible systems, such as spacecraft, while minimizing residual vibration.

11. My initial work in this area utilized three types of neural networks to generate time-optimal and fuel-efficient commands. The first neural network was a two-layer network with nonlinear transfer functions in the hidden layer and linear functions in the output layer. The second neural network was a three-layer structure with two hidden layers with nonlinear transfer functions and a linear output layer. The final neural network was a radial basis function network. The results of my work

in this area appeared in my Ph.D. thesis [1], as well as in a peer-reviewed publication [2].

12. I have worked in the area of image processing throughout my career. For example, in the early 2000's I developed methods to use optical-flow based tracking to extract data from video of human movement [3] [4]. Applications of this work were extended to tracking formation-flying satellite testbeds [5]. I have also used image processing extensively for tracking the position of cranes and crane payloads [6] [7] [8]. In fact, my developments in this area lead to the formation of a company - CAMotion Cranes - that successfully implemented image-tracking based control on hundreds of cranes.

IV. LIST OF EXHIBITS

13. In forming my opinions, I have reviewed the '711 Patent, its prosecution history and references cited by the Examiner, the materials cited in the List of Exhibits, and the materials cited throughout my Original Declaration, and this declaration.

Table 1: List of Exhibits

Ex. No.¹	Description
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¹ Citations to patents are made by column and line cite; citations to patent publications are made by paragraph number; citations to Exhibit 1002 are made with

1001	U.S. Patent No. 10,514,711 to Bar-Nahum <i>et al.</i> , “Flight Control Using Computer Vision” (the “711 Patent”)
1002	File History for U.S. Patent No. 10,514,711
1003	Declaration of Dr. William Singhose
1004	Complaint for Patent Infringement, <i>Airspace Systems, Inc. v. Dedrone Holdings, Inc.</i> , Case No. 1-24-cv-01625 (E.D. VA), September 13, 2024
1005	U.S. Patent Application Publication No. 2017/0160751 to Pierce <i>et al.</i> , “System and Method for Controlling Drone Movement for Object Tracking Using Estimated Relative Distances and Drone Sensor Inputs” (“Pierce”) filed December 5, 2016, published June 8, 2017
1006	U.S. Provisional Application No. 62/263,510 to Pierce <i>et al.</i> , “System and Method for Controlling Drone Movement for Object Tracking Using Estimated Relative Distances and Drone Sensor Inputs” (“Pierce Provisional”), filed December 4, 2015
1007	U.S. Patent Application Publication No. 2017/0161911 to Kumar <i>et al.</i> , “System and Method for Improved Distance Estimation of Detected Objects” (“Kumar”) filed December 5, 2016, published June 8, 2017
1008	U.S. Provisional Application No. 62/263,496 to Kumar <i>et al.</i> , “System and Method for Improved Distance Estimation of Detected Objects” (“Kumar Provisional”), filed December 4, 2015
1009	U.S. Patent No. 9,769,387 to Beard <i>et al.</i> , “Action Camera System for Unmanned Aerial Vehicle” (“Beard”) filed November 5, 2014, published September 19, 2017

reference to the Bates-stamped pagination; citations to other exhibits are made to the page number of the document itself. Cites to EX1035 and 1036 are made to the underlying publication/paper itself.

1010	U.S. Patent Application Publication No. 2017/0059692 to Laufer <i>et al.</i> , “Mitigation of Small Unmanned Aircraft Systems Threats” (“Laufer”) filed August 26, 2016, published March 2, 2017
1011	U.S. Patent No. 8,874,283 to Cavote, “Drone for Inspection of Closed Space and Method Thereof” (“Cavote”) filed December 4, 2012, published October 28, 2014
1012	Internet Archive Wayback Machine screenshot of www.lauferradarsystems.com/technology , dated August 1, 2017
1013	Laufer Wind, Eagle Take Minimization System, Contract DE-EE0007884.0000, Final Technical Report, dated March 28, 2018
1014	U.S. Patent Application Publication No. 2003/0143524 to Lerner, “Method and System for Determining the Amount, Distribution and Confirmation of Genetic Material in a Cell” (“Lerner”) filed January 31, 2002, published July 31, 2003
1015	U.S. Provisional Application No. 62/405,972 to Bar-Nahum <i>et al.</i> , “Multimodal Sensor Empowered Awareness Engine for Target Recovery and Object Path Prediction” (“’972 Provisional”), filed October 9, 2016
1016	Quadrotor Helicopter Flight Dynamics and Control: Theory and Experiment, Hoffmann <i>et al.</i> , American Institute of Aeronautics and Astronautics
1017	DJI Spreading Wings S1000+ User Manual, Version 1.4, dated January 2016
1018	Excerpts from <i>Control Theory for Humans</i> , Jagacinski and Flach, 2003
1019	Excerpts from <i>Control Systems Engineering</i> , Nise, 2004
1020	Excerpts from <i>Modern Control Systems</i> , Dorf and Bishop, 2005
1021	U.S. Patent Application Publication No. 2012/0106800 to Khan <i>at al.</i> , 3-D Model Based Method for Detecting and Classifying Vehicles in Aerial Imagery (“Khan”), filed October 28, 2010, published May 3, 2012
1022	PCT International Publication Number WO2017/123477 to Hogasten, Vehicle Based Radar Upsampling (“Hogasten”), filed January 6, 2017, published July 20, 2017, designating the U.S. and filed in English

1023	U.S. Provisional Application No. 62/277186 to Hogasten, “Vehicle Based Radar Upsampling” (“Hogasten Provisional”), filed January 11, 2016
1024	U.S. Patent Application Publication 2013/0301905 to Malecki et al., “System and Method for Determining an Orientation and Position of an Object” (“Malecki”), filed April 10, 2013, published November 14, 2013
1025	U.S. Patent Application Publication 2012/0004844 to Sahasrabudhe et al., “Formation Flying Method and System” (“Sahasrabudhe”), filed June 29, 2011, published January 5, 2012
1026	Claim Listing of Challenged Claims
1027	Siemens SIMATIC VS72X Manual, 2005
1028	<i>Command Limiting in Reconfigurable Flight Control</i> , Bodson et al., Journal of Guidance, Control, and Dynamics, Vol. 21, No. 4, July-August 1998
1029	Stipulation Email on May 29, 2025
1030	Second Declaration of Dr. William Singhose
1031	Definition of “autonomous” dated September 16, 2016
1032	Definition of “autopilot” dated September 22, 2015
1033	Transcript of Deposition of Dr. Nikolaos Papanikolopoulos in IPR2025-00629
1034	U.S. Patent No. 9,760,806 to Ning et al., “Method and System for Vision-Centric Deep-Learning-Based Road Situation Analysis” (“Ning”) filed May 11, 2016, published September 12, 2017
1035	Big/Little Deep Neural Network for Ultra Low Power Inference, Park et al., <i>2015 International Conference on Hardware/Software Codesign and System Synthesis Proceedings</i> , January 20, 2016 (“Park”)
1036	You Only Look Once: Unified, Real-Time Object Detection, Redmon et al., <i>2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Proceedings</i> , February 6, 2017 (“Redmon”)

1037	Declaration of Professor Hall-Ellis
1038	Transcript of Deposition of Dr. Nikolaos Papanikolopoulos for IPR2025-00530
1040	CV of Professor Hall-Ellis

V. TECHNICAL BACKGROUND

14. See Section IX of my Original Declaration (EX1003) for a technology background pertinent to the '711 Patent.

VI. OVERVIEW OF THE CHALLENGED PATENT

15. See Section VI of my Original Declaration (EX1003) for an overview of the '711 Patent.

VII. LEGAL STANDARDS

16. The Legal Standards provided to me were described in my Original Declaration.² In addition to those legal standards, I have been informed by counsel as to the legal requirements under Section 112 of the patent code. I briefly review my understanding of those requirements here.

A. INDEFINITENESS

17. I have been informed that, in order to be valid, the claims of a patent must be sufficiently definite that one skilled in the art can determine the metes and bounds of the claimed invention. I have been informed that a patent claim is deemed

² EX1003 (Original Declaration), § V.

“indefinite” if the claim, read in light of the patent’s specification and prosecution history, fails to inform, with reasonable certainty, those skilled in the art about the scope of the invention. I understand that a claim must be precise enough to afford clear notice of what is claimed, thereby apprising the public of what is still open to them.

B. WRITTEN DESCRIPTION

18. I have been informed that, in order for claims to be valid, the claims of a patent must provide written description support for each limitation of the claims. I have been informed that a patent claim lacks written description if the specification fails to convey with reasonable clarity to a POSITA that the inventor was in possession of the invention as of the filing date sought. I have been informed that this requirement relies on an objective inquiry into what is contained within the specification, and that while the precise terms appearing in the claims need not necessarily appear in the specification, there must be sufficient detail in the specification that a POSITA can clearly conclude that the invention described in the claims had been invented as of the filing date sought.

19. I have been informed that to satisfy the written description requirement, the specification must actually or inherently disclose each element of the claims.

20. I have been informed that for the disclosure to be inherent, the missing descriptive matter must necessarily be present in or unavoidably be taught by the specification, such that a POSITA would recognize such disclosure.

21. I have been informed that subject matter that is not disclosed, but would be obvious over what is expressly disclosed, does not satisfy the written description requirement.

C. ENABLEMENT

22. I have been informed that, in order for claims to be valid, the specification must enable the full scope of the invention as defined by its claims. The specification must teach POSITAs how to make and use the full scope of the invention without undue experimentation. I have been informed that to determine whether experimentation is undue, various factors are analyzed. These factors are as follows: (A) The breadth of the claims; (B) The nature of the invention; (C) The state of the prior art; (D) The level of one of ordinary skill; (E) The level of predictability in the art; (F) The amount of direction provided by the inventor; (G) The existence of working examples; and (H) The quantity of experimentation needed to make or use the invention based on the content of the disclosure. I understand that a conclusion of lack of enablement means that, based on the evidence regarding each of the above factors, the specification, at the time the application was filed, would

not have taught one skilled in the art how to make and/or use the full scope of the claimed invention without undue experimentation.

VIII. OVERVIEW OF THE SUBSTITUTE CLAIMS

A. TABLE CORRELATING ORIGINAL CLAIMS TO SUBSTITUTE CLAIMS

23. I understand that in Patent Owner's Revised Motion to Amend, Patent Owner has sought to amend the independent claims by proposing new substitute claims. The table below compares the Original Claims to the Substitute Claims, with independent claims emphasized in bold italics.

Original Claim	Dependency	Substitute Claim	Dependency
<i>1</i>	None	<i>21</i>	None
2	1	22	21
3	1	23	21
4	1	24	21
5	1	Canceled	None
6	5	Canceled	None
7	1	Canceled	None
8	7	25	21
9	1	26	21
10	1	27	21
11	1	28	21

12	1	29	21
13	1	30	21
14	1	31	21
15	1	32	21
16	15	33	21
17	1	34	21
18	1	35	21
19	None	36	None
20	None	37	None

B. LIST OF SUBSTITUTE CLAIMS

24. Patent Owner also provided annotations showing the changes it made to the Original Claims of the '711 Patent. This is found in "Claims Appendix" of the Motion to Amend. These changes are shown below with the added limitations underlined.

25. Substitute Claim 21:

[[1]]21.^[pre] A method of performing a flight control operation of a reference aerial vehicle, comprising:

[21.a] receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle;

[21.b] detecting at the reference aerial vehicle a target in the image including by applying at the reference aerial vehicle a machine learning model to the image, to identify a bounding box outlining a portion of the image that includes detected features of the target, and to identify a classification of the detected target;

[21.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image including by determining a distance to the target based at least in part on a size of the bounding box of the target detected within the image and on a physical size corresponding to the classification of the target detected within the image; and

[21.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a first speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

26. Substitute Claim 22:

22. The method of claim 21, wherein the reference aerial vehicle is a multirotor unmanned aerial vehicle and the target is an aerial vehicle.

27. Substitute Claim 23:

23. The method of claim 21, wherein performing the flight control operation includes one or more of the following: turning the reference aerial vehicle towards the target, adjusting a speed of the reference aerial vehicle, or engaging a mechanism to capture the target.

28. Substitute Claim 24:

24. The method of claim 21, wherein detecting the target in the image including by applying at the reference aerial vehicle the machine learning model to the image includes identifying a model type of the target based on the classification of the detected target.

29. Substitute Claim 25:

[[8]]25. The method of claim [[7]]21 wherein performing the flight control operation includes determining a second speed adjustment factor based on the determined distance to the target.

30. Substitute Claim 26:

[[9]]26. The method of claim 21, wherein determining the three-dimensional relative location of the target includes determining a direction of the target with respect to the reference aerial vehicle.

31. Substitute Claim 27:

[[10]27. The method of claim 21, wherein determining the three-dimensional relative location of the target includes determining an azimuth angle and an altitude angle to the target from the reference aerial vehicle.

32. Substitute Claim 28:

[[11]]28. The method of claim 21, wherein determining the three-dimensional relative location of the target includes converting a two-dimensional vector to a three-dimensional vector representing the three-dimensional relative location.

33. Substitute Claim 29:

[[12]29.^[pre] The method of claim 21, further comprising:

[29.a] receiving a geographical location associated with the target detected at least in part using a ground-based sensor;

[29.b] autonomously navigating the reference aerial vehicle towards the received geographical location; and

[29.c] determining to allow image-based navigation.

34. Substitute Claim 30:

[[13]]30. The method of claim 21, wherein the speed adjustment factor is greater for a smaller magnitude of deviation as compared to for a greater magnitude of deviation.

35. Substitute Claim 31:

[[14]]31. The method of claim 21, wherein performing the flight control operation includes scaling [[a]]the speed adjustment factor to smooth and limit a rate of change of a speed of the reference aerial vehicle.

36. Substitute Claim 32:

[[15]]32. The method of claim 21, wherein performing the flight control operation includes determining a direction adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

37. Substitute Claim 33:

[[16]]33. The method of claim [[15]]32, wherein performing the flight control operation includes scaling the direction adjustment factor to smooth and limit a rate of change of a direction of the reference aerial vehicle.

38. Substitute Claim 34:

[[17]]34. The method of claim 21, wherein the distance to the target is determined based at least in part using a radar.

39. Substitute Claim 35:

[[18]]35. The method of claim 21, wherein it is determined to allow the image based navigation based on whether the reference aerial vehicle is within a threshold distance away from the received geographical location.

40. Substitute Claim 36:

[[19]]36.[pre] A reference aerial vehicle, comprising:

[36.a] an image sensor configured to capture an image;

[36.b1] a processor configured to: detect at the reference aerial vehicle a target in the image; and

[36.b2] determine at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image; and

[36.c] a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control

operation including by being configured to determine a speed adjustment factor based on a magnitude of deviation of a direction of the three dimensional relative location with respect to a current flight direction of the reference aerial vehicle[[.]], [36.d] wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a first neural network at a first robustness and a first compute cost, and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a second neural network at a second robustness and a second compute cost, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.

41. Substitute Claim 37:

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[[.]],

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural

networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

IX. PRIORITY DATE OF THE SUBSTITUTE CLAIMS

42. I note that the Petition argued, and the Board acknowledged, that the claims of the '711 Patent are not entitled to a priority date of October 9, 2016, and

Petitioner assumes a priority date of October 1, 2017. [Pet. at 3-4; Institution Decision (Paper 16) at 11-12.] I further note that Patent Owner did not contest Petitioner's priority date contention in the RMTA or the Patent Owner's Response (Paper 20). Furthermore, Patent Owner concedes priority by citing only to the '711 Patent's underlying application as alleged support for the SCs. [RMTA at 2-25 (citing to support only in the "'452 App.'")]

43. As the Substitute Claims suffer from the same issues identified for the original claims, I understand that the Substitute Claims are also not entitled to a priority date of October 9, 2016. I thus assume a priority date of October 1, 2017 for the Substitute Claims. However, I do not concede that the Substitute Claims are necessarily entitled to this October 1, 2017 date, application 15/729,581's filing date, or that the Substitute Claims are supported by application 16/142,452.

X. CLAIM CONSTRUCTION

44. I have been informed by counsel for Petitioner that the challenged claims of the '711 Patent are to be given their ordinary and customary meaning as understood by one of ordinary skill in the art at the time of the invention in light of the specification and the prosecution history pertaining to the patent. I also understand, however, that a claim term will not receive its ordinary meaning if the patentee acted as his own lexicographer and clearly set forth a definition of the claim term in the specification. In such a case, the claim term will receive the definition

set forth in the patent. I have followed these principles in my analysis set forth in this Declaration.

45. To the extent the Applicant has expressly defined a claim term in the specification, I have used that definition. With respect to claim terms for which the applicant has not provided an express definition, I have applied the ordinary and customary meaning of the claim terms in light of the specification and the prosecution history in my analysis of the claims and the prior art herein.

46. I note that Patent Owner has proposed a POSITA definition that differs from what I proposed. [RMTA at 1-2.] I do not agree with this definition of a POSITA. However, I qualify under this definition of a POSITA. And under this definition or the definition I applied in the Petition (which is correct), my determinations are the same.

XI. SUMMARY OF CONCLUSIONS AND GROUNDS FOR CHALLENGE

A. OBVIOUSNESS

47. Based upon my review of the Petition, the Revised Motion to Amend, the materials cited in my Original Declaration, Second Declaration, and this Third Declaration, and the materials listed in the LIST OF EXHIBITS above, it is my opinion that Substitute Claims 21-36 of the '711 Patent are rendered obvious by the Grounds listed in the table below:

GND	SCs	Basis	Prior Art
23	21-27, 29, 31-33, 35	§103	Beard, Laufer, Pierce, Khan, Kumar
24	28	§103	Beard, Laufer, Malecki, Pierce, Khan, Kumar (“BLMPKK”)
25	30	§103	Beard, Laufer, Sahasrabudhe, Pierce, Khan, Kumar (“BLSPKK”)
26	34	§103	Beard, Laufer, Hogasten, Pierce, Khan, Kumar (“BLHPKK”)
27	36	§103	Beard, Laufer, Pierce, Ning
28	21, 23-26, 32	§103	Pierce, Kumar, Khan, Beard
29	22, 29, 35	§103	Pierce, Kumar, Khan, Beard, Laufer (PKKBL)
30	34	§103	Pierce, Kumar, Khan, Beard, Hogasten (PKKBH)
31	36	§103	Pierce, Kumar, Ning, Beard
32	21, 23-26, 31-33	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe (“PKKBS”)
33	22, 29, 35	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe, Laufer (“PKKBSL”)
34	34	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe, Hogasten (“PKKBSh”)
35	36	§103	Pierce, Kumar, Sahasrabudhe, Ning (“PKSN”)

48. I provide a summary of the grounds below.

49. Grounds 23-26 rely on original grounds 1-6 from the Petition and add Pierce (EX1005), Khan (EX1021), and Kumar (EX1007).

50. Ground 27 relies on original ground 1 from the Petition and adds (1) Pierce and Ning (EX1034).

51. Grounds 28-30 rely on original grounds 7-14 from the Petition and adds Kumar and/or Khan and Beard (EX1009).

52. Ground 31 relies on original grounds 7 and 8 and adds Ning and Beard.

53. Grounds 32-34 rely on original grounds 15-22 and add Kumar and/or Khan and Beard.

54. Grounds 35 relies on original grounds 15 and 16 and adds Ning.

55. Khan was used in original grounds 2, 11, 12, 19, and 20 of the Petition, Kumar was used in original grounds 3, 8, 10, 12, 14, 16, 18, 20, and 22, Beard was used in original grounds 1-6, and Pierce was used in original grounds 7-22, and each of these references is prior art to and in the same field of endeavor of the '711 Patent, as the Petition demonstrated. [Pet at 4-7.]

56. Ning (EX1034) is from the same field of endeavor as the '711 Patent and reasonably pertinent to the problem the patent was trying to solve as well. [EX1034, Abstract, 4:29-5:3, 6:4-14, 11:1-3, 12:55-13:16]. Ning (filed May 11, 2016, published Sept. 12, 2017) is prior art under §§102(a)(1), (a)(2). [EX1034.]

B. LACK OF WRITTEN DESCRIPTION

57. Based upon my review of the Petition, the Revised Motion to Amend, the materials cited in my Original Declaration, Second Declaration, and this Third Declaration, and the materials listed in the LIST OF EXHIBITS above, it is my opinion that Substitute Claims 37, 24, and 35 of the '711 Patent are invalid based on 35 U.S.C. § 112(a) for lack of written description, due to the limitations/reasons listed in the table below:

	Lack of Written Description - § 112(a)
SCs	Terms
37	“wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image,” “when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image,” and “when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.
24	“identifying a model type of the target based on the classification of the detected target.”

25	performance of a “flight control operation” including determining two “speed adjustment factors;” one based on a “magnitude of deviation of a direction,” and another based on “the determined distance.”
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58. Indeed, it is my opinion that Substitute Claims 37, 24, and 25 are invalid for lack of written description because the specification of the ’711 Patent has not been shown to reasonably convey to a POSITA that the inventor had possession of the claims.

59. Substitute Claim 37 is invalid for lack of written description because the specification of the ’711 Patent does not reasonably convey to a POSITA that the inventor had possession of “wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image,” “when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image,” and “when the first neural

network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.”

60. It is additionally my opinion that Substitute Claim 24 is invalid for lack of written description because the specification of the ’711 Patent does not reasonably convey to a POSITA that the inventor had possession of “identifying a model type of the target based on the classification of the detected target.”

61. It is additionally my opinion that Substitute Claim 25 is invalid for lack of written description because the specification of the ’711 Patent does not reasonably convey to a POSITA that the inventor had possession of performance of a “flight control operation” including determining two “speed adjustment factors;” one based on a “magnitude of deviation of a direction,” and another based on “the determined distance.”

62. It is additionally my opinion that the Substitute Claims are invalid for lack of written description for any additional reasons I state in the relevant section below.

C. LACK OF ENABLEMENT

63. Based upon my review of the Petition, the Revised Motion to Amend, the materials cited in my Original Declaration, Second Declaration, and this Third

Declaration, and the materials listed in the LIST OF EXHIBITS above, it is my opinion that Substitute Claims 37, 24, and 35 of the '711 Patent are invalid based on 35 U.S.C. § 112(a) for lack of enablement, due to the limitations/reasons listed in the table below:

	Lack of Enablement - § 112(a)
SCs	Terms
21-37	The specification does not inform a POSITA regarding “speed adjustment factor” recited in one or more of Substitute Claims 21, 36, and 37 (and thus required by all dependent claims).
36 and 37	The specification does not inform a POSITA regarding “first robustness and a first compute cost” and “a second robustness and a second compute cost,” and “a first robustness and a first refresh rate” and “a second robustness and a second refresh rate,” recited in one or more of Substitute Claims 21, 36, and 37 (and thus required by all dependent claims).
37	The specification further does not inform a POSITA regarding “a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold” as recited by Substitute Claim 37.

64. Indeed, it is my opinion that Substitute Claims 21-37 are invalid as not enabled because the specification does not inform a POSITA how to make and use the full scope of the invention without undue experimentation.

65. The specification does not inform a POSITA regarding “speed adjustment factor,” “first robustness and a first compute cost” and “a second

robustness and a second compute cost,” and “a first robustness and a first refresh rate” and “a second robustness and a second refresh rate,” recited in one or more of Substitute Claims 21, 36, and 37 (and thus required by all dependent claims).

66. The specification further does not inform a POSITA regarding “a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold” as recited by Substitute Claim 37.

67. It is additionally my opinion that the Substitute Claims are invalid for lack of enablement for any additional reasons I state in the relevant section below.

D. INDEFINITENESS

68. Based upon my review of the Petition, the Revised Motion to Amend, the materials cited in my Original Declaration, Second Declaration, and this Third Declaration, and the materials listed in the LIST OF EXHIBITS above, it is my opinion that Substitute Claims 37, 24, and 35 of the ’711 Patent are invalid based on 35 U.S.C. § 112(b) for indefiniteness, due to the limitations/reasons listed in the table below:

	Indefiniteness - § 112(b)
SCs	Terms
21-37	“a speed adjustment factor,” “first robustness,” “second robustness,” “first compute cost,” “second compute cost,” “first refresh rate,” and “second refresh rate.”
21-37	“wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the

	current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image” and the other recitations of the “confidence level”
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69. Indeed, it is my opinion that Substitute Claims 21-37 are invalid as indefinite because a POSITA lacks reasonable certainty as to the scope of “a speed adjustment factor,” “first robustness,” “second robustness,” “first compute cost,” “second compute cost,” “first refresh rate,” and “second refresh rate,” recited in one or more of Substitute Claims 21, 36, and 37 (and thus required by all dependent claims).

70. It is further my opinion that Substitute Claim 37 is invalid as indefinite because a POSITA lacks reasonable certainty as to the scope of “wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image” and the other recitations of the “confidence level” recited in Substitute Claim 37.

71. It is additionally my opinion that the Substitute Claims are invalid for indefiniteness for any additional reasons I state in the relevant section below.

XII. SUBSTITUTE CLAIMS 37, 24, 25 LACK WRITTEN DESCRIPTION SUPPORT

A. SUBSTITUTE CLAIM 37: [37.E1], [37.E3], [37.E4]

72. Substitute claim 37, element [37.e1] recites: “*wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image.*”

73. Substitute claim 37, element [37.e3] recites: “*when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image.*”

74. Substitute claim 37, element [37.e4] recites: “*when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.*”

75. Taken together, these elements recite *a first neural network or a second neural network was applied to an immediately preceding image*, and that detecting a target in a *current image* comprises selecting *only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image*. [RMTA, 21-25]. The selection of the neural network applied to the current image depends on whether the *first neural network* or the *second neural network* was applied to the *immediately preceding image*. [Id.]

76. This is an image-by-image decision-making process based on both the *immediately preceding image* and the *current image*. However, the specification never describes such a processing scheme. The specification does describe switching between processing scheme algorithms; however, that switching is never described in terms of a decision made on a per-image basis, where the choice of network for the *current image* depends on which specific algorithm that was applied to the *immediately preceding image*. [EX2019, ¶¶141-152].

77. With respect to EX2019 at ¶¶141, 146, and 147 in particular—which I note are the only paragraphs cited by PO to support [37.e1]—these paragraphs describe processing “frames of one or more video data streams,” examining processing schemes “from group to group,” and switching between processing groups. None of these paragraphs disclose the requirements of [37.e1], [37.e3], and [37.e4] that relate to using an *immediately preceding image* and *current image* in the

processing scheme. Furthermore, there is no teaching of how to select the neural network applied to the current image as a function of whether the *first neural network* or the *second neural network* was applied to the *immediately preceding image*. [RMTA, 21-25]. The specification also describes “repeatedly determining an active processing scheme based on the processing scheme with the highest performance score.” Once again, this is a general scheduling mechanism and not the specific, image-by-image sequential decision logic using both current and past images, as required by SC 37. [EX2019, ¶112]. And PO cannot impermissibly require obviousness to show possession.

B. SUBSTITUTE CLAIM 37: [37.E3]

78. Substitute claim 37, element [37.e3] recites: “*when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image.*”

79. This element recites *a range defined by the first threshold and a second threshold greater than or equal to the first threshold*. [RMTA, 24]. However, in my opinion, the specification fails to provide support for both creating and using the

range as claimed. PO relies exclusively on ¶¶146 and 147 of EX2019. [RMTA, 24]. However, ¶146 does not mention a “range” or “threshold.” And, while ¶147 makes passing reference to a “low threshold” and a “range,” simply using isolated words in a paragraph does not demonstrate possession of the specifically claimed range having two separate thresholds that can be equal to each other. Indeed, nowhere in ¶¶146, 147, or the rest of the intrinsic record did PO describe a range defined by two separate thresholds. The cited disclosures further never describe a range where separate thresholds can be set *equal* to one another—a condition that collapses the claimed “range” into an unusable void.

C. SUBSTITUTE CLAIM 37: [37.E4]

80. Substitute claim 37, element [37.e4] recites: “*when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.*”

81. This element recites *selecting and applying the second neural network to the current image when the confidence level is above the second threshold*. [RMTA, 24-25]. Recall that according to [37.e3], the *second threshold* is greater than or equal to the *first threshold*, and these two thresholds *define a range*. [*Id.*, 24]. However, no support exists for selecting/applying a neural network when a

confidence level is above such a *second threshold*. Within the context of a “low” threshold, the specification refers to a confidence as “fall[ing] outside of a range.” [EX2019, 147]. The specification further references a “high” confidence generally, as well as “satisfy[ing]” a threshold and confidence being “higher than an activation number.” [*Id.*, 112, 116, 146-147]. But confidence is never described as being *above* a *second threshold* that defines a *range* as claimed, let alone *selecting and applying the second neural network* in such a situation. A confidence is also never described as being *above a second threshold* that is set *equal to a first threshold*. SC 37 thus lacks written description support.

D. DEPENDENT SUBSTITUTE CLAIM 24

82. Dependent substitute claim 24 recites “[t]he method of claim 21, wherein detecting the target in the image including by applying at the reference aerial vehicle the machine learning model to the image includes identifying a model type of the target based on the classification of the detected target.”

83. In my opinion, the PO has not shown support for “*identifying a model type...based on the classification....*” [RMTA, 9]. EX2019, ¶¶94-95 describes classifying a target by “type” or “model.” But this is not the same as identifying a “type” *based on* “classification,” which is what the claim requires. In fact, while the specification’s teaching is not clear, the specification apparently teaches that

determining a model type is, in and of itself, a classification. As such, substitute claim 24 lacks written description support.

E. DEPENDENT SUBSTITUTE CLAIM 25

84. Dependent substitute claim 25 recites “[t]he method of claim 21 wherein performing the flight control operation includes determining a second speed adjustment factor based on the determined distance to the target.”

85. In my opinion, the PO has not shown support for both a *first speed adjustment factor*, and a *second speed adjustment factor* based on determined distance. [RMTA, 6-7, 9-10]. EX2019, ¶97 describes “a factor based on an associated distance or speed,” but this at best suggests a “distance”-based factor or a “speed”-based factor—not a *first speed adjustment factor* and then a *second speed adjustment factor* that is based on determined distance. Moreover, “a distance value” that is “mapped to a desired speed” says nothing about *first* and *second* speed adjustment factors. [EX2019, ¶97]. I also note that PO’s explanation of the relied-upon disclosures do not even contend that there is a *second* speed adjustment factor in addition to the *first* speed adjustment factor. [RMTA, 10].

XIII. THE SUBSTITUTE CLAIMS ARE NOT ENABLED

A. SUBSTITUTE CLAIMS 21-37 ARE NOT ENABLED

1. Independent Substitute Claim 21: Element [21.d],
Independent Substitute Claim 36: Element [36.c],
Independent SC 37: Element [37.d]

86. Substitute Claim 21, Element [21.d] recites “*performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes **determining a first speed adjustment factor** based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle*” (emphasis added).

87. Substitute Claim 36, Element [36.c] recites “*a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to **determine a speed adjustment factor** based on a magnitude of deviation of a direction of the three dimensional relative location with respect to a current flight direction of the reference aerial vehicle*” (emphasis added).

88. Substitute Claim 37, Element [37.d] recites “*performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes **determining a speed adjustment factor** based on a magnitude of deviation of a direction of the three-dimensional*

relative location with respect to a current flight direction of the reference aerial vehicle.”

89. These elements recite *determining a speed adjustment factor*. [MTA, 6-7, 17-18, 20]. The specification never explains how to determine such a factor. A POSITA cannot practice the claimed invention without undue experimentation. The following factors make that deficiency clear.

90. **No direction or guidance:** In my opinion, the specification's disclosure of the *speed adjustment factor* is vague and ambiguous. The specification says “[m]odifying the speed and/or acceleration associated with the vector includes adjusting a factor used to control the speed and/or acceleration of the interceptor aerial vehicle based on an amount of directional change specified by the vector.” [EX2019, ¶99]. It adds that “when a large directional change is required by the interceptor aerial vehicle to fly towards the target, a slower speed is desirable” and that “a faster speed [] is desirable to reach the target quicker when no or minor directional change is required. [*Id.*] This describes to a POSITA desirable performance characteristics: go slower when turning hard, go faster when flying straight. But, in my opinion, it says nothing about how to determine a *speed adjustment factor*. No formula, algorithm, or procedure is provided.

91. The other aspects of the specification are further deficient. The specification says that the speed adjustment factor is “multiplied by one or more

scalar values that change in magnitude based on a directional deviation of the vector from a current direction of movement” and that “plotting the scalar value with respect to a directional deviation results in a bell curve.” [EX2019, ¶¶99]; [*id.*, ¶¶97-98]. Elsewhere, it offers the alternative that “the scalar value may decrease linearly on either side of the center as the directional deviation increases.” [*Id.*] And it says that the scaler may be applied to limit a magnitude change of speed or acceleration. [*Id.*] But all of this relates to a “scaler” that multiplies a *speed adjustment factor* rather than the factor itself. [*Id.*] And even if the scaler were a *speed adjustment factor*, these disclosures are unclear in that they describe a curve shape; they do not disclose how to actually determine the scaler. A bell curve could be any number of mathematical functions. No guidance is provided on the standard deviation, parameters, or input and output ranges, for example. The specification is silent on all of this information, which would be necessary for a POSITA to practice the claims.

92. Furthermore, the specification’s explanation regarding Equations 7 and 8 and “speed factor” fare no better. [EX2019, ¶106, Fig. 10]. These equations involve constants “a, b, and c,” but the specification never reveals what those constants are. [*Id.*] All it says is that they “may be the same value or they may be different values” and that they “may differ based on whether applied to the speed factor for degX or degY.” [*Id.*] But that is not guidance. That is an unknown choice

that can extend to infinity. Constants with no values, just generic description that they may be the same or different, are not constants at all—they are unbounded unknowns. And without them, a POSITA has no direction on how to determine a *speed adjustment factor*. To summarize: the specification tells a POSITA what the speed adjustment factor should accomplish but **never** tells a POSITA how it is determined.

93. **No Working Examples:** The specification contains no working examples of the *speed adjustment factor*. There is not a single numerical instance in which a directional deviation is used in a formula to produce a *speed adjustment factor* or a single scenario in which constants “a, b, and c” are assigned actual numbers. There is further not a single demonstration of how a bell curve or linear relationship is parameterized for any flight scenario. The specification points to FIGS. 9 and 10 as allegedly showing “examples of functions utilized to adjust component values of a vector” and “example equations that can [be] utilized to scale/alter components values of a vector.” [EX2019, ¶¶105-106, Figs. 9-10]. However, these figures are not working examples, and it is not clear how, or even if, they are used to determine a *speed adjustment factor*. They are abstractions containing undefined constants.

94. FIG. 9 is particularly demonstrative of the lack of enablement. The figure apparently shows “logic smoothing functions” as bell-curve-shaped graphs,

but they are purely qualitative sketches, not quantitatively specified functions. [EX2019, ¶105, Fig. 9]. A POSITA studying those curves could only conclude that the inventors wanted to use a smoothing function for some purpose. However, the specification provides no guidance or examples of the parameters or other aspects that are necessary to build one. [*Id.*]. Looking beyond figures and equations, the specification provides no experimental data, no simulation results, and no real-world demonstrations. There is no evidence that any implementation of the *speed adjustment factor* has ever been tested—let alone shown to work. A POSITA is left with nothing to confirm that any particular implementation would function as intended.

95. **Quantity of Experimentation:** To determine a *speed adjustment factor* as claimed, a POSITA must, at the very least, (1) select or devise a mathematical function that relates directional deviation to a speed adjustment factor, (2) determine the parameters and constants of that function, (3) determine the input and output ranges, and (4) determine any rate-of-change limits. [EX2019, ¶¶97-99, 105-106, Figs. 9-10]. The specification provides no concrete method for performing any of these required steps. A POSITA would, therefore, be forced to experiment across the entire space of possible functions (e.g., Gaussian, logistic, linear, etc.), possible parameter values (including the undefined constants a, b, and c discussed above), and possible saturation strategies (e.g., some maximum limit as discussed)—

all before a single flight test could even begin. In my opinion, the quantity of experimentation required is enormous, because the specification leaves the POSITA with only vague ideas as to how to accomplish the desired objectives.

96. **Nature of the invention:** SCs 21, 36, and 37 involve flight control, of which the *speed adjustment factor* is central, rather than some peripheral detail, in that it determines how speed is adjusted. An improperly determined *speed adjustment factor* could conceivably cause the vehicle to overshoot a target, oscillate, or crash. Within this context, the nature of the invention demands more specificity in the specification than corresponding ground-based control technology.

97. **State of the Prior Art:** The specification does not point to any prior art reference that teaches how to determine a *speed adjustment factor* from a magnitude of *directional deviation*. Therefore, the specification fails to bridge the gap between general control theory objectives and the specific claimed determination. .

98. **Level of Skill:** Even under PO's elevated POSITA definition (RMTA, 1-2), the specification's failures are not cured. The claims require *determining* a specific *speed adjustment factor* and the specification provides no methodology for this as discussed previously in this section. Skilled artisans, left to their own devices, would have to generate different functions (e.g., Gaussian, logistic, linear, etc.), select different parameters, determine different rate-of-change limits, and implement different saturation strategies.

99. **Predictability of the Art:** The behavior of a *speed adjustment factor* depends on the dynamics of the specific aerial vehicle (e.g., mass, thrust, drag, and natural frequencies), the responsiveness of the flight controller, environmental conditions (e.g., wind, turbulence), and the characteristics of the target being tracked. The specification acknowledges this by noting “flight hardware limitations” impact how an aircraft changes its speed—but never explains *how* to account for them. [EX2019, ¶¶99-100].

100. **Breadth of the claims:** SCs 21, 36, and 37 claim any *speed adjustment factor* determined from any *magnitude of deviation* of any *direction of the three-dimensional relative location* with respect to any *current flight direction* of the reference aerial vehicle but as discussed above, the specification does not teach how to determine such a factor. [RMTA, 6-7, 18, 21].

101. For at least the foregoing reasons, a POSITA attempting to practice SCs 21, 36, and 37 would not have a clear method to determine a *speed adjustment factor* and would have been forced into extensive trial-and-error to devise an appropriate function, select appropriate parameters, and assign appropriate constant values. As such, SCs 21, 36, and 37 are not enabled. Furthermore, SCs 22-35 are not enabled for the same reasons as for SC 21.

**2. Independent Substitute Claim 36: Element [36.d];
Independent Substitute Claim 37: Element [37.e2]**

102. Substitute Claim 36, element [36.d] recites “*wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a first neural network at a first robustness and a first compute cost, and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a second neural network at a second robustness and a second compute cost, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.*”

103. Substitute Claim 37, element [37.e2] recites “*wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate.*”

104. Thus, element [36.d] recites a *first robustness and a first compute cost* and a *second robustness and a second compute cost*. [RMTA., 18-19]. Element [37.e2] recites a *first robustness and a first refresh rate* and a *second robustness and a second refresh rate*. [*Id.*, 22-23]. In my opinion, none of these terms are enabled. A POSITA looking for guidance on how to determine any of these values would find nothing actionable in the specification. The following factors make that clear.

105. **No direction or guidance:**

- **compute cost**

106. For the term *compute cost*, the specification says that “[c]osts on all data inputs for the processing schemes can be pre-determined, estimated, or calculated.” [EX2019, ¶142]. However, this provides no instruction on how to do any of the pre-determining, estimating, or calculating. Furthermore, ¶142 vaguely states that “a type of algorithm that operates on visual ‘features’ can be dependent on the number of features in the video frame, and its cost estimated based on the number of features.” [Id.] This points out that cost estimates relate to features. But there is no way to know the number of features in a frame until after it is examined. Furthermore, the specification does not say how, or by which standard any of this is measured. For example, the specification does not say whether compute cost is measured in CPU cycles, milliseconds, floating point operations, memory consumption, or some other unit. The specification observes that “[o]n a fixed compute budget there is a negative relation between robustness of an algorithm and the cost and/or latency of the algorithm per spacio-temporal frame.” [EX2019, ¶109]. This explains the well-known fact that better algorithms generally cost more. But, this teaches a POSITA nothing about how to quantify *compute cost* for any particular algorithm, on any particular hardware, processing any particular input. [Id.] Note that the claims require the compute cost to be measured in some way so

that different compute costs can be compared. Therefore, the claims require a step that is unspecified.

107. The specification further sorts processing schemes into three bins: “(i) High cost (low refresh rate), high robustness algorithm,” “(ii) Medium cost, medium robustness algorithms,” and “(iii) Low cost (high refresh rate), low robustness algorithms.” [EX2019, ¶145]. However, the specification says nothing about what separates “high” from “medium” from “low.” The specification adds that the system can “statically assign each processing scheme in a set of processing schemes to a group based on each processing scheme's **determined** cost and/or robustness estimations on the selected input group.” [*Id.*, ¶144 (emphasis added)]. But again, it never explains how to determine the cost (or robustness) here. The specification further notes that “as the number of features increases the cost can increase dramatically.” [*Id.*, ¶142]. But again, this description does not provide an equation or technical explanation that explains how the cost is determined or measured. In my opinion, the specification lacks any guidance for a POSITA that demonstrates enablement.

- **robustness:**

108. The specification says that “[r]obustness of each algorithm (e.g., processing scheme) can be compared by measuring a population of inputs that are selected as representative of sample conditions (e.g., real-life data sets) and

prioritized by application requirements.” [EX2019, ¶143]. However, the specification does not say what these “population of inputs” that are “representative of sample conditions” and “real-life data sets” actually are, nor does it provide a method. [*Id.*] The specification also does not say by what metric the “population” can be measured with for generating such a population of inputs, providing now indication as to whether it is a number, score, percentage, letter grade, or something else. Instead, the specification deploys “robustness” as a bare adjective. For example, the specification says DNN-based detection “provides robustness at a high compute cost” and certain algorithms of “high robustness” or “low robustness.” [EX2019, ¶¶110, 145-146, 150]. A background tracker operates with “low compute cost and average robustness.” [*Id.*] The use of “high” and “average” and “low” does not explain how these labels are determined or measured, or against what baseline they are compared. Without a metric, “high robustness” and “average robustness” are not measurements that a POSITA can reliably determine.

109. Moreover, the specification says that “[g]roup (iii) algorithms,” may “operate like group (ii) with a similar validation method but have secondary factors such as faster and more brittle performance.” [EX2019, ¶147]. This suggests “[b]rittle” is opposite to “robust.” [*Id.*, ¶¶145-147]. However, the specification does not say what the dividing line is between a “brittle” processing scheme and one that is “robust.” No metric, threshold, or formula is disclosed.

- *refresh rate*:

110. The term “refresh rate” appears in the specification only as a parenthetical aside. [EX2019, ¶¶145-146, 150]. Group (i) processing schemes are “[h]igh cost (low refresh rate)” while group (iii) are “[l]ow cost (high refresh rate).” [Id.] The specification never defines what *refresh rate* means in the context of a processing scheme, and never explains how to measure it or what its units are. For instance, the specification never explains whether *refresh rate* is defined in terms of frames per second, iterations per second, cycles per time interval, or something else.

111. The specification also says that “[m]edium cost algorithms can be run from group (ii) in higher refresh rate, while monitoring the confidence level of the result.” [EX2019, ¶146]. This disclosure again is problematic because it does not say what the refresh rate is “higher” than, how refresh rate is measured, on what hardware this occurs, or under what conditions. The specification essentially conveys one intuition: cheap algorithms have higher refresh rate, while expensive ones have lower refresh rate. In my opinion, a POSITA learns the direction of a relationship —cheaper means a higher rate—but nothing about how to determine, quantify, or assign a *refresh rate* to any particular processing scheme. Note that the claims require the refresh rates be determined such that they can be used in comparisons.

112. **Presence or Absence of Working Examples:** The specification provides zero working examples of how to determine any of *compute cost*, *robustness*, or *refresh rate*. The specification does provide examples of algorithms falling in the groups (i), (ii), or (iii). For example, high cost schemes can include “modified tiny You only look once (YOLO) Convolutional Neural Networks (CNN) on 448 pixels input tiles in the frame,” or “modified SSD (Single Shot Detection) CNN on 300 pixels multi-scale classification,” grouped (ii) and (iii) schemes can include “color-based tracking—hue, saturation, value (HSV) channel statistical modeling,” and “SqueezeNet super fast rejection CNN.” [EX2019, ¶¶150-152]. While these algorithms are mentioned, the specification does not teach a POSITA how to determine the *compute cost*, *robustness*, or *refresh rate* of any of them. It simply reveals what buckets the inventors placed the algorithms into—without any explanation on how or why the metrics by which they were grouped were actually determined. A POSITA finishes reading this specification knowing, for example, that the described modified tiny YOLO can be “high cost” and “high robustness,” but “low refresh rate,” and template matching is supposedly “low cost” and “low robustness” but “high refresh rate.” [EX2019, ¶¶145-152]. However, the specification does not say what these labels actually mean, or how they are derived. The specification does not explain how a POSITA would determine a refresh rate, compute cost, and robustness for different algorithms. Across all three terms, there

is not a single illustrative scenario. The specification announces that algorithms fall into groups but never shows how. As such, the specification does not enable the *compute cost*, *robustness*, or *refresh rate* limitations of SCs 36 and 37.

113. **Quantity of experimentation**: To practice claims 36 and 37, a POSITA must determine *compute cost*, *robustness*, and *refresh rate*; but no methodology for determining those characteristics is disclosed for any of them, as discussed above. In my opinion, a POSITA would need to devise a metric for each of these terms and a process to measure all three. This process is not one experiment—it is an entire research program in which three undefined measurement problems, each requiring independent resolution, would need to be resolved before the claims can be practiced with certainty. Thus, in my opinion, the quantity of required experimentation is substantial.

114. **Level of skill**: Even under PO's elevated POSITA definition (RMTA, 1-2), which I meet, the specification's failures are not cured. The claims require specific values for *compute cost*, *robustness*, and *refresh rate*, but determining these depends on undefined metrics that would require undue experimentation under an elevated POSITA definition. A POSITA cannot fill in a metric that the specification never identifies.

115. **State of the prior art**: The specification acknowledges algorithms are known in the prior art, but what is not disclosed by the specification—and what the

claims require—is the particular methodology for determining *compute cost*, *robustness*, and *refresh rate* for algorithms so that these values can be compared and determined as greater or less than each other. [EX2019, ¶¶145-152]. The specification does not supply a single, accepted methodology for quantifying these terms in the context claimed. [*Id.*] Different platforms, hardware configurations, and application requirements would yield different values—and the specification provides no guidance on how to account for any of these variables. [*Id.*]

116. **Predictability of the art:** Algorithm *compute cost*, *robustness*, and *refresh rate* would depend on the hardware it runs on, its inputs, implementation, the acquired images, and the overall system. [*Id.*; see e.g., EX2019, ¶142]. This demands specification guidance. The specification provides less guidance for these terms than it does for nearly any other aspect of the invention.

117. **Breadth of the claims:** SCs 36 and 37 recite generic neural networks having *compute cost*, *robustness*, and *refresh rate*—yet the specification does not teach how to assign **any** of these values to **any** algorithm..

118. **Nature of the alleged invention:** SCs 36 and 37 relate to using neural networks having a *robustness*, *compute cost*, and/or *refresh rate*. There is no definition of how any of these parameters are determined or measured as discussed. Thus, in my opinion, a POSITA would not have been able to practice SCs 36 and 37 without undue experimentation.

3. Independent Substitute Claim 37: Element [37.e3]

119. As discussed in Section XII.B., the full scope of SC 37 includes where the *first threshold* and *second threshold* defining a *range* are set equal to each other. However, but the specification never discloses this case, and no disclosure exists regarding the formation of a range by two separate values that are equal. [RMTA, 24]. As such, the specification fails to provide any direction or guidance with respect to these limitations and provides no working examples. Section XII.B, *supra*. Moreover, the other *Wands* factors discussed above apply to these limitations for at least the same reasons discussed above. Claim 37 is thus not enabled for this additional reason.

XIV. THE SUBSTITUTE CLAIMS ARE INDEFINITE

A. INDEPENDENT SUBSTITUTE CLAIM 21: ELEMENT [21.D]; INDEPENDENT SUBSTITUTE CLAIM 36: ELEMENTS [36.C], [36.D]; INDEPENDENT SUBSTITUTE CLAIM 37: ELEMENTS [37.D], [37.E2]

120. Substitute Claim 21, Element [21.d] recites “*performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes **determining a first speed adjustment factor** based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle*” (emphasis added).

121. Substitute Claim 36, Element [36.c] recites “a *flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to **determine a speed adjustment factor** based on a magnitude of deviation of a direction of the three dimensional relative location with respect to a current flight direction of the reference aerial vehicle*” (emphasis added).

122. Substitute Claim 36, element [36.d] recites “*wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a **first neural network at a first robustness and a first compute cost**, and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a **second neural network at a second robustness and a second compute cost, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.***” (emphasis added).

123. Substitute Claim 37, Element [37.d] recites “*performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes **determining a speed adjustment***

factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.” (emphasis added).

124. Substitute Claim 37, element [37.e2] recites “*wherein the first neural network has a **first robustness and a first refresh rate**, and the second neural network has a **second robustness and a second refresh rate**, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate.*” (emphasis added).

125. These elements recite *a speed adjustment factor* ([21.d], [36.c], and [37.d]), *first robustness*, *second robustness*, *first compute cost*, and *second compute cost* ([36.d]), and *first robustness*, *second robustness*, *first refresh rate*, and *second refresh rate* ([37.e2]). [RMTA, 6-7, 18-24].

126. In my opinion, substitute claims 21, 36, and 37 are indefinite as these terms are ambiguous. It is unclear from the specification what the terms mean as discussed in Section XIII.A, and the claims and prosecution history do not resolve this ambiguity. [EX1002]; [RMTA, 6-7, 18-24]. Due to this, a POSITA would not have had any way of knowing the boundaries of the terms.

127. Moreover, with respect to the *robustness*, *compute cost*, and *refresh rate* terms, their recitations have a comparative relationship where some are “greater” or “less” than others. [RMTA, 6-7, 18-24]. Without knowing the

boundaries of these terms or how they are determined or measured, there is no way of comparing them to determine such a relationship. As such, the claims are indefinite. [*Id.*]

128. **SCs 22-35:** I note that as substitute claim 21 is indefinite, dependent substitute claims 22-35 are also indefinite.

B. INDEPENDENT SUBSTITUTE CLAIM 37: ELEMENTS [37.E1], [37.E2], [37.E3], AND [37.E4]

129. Substitute Claim 37, Element [37.e1] recites “*wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image.*”

130. Substitute Claim 37, Element [37.e2] recites “*wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate.*”

131. Substitute Claim 37, Element [37.e3] recites “*when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current*

image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image.”

132. Substitute Claim 37, Element [37.e4] recites “*when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.*”

133. These elements contain an irreconcilable logical paradox that leaves a POSITA unable to determine, with reasonable certainty, what is claimed. Element [37.e1] states that *the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image.* [RMTA, 20-22]. The selection—which determines *which network to apply to the **current image***—is made *based on a confidence level for a detection of the target in the **current image**.* [Id.] But if the system has not yet applied a neural network to the current image, how does it have a confidence level *for a detection of the target in the **current image***? In my opinion, it cannot. I also note that the specification is not helpful in addressing this paradox.

The specification describes the confidence level as the **output** or result of applying a network, that is a “measure of quality for that prediction.” [EX2019, ¶141]. Within the context of the specification’s teachings applied to claim substitute claim 37, the *confidence value* would thus measure confidence for a prior prediction—not a prediction for a *current image* that has not yet occurred. The term *confidence level for a detection of the target in the current image* thus introduces a logical impossibility, because the confidence level cannot indicate confidence for a *current image* that has not yet been analyzed.

134. Finally, substitute claim 37 repeatedly conditions on which neural network *was applied to an immediately preceding image*. [RMTA, 24-25]. But the specification never discusses such a discrete, sequential, image-by-image processing technique in which exactly one neural network is applied per frame in alternation with a selection decision. [EX2019]. In general, the specification discusses continuous video data stream processing in which processing schemes operate over streams, but does not specify how individual frames are analyzed, including frames in which one is considered *immediately preceding* the other. [EX2019, ¶¶34, 94, 112, 113, 116-118, 141, Fig. 12]. And, in my opinion, a POSITA cannot determine what *immediately preceding image* means within the SC 37’s context. It is not clear to POSITAs whether the *immediately preceding image* is captured one time-step before, or if the *immediately preceding image* is the last frame to which *any* neural

network was applied (which might not be the temporally adjacent frame if processing is asynchronous). Or, whether the *immediately preceding* image is instead the last image processed by the same neural network pipeline. The specification provides no guidance on the term's meaning. I also note that if the system processes images at different rates depending on which neural network is active (as recited by the different *refresh rates* of the *first* and *second* neural networks in substitute claim 37), then the *immediately preceding image* processed by the *first neural network* may not be the same temporal frame as the *immediately preceding image* processed by the *second neural network*. [RMTA,22-25]. The claim does not account for this, and the specification fails to shed any light on this issue, thus rendering substitute claim 37 indefinite.

XV. SUBSTITUTE CLAIMS 21-36 ARE OBVIOUS

135. In my opinion, Substitute Claims 21-36 would have been obvious under 35 U.S.C. §103. In the grounds below, I address the limitations from these Substitute Claims added by Patent Owner in the MTA and certain other relevant limitations. Limitations from the original claims not addressed below are addressed in the Petition and in my original declaration. I note that elements that are indefinite, lack enablement, and/or lack written description support are addressed based on my understanding of PO's position and as best understood by a POSITA.

136. I reproduce a table below that summarizes the grounds.

GND	SCs	Basis	Prior Art
23	21-27, 29, 31-33, 35	§103	Beard, Laufer, Pierce, Khan, Kumar
24	28	§103	Beard, Laufer, Malecki, Pierce, Khan, Kumar (“BLMPKK”)
25	30	§103	Beard, Laufer, Sahasrabudhe, Pierce, Khan, Kumar (“BLSPKK”)
26	34	§103	Beard, Laufer, Hogasten, Pierce, Khan, Kumar (“BLHPKK”)
27	36	§103	Beard, Laufer, Pierce, Ning
28	21, 23-26, 32	§103	Pierce, Kumar, Khan, Beard
29	22, 29, 35	§103	Pierce, Kumar, Khan, Beard, Laufer (PKKBL)
30	34	§103	Pierce, Kumar, Khan, Beard, Hogasten (PKKBH)
31	36	§103	Pierce, Kumar, Ning, Beard
32	21, 23-26, 31-33	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe (“PKKBS”)
33	22, 29, 35	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe, Laufer (“PKKBSL”)
34	34	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe, Hogasten (“PKKBSh”)
35	36	§103	Pierce, Kumar, Sahasrabudhe, Ning (“PKSN”)

137. Grounds 23-26 rely on original grounds 1-6 from the Petition and add Pierce (EX1005), Khan (EX1021), and Kumar (EX1007).

138. Ground 27 relies on original ground 1 from the Petition and adds (1) Pierce and Ning (EX1034).

139. Grounds 28-30 rely on original grounds 7-14 from the Petition and adds Kumar and/or Khan and Beard (EX1009).

140. Ground 31 relies on original grounds 7 and 8 and adds Ning and Beard.

141. Grounds 32-34 rely on original grounds 15-22 and add Kumar and/or Khan and Beard.

142. Ground 35 relies on original grounds 15 and 16 and adds Ning.

143. Khan was used in original grounds 2, 11, 12, 19, and 20 of the Petition, Kumar was used in original grounds 3, 8, 10, 12, 14, 16, 18, 20, and 22, Beard was used in original grounds 1-6, and Pierce was used in original grounds 7-22, and each of these references is prior art to and in the same field of endeavor of the '711 Patent, as the Petition demonstrated. [Pet at 4-7.]

144. Ning (EX1034) is from the same field of endeavor as the '711 Patent and reasonably pertinent to the problem the patent was trying to solve as well. [EX1034, Abstract, 4:29-5:3, 6:4-14, 11:1-3, 12:55-13:16]. Ning (filed May 11, 2016, published Sept. 12, 2017) is prior art under §§102(a)(1), (a)(2). [EX1034.]

A. OVERVIEW OF NING (EX1034)

145. Ning discloses a “vision-centric deep-learning-based” object detection and tracking system. [EX1034, Abstract.] Ning’s system is a “Recurrent You Only Look Once or ROLO” system, where a “You Only Look Once” (or YOLO) object recognition architecture is used in conjunction with “Long short-term memory (LSTM)” object tracking. [EX1034, Abstract, 1:51-2:3, 2:15-19, 2:35-62, 3:3-17, , 5:46-54, 6:15-53, 6:59-8:33, 8:41-9:4, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4, 5, 6, 8.] The LSTM is a “type of recurrent neural network (RNN)

architecture;” indeed, the ROLO system operates by “connect[ing] the convolutional layers of YOLO to a recurrent neural network (RNN) long short-time memory (LSTM), for the purpose of real-time object detection and tracking.” [*Id.*, 4:55-5:3.] Ning’s system is applicable to vehicles in that it “can be amount[ed] on any suitable vehicle.” [*Id.*, 5:35-38.]

B. GROUND 23: SUBSTITUTE CLAIMS 21-27, 29, 31-33, 35

1. Motivation to Combine

146. A POSITA would have been motivated to combine Beard, Laufer, Pierce, Khan, and Kumar (the “BLPKK combination”). First, a POSITA would have been motivated to combine Beard, Laufer, Khan, and Kumar for the same reasons discussed in the Petition and my original declaration with respect to Beard and Laufer (Pet. at 10-13), Beard, Laufer, and Khan (Pet. at 36-38), and Beard, Laufer, and Kumar (Pet. at 38-41). Moreover, a POSITA would have been motivated to combine Beard, Laufer, Khan, and Kumar with Pierce’s teachings of a drone having an on-board object tracking module that implements neural networks for object detection and tracking. [EX1005, ¶¶0027, 0042, 0044-0046, Figs. 1, 6.] Pierce’s teachings provide explicit implementation details for how a drone utilizes on-board neural networks for object detection and tracking, which furthers Beard, Laufer, Khan, and Kumar’s combined teachings related to such concepts. [*Id.*; Pet. at 10-27, 36-41.] Utilizing Pierce’s teachings would have been applying a known technique

(drone having on-board object identification and tracking capabilities that use neural networks) to improve similar devices (drones that identify and track objects) in the same way (using the on-board object identification and tracking capabilities) [*Id.*] The combination would have yielded the predictable result of Beard's UAV performing on-board object identification and tracking using neural networks. [*Id.*] Moreover, for the same reasons noted above, and given that the combination reflects mere implementation details, and also due to the overlap in subject matter between the references and compatibility of the references, a POSITA would have had a reasonable expectation of success in making the combination. [*Id.*]

2. **Claim 21**

a) Element [21.a]

147. **Element [21.a]:** “receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle;”

148. The BLPKK combination teaches Beard's image processor 234 “aboard UAV 100” receives and analyzes images captured by camera 210 and image sensor 212 that are also aboard UAV 100 (*receiving at a processor at the reference aerial vehicle an image...*). [Petition at 10-16; EX1009, 3:57-4:21, 7:13-53, Fig. 5.]

b) Element [21.b]

149. **Element [21.b]:** “[21.b] detecting at the reference aerial vehicle a target in the image including by applying at the reference aerial vehicle a machine learning model to the image, to identify a bounding box outlining a portion of the image that

includes detected features of the target, and to identify a classification of the detected target;

150. **Pierce** teaches a “drone system 600 [that] may be drone 102,” where the system 600 includes an “object tracking module 615.” [EX1005, ¶¶0027, 0042, 0044-0046, Figs. 1, 6.] Images of the “surrounding area” of the drone may include objects “such as a moving target,” and the object tracking module 615 on board the drone implements “various neural networks” that analyze the images “to identify and track the moving target, and thereby estimate its position and velocity from [the] drone.” [*Id.* at ¶0045, Fig. 6.]

151. **Khan** discloses a “method and a digital processing system for real-time or near-real-time automatic video classification of vehicle model types in aerial imagery.” [EX1021, ¶0003.] Khan discloses an “on-board computing platform 114,” located on-board a UAV 100, that is used to implement “detecting and classifying types of vehicle models in aerial imagery captured by one or more image capturing devices 106 associated with the UAV 100.” [*Id.*, ¶¶0037-0039.] Khan’s computer processes captured images 700 by determining “salient features of a vehicle 702 in the captured images 700,” where the features are “shape and appearance” features at feature locations 804, 806, and 808, and are located within a bounding box surrounding vehicle 702 as shown by Figures 7 and 8. [*Id.*, 0045-0050, Figs. 7-8.] These detected features of the vehicle 702 are then compared to corresponding 3D

vehicle model features at the same location to determine an “appropriate classification” of the vehicle. [*Id.*, ¶¶0045-0063.] For example, the vehicle is classified into a vehicle type such as a “full sedan, mid sedan, compact sedan, station wagon, van, SUV, compact/crossover SUV, and truck.” [*Id.*, ¶¶0044, 0062.] Classification may be performed using a “linear classifier” such as a “support vector machine classifier (SVM)” machine learning model. [*Id.*, ¶0062.]

152. Moreover, **Kumar** discloses that “bounding boxes” around “all objects of interest” in an image are output by a neural network. [EX1007, ¶0019; EX1008, ¶0029.] A neural network is a known type of machine learning model. [EX1007, ¶0002; EX1008, ¶0001.]

153. As such, the BLPKK combination teaches Beard’s on board UAV image processor 234 detects a target 118 in image frames by applying a machine learning/neural network algorithm to image frames to “identify potential target objects 112a, 112b, 112c, and 112d,” which can be aircraft, “via bounding boxes 116a, 116b, 116c, and 116d” that each surround a portion of an image including the potential target objects, where a target object is selected as target object 118 (*detecting at the reference aerial vehicle a target in the image including by applying at the reference aerial vehicle a machine learning model to the image, to identify a bounding box outlining a portion of the image*). [Petition at 15-16; EX1009, 3:9-4:21, 4:22-25, 2:2-8, 7:13-53, Figs. 1A-1C, 5; EX1003, ¶¶117-118.]

154. In the combination, by performing the detecting of a target (*detecting at the reference aerial vehicle...*), the identified bounding boxes would have outlined detected “shape and appearance” features of the potential target objects 112 (and thus the determined selected target object 118) as taught by Khan (*to identify a bounding box outlining a portion of the image that includes detected features of the target*). [*Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7.] Moreover, by performing the detecting of a target (*detecting at the reference aerial vehicle...*), these features would have been used to classify a selected target object 118 as a particular type of target as taught by Khan (*and to identify a classification of the detected target.*) [*Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7.]

155. Additionally, under an alternative interpretation, Beard’s on board UAV image processor 234 would apply the machine learning/neural network algorithm (*applying at the reference aerial vehicle a machine learning model...*) to generate the identified bounding boxes, and these bounding boxes would have outlined detected “shape and appearance” features of the potential target objects 112 (and thus the determined selected target object 118) as taught by Khan and Kumar (*to identify a bounding box outlining a portion of the image that includes detected features of the target*). [*Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7; EX1007, ¶¶0002, 0019; EX1008, ¶¶0001, 0029.] Moreover, Beard’s on board UAV image processor 234 applying the machine learning/neural network algorithm (*applying at the*

reference aerial vehicle a machine learning model...) would have classified a selected target object 118 as a particular type of target based on the features as taught by Khan (and to identify a classification of the detected target). [EX1021, 0045-0063, Figs. 6, 7; EX1007, ¶¶0002, 0019; EX1008, ¶¶0001, 0029.]

c) Element [21.c]

156. **Element [21.c]:** “determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image including by determining a distance to the target based at least in part on a size of the bounding box of the target detected within the image and on a physical size corresponding to the classification of the target detected within the image; and”

157. The BLPKK combination teaches Beard’s on-board UAV image processor 234 determines tracking parameters between the UAV and a target 118 including distance, angle of elevation, and bearing (determining at the reference aerial vehicle a three-dimensional relative location of the target...). [Pet. at 16-18.] Beard further explains this determined distance is “based on the pixel size of the target 118...relative to that of the frame” and specifically the area (i.e., the size) of bounding box 116 around a target, calculated by multiplying the bounding box’s width of “ γ pixels” with the bounding box’s height of “ δ pixels” (i.e., “ $\gamma*\delta$ ”), as shown in Figure 1C (determining...a three-dimensional relative location of the

target...including by determining a distance to the target based at least in part on a size of the bounding box of the target detected within the image). [Pet. at 16-18, 28-29.]

158. Moreover, Khan teaches classification of a target into a particular type (e.g., an SUV, sedan, etc.) as discussed above for Element [21.b], and Kumar teaches a target tracking system that recognizes a target in captured images and produces a bounding box around the target. [EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8; EX1007, ¶¶0020, 0035, Fig. 2; EX1008, ¶¶0018, 0030, Fig. 2.] Kumar's system determines the relative position of a target to the camera capturing the images based on the "known physical [bounding] box size of the object of interest's type of object" and the "physical length of the diagonal across the [bounding] box for an average instance of the object." [EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; EX1003, ¶¶157-158.] Thus, Khan teaches classifying a target in an image as a particular type, and Kumar teaches determining a relative position using a known physical size of such a type of target. [EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; Petition at Section VIII.C; EX1003, ¶¶162-163.]. Therefore, the BLPKK combination teaches that the distance between Beard's UAV 100 and target 118 would further have been based on a physical size (as taught by Kumar) corresponding to the classified type of target object identified

in a captured image (as taught by Khan) (*determining a distance to the target based at least in part on ...and on a physical size corresponding to the classification of the target detected within the image*). [EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; Petition at Section VIII.C; EX1003, ¶¶162-163.]

d) Element [21.d]

159. **Element [21.d]**: “performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.”

160. Beard describes performing flight control operations, such as controlling the speed of one or more rotors, takes place on board UAV 100 using attitude control system 232 (*performing at the reference aerial vehicle the flight control operation...*). [Pet. at 10-13, 18-27.] Beard also discloses or at least renders obvious a *first speed adjustment factor* for the same reasons discussed in the petition at those portions. [*Id.*]

161. Claim 21 is thus obvious.

3. Claim 24

162. Claim 24 recites: “The method of claim 21, wherein detecting the target in the image including by applying at the reference aerial vehicle the machine leaning model to the image includes identifying a model type of the target based on the classification of the detected target.”

163. Khan teaches type classification of an object in an image, such as an SUV, sedan, van, etc. [EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8.] The BLPKK combination thus teaches that the target detection by Beard’s on board UAV image processor 234, applying a machine learning/neural network algorithm to image frames, includes identifying a model type (e.g., a vehicle model type such as an SUV, sedan, van, etc.) based on the classification of the target object as such a particular model type (*wherein detecting the target in the image including by applying at the reference aerial vehicle the machine leaning model to the image includes identifying a model type of the target based on the classification of the detected target*). [Supra Section XV.B.1-2; Pet. at 36-38.]

4. Claims 22, 23, 25-27, 29, 31-33, and 35

164. Claims 22, 23, 25-27, 29, 31-33, and 35 depend from claim 21, and are obvious for the same reasons discussed above for claim 21, as well as the same reasons discussed in the Petition for claims 2, 3, 8-10, 12, 14-16, and 18, respectively. [Pet. at 27-43.] The same reasoning there applies to the BLPKK

combination. Further, for substitute claim 25, the combination teaches a *second* speed adjustment factor for the reasons discussed in the Pet. at 42-43.

C. GROUND 24, 25, AND 26

165. Beard, Laufer, Pierce, Khan, Kumar, and Malecki is Ground 24.

166. Beard, Laufer, Pierce, Khan, Kumar, and Sahasrabudhe is Ground 25.

167. Beard, Laufer, Pierce, Khan, Kumar, and Hogasten is Ground 26.

168. Substitute Claims 28, 30, and 34 depend from Independent Substitute Claim 21. Grounds 24, 25, and 26 render obvious Substitute Claims 28, 30, and 34, respectively, for the same reasons discussed above regarding Independent Substitute Claim 21, as well as the same reasons discussed in the Petition regarding claims 11, 13, and 17, respectively. [Pet. at 43-50.] Moreover, a POSITA would have been motivated to combine Malecki, Sahasrabudhe, and Hogasten with Beard, Laufer, Pierce, Khan, and Kumar for at least the same reasons discussed in the Petition (Pet. at 43-50), as well as the same reasons discussed above in Section XV.B.1.

D. GROUND 27: SUBSTITUTE CLAIM 36

1. Motivation to Combine

169. A POSITA would have been motivated to combine Beard, Laufer, Pierce, and Ning (the “BLPN combination”) for the same reasons discussed above with respect to Beard, Laufer, and Pierce. [*Supra* Section XV.B.1.] Moreover, a POSITA would have been motivated to combine Beard, Laufer, and Pierce with Ning’s teachings of performing object detection using a “You Only Look Once”

(YOLO) and object tracking using an LSTM neural network. [EX1034, Abstract, 1:51-2:3, 2:15-19, 2:35-62, 3:3-17, 4:38-5:3, 5:46-54, 6:15-53, 6:59-8:33, 8:41-9:4, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4, 5, 6, 8; *See supra* Sections XV.B.1, XV.B.2 at Elements [21.b], [21.c]; Pet. at 35-36.] A POSITA would have recognized that Ning’s YOLO and LSTM neural networks provide “real time” object detection and tracking that is “efficient yet accurate.” [EX1034, Abstract, 4:55-58, 5:4-9, 9:18-39; Pet. at 10-13, 35-36.] As such, Ning enhances Beard’s object detection and tracking. [*Id.*] Moreover, the need for “[f]ast, accurate algorithms for object detection” that “allow computers to drive” vehicles was known to POSITAs, and using YOLO, which operates “extremely fast,” was a favorable solution that “generalizes well to new domains, making it ideal for applications that rely on fast, robust object detection” like object recognition and tracking algorithms used by drones. [EX1036, 779, 785-786.] Additionally, Ning’s system “can be amounted on any suitable vehicle” and is thus compatible with the Beard-Laufer-Pierce drone system. [EX1034, 5:35-38.]

170. A POSITA would have thus readily utilized the teachings of Ning with the Beard-Laufer-Pierce drone system, and the combination would have had the predictable result of Beard’s on board UAV image processor 234 detecting a target 118 in image frames by applying a YOLO neural network. [EX1034, Abstract, 1:51-2:3, 2:15-19, 2:35-62, 3:3-17, 4:38-5:3, 5:46-54, 6:15-53, 6:59-8:33, 8:41-9:4, 9:30-

37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4, 5, 6, 8; *See supra* XIX.D.1, XIX.D.2 at Elements [21.b], [21.c]; Pet. at 35-36.] Furthermore, the combination would have had Beard's on board UAV image processor 234 determining tracking parameters by using a LSTM neural network to predict and track the location of a target in an analyzed image. [EX1034, Abstract, 1:51-2:3, 2:15-19, 2:35-62, 3:3-17, 4:38-5:3, 5:46-54, 6:15-53, 6:59-8:33, 8:41-9:4, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4, 5, 6, 8; *See supra* XIX.D.1, XIX.D.2 at Elements [21.b], [21.c]; Pet. at 35-36.] The combination would have had a reasonable expectation of success because YOLO and LSTM were known object detection and tracking techniques well suited for use in vehicle applications due to their speed and ability to provide real-time results. [EX1034, Abstract, 1:51-2:3, 2:15-19, 2:35-62, 3:3-17, 4:38-5:3, 5:46-54, 6:15-53, 6:59-8:33, 8:41-9:4, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4, 5, 6, 8; EX1036, 779, 785-786.]

2. Claim 36

a) Elements [36.b1], [36.b2], [36.c]

171. **Elements [36.b1]:** “a processor configured to: detect at the reference aerial vehicle a target in the image; and”

172. **Element [36.b2]:** “determine at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image; and”

173. **Element [36.c]:** “a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to determine a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.”

174. The BLPN combination teaches Beard’s on-board UAV image processor 234 detects a target 118 in image frames by applying a machine learning/neural network algorithm to image frames and determines tracking parameters between the UAV and a target including distance, angle of elevation, and bearing (*processor configured to: detect at the reference aerial vehicle a target in the image; and determine at the reference aerial vehicle a three-dimensional relative location...*). [See *supra* XIX.D.2 at Elements [21.b], [21.c]; Pet. at 35-36.] Moreover, attitude control system 232 aboard the UAV performs flight control operations such as controlling the speed of one or more UAV rotors (*a flight controller configured to perform a flight control operation...*). [See *supra* Section XV.B.2 at Element [21.d]; Section XV.D.1; Pet. at 35-36.]

b) Element [36.d]

175. **Element [36.d]:** “[36.d] wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a first neural network at a first robustness and a first compute cost, and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a second neural network at a second robustness and a second compute cost, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.”

176. The BLPN combination teaches Beard’s on board UAV image processor 234 detection of target 118 in image frames occurs by applying a “You Only Look Once” (“YOLO”) neural network having a high robustness and high compute cost (*“wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a first neural network at a first robustness and a first compute cost*). [EX1034, Abstract, 1:51-2:3, 2:35-57, 3:3-6, 4:38-54, 5:46-54, 6:15-43, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 8; *See supra* Sections XV.B.1, XV.B.2 at Elements [21.b], [21.c]; Section XV.D.1; Pet. at 35-36.] The ’711 Patent acknowledges that YOLO neural networks have a “high robustness” and “high cost.” [’711 Patent, 27:54-56, 28:40-47.] Moreover, high cost and high robustness processing schemes are explained by the ’711 patent as being those that “produce an object location estimation independent of historical

information.” [’711 Patent, 27:54-56.] That is just what Ning’s YOLO neural network does because it performs object location estimates based only on the current full image being analyzed. [EX1034, Abstract, 1:51-2:3, 2:35-57, 3:3-6, 4:38-54, 5:46-54, 6:15-43, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 8; EX1036, 779-780, Figs. 1-2 (discussing YOLO operating on a single input image).]

177. The BLPN combination further teaches Beard’s on board UAV image processor 234 determines tracking parameters by using a “long short-time memory” (LSTM) neural network at a medium/low robustness and medium/low compute cost to predict and track the location of a target in an analyzed image, where the prediction is continually updated (*and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a second neural network at a second robustness and a second compute cost*). [See *supra* Sections XV.B.1, XV.B.2 at Elements [21.b], [21.c]; Pet. at 35-36; EX1034, Abstract, 1:51-2:3, 2:15-19, 2:58-62, 3:10-17, 4:55-5:3, 6:33-53, 6:59-8:33, 8:41-9:4, 10:64-11:13, 12:55-13:2, Figs. 4, 5, 6.] Ning teaches the LSTM neural network “refin[ing]” its predicting and tracking of an object’s location, as well as repeating its predicting and tracking of an object’s location, and that a detected object is “follow[ed] over time.” [EX1034, 6:33-53, 6:59-8:33, Figs. 1, 4.] Therefore, it teaches that the location of the object is predicted *incrementally* as claimed. [*Id.*]

Moreover, the '711 Patent explains that medium robustness, medium cost algorithms use a “last known location of the object location estimation” and low robustness, low cost algorithms use a “known location of the object location estimation.” [’711 Patent, 27:57-64.] Ning’s LSTM neural network aligns with both explanations and thus has a medium robustness, medium cost or low robustness, low cost because it uses previous known location predictions (e.g., “the output of itself [the LSTM] from the last time step t-1, i.e., the location prediction”), uses memory cells “to store and output information, allowing it to better discover long-range temporal relations,” and “learns from experience” to perform its object location prediction. [EX1034, 4:55-5:3, 8:49-52, 10:50-54.]

178. The YOLO neural network of the combination has a “high robustness” and “high cost” (*the first robustness and the first compute cost being greater, respectively,*) and the LSTM neural network has a “medium robustness” and “medium cost” or “low robustness” and “low cost” (*than the second robustness and the second compute cost*). [*Supra* Section XV.D.1, 2; ’711 Patent, 27:54-64, 28:40-47.] Therefore, the combination renders obvious element [36.d].

E. GROUND 28: SUBSTITUTE CLAIMS 21, 23-26, 32

1. Motivation to Combine

179. A POSITA would have been motivated to combine Pierce, Kumar, Khan, and Beard (the “PKKB combination”) for the same reasons discussed in the

Petition with respect to Pierce and Kumar (Pet. at 50-53), Pierce and Khan/Pierce, Kumar, and Khan (Pet. at 72-73). Moreover, a POSITA would have been motivated to combine Pierce, Kumar, and Khan with Beard's teachings of a drone having an on-board control system that controls movement of the drone to track an object. [EX1009, 4:60-63, 5:54-59, Fig. 5.] Beard's teachings provide explicit implementation details (i.e., use of a controller on-board the UAV) for how a drone implements flight control. [*Id.*; Pet. at 50-60, 72-73.] This teaching furthers Pierce, Kumar, and Khan's combined teachings related to such concepts. [*Id.*; Pet. at 50-60, 72-73.] Utilizing Beard's teachings would have been applying a known technique (drone having an on-board control system that controls movement of the drone) to improve similar devices (drones that control their movement) in the same way. [*Id.*] The combination would have had the predictable result of Pierce's UAV implementing on-board flight control that controls drone rotor speed and moves the drone to track an object. [*Id.*] Moreover, for the same reasons noted above that the combination reflects mere implementation details, and the overlap in subject matter between the references and compatibility of the references, a POSITA would have had a reasonable expectation of success in making the combination. [*Id.*]

2. Claim 21

a) Element [21.a]

180. **Element [21.a]:** “receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle.”

181. The PKKB combination teaches a “drone system 600 [that] may be drone 102,” and system 600 includes an “object tracking module 615.” [EX1005, ¶¶0027, 0042, 0044-0046, Figs. 1, 6.] A POSITA would have understood or at least found obvious that this module would have been implemented on or as a processor, on drone 102. [EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015.] Object tracking module 615 of the drone 102 receives images of a surrounding area of the drone captured by camera 104 and analyzes them using “various neural networks” (*receiving at a processor at the reference aerial vehicle an image...*). [*Id.*; Pet. at 50-54.]

b) Element [21.b]

182. **Element [21.b]:** “detecting at the reference aerial vehicle a target in the image including by applying at the reference aerial vehicle a machine learning model to the image, to identify a bounding box outlining a portion of the image that includes detected features of the target, and to identify a classification of the detected target.”

183. *See supra* Ground 23, Element [21.b], for teachings of Kumar and Khan regarding bounding box and classification. In view of such teachings, the PKKB combination teaches Pierce’s on-board object tracking module 615 of drone 102 detects an object (e.g., vehicle) in an image using a neural network applied to the

image, which produces a bounding box around the detected object (*detecting at the reference aerial vehicle a target in the image including by applying at the reference aerial vehicle a machine learning model to the image, to identify a bounding box outlining a portion of the image*). [Petition at 50-55; EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015.] In the combination, by performing the detecting of a object (*detecting at the reference aerial vehicle...*), the identified bounding boxes would have outlined detected “shape and appearance” features of the object as taught by Khan (*to identify a bounding box outlining a portion of the image that includes detected features of the target*). [*Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7.] Moreover, by performing the detecting of a target (*detecting at the reference aerial vehicle...*), these features would have been used to classify an object as a particular type of object (e.g., vehicle) as taught by Khan (*and to identify a classification of the detected target.*) [*Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7.]

184. Under an alternative interpretation, Pierce’s on board object tracking module 615 of drone 102 applies neural networks to images (*applying at the reference aerial vehicle a machine learning model...*) to generate the bounding box. [*Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7; EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015; Pet. at 50-55.] The bounding box would have outlined detected “shape and appearance” features of the object as taught by Khan and Kumar (*to identify a bounding box outlining a portion of the image that includes detected*

features of the target). [Id.; EX1021, ¶¶0045-0063, Figs. 6, 7; EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015; Pet. at 50-55.] Moreover, Pierce’s on board object tracking module 615 applies neural networks (*applying at the reference aerial vehicle a machine learning model...*) that would have classified the object as a particular type of object based on the features as taught by Khan (*and to identify a classification of the detected target*). [Id.]

c) Element [21.c]

185. **Element [21.c]:** “determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image including by determining a distance to the target based at least in part on a size of the bounding box of the target detected within the image and on a physical size corresponding to the classification of the target detected within the image.”

186. The PKKKB combination teaches Pierce’s on board object tracking module 615 of drone 102 determines relative position (x_0, x_1, x_2) of the object with respect to the drone (*determining at the reference aerial vehicle a three-dimensional relative location of the target...*). [Pet. at 50-56; EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015.] This determination of relative location uses the “straight-line distance” value d ; this value d is determined using (1) a value A that represents the “area of the bounding box in pixels,” specifying the area of a

bounding box of a target object that is detected and tracked in the processed image, and (2) a value *s* that represents the “physical length of the diagonal across the box for an average instance of the object” (*determining...a three-dimensional relative location of the target...including by determining a distance to the target based at least in part on a size of the bounding box of the target detected within the image*). [Pet. at 50-56.]

187. Moreover, Khan teaches classification of a target into a particular type (e.g., an SUV, sedan, etc.) as discussed above for Element [21.b]. [EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8; EX1007, ¶¶0020, 0035, Fig. 2; EX1008, ¶¶0018, 0030, Fig. 2.] Kumar teaches a target tracking system that recognizes a target in captured images and produces a bounding box around the target. [EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8; EX1007, ¶¶0020, 0035, Fig. 2; EX1008, ¶¶0018, 0030, Fig. 2.] Kumar’s system determines the relative position of a target to the camera capturing the images based on the “known physical [bounding] box size of the object of interest’s type of object” and the “physical length of the diagonal across the [bounding] box for an average instance of the object.” [EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; EX1003, ¶¶157-158.] Thus, Khan teaches classifying a target in an image as a particular type, and Kumar teaches determining a relative position using a physical size of such a type of target. [EX1007, ¶¶0019-0025, 0037, Fig. 3A;

EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; Petition at 50-56, 72-73; EX1003, ¶¶162-163.] Therefore, the PKKB combination teaches that the distance between Pierce's drone 102 and target object would further have been based on a physical size (as taught by Kumar) corresponding to the classified type of target object identified in a captured image (as taught by Khan) *(determining a distance to the target based at least in part on...and on a physical size corresponding to the classification of the target detected within the image)*. [EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; Petition at 50-56, 72-73; EX1003, ¶¶162-163.]

d) Element [21.d]

188. **Element [21.d]**: “performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.”

189. Pierce describes controlling movement of its drone, and a POSITA would have understood or at least found obvious that this occurs using the processor 601 on board drone 102 and/or a drone controller on board drone 102 *(performing at the reference aerial vehicle the flight control operation...)*. [Pet. at 50-53, 56-60;

EX1005, ¶¶0017, 0019, 0025-0027, 0042, 0044-0046, Figs. 1, 6.] Additionally, Beard teaches using an “attitude control system” that is on-board a drone that controls the speed of one or more drone rotors, “thereby adjusting the speed, direction, or rotational orientation” and “pitch, yaw, or roll angle” of the drone. [EX1009, 4:60-63, 5:54-59, Fig. 5.] In view of this teaching, the PKKB combination thus teaches that a control system on-board Pierce’s drone 102 implements flight control operations that move the drone to track a moving object (*performing at the reference aerial vehicle the flight control operation...*). [*Id.*; Pet. at 50-53, 56-60; EX1005, ¶¶0017, 0019, 0025-0027, 0042, 0044-0046, Figs. 1, 6.]. Pierce/Pierce and Kumar also disclose or at least renders obvious a *first speed adjustment factor* for the same reasons discussed in the Petition. [Pet., 50-53, 56-60].

3. Claim 24

190. Claim 24 recites: “The method of claim 21, wherein detecting the target in the image including by applying at the reference aerial vehicle the machine leaning model to the image includes identifying a model type of the target based on the classification of the detected target.”

191. Khan teaches classification of an object in an image into a type such as an SUV, sedan, van, etc. [EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8.] The PKKB combination thus teaches that the target detection by Pierce’s object tracker 615 on-board drone 102 applying neural networks to image frames includes

identifying a model type (e.g., a vehicle model type such as an SUV, sedan, van, etc) based on the classification of the target object as a particular model type (*wherein detecting the target in the image including by applying at the reference aerial vehicle the machine learning model to the image includes identifying a model type of the target based on the classification of the detected target*). [Supra Section XV.E.1-2; Pet. at 72-73.]

4. Claims 23, 25, 26, and 32

192. Claims 23, 25, 26, and 32 are obvious for the same reasons discussed in the Petition regarding claims 3, 8, 9, and 15, respectively. [Pet. at 50-53, 60, 62-66.] The same reasoning there applies to the PKKB combination.

193. Further, for substitute claim 25, the combination teaches the value $(x_t - _ (x_d))$, as well as the value $P^*(x_t - _ (x_d))$, each individually form a *second speed adjustment factor*. [Pet., 62-64].

F. GROUND 29 AND 30

194. Claims 22, 29, and 35 depend from claim 21. Pierce, Khan, Kumar, Beard, and Laufer is Ground 29 and renders obvious Substitute Claims 22, 29, and 35 for the same reasons discussed above for claim 21, as well as the same reasons discussed in the Petition regarding claims 2, 12, and 18, respectively. [Pet. at 68-75.]

195. Substitute Claim 34 depends from Substitute Claim 21. Pierce, Khan, Kumar, Beard, and Hogasten is Ground 30 and renders obvious Substitute Claim 34

for the same reasons discussed above regarding Independent Substitute Claim 21, as well as the same reasons discussed in the Petition regarding claim 17. [Pet. at 68-75.]

196. Moreover, a POSITA would have been motivated to combine Laufer with Pierce, Khan, Kumar, and Beard, as well as Hogasten with Pierce, Khan, Kumar, and Beard, for at least the same reasons discussed in the Petition, as well as the same reasons discussed above in Section XV.E.1 and Pet. at 68-75.

G. GROUND 31: SUBSTITUTE CLAIM 36

1. Motivation to Combine

197. A POSITA would have been motivated to combine Pierce, Kumar, Ning, and Beard for the same reasons discussed in Section XV.D.1 regarding Ning and Section XV.E.1 regarding Beard. The combination would have resulted in the predictable result of Pierce's drone 102 performing on-board flight control and on-board object tracking module 615 of drone 102 detecting an object (e.g., vehicle) in an image by applying a YOLO neural network and determining a relative location (x_0, x_1, x_2) of an object by using a LSTM neural network to predict and track the location of a target in an analyzed image. [*Supra* Sections XV.D.1, XV.E.1; Pet. 50-60, 66-68.] The combination would have had a reasonable expectation of success because YOLO and LSTM were known object detection and tracking techniques well suited for use in vehicle applications due to their speed and ability to provide

real-time results. [EX1034, Abstract, 1:51-2:3, 2:15-19, 2:35-62, 3:3-17, 4:38-5:3, 5:46-54, 6:15-53, 6:59-8:33, 8:41-9:4, 9:30-37, 9:61-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4, 5, 6, 8; EX1036, 779, 785-786.]

2. Claim 36

a) Elements [36.b1], [36.b2], [36.c]

198. **Element [36.b1]:** “a processor configured to: detect at the reference aerial vehicle a target in the image; and”

199. **Element [36.b2]:** “determine at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image; and”

200. **Element [36.c]:** “a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to determine a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.”

201. Pierce’s on-board object tracking module 615 of a drone detects an object in image frames by applying neural networks to image frames and determines a relative location between the UAV and an object. Flight control is performed on

board the drone as taught by Beard. [Sections XV.D.2.a (Elements [36.b1], [36.b2], [36.c]), XV.E.1-2; Pet. at 66-67.] This teaches elements [36.b1], [36.b2], and [36.c].

b) Element [36.d]

202. **Element [36.d]:** “ “[36.d] wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a first neural network at a first robustness and a first compute cost, and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a second neural network at a second robustness and a second compute cost, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.”

203. Pierce’s drone 102 performs on-board flight control, and on-board object tracking module 615 of drone 102 detects an object (e.g., vehicle) in an image by applying a YOLO neural network and determines a relative location (x_0 , x_1 , x_2) of an object by using a LSTM neural network to predict and track the location of a target in an analyzed image. [*Supra* Sections XV.D.1, XV.E.1; Pet. 50-60, 66-68.] The combination teaches element [36.d] for the same reasons discussed with respect to Ning in Section XV.D.2.b.

H. GROUND 32-35

204. Pierce, Khan, Kumar, Beard, and Sahasrabudhe (Ground 32) render obvious claims 21, 23-26, and 32 for the same reasons as discussed for Ground 28 above and in the Petition regarding claims 1, 3, 8, 9, 15, and further render obvious claims 31 and 33 for the same reasons discussed in the Petition regarding claims 14 and 16. [Pet. at 75-80.]. Moreover, for substitute claim 31, Pierce discloses or at least renders obvious *scaling the speed adjustment factor* because a constant P multiplies the value $(\alpha_t - \alpha_d)$, where this value is *the speed adjustment factor*. [Pet., 56-60, 79].

205. Pierce, Khan, Kumar, Beard, Sahasrabudhe, and Laufer (Ground 33) render obvious claims 22, 29, and 35 for the same reasons as discussed for Ground 30 above and in the Petition regarding claims 2, 12, and 18. [*Id.* at 80.]

206. Pierce, Khan, Kumar, Beard, Sahasrabudhe, and Hogasten (Ground 34) render obvious claim 34 for the same reasons as discussed for Ground 30 above and in the Petition regarding claim 17. [*Id.*]

207. Pierce, Kumar, Sahasrabudhe, and Ning (Ground 35) render obvious claim 36 for the same reasons discussed for Ground 31 above. [*Id.*]

208. A POSITA would have been motivated to combine the references of each of Grounds 32-35 for the reasons discussed in the Petition at pages 75-80, as well as the reasons discussed above for Grounds 28-31, respectively.

XVI. CONCLUSION

209. All statements made herein of my own knowledge are true, and all statements made on information and belief are believed to be true. I further understand that willful false statements and the like are punishable by fine or imprisonment, or both, under Section 1001 of Title 18 of the United States Code. I declare under penalty of perjury that the foregoing is true and correct.

Executed on June 1, 2026.



Dr. William Singhose

APPENDIX

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- [8] K. L. Sorensen, W. Singhose, and S. Dickerson, "Combined feedback and command shaping controller for multistate control with application to improving positioning and reducing cable sway in cranes " Patent US 7,970,521, June 28, 2011, 2011.