

**UNITED STATES PATENT AND TRADEMARK OFFICE**

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**BEFORE THE PATENT TRIAL AND APPEAL BOARD**

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TESLA, INC.,  
Petitioner,

v.

INTELLECTUAL VENTURES II LLC,  
Patent Owner.

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IPR2025-00340  
U.S. Patent No. 6,894,639

**DECLARATION OF JEFFREY J. RODRIGUEZ, PH.D.  
UNDER 37 C.F.R. § 1.68 IN SUPPORT OF PETITION FOR  
*INTER PARTES* REVIEW**

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## **I. INTRODUCTION**

1. I am making this declaration at the request of Tesla, Inc. in the matter of the *Inter Partes* Review of U.S. Patent No. 6,894,639 (“the ’639 patent”) to Katz.

2. I am being compensated at my usual and customary rate for the time I spend in connection with this IPR. I am also being reimbursed for reasonable and customary expenses associated with my work and testimony in this investigation. My compensation is not contingent on the outcome of this matter or the specifics of my testimony, and I have no other interest in this case or the parties thereto.

3. I have been asked to provide my opinions regarding whether claims 1-7 (“the Challenged Claims”) of the ’639 patent are unpatentable as they would have been obvious to a person having ordinary skill in the art (“POSITA”) at the time of filing, in light of the prior art.

## **II. QUALIFICATIONS AND PROFESSIONAL EXPERIENCE**

4. My current curriculum vitae is attached as Exhibit 1004, which includes a detailed listing of my education, work experience, honors, awards, professional associations, publications, and a list of expert consulting activities during the past five years in which I have testified as an expert at deposition or trial.

5. I am a professor at The University of Arizona in the Department of

Electrical & Computer Engineering, where I hold or have held the following positions: (a) Associate Professor of Electrical & Computer Engineering, with tenure (1997–present), (b) Associate Professor of Biomedical Engineering, with tenure (2017–present), (c) Director of ECE Online Programs (2023–present), (d) Director of the Signal and Image Laboratory (1990–present), (e) Director of Image Analysis, Cancer Imaging Shared Services, Arizona Cancer Center (2009–2014), (f) Co-Director of Connection One, a National Science Foundation industry/university cooperative research center for wired and wireless communication circuits and systems, (g) Director of Graduate Studies for the Department of Electrical & Computer Engineering (2000–2003, 2005–2016).

6. My formal education includes a Bachelor of Science degree in Electrical Engineering from the University of Texas at Austin in May 1984, a Master of Science degree in Electrical Engineering from the Massachusetts Institute of Technology in June 1986, and a Ph.D. Degree in Electrical Engineering from the University of Texas at Austin in May 1990.

7. I teach courses at both the graduate and undergraduate level through the Dept. of Electrical & Computer Engineering and the College of Optical Sciences. The courses I have taught include Digital Image Processing, Digital Image Analysis, Digital Signal Processing, Advanced Digital Signal Processing,

Signals and Systems, and Circuit Analysis. I have been awarded the Outstanding Teaching Award by the IEEE and Eta Kappa Nu (IEEE-HKN), given by students at The University of Arizona to one outstanding professor each year.

**8.** My research activity focuses on systems for digital signal/image/video processing and analysis. My research activities include automated detection/classification/recognition of regions/objects/targets using neural networks and other machine learning methods, as well as conventional technologies. My research has included applications such as military target recognition, biomedical image analysis, animal species classification, convolutional neural networks for driver distraction detection, and real-time video processing for analysis of zebrafish.

**9.** In a research project involving biomedical image analysis, we developed a 3D convolutional neural network, based on the U-Net architecture, to jointly perform segmentation and detection of cells in 3D microscopy images. The segmentation portion of the network distinguishes cells from background clutter, and the detection portion of the network classifies each segmented cell region based on its calculated properties. This unified approach outperformed benchmark methods for both cell segmentation and detection accuracy.

**10.** Another research project involved the design and development of a

real-time image and video processing system for automated detection and behavioral analysis of zebrafish for use in ototoxicity assessment of drugs. The system we designed and built includes an array of Raspberry Pi microcomputer systems configured for parallel video capture of sixteen zebrafish populations. Each Raspberry Pi features a system on a chip, which includes a CPU, a video graphics processing unit (GPU), a disk storage system, and a memory system. Our zebrafish analysis system automatically captures and transmits compressed MPEG video data to a local personal computer or to a high-performance computing cluster to decode the video and implement customized algorithms for detection of zebrafish pose and motion using multi-scale edge map analysis, resulting in automated assessment of zebrafish swimming behavior.

**11.** I am a Senior Member of the Institute of Electrical and Electronics Engineers (IEEE) and the IEEE Signal Processing Society. I served as Treasurer of the 2024 IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI), General Chair of SSIAI 2016, and General Chair of the 2007 IEEE International Conference on Image Processing (ICIP). In addition, I served on the IEEE Signal Processing Society Technical Committee on Image, Video, and Multidimensional Signal Processing (2005–2011) and served as Associate Editor of the IEEE Transactions on Image Processing (1996–2000). Over the years, I have served on numerous other professional committees, and I have served as a

technical reviewer for numerous journals and professional conferences.

**12.** I am named as an inventor on a patent involving polar dynamic programing for automated image segmentation. I have authored or co-authored over 140 technical publications. Over the past 30 years, I have trained hundreds of students in signal/image/video processing, including directing the research of numerous graduate students, resulting in more than 50 graduate theses and dissertations. I have served as an expert in patent cases since 2005, involving signal/image/video processing, data compression systems, video receivers, document cameras, cellular camera phones, signal/image/video transmission over wireless networks, etc.

### **III. MATERIALS CONSIDERED**

**13.** In preparation of this declaration, I have studied:

| Exhibit | Description                                                                                   |
|---------|-----------------------------------------------------------------------------------------------|
| Ex.1001 | U.S. Patent No. 6,894,639 to Katz (“’639 Patent”)                                             |
| Ex.1002 | Prosecution History for U.S. Patent No. 6,894,639 to Katz (“’639 Patent Prosecution History”) |
| Ex.1005 | U.S. Patent No. 5,027,413 to Barnard (“Barnard”)                                              |
| Ex.1006 | PCT Application Publication WO 90/16038 to Lawrence (“Lawrence”)                              |
| Ex.1007 | U.S. Patent No. 5,341,439 to Hsu (“Hsu”)                                                      |
| Ex.1008 | U.S. Patent No. 5,341,142 to Reis et al. (“Reis”)                                             |

| Exhibit | Description                                                                                                                                                                                                             |
|---------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Ex.1009 | “Bayesian and neural network pattern recognition : a theoretical connection and empirical results with handwritten characters” (“Lee”)                                                                                  |
| Ex.1015 | “Artificial Neural Networks for Automatic Target Recognition” (“Rogers”), Published in Proceedings of SPIE Conference on Applications of Artificial Neural Networks, Orlando, Florida April 1990 (Paper Number 1294-01) |
| Ex.1016 | U.S. Patent No. 4,881,270 (“Knecht”)                                                                                                                                                                                    |
| Ex.1017 | U.S. Patent No. 5,010,512 (“Hartstein”)                                                                                                                                                                                 |
|         | Any other document(s) referenced below.                                                                                                                                                                                 |

**14.** In forming the opinions expressed below, I have considered:

- a) the documents listed above;
- b) the relevant legal standards, including the standard for obviousness, as explained to be by counsel, and any additional authoritative documents as cited in the body of this declaration; and
- c) my own knowledge and experience based upon my work in the field as described below.

**15.** Unless otherwise noted, all emphasis in any quoted material has been added.

#### **IV. LEVEL OF ORDINARY SKILL IN THE ART**

**16.** I understand there are multiple factors relevant to determining the

level of ordinary skill in the pertinent art, including (1) the levels of education and experience of persons working in the field at the time of the invention; (2) the sophistication of the technology; (3) the types of problems encountered in the field; and (4) the prior art solutions to those problems.

**17.** For my analysis, I have been asked to assume that the time of the claimed invention is the filing date of the '639 patent, which is December 18, 1991.

**18.** A person of ordinary skill in the art ("POSITA") in the field of the '639 Patent, at the time of the claimed invention, would have been someone knowledgeable and familiar with the image processing systems pertinent to the '639 Patent. That person would have had a bachelor's degree in computer science, computer engineering, electrical engineering, or equivalent training, and approximately four years of experience working in the field of image processing. Additional education would offset a lesser amount of experience, and vice versa.

**19.** For purposes of this Declaration, in general, and unless otherwise noted, when I provide my understanding and analysis below it is from the perspective of a POSITA as of the filing date of the '639 Patent.

## **V. LEGAL PRINCIPLES**

**20.** I am not an attorney and offer no legal opinions. For the purpose of this Declaration, I am relying on certain basic legal principles that counsel have

explained to me. These principles are discussed below, and the analysis in this Declaration is in accordance with these legal principles.

**A. Prior Art**

21. I understand that prior art to the '639 Patent includes patents and printed publications in the relevant art that predate the date of the claimed invention recited in the '639 Patent.

**B. Obviousness**

22. I have been informed that a claimed invention is unpatentable under 35 U.S.C. § 103 if the differences between the invention and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which the subject matter pertains. I have also been informed by counsel that the obviousness analysis takes into account factual inquiries including the level of ordinary skill in the art, the scope and content of the prior art, and the differences between the prior art and the claimed subject matter.

23. I have been informed by counsel that the Supreme Court has recognized several rationales for combining references or modifying a reference to show obviousness of claimed subject matter. Some of these rationales include the following: (a) combining prior art elements according to known methods to yield predictable results; (b) simple substitution of one known element for another to

obtain predictable results; (c) use of a known technique to improve a similar device (method, or product) in the same way; (d) applying a known technique to a known device (method, or product) ready for improvement to yield predictable results; (e) choosing from a finite number of identified, predictable solutions with a reasonable expectation of success; and (f) some teaching, suggestion, or motivation in the prior art that would have led one of ordinary skill to modify the prior art reference or to combine prior art reference teachings to arrive at the claimed invention.

**24.** I further understand that a claim would have been obvious if it unites old elements with no change to their respective functions or alters prior art by mere substitution of one element for another known in the field and that combination yields predictable results. Also, I understand that obviousness does not require physical combination/bodily incorporation, but rather consideration of what the combined teachings would have suggested to persons of ordinary skill in the art at the time of the claimed invention. I understand that the combination of familiar elements according to known methods is likely to be obvious when it does no more than yield predictable results.

**25.** As mentioned above, I understand that a claim would have been obvious if it unites old elements with no change to their respective functions or alters prior art by mere substitution of one element for another known in the field

and that combination yields predictable results. While it may be helpful to identify a reason for this combination, I understand that there is no rigid requirement of finding an express teaching, suggestion, or motivation to combine within the references. When a product is available, design incentives and other market forces can prompt variations of it, either in the same field or a different one. I understand that if a POSITA can implement a predictable variation, obviousness likely bars its patentability. For the same reason, I understand that if a technique has been used to improve one device and a POSITA would recognize that it would improve similar devices in the same way, using the technique would have been obvious. I understand that a claim would have been obvious if common sense directs one to combine multiple prior art references or add missing features to reproduce the claimed invention.

**26.** I further understand that certain factors may support or rebut the obviousness of a claim. I understand that such secondary considerations include, among other things, commercial success of the patented invention, skepticism of those having ordinary skill in the art at the time of invention, unexpected results of the invention, any long-felt but unsolved need in the art that was satisfied by the claimed invention, the failure of others to make the claimed invention, praise of the claimed invention by those having ordinary skill in the art, and copying of the claimed invention by others in the field. I understand that there must be a nexus—a

connection—between any such secondary considerations and the claimed invention. I also understand that contemporaneous and independent invention by others is a secondary consideration tending to show obviousness.

27. I am not aware of any allegations by the named inventor or assignee of the '639 Patent that any secondary considerations tend to rebut the obviousness of the Challenged Claims of the '639 Patent.

28. I understand that in considering obviousness, it is important not to determine obviousness using the benefit of hindsight derived from the patent being considered.

**C. Other Challenges to Validity**

29. I understand that other challenges to the validity of a patent, including patent ineligibility, enablement, written description, and indefiniteness, cannot be raised in *inter partes* review proceedings to challenge the validity of the '639 Patent. Accordingly, I did not consider these other challenges.

**D. Level of Proof**

30. I understand that Petitioner has the burden of proving unpatentability by a preponderance of evidence, which means it is more likely than not that the claims are unpatentable.

**E. Interpretation of Claims**

31. I understand that the claims are to be construed according to the same

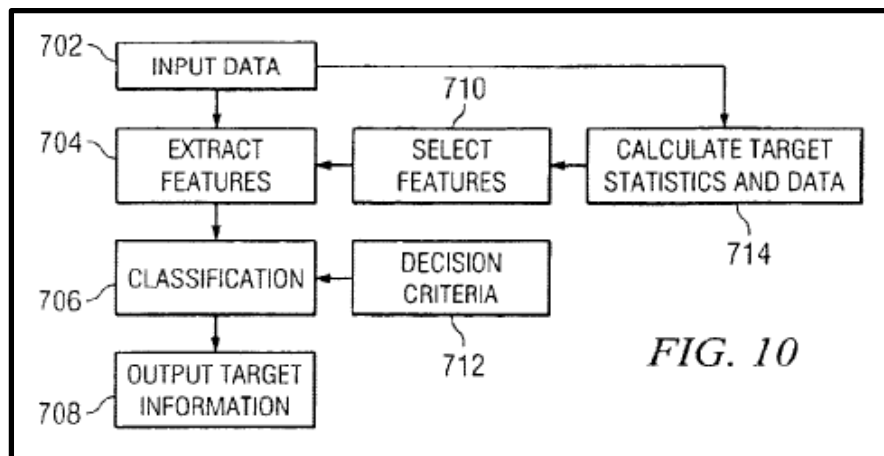
claim construction standard that district courts use wherein claim terms are given their ordinary and customary meaning from the perspective of a person of ordinary skill in the art at the time of the invention in light of the specification and prosecution history, unless the inventor has set forth a special meaning for a term.

## **VI. THE '639 PATENT**

### **A. '639 Patent Overview**

**32.** The '639 patent, titled “Generalized Hebbian Learning for Principal Component Analysis and Automatic Target Recognition, Systems and Method,” issued to Alan Jerry Katz on May 17, 2005. The '639 patent derives from U.S. Patent Application No. 07/810,005 (“Application”), which was filed on Dec. 18, 1991. The '639 Patent is directed to a method of distinguishing targets from background clutter. EX1001, Abstract.

**33.** More specifically, the '639 Patent calculates data statistics from input data and uses the data statistics to select target specific information that is used to distinguish targets from background clutter. EX1001, Abstract. The approach described by the '639 Patent is generally shown in Fig. 10, reproduced below.



**'639 Patent, Fig. 10.**

**34.** The method described by the '639 Patent is based on a particular implementation of Hebbian learning techniques. *See* EX1001, Title; 5:30-32; 5:55-62; 7:46-57; 7:63-9:40. The '639 Patent is titled “**GENERALIZED HEBBIAN LEARNING FOR PRINCIPAL COMPONENT ANALYSIS AND AUTOMATIC TARGET RECOGNITION, SYSTEMS AND METHOD.**” EX1001, Title. In the “SUMMARY OF THE INVENTION” section, the '639 Patent explains “In particular, **this method uses the Hebbian Learning** to distinguish and take advantage of second order correlation information.” EX1001, 5:30-32. The “SUMMARY OF THE INVENTION” section further explains the method “uses a **variation of the Hebbian learning algorithm** ... to generate a set of distinguishing target characteristics pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.” EX1001, 5:56-62. The “DETAILED DESCRIPTION OF THE PREFERRED

EMBODIMENTS” section of the ’639 Patent details that “[t]he **generalized Hebbian learning algorithm** employed ... was discussed in the Sanger, T. D. “Optimal Unsupervised Learning.” *Neural Networks* vol. 2, pp. 459-473 (1989).” EX1001, 7:50-53.

**35.** Despite the fact the Title, Summary of Invention, and Detailed Description of the ’639 Patent all require a particular implementation of Hebbian learning, the vast majority of the claims of the ’639 Patent do not. Instead, the claims of the ’639 Patent broadly recite well-known image processing techniques that had long been used to distinguish targets from background clutter. *See* EX1001, 12:2-14:31. Only a few dependent claims of the ’639 Patent actually require the use of Hebbian learning. EX1001, claims 8, 15, 17, and 19.

#### **B. ’639 Prosecution History**

**36.** The ’639 Patent was not subject to any prior art rejections during prosecution. *See* EX1002, 25-28; 42-45; 99; 159-160. The Notice of Allowance indicated that “none of the prior art of record either taken alone or taken in any possible combination would anticipate or tend to render obvious Applicant’s method as set forth in independent claim 1 that is particularly characterized at least by parts (b) through (f) of claim 1 taken together and taken in the overall context of independent claim 1.” EX1002, 26. However, as established below, prior art—not considered by the examiner during prosecution—shows the claims of the ’639

Patent recite a combination of well-known image processing steps that were already being used to distinguish targets from background clutter.

**C. Challenged Claims of the '639 Patent**

**37.** I have been asked to provide my opinions regarding whether claims 1-7 (“the Challenged Claims”) of the '639 patent are unpatentable as they would have been obvious to a POSITA at the time of the claimed invention, in light of the prior art. For example, claim 1 is recited as follows, where reference labels [1.0], [1.1], etc. have been added to individual portions of the claim for convenience:

**Claim 1.** [1.0] A method for distinguishing targets from background

clutter, comprising the steps of

[1.1] (a) inputting data;

[1.2] (b) calculating data statistics from said data and using said data statistics to select target specific feature information to distinguish specific targets from background clutter;

[1.3] (c) generating said target feature information from said data statistics;

[1.4] (d) extracting said target specific feature information from said data;

[1.5] (e) using said target specific feature information to distinguish specific targets from background clutter; and

[1.6] (f) outputting target and background clutter information.

## VII. CLAIM CONSTRUCTION

38. It is my understanding that in order to properly evaluate the '639 Patent, the terms of the claims must first be interpreted. It is my understanding that for the purposes of this *inter partes* review, the claims are to be given their ordinary and customary meaning as would be understood by one of ordinary skill in the art at the time of invention in light of the specification and prosecution history, unless the inventor has set forth a special meaning for a term.

39. It is my opinion that none of the claim terms require a specific construction for the purposes of my analysis in this declaration, and all will be given their ordinary and customary meaning in light of the specification and prosecution history of the '639 Patent.

## VIII. PRIOR ART

### A. Barnard

40. U.S. Patent No. 5,027,413, titled "Target Detection Systems," ("Barnard") issued to Michael E. Barnard on June 25, 1991 and derives from U.S. Patent Application 366,102, which was filed on June 13, 1989. Like the '639 Patent, Barnard describes a method for distinguishing targets from background clutter. EX1005, Title; Abstract; 2:4-8.

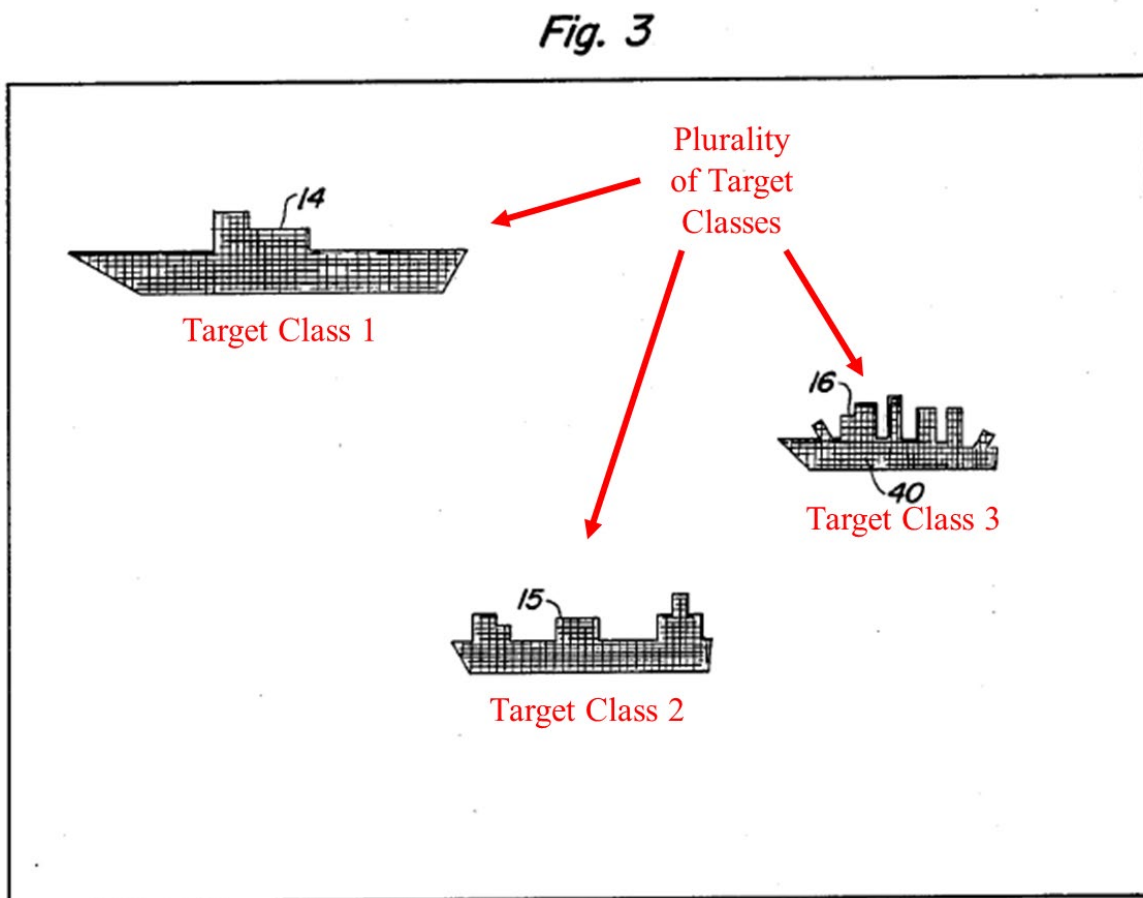
41. The method calculates a plurality of features from the image data and selects a set of features that "effectively separate[] target objects from background

objects.” EX1005, 4:50-5:3; 5:13-17. A feature is excluded or discarded from the set if the statistical distribution of the feature exceeds a threshold or if the feature mean varies beyond a preset amount. EX1005, 2:28-39; *see also* 6:12-15. For the selected set of features, Barnard generates a target detection threshold that is utilized to distinguish targets from background objects. EX1005, 5:13-17; 5:49-66. To this end, Barnard describes that the target detection threshold may be a threshold hypersurface in the feature space that is located where the probabilities of an object being a target or background are equal “in accordance with Baye’s criterion.” EX1005, 5:13-17; 5:49-66. The target detection threshold is generated based on “statistical information”—including the means and variances for both background and target objects—and adapts as new image data is received. EX1005, 5:47-6:15.

**B. Knecht**

**42.** U.S. Patent No. 4,881,270, titled “Automatic Classification of Images,” (“Knecht”) issued to John A. Knecht et al. on November 14, 1989 and derives from U.S. Patent Application 546,755, which was filed on October 28, 1983. Like the ’639 Patent and Barnard, Knecht relates to the field of image processing and, more specifically, to automatic target recognition. EX1016, Title (“AUTOMATIC CLASSIFICATION OF IMAGES”). In this regard, Knecht describes “a method and system for the automatic classification of images” and

“more particularly, [] a method and system for classifying the image, of a scanned object as the image of an object of one of a plurality of predetermined classes of objects[.]” EX1016, 1:6-11. Knecht provides the specific example of “**classifying a potential target object, such as a ship, as a member of one class of several predetermined classes of ships,**” as shown in Fig. 3 reproduced below. EX1016, 1:11-14, Fig. 3.



Knecht, Fig. 3 (annotated).

To this end, Knecht explains that each of the plurality of classes has an associated set of feature vectors and corresponding decision rules that are used to classify

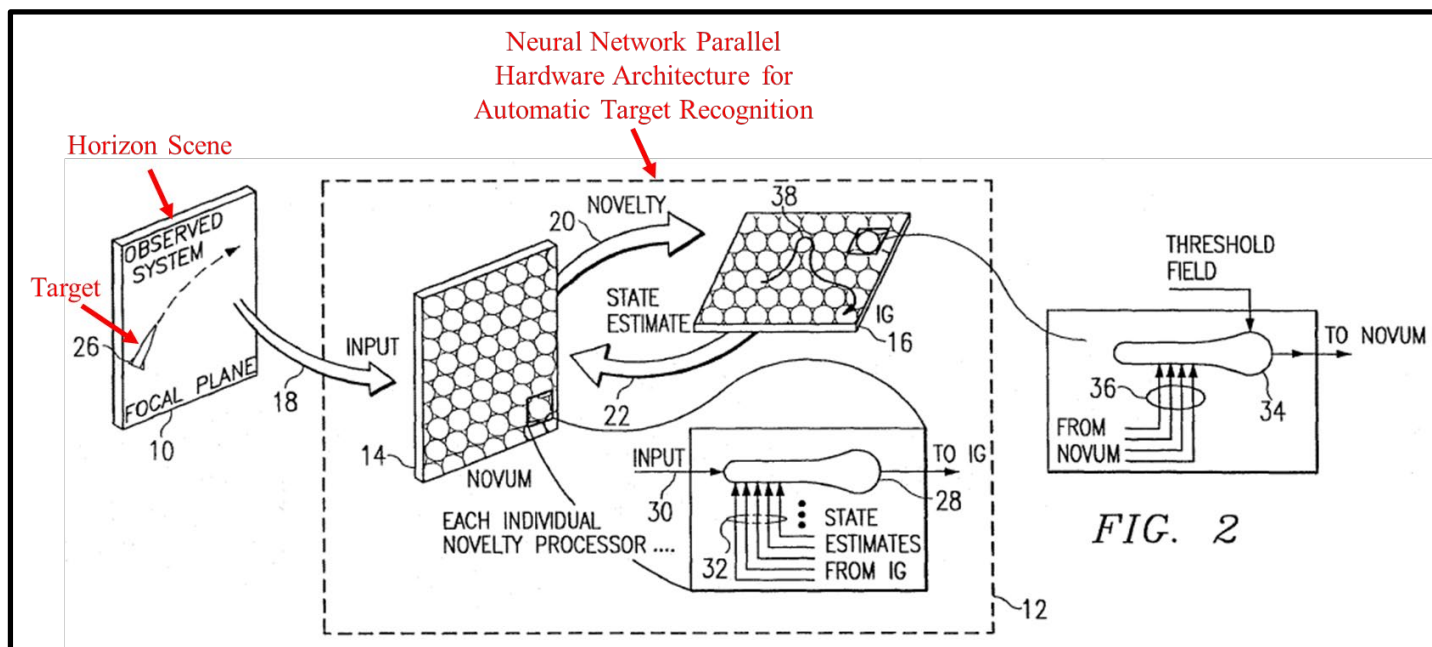
potential targets in real time. EX1016, 6:22-27 (“This **plurality of vectors** is then stored in a memory unit ... for deriving in any suitable manner **decision rules corresponding individually to each such class**. These rules are then stored in a memory unit of system 12 for use thereby in **classifying in real time ....**”). Knecht notes “any suitable classifier such as a well known Bayes classifier” may be used to classify a potential target as one of the plurality of target classes.

### C. Lawrence

43. PCT Application Publication WO 90/16038, titled “Continuous Bayesian Estimation with a Neural Network Architecture,” (“Lawrence”) lists applicant Malcolm G. Lawrence and inventor Robert L. Dawes and was published on December 27, 1990. Like the ’639 Patent and Barnard, Lawrence relates to the field of image processing and, more specifically, to the use of a neural network for automatic target recognition. EX1006, Title, 45:15-25; *see also* 11:23-26, 18:33-19:2, 27:7-13.

44. Lawrence performs image processing to achieve automatic target recognition. EX1006, 45:15-25 (“By way of example, the mechanism by which the PA can **accomplish automatic target recognition** and parameter estimation is described, and how to train and operate a system. ... Then **the target recognition and tracking mechanism** will be described, which **detects the features in the input signal, uses them to build a representation of the estimated target and**

tracks the target while it moves.”), *see also* 11:23-26 (“The observed system 10 is illustrated [in Fig. 2] in the form of a focal plane wherein an object, illustrated as a rocket 26, traverses the focal plane in a predetermined path. This constitutes the observation.”), 18:33-19:2 (“... a well-known neural network architecture which utilizes Hebbian learning and an outstar sequencing scheme to effect the recording of a **sequence of images** into the synapses of **each pixel of a focal plane** array of neurons.”), 27:7-13 (“Also, it is possible to arrange to store not the **whole image** sequence as it comes in -- which would quickly deplete the storage capacity of this and any other conventional design -- but only the novel residual that is left over after everything that has previously been stored in the current context has been subtracted from the scene.”), Fig. 2.



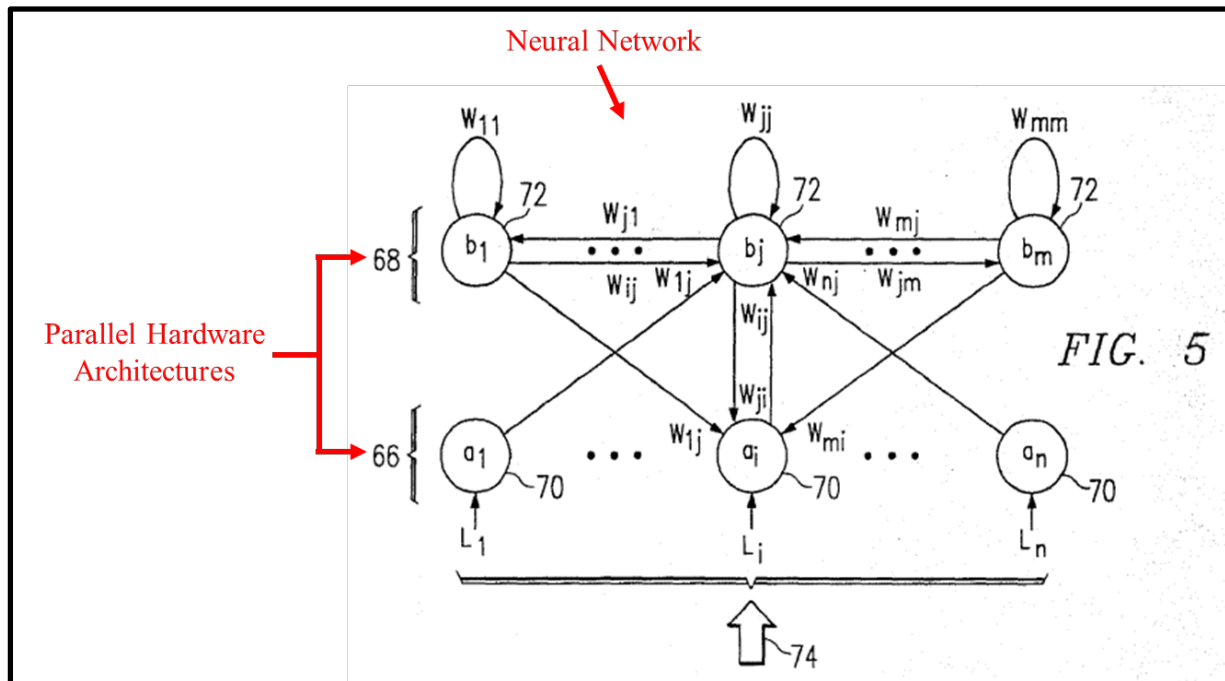
Lawrence, Fig. 2 (annotated).

45. Lawrence is titled “**CONTINUOUS BAYESIAN ESTIMATION WITH A NEURAL NETWORK ARCHITECTURE**” and “pertains in general to a **neural network architecture**, and more particularly, to an architecture which is **designed to perform adaptive, continuous Bayesian estimation** on unprocessed large dimensional data” and “can accomplish automatic target recognition”. EX1006, Title, 1:2-6, 45:15-18. As Lawrence explains, “Referring now to Figure 1, there is illustrated a block diagram of the neural network of the present invention. ... The observing system 12 is essentially the neural network. In the present invention, the neural network is comprised of a two-layer recurrent network. There is an input layer which is referred to as the novum, illustrated by a block 14. The second layer provides a classification layer and is referred to as the IG as illustrated in block 16. The abbreviation IG refers to Infinitesimal Generator. The two blocks 14 and 16 operate together to continuously process information and provide a retrospective classification and prediction (estimate) of the evolution of the classified observation.” EX1006, 9:2-19, Fig. 1.

46. Lawrence further explains that “The **neural network** of the present invention as illustrated by the observing system 12 is referred to as a ‘parametric avalanche’ (PA)” and referring to Figure 2, “there is illustrated a block diagram of the PA 12 illustrating the novum 14 as an array of separate neurons and the IG 16 as an array of separate neurons.” EX1006, 11:1-3, 11:14-17, Fig. 2. “The PA 12 is

a two-layer architecture as described above, consisting of novum 14 and the IG 16, this architecture being somewhat similar to that illustrated in Figure 5.”

EX1006, 29:10-13, Fig. 5.



Lawrence, Fig. 5 (annotated).

47. As discussed below, it would have been obvious to a POSITA to use a neural network architecture designed to perform adaptive, continuous Bayesian estimation, as taught by Lawrence, to calculate the target detection threshold of Barnard that is determined “in accordance with Baye’s criterion.”

EX1016, 6:35-40.

## IX. SUMMARY OF OPINIONS

48. It is my opinion that claims 1-3, 6, and 7 of the '639 Patent are

obvious over Barnard.

**49.** It is my opinion that claim 7 is obvious over Barnard in view of Knecht.

**50.** It is my opinion that claims 1-7 are obvious over Barnard in view of Lawrence.

**51.** It is my opinion that claim 7 is obvious over Barnard in view of Lawrence and Knecht.

## **X. ANALYSIS OF UNPATENTABILITY**

**52.** I have been asked to provide my opinion as to whether the Challenged Claims of the '639 Patent would have been obvious in view of the prior art. The discussion below provides a detailed analysis of how the prior art references identified below teach the limitations of the Challenged Claims of the '639 Patent.

**53.** As part of my analysis, I have considered the scope and content of the prior art and any differences between the claimed invention and the prior art. I describe in detail below the scope and content of the prior art, as well as any differences between the claimed invention and the prior art, on an element-by-element basis for each Challenged Claim of the '639 Patent.

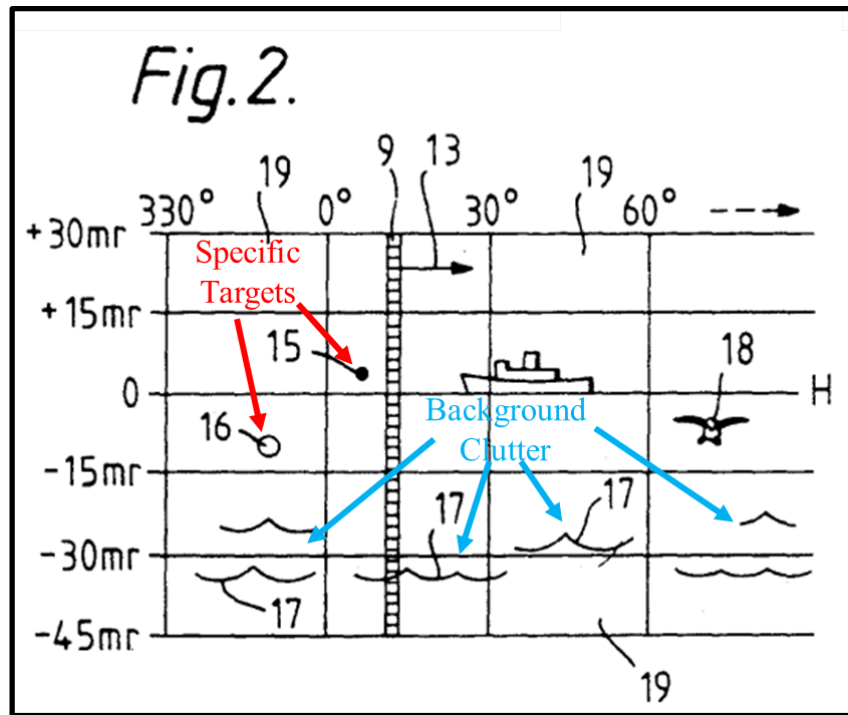
**A. Ground 1: Claims 1-3, 6, and 7 are obvious over Barnard**

**1. Claim 1**

**[1.0] *A method for distinguishing targets from background clutter, comprising the steps of***

**54.** Barnard discloses or renders obvious element [1.0].

**55.** Barnard teaches a method for distinguishing targets from background clutter. For example, Barnard discloses a “target detection system ... for **examining picture signals of a scene** which may contain a **target signal (15,16) to be detected against background signals (17,18).**” EX1005, Abstract; *see also* 1:1-10. Barnard’s system “**effectively separates target objects from background objects,**” as shown in Fig. 2 below. EX1005, 5:16-17. Operation of Barnard’s target detection system performs a method of distinguishing targets from background clutter.



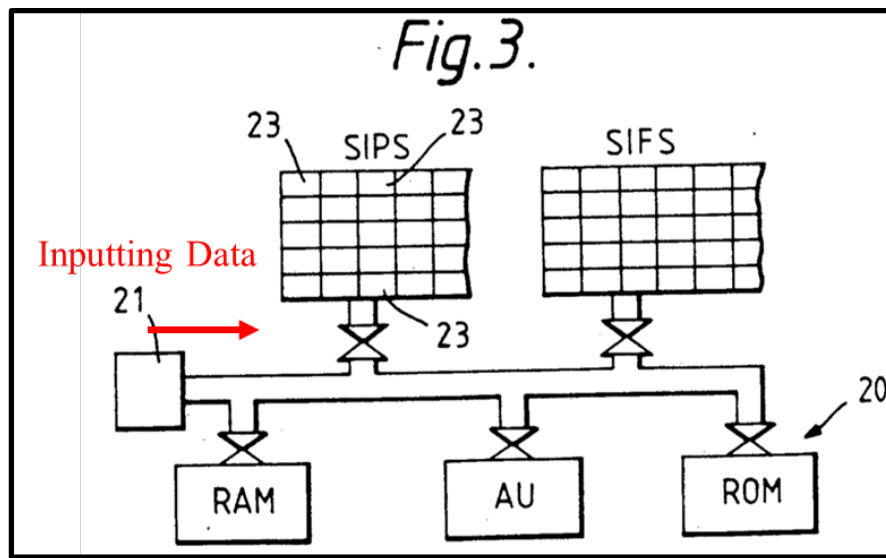
Barnard, Fig. 2 (annotated).

56. Accordingly, Barnard discloses *a method for distinguishing targets from background clutter*.

[1.1] (a) *inputting data*;

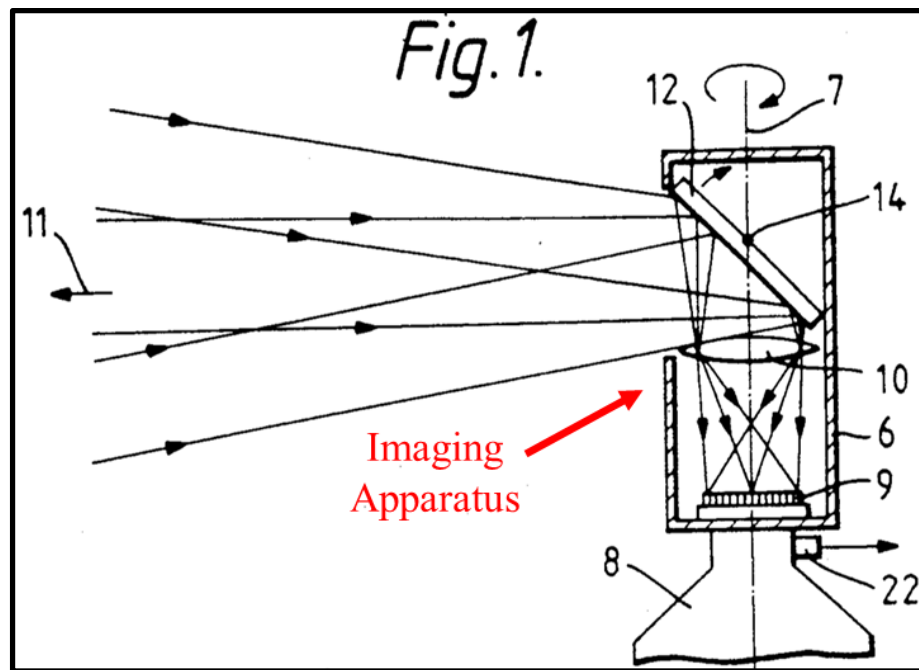
57. Barnard discloses or renders obvious element [1.1].

58. Barnard teaches inputting data. For example, Barnard describes “a digital computer 20 ... **receive[s] the stream of digitised pixel values** from a signal pre-processing unit 21.” EX1005, 4:19-21.



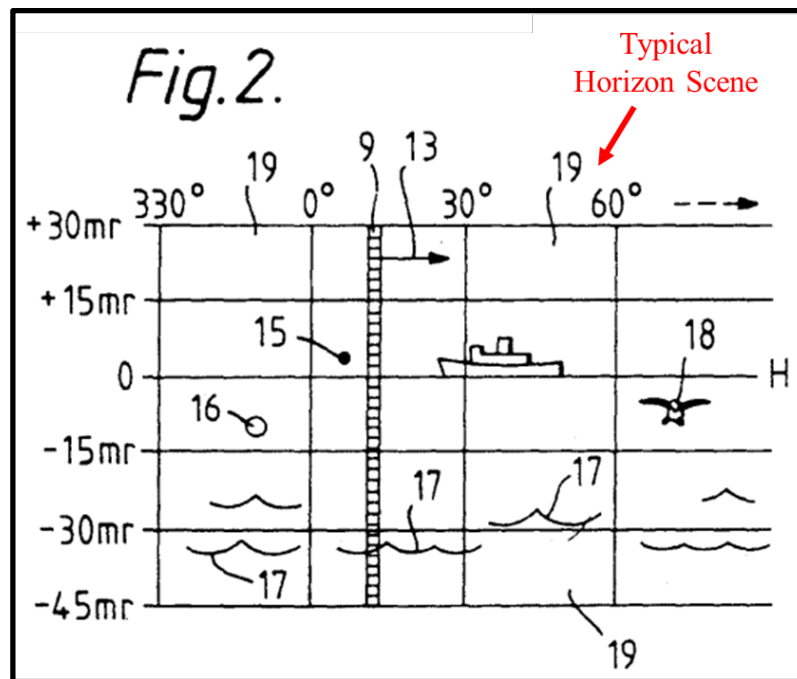
Barnard, Fig. 3 (annotated).

59. Barnard explains the digitized pixel values are based on images obtained by “a thermal imaging apparatus.” EX1005, 3:5-11 (“Referring to FIG. 1, there is shown the optical and mechanical components, in schematic form, of a thermal imaging apparatus which is provided as a means of observation, typically set high in the superstructure of a ship, to watch for hostile incoming missiles, aircraft, etc.”); 3:42-59 (describing how each detector is utilized to provide pixel values for a whole horizon image that are retained in a store and utilized for the target detection process).



Barnard, Fig. 1 (annotated).

60. Barnard further describes “**examining picture signals of a scene** which may contain a target signal (15,16) to be detected against background signals (17,18).” EX1005, Abstract. Barnard explains that the “**picture signals represent[] an image of a scene.**” EX1005, 1:7-8. In this regard, the image may be a two-dimensional image of “a typical horizon scene,” as shown in Fig. 2.



Barnard, Fig. 2 (annotated).

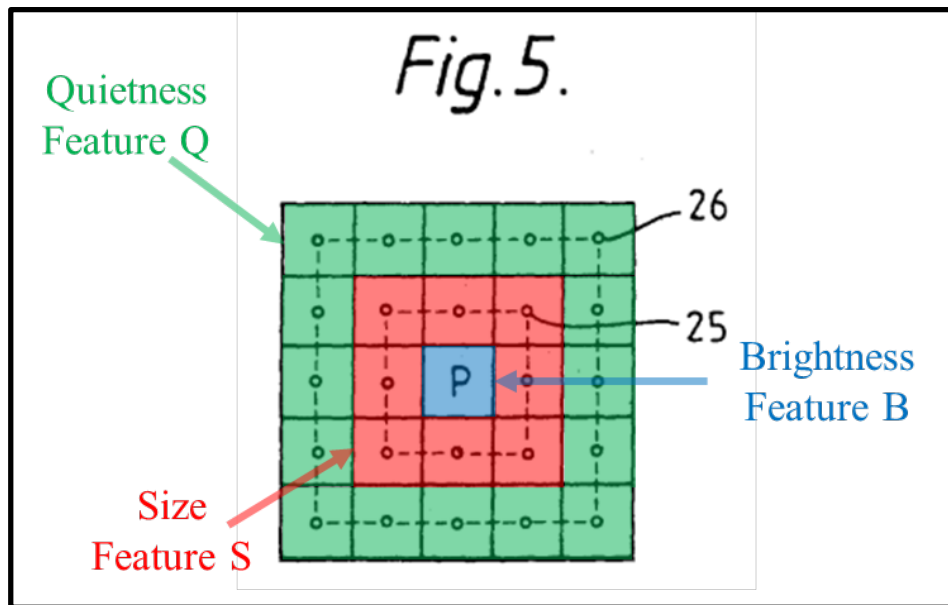
61. Accordingly, Barnard discloses *inputting data* (e.g., inputting the stream of digitized pixel values or picture signals representing an image of a scene to the digital computer).

**[1.2] (b) calculating data statistics from said data and using said data statistics to select target specific feature information to distinguish specific targets from background clutter;**

62. Barnard discloses or renders obvious element [1.2].

63. As discussed in [1.1], Barnard teaches *inputting data* (e.g., inputting the stream of digitized pixel values or picture signals). Barnard further describes calculating various data statistics for features from the input image data, including “brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther

features” that “may indicate shape, width, height, symmetry or lack of symmetry.” EX1005, 2:9-27; 4:50-5:1; 4:46-49 (“FIG. 5 shows the square array of 24 pixels surrounding each pixel P in each of the sub-image pixel stores SIPS, each square indicating a storage location holding a pixel value. Assuming P to be a non-zero value, P will usually be surrounded by other non-zero pixels.”); 5:2-3 (“several features can be calculated and each will have a numerical value in a range of values.”).



Barnard, Fig. 5 (annotated).

**64.** Barnard teaches calculating data statistics for the various features (“brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features”) from the input image data. *See, e.g.*, EX1005, 2:30-36; 5:36-49; 6:62-68. For example, Barnard teaches calculating data statistics in multiple ways,

including:

- (1) calculating the width of the statistical distributions of features of the image data; and
- (2) calculating the progressive means and associated variances of features of the image data. EX1005, 2:30-36; 5:36-49; 6:62-68.

**65.** Barnard teaches using the calculated data statistics (e.g., “width of the statistical distributions,” “progressive means,” “variances,” and/or “statistical information”) to select target specific feature information, and more specifically, to select the set of features and an associated target detection threshold used to distinguish specific targets from background clutter. EX1005, 2:30-36; 5:36-66; 6:62-68.

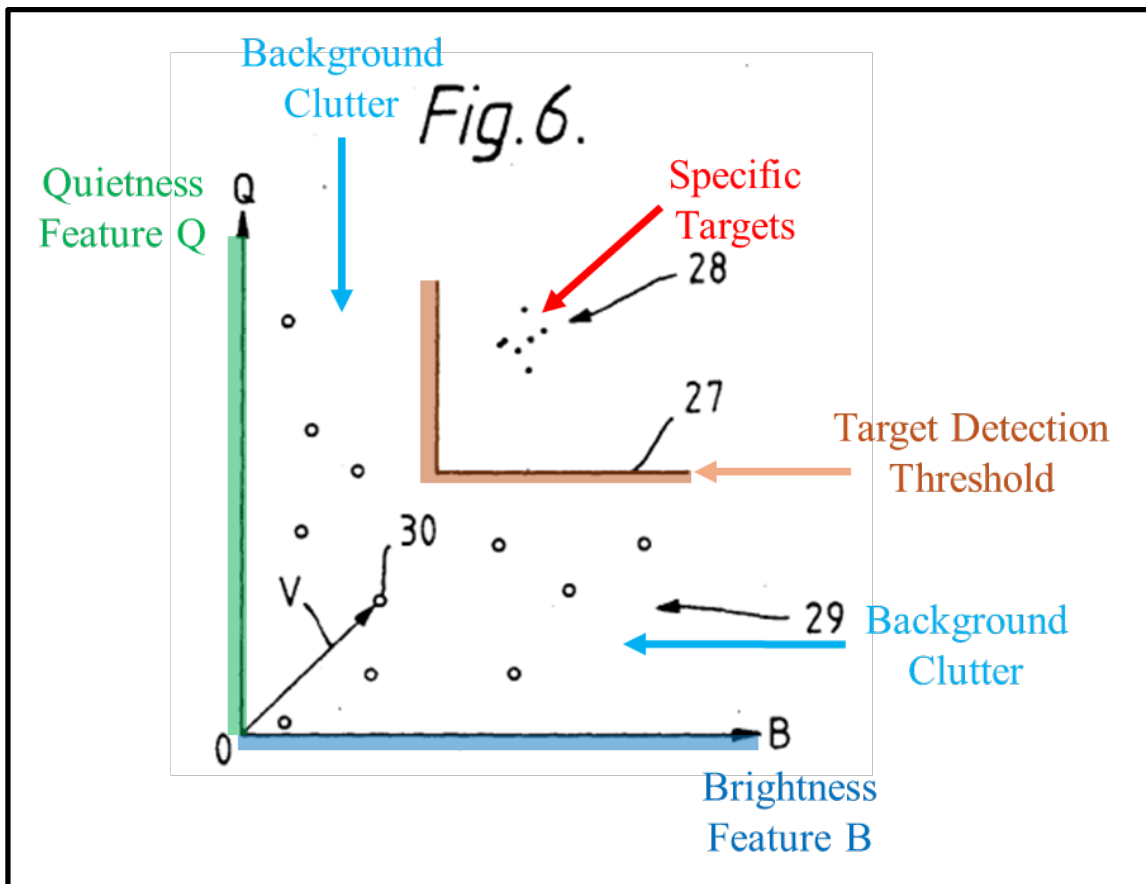
**66.** For example, Barnard describes using the calculated width of the statistical distributions of features to select which features are used to distinguish specific targets from background clutter. Barnard discloses **“calculat[ing] the width of the statistical distributions of the background and target features.”** EX1005, 2:28-34. The statistical distribution and its associated width are data statistics calculated from the input image data. Barnard further describes **“discard[ing] a feature as a threshold parameter if the width of the statistical distribution of that feature exceeds a predetermined amount.”** EX1005, 2:28-

34. Barnard explains that if a feature has “[too] wide a spread,” then it “may be unreliable as a guide to discriminating between background and target features.” EX1005, 2:36-39. In discarding or excluding features that have a statistical distribution width exceeding a predetermined amount, Barnard is selecting features (i.e., the remaining features not excluded) that are used to distinguish specific targets from background clutter.

67. As another example, Barnard teaches using the calculated progressive means of features to select which features are used to distinguish specific targets from background clutter. Barnard discloses “**calculating the progressive means of each feature.**” EX1005, 5:34-38. The means of each feature are data statistics calculated from the input image data. Barnard further describes discarding the feature “**if the feature mean varies by more than a preset amount** over a succession of scene images.” 2:34-36. In discarding or excluding one or more features that have a mean that varies by more than the preset amount, Barnard is selecting features (i.e., the remaining features not excluded) that are used to distinguish specific targets from background clutter.

68. Barnard goes on to explain that “A **selection of features** can usually be found in which it is possible to place a **threshold hypersurface** in the feature space which **effectively separates target objects from background objects.** FIG.

6 illustrates this known approach using only two features B and Q, but only for clarity of drawing.” EX1005, 5:13-19. The threshold hypersurface is an example of a target detection threshold. EX1005, 1:18-21, 5:13-19. Barnard explains that the “target detection threshold” is generated “from the **statistical information**” and is located “at the intersection of the two probability surfaces, i.e. where the probabilities of an object being a target or a background point are equal, that is, in accordance with Baye’s criterion.” EX1005, 5:59-66.

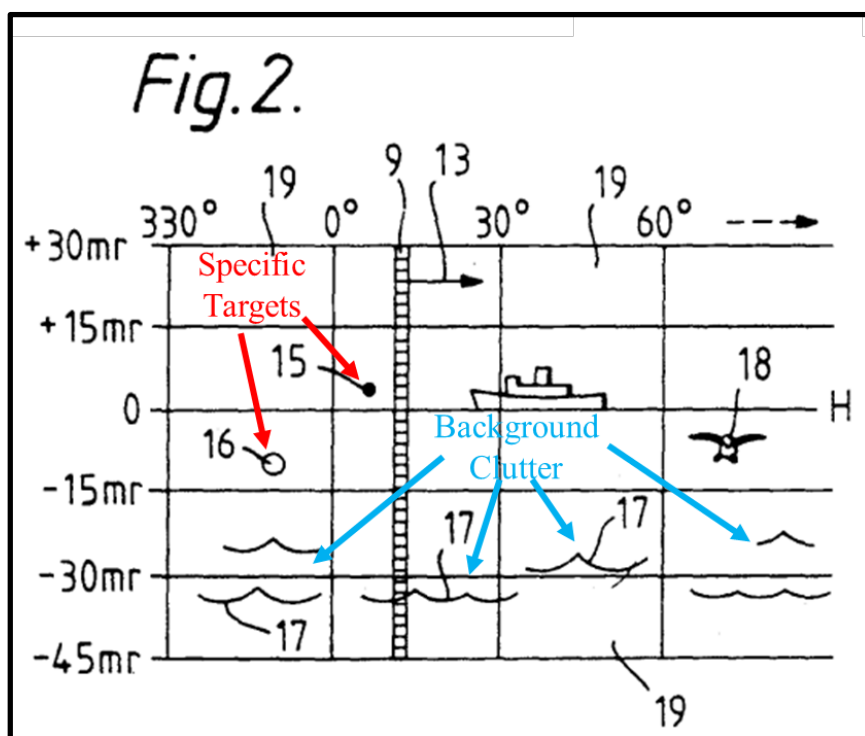


Barnard, Fig. 6 (annotated).

69. In this manner, Barnard uses the calculated data statistics to select

target specific feature information—the set of features and associated target detection threshold—used to distinguish specific targets from background clutter.

70. As shown and described in the context of Fig. 2, Barnard provides the specific example of distinguishing specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., a sea-skimming missile), from background clutter, such as wave crests 17. EX1005,1:24-36, 3:34-41.



Barnard, Fig. 2 (annotated).

The wave crests in Barnard are an example of background clutter analogous to the trees or tree lines provided as an example of background clutter in the '639 Patent. See EX1001, Fig. 11, 7:33-37, 10:26-30; EX1005, Fig. 2, 3:34-41. Further, Barnard discloses distinguishing specific targets, not just any targets, from the

background clutter by distinguishing intended targets, such as point source 15 or sea-skimming source 16 (e.g., such as a sea-skimming missile), from other potential targets, such as a seagull 18. EX1005, 3:34-41; Fig. 2.

71. The selected features and associated target detection threshold of Barnard used to distinguish specific targets from background clutter are separately, and collectively, “*target specific feature information*” as claimed by the ’639 Patent. In other words, (1) the set of features, (2) the target detection threshold associated with the set of features; and/or (3) the combination of the set of features with the associated target detection threshold are “*target specific feature information*” as claimed by the ’639 Patent.

72. The use of the phrase “*target specific feature information*” in the ’639 Patent is limited and largely mirrors the claim language. Notably, “*target specific feature information*” is not used in the “DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS” section of the ’639 Patent. *See* EX1001, 7:12-11:67. However, the ’639 Patent indicates to a POSITA that “*target specific feature information*” can at least include information related to target specific feature(s) used to distinguish a target from background clutter, including the type(s) of target specific features, value(s) and/or threshold(s) for the type(s) of target specific feature(s), other information related to the target specific feature(s),

and/or combinations thereof. EX1001, 5:15-30; 5:55-6:2; 7:15-29; 7:46-57.

73. With respect to the types of target specific features used to distinguish a target from background clutter, the '639 Patent explains “**a set of distinguishing target characteristics**”<sup>1</sup> may be used to distinguish a target from background clutter. EX1001, 5:55-62 (“us[ing] a variation of the Hebbian learning algorithm and recently discovered relationships between neural network Hebbian learning algorithms and statistically-based principal component analysis to generate **a set of distinguishing target characteristics** pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.”).

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<sup>1</sup> In some instances, the '639 Patent refers to the target characteristics or target specific features as “principal components,” “receptive features,” or “principal component features.” EX1001, 7:54-56 (“The generalized Hebbian Learning algorithm generates principal components or receptive features.”); 8:45-47 (“[T]he principal components generally correspond to prominent intensity patterns or features in the object of interest.”); 8:52-54 (“The generated principal components are arrayed in rxs matrices to produce receptive fields or filters that are convolved with the original image data during classification.”); 9:60-63 (“The inventor then used this definition to measure the capability of the principal component features to distinguish targets from objects similar in appearance.”).

That is, the '639 Patent also describes using a set of characteristics or target specific features to distinguish specific targets from background clutter.

74. The '639 Patent also notes that “*target specific feature information*” may include different types of characteristics or features, including “contrast-based” and “texture-based.” EX1001, 5:15-49 (“select **target specific feature information (e.g., contrast-based and texture-based)** to distinguish specific targets from background clutter”). The various features (“brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features”) described by Barnard include contrast-based and texture-based features, consistent with the examples in the '639 Patent. EX1005, 4:46-5:3; Fig. 5; *see also* EX1007, 5:26-29 (“In general, **texture of a scene, image or object can be defined as the spatial variation or distribution of tonal or intensity values of picture elements**, wherein the spatial variation extends over a given area.”).

75. Further, the '639 Patent indicates the target specific feature information may be used “to distinguish specific targets from background clutter” using techniques such as “parametric and non-parametric techniques and one-class, two-class, or multi-class classification procedures.” 5:27-29. These disclosed examples are common data processing techniques that utilize values for the selected target specific features to distinguish targets from background clutter.

EX1006, 45:15-25 (describing “automatic target recognition” using a “Parametric Avalanche” approach); EX1008, 23:59-24:2 (describing a “target classification approach” based on a non-parametric estimation technique). For example, as described in the ’639 Patent—as well as Barnard—the values of the selected target specific features may be utilized to distinguish targets from background clutter in an image. EX1001, 5:15-30, 5:55-62; EX1005, 5:3-17. In this regard, as further discussed in the analysis of element [1.4], below, the values of the selected target specific features extracted from a region of interest of an image may indicate the region of interest contains a target or may indicate the region of interest contains background clutter. EX1001, 5:15-30, 5:55-62, 8:35-38, 8:57-60; EX1005, 5:3-17; 6:11-15.

76. Thus, Barnard teaches *calculating data statistics* (e.g., “width of the statistical distributions” of features and/or “progressive means” of features, such as brightness feature B, size feature S, quietness feature Q, and other features and/or “statistical information”) *from said data* (e.g., the input image data (stream of digitized pixel values or picture signals)) *and using said data statistics to select target specific feature information to distinguish specific targets from background clutter* (e.g., selecting the set of features and an associated target detection threshold used to distinguish specific targets from background clutter by excluding features whose width of statistical distribution exceeds a predetermined amount or

whose mean varies by more than a preset amount and/or using statistical information).

77. Accordingly, Barnard discloses *calculating data statistics from said data and using said data statistics to select target specific feature information to distinguish specific targets from background clutter.*

**[1.3] (c) *generating said target feature information from said data statistics;***

78. Barnard discloses or renders obvious element [1.3].

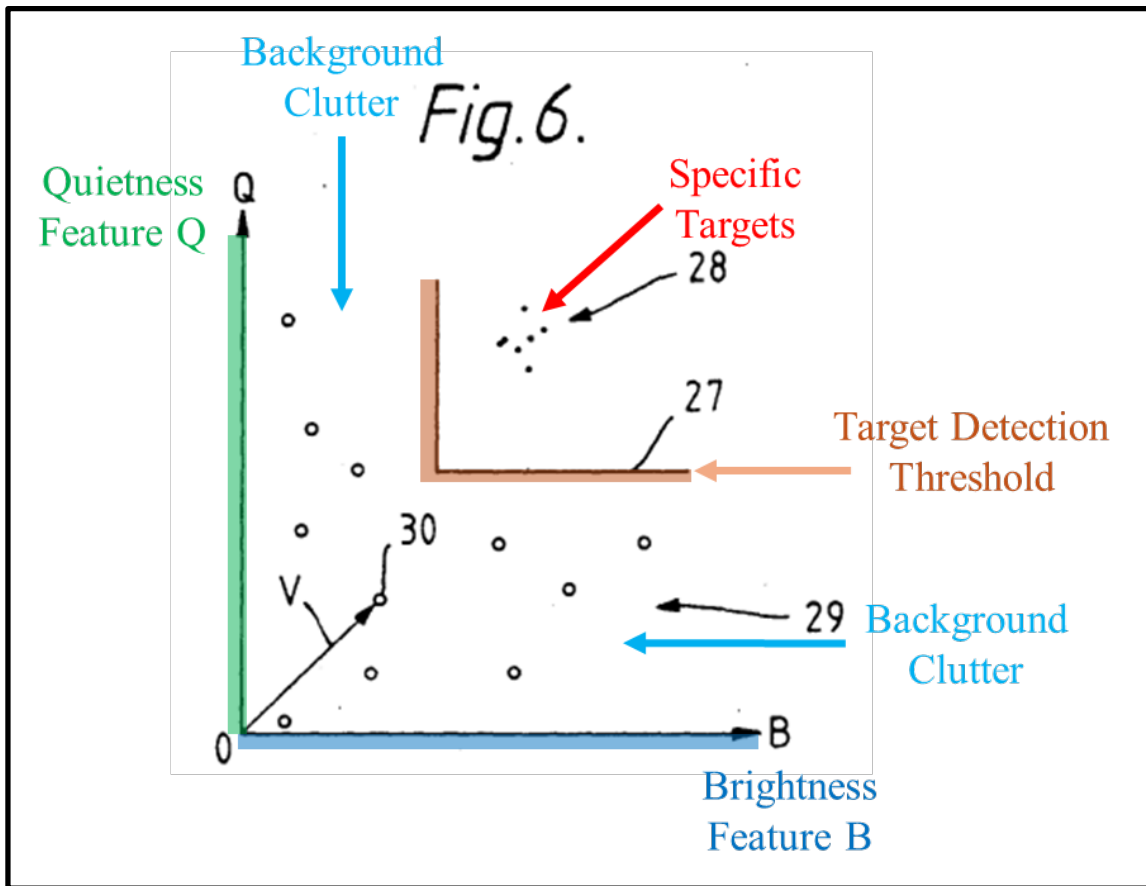
79. As an initial matter, I note that [1.3] recites “*target feature information,*” not “*target **specific** feature information*” as used in [1.2]. I also understand from counsel that the use of “*said*” in a patent claim indicates reference to an element that was previously introduced in the claim. However, there is no prior (or subsequent) use of “*target feature information*” in claim 1. Also, I did not find any use of “*target feature information*” in the ’639 Patent outside of the claims. *See*, EX1001, 1:1-11:67. In the ABSTRACT and SUMMARY OF THE INVENTION sections, the ’639 Patent describes “generating the target **specific** feature information from the data statistics.” EX1001, Abstract, 5:23-25, 5:41-42. Accordingly, for the purpose of this declaration, I am treating “*said target feature information*” recited in [1.3] as referring to the “*target **specific** feature information*” recited in [1.2], as well as [1.4] and [1.5].

**80.** The '639 Patent describes “generating target specific feature information” includes “generat[ing] a set of distinguishing target characteristics pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.” EX1001, 5:59-62. The '639 Patent also describes that the target specific feature information generated may include “principal components or receptive features.” EX1001, 7:55-56, 8:32-67.

**81.** Similarly, Barnard teaches generating, based on data statistics, the target specific feature information used to distinguish specific targets from background clutter. More specifically, Barnard teaches generating the set of selected features and associated target detection threshold for distinguishing specific targets from background clutter based on data statistics calculated from the input image data.

**82.** For example, Barnard describes that “[a] selection of features can usually be found in which it is possible to **place a threshold hypersurface in the feature space which effectively separates target objects from background objects.**” EX1005, 5:13-17. Barnard further explains the “target detection threshold” for a set of features is generated “from the **statistical information**” and is located “at the intersection of the two probability surfaces, i.e. where the probabilities of an object being a target or a background point are equal, that is, in

accordance with Baye's criterion." EX1005, 5:59-66. In this regard, once the set of features is selected (e.g., as discussed in element [1.2]), Barnard determines a target detection threshold (e.g., threshold hypersurface) for the selected set of features. EX1005, 5:13-17. In calculating the target detection threshold based on statistical information, Barnard is generating target specific feature information based on data statistics. Barnard notes that "FIG. 6 illustrates this known approach using only two features B and Q" and "[e]ach plotted set of features for an object, 30 for example, can be regarded as a vector V plotted in the hyperspace, target and background vectors being separated by the threshold hypersurface 27." EX1005, 5:13-19, 25-28.



Barnard, Fig. 6 (annotated).

**83.** Further, as also shown in Fig. 6, Barnard generates a set of features (e.g., Brightness Feature B and Quietness Feature Q) corresponding to the selected set of features. EX1005, 5:13-17, Fig. 6. As discussed in the [1.2] analysis above, Barnard teaches using the calculated data statistics (e.g., “width of the statistical distributions,” “progressive means,” and/or “statistical information”) to select the set of features, including excluding from the set of features any features whose width of statistical distribution exceeds a predetermined amount or whose mean varies by more than a preset amount, such that the generated set of features is

generated from the data statistics. EX1005, Fig. 6.

**84.** In this manner, Barnard teaches using the calculated data statistics to generate target specific feature information—the set of features and associated target detection threshold—used to distinguish specific targets from background clutter. Consistent with the '639 Patent, the generated set of selected features and associated target detection threshold define the principal features for separating specific targets from background clutter. *See* EX1001, 5:55-62, 7:55-58, 8:45-51; EX1005, 5:3-28.

**85.** Accordingly, generating the set of features and associated target detection threshold in Barnard is generating target specific feature information from the data statistics. More specifically, generating one or more of (1) the set of features, (2) the target detection threshold associated with the set of features; and/or (3) the combination of the set of features with the associated target detection threshold is “*generating said target [specific] feature information from said data statistics*” as claimed by the '639 Patent.

**86.** Thus, Barnard teaches *generating said target [specific] feature information from said data statistics* (e.g., generating the set of selected features and associated target detection threshold from the calculated data statistics (e.g., width of the statistical distributions of features, progressive means of features,

and/or statistical information)).

87. Accordingly, Barnard discloses *generating said target feature information from said data statistics*.

[1.4] (d) *extracting said target specific feature information from said data;*

88. Barnard discloses or renders obvious element [1.4].

89. Barnard teaches extracting target specific feature information from the input image data. For example, Barnard teaches the set of selected features and associated target detection threshold used to distinguish specific targets from background clutter are extracted from the input image data.

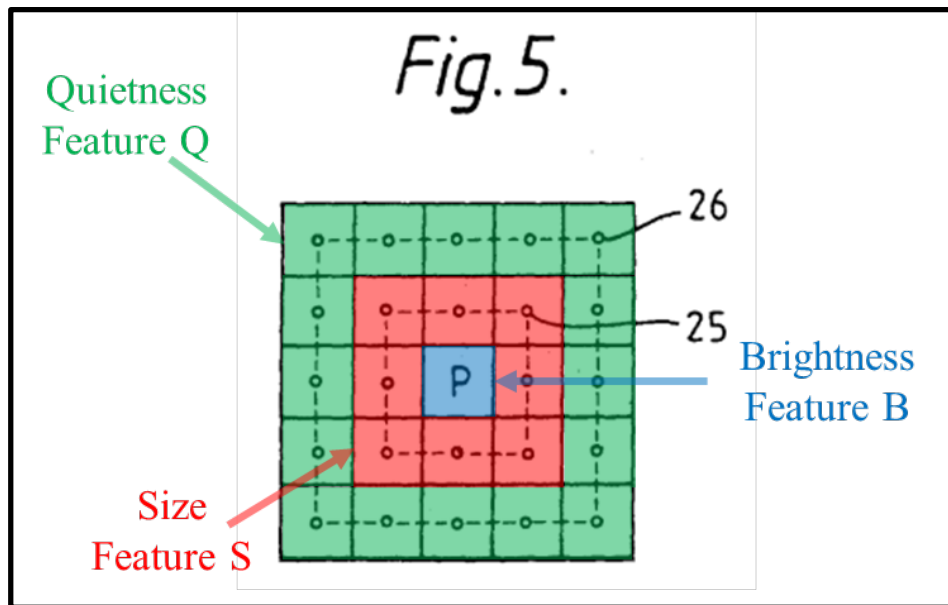
90. In the context of performing the selecting and generating aspects of [1.2] and [1.3], Barnard explains how the features included in the set of selected features are extracted from the input image data and how the associated target detection threshold for the set of selected features is extracted from the input image data. EX1005, 5:2-3 (“Thus **several features can be calculated and each will have a numerical value** in a range of values.”); 5:13-17 (“A **selection of features** can usually be found in which it is possible to **place a threshold hypersurface in the feature space which effectively separates target objects from background objects.**”); 5:59-66 (“**The location of the target detection threshold is calculated** at the intersection of the two probability surfaces, i.e. where the probabilities of an

object being a target or a background point are equal, that is, in accordance with Baye's criterion.""). For example, the set of selected features may be extracted from the input image data by calculating numerical values of the selected features of the image data. EX1005, 2:28-39, 5:13-17, 5:36-49, 6:62-68.

**91.** Further, the target detection threshold for the set of selected features is also extracted from the input image data. In this regard, Barnard explains that the target detection threshold may be extracted from the input image data by finding "the intersection of the two probability surfaces, i.e. where the probabilities of an object being a target or a background point are equal, that is, in accordance with Baye's criterion." EX1005, 5:59-66. Because the target detection threshold is determined from the input image data, the target detection threshold is extracted from the input image data.

**92.** In addition, consistent with the '639 Patent, Barnard also teaches extracting target specific feature information from the input image data when Barnard describes calculating values for each of the features from the input image data. *See* EX1001, 7:17-22. For example, Barnard describes that "[e]ach object detected in a sub-image has its features calculated." EX1005,6:1-2. Barnard notes that "several features can be calculated and each will have a numerical value in a range of values." EX1005,5:2-3. In this regard, Barnard describes

calculating various features from the input image data, including “brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features” that “may indicate shape, width, height, symmetry or lack of symmetry,” as shown in Figs. 5-6. EX1005,4:50-5:1, 4:46-49 (“FIG. 5 shows the square array of 24 pixels surrounding each pixel P in each of the sub-image pixel stores SIPS, each square indicating a storage location holding a pixel value. Assuming P to be a non-zero value, P will usually be surrounded by other non-zero pixels.”).



Barnard, Fig. 5 (annotated).

93. Accordingly, calculating values for each of the features and determining the set of features and associated target detection threshold for distinguishing targets from background clutter from the input image data as described in Barnard are extracting target specific feature information from the

input image data. More specifically, extracting one or more of (1) the set of features, (2) the target detection threshold associated with the set of features; (3) the combination of the set of features with the associated target detection threshold, and/or (4) values for each of the features is “*extracting said target specific feature information from said data*” as claimed by the ’639 Patent.

94. Thus, Barnard teaches *extracting said target specific feature information from said data* (e.g., determining or calculating the values of the features, the set of features, and/or the target detection threshold from the input image data).

95. Accordingly, Barnard discloses *extracting said target specific feature information from said data*.

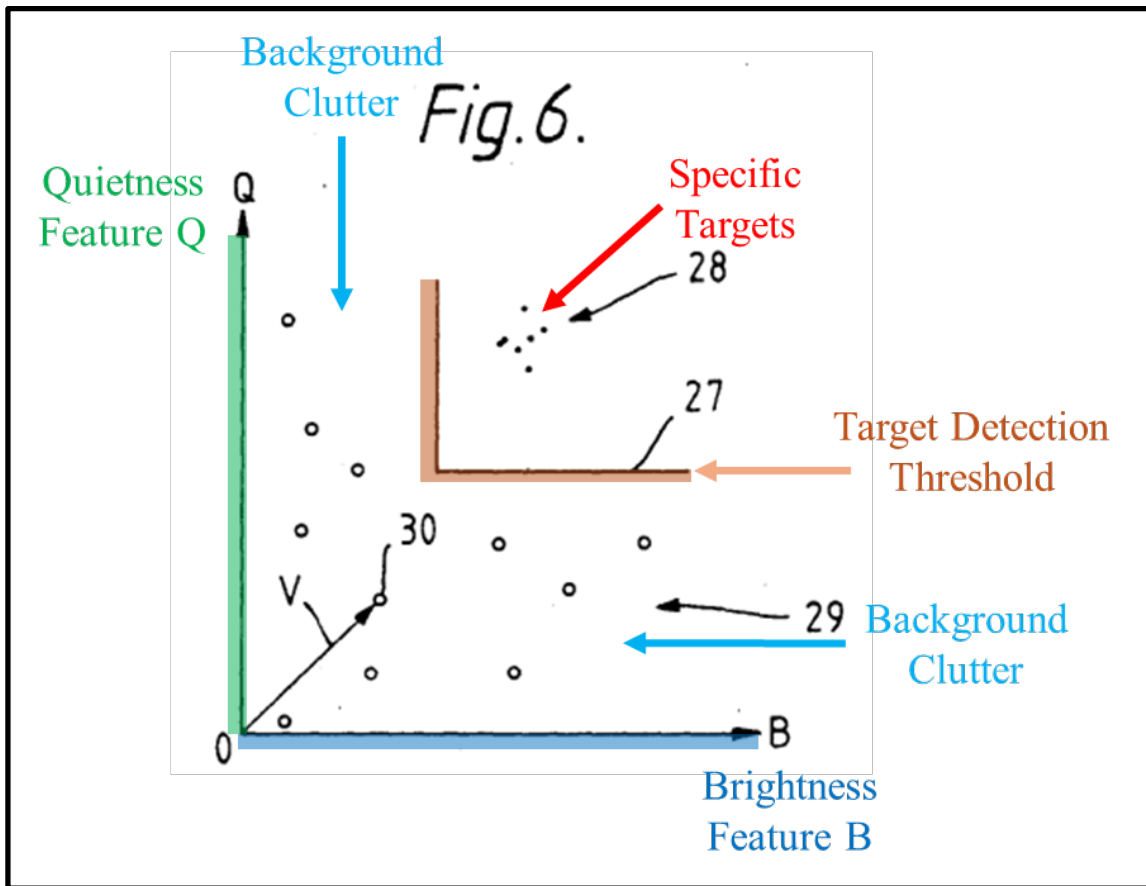
**[1.5] (e) using said target specific feature information to distinguish specific targets from background clutter; and**

96. Barnard discloses or renders obvious element [1.5].

97. Barnard teaches using the target specific feature information, and more specifically, the set of selected features and associated target detection threshold, to distinguish specific targets from background clutter. For example, Barnard describes “**comparing the feature values of an incoming picture signal with the threshold to detect a target.**” EX1005, 1:21-23, *see also* 6:57-60 (“comparing feature values of an incoming picture signal in a sub-image with the

target decision threshold in the associated sub-store to detect a target.”). Barnard explains that incoming picture signal “may contain **a target signal to be detected against background signals.**” EX1005, 1:9-10. For the incoming picture signal, Barnard calculates feature values for each of the features included in the set of selected features used to distinguish specific targets from background clutter. EX1005, 4:50-5:1. Barnard then compares the calculated feature values of the incoming image to the target detection threshold associated with the set of selected features. EX1005, 1:21-23. The “target detection threshold” “effectively separates target objects from background objects.” EX1005, 5:13-17. Accordingly, by comparing the calculated feature values of the incoming image to the target detection threshold associated with the set of selected features, Barnard detects either a specific target or background clutter, thereby distinguishing specific targets from background clutter. EX1005, 5:13-28.

**98.** Fig. 6 of Barnard, reproduced below, shows an example of using a set of selected features—made up of the brightness feature B and the quietness feature Q—and an associated target detection threshold 27 to distinguish specific targets from background clutter.

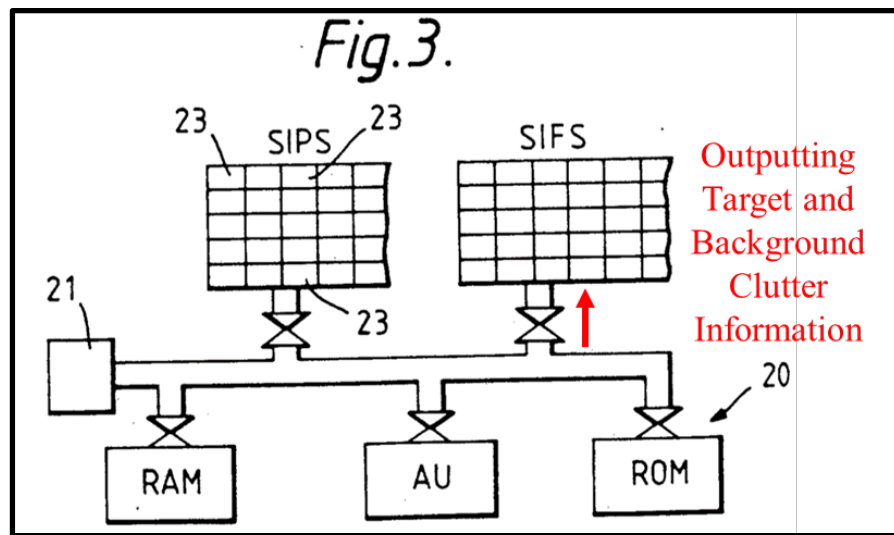


Barnard, Fig. 6 (annotated).

99. Fig. 2 shows an example of a real-world application of using a set of selected features and an associated target detection threshold to distinguish specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), from background clutter, such as wave crests 17. EX1005, 1:24-36, 3:34-41. Fig. 2 also illustrates that the specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), are distinguished from other potential targets, such as a seagull 18.



for carrying out the programme steps, and a random access memory RAM for storing intermediate results obtained during the programme calculations,” may output target and background clutter information to a “sub-image feature store SIFS.” EX1005,4:19-34, 1:53-57; *see also* Abstract (“The values of a set of features, such as brightness, volume or quietness, of the background and target picture signals associated with each sub-image in the respective sub-store are calculated and stored.”). Barnard explains that the “sub-image feature store SIFS is provided to store information about features of detected objects.” EX1005,4:32-34. More specifically, Barnard teaches “**storing the calculated values of the set of features of the background and target picture signals** associated with each sub-image in the respective sub-store.” EX1005,1:53-57. When the computer outputs the calculated feature values of the background and target picture signals to the SIFS, Barnard is outputting target and background clutter information.



Barnard, Fig. 3 (annotated).

**104.** With respect to “*outputting*” the ’639 Patent consistently refers to communications between components within the target recognition system as being “*outputted*” from a component. EX1001, 2:47-52 (“Referring to FIG. 2, ... signals are inputted through communication links 2 which direct the input signals, flow through the communication links 6 to the neurons 4 in the neural network in a layer-by-layer fashion, and **outputted through the communications links 8 which direct the output signals.**”), 3:2-4 (“Input voltages  $V_1, V_2, V_3, \dots V_N$  are received from other neurons and **output voltage  $V_i$  is outputted to other neurons.**”), 12:38-45 (“... said data statistics outputted from said calculator ...”), *see also* 7:16-22 (“As shown in FIG. 10, the classification system inputs the data in module 2, extracts feature information from the inputted data in module 4 and inputs the feature information into the classification module 6 which uses decision

criteria 12 to classify the target from background clutter and **outputs this information in module 8.**”), 5:55-58 (“FIG. 3 shows an example of this type of network, wherein all neurons 4 are connected to all other neurons 4 through corresponding communication linkS 6 with input and **output communication links** as shown.”). Therefore, when the computer communicates the calculated feature values of the background and target picture signals to the SIFS, the system of Barnard is “*outputting*” target and background clutter information as required by [1.6].

**105.** Thus, Barnard teaches *outputting target and background clutter information* (e.g., outputting the calculated feature values of the background and target picture signals from the computer to the sub-image feature store (SIFS)).

**106.** Accordingly, Barnard discloses *outputting target and background clutter information*.

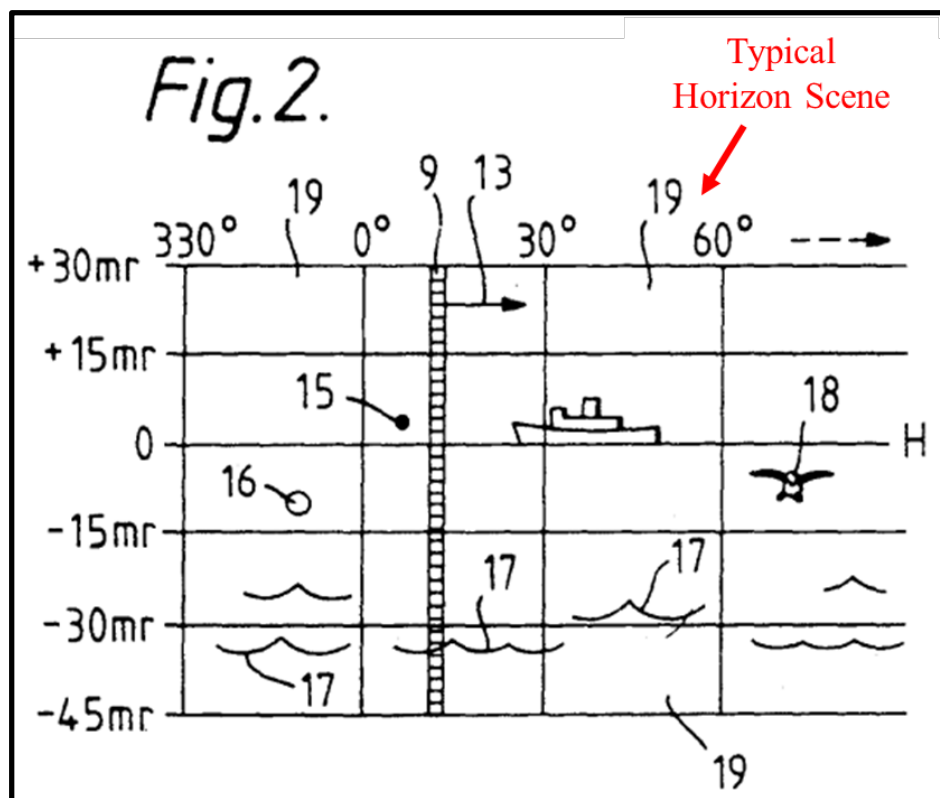
## **2. Claim 2**

**[2.0]** *The method of claim 1, wherein said data is one-dimensional, two-dimensional, or multi-dimensional.*

**107.** Barnard discloses or renders obvious element [2.0].

**108.** As discussed in [1.1], Barnard teaches inputting data such as a “stream of digitized pixel values” or “picture signals” that includes two-dimensional data. In this regard, Barnard explains that the “picture signals

represent[] an image of a scene.” 1:7-8. Barnard provides a specific example in Fig. 2 showing a two-dimensional image of “a typical horizon scene.” EX1005, 2:59-61. Accordingly, the stream of digitized pixel values or picture signals associated with the horizon scene are an example of the data being two-dimensional.



Barnard, Fig. 2 (annotated).

109. Related, Barnard notes that the digitized pixel values are “retained in a store preserving their relative positions.” EX1005, 3:56-57. In this regard, a POSITA understands that Barnard’s description of preserving “the relative positions” of the pixel values is in the context of the two-dimensional image of the

horizon scene. That is, Barnard teaches the pixel values are stored in a manner that retains the relative positions of the pixels in the two-dimensional image. EX1005, 3:56-57.

**110.** Accordingly, Barnard discloses *wherein said data is one-dimensional, two-dimensional, or multi-dimensional* (e.g., the input image data (e.g., digitized pixel values or picture signals) is two-dimensional image data).

### **3. Claim 3**

**[3.0]** *The method of claim 1, wherein said data is digitized imagery, speech signals, or radar signals.*

**111.** Barnard discloses or renders obvious element [3.0].

**112.** As discussed in [1.1] and [2.0], Barnard teaches inputting data such as a “stream of digitized pixel values” or “picture signals” that includes two-dimensional image data. In this regard, Barnard explains that the “picture signals represent[] an image of a scene.” 1:7-8. Barnard provides a specific example in Fig. 2 showing a two-dimensional image of “a typical horizon scene.” EX1005, 2:59-61. Accordingly, the stream of digitized pixel values or picture signals associated with the horizon scene are an example of the data being “*digitized imagery*.”

**113.** Accordingly, Barnard discloses *wherein said data is digitized imagery, speech signals, or radar signals*.

4. Claim 6

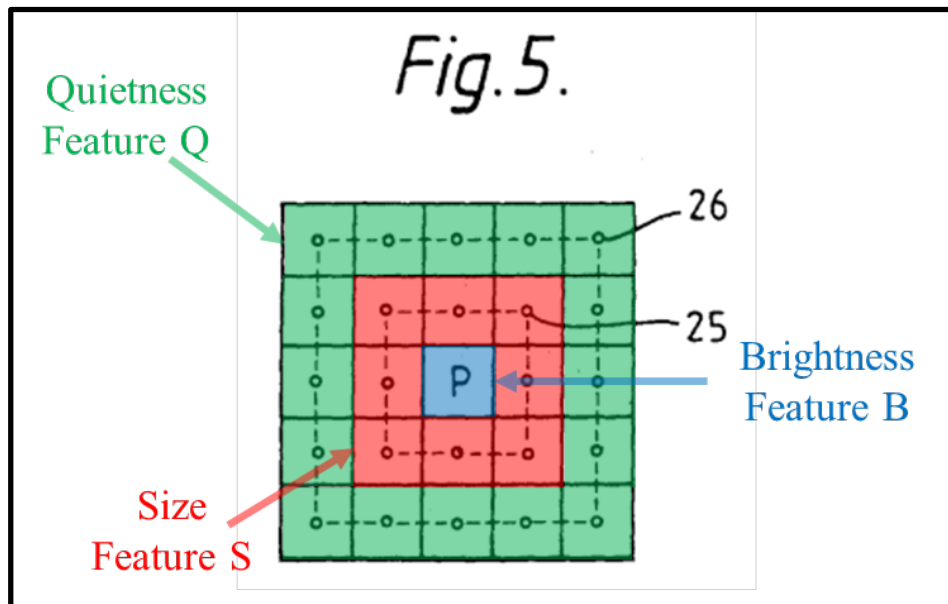
[6.0] *The method of claim 1, wherein said feature information is contrast-based or texture-based.*

114. Barnard discloses or renders obvious element [6.0].

115. As an initial matter, I note that [6.0] recites “*feature information*,” not “*target specific feature information*” as used in [1.2], [1.4], and [1.5] or “*target feature information*” as used in [1.3]. I also understand from counsel that the use of “*said*” in a patent claim indicates reference to an element that was previously introduced. However, there is no prior (or subsequent) use of “*feature information*”—without “*target specific*” or “*target*”—in claim 6 or claim 1 from which claim 6 depends. I found several instances of “*feature information*” in the ’639 Patent. *See, e.g.,* EX1001, 7:17-22 (“As shown in FIG. 10, the classification system inputs the data in module 2, extracts **feature information** from the inputted data in module 4 and inputs the **feature information** into the classification module 6 which uses decision criteria 12 to classify the target from background clutter and outputs this information in module 8.”), 7:37-39 (“Various procedures are used to extract **feature information** ....”). Accordingly, for the purpose of this declaration, I am treating “*said feature information*” recited in [6.0] as referring to the “*target specific feature information*” recited in claim 1.

116. As discussed in [1.2], Barnard discloses calculating various features

and associated data statistics, including “brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features” that “may indicate shape, width, height, symmetry or lack of symmetry.” EX1005, 2:9-27; 4:50-5:1; 4:46-49 (“FIG. 5 shows the square array of 24 pixels surrounding each pixel P in each of the sub-image pixel stores SIPS, each square indicating a storage location holding a pixel value. Assuming P to be a non-zero value, P will usually be surrounded by other none-zero pixels.”); 5:2-3 (“several features can be calculated and each will have a numerical value in a range of values.”).



Barnard, Fig. 5 (annotated).

117. A POSITA would have understood that “In general, texture of a scene, image or object can be defined as the spatial variation or distribution of tonal or intensity values of picture elements, wherein the spatial variation extends

over a given area.” EX1007, 5:26-29.

**118.** Barnard’s brightness feature B measures the level of brightness of the pixel value at the center of a given 25-pixel area. EX1005, 4:50-52, Fig .5; *see also* 2:9-11 (“picture elements which are each of more than a threshold level of brightness”). Quietness feature Q measures “the sum of the sixteen pixels 26 next surrounding the pixels 25” — i.e., the sixteen pixels with green highlighting in the annotated Fig. 5 above. EX1005, 4:62-66, Fig. 5. Thus, a POSITA would have understood that the combination of brightness feature B and quietness feature Q provide target specific feature information that is texture-based because it represents the spatial variation of pixel intensity values over a given area – namely, the variation between the center pixel (item P in Fig. 5 above) and the second ring of surrounding pixels (item 26 in Fig. 5 above). For example, relative to target decision thresholds for B and Q, there are at least four distinct types of texture: small B and small Q (bright pixel with dark pixels surrounding nearby), small B and large Q (dark pixel with bright pixels surrounding nearby), large B and small Q (bright pixel with dark pixels surrounding nearby), large B and large Q (bright pixel with bright pixels surrounding nearby). Further, a POSITA would have understood that the combination of brightness feature B and quietness feature Q provide target specific feature information that is contrast-based because it represents the level of difference between pixel intensity values between two areas

– i.e., between the center pixel and the second ring of surrounding pixels. For example, small B with large Q, or large B with small Q, represent larger contrast than small B with small Q, or large B with large Q.

**119.** A POSITA would have understood that Barnard’s B and Q features can be combined in this way because Barnard teaches the benefit of doing so. EX1005, 5:2-13 (“Thus several features can be calculated and each will have a numerical value in a range of values. For some features a high value may be more indicative of a target, whereas for other features a low value may indicate a target. For any one feature, the feature values of predetermined targets may lie in the range of values found for background objects and hence that feature alone is not sufficient to discriminate the target from the background. It is known to resolve this problem by taking the numerical values of a number of selected features for objects found in the image and plotting them in a multi-dimensional feature hyperspace.”); *see also* 6:22-33.

**120.** The various features (“brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features”) described by Barnard include target specific feature information that is contrast-based and texture-based, consistent with the examples in the ’639 Patent. EX1001, 5:15-49 (“select **target specific feature information (e.g., contrast-based and texture-based)** to distinguish

specific targets from background clutter”). EX1005, 4:46-5:3; Fig. 5; *see also* EX1007, 5:26-29 (“In general, **texture of a scene, image or object can be defined as the spatial variation or distribution of tonal or intensity values of picture elements**, wherein the spatial variation extends over a given area.”).

**121.** Thus, Barnard teaches *wherein said feature information is contrast-based or texture-based* (e.g., the set of selected features and associated target detection threshold are contrast-based and/or texture-based).

**122.** Accordingly, Barnard discloses *wherein said feature information is contrast-based or texture-based*.

## **5. Claim 7**

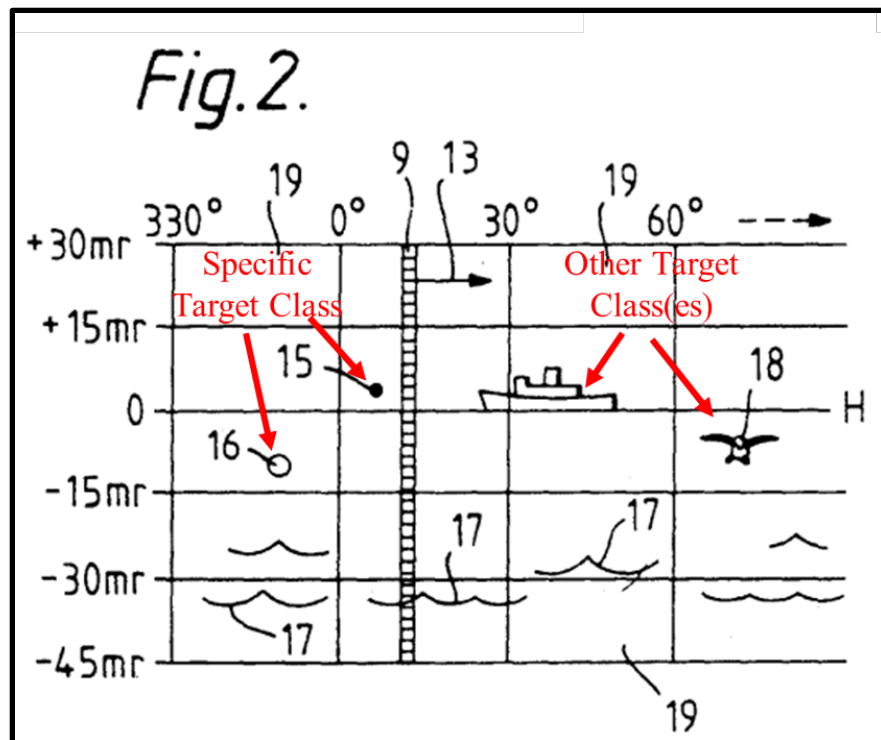
**[7.0]** *The method of claim 1, wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.*

**123.** Barnard discloses or renders obvious element [7.0].

**124.** As an initial matter, I note that [7.0], like [6.0], recites “*feature information*,” not “***target specific feature information***” as used in [1.2], [1.4], and [1.5] or “***target feature information***” as used in [1.3]. Accordingly, for similar reasons as discussed regarding [6.0], for the purpose of this declaration I am treating “*said feature information*” recited in [7.0] as referring to the “***target specific feature information***” recited in claim 1.

**125.** As discussed in [1.5], Barnard teaches using the target specific feature

information, and more specifically, the set of selected features and associated target detection threshold, to distinguish specific targets from background clutter. Beyond distinguishing specific targets from background clutter, Barnard further teaches using the target specific feature information to distinguish between at least two different target classes. For example, Fig. 2 shows an example of a real-world application of using a set of selected features and an associated target detection threshold to distinguish specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., a sea-skimming missile), from other potential targets, such as seagull 18 and a ship. EX1005, 1:24-36, 3:34-41.



Barnard, Fig. 2 (annotated).

**126.** In using the set of selected features and associated target detection

threshold to distinguish the point source 15 and the sea-skimming source 16 from the seagull 18 and the ship, Barnard is distinguishing at least two target classes (e.g., specific target class (including the point source 15 and/or the sea-skimming source 16 such as a sea-skimming missile) from another target class (including the seagull 18 and/or the ship)) or a plurality of target classes (e.g., a first target class (including the point source 15 and/or the sea-skimming source 16), a second target class (e.g., including the seagull 18), and a third target class (e.g., including the ship)) from one another.

**127.** Thus, Barnard teaches *wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another* (e.g., using the set of selected features and associated target detection threshold to distinguish specific targets from other targets in incoming picture signals).

**128.** Accordingly, Barnard discloses *wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another*.

**B. Ground 2: Claim 7 is obvious over Barnard in view of Knecht**

**129.** Knecht provides additional evidence as to the obviousness of claim 7 through the explicit disclosure of distinguishing a plurality of target classes from

one another in an image-based target detection method similar to Barnard's.

**6. Reasons to combine Barnard and Knecht**

***a) Analogous art***

**130.** It is my opinion that a POSITA when considering the teachings of Barnard would have naturally considered the teachings of Knecht, as Knecht is also analogous prior art pertaining to the same field of endeavor as both the '639 Patent and Barnard, namely, image processing and, more specifically, image processing for automatic target recognition. EX1001, 6:13 ("... our focus is on automatic target recognition ...."); EX1005, Abstract ("A target detection system is provided ...."); EX1016, 1:6-11 ("This invention pertains to a method and system for the automatic classification of images, more particularly, it pertains to such a method and system for classifying the image, of a scanned object as the image of an object of one of a plurality of predetermined classes of objects[.]").

**131.** Both Barnard and Knecht, like the '639 Patent, describe using a set of features to distinguish targets. EX1001, 5:60-62 ("... a set of distinguishing target characteristics pertinent to the classification and separation of targets from background clutter in automatic target recognition applications."); EX1005, 5:13-17 ("A selection of features can usually be found in which it is possible to place a

threshold hypersurface in the feature space which effectively separates target objects from background objects.”); EX1016, 6:22-27 (“This plurality of vectors is then stored in a memory unit ... for deriving in any suitable manner decision rules corresponding individually to each such class. These rules are then stored in a memory unit of system 12 for use thereby in classifying in real time ....”). Accordingly, a POSITA would recognize that Barnard and Knecht are analogous prior art to the ’639 Patent.

***b) Motivations to combine***

***(1) Use of a known technique to improve a similar method in the same way***

**132.** It is my opinion that a POSITA would have been motivated to combine Barnard and Knecht, as doing so would have been the use of a known technique (distinguishing between multiple target classes in an image processing-based target detection method, per Knecht) to improve a similar method (an image processing-based target detection method, per Barnard) in the same, predictable way (an image processing-based target detection method, per Barnard, that distinguishes between multiple target classes, per Knecht). In the combination, Barnard’s target recognition method would be modified to explicitly include a plurality of different target classes, as taught by Knecht. In the combination, each target class would have an associated set of selected features and a corresponding

target detection threshold, per Barnard, to facilitate classifying a potential target into one of the plurality of target classes, per Knecht. The combination does not require bodily incorporation of the specific approaches described by Knecht but does not preclude such bodily incorporation either.

**133.** Barnard teaches distinguishing specific targets from background clutter and other potential targets. For example, Fig. 2 shows an example of a real-world application of Barnard's method to distinguish specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., a sea-skimming missile) sea-skimming source 16 (e.g., such as a sea-skimming missile), from background clutter, such as wave crests 17, and other potential targets, such as seagull 18 and a ship. EX1005, 1:24-36, 3:34-41. While Barnard provides this example of distinguishing multiple target classes from one another, Barnard does not *explicitly* state multiple target classes are being utilized.

**134.** Knecht teaches that it was well-known in the context of a target recognition method like Barnard's to distinguish between a plurality of target classes. For example, Knecht describes “**“classifying a potential target object ... as a member of one class of several predetermined classes ....”** EX1016, 1:11-14. A POSITA would have recognized the multiple target class approach described by Knecht is a natural fit to improve Barnard's target detection method. In this

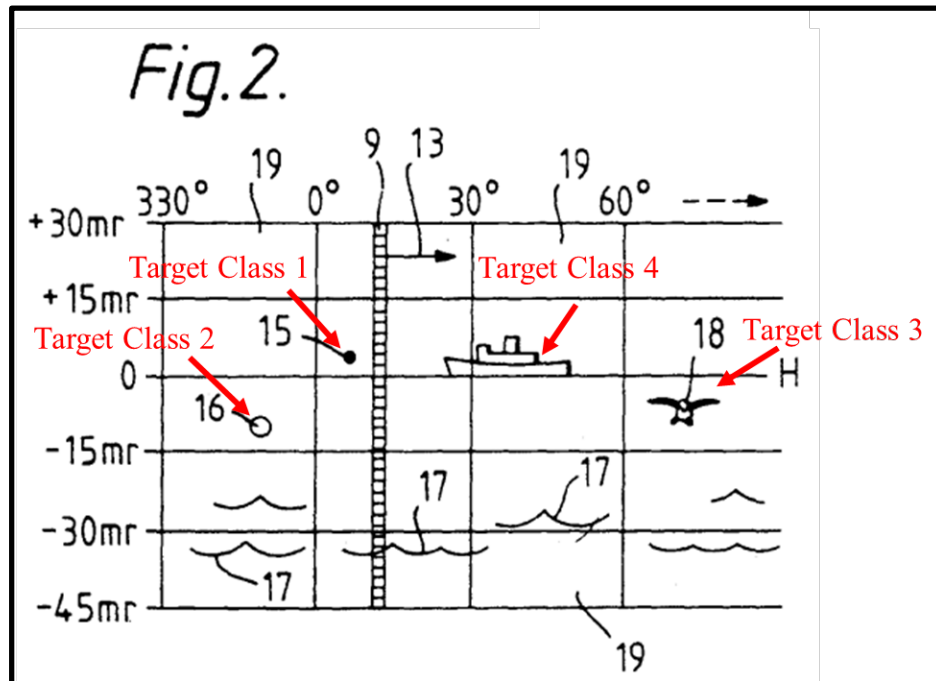
regard, using the specific examples from Fig. 2 of Barnard, distinguishing an aerial missile 15 from a sea-skimming source 16 (e.g., such as a sea-skimming missile) from a seagull 18 from a ship can be important for determining an appropriate response, if any. In this regard, a POSITA recognizes the risks presented by aerial missiles and sea-skimming missiles are quite different than those presented by a seagull 18. Further, even between an aerial missile and a sea-skimming missile, a POSITA recognizes that different defense mechanisms and/or counter measures may be better suited for dealing with each type of missile. Accordingly, distinguishing between the different types of targets can be important for deploying the most effective response.

**135.** Therefore, a POSITA would recognize that it would be advantageous to have different target classes for distinguishing between the different types of targets. For example, continuing the example from Fig. 2 of Barnard, a POSITA would recognize that different target classes could be defined for one or more of the aerial missile 15, the sea-skimming source 16 (e.g., such as a sea-skimming missile), the seagull 18, and/or the ship, as illustrated in Fig. 2 below.<sup>2</sup> To this end,

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<sup>2</sup> While these examples of target classes are based on the specific scenario illustrated in Fig. 2 of Barnard, a POSITA would have recognized that the ability

each target class would have a set of selected features and a corresponding target detection threshold for each target class in accordance with Barnard.



Barnard, Fig. 2 (annotated to illustrate exemplary combination with Knecht).

**136.** In modifying Barnard's target recognition method to include multiple target classes, Knecht's known technique of distinguishing between multiple target classes would be used to improve the similar automatic target detection method of Barnard in the same way.

**(2) Combining prior art elements according to**

to distinguish between different target classes is advantageous to a wide variety of applications of automatic target recognition systems. In fact, Knecht provides another example of distinguishing between different ship types. EX1016, Fig. 3.

***known methods to obtain predictable results***

**137.** It is my opinion that a POSITA would have been motivated to combine Barnard and Knecht because doing so would have been no more than combining prior art elements (using a plurality of target classes in an image-based target detection method, per Knecht, and an image-based target detection method, per Barnard) according to known methods to obtain predictable results (an image processing-based target detection method, per Barnard, that distinguishes between multiple target classes, per Knecht). In the combination, Barnard's target recognition method would be modified to explicitly include a plurality of different target classes, as taught by Knecht. In the combination, each target class would have an associated set of selected features and a corresponding target detection threshold, per Barnard, to facilitate classifying a potential target into one of the plurality of target classes, per Knecht. The combination does not require bodily incorporation of the specific approaches described by Knecht but does not preclude such bodily incorporation either.

**138.** As noted above, Barnard teaches distinguishing specific targets from background clutter and other potential targets, but does not *explicitly* state how many target classes are being utilized. As also discussed above, Knecht teaches that it was well-known in the context of a target recognition method like Barnard's to distinguish between a plurality of target classes.

**139.** A POSITA would have recognized that modifying Barnard’s target recognition method to utilize Knecht’s plurality of target classes instead of the unspecified number of target classes of Barnard would be the combination of known elements according to known methods to obtain predictable results.

***c) Reasonable expectation of success***

**140.** Not only would utilizing multiple target classes—as taught by Knecht—in the context of Barnard’s target detection method provide advantages as discussed above, but a POSITA would have found the combination predictable and had a reasonable expectation of success.

**141.** A POSITA would have had a reasonable expectation of success in combining Barnard and Knecht because Knecht explicitly teaches that target detection methods like Barnard’s can be used to distinguish between a plurality of target classes. EX1016, 1:6-14 (“This invention pertains to a method and system for the automatic classification of images, more particularly, it pertains to such a method and system for classifying the image, of a scanned object as the image of an object of one of a plurality of predetermined classes of objects Most particularly, this invention relates to such a method and system useful in a missile for classifying a potential target object, such as a ship, as a member of one class of several predetermined classes of ships.”).

**142.** In this regard, Knecht describes the use of multiple target classes in the context of an automatic target recognition system, like the system of Barnard, that relies on a set of features to distinguish targets from background clutter.

EX1016, 6:22-27 (“This **plurality of [feature] vectors** is then stored in a memory unit ... for deriving in any suitable manner **decision rules corresponding individually to each such class**. These rules are then stored in a memory unit of system 12 for use thereby in **classifying in real time ....**”); EX1005, 5:13-17 (“A selection of features can usually be found in which it is possible to place a threshold hypersurface in the feature space which effectively separates target objects from background objects.”). Further, Knecht describes using the same Bayesian approach used by Barnard to distinguish between the plurality of target classes. EX1016, 6:35-40 (“... any suitable classifier such as a well known Bayes classifier ....”); EX1005, 5:59-63 (“... in accordance with Baye’s criterion.”).

**143.** Because Knecht explicitly describes distinguishing between a plurality of targets in an image-based target detection method, a POSITA would have had full expectation of success in implementing the same type of approach in the context of Barnard’s similar image-based target detection method. More specifically, based on Knecht, a POSITA would have had full expectation of success in implementing a plurality of target classes in the context of Barnard’s target detection method such that a potential target could be categorized into one of

the plurality of target classes.

**144.** Thus, for at least these reasons, a POSITA would have had a reasonable expectation of success in implementing a plurality of target classes, as taught by Knecht, in the target detection method of Barnard.

**7. Claim 7**

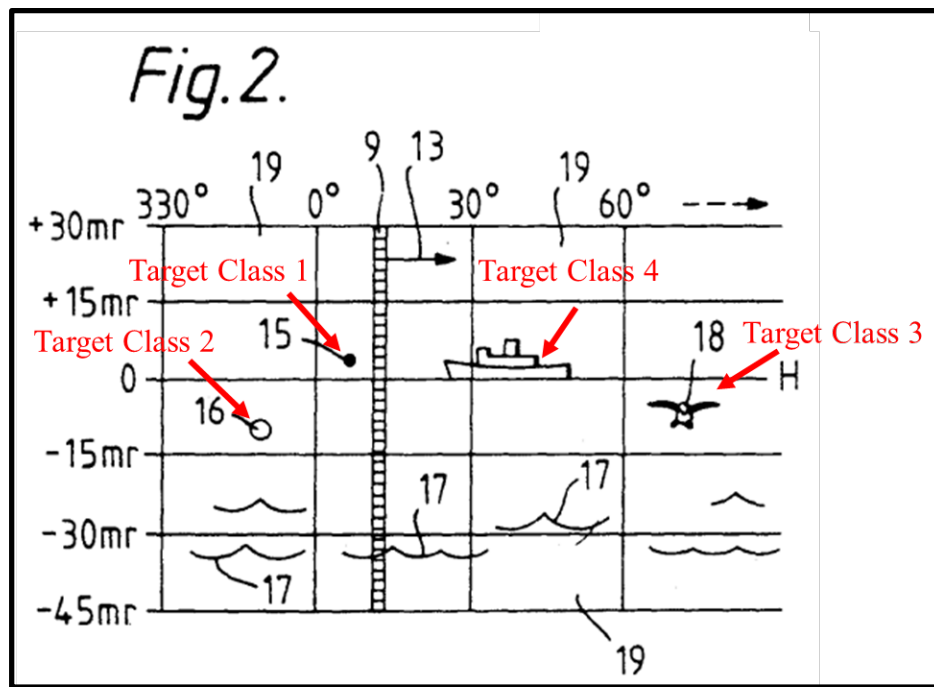
**[7.0]** *The method of claim 1, wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.*

**145.** Barnard in combination with Knecht renders obvious element [7.0].

**146.** As discussed above in the analysis of [7.0] in Section X.A, Barnard teaches distinguishing between at least two different target classes. For example, Fig. 2 shows an example of a real-world application of distinguishing specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), from other potential targets, such as seagull 18 and a ship. EX1005, 1:24-36, 3:34-41. While Barnard provides this example of distinguishing multiple target classes from one another, Barnard does not *explicitly* state multiple target classes are being utilized.

**147.** As discussed above, it would have been obvious to combine Barnard and Knecht at least because doing so would have been no more than the use of a known technique to improve a similar method in the same way and because doing so would be the simple substitution of one known element for another to obtain

predictable results. In the combination, Barnard's target recognition method would be modified to explicitly include a plurality of different target classes, as taught by Knecht. In the combination, each target class would have corresponding target specific feature information, such as an associated set of selected features and a corresponding target detection threshold, to facilitate classifying a potential target into one of the plurality of target classes in accordance with Barnard's existing target detection approach. For example, in the combination, the target specific feature information may be utilized to distinguish a potential target between Target Class 1 (e.g., aerial missiles or other aerial threats), Target Class 2 (e.g., sea-skimming missiles or other surface and/or sub-surface threats), Target Class 3 (e.g., seagulls or other non-threatening aerial objects), and Target Class 4 (e.g., ships or other floating structures).



Barnard, Fig. 2 (annotated to illustrate exemplary combination with Knecht).

**148.** This is just one example of the application of multiple target classes to the specific scenario illustrated in Fig. 2 of Barnard. A POSITA would have recognized that various other target class groupings may be utilized in this context. Similarly, as discussed above, a POSITA would have recognized that the ability to distinguish between different target classes is advantageous to a wide variety of applications of automatic target recognition systems and, therefore, various target class groupings may be utilized in a variety of other contexts.

**149.** Thus, Barnard in combination with Knecht discloses *wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another* (e.g., using the sets of selected features and

associated target detection thresholds for a plurality of target classes to distinguish between a plurality of target classes).

**150.** Accordingly, Barnard in combination with Knecht discloses *wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.*

**C. Ground 3: Claims 1-7 are obvious over Barnard in view of Lawrence**

**151.** As discussed below, it would have been obvious to a POSITA to use a neural network architecture designed to perform adaptive, continuous Bayesian estimation, as taught by Lawrence, to calculate the target detection threshold of Barnard that is determined “in accordance with Baye’s criterion.”

**1. Reasons to combine Barnard and Lawrence**

**d) Analogous art**

**152.** It is my opinion that a POSITA when considering the teachings of Barnard would have naturally considered the teachings of Lawrence, as Lawrence is also analogous prior art pertaining to the same field of endeavor as both the ’639 Patent and Barnard, namely, image processing and, more specifically, image processing for automatic target recognition. EX1001, 6:13 (“... our focus is on automatic target recognition ....”); EX1005, Abstract (“A target detection system is provided ....”); EX1006, 45:22-23 (“... the target recognition and tracking

mechanism will be described ....”). Both Barnard and Lawrence, like the ’639 Patent, describe using a set of features to distinguish targets from background clutter and other potential targets. EX1001, 5:60-62 (“... a set of distinguishing target characteristics pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.”); EX1005, 5:13-17 (“A selection of features can usually be found in which it is possible to place a threshold hypersurface in the feature space which effectively separates target objects from background objects.”); EX1006, 45:27-29 (“... a set of basic features which are needed to distinguish targets of interest ....”). Accordingly, a POSITA would recognize that Barnard and Lawrence are analogous prior art to the ’639 Patent.

*e) Motivations to combine*

*(1) Use of a known technique to improve a similar method in the same way*

**153.** It is my opinion that a POSITA would have been motivated to combine Barnard and Lawrence, as doing so would have been no more than the use of a known technique (using a neural network architecture for Bayesian estimation in a target detection method, per Lawrence) to improve a similar method (using an unspecified Bayesian estimation technique in a target detection method, per Barnard) in the same, predictable way (Bayesian estimation in a target detection



“in accordance with Baye’s criterion.” 5:59-63. However, Barnard notes that “[s]ince this threshold calculation from the statistical information is a well known mathematical technique **it will not be described further** ....” EX1005, 5:63-66. Barnard further notes that “modifications will be apparent to persons skilled in the art.” EX1005, 6:16-17.

**155.** Lawrence provides details of a known way to perform the Bayesian estimation referenced, but “not ... described further,” in Barnard. EX1005, 5:63-66. More specifically, Lawrence describes “**a neural network architecture ... designed to perform adaptive, continuous Bayesian estimation**” also in the context of automatic target recognition. EX1006, 1:2-5, *see also* Title (“CONTINUOUS BAYESIAN ESTIMATION WITH A NEURAL NETWORK ARCHITECTURE”), 1:2-6 (“The present invention pertains in general to **a neural network architecture**, and more particularly, to an architecture which is **designed to perform adaptive, continuous Bayesian estimation** on unprocessed large dimensional data.”), 45:15-25 (“By way of example, the mechanism by which the PA can accomplish **automatic target recognition** and parameter estimation is described, and how to train and operate a system. ... Then the target recognition and tracking mechanism will be described, which detects the features in the input signal, uses them to build a representation of the estimated target and tracks the target while it moves.”).

**156.** A POSITA would have recognized the neural network-based Bayesian estimation approach described by Lawrence is a natural fit to improve the Bayesian estimation used in Barnard's target detection method. As an initial matter, Lawrence's neural network-based Bayesian estimation approach is already described in the context of automatic target recognition applications, like Barnard's. EX1006, 1:2-6, 45:15-25, Fig. 2. Accordingly, a POSITA would have understood that Lawrence's approach is suitable for use with Barnard's target detection method.

**157.** Further, a POSITA would have recognized that this type of hybrid approach—combining a neural network approach (such as Lawrence's) with existing target recognition technology (such as Barnard's)—would be used “to make an automatic target recognizer.” EX1015, 2 (“The authors do not necessarily feel that [automatic target recognition] systems must be all neural networks, but can in fact be hybrid systems with existing or other emerging technologies combined to make an automatic target recognizer.”; “... many of the neural network results will be shown wedged in between other technologies.”).

**158.** Further, a POSITA would have recognized the adaptability and flexibility benefits of the automatic target recognition system resulting from implementing neural network-based Bayesian estimation, as taught by Lawrence,

in the context of Barnard's target detection method. In this regard, combining Lawrence's neural network approach with Barnard's target detection technology provides the advantages associated with using "artificial neural networks in an ATR system," while maintaining underlying framework of an existing target detection system allowing the resulting system to be adaptable and flexible to take advantage of the strengths of the combined technologies. EX1015, 2 (Describing hybrid systems combining neural networks "with existing or other emerging technologies ... to make an automatic target recognizer," including describing that "... many of the neural network results will be shown wedged in between other technologies," and discussing the "advantages/disadvantages of artificial neural networks in an ATR system.").

**159.** In modifying Barnard's target recognition method to utilize a neural network to calculate the target detection threshold in accordance with Baye's criterion, Lawrence's known technique of using a neural network to perform Bayesian estimation would be used to improve the similar automatic target detection method of Barnard in the same way.

***(2) Simple Substitution of one known element for another to obtain predictable results***

**160.** It is my opinion that a POSITA would have been motivated to combine Barnard and Lawrence because doing so would have been no more than

the simple substitution of one known element (using an unspecified Bayesian estimation technique in a target detection method, per Barnard) for another (using a neural network architecture for Bayesian estimation in a target detection method, per Lawrence) to obtain predictable results (performing Bayesian estimation in a target detection method, per Barnard (and Lawrence), through the use of a neural network, per Lawrence). In the combination, Barnard's target recognition system would be modified to utilize a neural network, per Lawrence, to calculate Barnard's target detection threshold in accordance with Baye's criterion. The combination does not require bodily incorporation of the specific neural network architecture described by Lawrence but does not preclude such bodily incorporation either.

**161.** As noted above, Barnard indicates the target detection threshold is calculated "in accordance with Baye's criterion" but does not provide any additional details of the "well known mathematical technique." EX1005, 5:59-66. Prompted at least by Barnard's teachings, a POSITA would have been motivated to look to other references, such as Lawrence, disclosing known ways of performing Bayesian estimation. Because Barnard describes a target detection method, a POSITA would have been particularly motivated to consider references, like Lawrence, disclosing known ways of performing Bayesian estimation in the specific context of automatic target detection methods.

**162.** A POSITA would have recognized that modifying Barnard’s target recognition method to utilize Lawrence’s known neural network-based Bayesian estimation technique instead of Barnard’s unspecified Bayesian estimation technique is the simple substitution of one known element for another to obtain predictable results.

*f) Reasonable expectation of success*

**163.** Not only would utilizing a neural network Bayesian estimation approach—as taught by Lawrence—in the context of Barnard’s target detection method provide advantages as discussed above, but a POSITA would have found the combination predictable and had a reasonable expectation of success.

**164.** A POSITA would have had a reasonable expectation of success in combining Barnard and Lawrence because Lawrence teaches that “a neural network architecture” can be used to perform “Bayesian estimation,” which is consistent with Barnard’s calculation of the target detection threshold “in accordance with Baye’s criterion.” EX1006, 1:2-6 (“The present invention pertains in general to a neural network architecture, and more particularly, to an architecture which is designed to perform adaptive, continuous Bayesian estimation ....”); EX1005, 5:59-66 (“The location of the target detection threshold is calculated ... in accordance with Baye’s criterion.”).

**165.** Further, Lawrence explicitly describes the use of its neural network architecture for Bayesian estimation in the context of an automatic target recognition system, like the system of Barnard, which relies on a set of features to distinguish targets from background clutter. EX1006, 45:15-25 (“By way of example, the mechanism by which the PA can accomplish **automatic target recognition and parameter estimation** is described, and how to train and operate a system. ... Then the target recognition and tracking mechanism will be described, which **detects the features** in the input signal, uses them to build a representation of the estimated target and tracks the target while it moves.”), 45:27-29 (“... a set of basic **features which are needed to distinguish targets of interest** ....”); EX1005, 5:13-17 (“A selection of features can usually be found in which it is possible to place a threshold hypersurface in the feature space which effectively separates target objects from background objects.”).

**166.** Because Lawrence explicitly describes implementation of a neural network architecture to perform adaptive, continuous Bayesian estimation in a target detection method, a POSITA would have had full expectation of success in implementing the same type of approach in the context of Barnard’s target detection method. More specifically, based on Lawrence, a POSITA would have had full expectation of success in implementing a neural network architecture to perform adaptive, continuous Bayesian estimation of the target detection threshold

of Barnard. In this regard, a POSITA would have recognized that this type of hybrid approach—combining a neural network approach (such as Lawrence’s) with existing target recognition technology (such as Barnard’s)—would be used “to make an automatic target recognizer.” EX1015, 2 (“The authors do not necessarily feel that [automatic target recognition] systems must be all neural networks, but can in fact be hybrid systems with existing or other emerging technologies combined to make an automatic target recognizer.”; “... many of the neural network results will be shown wedged in between other technologies.”).

167. Thus, for at least these reasons, a POSITA would have had a reasonable expectation of success in implementing a neural network architecture, as taught by Lawrence, to perform the Bayesian estimation for calculating the target detection threshold of Barnard.

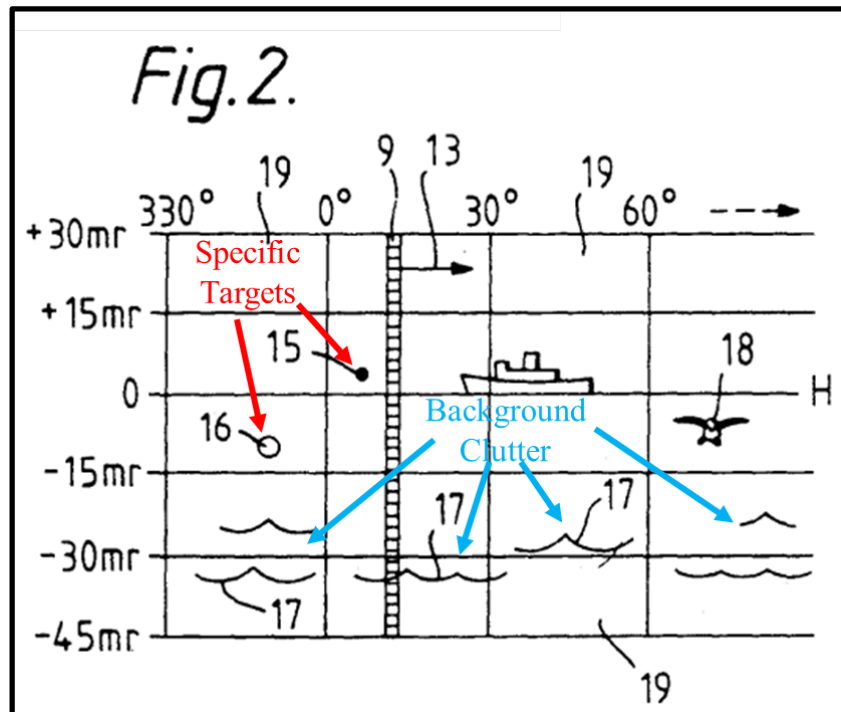
## 2. Claim 1

**[1.0] *A method for distinguishing targets from background clutter, comprising the steps of***

168. Barnard discloses or renders obvious element [1.0].

169. Barnard teaches a method for distinguishing targets from background clutter. For example, Barnard discloses a “target detection system ... for **examining picture signals of a scene which may contain a target signal (15,16) to be detected against background signals (17,18).**” EX1005, Abstract; *see also*

1:1-10. Barnard's system "effectively separates target objects from background objects," as shown in Fig. 2 below. EX1005, 5:16-17. Operation of Barnard's target detection system performs a method of distinguishing targets from background clutter.



Barnard, Fig. 2 (annotated).

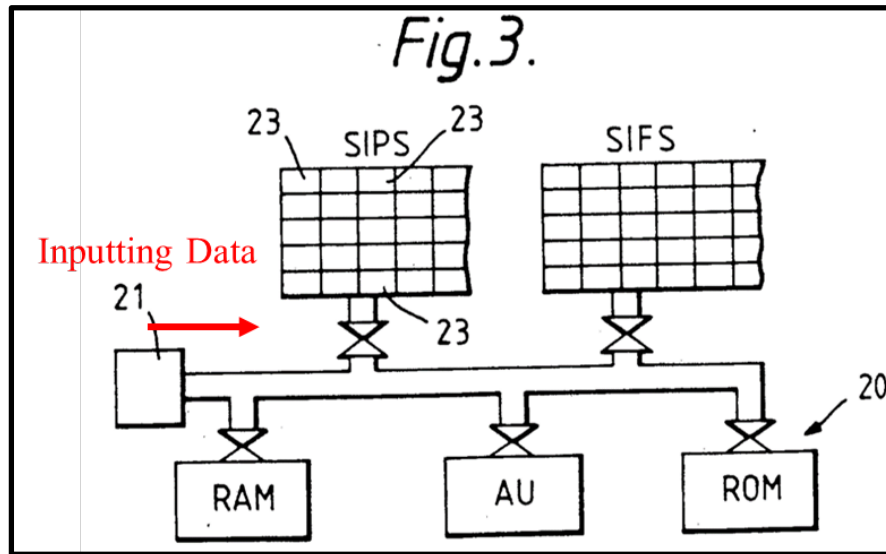
170. Accordingly, Barnard discloses *a method for distinguishing targets from background clutter*.

[1.1] (a) *inputting data*;

171. Barnard discloses or renders obvious element [1.1].

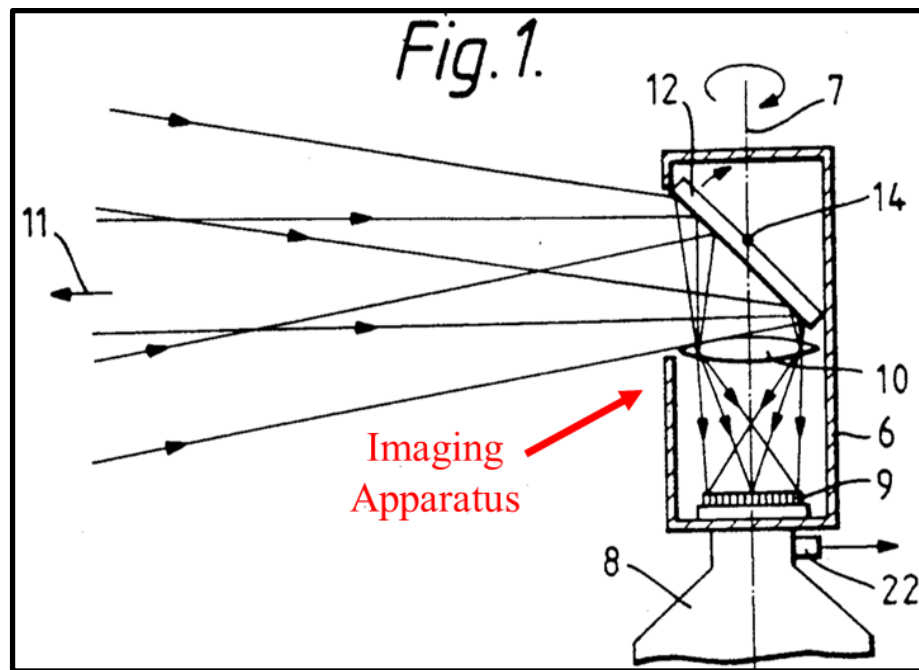
172. Barnard teaches inputting data. For example, Barnard describes "a

digital computer 20 ... receive[s] the stream of digitised pixel values from a signal pre-processing unit 21.” EX1005, 4:19-21.



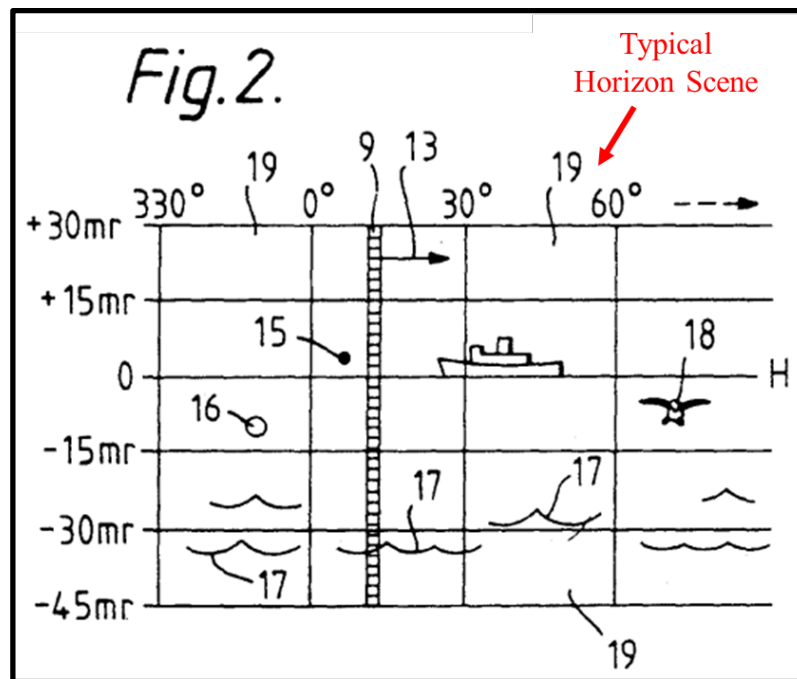
Barnard, Fig. 3 (annotated).

173. Barnard explains the digitized pixel values are based on images obtained by “a thermal imaging apparatus.” EX1005, 3:5-11 (“Referring to FIG. 1, there is shown the optical and mechanical components, in schematic form, of a thermal imaging apparatus which is provided as a means of observation, typically set high in the superstructure of a ship, to watch for hostile incoming missiles, aircraft, etc.”); 3:42-59 (describing how each detector is utilized to provide pixel values for a whole horizon image that are retained in a store and utilized for the target detection process).



Barnard, Fig. 1 (annotated).

174. Barnard further describes “**examining picture signals of a scene** which may contain a target signal (15,16) to be detected against background signals (17,18).” EX1005, Abstract. Barnard explains that the “**picture signals represent[] an image of a scene.**” EX1005, 1:7-8. In this regard, the image may be a two-dimensional image of “a typical horizon scene,” as shown in Fig. 2.



Barnard, Fig. 2 (annotated).

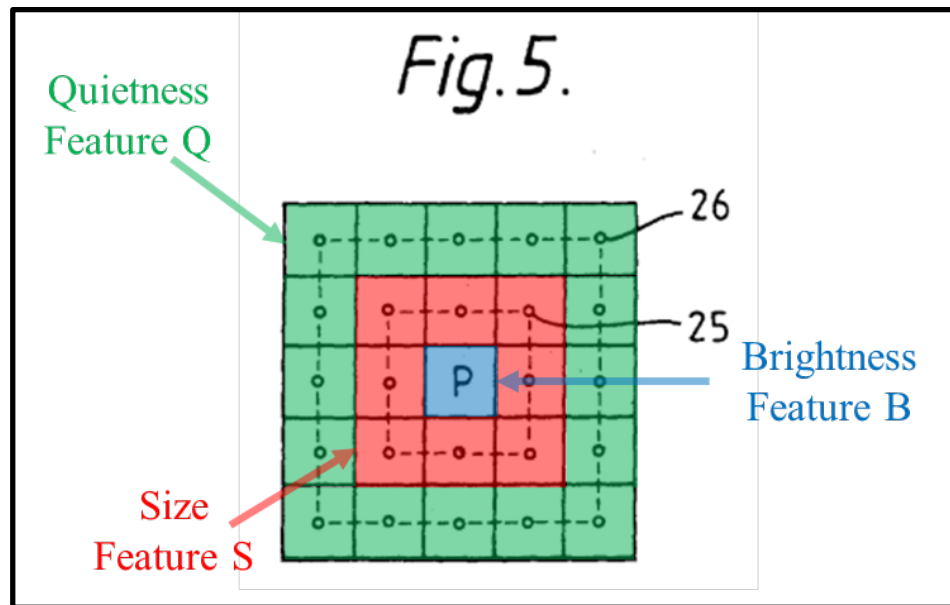
175. Accordingly, Barnard discloses or renders obvious *inputting data* (e.g., inputting the stream of digitized pixel values or picture signals representing an image of a scene to the digital computer).

**[1.2] (b) calculating data statistics from said data and using said data statistics to select target specific feature information to distinguish specific targets from background clutter;**

176. Barnard in combination with Lawrence renders obvious element [1.2].

177. As discussed in [1.1], Barnard teaches *inputting data* (e.g., inputting the stream of digitized pixel values or picture signals). Barnard further describes calculating various data statistics for features from the input image data, including “brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther

features” that “may indicate shape, width, height, symmetry or lack of symmetry.” EX1005, 2:9-27; 4:50-5:1; 4:46-49 (“FIG. 5 shows the square array of 24 pixels surrounding each pixel P in each of the sub-image pixel stores SIPS, each square indicating a storage location holding a pixel value. Assuming P to be a non-zero value, P will usually be surrounded by other non-zero pixels.”); 5:2-3 (“several features can be calculated and each will have a numerical value in a range of values.”).



Barnard, Fig. 5 (annotated).

**178.** Barnard teaches calculating data statistics for the various features (“brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features”) from the input image data. *See, e.g.*, EX1005, 2:30-36; 5:36-49; 6:62-68. For example, Barnard teaches calculating data statistics in multiple ways,

including:

- (1) calculating the width of the statistical distributions of features of the image data; and
- (2) calculating the progressive means and associated variances of features of the image data. EX1005, 2:30-36; 5:36-49; 6:62-68.

**179.** Barnard teaches using the calculated data statistics (e.g., “width of the statistical distributions,” “progressive means,” “variances,” and/or “statistical information”) to select target specific feature information, and more specifically, to select the set of features and an associated target detection threshold used to distinguish specific targets from background clutter. EX1005, 2:30-36; 5:36-66; 6:62-68.

**180.** For example, Barnard describes using the calculated width of the statistical distributions of features to select which features are used to distinguish specific targets from background clutter. Barnard discloses **“calculat[ing] the width of the statistical distributions of the background and target features.”** EX1005, 2:28-34. The statistical distribution and its associated width are data statistics calculated from the input image data. Barnard further describes **“discard[ing] a feature as a threshold parameter if the width of the statistical distribution of that feature exceeds a predetermined amount.”** EX1005, 2:28-

34. Barnard explains that if a feature has “[too] wide a spread,” then it “may be unreliable as a guide to discriminating between background and target features.” EX1005, 2:36-39. In discarding or excluding features that have a statistical distribution width exceeding a predetermined amount, Barnard is selecting features (i.e., the remaining features not excluded) that are used to distinguish specific targets from background clutter.

**181.** As another example, Barnard teaches using the calculated progressive means of features to select which features are used to distinguish specific targets from background clutter. Barnard discloses “**calculating the progressive means of each feature.**” EX1005, 5:34-38. The means of each feature are data statistics calculated from the input image data. Barnard further describes discarding the feature “**if the feature mean varies by more than a preset amount** over a succession of scene images.” 2:34-36. In discarding or excluding one or more features that have a mean that varies by more than the preset amount, Barnard is selecting features (i.e., the remaining features not excluded) that are used to distinguish specific targets from background clutter.

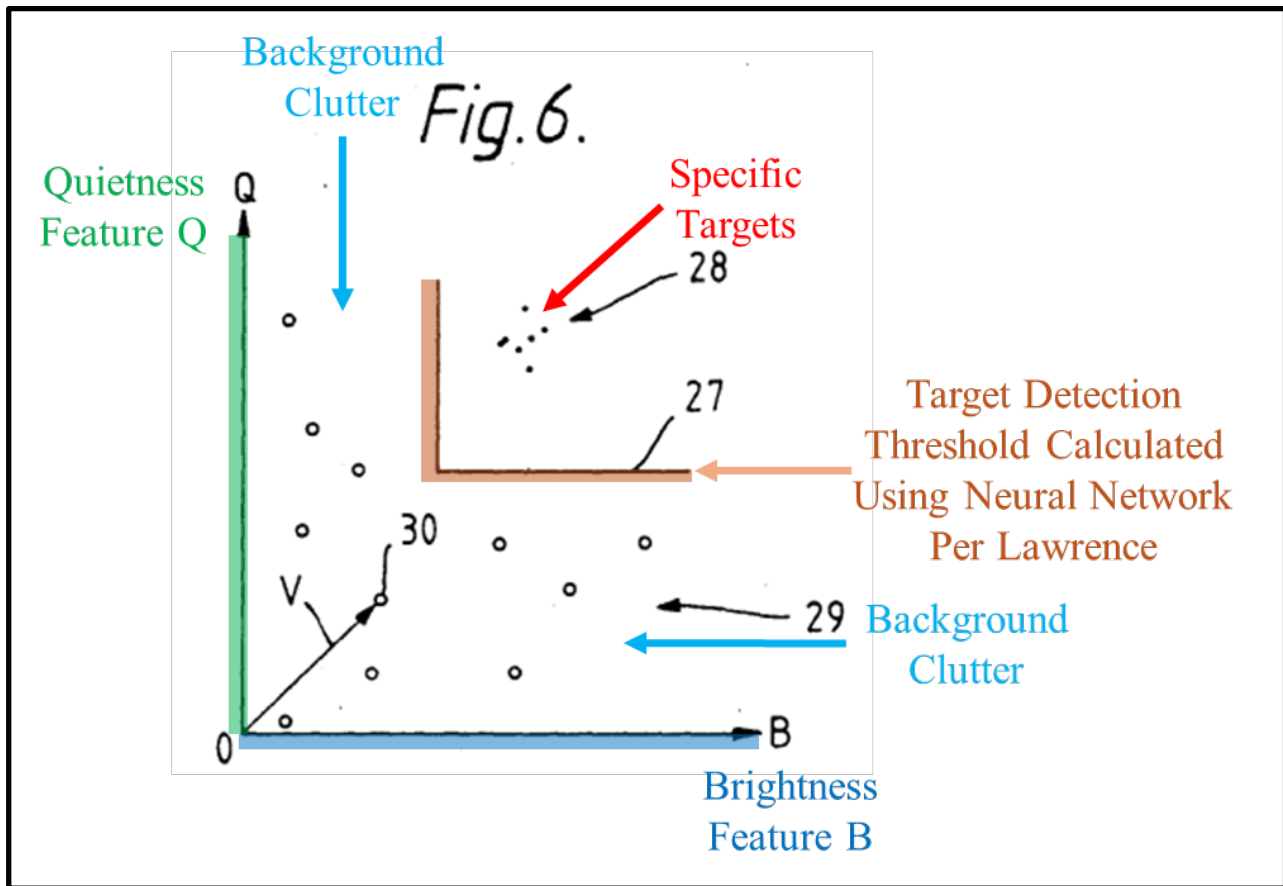
**182.** Barnard goes on to explain that “A **selection of features** can usually be found in which it is possible to place a **threshold hypersurface** in the feature space which **effectively separates target objects from background objects.** FIG.

6 illustrates this known approach using only two features B and Q, but only for clarity of drawing.” EX1005, 5:13-19. Barnard explains that the “target detection threshold” is generated “from the **statistical information**” and is located “at the intersection of the two probability surfaces, i.e. where the probabilities of an object being a target or a background point are equal, that is, in accordance with Baye’s criterion.” EX1005, 5:59-66.

**183.** However, Barnard notes that “[s]ince this threshold calculation from the statistical information is a well known mathematical technique **it will not be described further** ....” EX1005, 5:63-66. Lawrence provides details of a known way to perform the Bayesian estimation referenced, but “not ... described further,” in Barnard. EX1005, 5:63-66. More specifically, Lawrence describes “**a neural network architecture ... designed to perform adaptive, continuous Bayesian estimation**” in the context of automatic target recognition. EX1006, 1:2-5, *see also* Title (“CONTINUOUS BAYESIAN ESTIMATION WITH A NEURAL NETWORK ARCHITECTURE”), 1:2-6 (“The present invention pertains in general to **a neural network architecture**, and more particularly, to an architecture which is **designed to perform adaptive, continuous Bayesian estimation** on unprocessed large dimensional data.”), 45:15-25 (“By way of example, the mechanism by which the PA can accomplish **automatic target recognition** and parameter estimation is described, and how to train and operate a

system. ... Then the target recognition and tracking mechanism will be described, which detects the features in the input signal, uses them to build a representation of the estimated target and tracks the target while it moves.”).

**184.** As discussed above, it would have been obvious to combine Barnard and Lawrence at least because doing so would have been no more than the use of a known technique to improve a similar method in the same way and because doing so would be the simple substitution of one known element for another to obtain predictable results. In the combination, Barnard’s target recognition method would be modified to utilize a neural network, per Lawrence, to calculate Barnard’s target detection threshold in accordance with Baye’s criterion.

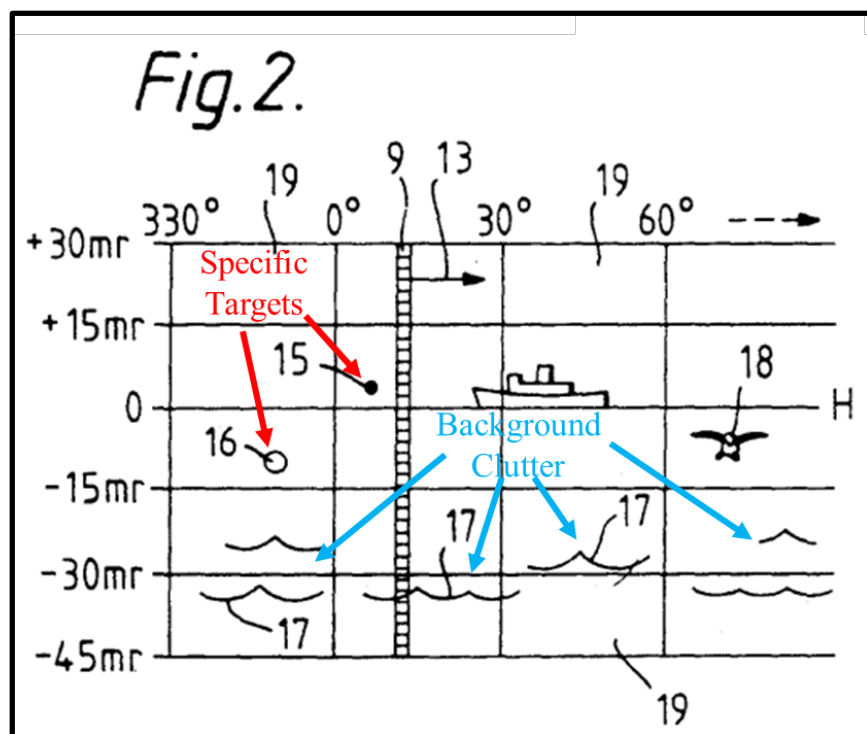


Barnard, Fig. 6 (annotated to illustrate exemplary combination with Lawrence).

**185.** In this regard, the neural network determines the target detection threshold for the features selected based on the calculated data statistics. More specifically, the neural network architecture is utilized to perform a Bayesian estimation such that the target detection threshold is calculated in accordance with Baye's criterion based on each of the selected features. That is, the target detection threshold for distinguishing targets from background clutter is based on thresholds calculated for each of the selected features using the neural network architecture.

In this manner, the combination of Barnard and Lawrence uses the calculated data statistics to select target specific feature information—the set of features and associated target detection threshold—used to distinguish specific targets from background clutter.

**186.** As shown and described in the context of Fig. 2, Barnard provides the specific example of distinguishing specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), from background clutter, such as wave crests 17. EX1005,1:24-36, 3:34-41.



Barnard, Fig. 2 (annotated).

The wave crests in Barnard are an example of background clutter analogous to the trees or tree lines provided as an example of background clutter in the '639 Patent.

See EX1001, Fig. 11, 7:33-37, 10:26-30; EX1005, Fig. 2, 3:34-41. Further, Barnard discloses distinguishing specific targets, not just any targets, from the background clutter by distinguishing intended targets, such as point source 15 or sea-skimming source 16 (e.g., such as a sea-skimming missile), from other potential targets, such as a seagull 18. EX1005, 3:34-41; Fig. 2.

**187.** The selected features of Barnard and associated target detection threshold—calculated using a neural network, in accordance with Lawrence—that are used to distinguish specific targets from background clutter are separately, and collectively, “*target specific feature information*” as claimed by the ’639 Patent. In other words, (1) the set of features, (2) the target detection threshold associated with the set of features (calculated using a neural network, per Lawrence, for each of the selected features); and/or (3) the combination of the set of features with the associated target detection threshold are “*target specific feature information*” as claimed by the ’639 Patent.

**188.** The use of the phrase “*target specific feature information*” in the ’639 Patent is limited and largely mirrors the claim language. Notably, “*target specific feature information*” is not used in the “DETAILED DESCRIPTION OF THE PREFERRED EMBODIMENTS” section of the ’639 Patent. See EX1001, 7:12-11:67. However, the ’639 Patent indicates to a POSITA that “*target specific*

*feature information*” can at least include information related to target specific feature(s) used to distinguish a target from background clutter, including the type(s) of target specific features, value(s) and/or threshold(s) for the type(s) of target specific feature(s), other information related to the target specific feature(s), and/or combinations thereof. EX1001, 5:15-30; 5:55-6:2; 7:15-29; 7:46-57.

**189.** With respect to the types of target specific features used to distinguish a target from background clutter, the ’639 Patent explains “**a set of distinguishing target characteristics**”<sup>3</sup> may be used to distinguish a target from background clutter. EX1001, 5:55-62 (“us[ing] a variation of the Hebbian learning algorithm

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<sup>3</sup> In some instances, the ’639 Patent refers to the target characteristics or target specific features as “principal components,” “receptive features,” or “principal component features.” EX1001, 7:54-56 (“The generalized Hebbian Learning algorithm generates principal components or receptive features.”); 8:45-47 (“[T]he principal components generally correspond to prominent intensity patterns or features in the object of interest.”); 8:52-54 (“The generated principal components are arrayed in rxs matrices to produce receptive fields or filters that are convolved with the original image data during classification.”); 9:60-63 (“The inventor then used this definition to measure the capability of the principal component features to distinguish targets from objects similar in appearance.”).

and recently discovered relationships between neural network Hebbian learning algorithms and statistically-based principal component analysis to **generate a set of distinguishing target characteristics** pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.”). That is, the ’639 Patent describes using a set of characteristics or target specific features to distinguish specific targets from background clutter like Barnard and Lawrence.

**190.** The ’639 Patent also notes that “*target specific feature information*” may include different types of characteristics or features, including “contrast-based” and “texture-based.” EX1001, 5:15-49 (“select **target specific feature information (e.g., contrast-based and texture-based)** to distinguish specific targets from background clutter”). The various features (“brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features”) described by Barnard include contrast-based and texture-based features, consistent with the examples in the ’639 Patent. EX1005, 4:46-5:3; Fig. 5; *see also* EX1007, 5:26-29 (“In general, **texture of a scene, image or object can be defined as the spatial variation or distribution of tonal or intensity values of picture elements**, wherein the spatial variation extends over a given area.”).

**191.** Further, the ’639 Patent indicates the target specific feature

information may be used “to distinguish specific targets from background clutter” using techniques such as “parametric and non-parametric techniques and one-class, two-class, or multi-class classification procedures.” 5:27-29. These disclosed examples are common data processing techniques that utilize values for the selected target specific features to distinguish targets from background clutter. EX1008, 23:59-24:2 (describing a “target classification approach” based on a non-parametric estimation technique). For example, as described in the ’639 Patent—as well as Barnard and Lawrence—the values of the selected target specific features may be utilized to distinguish targets from background clutter in an image. EX1001, 5:15-30, 5:55-62; EX1005, 5:3-17; EX1006, 45:18-25. In this regard, the values of the selected target specific features in a region of interest of an image may indicate the region of interest contains a target or may indicate the region of interest contains background clutter. EX1001, 5:15-30, 5:55-62, 8:35-38, 8:57-60; EX1005, 5:3-17; 6:11-15.

**192.** Thus, Barnard in combination with Lawrence teaches *calculating data statistics* (e.g., “width of the statistical distributions” of features and/or “progressive means” of features, such as brightness feature B, size feature S, quietness feature Q, and other features and/or “statistical information”) *from said data* (e.g., the input image data (stream of digitized pixel values or picture signals)) *and using said data statistics to select target specific feature information to*

*distinguish specific targets from background clutter* (e.g., selecting the set of features (e.g., by excluding features whose width of statistical distribution exceeds a predetermined amount or whose mean varies by more than a preset amount and/or using statistical information) and an associated target detection threshold (e.g., calculated using a neural network) to distinguish specific targets from background clutter).

**193.** Accordingly, Barnard in combination with Lawrence renders obvious *calculating data statistics from said data and using said data statistics to select target specific feature information to distinguish specific targets from background clutter*.

**[1.3] (c) generating said target feature information from said data statistics;**

**194.** Barnard in combination with Lawrence renders obvious element [1.3].

**195.** As an initial matter, I note that [1.3] recites “*target feature information*,” not “*target **specific** feature information*” as used in [1.2]. I also understand from counsel that the use of “*said*” in a patent claim indicates reference to an element that was previously introduced in the claim. However, there is no prior (or subsequent) use of “*target feature information*” in claim 1. Also, I did not find any use of “*target feature information*” in the ’639 Patent outside of the claims. *See*, EX1001, 1:1-11:67. In the ABSTRACT and SUMMARY OF THE

INVENTION sections, the '639 Patent describes “generating the target **specific** feature information from the data statistics.” EX1001, Abstract, 5:23-25, 5:41-42. Accordingly, for the purpose of this declaration, I am treating “*said target feature information*” recited in [1.3] as referring to the “*target **specific** feature information*” recited in [1.2], as well as [1.4] and [1.5].

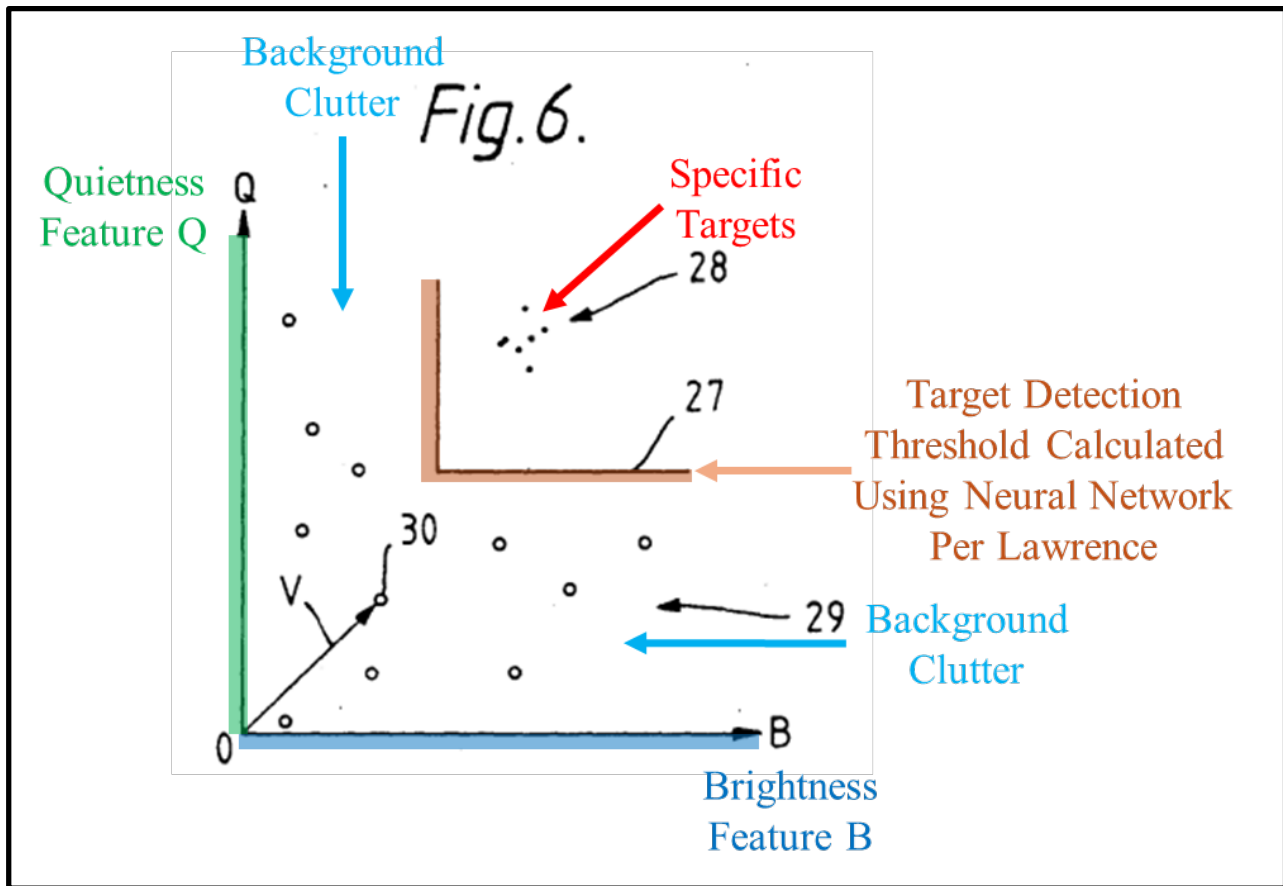
**196.** The '639 Patent describes “generating target specific feature information” includes “generat[ing] a set of distinguishing target characteristics pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.” EX1001, 5:59-62. The '639 Patent also describes that the target specific feature information generated may include “principal components or receptive features.” EX1001, 7:55-56, 8:32-67.

**197.** Similarly, Barnard teaches generating, based on data statistics, the target specific feature information used to distinguish specific targets from background clutter. More specifically, Barnard teaches generating the set of selected features and associated target detection threshold for distinguishing specific targets from background clutter based on data statistics calculated from the input image data. Barnard describes that “A **selection of features** can usually be found in which it is possible to **place a threshold hypersurface in the feature space** which **effectively separates target objects from background objects.**”

EX1005, 5:13-17.

**198.** The combination of Barnard and Lawrence teaches using the calculated data statistics (e.g., “width of the statistical distributions,” “progressive means,” and/or “statistical information”) to generate the set of features, in accordance with Barnard, and generating an associated target detection threshold using a neural network, in accordance with Lawrence. The set of features and associated target detection threshold are used to distinguish specific targets from background clutter.

**199.** As discussed above, it would have been obvious to combine Barnard and Lawrence at least because doing so would have been no more than the use of a known technique to improve a similar method in the same way and because doing so would be the simple substitution of one known element for another to obtain predictable results. In the combination, Barnard’s target recognition method would be modified to utilize a neural network, per Lawrence, to calculate Barnard’s target detection threshold for the selected features in accordance with Baye’s criterion.



Barnard, Fig. 6 (annotated to illustrate exemplary combination with Lawrence).

**200.** In this regard, the neural network generates the target detection threshold for the features selected based on the calculated data statistics. More specifically, the neural network architecture is utilized such that the target detection threshold is calculated in accordance with Baye's criterion based on each of the selected features. In this manner, the combination of Barnard and Lawrence uses the calculated data statistics to generate target specific feature information—the set of features and associated target detection threshold—used to distinguish

specific targets from background clutter. Consistent with the '639 Patent, the generated set of selected features and associated target detection threshold define the target specific feature information for separating specific targets from background clutter. *See* EX1001, 5:55-62, 7:55-58, 8:45-51; EX1005, 5:3-28; EX1006, 45:15-25.

**201.** Accordingly, generating the set of features and associated target detection threshold in the combination of Barnard and Lawrence is generating target specific feature information from the data statistics. More specifically, generating one or more of (1) the set of features, (2) the target detection threshold associated with the set of features (calculated using a neural network, per Lawrence, for each of the selected features); and/or (3) the combination of the set of features with the associated target detection threshold is “*generating said target [specific] feature information from said data statistics*” as claimed by the '639 Patent.

**202.** Thus, Barnard in combination with Lawrence teaches *generating said target [specific] feature information from said data statistics* (e.g., generating the set of selected features and associated target detection threshold (e.g., using a neural network) from the calculated data statistics (e.g., width of the statistical distributions of features, progressive means of features, and/or statistical

information)).

**203.** Accordingly, Barnard in combination with Lawrence discloses *generating said target feature information from said data statistics.*

**[1.4] (d) extracting said target specific feature information from said data;**

**204.** Barnard in combination with Lawrence renders obvious element [1.4].

**205.** Barnard teaches extracting target specific feature information from the input image data. For example, Barnard teaches the set of selected features and associated target detection threshold used to distinguishing specific targets from background clutter are extracted from the input image data.

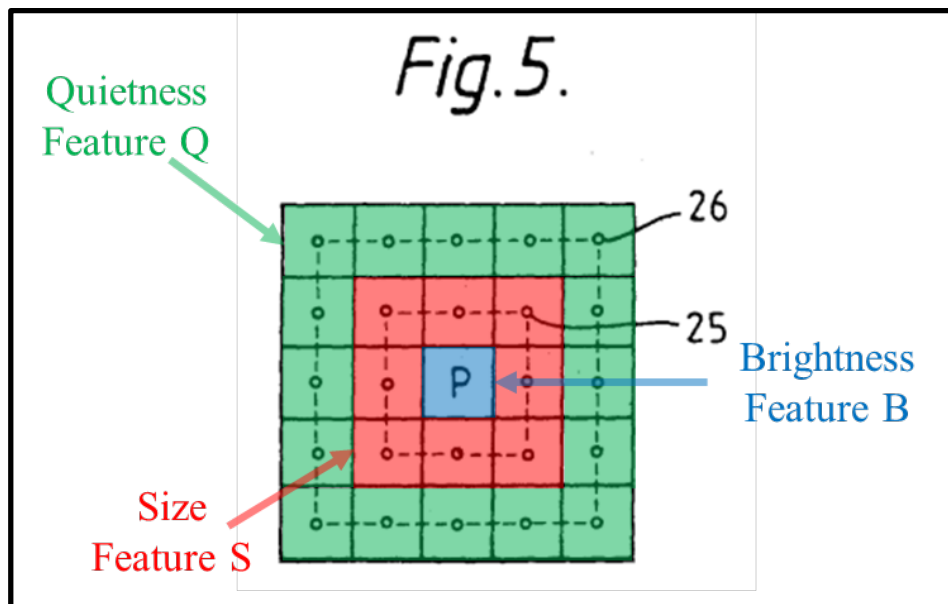
**206.** In the context of performing the selecting and generating aspects of [1.2] and [1.3], Barnard explains how the features included in the set of selected features are extracted from the input image data and how the associated target detection threshold for the set of selected features is extracted from the input image data. EX1005, 5:2-3 (“Thus **several features can be calculated and each will have a numerical value** in a range of values.”); 5:13-17 (“A **selection of features** can usually be found in which it is possible to **place a threshold hypersurface in the feature space which effectively separates target objects from background objects.**”); 5:59-66 (“**The location of the target detection threshold is calculated** at the intersection of the two probability surfaces, i.e. where the probabilities of an

object being a target or a background point are equal, that is, in accordance with Baye's criterion.""). For example, the set of selected features may be extracted from the input image data by calculating numerical values of features of the image data, calculating the width of the statistical distributions and/or progressive means of the features, and excluding from the set of selected features any features with a statistical distribution width exceeding a predetermined amount or a mean that varies by more than a preset amount. EX1005, 2:28-39, 5:13-17, 5:36-49, 6:62-68.

**207.** Further, the target detection threshold for the set of selected features is also extracted from the input image data. In this regard, Barnard explains that the target detection threshold may be extracted from the input image data by finding "the intersection of the two probability surfaces, i.e. where the probabilities of an object being a target or a background point are equal, that is, in accordance with Baye's criterion." EX1005, 5:59-66. As discussed above, in the combination of Barnard and Lawrence, a neural network is utilized to find the target detection threshold from the input image data based on the selected features. In this regard, the neural network extracts a threshold for each of the selected features from the input image data. More specifically, the neural network architecture is utilized such that the target detection threshold is calculated for the selected features from the input image data in accordance with Baye's criterion. In this manner, the combination of Barnard and Lawrence extracts target specific feature

information—the set of features and associated target detection threshold—from the input image data.

**208.** In addition, Barnard teaches extracting target specific feature information from the input image data when Barnard describes calculating values for each of the features from the input image data. For example, Barnard describes that “[e]ach object detected in a sub-image has its features calculated.” EX1005,6:1-2. Barnard notes that “**several features can be calculated** and each will have a numerical value in a range of values.” EX1005,5:2-3. In this regard, Barnard describes calculating various features from the input image data, including “brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features” that “may indicate shape, width, height, symmetry or lack of symmetry,” as shown in Figs. 5-6. EX1005,4:50-5:1, 4:46-49 (“FIG. 5 shows the square array of 24 pixels surrounding each pixel P in each of the sub-image pixel stores SIPS, each square indicating a storage location holding a pixel value. Assuming P to be a non-zero value, P will usually be surrounded by other none-zero pixels.”).



Barnard, Fig. 5 (annotated).

**209.** Accordingly, calculating values for each of the features and determining the set of features and associated target detection threshold (using a neural network, per Lawrence) for distinguishing targets from background clutter from the input image data as described in Barnard are extracting target specific feature information from the input image data. More specifically, extracting one or more of (1) the set of features, (2) the target detection threshold associated with the set of features (using a neural network, per Lawrence, for each of the selected features); (3) the combination of the set of features with the associated target detection threshold, and/or (4) values for each of the features is “*extracting said target specific feature information from said data*” as claimed by the ’639 Patent.

**210.** Thus, Barnard in combination with Lawrence teaches *extracting said*

*target specific feature information from said data* (e.g., determining or calculating the values of the features, the set of features, and/or the target detection threshold (e.g., using a neural network) from the input image data).

211. Accordingly, Barnard in combination with Lawrence renders obvious *extracting said target specific feature information from said data*.

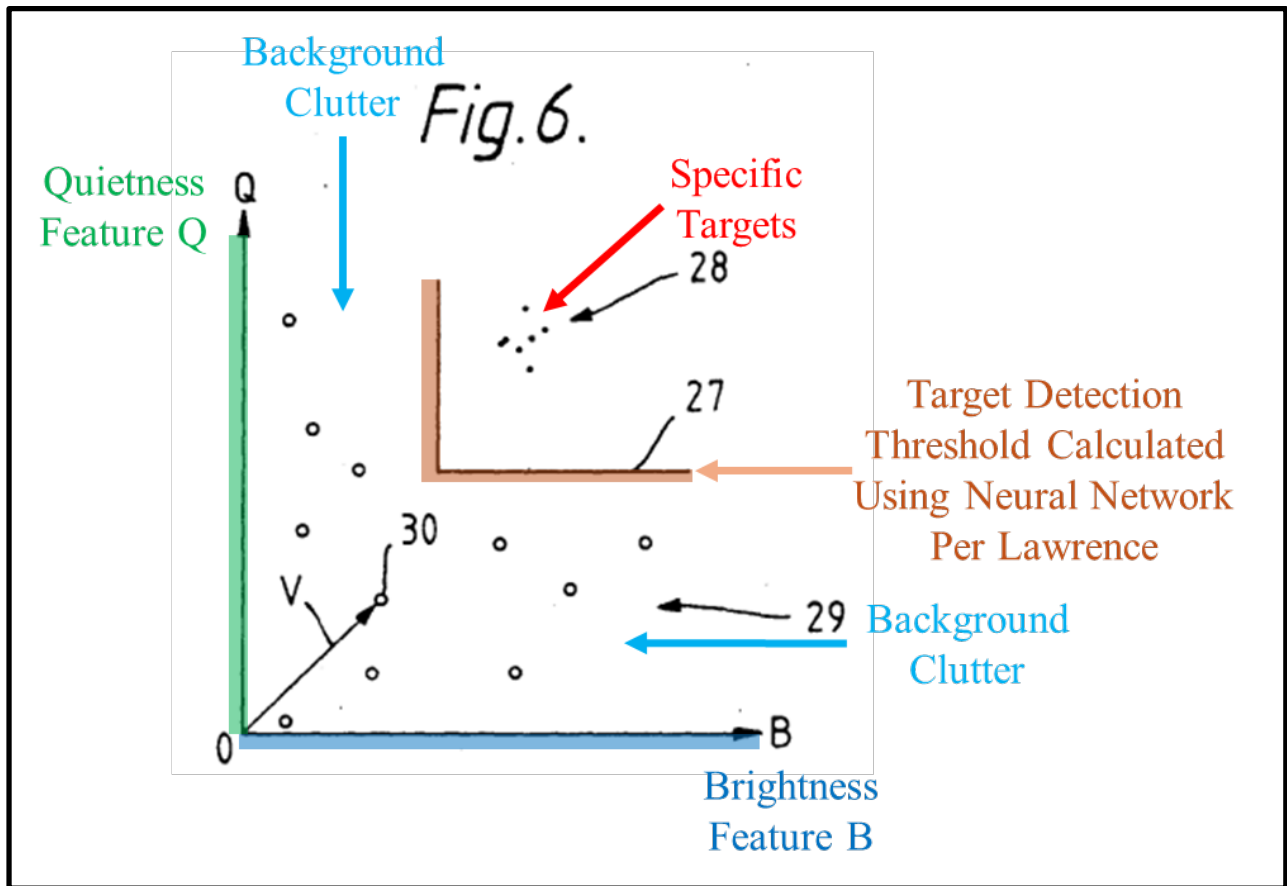
**[1.5] (e) using said target specific feature information to distinguish specific targets from background clutter; and**

212. Barnard in combination with Lawrence renders obvious element [1.5].

213. Barnard teaches using the target specific feature information, and more specifically, the set of selected features and associated target detection threshold, to distinguish specific targets from background clutter. For example, Barnard describes “**comparing the feature values of an incoming picture signal with the threshold to detect a target.**” EX1005, 1:21-23, *see also* 6:57-60 (“comparing feature values of an incoming picture signal in a sub-image with the target decision threshold in the associated sub-store to detect a target.”). Barnard explains that incoming picture signal “may contain **a target signal to be detected against background signals.**” EX1005, 1:9-10. For the incoming picture signal, Barnard calculates feature values for each of the features included in the set of selected features used to distinguish specific targets from background clutter. EX1005, 4:50-5:1. Barnard then compares the calculated feature values of the

incoming image to the target detection threshold associated with the set of selected features. EX1005, 1:21-23. In the combination of Barnard and Lawrence, the calculated feature values are compared to the target detection threshold calculated using a neural network, per Lawrence, for each of the selected features. In this regard, the target detection threshold calculated using the neural network “effectively separates target objects from background objects.” EX1005, 5:13-17. Accordingly, by comparing the calculated feature values of the incoming image to the target detection threshold associated with the set of selected features, the system either detects a specific target or background clutter, thereby distinguishing specific targets from background clutter. EX1005, 5:13-28.

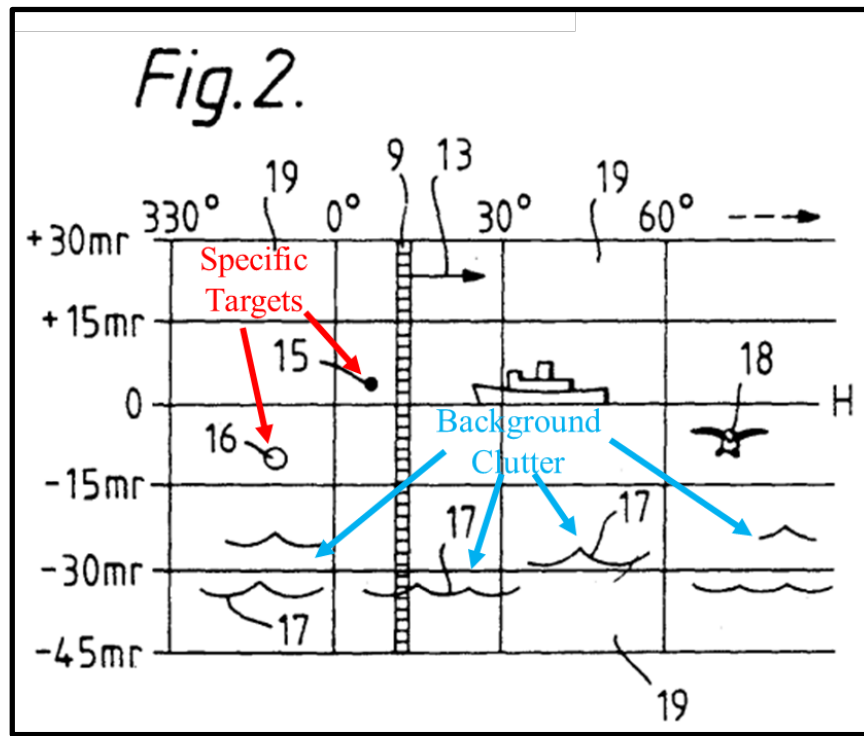
**214.** Fig. 6 of Barnard, reproduced below, shows an example of using a set of selected features—made up of the brightness feature B and the quietness feature Q—and an associated target detection threshold 27 represented by thresholds associated with feature B and feature Q) calculated using a neural network, per Lawrence, to distinguish specific targets from background clutter.



Barnard, Fig. 6 (annotated to illustrate exemplary combination with Lawrence).

**215.** Fig. 2 of Barnard shows an example of a real-world application of using a set of selected features and associated target detection threshold to distinguish specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), from background clutter, such as wave crests 17. EX1005, 1:24-36, 3:34-41. Fig. 2 also illustrates that the specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), are distinguished from other potential targets, such as a seagull

18.



Barnard, Fig. 2 (annotated).

**216.** Thus, Barnard in combination with Lawrence teaches *using said target specific feature information to distinguish specific targets from background clutter* (e.g., using the set of selected features and associated target detection threshold(s) calculated using a neural network to distinguish specific targets from background clutter in incoming picture signals).

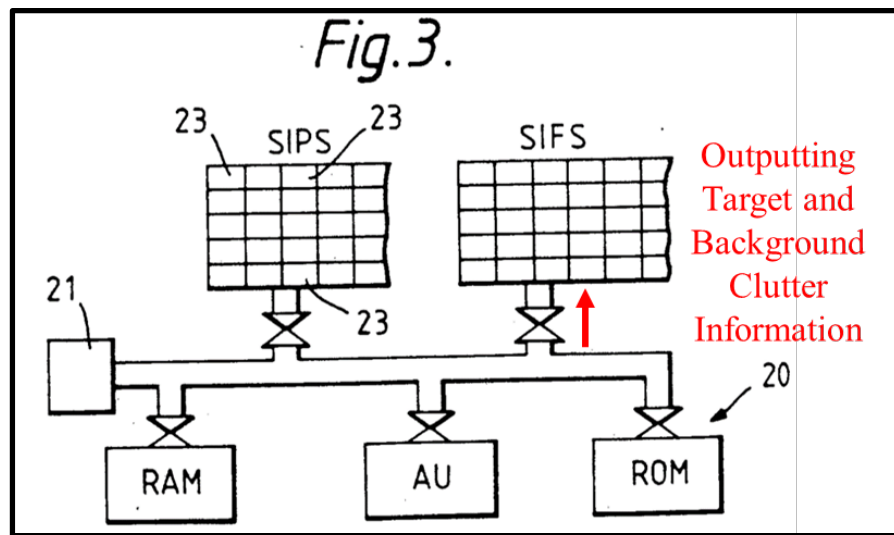
**217.** Accordingly, Barnard in combination with Lawrence renders obvious *using said target specific feature information to distinguish specific targets from background clutter*.

**[1.6] (f) outputting target and background clutter information.**

**218.** Barnard discloses or renders obvious element [1.6].

**219.** Barnard teaches outputting target and background clutter information.

Barnard describes that “a digital computer 20” that includes “an arithmetic unit AU for carrying out the programme steps, and a random access memory RAM for storing intermediate results obtained during the programme calculations,” may output target and background clutter information to a “sub-image feature store SIFS.” EX1005,4:19-34, 1:53-57; *see also* Abstract (“The values of a set of features, such as brightness, volume or quietness, of the background and target picture signals associated with each sub-image in the respective sub-store are calculated and stored.”). Barnard explains that the “sub-image feature store SIFS is provided to store information about features of detected objects.” EX1005,4:32-34. More specifically, Barnard teaches “**storing the calculated values of the set of features of the background and target picture signals** associated with each sub-image in the respective sub-store.” EX1005,1:53-57. When the computer outputs the calculated feature values of the background and target picture signals to the SIFS, the system is outputting target and background clutter information.



Barnard, Fig. 3 (annotated).

**220.** With respect to “*outputting*” the ’639 Patent consistently refers to communications between components within the target recognition system as being “*outputted*” from a component. EX1001, 2:47-52 (“Referring to FIG. 2, ... signals are inputted through communication links 2 which direct the input signals, flow through the communication links 6 to the neurons 4 in the neural network in a layer-by-layer fashion, and **outputted through the communications links 8 which direct the output signals.**”), 3:2-4 (“Input voltages  $V_1, V_2, V_3, \dots V_N$  are received from other neurons and **output voltage  $V_i$  is outputted to other neurons.**”), 12:38-45 (“... said data statistics outputted from said calculator ...”), *see also* 7:16-22 (“As shown in FIG. 10, the classification system inputs the data in module 2, extracts feature information from the inputted data in module 4 and inputs the feature information into the classification module 6 which uses decision

criteria 12 to classify the target from background clutter and **outputs this information in module 8.**”), 5:55-58 (“FIG. 3 shows an example of this type of network, wherein all neurons 4 are connected to all other neurons 4 through corresponding communication linkS 6 with input and **output communication links** as shown.”). Therefore, when the computer communicates the calculated feature values of the background and target picture signals to the SIFS, the system of Barnard is “*outputting*” target and background clutter information as required by [1.6].

**221.** Thus, Barnard teaches *outputting target and background clutter information* (e.g., outputting the calculated feature values of the background and target picture signals from the computer to the sub-image feature store (SIFS)).

**222.** Accordingly, Barnard discloses or renders obvious *outputting target and background clutter information*.

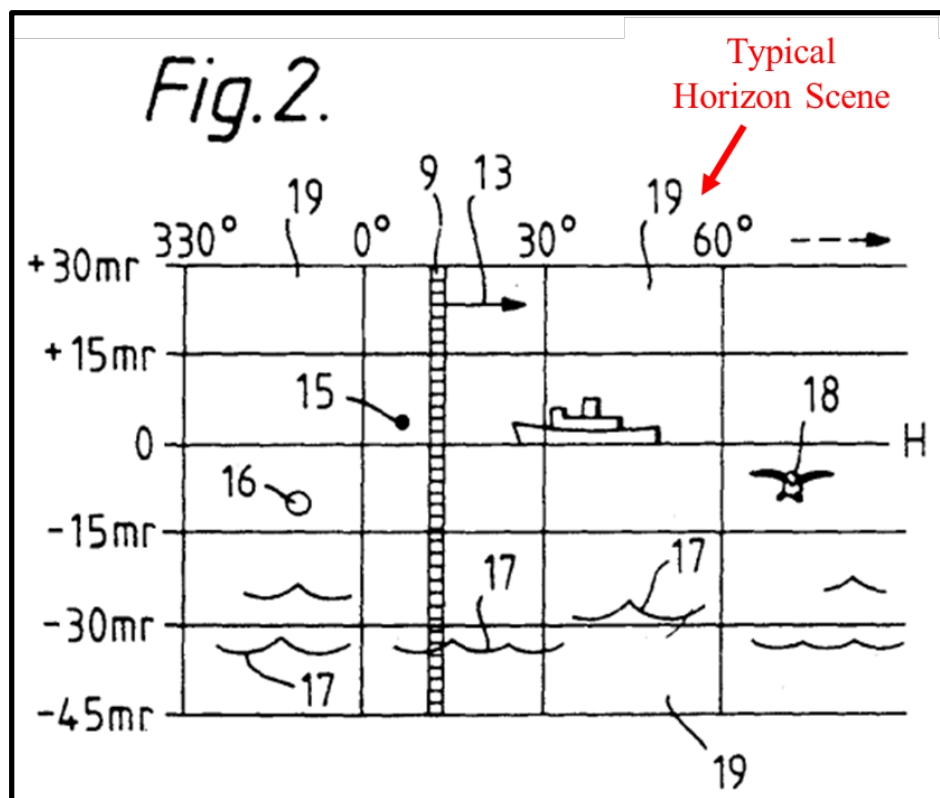
### **3. Claim 2**

**[2.0]** *The method of claim 1, wherein said data is one-dimensional, two-dimensional, or multi-dimensional.*

**223.** Barnard discloses or renders obvious element [2.0].

**224.** As discussed in [1.1], Barnard teaches inputting data such as a “stream of digitized pixel values” or “picture signals” that includes two-dimensional data. In this regard, Barnard explains that the “picture signals

represent[] an image of a scene.” 1:7-8. Barnard provides a specific example in Fig. 2 showing a two-dimensional image of “a typical horizon scene.” EX1005, 2:59-61. Accordingly, the stream of digitized pixel values or picture signals associated with the horizon scene are an example of the data being two-dimensional.



Barnard, Fig. 2 (annotated).

**225.** Related, Barnard notes that the digitized pixel values are “retained in a store preserving their relative positions.” EX1005, 3:56-57. In this regard, a POSITA understands that Barnard’s description of preserving “the relative positions” of the pixel values is in the context of the two-dimensional image of the

horizon scene. That is, Barnard teaches the pixel values are stored in a manner that retains the relative positions of the pixels in the two-dimensional image. EX1005, 3:56-57.

**226.** Accordingly, Barnard discloses or renders obvious *wherein said data is one-dimensional, two-dimensional, or multi-dimensional* (e.g., the input image data (e.g., digitized pixel values or picture signals) is two-dimensional image data).

#### **4. Claim 3**

**[3.0]** *The method of claim 1, wherein said data is digitized imagery, speech signals, or radar signals.*

**227.** Barnard discloses or renders obvious element [3.0].

**228.** As discussed in [1.1] and [2.0], Barnard teaches inputting data such as a “stream of digitized pixel values” or “picture signals” that includes two-dimensional image data. In this regard, Barnard explains that the “picture signals represent[] an image of a scene.” 1:7-8. Barnard provides a specific example in Fig. 2 showing a two-dimensional image of “a typical horizon scene.” EX1005, 2:59-61. Accordingly, the stream of digitized pixel values or picture signals associated with the horizon scene are an example of the data being “*digitized imagery*.”

**229.** Accordingly, Barnard discloses or renders obvious *wherein said data is digitized imagery, speech signals, or radar signals*.

**5. Claim 4**

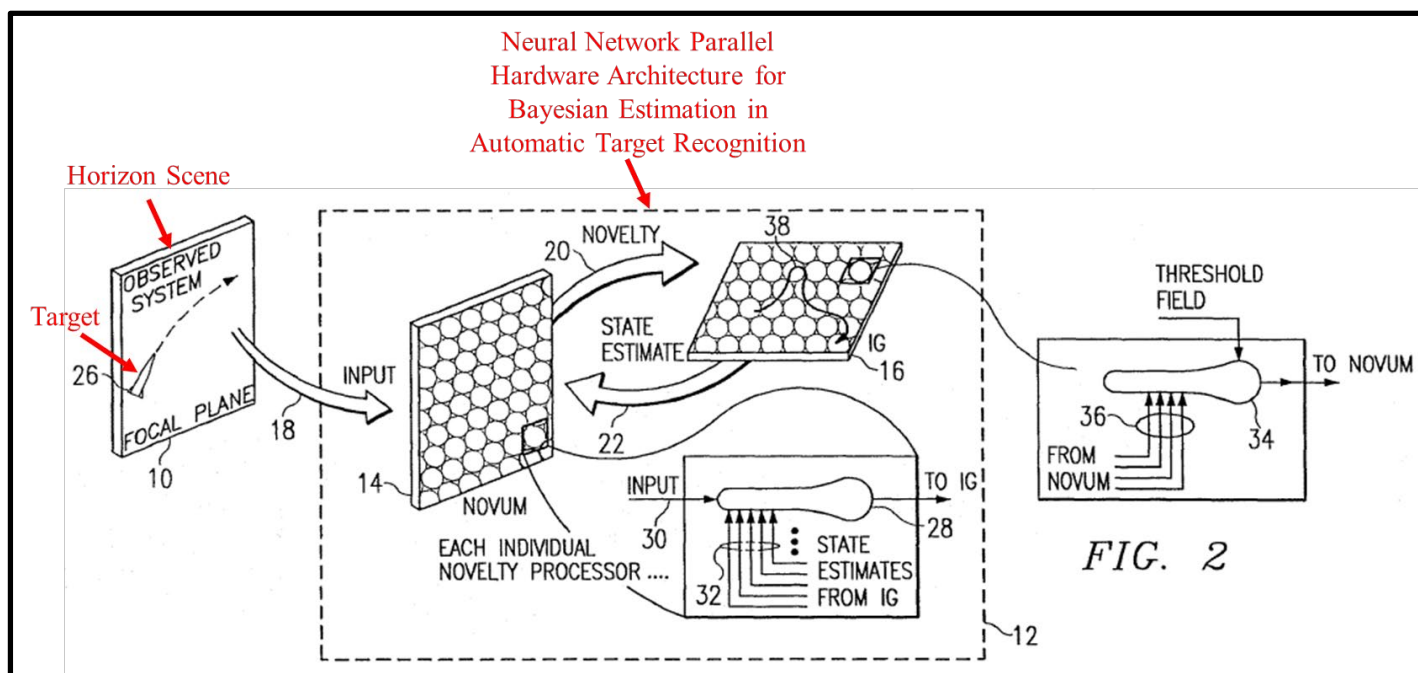
**[4.0]** *The method of claim 1, wherein parallel hardware architectures are employed to use said feature information to distinguish particular targets from background clutter.*

**230.** Barnard in combination with Lawrence renders obvious element [4.0].

**231.** Barnard does not explicitly disclose employing parallel hardware architectures to use target specific feature information to distinguish particular targets from background clutter. However, as discussed above, it would have been obvious to use parallel hardware architectures, such as the neural networks taught by Lawrence, to calculate the target detection threshold of Barnard because doing so would have been no more than the use of a known technique to improve a similar method in the same way and because doing so would be the simple substitution of one known element for another to obtain predictable results. In the combination, Barnard's target recognition method would be modified to utilize neural network architectures, per Lawrence, to calculate Barnard's target detection threshold in accordance with Baye's criterion. In this regard, as discussed in [1.5], the combination of Barnard and Lawrence teaches using the set of selected features and associated target detection threshold (calculated using the parallel hardware architectures associated with a neural network) to distinguish specific targets from background clutter in incoming picture signals.

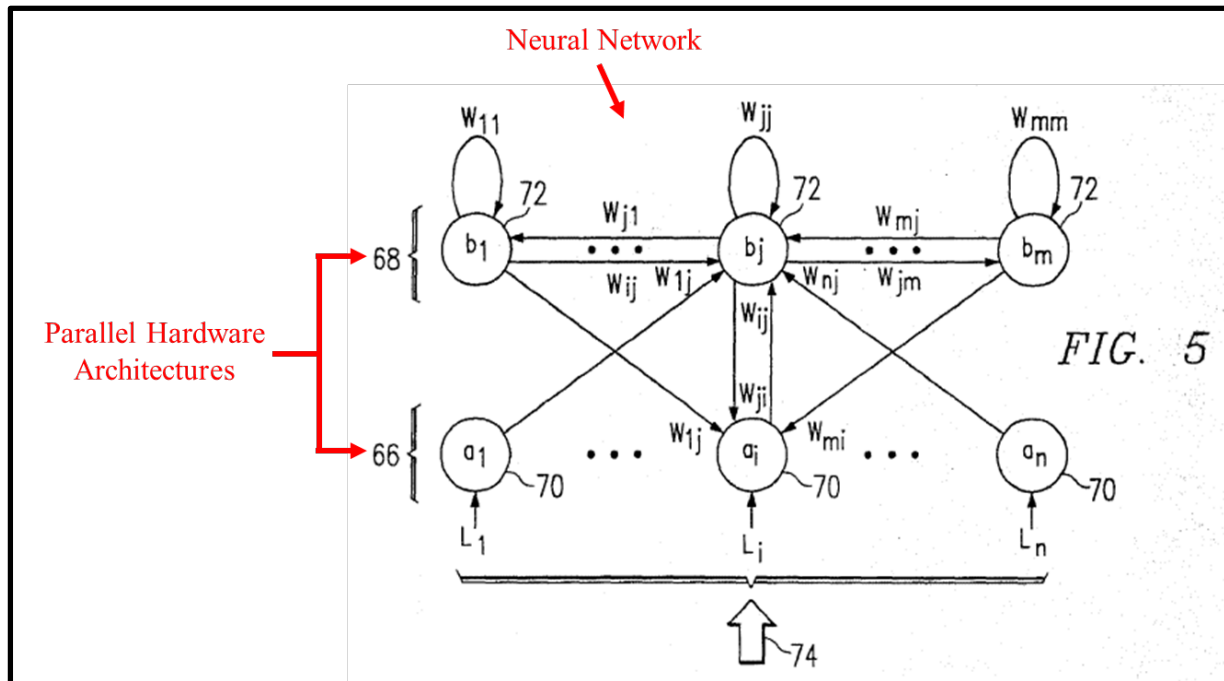
232. Lawrence discloses that the neural network architecture used for the Bayesian estimation includes parallel hardware architectures. In this regard, Lawrence “pertains in general to **a neural network architecture**, and more particularly, to an architecture which is **designed to perform adaptive, continuous Bayesian estimation**” as shown in Fig. 2, reproduced below, that uses “**a two-layer architecture** as described above, consisting of novum 14 and the IG 16, this architecture being somewhat **similar to that illustrated in Figure 5.**”

EX1006, Title, 1:2-6, 11:1-3, 23:26-28.



Lawrence, Fig. 2 (annotated).

233. Fig. 5 of Lawrence, reproduced below, illustrates exemplary parallel hardware architectures for performing Bayesian estimation.



Lawrence, Fig. 5 (annotated).

**234.** The understanding that a neural network is an example of parallel hardware architectures is confirmed by the '639 Patent, which describes “Parallel computer architectures [sic], such as neural networks, are used extensively.” Ex.1001, 6:17-18.

**235.** Thus, Barnard in combination with Lawrence teaches *wherein parallel hardware architectures* (e.g., parallel hardware architectures of a neural network, per Lawrence) *are employed to use said feature information to distinguish particular targets from background clutter* (e.g., using the set of selected features and associated target detection threshold calculated using a neural

network to distinguish specific targets from background clutter in incoming picture signals).

**236.** Accordingly, Barnard in combination with Lawrence renders obvious *wherein parallel hardware architectures are employed to use said feature information to distinguish particular targets from background clutter.*

**6. Claim 5**

**[5.0]** *The method of claim 4, wherein said parallel hardware architectures comprise neural networks.*

**237.** Barnard in combination with Lawrence render obvious element [5.0].

**238.** See the analysis above for [4.0]. As discussed in detail there, the parallel hardware architectures employed by the combination of Barnard and Lawrence to distinguish particular targets from background clutter comprise neural networks. More specifically, the combination utilizes the neural networks of Lawrence that include parallel hardware architectures.

**239.** Accordingly, Barnard in combination with Lawrence renders obvious *wherein said parallel hardware architectures comprise neural networks.*

**7. Claim 6**

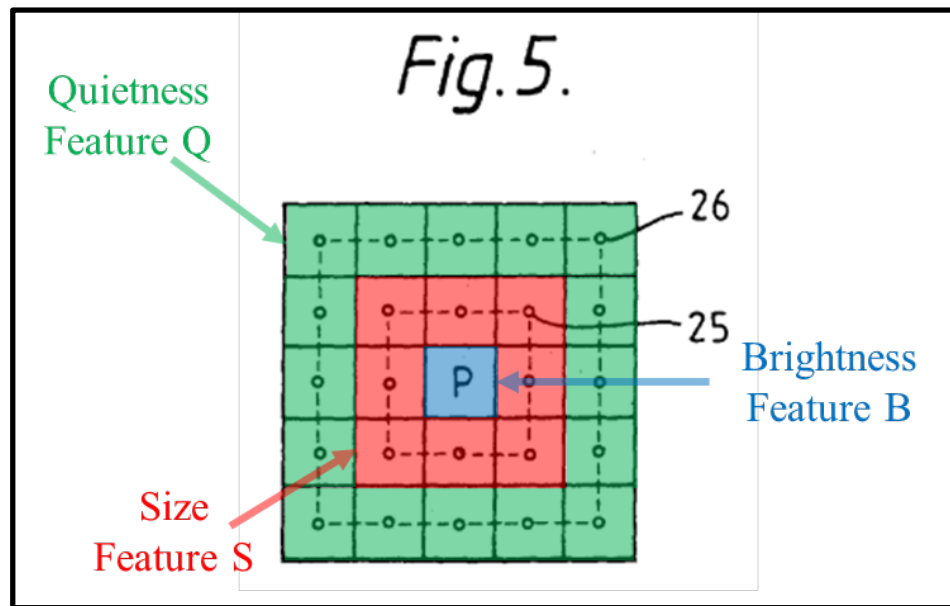
**[6.0]** *The method of claim 1, wherein said feature information is contrast-based or texture-based.*

**240.** Barnard discloses or renders obvious element [6.0].

**241.** As an initial matter, I note that [6.0] recites “*feature information*,” not “*target specific feature information*” as used in [1.2], [1.4], and [1.5] or “*target feature information*” as used in [1.3]. I also understand from counsel that the use of “*said*” in a patent claim indicates reference to an element that was previously introduced. However, there is no prior (or subsequent) use of “*feature information*”—without “target specific” or “target”—in claim 6 or claim 1 from which claim 6 depends. I found several instances of “*feature information*” in the ’639 Patent. *See*, e.g., EX1001, 7:17-22 (“As shown in FIG. 10, the classification system inputs the data in module 2, extracts **feature information** from the inputted data in module 4 and inputs the **feature information** into the classification module 6 which uses decision criteria 12 to classify the target from background clutter and outputs this information in module 8.”), 7:37-39 (“Various procedures are used to extract **feature information** ....”). Accordingly, for the purpose of this declaration, I am treating “*said feature information*” recited in [6.0] as referring to the “*target specific feature information*” recited in claim 1.

**242.** As discussed in the [1.2] analysis, Barnard discloses calculating various features and associated data statistics, including “brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features” that “may indicate shape, width, height, symmetry or lack of symmetry.” EX1005, 2:9-27; 4:50-5:1; 4:46-49 (“FIG. 5 shows the square array of 24 pixels surrounding each pixel P in

each of the sub-image pixel stores SIPS, each square indicating a storage location holding a pixel value. Assuming P to be a non-zero value, P will usually be surrounded by other none-zero pixels.”); 5:2-3 (“several features can be calculated and each will have a numerical value in a range of values.”).



Barnard, Fig. 5 (annotated).

**243.** A POSITA would have understood that “In general, texture of a scene, image or object can be defined as the spatial variation or distribution of tonal or intensity values of picture elements, wherein the spatial variation extends over a given area.” EX1007, 5:26-29.

**244.** Barnard’s brightness feature B measures the level of brightness of the pixel value at the center of a given 25-pixel area. EX1005, 4:50-52, Fig .5; *see also* 2:9-11 (“picture elements which are each of more than a threshold level of

brightness”). Quietness feature Q measures “the sum of the sixteen pixels 26 next surrounding the pixels 25” — i.e., the sixteen pixels with green highlighting in the annotated Fig. 5 above. EX1005, 4:62-66, Fig. 5. Thus, a POSITA would have understood that the combination of brightness feature B and quietness feature Q provide target specific feature information that is texture-based because it represents the spatial variation of pixel intensity values over a given area — namely, the variation between the center pixel (item P in Fig. 5 above) and the second ring of surrounding pixels (item 26 in Fig. 5 above). For example, relative to target decision thresholds for B and Q, there are at least four distinct types of texture: small B and small Q (bright pixel with dark pixels surrounding nearby), small B and large Q (dark pixel with bright pixels surrounding nearby), large B and small Q (bright pixel with dark pixels surrounding nearby), large B and large Q (bright pixel with bright pixels surrounding nearby). Further, a POSITA would have understood that the combination of brightness feature B and quietness feature Q provide target specific feature information that is contrast-based because it represents the level of difference between pixel intensity values between two areas — i.e., between the center pixel and the second ring of surrounding pixels. For example, small B with large Q, or large B with small Q, represent larger contrast than small B with small Q, or large B with large Q.

**245.** A POSITA would have understood that Barnard’s B and Q features

can be combined in this way because Barnard teaches the benefit of doing so.

EX1005, 5:2-13 (“Thus several features can be calculated and each will have a numerical value in a range of values. For some features a high value may be more indicative of a target, whereas for other features a low value may indicate a target. For any one feature, the feature values of predetermined targets may lie in the range of values found for background objects and hence that feature alone is not sufficient to discriminate the target from the background. It is known to resolve this problem by taking the numerical values of a number of selected features for objects found in the image and plotting them in a multi-dimensional feature hyperspace.”); *see also* 6:22-33.

**246.** The various features (“brightness feature B,” “size feature S,” “quietness feature Q,” and “[o]ther features”) described by Barnard include target specific feature information that is contrast-based and texture-based, consistent with the examples in the ’639 Patent. EX1001, 5:15-49 (“select **target specific feature information (e.g., contrast-based and texture-based)** to distinguish specific targets from background clutter”). EX1005, 4:46-5:3; Fig. 5; *see also* EX1007, 5:26-29 (“In general, **texture of a scene, image or object can be defined as the spatial variation or distribution of tonal or intensity values of picture elements**, wherein the spatial variation extends over a given area.”).

247. Thus, Barnard teaches *wherein said feature information is contrast-based or texture-based* (e.g., the set of selected features and associated target detection threshold is contrast-based and/or texture-based features).

248. Accordingly, Barnard discloses or renders obvious *wherein said feature information is contrast-based or texture-based*.

## 8. Claim 7

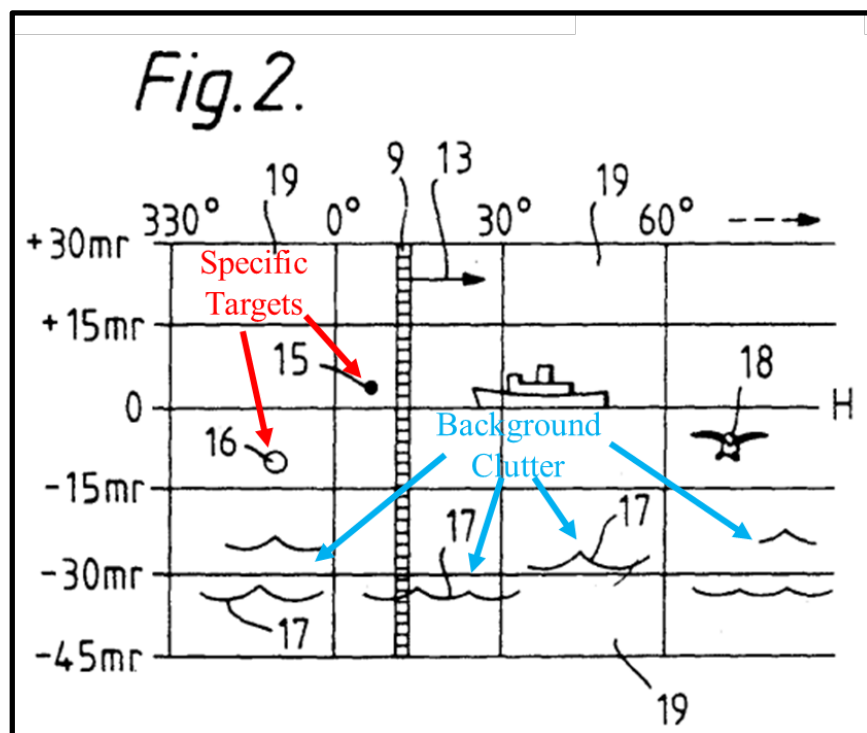
**[7.0] *The method of claim 1, wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.***

249. Barnard discloses or renders obvious element [7.0].

250. As an initial matter, I note that [7.0], like [6.0], recites “*feature information*,” not “***target specific feature information***” as used in [1.2], [1.4], and [1.5] or “***target feature information***” as used in [1.3]. Accordingly, for similar reasons, for the purpose of this declaration I am treating “*said feature information*” recited in [7.0] as referring to the “***target specific feature information***” recited in claim 1.

251. As discussed in the [1.5] analysis, Barnard teaches using the target specific feature information, and more specifically, the set of selected features and associated target detection threshold, to distinguish specific targets from background clutter. Beyond distinguishing specific targets from background clutter, Barnard further teaches using the target specific feature information to

distinguish between at least two different target classes. For example, Fig. 2 shows an example of a real-world application of using a set of selected features and an associated target detection threshold to distinguish specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., such as a sea-skimming missile), from other potential targets, such as seagull 18. EX1005, 1:24-36, 3:34-41.



Barnard, Fig. 2 (annotated).

**252.** In using the set of selected features and associated target detection threshold to distinguish the point source 15 and the sea-skimming source 16 (e.g., such as a sea-skimming missile) from the seagull 18, Barnard is distinguishing at least two target classes from one another.

**253.** Thus, Barnard teaches *wherein said feature information is further*

*used to distinguish two target classes or a plurality of target classes from one another (e.g., using the set of selected features and associated target detection threshold to distinguish specific targets from other potential targets in incoming picture signals).*

**254.** Accordingly, Barnard discloses or renders obvious *wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.*

**D. Ground 4: Claim 7 is obvious over Barnard in view of Lawrence and Knecht**

**9. Reasons to combine**

**255.** It is my opinion that a POSITA when considering the teachings of Barnard, would have naturally considered the teachings of both Lawrence and Knecht. Exemplary reasons for combining Barnard with Lawrence are set forth above in the context of Ground 3. Similarly, exemplary reasons for combining Barnard with Knecht are set forth above in the context of Ground 2. The reasons for combining Barnard with Lawrence and the reasons for combining Barnard with Knecht are equally applicable in the context of combining all three of Barnard, Lawrence, and Knecht. That is, the same reasons, and associated benefits and expectations of success, described in the context of combining Barnard with each of Lawrence and Knecht individually also exist when considering the combination

of Barnard with both Lawrence and Knecht.

**256.** In the combination of Barnard, Lawrence, and Knecht, Barnard's target recognition method would be modified to explicitly include a plurality of different target classes, as taught by Knecht. Each target class would have an associated set of selected features and a corresponding target detection threshold, per Barnard, to facilitate classifying a potential target into one of the plurality of target classes, per Knecht. The target detection threshold for each target class would be calculated utilizing a neural network, per Lawrence.

***a) Analogous art***

**257.** As explained in X.B.2 and X.C.2, Barnard, Lawrence, and Knecht are all analogous prior art pertaining to the same field of endeavor as the '639 patent. Accordingly, a POSITA would recognize that Barnard, Lawrence, and Knecht are analogous prior art to the '639 Patent.

***b) Motivations to combine***

***(1) Use of a known technique to improve a similar method in the same way***

**258.** For the same and similar reasons discussed in X.B.2.b and X.C.2.b, the combination of Barnard, Lawrence, and Knecht would have been the use of a known technique (distinguishing between multiple target classes in an image processing-based target detection method, per Knecht, and using a neural network

architecture for Bayesian estimation in a target detection method, per Lawrence) to improve a similar method (the image-based target detection method of Barnard) in the same, predictable way (an image processing-based target detection method, per Barnard, that distinguishes between multiple target classes, per Knecht, using a neural network architecture for Bayesian estimation, per Lawrence).

***(2) Combining prior art elements according to known methods to obtain predictable results***

**259.** For the same and similar reasons discussed in X.B.2.b and X.C.2.b, the combination of Barnard, Lawrence, and Knecht would have been the combination of prior art elements (an image-based target detection method, per Barnard, using a plurality of target classes in an image-based target detection method, per Knecht, and using a neural network architecture for Bayesian estimation, per Lawrence) according to known methods to obtain predictable results (an image processing-based target detection method, per Barnard, that distinguishes between multiple target classes, per Knecht, using a neural network architecture for Bayesian estimation, per Lawrence).

***c) Reasonable expectation of success***

**260.** A POSITA would have had a reasonable expectation of success in combining Barnard with Lawrence and Knecht for the same reasons a POSITA would have had a reasonable expectation of success in combining Barnard with

Lawrence and Knecht separately. Accordingly, utilizing neural network-based Bayesian estimation in accordance with Lawrence is particularly well suited to support distinguishing between a plurality of different target classes in accordance with Knecht.

**261.** Thus, a POSITA would have had a reasonable expectation of success in implementing neural networks, per Lawrence, for calculating target detection thresholds for a plurality of target classes, per Knecht, in the context of Barnard's image-based target detection method.

#### **10. Claim 7**

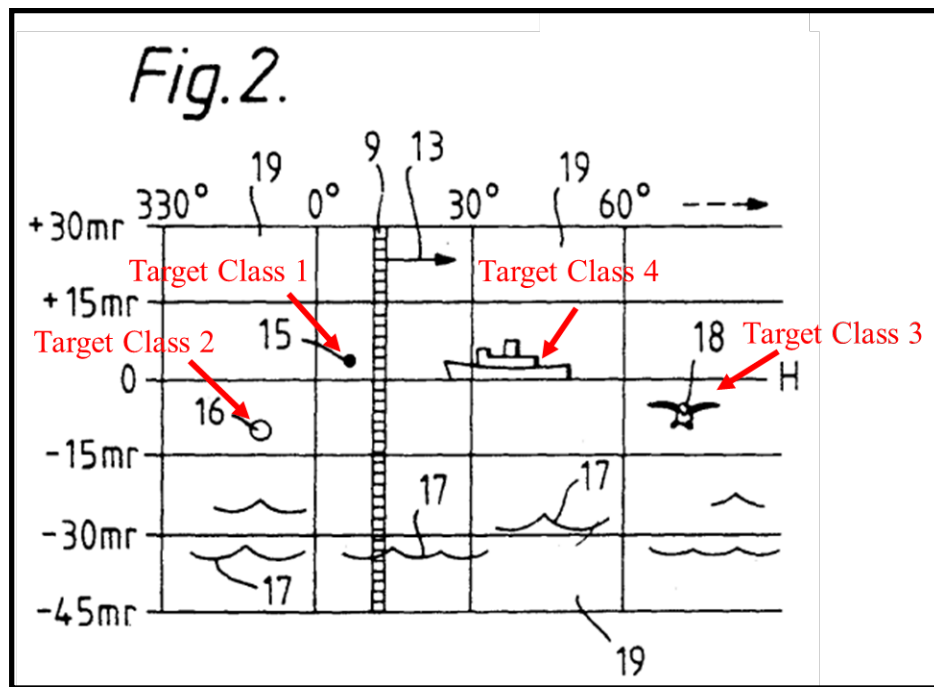
**[7.0]** *The method of claim 1, wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.*

**262.** Barnard in view of Lawrence and Knecht renders obvious element [7.0].

**263.** As discussed in the analysis of [1.5] of Ground 1 and [7.0] of Ground 2, Barnard discloses distinguishing between at least two different target classes. Ex.1005, 1:24-36, 3:34-41, Fig. 2. While Barnard provides an example of distinguishing multiple target classes from one another, Barnard does not *explicitly* state that multiple target classes are being utilized.

**264.** As discussed in Section X.D.1 above, it would have been obvious to combine Barnard, Lawrence, and Knecht. In the combination, Barnard's target

recognition method is modified to include a plurality different target classes, as taught by Knecht. In the combination, each target class has corresponding target specific feature information, such as an associated set of selected features and a corresponding target detection threshold (determined using a neural network in accordance with Lawrence), to facilitate classifying a potential target into one of the plurality of target classes in accordance with Barnard's existing target detection approach. For example, in the combination, the target specific feature information may be utilized to distinguish a potential target between Target Class 1 (e.g., aerial missiles or other aerial threats), Target Class 2 (e.g., sea-skimming missiles or other surface and/or sub-surface threats), Target Class 3 (e.g., seagulls or other non-threatening aerial objects), and Target Class 4 (e.g., ships or other floating structures), as shown below.



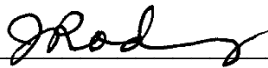
Barnard, Fig. 2 (annotated to illustrate exemplary combination with Knecht).

**265.** Thus, Barnard in view of Lawrence and Knecht renders obvious wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another (e.g., using the sets of selected features and associated target detection thresholds for a plurality of target classes to distinguish between a plurality of target classes).

**266.** Accordingly, Barnard in view of Lawrence and Knecht renders obvious *wherein said feature information is further used to distinguish two target classes or a plurality of target classes from one another.*

**XI. CONCLUSION**

**267.** This declaration and my opinions herein are made to the best of my knowledge and understanding, and based on the material available to me, at the time of signing this declaration. I declare that all statements made herein on my own knowledge are true and that all statements made on information and belief are believed to be true, and further, that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 or Title 18 of the United States Code.



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Jeffrey J. Rodriguez, Ph.D.

Jan. 17, 2025

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Date