

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.,
Petitioner

v.

INTELLECTUAL VENTURES II LLC,
Patent Owner.

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

**PETITION FOR *INTER PARTES* REVIEW
UNDER 35 U.S.C. § 312 AND 37 C.F.R. § 42.104**

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PETITIONER’S EXHIBIT LIST

Ex.1001	U.S. Patent No. 6,894,639 to Katz (“’639 patent”)
Ex.1002	Prosecution File History of U.S. Patent No. 6,894,639
Ex.1003	Declaration of Jeffrey J. Rodriguez, Ph.D. under 37 C.F.R. § 1.68
Ex.1004	<i>Curriculum Vitae</i> of Jeffrey J. Rodriguez, Ph.D.
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”)
Ex.1009	“Bayesian and neural network pattern recognition : a theoretical connection and empirical results with handwritten characters” (“Lee”)
Ex.1010	IV’s Complaint, <i>Intellectual Ventures II, LLC v. Tesla, Inc.</i> , No. 6:24-cv-188-ADA (WDTX)
Ex.1011	Proposed Scheduling Order, <i>Intellectual Ventures II, LLC v. Tesla, Inc.</i> , No. 6:24-cv-188-ADA (WDTX)
Ex.1012	Statistics on District Court Timing
Ex.1013	Interim Procedure for Discretionary Denials in AIA Parallel District Court Litigation, June 21, 2022
Ex.1014	IV’s Preliminary Infringement Contentions, <i>Intellectual Ventures II, LLC v. Tesla, Inc.</i> , No. 6:24-cv-188-ADA (WDTX)
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”)

I. INTRODUCTION

U.S. Patent No. 6,894,639 (“the ’639 patent,” Ex.1001) is directed to a method of distinguishing targets from background clutter in images. As the title and specification of the ’639 patent indicate, the disclosed method is based on a particular implementation of Hebbian learning. However, the Challenged Claims of the ’639 patent do not require Hebbian learning, which is the heart of the disclosed method. Instead, the Challenged Claims recite an obvious combination of well-known image processing steps that had long been used to distinguish targets from background clutter.

Accordingly, pursuant to 35 U.S.C. §§ 311, 314(a), and 37 C.F.R. § 42.100, Tesla, Inc. (“Petitioner”) respectfully requests that the Board review and cancel as unpatentable under (pre-AIA) 35 U.S.C. §103(a) claims 1-7 (the “Challenged Claims”) of the ’639 patent.

II. GROUNDS FOR STANDING

Petitioner certifies that the '639 patent is eligible for IPR and that Petitioner is not barred or estopped from requesting IPR challenging the patent claims.

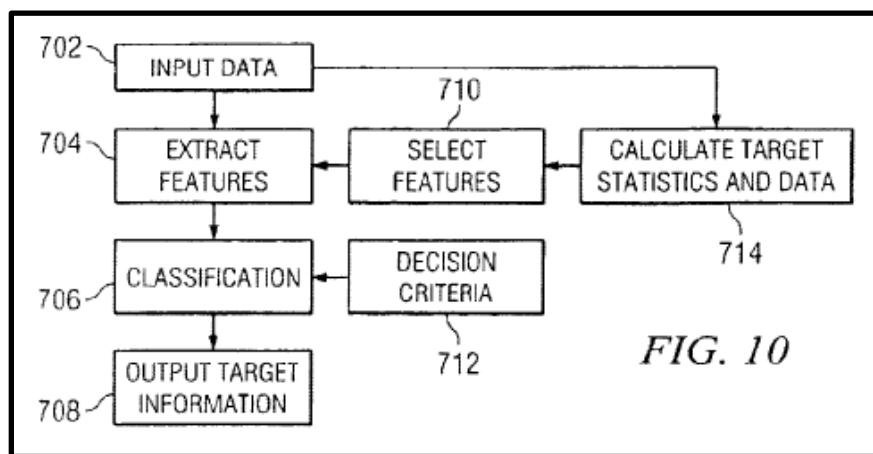
III. NOTE

Petitioner cites to exhibits' original page numbers, unless noted otherwise.

Emphasis in quoted material has been added. Claim terms are presented in *italics*.

IV. THE '639 PATENT

The '639 patent is directed to a method of distinguishing targets from background clutter. Ex.1001, Abstract. 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. Ex.1001, Abstract. The approach described by the '639 patent is generally shown in Fig. 10, reproduced below. Ex.1003, ¶33.



'639 patent, Fig. 10.

The method described by the '639 patent is based on a particular implementation of Hebbian learning, which had been around for more than forty years before the '639 patent was filed in December 1991. *See* Ex.1001, Title, 5:30-32 (“this method uses...Hebbian Learning”), 5:55-62 (“uses a variation of the Hebbian learning algorithm”), 7:50-53 (“[t]he generalized Hebbian learning algorithm employed”), 7:46-57, 7:63-9:40; Ex.1017, 6:45-48 (“This is essentially a simple Hebbian learning rule see, **Hebb, *Organization of Behavior***, John Wiley & Sons, **1949**”).

The '639 patent is titled “**Generalized Hebbian Learning** for Principal Component Analysis and Automatic Target Recognition, Systems and Method.” Ex.1001, Title. In its Summary of the Invention section, the '639 patent explains that “**this method uses the Hebbian Learning** to distinguish and take advantage of second order correlation information.” Ex.1001, 5:30-32. The Summary further explains that 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.” Ex.1001, 5:56-62. Likewise, the Detailed Description notes 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).” Ex.1001, 7:50-53.

Despite the Title, Summary of Invention, and Detailed Description of the '639 patent all requiring a particular implementation of Hebbian learning, the Challenged Claims of the '639 patent do not.¹ Ex.1003, ¶¶34-35. Instead, the Challenged Claims broadly recite well-known image processing techniques that had long been used to distinguish targets from background clutter. *See* Ex.1001, 12:2-14:31; Ex.1003, ¶35. As explained below, prior art—not considered by the Examiner during prosecution—shows that the Challenged Claims would have been obvious. Ex.1003, ¶36.

V. LEVEL OF ORDINARY SKILL IN THE ART

A person of ordinary skill in the art in December of 1991 (“POSITA”) would have been someone knowledgeable and familiar with the image processing systems pertinent to the '639 patent. That person would have a bachelor’s degree in computer science, computer engineering, electrical engineering, or equivalent training, and four years of experience working in the field of image processing. Lack of work experience can be remedied by additional education, and vice versa. Ex.1003, ¶18.

¹ The fact that the Challenged Claims do not require Hebbian learning is confirmed through claim differentiation by dependent claim 8 that explicitly requires “*wherein Hebbian learning techniques are used*” Ex.1001, claim 8.

VI. CLAIM CONSTRUCTION

Petitioner submits that, for the purposes of this proceeding and the grounds presented herein, no claim term requires express construction. *Nidec Motor Corp. v. Zhongshan Broad Ocean Motor Co.*, 868 F.3d 1013, 1017 (Fed. Cir. 2017). Ex.1003, ¶¶38-39.

VII. RELIEF REQUESTED AND THE REASONS FOR THE REQUESTED RELIEF

Petitioner asks that the Board institute an IPR trial and find the Challenged Claims unpatentable in view of the analysis below.

VIII. IDENTIFICATION OF HOW THE CLAIMS ARE UNPATENTABLE

A. Challenged claims

Petitioner challenges claims 1-7 of the '639 patent.

B. Statutory grounds for challenges

Grounds	Claims	Pre-AIA Basis
#1	1-3, 6, and 7	§103 over Barnard
#2	7	§103 over Barnard in view of Knecht
#3	1-7	§103 over Barnard in view of Lawrence
#4	7	§103 over Barnard in view of Lawrence and Knecht

Barnard (Ex.1005): U.S. Patent No. 5,027,413 to Barnard (“Barnard”) was filed June 13, 1989 and issued on June 25, 1991. Barnard is prior art to the '639 patent under pre-AIA §§ 102(a) and (e).

Knecht (Ex.1006): U.S. Patent No. 4,881,270 to Knecht et al. (“Knecht”) was filed October 28, 1983 and issued on November 14, 1989. Knecht is prior art to the ’639 patent under pre-AIA §§ 102(a), (b), and (e).

Lawrence: PCT Patent Application Publication No. WO 90/16038 to Lawrence (“Lawrence”) was filed June 15, 1990 and published on December 27, 1990. Lawrence is prior art to the ’639 patent under pre-AIA § 102(a) and (e).

Petitioner’s § 103 obviousness grounds rely on the combined teachings of the references and not on a physical incorporation of elements. *See In re Mouttet*, 686 F.3d 1322, 1332 (Fed. Cir. 2012).

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

1. Barnard

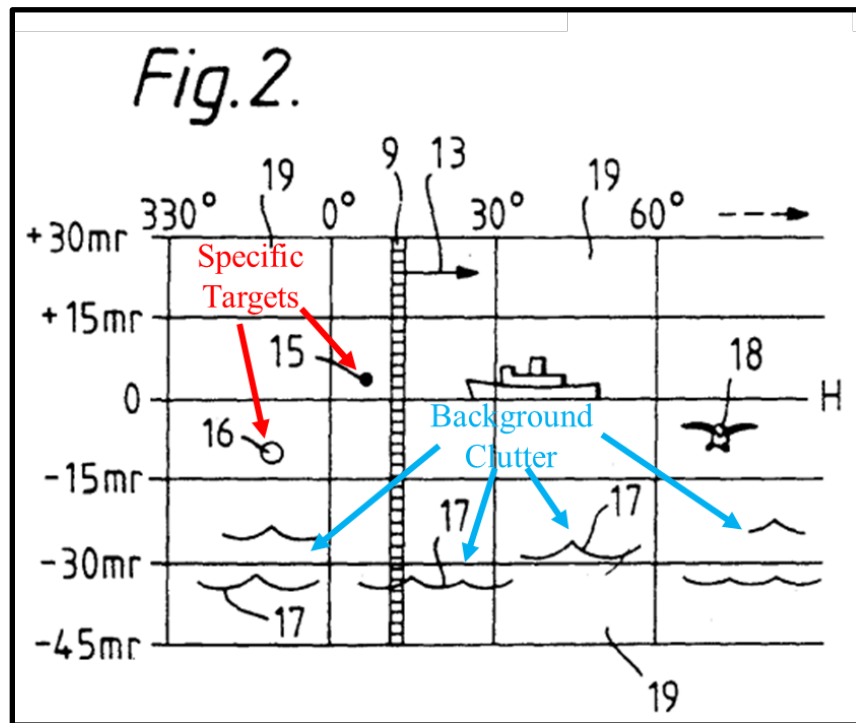
Like the ’639 patent, Barnard describes a method for distinguishing targets from background clutter in images. Ex.1005, Title; Abstract. Barnard’s method calculates a plurality of features from the image data and selects a set of features that “effectively separate[] target objects from background objects.” Ex.1005, 4:50-5:3; 5:13-17. A feature may be excluded or discarded from the set of selected features based on calculated data statistics. Ex.1005, 2:28-39 (describing excluding a feature if the statistical distribution of the feature exceeds a threshold or if the feature mean varies beyond a preset amount); *see also id.*, 6:12-15. For the selected set of features, the method generates a target detection threshold that is utilized to

distinguish targets from background clutter. Ex.1005, 5:13-17; 5:49-66. The target detection threshold is generated “in accordance with Baye’s criterion” and adapts over time as new image data is received. Ex.1005, 5:13-17; 5:47-6:15.

1. Claim 1

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

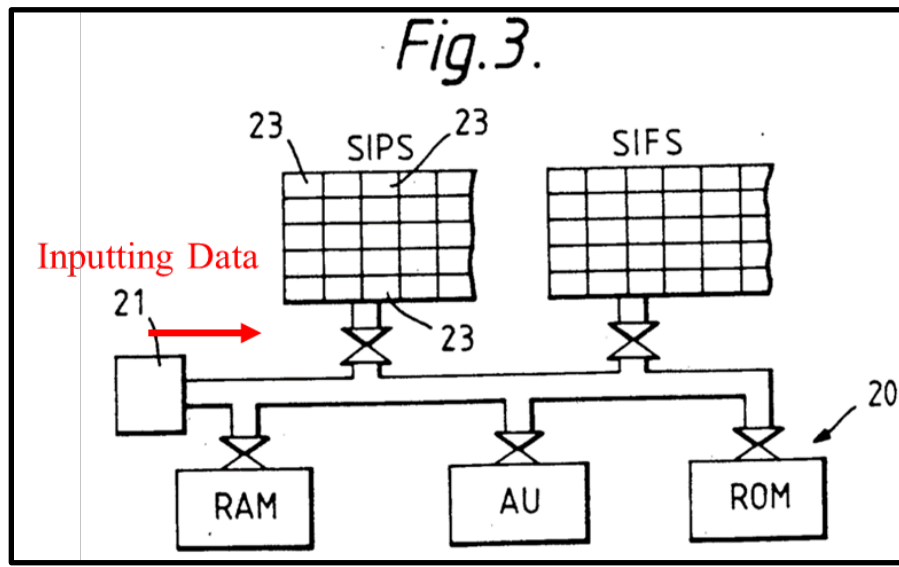
Barnard discloses or renders obvious *a method for distinguishing targets from background clutter*. Ex.1003, ¶¶54-56. For example, Barnard discloses a “target detection system ... for **examining picture signals of a scene** which may contain **a target signal (15,16) to be detected against background signals (17,18).**” Ex.1005, Abstract; *see also id.*, 1:1-10. Barnard’s system “**effectively separates target objects from background objects,**” as shown in Fig. 2 below. Ex.1005, 5:16-17. The operation of Barnard’s target detection system performs *a method for distinguishing targets from background clutter* because Barnard’s “target detection system is provided for examining picture signals of a scene” to distinguish a target signal (15,16) against background signals (17,18),” as shown in Fig. 2 below. Ex.1005, Abstract; Ex.1003, ¶55



Barnard, Fig. 2 (annotated).

[1.1] (a) *inputting data*;

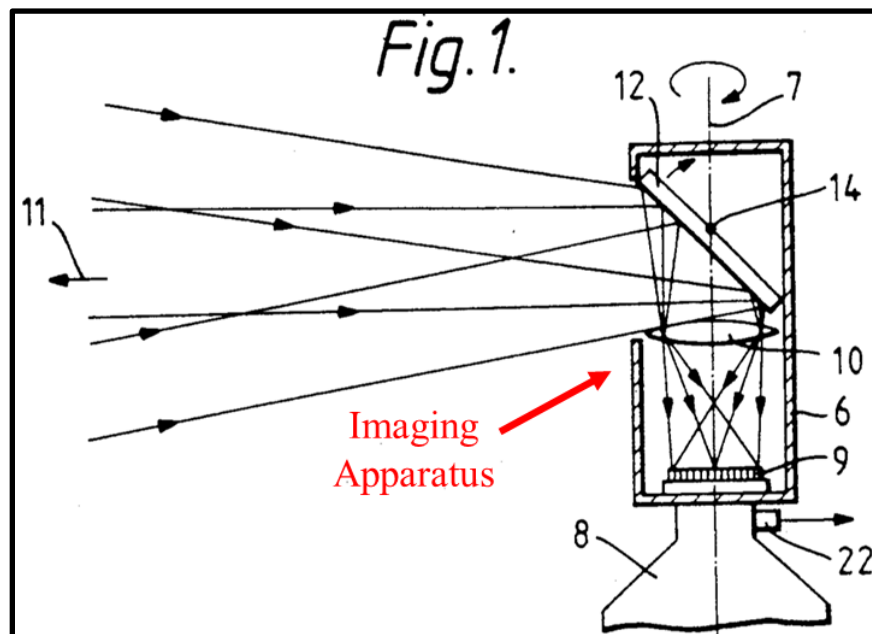
Barnard discloses or renders obvious *inputting data*. Ex.1003, ¶¶57-61. For example, Barnard describes “a digital computer 20 ... **receive[s] the stream of digitised pixel values** from a signal pre-processing unit 21.” Ex.1005, 4:19-21; Ex.1003, ¶58.



Barnard, Fig. 3 (annotated).

Barnard explains the digitized pixel values are based on images obtained by “a thermal imaging apparatus,” such as the one illustrated in Fig. 1, below.

Ex.1005, 3:5-11, 3:42-59, Fig. 1; Ex.1003, ¶59.

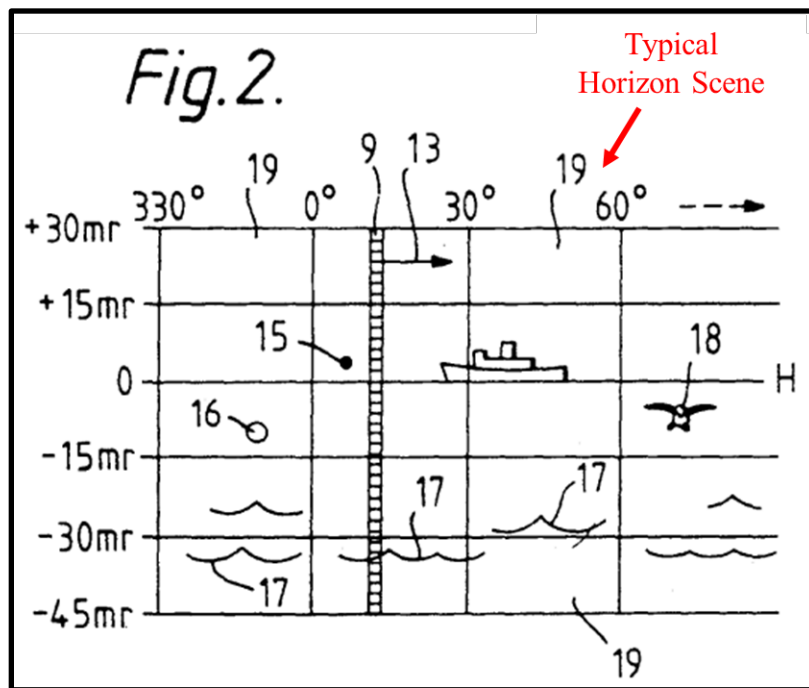


Barnard, Fig. 1 (annotated).

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).”

Ex.1005, Abstract, *see also id.*, 1:7-8. In this regard, the image may be a two-dimensional image of “a typical horizon scene,” as shown in Fig. 2, below.

Ex.1003, ¶60.



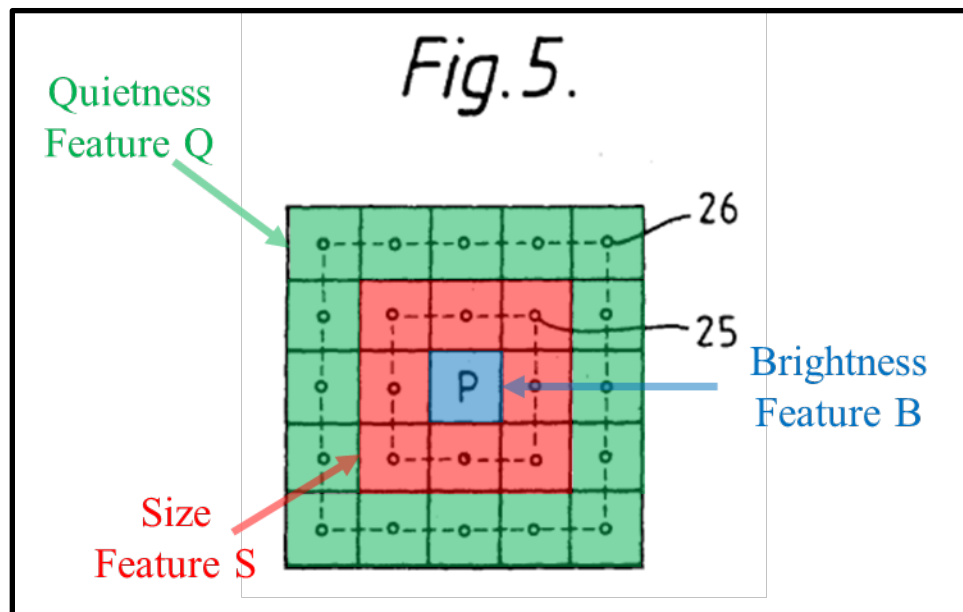
Barnard, Fig. 2 (annotated).

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). Ex.1003, ¶61.

[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;

Barnard discloses or renders obvious [1.2]. Ex.1003, ¶¶62-77.

As discussed in [1.1], Barnard discloses *inputting data* (e.g., inputting the stream of digitized pixel values or picture signals). Barnard 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.” Ex.1005, 2:9-27; 4:50-5:1; 4:46-49; 5:2-3 (“several features can be calculated and each will have a numerical value in a range of values.”). Fig. 5, reproduced below, illustrates a few exemplary features. Ex.1003, ¶¶63-64.



Barnard, Fig. 5 (annotated).

Barnard discloses calculating data statistics (e.g., “width of the statistical distributions,” “progressive means,” “variances,” and/or “statistical information”) for the various features from the input image data. Ex.1005, 2:30-36, 5:36-49, 6:62-68; Ex.1003, ¶¶64-65.

Barnard discloses using the calculated data statistics 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. Ex.1003, ¶¶65-68 (citing to Ex.1005, 2:30-36; 5:36-49; 6:62-68). 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. Ex.1005, 2:28-39; Ex.1003, ¶66. More specifically, Barnard describes **“discard[ing] a feature as a threshold parameter if the width of the statistical distribution of that feature exceeds a predetermined amount.”** Ex.1005, 2:28-34. Barnard explains that if a feature has “t[o]o wide a spread,” then it “may be unreliable as a guide to discriminating between background and target features.” Ex.1005, 2:36-39. In discarding or excluding features that have a statistical distribution width exceeding a predetermined amount, Barnard selects features (i.e., the remaining features not excluded) that are used to distinguish specific targets from background clutter. Ex.1005, 2:28-39; Ex.1003, ¶66.

As another example, Barnard discloses using the calculated progressive means of features to select features. Ex.1003, ¶67. Barnard discloses “**calculating the progressive means of each feature**” from the input image data and discarding a feature “**if the feature mean varies by more than a preset amount** over a succession of scene images.” Ex.1005, 5:34-38, 2:34-36; Ex.1003, ¶67. In discarding or excluding one or more features that have a mean that varies by more than the preset amount, Barnard selects features (i.e., the remaining features not excluded) that are used to distinguish specific targets from background clutter. Ex.1003, ¶67.

Barnard further explains 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**.” Ex.1005, 5:13-17. The threshold hypersurface is an example of a target detection threshold. Ex.1005, 1:18-21, 5:13-19; Ex.1003, ¶68. 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.” Ex.1005, 5:59-66, *see also* Figs. 2 and 6; Ex.1003, ¶68.

In this manner, Barnard uses the calculated data statistics (e.g., “width of the

statistical distributions,” “progressive means,” “variances,” and/or “statistical information”) to select target specific feature information—the set of features and/or associated target detection threshold—used to distinguish specific targets from background clutter. Ex.1005, 2:28-36; 5:13-66; 6:62-68, *see also* Figs. 2 and 6; Ex.1003, ¶¶69-70.

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. Ex.1003, ¶71. 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 section of the ’639 patent. *See generally* Ex.1001, 7:12-11:67. However, the ’639 patent indicates 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. Ex.1001, 5:15-30; 5:55-6:2; 7:15-29; 7:46-57; Ex.1003, ¶72.

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**”² may be used to distinguish a target from background clutter. Ex.1001, 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.”). That is, like Barnard, the '639 patent also describes using a set of characteristics or target specific features to distinguish specific targets from background clutter. Ex.1003, ¶73.

The '639 patent also notes that “*target specific feature information*” may include different types of characteristics or features, including “contrast-based” and “texture-based.” Ex.1001, 5:15-49 (“select **target specific feature information (e.g., contrast-based and texture-based)** to distinguish specific targets from background clutter”). As Dr. Rodriguez explains, consistent with the

² In some instances, the '639 patent alternatively refers to the target characteristics or target specific features as “principal components,” “receptive features,” or “principal component features.” *See, e.g.*, Ex.1001, 7:54-56, 8:45-47, 8:52-54, 9:60-63; Ex.1003, ¶73.

examples in the '639 patent, “[t]he 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....” Ex.1003, ¶74; Ex.1005, 4:46-5:3; Fig. 5; *see also* Ex.1007, 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.”).

Further, the '639 patent indicates that the target specific feature information is 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.” Ex.1001, 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. Ex.1008, 23:59-24:2 (describing a “target classification approach” based on a non-parametric estimation technique); Ex.1006, 45:15-46:16 (describing “automatic target recognition” using a “Parametric Avalanche” approach). As described in the '639 patent—as well as Barnard—values of the selected target specific features extracted from the image data are utilized to distinguish targets from background clutter by determining whether the values indicate the presence of a target or background clutter. Ex.1001, 5:15-30, 5:55-62, 8:35-38, 8:57-60; Ex.1005, 5:3-17;

6:11-15; Ex.1003, ¶75.

Thus, Barnard discloses or renders obvious *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). Ex.1003, ¶¶76-77.

[1.3] (c) *generating said target feature information*³ from said data statistics;

Barnard discloses or renders obvious [1.3]. Ex.1003, ¶¶78-87.

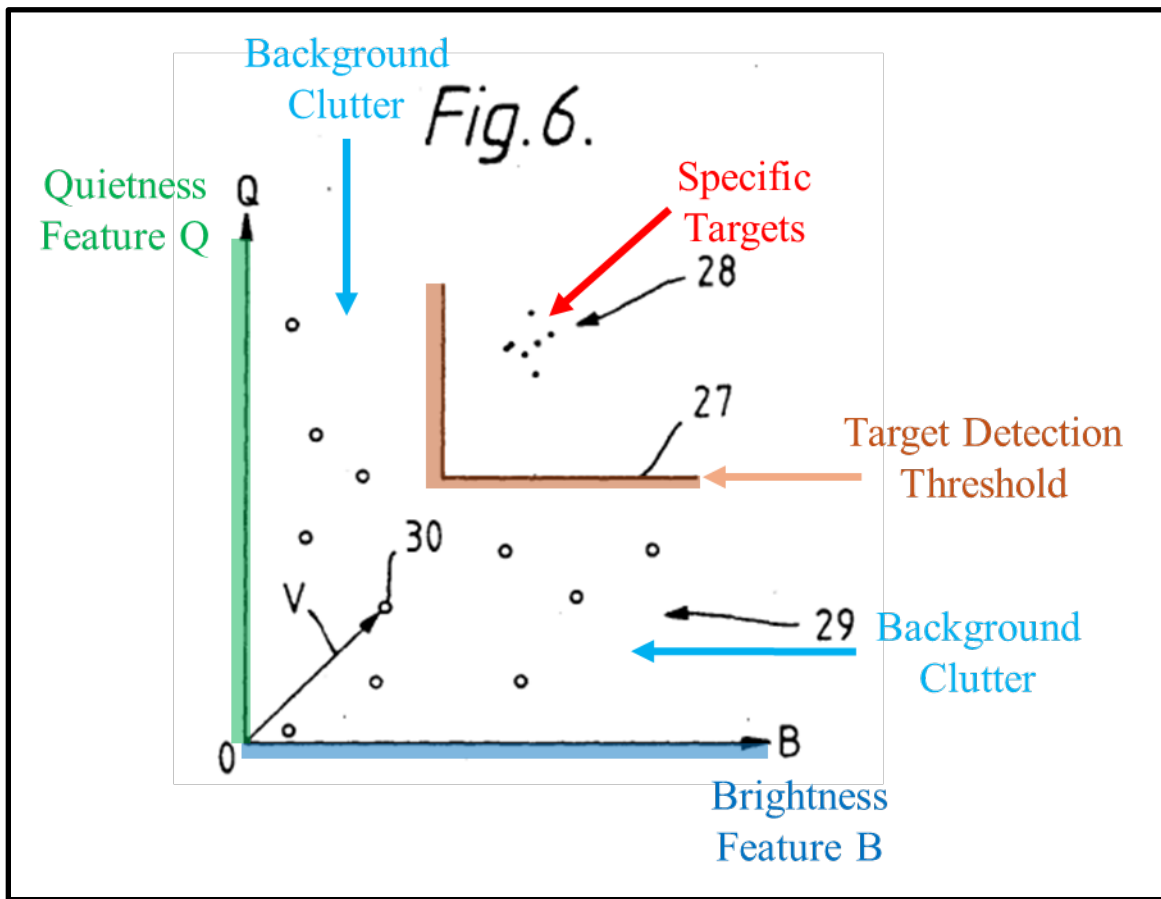
The '639 patent describes “generating target specific feature information” includes “generat[ing] a set of distinguishing target characteristics pertinent to the classification and separation of targets from background clutter in automatic target recognition applications.” Ex.1001, 5:59-62; Ex.1003, ¶80.

Similarly, as explained below, Barnard discloses generating, based on data statistics, the target specific feature information used to distinguish specific targets from background clutter. Ex.1003, ¶81. More specifically, Barnard discloses 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. *Id.*

³ As Dr. Rodriguez explains, [1.3] recites “*target feature information*,” not “*target **specific** feature information*” as used in [1.2]. Ex.1003, ¶79. Consistent with Dr. Rodriguez, the Petition assumes, for purposes of the unpatentability grounds presented herein, that “*said target feature information*” recited in [1.3] is the “*target **specific** feature information*” recited in [1.2], as well as [1.4] and [1.5]. Petitioner reserves the right to raise challenges under 35 U.S.C. § 112 in other forums.

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.**” Ex.1005, 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.” Ex.1005, 5:59-66. Once the set of features is selected (e.g., as discussed in element [1.2]), Barnard determines the target detection threshold (e.g., threshold hypersurface) for the selected set of features. Ex.1005, 5:13-17; Ex.1003, ¶82. In calculating the target detection threshold based on statistical information, Barnard is generating target specific feature information based on data statistics. Ex.1003, ¶82.

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.” Ex.1005, 5:13-19, 25-28; Ex.1003, ¶82.



Barnard, Fig. 6 (annotated).

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 set of features selected using the calculated data statistics (e.g., “width of the statistical distributions,” “progressive means,” and/or “statistical information”), such that the set of features is generated from the data statistics. Ex.1005, Fig. 6; Ex.1003, ¶83

In this manner, Barnard discloses using the calculated data statistics to generate target specific feature information—the set of features and/or associated

target detection threshold—used to distinguish specific targets from background clutter. Ex.1005, 2:28-36; 5:13-66; 6:62-68; *see also id.* Figs. 2 and 6; Ex.1003, ¶84. Consistent with the '639 patent, the generated set of selected features and associated target detection threshold define the principal components for separating specific targets from background clutter. *See* Ex.1001, 5:55-62, 7:55-58, 8:45-51; Ex.1005, 5:3-28; Ex.1003, ¶84.

Accordingly, 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. Ex.1003, ¶85.

Thus, Barnard discloses or renders obvious *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)). Ex.1003, ¶¶86-87.

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

Barnard discloses or renders obvious [1.4]. Ex.1003, ¶¶88-95.

As explained below, Barnard discloses extracting target specific feature

information from the input image data. Ex.1003, ¶89. In this regard, 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. Ex.1003, ¶89.

Barnard explains how the features included in the set of selected features and associated target detection threshold are extracted from the input image data. Ex.1005, 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 ... 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. Ex.1005, 2:28-39, 5:13-17, 5:36-49, 6:62-68. 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." Ex.1005, 5:59-66; Ex.1003, ¶90. As Dr. Rodriguez explains, "[b]ecause the target detection threshold is determined from the input image data, the target detection threshold is extracted from the input image data." Ex.1003, ¶91.

In addition, consistent with the '639 patent, Barnard also discloses 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. Ex.1001, 7:17-22; Ex.1003, ¶92. For example, Barnard describes that "[e]ach object detected in a sub-image has its features calculated." Ex.1005, 6:1-2. Barnard notes that "several features can be calculated and each will have a numerical value in a range of values." Ex.1005, 5:2-3. By calculating feature values for each feature from the image data, Barnard is extracting target specific feature information. Ex.1003, ¶¶92-93.

Accordingly, 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. Ex.1003, ¶93.

Thus, Barnard discloses or renders obvious *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). Ex.1003, ¶¶94-95.

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

Barnard discloses or renders obvious [1.5]. Ex.1003, ¶¶96-101.

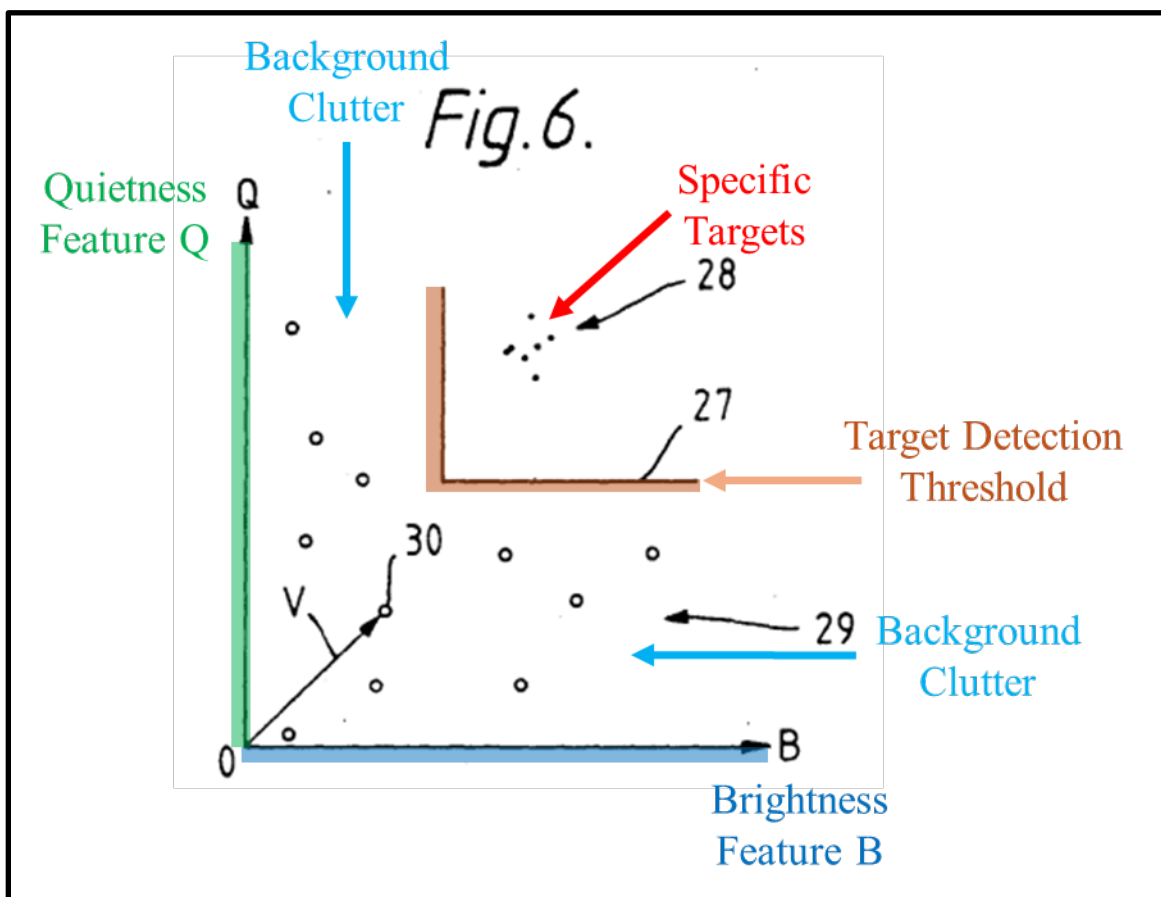
Barnard discloses using the target specific feature information, and more specifically, the set of selected features and associated target detection threshold, to distinguish specific targets from background clutter. Ex.1003, ¶97. For example, Barnard describes **“comparing the feature values of an incoming picture signal with the threshold to detect a target.”** Ex.1005, 1:21-23, *see also* 6:57-60.

Barnard explains that incoming picture signal **“may contain a target signal to be detected against background signals.”** Ex.1005, 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.

Ex.1005, 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. Ex.1005, 1:21-23. The “target detection threshold” “effectively separates target objects from background objects.” Ex.1005, 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 either detects a specific target or background clutter, thereby distinguishing specific targets from background clutter. Ex.1005, 5:13-28; Ex.1003, ¶97.

Fig. 6 of Barnard, 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. Ex.1003, ¶98.



Barnard, Fig. 6 (annotated).

specific targets from background clutter in incoming picture signals). Ex.1003, ¶¶100-101.

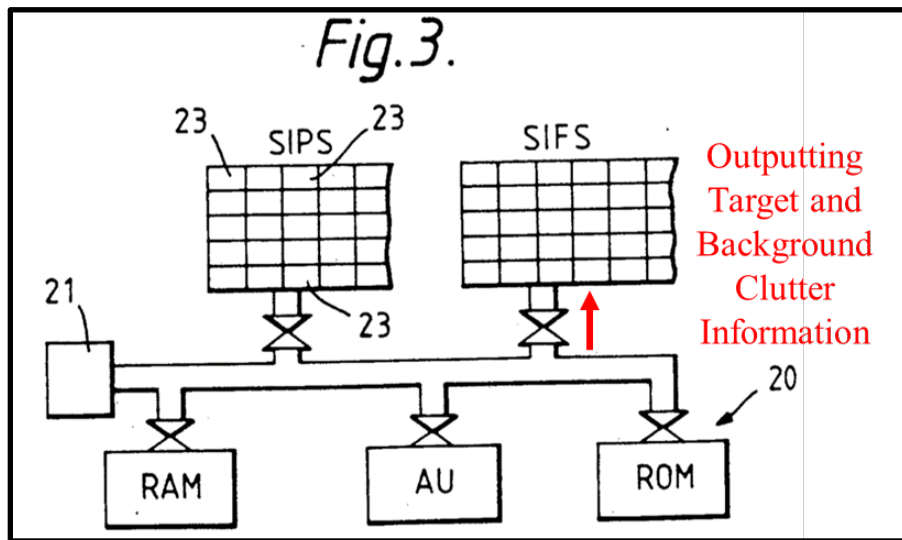
[1.6] (f) outputting target and background clutter information.

Barnard discloses or renders obvious [1.6]. Ex.1003, ¶¶102-106.

Barnard discloses 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.” Ex.1005,4:19-34, 1:53-57; *see also id.*, Abstract. Barnard explains that the “sub-image feature store SIFS is provided to store information about features of detected objects.” Ex.1005,4:32-34. More specifically, Barnard discloses “**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.”

Ex.1005,1:53-57. 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, as shown in Fig. 3 below. Ex.1003, ¶103.



Barnard, Fig. 3 (annotated).

With respect to “*outputting*,” the ’639 patent consistently refers to communications between components within the target recognition system as being “outputted.” Ex.1001, 2:47-52 (“Referring to FIG. 2, ... signals are ... **outputted through the communications links 8 which direct the output signals.**”), 3:2-4, 12:38-45 (“... said data statistics outputted [sic] from said calculator ...”), *see also id.*, 7:16-22, 5:55-58. 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]. Ex.1003, ¶104.

Thus, Barnard discloses or renders obvious *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

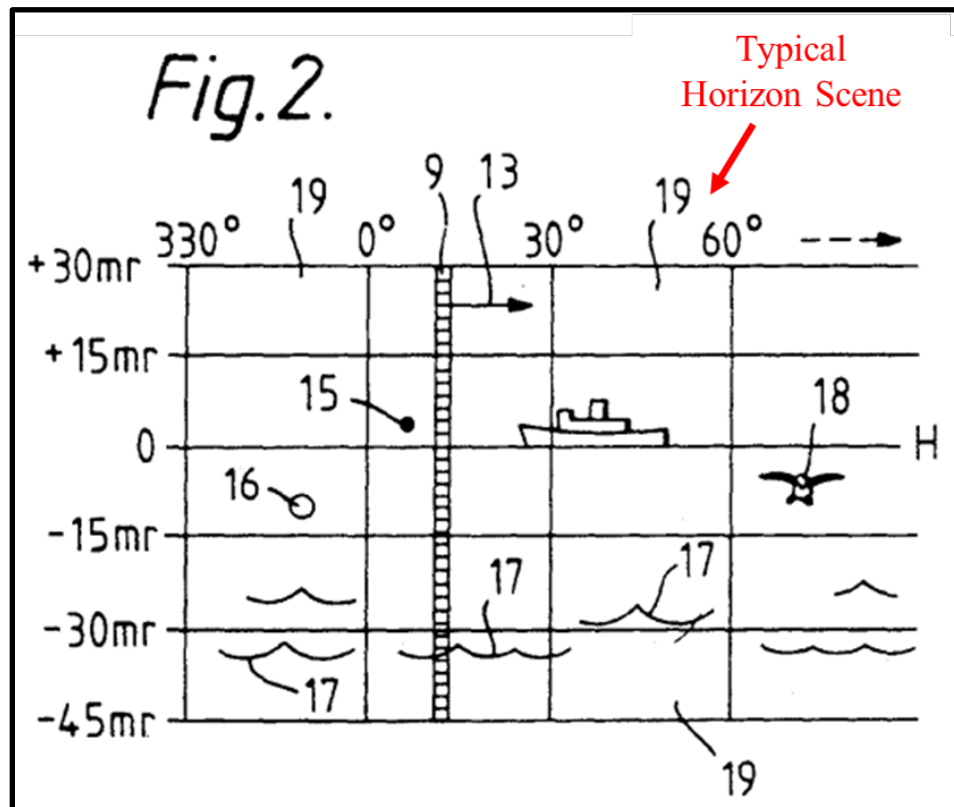
store (SIFS)). Ex.1003, ¶¶105-106.

2. Claim 2

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

Barnard discloses or renders obvious [2.0]. Ex.1003, ¶¶107-110.

As discussed in [1.1], Barnard discloses 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.” Ex.1005, 1:7-8. Barnard provides a specific example in Fig. 2 showing a two-dimensional image of “a typical horizon scene.” Ex.1005, 2:59-61, *see also* 3:56-57 (describing that the digitized pixel values are “retained in a store preserving their relative positions.”). Ex.1003, ¶¶108-109.



Barnard, Fig. 2 (annotated).

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).

Ex.1003, ¶110.

3. Claim 3

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

Barnard discloses or renders obvious [3.0]. Ex.1003, ¶¶111-113.

As discussed in [1.1] and [2.0], Barnard discloses inputting data such as a “stream of **digitized pixel values**” or “**picture signals**” that includes two-

dimensional image data, such as “a typical horizon scene.” Ex.1005, 1:7-8, 2:59-61. The stream of digitized pixel values or picture signals associated with the horizon scene are an example of the data being *digitized imagery*. Ex.1003, ¶112.

Accordingly, Barnard discloses or renders obvious *wherein said data is digitized imagery, speech signals, or radar signals*. Ex.1003, ¶113.

4. Claim 6

[6.0] *The method of claim 1, wherein said feature information⁴ is contrast-based or texture-based.*

Barnard discloses or renders obvious [6.0]. Ex.1003, ¶¶114-122.

As discussed in [1.2], Dr. Rodriguez explains that “[t]he various features (‘brightness feature B,’ ‘size feature S,’ ‘quietness feature Q,’ and ‘[o]ther

⁴ As Dr. Rodriguez explains, [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]. Ex.1003, ¶115. Like [6.0], [4.0] and [7.0] also recite “*feature information*.” Consistent with Dr. Rodriguez, the Petition assumes, for purposes of the unpatentability grounds presented herein, that “*feature information*” as recited in [4.0], [6.0], and [7.0] is the “***target specific feature information***” recited in claim 1. Petitioner reserves the right to raise challenges under 35 U.S.C. § 112 in other forums.

features’) described by Barnard include contrast-based and texture-based features, consistent with the examples in the ’639 patent.” Ex.1003, ¶¶116-120; Ex.1001, 5:15-49 (“select target specific feature information (e.g., contrast-based and texture-based) to distinguish specific targets from background clutter”); Ex.1005, 4:46-5:3; Fig. 5; *see also* Ex.1007, 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.”).

Thus, Barnard discloses *wherein said feature information is contrast-based or texture-based* (e.g., the set of selected features and associated target detection threshold includes contrast-based and/or texture-based features). Ex.1003, ¶¶121-122.

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.*

Barnard discloses or renders obvious [7.0]. Ex.1003, ¶¶123-128.

As discussed in [1.5], in addition to distinguishing specific targets from background clutter, Barnard further discloses using the target specific feature information to distinguish between at least two different target classes. Ex.1005, Ex.1005, 1:24-36, 3:34-41, Fig. 2; Ex.1003, ¶125. For example, Fig. 2 shows an

a third target class (e.g., including the ship)) from one another. Ex.1005, 1:24-36, 3:34-41, Fig. 2; Ex.1003, ¶126.

Thus, 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* (e.g., using the set of selected features and associated target detection threshold to distinguish specific targets from other targets in incoming picture signals). Ex.1003, ¶¶127-128.

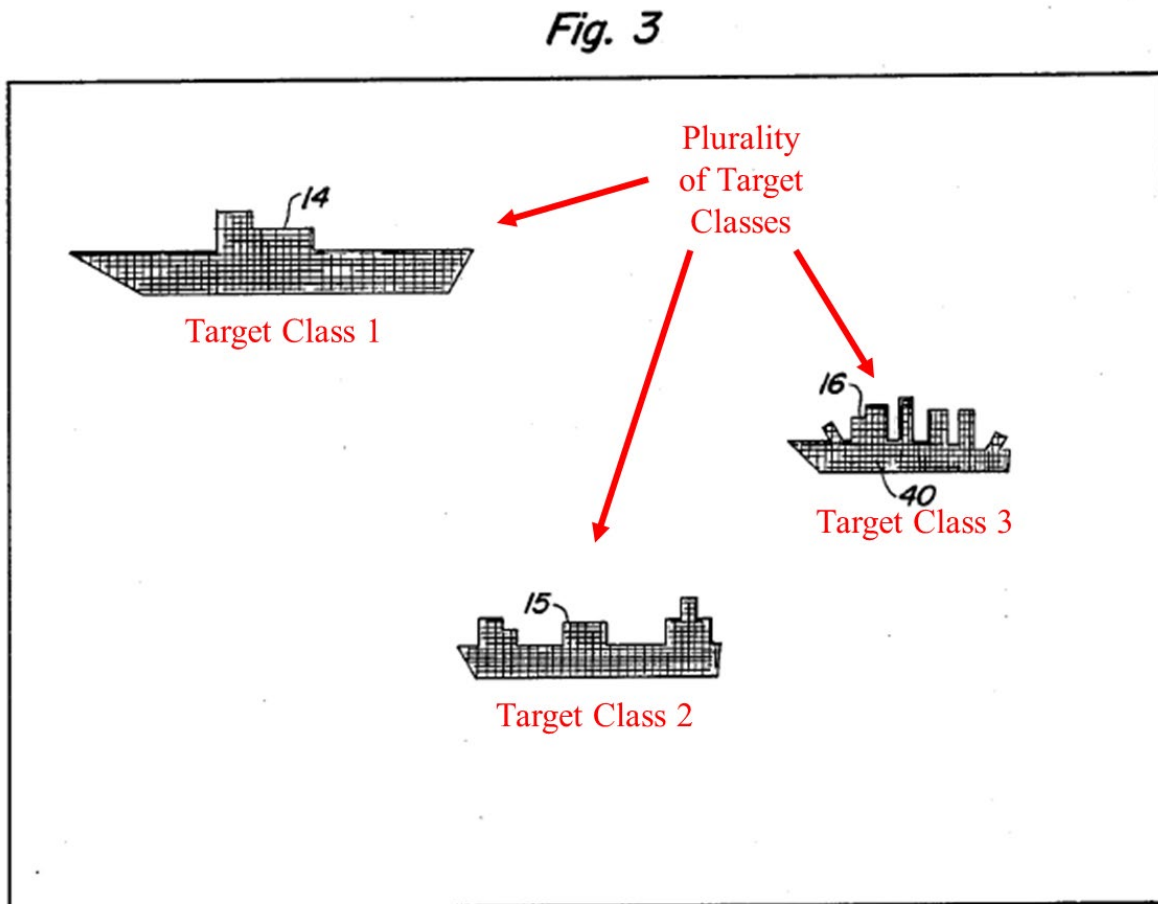
D. Ground 2: Claim 7 is obvious under 35 U.S.C. § 103 over Barnard and Knecht.

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. Ex.1003, ¶129.

1. Knecht

Like the '639 patent and Barnard, Knecht relates to the field of image processing and, more specifically, to automatic target recognition. Ex.1016, 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[.]” Ex.1016, 1:6-11. Knecht describes “**classifying a potential target object ... as a member of**

one class of several predetermined classes,” as shown in Fig. 3 below. Ex.1016, 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 features and corresponding decision rules that are used to classify potential targets in real time. Ex.1016, 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 into one of the plurality of target classes. Ex.1016, 6:35-40.

2. Reasons to combine Barnard and Knecht

a) Analogous art

Barnard and Knecht are analogous prior art pertaining to the same field of endeavor as the '639 patent, namely, image processing and, more specifically, image processing for automatic target recognition. Ex.1001, 6:13 (“... our focus is on automatic target recognition”); Ex.1005, Abstract (“A target detection system is provided”); Ex.1016, 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[.]”); Ex.1003, ¶130. Both Barnard and Knecht, like the '639 patent, describe using a set of features to distinguish targets. Ex.1005, 5:13-17; Ex.1016, 6:22-27. Accordingly, Barnard and Knecht are analogous prior art to the '639 patent. Ex.1003, ¶131.

b) Motivations to combine

First, a POSITA would have been motivated to combine Barnard and Knecht, as doing so would have been the use of a known technique (distinguishing

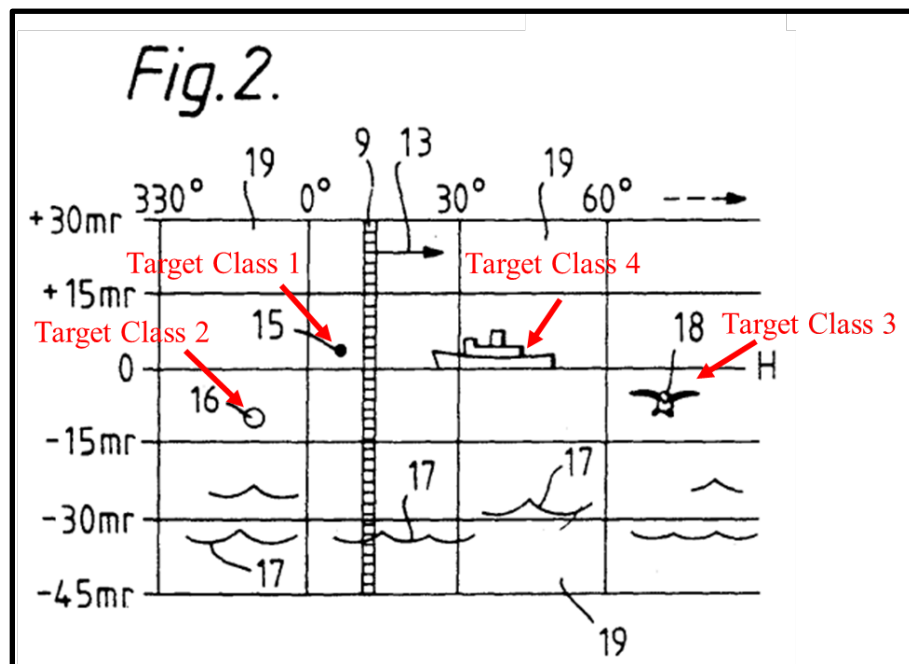
between multiple target classes in an image processing-based target detection method, per Knecht) to improve a similar method (an image processing-based target detection method, per Barnard) in the same, predictable way (an image processing-based target detection method, per Barnard, that distinguishes between multiple target classes, per Knecht). *See KSR Int’l v. Teleflex Inc.*, 550 U.S. 398, 417 (2007) (finding obvious the use of a known technique to improve similar methods in the same way); Ex.1003, ¶132. In the combination, Barnard’s target recognition method would be modified to explicitly include a plurality different target classes, as taught by Knecht. Ex.1003, ¶132. 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. Ex.1003, ¶132.

Knecht shows that it was well-known in the context of a target recognition method like Barnard’s to distinguish between a plurality of target classes. Ex.1003, ¶¶133-134. For example, Knecht describes “**“classifying a potential target object ... as a member of one class of several predetermined classes”** Ex.1016, 1:11-14. As Dr. Rodriguez explains, “[a] POSITA would have recognized the multiple target class approach described by Knecht is a natural fit to improve Barnard’s target detection method.” Ex.1003, ¶134. In this regard, using the specific examples from Barnard’s Fig. 2 below, Dr. Rodriguez explains that

“distinguishing an aerial missile 15 from a sea-skimming missile 16 from a seagull 18 from a ship can be important for determining an appropriate response, if any.”

This is clear, because the risks presented by each are quite different. Ex.1003, ¶134. Accordingly, distinguishing between the different types of targets may be important for deploying the most effective response. Ex.1003, ¶134.

Dr. Rodriguez explains that it would have been obvious to a POSITA, based on Knecht, that “different target classes could be defined for one or more of the aerial missile 15, the sea-skimming missile 16, the seagull 18, and/or the ship, as illustrated in Fig. 2 below,” with each target class having “a set of selected features and a corresponding target detection threshold” in accordance with Barnard.” Ex.1003, ¶135.



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

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. Ex.1003, ¶136.

Second, a POSITA would have also been motivated to combine Barnard and Knecht because doing so would have been the combination of 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). *KSR*, 550 U.S. at 416 (finding obvious “[t]he combination of familiar elements according to known methods” to “yield predictable results”); Ex.1003, ¶137. The resulting combination would be the same as described above. Ex.1003, ¶¶137-138.

Barnard discloses distinguishing specific targets from background clutter and other potential targets but does not *explicitly* state how many target classes are utilized. Ex.1003, ¶138. However, as discussed above, Knecht shows that it was well-known in the context of a target recognition method like Barnard’s to distinguish between a plurality of target classes. Ex.1003, ¶138.

A POSITA would have recognized that modifying Barnard’s target recognition method to utilize a plurality of target classes—as taught by Knecht—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. Ex.1003, ¶139.

Third, 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 may be used to distinguish between a plurality of target classes. Ex.1003, ¶¶140-141; Ex.1016, 1:6-11 (“This invention pertains to ... classifying the image, of a scanned object as the image of an object of one of a plurality of predetermined classes of objects[.]”). Accordingly, a POSITA would have found the combination predictable and had a reasonable expectation of success because Knecht expressly teaches utilizing multiple target classes in the context of Barnard’s target detection method. Ex.1003, ¶¶140-141.

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. Ex.1016, 6:22-27; Ex.1005, 5:13-17. Further, Knecht describes using the same Bayesian approach as Barnard to distinguish between the plurality of target classes. Ex.1016,

6:35-40 (“... any suitable classifier such as a well known Bayes classifier”); Ex.1005, 5:59-63 (“... in accordance with Baye’s criterion.”). *see also* 6:16-17. Barnard also notes that “modifications will be apparent to persons skilled in the art.” Ex.1005, 6:16-17; Ex.1003, ¶142.

Because Knecht explicitly describes distinguishing between a plurality of target classes in an image-based target detection method, a POSITA would have had a reasonable 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 a reasonable 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. Ex.1003, ¶143.

Accordingly, a POSITA would have had a reasonable expectation of success, to implement a plurality of target classes, as taught by Knecht, in the target detection method of Barnard. Ex.1003, ¶144.

3. 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.*

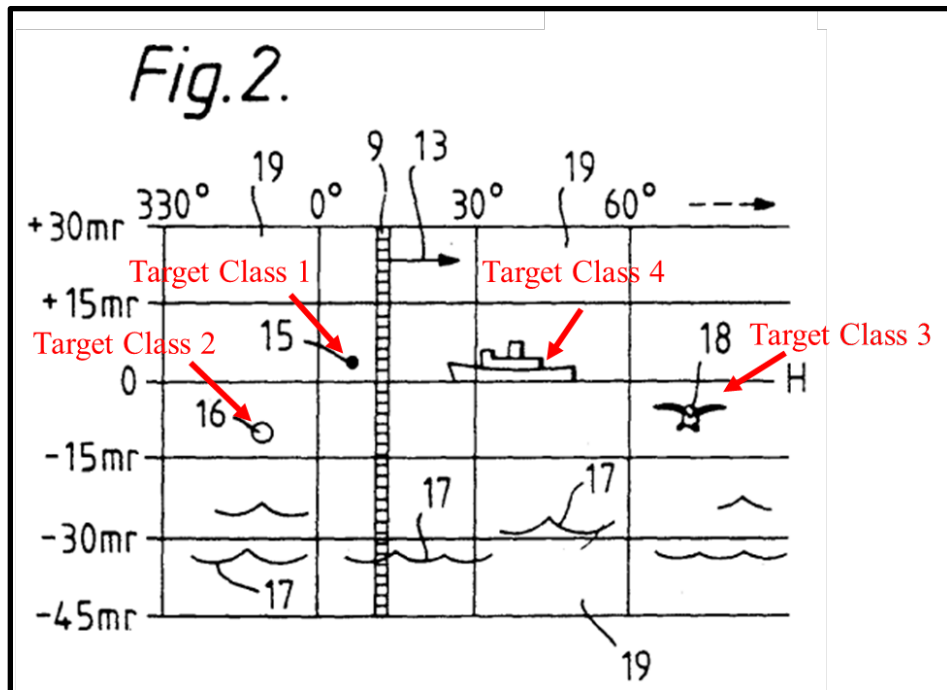
Barnard in view of Knecht renders obvious [7.0]. Ex.1003, ¶¶145-150.

As discussed in Ground 1:[7.0], 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. Ex.1003, ¶146.

As discussed in Section VIII.D.2 above, it would have been obvious to combine Barnard 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, 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.⁵ Ex.1003, ¶147.



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

Thus, Barnard in view of 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). Ex.1003, ¶¶149-150.

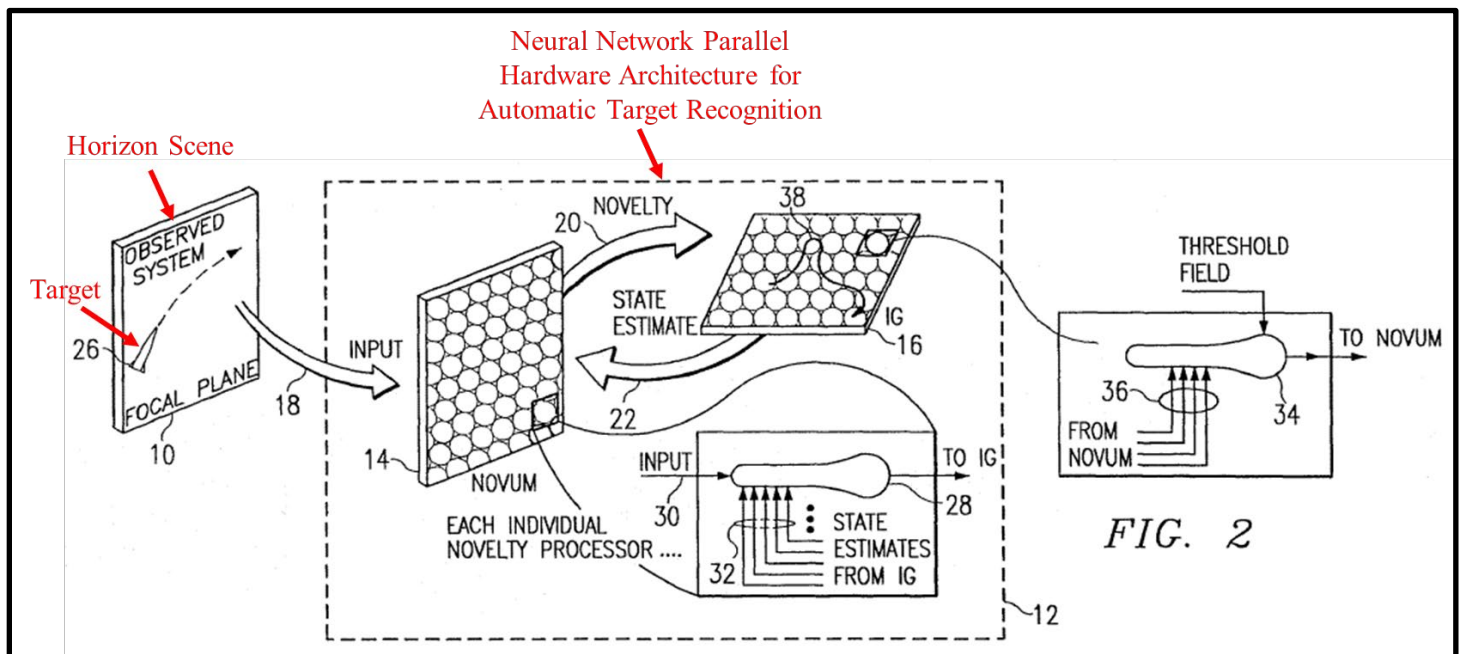
⁵ This is just one example of the application of multiple target classes to Barnard.

As Dr. Rodriguez explains, a POSITA recognizes that “various target class groupings may be utilized in a variety of other contexts.” Ex.1003, ¶148.

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

1. Lawrence

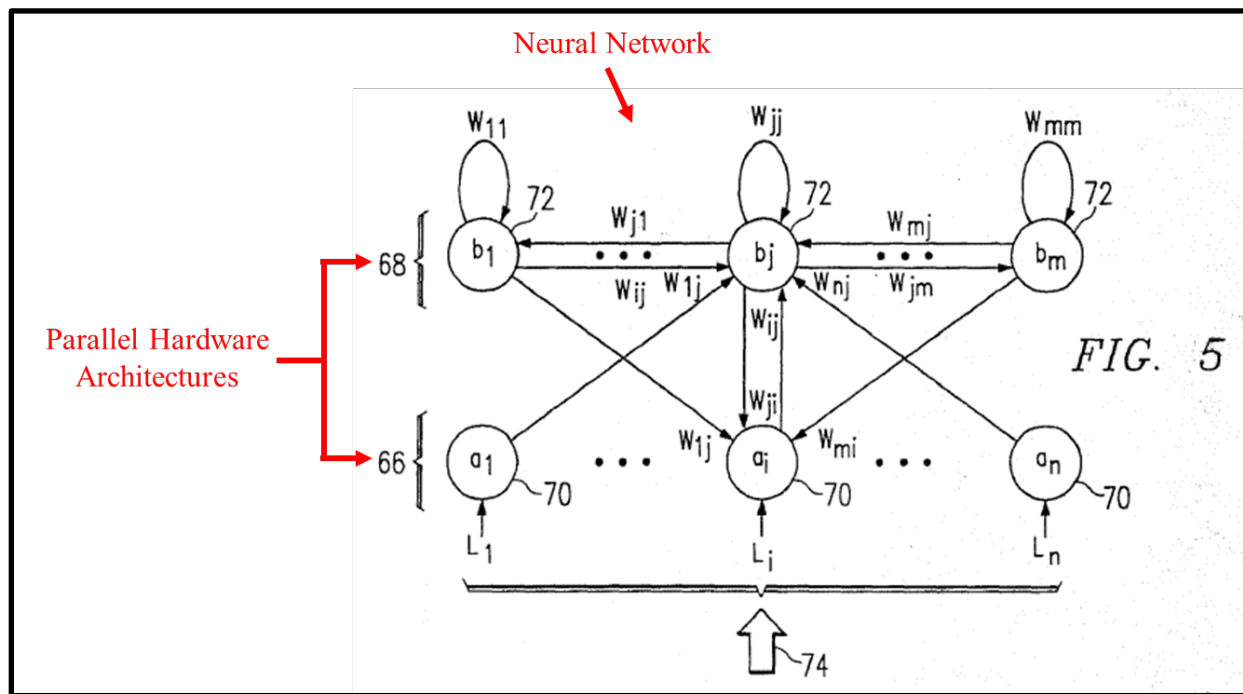
Like the '639 patent and Barnard, Lawrence relates to the field of image processing and, more specifically, to automatic target recognition. Ex.1006, 45:15-25 (“... **accomplish automatic target recognition** ... Then **the target recognition and tracking mechanism** will be described ...”), *see also id.*, 11:23-26, 18:33-19:2, 27:7-13, Fig. 2.



Lawrence, Fig. 2 (annotated).

Lawrence is titled “Continuous Bayesian Estimation with a Neural Network Architecture” and relates to “**a neural network architecture**, and more particularly, to an architecture which is **designed to perform adaptive**,

continuous Bayesian estimation.” Ex.1006, Title, 1:2-6. In this regard, Lawrence explains that “[t]he **neural network** of the present invention as illustrated by the observing system 12 is referred to as a ‘parametric avalanche’ (PA)” and “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** [below].” Ex.1006, 11:1-3, 23:26-28.



Lawrence, Fig. 5 (annotated).

2. Reasons to combine Barnard and Lawrence

As explained 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, which uses a Bayesian estimation technique in its target detection method. Ex.1003, ¶151.

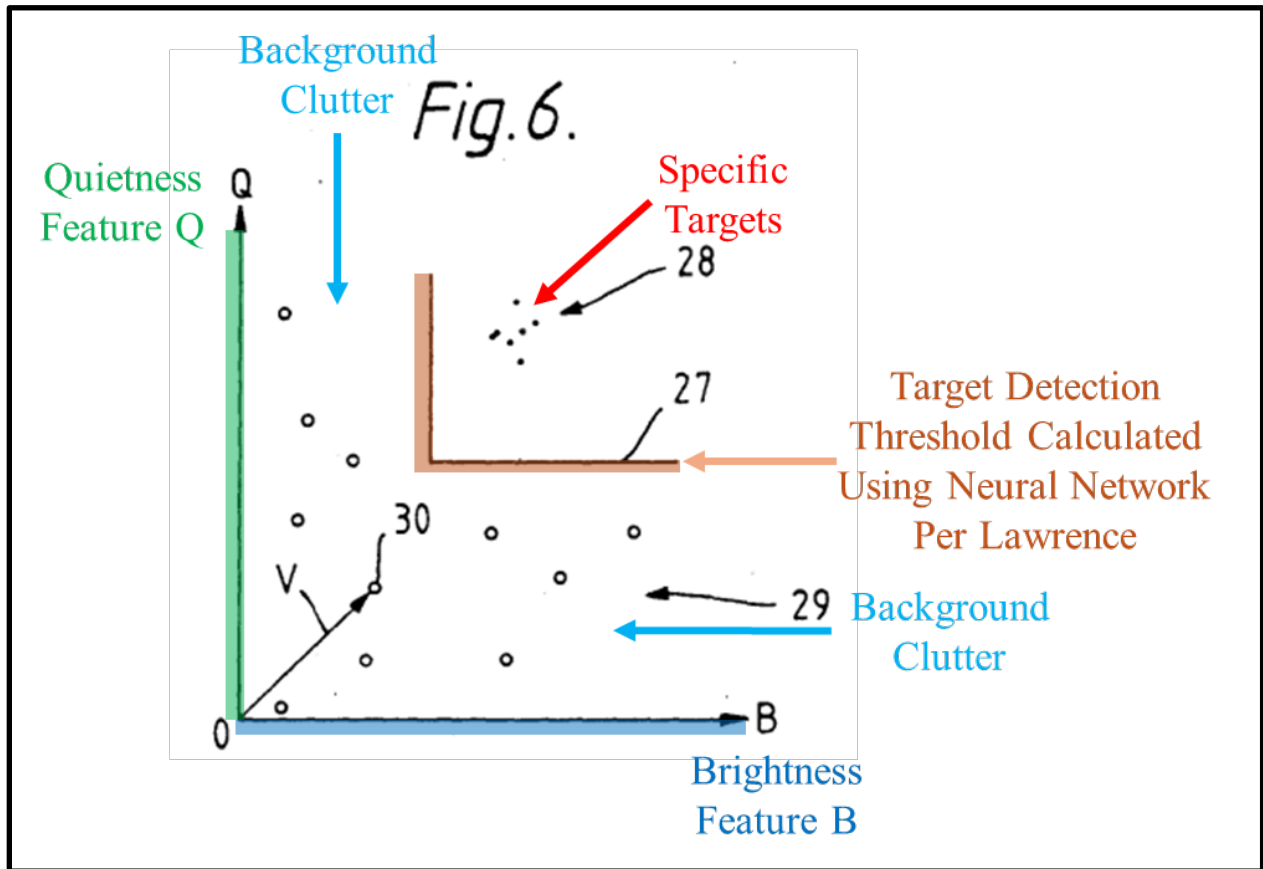
a) Analogous art

Barnard and Lawrence are each analogous prior art pertaining to the same field of endeavor as the '639 patent, namely, image processing and, more specifically, image processing for automatic target recognition. Ex.1001, 6:13 (“... our focus is on automatic target recognition”); Ex.1005, Abstract (“A target detection system is provided”); Ex.1006, 45:22-23 (“... the target recognition and tracking mechanism will be described”); Ex.1003, ¶152.

Further, both Barnard and Lawrence are analogous art to the '639 patent because they are reasonably pertinent to a problem addressed by the '639 patent, namely using a set of features to distinguish targets from background clutter and other potential targets. Ex.1001, 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.”); Ex.1005, 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.”); Ex.1006, 45:27-29 (“... a set of basic features which are needed to distinguish targets of interest”). Accordingly, Barnard and Lawrence are analogous prior art to the '639 patent. Ex.1003, ¶152.

b) Motivations to combine

First, a POSITA would have been motivated to combine Barnard and Lawrence because doing so would have been 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 method, per Barnard (and Lawrence), through the use of a neural network, per Lawrence). *KSR*, 550 U.S. at 417 (finding obviousness when a known technique “would improve similar devices in the same way”); Ex.1003, ¶153. 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. Ex.1003, ¶153.



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

Barnard describes the implementation of a target detection threshold “in accordance with Baye’s criterion.” Ex.1005, 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**” Ex.1005, 5:63-66. Barnard also notes that “modifications will be apparent to persons skilled in the art.” Ex.1005, 6:16-17; Ex.1003, ¶154.

Lawrence provides details of a known way to perform the Bayesian estimation referenced, but “not ... described further” in Barnard. Ex.1005, 5:63-66.

Specifically, Lawrence describes “**a neural network architecture ... designed to perform adaptive, continuous Bayesian estimation**” also in the context of automatic target recognition. Ex.1006, 1:2-6, *see also* Title, 45:15-25; Ex.1003, ¶155.

As Dr. Rodriguez explains, “[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.” Ex.1003, ¶156. Lawrence’s neural network-based Bayesian estimation approach is already described in the context of automatic target recognition applications, like Barnard’s. Ex.1006, 1:2-11, 45:15-25, Fig. 2; Ex.1003, ¶156. Accordingly, a POSITA would have been motivated to utilize Lawrence’s approach with Barnard’s target detection method because Lawrence’s neural network-based Bayesian estimation approach is utilized for automatic target recognition applications. Ex.1003, ¶156.

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.” Ex.1015, 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.”). Ex.1003, ¶157.

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. Ex.1003, ¶158. 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. Ex.1015, 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.”). Ex.1003, ¶158. “There is a motivation to combine when a known technique ‘has been used to improve one device, and a person of ordinary skill in the art would recognize that it would improve similar devices in

the same way,’ using the ‘prior art elements according to their established functions.’” *Intel Corp. v. PACT XPP Schweiz AG*, 61 F.4th 1373, 1380–81 (Fed. Cir. 2023).

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. Ex.1003, ¶159.

Second, a POSITA would have also been motivated to combine Barnard and Lawrence because doing so would have been 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). *KSR*, 550 U.S. at 417 (finding obvious “the mere substitution of one element for another known in the field” to “yield a predictable result”); Ex.1003, ¶160. 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. Ex.1003, ¶160.

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.” Ex.1005, 5:59-66. Prompted by Barnard's disclosure, a POSITA would have been motivated to look to other references disclosing known ways of performing Bayesian estimation and would have been particularly motivated to consider references, like Lawrence, performing Bayesian estimation in the specific context of automatic target detection methods. Ex.1003, ¶161.

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. Ex.1003, ¶162.

Third, a POSITA would have had a reasonable expectation of success in combining Barnard and Lawrence because Lawrence teaches that “a neural network architecture” may be used to perform “Bayesian estimation,” which is what Barnard uses to calculate the target detection threshold in its target detection method. Ex.1003, ¶164; Ex.1006, 1:2-6; Ex.1005, 5:59-66. 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, that relies on a set of features to distinguish targets from background clutter. Ex.1006, 45:15-25, 45:27-29; Ex.1005, 5:13-17. In addition, Lawrence—like Barnard—describes that target detection thresholds will be updated over time in response to changes in the input images. Ex.1005, 1:66-2:3, 6:5-10; Ex.1006, 5:25-6:9.

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. Ex.1003, ¶163.

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 full expectation of success in implementing the same type of approach in the context of Barnard’s target detection method. Ex.1003, ¶166. More specifically, based on Lawrence, a POSITA would have a reasonable expectation of success in implementing a neural network architecture to perform adaptive, continuous Bayesian estimation of the

target detection threshold of Barnard. Ex.1003, ¶166. 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.”). Ex.1003, ¶166.

Thus, 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. Ex.1003, ¶167.

3. Claim 1

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

Barnard discloses or renders obvious [1.0]. See Ground 1:[1.0]. Ex.1003, ¶¶168-170, 54-56.

[1.1] *(a) inputting data;*

Barnard discloses or renders obvious [1.1]. See Ground 1:[1.1]. Ex.1003,

¶¶171-175, 57-61.

[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;

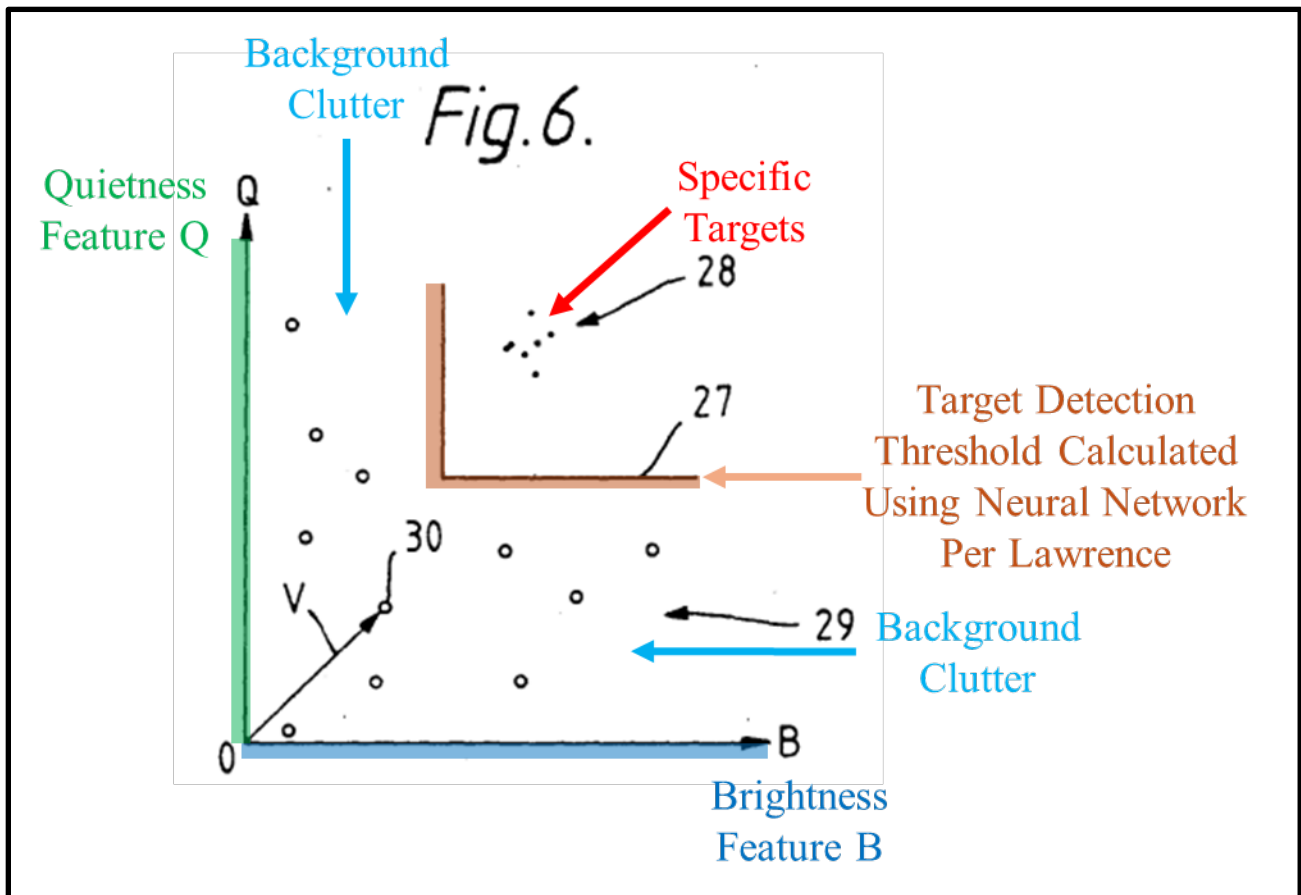
Barnard in view of Lawrence renders obvious [1.2]. Ex.1003, ¶¶176-193.

Barnard explains 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.**” Ex.1005, 5:13-17; see also Ground 1:[1.2]. Barnard notes that the “target detection threshold” is generated “from the **statistical information**” and is calculated “in accordance with Baye’s criterion.” Ex.1005, 5:59-66. Barnard states that “[s]ince this threshold calculation from the statistical information is a well known mathematical technique **it will not be described further**” Ex.1005, 5:63-66; Ex.1003, ¶¶177-182.

Lawrence provides details of a known way to perform the Bayesian estimation referenced, but “not ... described further,” in Barnard. Ex.1005, 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. Ex.1006, 1:2-5, *see also* Title, 1:2-6, 45:15-25; Ex.1003, ¶183.

As explained in Section VIII.E.2 above, a POSITA would have been motivated to combine Barnard and Lawrence. 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. Ex.1003, ¶184.



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

In this regard, the neural network determines the target detection threshold for the features selected based on the calculated data statistics. Ex.1003, ¶185. 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. Ex.1003, ¶185. 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. Ex.1003, ¶185; *see also* Ex.1005, 5:13-17; 5:49-66. 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. Ex.1003, ¶185.

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. Ex.1003, ¶¶186-191.

Thus, Barnard in view of Lawrence renders obvious *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,

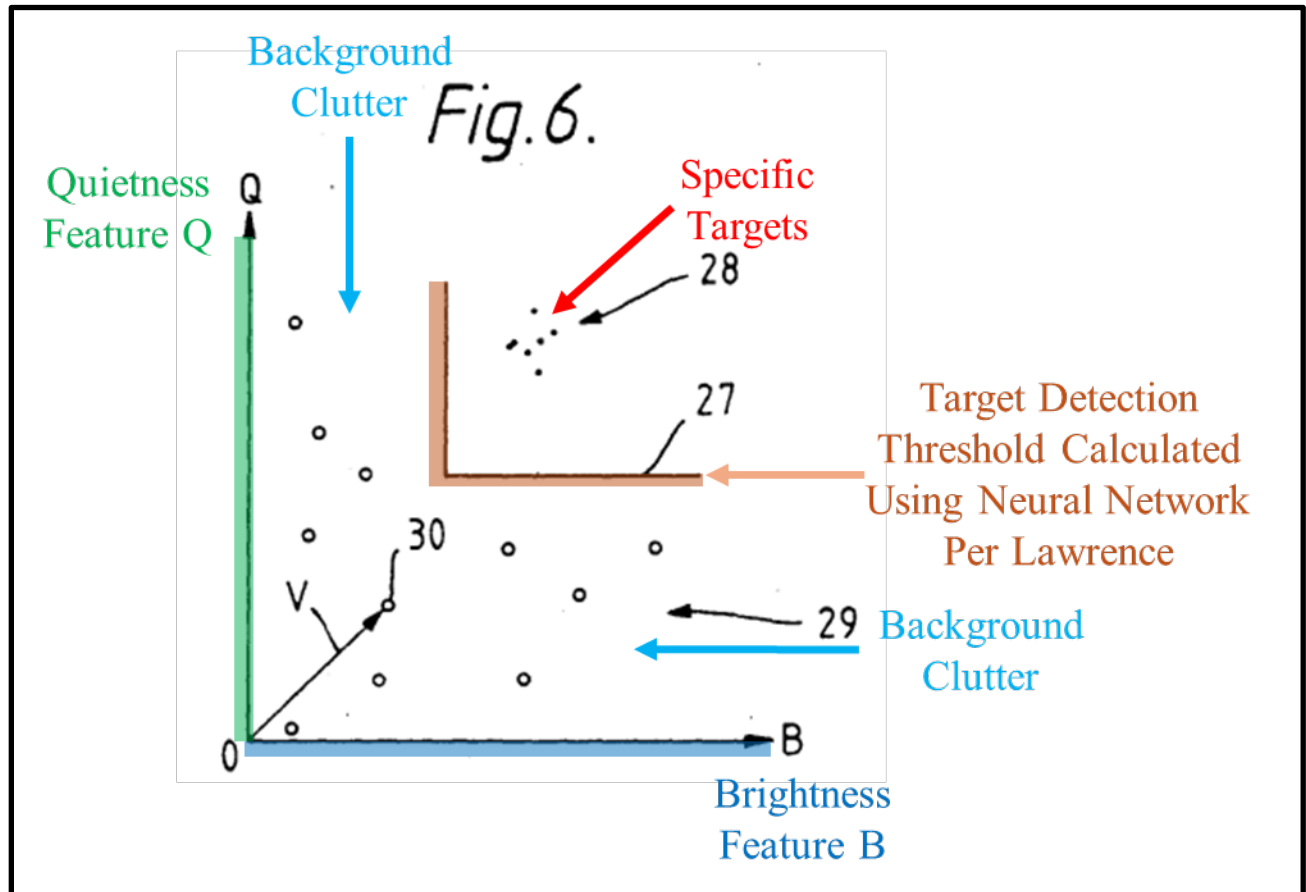
quietness feature Q, and other features and/or “statistical information”) *from said data* (e.g., the input image data (stream of digitized pixel values or picture signals)) *and using said data statistics to select target specific feature information to distinguish specific targets from background clutter* (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). Ex.1003, ¶¶192-193.

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

Barnard in view of Lawrence renders obvious [1.3]. Ex.1003, ¶¶194-203.

In the combination, Barnard’s target recognition method is 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. Ex.1003, ¶199. In this regard, the neural network generates the target detection threshold for the features selected based on the calculated data statistics (e.g., features selected based on “width of the statistical distributions,” “progressive means,” and/or “statistical information”). Ex.1005, 2:30-36, 5:36-49, 6:62-68; Ex.1003, ¶198; *see also* Ground 1:[1.2]-[1.3]. 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 for the selected features, as shown in Fig. 6 below. Ex.1003, ¶199.



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

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/or associated target detection threshold—used to distinguish specific targets from background clutter. Ex.1003, ¶200. Accordingly, 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. Ex.1003, ¶201.

Thus, Barnard in combination with Lawrence discloses *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)). Ex.1003, ¶¶202-203.

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

Barnard in view of Lawrence renders obvious [1.4]. Ex.1003, ¶¶204-211.

Barnard discloses extracting target specific feature information from the input image data. Ex.1005, 2:28-39, 5:2-3, 5:13-17, 5:36-49, 5:59-66, 6:62-68; Ex.1003, ¶¶205-206; see also Ground 1:[1.4]. For example, Barnard discloses 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. Ex.1005, 2:28-39, 5:2-3, 5:13-17, 5:36-49, 5:59-66, 6:62-68; Ex.1003, ¶¶205-206; *see also* Ground 1:[1.4]. As another example, Barnard discloses the values for each of the features are extracted from the input image data. Ex.1005, 4:50-5:1, 4:46-49,

5:2-3, 6:1-2; Ex.1003, ¶¶207-208; *see also* Ground 1:[1.4].

As discussed in Section VIII.E.2 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. Ex.1003, ¶207. In this regard, the neural network extracts a threshold for each of the selected features from the input image data. Ex.1003, ¶207. More specifically, the neural network is utilized to perform a Bayesian estimation on the input image data such that the target detection threshold is calculated for the selected features from the input image data in accordance with Baye’s criterion. Ex.1003, ¶207. In this manner, the combination of Barnard and Lawrence also extracts target specific feature information—the set of features and/or associated target detection threshold—from the input image data. Ex.1003, ¶207.

Accordingly, 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 recited in [1.4]. Ex.1003, ¶209.

Thus, Barnard in combination with Lawrence discloses *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). Ex.1003, ¶¶210-211.

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

Barnard in view of Lawrence renders obvious [1.5]. Ex.1003, ¶212-217.

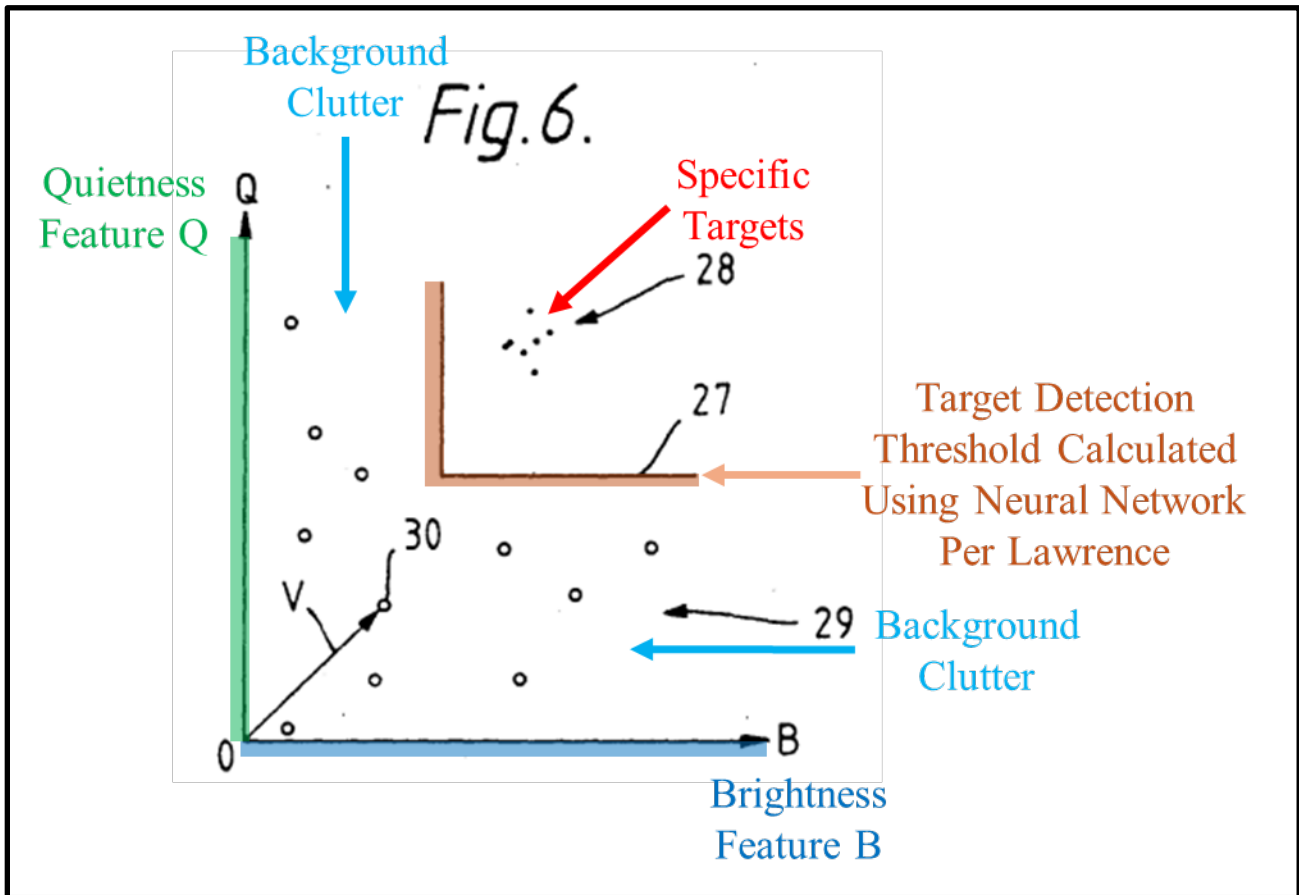
Barnard discloses using the target specific feature information, and more specifically, the set of selected features and associated target detection threshold, to distinguish specific targets from background clutter. Ex.1005, 1:21-23, 4:50-5:1; *see also* Ground 1:[1.5]. For example, Barnard describes “**comparing the feature values of an incoming picture signal with the threshold to detect a target.**” Ex.1005, 1:21-23, *see also* 6:57-60. 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. Ex.1005, 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. Ex.1005, 1:21-23; Ex.1003, ¶213.

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. Ex.1003, ¶213. In this regard, the target detection threshold calculated using the neural network “effectively

separate[] target objects from background objects.” Ex.1005, 5:13-17.

Accordingly, by comparing the calculated feature values to the target detection threshold, the system either detects a specific target or background clutter, thereby distinguishing specific targets from background clutter. Ex.1005, 5:13-28; Ex.1003, ¶213.

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 associated target detection thresholds calculated using a neural network, per Lawrence, to distinguish specific targets from background clutter. Ex.1003, ¶¶214-215.



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

Thus, Barnard in combination with Lawrence renders obvious *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 calculated using a neural network to distinguish specific targets from background clutter in incoming picture signals). Ex.1003, ¶¶216-217.

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

Barnard discloses or renders obvious [1.6]. See Ground 1:[1.6]. Ex.1003, ¶¶218-222, 102-106.

4. Claim 2

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

Barnard discloses or renders obvious [2.0]. See Ground 1:[2.0]. Ex.1003, ¶¶223-226, 107-110.

5. Claim 3

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

Barnard discloses or renders obvious [3.0]. See Ground 1:[3.0]. Ex.1003, ¶¶227-229, 111-113.

6. 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.*

Barnard in view of Lawrence renders obvious [4.0]. Ex.1003, ¶¶230-236.

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 in Section VIII.E.2, 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. Ex.1003, ¶231. In the combination, Barnard's target recognition method is modified to utilize neural network architectures, per Lawrence, to calculate

Barnard's target detection threshold in accordance with Baye's criterion. Ex.1003, ¶231. In this regard, as discussed in Ground 3:[1.5], the combination of Barnard and Lawrence renders obvious 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. Ex.1003, ¶231.

Lawrence discloses that the neural network architecture used for the Bayesian estimation includes parallel hardware architectures. Ex.1003, ¶232. In this regard, Lawrence describes “**a neural network architecture**, and more particularly, [] an architecture which is **designed to perform adaptive, continuous Bayesian estimation.**” Ex.1006, Title, 1:2-6, 11:1-3, 23:26-28. 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; Ex.1003, ¶234.

Further, Lawrence itself illustrates the neural network comprises parallel hardware architectures as shown in Figs. 2 and 5, reproduced below, illustrating “**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.**” Ex.1006, 29:10-13; Ex.1003, ¶¶232-233.

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 the neural network parallel hardware architecture) to distinguish specific targets from background clutter in incoming picture signals). Ex.1003, ¶¶235-236.

7. Claim 5

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

Barnard in view of Lawrence renders obvious [5.0]. Ex.1003, ¶¶237-239.

See the analysis above in Ground 3:[4.0]. The parallel hardware architectures employed by the combination of Barnard and Lawrence to distinguish particular targets from background clutter comprise neural networks as taught by Lawrence. Ex.1003, ¶238-239.

8. Claim 6

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

Barnard discloses or renders obvious [6.0]. See Ground 1:[6.0]. Ex.1003, ¶¶240-248, 114-122.

9. 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.

Barnard discloses or renders obvious [7.0]. See Ground 1:[7.0]. Ex.1003, ¶¶249-254, 123-128.

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

1. Reasons to combine Barnard, Lawrence, and Knecht

As established in Sections VIII.D.2 and VIII.E.2, Barnard, Lawrence, and Knecht are all analogous prior art pertaining to the same field of endeavor as the '639 patent. Further, the reasons for combining Barnard with Lawrence (*see* Section VIII.E.2) and the reasons for combining Barnard with Knecht (*see* Section VIII.D.2) are equally applicable in the context of combining Barnard with both Lawrence and Knecht. Ex.1003, ¶255. That is, it would have been obvious to a POSITA to combine Barnard with both Lawrence and Knecht for at least the same reasons it would have been obvious to combine Barnard with Lawrence and Knecht separately. Ex.1003, ¶255.

Further, 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). *KSR*, 550 U.S. 417 (finding obvious the use of known techniques to improve similar methods in the same way); Ex.1003, ¶258.

In addition, 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). *KSR*, 550 U.S. at 416 (finding obvious “[t]he combination of familiar elements according to known methods” to “yield predictable results”); Ex.1003, ¶259.

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. Ex.1003, ¶256. 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. Ex.1003, ¶256. The target detection threshold for each target class would be calculated utilizing a neural network, per Lawrence. Ex.1003, ¶256.

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. Ex.1003, ¶260. Accordingly, utilizing neural network-based Bayesian estimation in accordance with Lawrence is particularly well suited to support distinguishing between a plurality different target classes in accordance with Knecht. Ex.1003, ¶260.

Thus, a POSITA would have had a reasonable expectation of success in implementing neural networks to perform Bayesian estimation, 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. Ex.1003, ¶261.

2. 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.*

Barnard in view of Lawrence and Knecht renders obvious [7.0]. See Ground 3:[1.0]-[1.6], [7.0], Ground 2:[7.0], and Section VIII.F.1. Ex.1003, ¶¶262-266,

249-261, 123-128.

IX. DISCRETIONARY DENIAL IS INAPPROPRIATE

A. No basis for § 325(d) denial

The Board should not exercise its discretion to deny this Petition under § 325(d) because the challenges presented in this Petition are neither cumulative nor redundant to the prosecution of the '639 patent. The Examiner did not consider Barnard, Lawrence, or Knecht, or the combinations of Barnard, Lawrence, and Knecht as presented in this Petition.

B. No basis for *Fintiv* denial

The Board balances six factors in considering denial under § 314. *Apple Inc. v. Fintiv, Inc.*, IPR2020-00019, Paper 11 (Mar. 20, 2020) (precedential). These factors strongly favor institution. The district court case is in its very early stages. Patent Owner filed its complaint on April 12, 2024 (Ex.1010) and trial is currently scheduled for May 14, 2026. Ex.1011 (proposed Scheduling Order). Petitioner has worked diligently to prepare this Petition, which is being filed well within the one-year timeframe allowed by Congress.

1. No evidence regarding a stay

No motion to stay has been filed, so the Board should not infer the outcome of such a motion. *Sand Revolution II, LLC v. Continental Intermodal Group* –

Trucking LLC, IPR2019-01393, Paper 24 at 7 (June 16, 2020) (informative). Thus, this factor is neutral on discretionary denial.

2. Parallel proceeding trial date

This factor weighs against discretionary denial because the projected trial date—based on median time-to-trial statistics—is in January of 2027⁶, which is after the projected date for the Board to issue a Final Written Decision in July of 2026. While trial is currently proposed⁷ for May 14, 2026 (Ex.1011, 4), the Board recognizes that even “scheduled trial dates are unreliable and often change.” *See* Director’s Memorandum on Discretionary Denials (Ex.1013), 8. Moreover, Petitioner notes that “a court’s general ability to set a fast-paced schedule is not particularly relevant... where, like here, the forum itself has not historically resolved cases so quickly.” *In re Apple Inc.*, 979 F.3d 1332, 1344 (Fed. Cir. 2020). Accordingly, the Board uses median time-to-trial statistics in the relevant venue to determine a projected trial date for *Fintiv* purposes. Ex.1013, 9. Because the projected trial date is approximately six months *after* the Board’s expected date for issuing a Final Written Decision, this factor weighs against discretionary denial.

⁶ The current average time-to-trial for the district court hearing the co-pending litigation is 33.1 months. *See* Ex.1012.

⁷ The district court has not entered an order scheduling a trial date.

3. Investment in the parallel proceeding

The investment in the co-pending litigation has been minimal. As mentioned above, a claim construction hearing has not yet occurred, fact discovery is not scheduled until April 11, 2025, and expert discovery is not scheduled until November 20, 2025. Ex.1018, 3-6; *see PEAG LLC v. Varta Microbattery GmbH*, IPR2020-01214, Paper 8 at 17 (Jan. 6, 2021). This lack of investment favors institution.

Moreover, Petitioner only learned which claims were being asserted in August 2024. *See* Ex.1014 (infringement contentions cover pleading). Since then, Petitioner has worked expeditiously to file this petition within four months. And, as of this filing, Patent Owner has not yet served its final infringement contentions. Under *Fintiv*, Petitioner’s prompt filing “weigh[s] against exercising the authority to deny institution.” *Fintiv*, Paper 11 at 11.

4. Overlapping issues with the parallel proceeding

The co-pending litigation is in its early stages. Petitioner served its preliminary invalidity contentions on October 24, 2024 and supplemental invalidity contentions on November 27, 2024. However, Petitioner will not serve its final invalidity contentions until May 22, 2025, near when the Board would issue an institution decision in this case. Ex.1011, 3. The extent of overlap is thus speculative at this point in time.

5. Petitioner is a defendant

Petitioner is a defendant in the co-pending litigation. That is true of most Petitioners in IPR proceedings, making this factor neutral. *See HP Inc. v. Slingshot Printing LLC*, IPR2020-01084, Paper 13 at 9 (Jan. 14, 2021).

6. Other circumstances

“[T]he PTAB will not deny institution of an IPR or PGR under *Fintiv* (i) when a petition presents compelling evidence of unpatentability.” Ex.1013, 9. Here, the petition—along with Dr. Rodriguez’s expert testimony—plainly shows that the ’639 patent claims no more than what others had previously disclosed.

Because the *Fintiv* factors are either neutral or weigh against discretionary denial, institution should not be denied on discretionary factors.

C. No basis for *General Plastic* denial

The ’639 patent has not been challenged in any prior IPR petition, so *General Plastic* discretionary institution does not apply to this Petition. *See General Plastic Indus. Co., Ltd. v. Canon Kabushiki Kaisha*, IPR2016-01357, Paper 19 at 16 (Sept. 6, 2016) (Section II.B.4.i. precedential).

X. CONCLUSION

Petitioner has established a reasonable likelihood that the Challenged Claims are unpatentable.

Respectfully submitted,

Dated: January 17, 2025
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XI. MANDATORY NOTICES

A. Real party-in-interest

Pursuant to 37 C.F.R. § 42.8(b)(1), Petitioner certifies that the real party-in-interest is Tesla, Inc.

B. Related matters

Pursuant to 37 C.F.R. § 42.8(b)(2), to the best knowledge of the Petitioner, the '743 patent is or was involved in the following cases:

Case Heading	Number	Court	Filed
<i>Intellectual Ventures II LLC v. Tesla, Inc</i>	<i>WDTX-1-24-cv-00390</i> (terminated)	WDTX	Apr. 11, 2024
<i>Intellectual Ventures II LLC v. Tesla, Inc.</i>	<i>WDTX-6-24-cv-00188</i> (pending)	WDTX	Apr. 12, 2024
<i>Intellectual Ventures II LLC v. Tesla, Inc.</i>	<i>WDTX-1-24-cv-00884</i> (transferred)	WDTX	Apr. 12, 2024

C. Lead and back-up counsel and service information

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Please address all correspondence in this proceeding to lead and back-up counsel. Petitioner consents to service in this proceeding by email at the addresses above.

CERTIFICATE OF WORD COUNT

Pursuant to 37 C.F.R. § 42.24(d), Petitioner hereby certifies, in accordance with and reliance on the word count provided by the word-processing system used to prepare this Petition, that the number of words in this paper is 12,381. Pursuant to 37 C.F.R. § 42.24(d), this word count excludes the table of contents, table of authorities, mandatory notices under § 42.8, certificate of service, certificate of word count, appendix of exhibits, and any claim listing.

Dated: January 17, 2025

/Jonathan R. Bowser/
Jonathan R. Bowser
Lead Counsel for Petitioner
Registration No. 54,574

CERTIFICATE OF SERVICE

The undersigned certifies that, in accordance with 37 C.F.R. § 42.6(e) and 37 C.F.R. § 42.105, service was made on Patent Owner as detailed below.

Date of service January 17, 2025

Manner of service FEDERAL EXPRESS

Documents served Petition for *Inter Partes* Review Under 35 U.S.C. § 312 and 37 C.F.R. § 42.104 of U.S. 6,894,639;
Petitioner's Power of Attorney;
Petitioner's Exhibit List; and
Exhibits 1001-1017.

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