PATENT OWNER PRE-ORDER PAPER PROVIDING INFORMATION USEFUL IN MAKING THE SNQ DETERMINATION

In the **PATENT** of:
Intellectual Ventures II LLC
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For: GENERALIZED HEBBIAN LEARNING FOR PRINCIPAL COMPONENT ANALYSIS AND AUTOMATIC TARGET RECOGNITION, SYSTEMS AND METHOD
Group: 3992
Examiner: Cameron Saadat

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TABLE OF CONTENTS

I. INTRODUCTION

Patent Owner submits this pre-order paper to assist the Office in determining whether the Request establishes a substantial new question of patentability ("SNQ") for claims 1-7 of U.S. Patent No. 6,894,639. It does not. The Request's proposed rejections rest on the same fundamental error: they recast fixed-feature thresholding as the '639 Patent's claimed feature-generation pipeline.

Claim 1 is not directed to generic target detection using predefined features and a decision threshold. It recites an ordered method in which data statistics are calculated and used to select target-specific feature information; target feature information is generated from those data statistics; that generated target-specific feature information is extracted from the data; the extracted feature information is used to distinguish specific targets from background clutter; and target and background-clutter information is output. EX1001, claim 1. The specification confirms this ordered architecture by describing separate functions and components, including a calculator, selector, generator, and feature extractor. EX1001, 12:34-52, 13:1-18.

The Request does not identify the feature-generation pipeline in the cited art. Barnard begins with fixed, hand-engineered features such as brightness B, size S, and quietness Q. It uses simple statistics to decide whether those fixed features are reliable enough to use, and then places a Bayes/decision threshold in that fixed feature space. EX1005, 2:28-39, 4:50-65, 5:13-19, 5:34-38, 5:59-66. That is not generating target feature information from data statistics. It is fixed-feature pruning and thresholding.

Knecht and Lawrence do not cure that defect. Knecht classifies ship images using Fourier power-spectrum feature vectors and stored decision rules for predetermined ship classes. EX1016, 5:35-6:40. Those Fourier vectors are not generated from Barnard's B/S/Q statistics, are not the feature information allegedly selected in Barnard, and do not supply the missing select → generate → extract pipeline. Lawrence, in turn, is used by the Request only as a neural-network/Bayesian-estimation mechanism for calculating Barnard's threshold. But a neural-network calculation of a threshold remains threshold calculation. It does not transform Barnard's fixed features into target feature information generated from data statistics.

The Request also improperly treats "background clutter" as undifferentiated background. The prosecution record explains that clutter means “non-target regions in the image that have target-like characteristics.” EX2009, 4. The specification likewise treats background clutter as target-like non-target content that must be distinguished using the claimed target-specific feature information and included in the claimed output. EX1001, 10:22-27, 11:36-39, 12:34-52, 13:1-18. Barnard’s generic target/background threshold does not satisfy that requirement.

Because the Request never identifies target feature information generated from data statistics, it cannot establish an SNQ for independent claim 1. And because each challenged dependent claim depends from claim 1, the same failure defeats the requested reexamination of claims 2-7. The Office should therefore maintain the patentability determination made during examination and decline to order reexamination.

II. THE ‘639 PATENT

A. Overview

The ‘639 Patent is directed to systems and methods for detecting targets in environments where background clutter can obscure or resemble signals of interest. In many real-world scenarios—such as surveillance, missile tracking, or remote sensing—objects of interest may exhibit signal characteristics that overlap with those of non-target sources, making reliable detection difficult. The ‘639 Patent addresses this challenge by introducing a novel approach that generates and applies target-specific feature information—i.e., features that are selected based on their discriminative value for identifying a particular class of target. EX2007, ¶28-29.

Instead of applying uniform detection criteria to all potential targets, the disclosed system selects features that are uniquely suited to distinguishing a specific type of target from surrounding clutter. For example, the system may analyze statistical descriptors from known target data to identify features that are especially useful in separating a given target class (such as a missile or aircraft) from background signals (such as clouds, birds, or terrain). This target-specific information is then used during the detection process to improve classification accuracy and reduce false positives. EX2007, ¶30.

The architecture claimed in the ‘639 Patent includes several key steps. The system first receives input data, such as sensor measurements, and calculates statistical properties of that data. The system then uses those statistics to generate feature operators, for example principal-component or eigen filters learned by a Hebbian or PCA rule. The generated operators are then applied to the sensor data during extraction, typically by convolution, to produce operator response maps that indicate the degree of match between the scene content and each operator. The system derives simple summary measures of those response maps, such as means, variances, or variance ratios over a region. These summary values constitute the generated operator responses that the classifier uses to distinguish specific targets from background clutter and that form part of the output that includes target information and background-clutter information.

This approach provides substantial advantages in detection performance, particularly in cluttered or ambiguous environments. By selecting features that are optimized for identifying a particular target class—and by preserving and processing both target and background data—the system allows for more reliable and adaptive discrimination. The ‘639 Patent thus offers a flexible and data-driven detection framework that enables accurate separation of targets from complex backgrounds, even when signal characteristics overlap. The claims accordingly capture an inventive concept centered on adaptive feature selection and classification using target-specific criteria. EX2007, ¶32.

B. Sanger, T. D. “Optimal Unsupervised Learning.” (EX2006)

The “639 Patent states:

> “With respect to the feature selection process, the preferred embodiment uses target statistics and a neural network that implements a generalized Hebbian learning algorithm <u>**to select and generate features specific to a given target class**</u>. <u>**The generalized Hebbian learning algorithm employed, which was discussed in the Sanger, T. D. “Optimal Unsupervised Learning.” Neural Networks vol. 2, pp. 459-473 (1989), selects features for automatic target recognition from the inputted imagery.**</u> The generalized Hebbian Learning algorithm generates principal components or receptive features that resemble those found in Linsker’s work, discussed supra. Inter alia, Sanger shows that the GHA determines the principal components of the data set in order of decreasing eigenvalue, which is important because the higher eigenvalue components are generally the most important or prominent features.” EX1001, 7:46-62

Accordingly, the ‘639 Patent makes clear that in the preferred embodiment a generalized Hebbian learning algorithm, as taught in Sanger (EX2006), is used to select and generate features specific to a given target class.

Sanger describes a method of training a neural network to perform unsupervised learning by identifying the most informative patterns present in input data. The method centers on the Generalized Hebbian Algorithm (GHA), which is designed to adapt the weights of a single-layer linear network so that the network outputs represent the dominant statistical components—known as eigenvectors—of the input distribution. These outputs are ordered by their respective contribution to explaining variance in the input data, allowing for efficient dimensionality reduction. The GHA operates without requiring labeled training data and does not require computation of the full input correlation matrix. Instead, the algorithm incrementally updates the network weights using only the current input and output values, ensuring convergence to the optimal set of weight vectors that span the principal subspace of the input data. For instance, the article demonstrates that when the network is trained on image patches, the learned weights resemble filters found in the mammalian visual system, including those responsive to edges and spatial frequencies. These results support the assertion that the Generalized Hebbian Algorithm enables a network to discover significant structure in data without supervision, and that it does so using only localized, biologically plausible computations. EX2007, ¶37-41.

As Dr. Majumder explains:

> "A POSITA would understand that the '639 Patent implements Sanger's GHA both conceptually and algorithmically. It uses GHA to train a neural network on image patches containing target examples, learns principal components of those patches, treats those components as discriminative filters, and uses the resulting features for automatic target recognition in cluttered scenes. The implementation reflects Sanger's model in structure (single-layer feedforward network), in learning rule (GHA update equation), and in purpose (unsupervised, online extraction of ordered principal components)."
> EX2007, ¶42.

Therefore, Sanger provides the foundation for the '639 Patent feature selection process, applying it to learn and generate features specific to a given target class. By adapting the GHA to train a neural network on unlabeled image data, the system identifies the principal components of target-containing patches, which are then used as filters for automatic target recognition. This approach allows the network to extract the most informative and discriminative features from target imagery without relying on labeled training data or exhaustive preprocessing.

C. Prosecution History

1. Secrecy Order

The ‘639 Patent concerns technology for identifying targets—such as missiles or fighter jets—in radar samples and was subject to a Secrecy Order imposed by the United States Air Force. See EX1001, 5:19–20; EX1002, 162–166, 93–101, 82. Following the filing of the patent application in 1991, the Department of the Air Force determined that the disclosed invention involved “critical technology with military or space application, the unauthorized disclosure of which would be detrimental to the national security and which is subject to export control.” EX1002, 162. Under 35 U.S.C. § 181, a Secrecy Order is effective for one year but may be renewed annually upon an agency’s affirmative determination that continued secrecy remains necessary. Despite the Applicant’s objection (EX1002, 108), the Air Force renewed the Secrecy Order repeatedly—in 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2001, and 2002—before finally rescinding it in 2003. See EX1002, 70–71, 73–82, 86–91, 93–98, 100–101.

This decade-long sequence of secrecy renewals underscores the significance and non-obviousness of the invention. Each year, the Air Force reaffirmed that the technology disclosed in the application remained critical to national defense and was not appropriate for public dissemination. Such sustained classification would have been unnecessary if the subject matter were already known or obvious in view of the prior art. On the contrary, the repeated imposition of the Secrecy Order reflects the government’s recognition that the invention embodied novel and sensitive capabilities. That the Secrecy Order persisted through eleven annual reviews provides compelling evidence that the technology was far from routine or conventional—casting serious doubt on any hindsight-based assertion of obviousness in this re-examination.

2. Technical Report (EX2009)[1]

In opposing the Secrecy Order, Applicant submitted the inventor-authored report "Hebbian Learning, Principal Components and Automatic Target Recognition" (the "Technical Report") on January 8, 1993, and explained that the paper "covered the identical material covered in the patent application." EX1002, 108. The Technical Report, dated May 31, 1991, describes the same invention disclosed in the '639 patent and uses the same role-separated pipeline—select → generate → extract → classify.

Specifically, in the Technical Report, Katz states: "The novelty of our work lies in the use of GHA to generate a set of distinguishing target characteristics that separates targets from background clutter, where clutter is defined by a conventional screener algorithm to be non-target regions in the image that have target-like characteristics." (EX2009, 4.) Inventor Katz further explains: "We use only target statistics to generate the distinguishing features to enhance the robustness of the feature set: the background clutter can change significantly from one scene to the next, so using any particular set of clutter statistics to do feature generation can introduce unwanted biases[10]." EX2009, 4.

These statements, placed before the Office and expressly tied to "the identical material" as the application, confirm that "generating … from said data statistics" in claim 1 refers to deriving the feature operators themselves (e.g., principal-component/eigen filters learned by GHA/PCA) from statistics, not to computing a decision threshold in a fixed, hand-engineered feature space. They also confirm that the statistics used for generation are target statistics, precisely to avoid scene-dependent clutter bias, which is consistent with the specification's separation of selection (what operator family to pursue) from generation (deriving those operators from statistics) and extraction (applying them to data). See, e.g., EX1001, 12:34-52, 13:1-18.

[1] EX2009 can also be found on Pages 141-158 of EX1002

3. "Robust Classifiers without Robust Features" (EX2010)

The inventor's Reference 10 in the Technical Report cites "Robust Classifiers without Robust Features," Katz, Gately, and Collins, *Neural Computation* 2:472–479 (1990) (EX2010), supplies the theoretical backdrop for the invention. "Robust Classifiers without Robust Features" explains that as one moves from image set to image set, the clusters of target and clutter points—and thus the decision surfaces—shift and rotate in complex ways in the n-dimensional feature space, so "the statistical meanings of target and clutter … change from image to image." EX2010, 473. The paper formalizes this non-stationarity with a parameter set P (e.g., lighting, time-of-day, ambient temperature, scene context) that varies from image to image and drives transformations of the feature space and decision geometry, yielding a family of mappings rather than a single fixed one. (EX2010, 473–474.) Empirically, when networks are trained on one location and tested on others, the resulting decision boundaries are largely uncorrelated and the false-alarm rate can increase four-fold with no gain in probability of detection—direct evidence that clutter statistics are environment-dependent and do not transfer. EX2010, 476.

Accordingly, "Robust Classifiers without Robust Features" shows that clutter statistics are non-stationary across scenes and environmental conditions, so deriving feature operators from any particular scene's clutter will "bake in" scene-specific bias and degrade transferability. That is precisely why the Technical Report confines feature generation to target statistics and treats clutter downstream in classification via the operator responses produced by the generated filters. EX2010, 473–474, 476; EX2009, 4, 7–8.

III. CLAIM CONSTRUCTION

The Patent Owner maintains that the Challenged Claims should have their plain and ordinary meaning. However, a determination that a claim term "needs no construction" or has the "plain and ordinary meaning" may be inadequate when a term has more than one "ordinary" meaning or when reliance on a term's "ordinary" meaning does not resolve the parties' dispute." *O2 Micro Int'l Ltd. v. Beyond Innovation Tech. Co.*, 521 F.3d 1351, 1361 (Fed. Cir. 2008). Instead, "[t]he terms used in the claims bear a presumption that they mean what they say and have the ordinary meaning that would be attributed to those words by persons skilled in the relevant art." *Honeywell Int'l, Inc. v. ITC*, 341 F.3d 1332, 1338 (Fed. Cir. 2003). Accordingly, "Properly viewed, the 'ordinary meaning' of a claim term is its meaning to the ordinary artisan after reading the entire Patent." *Aylus Networks, Inc. v. Apple Inc.*, 856 F.3d 1353, 1358 (Fed. Cir. 2017).

A. "background clutter"

Patent Owner proposes that "background clutter" carries its plain and ordinary meaning in the Automatic Target Recognition (ATR) art and, in the context of this patent, refers to non-target portions of the sensed scene that produce measurements or signatures that may resemble those of targets. The intrinsic record and prosecution history confirm that understanding and provide helpful context. The inventor's Technical Report, submitted during prosecution and described as "cover[ing] the identical material" as the application, explains that clutter is "non-target regions in the image that have target-like characteristics," which is fully consistent with the ordinary meaning in ATR. EX2009, 4. The specification describes a pipeline that first selects target-specific feature information, then generates the feature operators from data statistics, then applies those operators to the data and uses operator-response measures in classification to distinguish "specific targets from background clutter." That usage treats "background clutter" as scene content other than the target that nonetheless yields measurable responses to the generated operators and is therefore expressly included in the classifier's decision procedure and in the claimed output. EX1001, 12:34-52, 13:1-18.

Further, "background clutter" must mean something narrower than "background" alone. Reading "background clutter" to mean simply "background" would render the word "clutter" superfluous, which is contrary to settled claim-construction law. The Federal Circuit presumes that different claim words carry different meanings and disfavors constructions that nullify language. See *Merck & Co. v. Teva Pharms. USA,* Inc., 395 F.3d 1364, 1372 (Fed. Cir. 2005) ("A claim construction that gives meaning to all the terms of the claim is preferred over one that does not"); *CAE Screenplates Inc. v. Heinrich Fiedler GmbH*, 224 F.3d 1308, 1317 (Fed. Cir. 2000) (different terms are presumed to have different meanings); *Wasica Fin. GmbH v. Cont'l Auto. Sys., Inc.*, 853 F.3d 1272, 1288 (Fed. Cir. 2017) (courts "must give effect to all claim terms").

The intrinsic record confirms that "clutter" is a meaningful modifier. The inventor's Technical Report, submitted during prosecution and described as covering "the identical material," defines clutter as "non-target regions in the image that have target-like characteristics." That is a subset of background: it is the portion of the non-target scene that is confusable with targets in the measured feature space. EX2009, 4. The specification uses "background clutter" in precisely this way within the role-ordered pipeline: the system selects target-specific feature information, generates the feature operators from data statistics, applies those operators to the data, and then uses operator-response measures to distinguish specific targets from background clutter. EX1001 12:34-52, 13:1-18. On that usage, "background" is the whole of the non-target scene content, while "background clutter" is the target-like portion that elicits operator responses similar to those of targets and thus must be separated at the classification stage.

The patent itself explains how "clutter" was operationalized in the inventor's testing, which is consistent with conventional ATR practice and reinforces that "clutter" narrows "background" to the target-like subset. Specifically:

> "The inventor defined clutter objects for both data sets as any region in the image passed by the screener and not a target fell into the clutter class, which is consistent with conventional screeners. The inventor then used this definition to measure the capability of the principal component features to distinguish targets from objects similar in appearance." EX1001, 9:57-63.

This usage confirms that "background clutter" is not all non-target content; it is the subset of non-targets that survive a coarse screener and remain confusable with targets in the feature space interrogated by the generated operators.

Building on that passage, the specification uses the learned operator responses to operationalize "background clutter" as a subset of non-target scene content with characteristically low response energy under the very operators that accentuate target structure. The patent explains that, under the learned receptive-field filters, "most of the background clutter has a much smaller vertical gradient content than the targets," so statistical summaries of those operator outputs naturally separate the two. EX1001, 10:25-30. In context, the pipeline first generates the operators from data statistics, then applies those operators to the image to obtain response maps, and then computes simple measures such as variances or variance ratios of those responses for decision making.

EX1001, 12:34-52, 13:1-18. Because clutter produces systematically smaller responses for the same generated operators while targets produce larger, more structured responses, the classifier can distinguish specific targets from background clutter using the operator-response statistics the patent teaches, and the system can output information that expressly includes both target and background-clutter characterizations on that common basis.

This record-anchored construction aligns with how the ATR art uses the term and with the inventor's contemporaneous explanation to the Office. It preserves the claim's language and the specification's pipeline by recognizing that "background clutter" is the subset of the background that appears target-like under the generated operators and therefore must be expressly modeled and output, rather than the background writ large.

B. "target specific feature information to distinguish specific targets from background clutter"

Patent Owner submits that the plain and ordinary meaning of "target specific feature information," read in view of the intrinsic record, refers to feature information generated for the target-detection task, including feature operators and associated statistical constructs that are then used to distinguish the target or targets at issue from background clutter. This construction does not import dependent claim 7's multi-class discrimination limitation into claim 1. Rather, it preserves the intrinsic record's distinction between producing target-specific feature information and using that generated information to separate targets from background clutter. EX1001, 12:34-52, 13:1-18.

The specification consistently treats "feature information" as more than a decision threshold or class label. In the disclosed embodiments, the feature information includes operators such as principal-component or eigen filters learned from data statistics, together with associated operator-response information, such as variances or variance ratios, that is used by the classifier. EX1001, 7:46-62, 12:34-52, 13:1-18. The specification also separates the roles of a selector, which selects target-specific feature information; a generator, which generates target feature information from statistics; and a feature extractor, which extracts the generated feature information from the data before classification distinguishes targets from clutter. EX1001, 12:34-52, 13:1-18. Reading "target specific feature information" to encompass a threshold alone would collapse those distinct roles and disregard claim 1's ordered verb sequence.

The prosecution record confirms the same understanding. In the inventor-authored Technical Report submitted during prosecution and described as covering the same material as the application, Katz explains that the invention uses GHA "to generate a set of distinguishing target characteristics that separates targets from background clutter." EX2009, 4. Katz further explains that the method uses "only target statistics to generate the distinguishing features" because background clutter can change significantly from scene to scene, and using clutter statistics for feature generation can introduce unwanted bias. EX2009, 4. This contemporaneous explanation confirms that the "feature information" is the target-focused feature construct generated from statistics and later used to distinguish targets from background clutter—not a mere target/background threshold in a fixed, hand-engineered feature space.

This construction is fully consistent with claim differentiation. Claim 1 requires distinguishing specific targets from background clutter using target-specific feature information. Claim 7, by contrast, separately adds that "said feature information is further used to distinguish two target classes or a plurality of target classes from one another." EX1001, claims 1, 7. Thus, claim 1 need not be limited to multi-class discrimination. But claim 1 still requires target-specific feature information that is selected, generated from data statistics, extracted from the data, and used to distinguish targets from background clutter. It does not permit the Request to substitute a preexisting fixed feature set and a decision threshold for the claimed target-specific feature information.

C. "generating said target feature information from said data statistics"

Patent Owner submits that, in view of the claim language and intrinsic record, "generating said target feature information from said data statistics" refers to deriving the target feature information itself from data statistics. In the disclosed embodiments, that includes deriving feature operators such as principal-component or eigen filters learned by generalized Hebbian learning or principal-component analysis. This is distinct from merely selecting which fixed features to consider, pruning unreliable features, or computing a decision threshold.

The intrinsic record treats "generating" as a separate stage in the claimed, role-ordered process. Claim 1 first recites calculating data statistics and using those statistics to select target-specific feature information. It then separately recites "generating said target feature information from said data statistics," followed by "extracting said target specific feature information from said data." EX1001, claim 1. The specification mirrors this structure through separate functional components: a calculator calculates statistics, a selector selects target-specific feature information, a generator generates target feature information, and a feature extractor extracts that generated feature information from the data. EX1001, 12:34-52, 13:1-18.

That ordered structure matters. The system must first select what target-specific feature information will be generated, then generate that feature information from the statistics, and only then extract the generated target-specific feature information from the data. EX1001, claim 1, 12:34-52, 13:1-18. The specification's examples confirm this meaning. It describes target statistics and a neural network implementing a generalized Hebbian learning algorithm being used to select and generate features specific to a given target class, such as principal-component or receptive-field features, which are later applied to input imagery and used for classification. EX1001, 7:46-62, 12:34-52, 13:1-21.

The phrase "from said data statistics" also requires derivation from the statistics themselves, not merely acting in some general way based on statistics. In the specification, generation from statistics produces feature information that did not exist before the statistics were calculated—for example, principal-component or receptive-field feature information learned from the data statistics. EX1001, 7:46-62, 12:34-52, 13:1-18. Thus, "from" denotes derivation, not mere association with later decision-making.

The prosecution record confirms the same understanding. The inventor-authored Technical Report, submitted during prosecution and described as covering the same material as the application, states that the novelty lies in using GHA "to generate a set of distinguishing target characteristics that separates targets from background clutter." EX2009, 4. The Technical Report further explains that the method uses "only target statistics to generate the distinguishing features" because background clutter changes significantly from scene to scene and using clutter statistics for feature generation can introduce unwanted bias. EX2009, 4. Those statements are consistent with the specification's distinction between generating target feature information from statistics and later using that generated information to distinguish targets from clutter.

Under this intrinsic understanding, the Request's mapping fails. The Request treats "generating" as satisfied by Barnard's calculation of statistics for fixed measures such as brightness B, size S, and quietness Q, its decision to discard unstable measures, and its placement of a Bayes or decision threshold hypersurface in that fixed feature space. EX1005, 2:28-39, 5:13-19, 5:34-38, 5:59-66. But Barnard does not derive target feature information from statistics. It computes values of predefined measures, prunes them using simple stability heuristics, and calculates a threshold. The threshold is a decision rule, not "target feature information" generated from data statistics.

The Request's reading collapses distinct claim verbs. On the Request's theory, "selection" and "generation" both amount to choosing fixed features and a threshold, leaving no generated feature information for the extractor to extract in limitation [1.4] and no generated feature-response basis for the later "using" and "outputting" steps. That is inconsistent with the claim language and the specification's calculator → selector → generator → feature extractor architecture. EX1001, claim 1, 12:34-52, 13:1-18.

Accordingly, Barnard's fixed-feature plus threshold framework does not satisfy "generating said target feature information from said data statistics." Nor is the deficiency cured by Knecht or Lawrence. Knecht supplies Fourier power-spectrum feature vectors and stored decision rules for ship classification, not feature information generated from Barnard's data statistics. EX1016, 5:35-6:40. Lawrence supplies, at most, a neural-network/Bayesian estimation mechanism for threshold calculation. But changing how a threshold is calculated does not convert a threshold into target feature information generated from data statistics. Thus, neither proposed rejection raises a substantial new question of patentability as to this limitation.

IV. MATERIALS RELIED ON IN THE REQUEST

A. Barnard - U.S. Patent No. 5,027,413 (EX1005)

Barnard is directed to a target detection system that identifies objects based on variations in infrared radiation received from a scene. The system uses a line-scanning infrared sensor to collect analog signals corresponding to radiance across the field of view, which are then subjected to standard preprocessing techniques to remove detector artifacts and background clutter. This preprocessing includes applying filters—such as prewhitening or bandpass filters—to suppress signal components associated with background noise. Following this analog preprocessing, the remaining signals are digitized, stored, and subjected to further analysis to identify high-contrast features suggestive of potential targets. EX2007, ¶45.

Barnard's detection pipeline primarily relies on thresholding techniques applied to these preprocessed signals, as well as statistical measures such as variance and distribution width, to determine which features are retained for additional evaluation. The system discards features that exhibit excessive variability or statistical inconsistency, thereby functioning as a generic filter that excludes unreliable data. While Barnard refers to various potential sources of infrared radiation—such as sea-skimming missiles, point sources, wave crests, and seagulls—it applies the same feature evaluation criteria uniformly across all such objects, without tailoring feature selection to any specific target type. The reference does not describe, suggest, or imply a method for selecting features based on their discriminative power for particular classes of targets, nor does it disclose using target-specific training data to guide feature generation or application. EX2007, ¶48.

Thus, Barnard describes a system oriented toward general-purpose target detection through uniform signal filtering and thresholding, without the adaptive, target-specific feature selection and analysis required by the challenged claims of the '639 Patent.

B. Knecht - U.S. Patent No. 4,881,270 (EX1016)

Knecht is directed to automatic classification of images, particularly scanned images of objects, such as ships. Knecht describes reducing a two-dimensional raster image to a one-dimensional signal profile, applying a Fourier transform, and generating a power-spectrum feature vector from selected frequency-domain components. EX1016, 5:35-6:40. The resulting feature vector is compared against stored decision rules corresponding to predetermined object classes, and a classifier, such as a Bayes classifier, may be used to classify the scanned object as belonging to one of those predetermined classes. EX1016, 6:15-40.

The Request relies on Knecht to supplement Barnard with a multi-class classification concept and to argue that a potential target may be classified into one of a plurality of predetermined target classes. But Knecht does not cure Barnard's core deficiency. Knecht's Fourier power-spectrum coefficients are not generated from

Barnard's B/S/Q statistics, are not selected by Barnard's statistical-distribution-width or progressive-mean tests, and are not the same target-specific feature information that the Request maps to Barnard's fixed feature set and threshold. EX1016, 5:35-6:40.

Thus, at most, Knecht discloses a different classification framework using Fourier-derived feature vectors and stored class decision rules. It does not disclose the '639 patent's ordered pipeline in which data statistics are used to select target-specific feature information, target feature information is generated from those data statistics, the generated target-specific feature information is extracted from the data, and that same generated feature information is used to distinguish targets from background clutter. EX1001, claim 1, 12:34-52, 13:1-18. Accordingly, Knecht does not supply the missing claim 1 limitations absent from Barnard.

C. Lawrence- PCT Application Publication WO 90/16038 (EX1006)

Lawrence is directed to a predictive modeling system that employs a self-organizing neural network to forecast time-varying data. The system is primarily concerned with learning and predicting temporal patterns by monitoring changes in input signals over time. Lawrence's architecture is based on a two-dimensional lattice of predictive units, each of which receives and processes local input signals to generate an "innovation signal"—a measure of the difference between predicted and actual inputs. These innovation signals are then compared across the network to identify unexpected changes in input behavior, which may indicate novel or anomalous events.

While the system may be used for event detection, anomaly recognition, or forecasting in dynamic environments, Lawrence does not disclose or suggest selecting features based on their ability to differentiate between particular classes of physical objects. As Dr. Majumder explains:

> "...there is no discussion in Lawrence of distinguishing specific types of targets from background clutter, nor is there any indication that the system uses training data labeled by target class. Instead, the network passively observes temporal signal patterns and adapts its internal model based on prediction error, without class-specific feature optimization or classification mechanisms."
> EX2007, ¶53.

Accordingly, while Lawrence describes a predictive learning architecture, it does not teach or suggest the claimed use of "target specific feature information to distinguish specific targets from background clutter." The reference lacks any teaching of selecting or applying features tailored to specific target classes, and is thus inapposite to the technology claimed in the '639 Patent.

V. ARGUMENT: The Request Does Not Establish a Substantial New Question of Patentability for Claims 1–7

The Request's two proposed rejections fail for the same reason identified above: neither combination teaches claim 1's ordered select → generate → extract → use → output pipeline. Barnard supplies fixed B/S/Q-type features, feature pruning, and a threshold; Knecht supplies Fourier feature vectors and class decision rules; Lawrence supplies, at most, neural-network threshold estimation. None teaches generating target feature information from data statistics and then extracting, using, and outputting information based on that generated feature information. Because all challenged dependent claims depend from claim 1, this missing claim 1 showing defeats both proposed rejections.

The Request also reads "background clutter" as if it meant undifferentiated background. That is wrong. The prosecution record explains that clutter means non-target regions that have target-like characteristics. EX2009, 4. The specification likewise treats background clutter as the target-like non-target content that must be distinguished using the claimed target-specific feature information and included in the claimed output. EX1001, 10:22-27, 11:36-39, 12:34-52, 13:1-18. Barnard's generic target/background threshold does not satisfy that requirement.

Accordingly, both proposed rejections fail for the same core reason. The Request never identifies target feature information generated from data statistics as claim 1 requires. It instead points to fixed features, feature pruning, class decision rules, and threshold calculation. Those disclosures do not teach or suggest the ordered select → generate → extract → use → output pipeline of claim 1. Because all challenged dependent claims depend from claim 1, the failure to establish the limitations of claim 1 defeats both proposed rejections.

A. Proposed Rejection 1: 35 U.S.C. §103 over Barnard in view of Knecht

Proposed Rejection 1 rises or falls on whether Barnard, alone or in combination with Knecht, teaches the core of claim 1's ordered pipeline: using data statistics to select target-specific feature information, generating that target feature information from the data statistics, extracting the generated target-specific feature information from the data, using the extracted feature information to distinguish specific targets from background clutter, and outputting target and background-clutter information. The Request does not show that Barnard or Knecht teaches this pipeline.

Barnard computes values for fixed, hand-defined measures such as brightness B, size S, and quietness Q, prunes unstable measures using simple statistical criteria, and places a Bayes/decision threshold in that fixed feature space to separate a generic "target" from "background." EX1005, 2:28-39, 4:50-65, 5:13-19, 5:34-38, 5:59-66. That framework does not generate target-specific feature operators from data statistics, does not apply generated operators to the data to produce operator-response measures, and does not use those operator-response measures as the claimed decision basis. Nor does it identify or output the claim-specific concept of background clutter as distinct from undifferentiated background. See EX1001, 10:22-27, 11:36-39, 12:34-52, 13:1-18; EX2009, 4.

The Request's mapping confirms the mismatch. For limitations [1.2] - [1.4], the Request equates the claimed target-specific feature information with Barnard's selection of fixed B/S/Q-type measures and an associated threshold hypersurface. For limitations [1.5] - [1.6], the Request then relies on Barnard's thresholded detection and, at most, storage of fixed-feature values. On that theory, there is never a feature operator generated from statistics that the extractor later applies to the data and whose responses the classifier uses. But that is what the intrinsic record describes and what the claims require. EX1001, 12:34-52, 13:1-18.

Knecht does not cure this defect. Knecht classifies ship images by collapsing a two-dimensional raster image into a one-dimensional vector, applying a Fourier transform, deriving a power-spectrum feature vector, and comparing that feature vector to stored decision rules for predetermined ship classes. EX1016, 5:35-6:40. Even if Knecht supplies a multi-class classification concept, Knecht does not teach generating the claimed target feature information from Barnard's data statistics, does not transform Barnard's B/S/Q measures into generated target-specific feature operators, and does not supply the missing select → generate → extract flow. Thus, the combination of Barnard and Knecht still lacks the claimed feature-generation pipeline.

Proposed Rejection 1 therefore fails for at least three independent reasons: (i) Barnard does not disclose "generating said target feature information from said data statistics;" (ii) the Request collapses the distinct ordered steps of selecting, generating, and extracting feature information; and (iii) the Request does not show the claimed use and output of target and background-clutter information tied to generated target-specific feature information, rather than to fixed features and a generic threshold.

1. Limitation [1.2]: "calculating data statistics … and using said data statistics to select target specific feature information"

The Request identifies Barnard's "selection" as the selection of a subset of predefined, hand-engineered measures—brightness B, size S, quietness Q, and similar fixed features—based on stability tests such as distribution width and progressive-mean variance. Barnard describes calculating feature statistics and discarding a feature as a threshold parameter if its statistical distribution is too wide or if its mean varies by more than a preset amount over successive scene images. EX1005, 2:28-39, 5:34-38, 6:12-16. The Request then treats the remaining fixed measures, together with an associated threshold hypersurface, as the claimed "target specific feature information." That is not what claim 1 requires.

In the '639 patent, selection is one step in an ordered, multi-stage feature-generation pipeline. The claimed method first calculates data statistics and uses those statistics to select target-specific feature information. It then separately requires "generating said target feature information from said data statistics," followed by "extracting said target specific feature information from said data." EX1001, claim 1. The specification likewise preserves this separation: a calculator calculates statistics, a selector selects feature information, a generator generates target feature information, and a feature extractor extracts the generated feature information from the data. EX1001, 12:34-52, 13:1-18.

That intrinsic structure matters. The "selection" step is not merely a decision to keep or discard fixed, preexisting B/S/Q measures. It is the front end of an operator-generation process in which the selected target-specific feature information is later generated from statistics and extracted from the data. The specification's examples confirm this meaning: target statistics and a neural network implementing a generalized Hebbian learning algorithm are used to select and generate features specific to a given target class, such as principal-component or receptive-field filters, which are then applied to image data to produce responses used in classification. EX1001, 7:46-62, 12:34-52, 13:1-18.

Barnard does not do that. Barnard starts with fixed feature definitions. Its brightness, size, quietness, shape, width, height, and symmetry measures are predefined quantities calculated from a pixel cluster. EX1005, 4:50-65, 5:1-6. Barnard may discard one of those fixed measures if its distribution is too wide or its mean is unstable, and it may calculate a threshold hypersurface using the remaining feature values. EX1005, 2:28-39, 5:13-19, 5:59-66. But a discard/keep screen over a fixed feature list is not the claimed selection of target-specific feature information that is then generated from data statistics and extracted from data.

The Request also improperly bundles Barnard's decision threshold into the claimed "target specific feature information." A threshold is a decision criterion applied after features have been defined. It is not the feature information itself. In Barnard, the threshold hypersurface is used to classify plotted feature vectors as target or background. EX1005, 5:13-28, 5:59-66. In the '639 patent, by contrast, the claimed feature information is generated from statistics and then extracted from the data before being used for classification. EX1001, 12:34-52, 13:1-18. Equating a threshold with the generated feature information collapses the claim's distinct selection, generation, extraction, and use steps.

This is a substantive difference. Under the Request's reading, any prior-art system that calculates statistics for fixed features and discards unstable ones would satisfy limitation [1.2]. But the '639 patent does not claim generic feature pruning. It claims a pipeline in which target-specific feature information is selected, generated from data statistics, extracted from the data, and then used to distinguish targets from background clutter. EX1001, claim 1; 13:17-31; 13:58-66. Barnard's fixed-feature thresholding architecture is not that pipeline.

Knecht does not change this conclusion. Knecht's Fourier power-spectrum coefficients are not selected from Barnard's B/S/Q statistics, are not generated from

Barnard's statistical distributions, and are not extracted using target-specific feature operators generated from those statistics. EX1016, 5:35-6:40. Knecht may teach classification among predetermined ship classes, but it does not supply the missing claim 1 step of using data statistics to select target-specific feature information in the sense required by the ordered claim language and the intrinsic record. Thus, limitation [1.2] is not taught or suggested by Barnard, Knecht, or their combination.

2. Limitation [1.3]: "generating said target feature information from said data statistics"

Limitation [1.3] requires "generating said target feature information from said data statistics." In light of the claim language and intrinsic record, this limitation requires generating the target feature information itself from the calculated data statistics—not merely selecting from a set of preexisting fixed features and not merely calculating a decision threshold. The specification separates these steps both textually and architecturally: the claimed process includes a selector, a generator, and a feature extractor, with the generator producing target feature information from statistics before the feature extractor extracts that information from the data. EX1001, 12:34-52, 13:1-18.

Barnard does not disclose this limitation. Barnard computes values of predefined, hand-engineered measures such as brightness B, size S, quietness Q, and other possible shape, width, height, or symmetry measures. EX1005, 4:50-65, 5:1-6. Barnard then uses simple statistical measures, such as distribution width, progressive means, and variances, to decide whether to discard a feature as unreliable. EX1005, 2:28-39, 5:34-38, 6:12-16. Finally, Barnard places or calculates a Bayes/decision threshold hypersurface in that fixed feature space. EX1005, 5:13-19, 5:59-66. None of those steps generates target feature information from data statistics as required by limitation [1.3].

The Request's contrary theory collapses distinct claim steps. The Request treats Barnard's fixed B/S/Q-type feature set, together with an associated threshold hypersurface, as the claimed generated target feature information. But a threshold is a classification decision rule, not target feature information generated from statistics. In Barnard, the threshold hypersurface is used after feature values already exist, to separate plotted feature vectors into target and background regions. EX1005, 5:13-28, 5:59-66. In the '639 patent, by contrast, target feature information is generated from data statistics and then extracted from the data before it is used for classification. EX1001, 12:34-52, 13:1-18.

This distinction is critical. Barnard's statistics are used to decide whether fixed, predefined features are reliable enough to use as threshold parameters. They do not produce the feature information itself. The '639 patent's specification describes a different process, in which data statistics are used to generate target-specific feature information, such as principal-component or receptive-field feature information, that can then be applied to the input data and used for classification. EX1001, 7:46-62, 12:34-52, 13:1-18. Barnard's threshold placement in a fixed feature space is therefore not "generating said target feature information from said data statistics."

Knecht does not cure this defect. Knecht classifies ship images by collapsing a two-dimensional image into a one-dimensional profile, applying a discrete Fourier transform, generating a power-spectrum feature vector, and comparing that feature vector to stored decision rules for predetermined ship classes. EX1016, 5:35-6:40. Even if Knecht supplies a multi-class classification concept, it does not teach generating the claimed target feature information from Barnard's data statistics. Knecht's Fourier coefficients are not generated from Barnard's B/S/Q statistics, are not selected by Barnard's statistical-distribution-width or progressive-mean tests, and are not the same feature information that the Request maps to Barnard's fixed feature set and threshold. Thus, the Barnard-Knecht combination still lacks limitation [1.3].

Lawrence does not cure the defect either. In Proposed Rejection 2, the Request relies on Lawrence to provide a neural-network implementation for Bayesian estimation or threshold calculation. But even if Lawrence were used to calculate Barnard's target detection threshold, that would still only change how the threshold is calculated. It would not transform Barnard's fixed B/S/Q-type features into target feature information generated from data statistics. A neural-network calculation of a threshold remains a decision-rule calculation; it is not the claimed generation of target feature information from statistics.

The Request therefore fails to identify any reference, or combination of references, that teaches the required "generating" step. Barnard selects or discards fixed features and calculates a threshold. Knecht supplies Fourier feature vectors and class decision rules. Lawrence supplies, at most, a neural-network Bayesian estimator for threshold-related processing. None of these disclosures generates the target feature information from data statistics in the manner required by limitation [1.3].

Accordingly, both proposed rejections fail at limitation [1.3]. Because the claimed later steps require extracting and using "said" generated target feature information, the failure to disclose the generation step also defeats the Request's mappings for limitations [1.4] - [1.6].

3. The Request Conflates "Background Clutter" with Undifferentiated Background

Claim 1 requires both "distinguish[ing] specific targets from background clutter" and "outputting target and background clutter information." In the intrinsic and prosecution records, "background clutter" is not undifferentiated background. It is the target-like subset of non-target scene content that can resemble the target in the relevant feature space. The inventor's Technical Report, submitted during prosecution, expressly describes clutter as "non-target regions in the image that have target-like characteristics." EX2009, 4. The specification uses the same concept in the claimed ordered pipeline: the system selects target-specific feature information, generates target feature information from data statistics, extracts that feature information from the data, uses it to distinguish specific targets from background clutter, and outputs target and background-clutter information. EX1001, 12:34-52, 13:1-18.

The Request does not identify any disclosure in Barnard of this claim-specific concept. Barnard operates a binary detector in a fixed feature space defined by hand-engineered measures such as brightness B, size S, quietness Q, and other possible shape, width, height, or symmetry measures. EX1005, 4:50-65, 5:1-6. Barnard applies statistical stability screens to determine whether such fixed features should be discarded as unreliable and then places a Bayes/decision threshold hypersurface to separate "target" from "background." EX1005, 2:28-39, 5:13-19, 5:34-38, 5:59-66. That is not the same as identifying, characterizing, using, and outputting information regarding background clutter as the target-like subset of non-target content addressed by the '639 patent.

The Request's mapping therefore collapses "background clutter" into ordinary background. Treating everything on the non-target side of Barnard's decision threshold as “background clutter” reads the word “clutter” out of the claim. Barnard’s non-target/background category includes whatever falls below or outside the threshold in the fixed B/S/Q feature space. But the ’639 patent’s “background clutter” is narrower: it is non-target content that has target-like characteristics and therefore must be distinguished from targets using the claimed target-specific feature information. EX2009, 4; EX1001, 10:22-27, 11:36-39, 12:34-52, 13:1-18.

This distinction matters because the claims require more than thresholded detection. The claimed method requires using the generated target-specific feature information to distinguish targets from background clutter and then outputting both target and background-clutter information. EX1001, claim 1. Barnard’s thresholding in a fixed feature space, at most, produces a target/background detection decision or stores fixed-feature values. EX1005, 5:13-19, 5:59-66. It does not disclose an operator-based characterization of background clutter produced by the claimed select → generate → extract pipeline, and it does not output background-clutter information in the sense required by the claim.

Knecht does not cure this defect. Knecht classifies ship images into predetermined ship classes using feature vectors and stored decision rules. EX1016, 5:35-6:40. But Knecht does not define background clutter as target-like non-target content, does not use Barnard’s fixed B/S/Q threshold framework to characterize such clutter, and does not supply the claimed output of target and background-clutter information. At most, Knecht adds a class-classification concept. It does not transform Barnard’s generic background category into the claimed “background clutter.”

Nor does Lawrence cure the defect. In Proposed Rejection 2, Lawrence is used, at most, to supply a neural-network/Bayesian estimation technique for Barnard’s threshold calculation. But changing how Barnard’s threshold is calculated does not change what Barnard is thresholding or what Barnard outputs. A neural-network implementation of threshold calculation still does not identify or output background-clutter information generated through the ’639 patent’s ordered feature-generation pipeline.

Accordingly, the Request fails to show that the cited art teaches or suggests the claimed treatment of “background clutter.” Barnard applies fixed measures and a threshold to separate generic target detections from background. Knecht supplies predetermined target-class decision rules. Lawrence supplies, at most, neural-network Bayesian estimation. None of these references teaches distinguishing targets from background clutter using generated target-specific feature information and outputting target and background-clutter information as claim 1 requires.

4. Limitations [1.4] - [1.6]: "extracting," "using," and "outputting"

Limitations [1.4] - [1.6] depend on the feature information selected and generated in limitations [1.2] and [1.3]. Claim 1 does not recite isolated acts of calculating feature values, applying a threshold, and reporting a detection. It recites an ordered pipeline: after data statistics are used to select target-specific feature information and after target feature information is generated from those data statistics, the method then "extract[s] said target specific feature information from said data," "us[es] said target specific feature information to distinguish specific targets from background clutter," and "output[s] target and background clutter information." EX1001, claim 1.

The specification confirms this ordered structure. It describes distinct components and functions: a calculator calculates statistics, a selector selects target-specific feature information, a generator generates target feature information, and a feature extractor extracts the generated feature information from the data. EX1001, 12:34-52, 13:1-18. Thus, the "extract," "use," and "output" limitations are tied to the same target-specific feature information that was previously selected and generated from data statistics. They cannot be satisfied by pointing to unrelated fixed-feature calculations and a generic threshold decision.

Barnard does not satisfy these ordered roles. The Request first equates limitation [1.3] with Barnard's selection of fixed measures and an associated decision threshold. It then treats Barnard's routine calculation of values for brightness B, size S, quietness Q, and similar hand-defined measures as the claimed "extracting" step, and treats Barnard's threshold hypersurface as the claimed "using" step. But if Barnard never generates target feature information from data statistics, then there is no generated target-specific feature information for Barnard to extract in limitation [1.4] or use in limitation [1.5]. Barnard's calculation of predefined feature values is not the claimed extraction of generated target-specific feature information. EX1005, 2:28-39, 4:50-65, 5:13-19, 5:34-38, 5:59-66; EX1001, 12:34-52, 13:1-18.

The same defect carries through to limitation [1.6]. The claimed output is not merely a target-detection decision or internal storage of fixed-feature values. It is the output of "target and background clutter information" produced after the method selects, generates, extracts, and uses the claimed target-specific feature information. EX1001, claim 1, 13:17-31, 13:58-66. Barnard, by contrast, at most stores or uses values of fixed features in its sub-image feature store and applies a threshold to determine whether an incoming signal is target-like. EX1005, 5:13-19, 5:59-66. That is not the same as outputting target and background-clutter information characterized through generated target-specific feature information.

Requester's reliance on Barnard's storage of feature values does not cure the problem. Barnard's sub-image feature store may store information about features of detected objects, but those are values of Barnard's predefined features and threshold-related statistical quantities. They are not responses produced by applying generated target-specific feature information to the data. Nor does Barnard disclose outputting background-clutter information as the '639 patent uses that term—i.e., information regarding non-target regions that have target-like characteristics and must be distinguished from the target using the claimed feature information. EX2009, 4; EX1001, 10:22-27, 11:36-39, 12:34-52, 13:1-18.

Barnard's architecture further illustrates the mismatch. Barnard applies preprocessing and filtering to remove detector artifacts and suppress background clutter before its later fixed-feature detection process. EX1005, 3:42-59. Patent Owner does not contend that any amount of preprocessing categorically precludes a system from later outputting background-clutter information. The narrower point is that Barnard's downstream output, as mapped by the Request, is based on fixed features and a threshold applied after such preprocessing, not on the operator-based target and background-clutter characterization required by the ordered claim language.

Knecht does not cure these deficiencies. Knecht extracts Fourier power-spectrum feature vectors from collapsed ship images and compares those vectors to stored decision rules for predetermined ship classes. EX1016, 5:35-6:40. But Knecht does not teach extracting the same target-specific feature information allegedly selected and generated from Barnard's data statistics. Nor does Knecht output target and background-clutter information. Knecht's ship-classification decision rules do not transform Barnard's fixed B/S/Q framework into the claimed select → generate → extract → use → output pipeline.

Lawrence likewise does not cure the deficiencies in Proposed Rejection 2. The Request relies on Lawrence, at most, to provide a neural-network or Bayesian-estimation implementation for calculating Barnard's threshold. But a neural-network calculation of a threshold remains threshold calculation. It does not supply generated target-specific feature information, does not provide an extraction step applying that generated feature information to the data, and does not output target and background-clutter information characterized through that generated feature information.

Accordingly, the Request fails to show limitations [1.4] - [1.6]. Because the cited art does not teach limitation [1.3]'s generation of target feature information from data statistics, the cited art necessarily fails to teach extracting "said" target-specific feature information, using "said" target-specific feature information, and outputting target and background-clutter information based on that same generated feature information. Barnard provides fixed features and a threshold; Knecht provides Fourier feature vectors and class decision rules; Lawrence provides, at most, neural-network threshold estimation. None teaches the ordered extraction, use, and output required by claim 1.

B. Proposed Rejection 2: 35 U.S.C. §103 over Barnard in view of Knecht and Lawrence

Proposed Rejection 2 challenges claims 1-7 over Barnard in view of Knecht and Lawrence. For purposes of this response, Patent Owner focuses on independent claim 1. Because all challenged dependent claims depend from claim 1, Proposed Rejection 2 fails at least because the cited combination does not teach or suggest the limitations of claim 1.

The addition of Lawrence does not cure the deficiencies of Barnard and Knecht. As explained above, Barnard does not teach claim 1's ordered feature-generation pipeline. Barnard computes values of predefined, hand-engineered measures such as brightness B, size S, quietness Q, and similar fixed features; uses simple statistics to discard unstable measures; and places a Bayes/decision threshold in that fixed feature space. EX1005, 2:28-39, 4:50-65, 5:13-19, 5:34-38, 5:59-66. That is not the claimed generation of target feature information from data statistics. Knecht likewise does not supply the missing generation step. Knecht classifies ship images using Fourier power-spectrum feature vectors and stored decision rules, but it does not generate the claimed target feature information from Barnard's data statistics or provide the ordered select → generate → extract → use → output pipeline. EX1016, 5:35-6:40.

Lawrence adds only a neural-network Bayesian-estimation implementation. The Request relies on Lawrence to modify Barnard so that a neural network is used to calculate Barnard's target detection threshold. But that theory addresses only how a decision boundary might be calculated. It does not address what claim 1 requires to be generated from data statistics.

The distinction is dispositive. Claim 1 does not merely require calculating feature values and applying a threshold. It requires: (i) calculating data statistics; (ii) using those statistics to select target-specific feature information; (iii) generating target feature information from those data statistics; (iv) extracting that target-specific feature information from the data; (v) using that target-specific feature information to distinguish specific targets from background clutter; and (vi) outputting target and background-clutter information. EX1001, claim 1. The specification preserves that same ordered structure through distinct functional components, including a calculator, selector, generator, and feature extractor. EX1001, 12:34-52, 13:1-18.

Lawrence does not supply the missing "generating" step. Even if Lawrence's neural network were used to calculate Barnard's target detection threshold, the resulting system would still begin with Barnard's fixed, hand-engineered B/S/Q-type measures and end with a threshold decision in that fixed feature space. A threshold is a classification rule applied after features already exist. It is not target feature information generated from data statistics. In Barnard, the threshold hypersurface separates feature vectors into target and background regions. EX1005, 5:13-19, 5:59-66. In the '639 patent, by contrast, the target feature information is generated from data statistics and then extracted from the data before being used for classification. EX1001, 12:34-52, 13:1-18.

Nor does Lawrence transform Barnard's fixed features into generated target-specific feature information. Lawrence's neural-network architecture is directed to continuous Bayesian estimation, prediction, novelty detection, and state estimation. It does not teach generating the claimed target feature information from Barnard's feature statistics. It does not generate principal-component, receptive-field, or other target-specific feature operators from data statistics. It does not apply generated target-specific feature operators to the data to obtain operator-response measures. And it does not output target and background-clutter information produced by the claimed select → generate → extract → use → output pipeline.

The Request therefore conflates two different things: generating target feature information from data statistics, and calculating a threshold for already-defined features. Lawrence may be cited for the latter, but claim 1 requires the former. Substituting Lawrence's neural-network Bayesian estimator for Barnard's threshold calculation merely changes how Barnard's decision boundary is computed. It does not supply the missing generated feature information, and it does not cure the failure of limitations [1.2] - [1.3].

That same failure carries through limitations [1.4] - [1.6]. The later claim steps refer back to "said" target-specific feature information. Thus, the feature information extracted in [1.4] and used in [1.5] must be the same target-specific feature information selected and generated in [1.2] - [1.3]. Because the Barnard-Knecht-Lawrence combination does not generate target feature information from data statistics, it necessarily does not extract or use that generated information in the later steps. Barnard's calculation of fixed feature values is not extraction of generated target-specific feature information. Knecht's Fourier feature vectors are not generated from Barnard's data statistics. Lawrence's calculation of a threshold is not extraction or use of generated target-specific feature information.

The proposed combination also fails to teach the claimed output. Claim 1 requires "outputting target and background clutter information." EX1001, claim 1. Barnard may store fixed-feature values or produce a target-detection decision. Lawrence may, at most, modify how a target detection threshold is calculated. But the Request identifies no output of target and background-clutter information arising from generated target-specific feature information. The cited combination remains a fixed-feature/threshold system, not the operator-based pipeline claimed in the '639 patent.

The Request's combination rationale does not overcome these defects. Barnard already discloses a Bayes-based thresholding approach in a fixed feature space. EX1005, 5:59-66. Adding Lawrence to perform Bayesian estimation by neural network does not change the nature of Barnard's features, does not generate target feature information from data statistics, and does not supply the missing ordered pipeline. At most, Lawrence changes the mechanism for calculating the threshold. But claim 1 is not satisfied by a better, different, or neural-network-based threshold calculation.

Accordingly, Proposed Rejection 2 fails. Barnard provides fixed features and a threshold; Knecht provides Fourier feature vectors and class decision rules; Lawrence provides, at most, neural-network Bayesian threshold estimation. None of the references, alone or in combination, teaches or suggests generating target feature information from data statistics, extracting that generated target-specific feature information from the data, using it to distinguish specific targets from background clutter, and outputting target and background-clutter information as required by claim 1.

VI. CONCLUSION

The Request does not establish a substantial new question of patentability for claims 1-7. Its proposed rejections depend on treating fixed-feature thresholding as the '639 patent's ordered feature-generation pipeline. But Barnard provides only predefined B/S/Q-type features, simple statistical pruning, and a threshold. Knecht provides Fourier feature vectors and class decision rules. Lawrence provides, at most, a neural-network implementation for calculating Barnard's threshold. None teaches or suggests generating target feature information from data statistics, extracting that generated target-specific feature information from the data, using it to distinguish specific targets from background clutter, and outputting target and background-clutter information as required by claim 1.

The Request's missing claim 1 showing is dispositive. Because all challenged dependent claims depend from claim 1, the Request fails to establish an SNQ for claims 1-7. The Office should maintain the original determination of patentability and deny the Request for ex parte reexamination.

Respectfully submitted,

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By: /Brandon R. Theiss/
Brandon R. Theiss
Registration No. 70,507
Counsel for Patent Owner
Intellectual Ventures II LLC