UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.,
Petitioner

v.

INTELLECTUAL VENTURES II LLC,
Patent Owner.

IPR No. 2025-00340

U.S. Patent No. 6,894,639

DECLARATION OF DR. ADITI MAJUMDER IN SUPPORT OF PATENT OWNER'S PRELIMINARY RESPONSE

9156586.3

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I. Introduction And Qualifications

1. I, Aditi Majumder, submit this Declaration on behalf of Intellectual Ventures II LLC, ("Patent Owner") to provide my opinions concerning the validity of claims 1-7 (the "Challenged Claims") of U.S. Patent No. 6,894,639 (the "'639 patent," EX1001), in support of Patent Owner's Preliminary Response to the Petitioner for *Inter Partes* review of the '639 Patent, which I understand was filed by Tesla Inc., (the "Petitioner") and accompanied by a Declaration of Dr. Jefferey Rodriguez (the "Rodriguez Declaration"), among other exhibits.

2. I am more than eighteen years of age, and I am a citizen of the United States, currently residing in the State of California.

3. In formulating my opinions, I have relied upon my knowledge, training, and experience in relevant art. My qualifications, along with a more detailed summary of my background and publications, are stated more fully in my *curriculum vitae*, which has been provided as Exhibit 2008. Here, I provide a concise summary of my qualifications.

4. I am a Professor in the Department of Computer Science in the School of Information and Computer Sciences (ICS) in University of California, Irvine (UCI).

5. I have founded Summit Technology Laboratory (STL) in 2015 to translate the research in my lab at UCI into a commercial entity. I am currently

the President and CTO of STL. During 2015-Present, I led the development of an automated projection mapping software, Artemis™, using advanced computer vision technologies and built the company from scratch to a 10 member entity. I helped procure $6.5M in SBIR funding from federal agencies to build the product and engage customers to start generating revenue.

6. I have also held the positions of Technical Advisor for Walt Disney Imagineering and Cubic Defense, helping them with computer vision based techniques for their immersive environments.

7. I have also been a Technical Advisor for Ostendo Technologies to help them build their first product on projection based desktop curved display that won the Best Display Award in CES 2009.

8. I have coauthored two books, one of which titled, "Introduction to Visual Computing: Core concepts in Computer Vision, Graphics and Image Processing," is considered a text book for UG or G courses of Visual Computing. In addition, I have authored two book chapters, and 80+ journal and refereed conference articles. I have been the recipient of the NSF CAREER award and have won Best Paper awards in reputed venues like IEEE Virtual Reality, IEEE Visweek, IEEE Projector Camera Systems and 3DTV conference. I have been a Link Foundation Fellow and Given's Associate Student Fellow of Argonne National Laboratories.

9. I have been the co-editor of several reputed publications like IEEE Computer Graphics and Applications and IEEE Transactions on Visualization and Computer Graphics. I have chaired highly reputed conferences like IEEE Virtual Reality, ACM Virtual Reality Software and Technology, and IEEE Workshop on Projector-Camera Systems. My work has received around 4000 citations with an h-index of 36 (based on Google Scholar).

10. I am a named inventor on several patents and published patent applications corresponding to the areas of my professional work. Accordingly, I have a general understanding of the U.S. patent prosecution process and of the novelty and non-obviousness requirements for patentability. Example patents include:

- US Patent 11,160,470- “Motion Tracking Apparatus and Method,” Bruce J. Tromberg, Kyle Cutler, Chris Van Wagenen, Seung-ha Lee, Thomas O’Sullivan, Gopi Meenakshisundaram, **Aditi Majumder**, Albert Cerussi, “, Nov 2021

- US Patent 9,218,061- “Video frame synchronization for a federation of projectors using camera feedback,” **Aditi Majumder**, Kiarash Amiri, Shih-Hsien Yang, Magda El Zarki, Fadi Kurdahi, Dec 2015.

- US Patent 9,183,771 – “A Projector with Enhanced Resolution Via Optical Pixel Sharing,” Behzad Sajadi, **Aditi Majumder**, M. Gopi, Nov 2015.

- US Patent 9,195,121- “Markerless Geometric Registration Of Multiple Projectors (With Or Without Distortions) On Cylindrical And Other Extruded Surfaces Using An Uncalibrated Camera,” Behzad Sajadi, **Aditi Majumder**, Nov 2015.

- US Patent 9,052,584 -"Color Seamlessness in Tiled Displays"- **Aditi Majumder**, M. Gopi, Behzad Sajadi, , June 2015.

- US Patent 9,064,312- "Augmented Reality Using Projector Camera Enabled Devices," Behzad Sajadi, **Aditi Majumder**, June 2015.

- US Patent 8,872,799 -"Scalable distributed/cooperative/collaborative paradigm for multi-user interaction with projection-based display walls," **Aditi Majumder**, Oct, 2015.

- US Patent 8,098,265- " Hierarchical multicolor primaries temporal multiplexing system," Hussein El-Ghoroury, **Aditi Majumder,** Robert G. Brown, Jan 2012.

- US Patent 7,942,530- ""Apparatus and Method for Self Calibrating Multi-Projector Displays Via Plug and Play Projectors," **Aditi Majumder**, Ezekiel Bhasker and Pinaki Sinha, May 2011.

- US Patent 7,038,727- Method to Smooth Photometric Variation Across Multi-Projector Displays, " **Aditi Majumder** and Rick Stevens, May 2006.

11. I believe that my extensive industry experience and educational background qualify me as an expert in the relevant field of visual computing, including image processing, computer vision and computer graphics.

12. I am knowledgeable of the relevant skill set that would have been possessed by a hypothetical person of ordinary skill in the art ("POSITA") at the time of the claimed invention of the '639 Patent, which I have treated as December 18, 1991 for purposes of this proceeding. Although, I was not a POSITA at the time of filing, I have the necessary expertise to provide my

informed opinions in this IPR based on what a POSITA would have understood in 1991 due to the following:

- I received my undergraduate, master's, and doctoral degrees in computer science and engineering, computer science, and computer science, respectively;
- I have extensive experience in visual computing. I have been conducting state-of-the-art research in the use of image processing, computer vision and graphics for a variety of disciplines including immersive environments, spatially augmented reality, computational photography, data visualization and rendering for the last three decades;
- I have supervised 10+ doctoral students in computer science and related fields and many of these students are currently employed by companies such as Facebook, Amazon, and Microsoft.

II. Summary Of Materials Reviewed And Considered

13. The opinions contained in this Declaration are based on the documents I reviewed and my knowledge and professional judgment. In forming the opinions expressed in this Declaration, while drawing on my experience, I reviewed the following documents:

	Description
Paper 2	Petition For Inter Partes Review
EX1001	United States Patent No. 6,894,639 B2 (“the ‘639 Patent”)
EX1002	Prosecution history of the ‘639 patent (‘639 File History)
EX1003	Declaration of Dr. Jeffrey Rodriguez (“Rodriguez Decl.”)
EX1005	U.S. Patent No. 5,027,413 to Barnard (“Barnard”)
EX1006	PCT Application Publication WO 90/16038 to Lawrence (“Lawrence”)
EX1016	U.S. Patent No. 4,881,270 (“Knecht”)
EX2006	Sanger, T. D. “Optimal Unsupervised Learning.” Neural Networks vol. 2, pp. 459-473 (1989)

14. My opinions are additionally guided by my appreciation of how a person of ordinary skill in the art (POSITA) would have understood the claims of the ‘639 Patent at the time of the invention, which I have been asked to assume is December 18, 1991. For the purpose of this Declaration, I will use the definition of POSITA as provided by Dr. Rodriguez (EX1003) and described in Section IV.

III. Legal Standards

15. I am not an attorney. However, I have been informed by counsel of

certain legal standards and have applied those standards, described below, in formulating my opinions.

16. I understand that the claims of a patent define the limits of a patentee's exclusive rights. I understand that to determine the scope of the claimed invention, courts may construe claim terms, the meaning of which the parties may dispute. I understand that claim terms should generally be given their ordinary and customary meaning as understood by a person of ordinary skill in the art at the time of filing of the patent application.

17. I understand that claims must be construed in light of and consistent with the intrinsic evidence. In this context, I understand that intrinsic evidence includes the claims themselves, the written disclosure in the specification, and the Patent's prosecution history. I understand that the specification is always highly relevant to the claim construction analysis and often is the single best guide to the meaning of a disputed term. I understand that extrinsic evidence may also be considered when construing claims and may include, for example, technical dictionaries, technical publications and books, treatises, and expert testimony, though the intrinsic record will be more persuasive as to the meaning of a particular term.

18. I understand that one or more prior art references can render a patent claim obvious to a person of ordinary skill in the art if the differences between

the subject matter set forth in the patent claim and the prior art are such that the subject matter of the claim would have been obvious at the time the claimed invention was made. In analyzing obviousness, I understand that it is important to consider the scope of the claims, the level of skill of a person of ordinary skill in the relevant art, the scope and content of the prior art, the differences between the prior art and the claims, and "secondary considerations" of non-obviousness, which I also understand can include, for example, evidence of commercial success of the invention, evidence of a long-felt need that was solved by an invention, evidence that others copied an invention, or evidence that an invention achieved an unexpected result.

19. I understand that the claimed subject matter can be obvious when a person of ordinary skill in the art would have been motivated to combine pre-existing elements, and that combination yields no more than what a person of ordinary skill in the art would have expected. I also understand that, in assessing whether a claim is obvious, one must consider whether the claimed improvement is more than the predictable use of prior art elements according to their established functions. I understand that there need not be a precise teaching in the prior art directed to the specific subject matter of a claim because one can take account of the inferences and creative steps that a person of ordinary skill in the art would employ. However, I further understand that obviousness cannot be

based on the hindsight combination of components selectively culled from the prior art.

20. I understand that for a reference to qualify as a relevant prior art reference in an obvious analysis, the reference must be "analogous"—meaning it is from the same field of endeavor as the patented technology, and if not, then the reference must be reasonable pertinent to the particular problem facing the inventors of the Patent at issue. I also understand that a reference is reasonably pertinent if a person of ordinary skill in the art would have reasonably consulted those references and applied their teachings in seeking a solution to the problem facing the inventors.

IV. Level Of Skill in the Art and Perspective Applied in This Declaration

21. I understand that certain issues relating to validity must be judged from the perspective of a person of ordinary skill in the art ("POSITA"). I further understand that factors that may be considered in determining the level of skill of a person of ordinary skill in the art include, but are not limited to, (1) the type of problems encountered in the art; (2) prior art solutions to those problems; (3) rapidity with which innovations are made; (4) sophistication of the technology; and (5) the educational level of active workers in the field.

22. I have been informed and understand that a person of ordinary skill in the art is a hypothetical person who is presumed to be aware of all pertinent

prior art, thinks along conventional wisdom in the art, and is a person of ordinary creativity. Importantly, this hypothetical person is of ordinary skill in the art to which the claimed subject matter pertains.

23. With respect to the '639 Patent, as per Dr. Rodriguez's Declaration, "A person of ordinary skill in the art ("POSITA") in the field of the '639 Patent, as of December 18, 1991, would have had 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." EX1003, ¶18

24. I agree with Dr. Rodriguez, and have applied the above-defined perspective of a person of ordinary skill in the art, as of December 18, 1991, in forming and expressing my opinions. Unless otherwise stated, my testimony below refers to the knowledge of one of ordinary skill in the art at that relevant time.

25. At the time of the earliest priority date for the '639 Patent (December 18, 1991), I did not meet the qualifications to be a POSITA as I did not complete my Bachelor's degree until 1999 and my PhD in 2003. However, counsel has informed me that an expert need not have acquired that skill level before the invention to be able to testify from the vantage point of a person of

ordinary skill in the art. Instead, an expert can acquire the necessary skill level later and develop an understanding of what a person of ordinary skill knew at the time of the invention. I believe that I also have a sufficient level of knowledge, experience, and education to be able to testify from the vantage point of a person of ordinary skill in the art of the ‘639 Patent.

V. Claim Construction

26. In my analysis, I have applied the plain and ordinary meanings of the claim terms in the ‘639 Patent, as a person of ordinary skill in the art would have understood them in the context of that Patent on December 18, 1991. And it is my opinion that the prior art set forth in the Petition fails to disclose or render obvious the subject matter of the challenged claims under any reasonable construction and interpretation of the challenged claims’ terms, including their plain meanings, as well as the constructions Petitioner’s expert, Dr. Rodriguez, proposes.

27. I reserve the right to further explain how skilled artisans would understand terms in the ‘639 Patent’s claims, including but not limited to the terms discussed above, in the event the Board institutes an *inter partes* review of the ‘639 Patent.

VI. The ‘639 Patent

A. Overview

28. I have reviewed U.S. Patent No. 6,894,639 ("the '639 Patent"), which is directed to a novel method and system for distinguishing specific targets from background clutter using data-driven, target-specific feature generation. The invention addresses long-standing challenges in automatic target recognition (ATR), particularly in scenarios where target and background objects exhibit overlapping signal characteristics. The solution disclosed in the '639 Patent is fundamentally different from prior ATR systems in that it does not rely on static, hand-crafted filters or global thresholding heuristics. Instead, it uses unsupervised learning—specifically, the Generalized Hebbian Algorithm (GHA)—to derive features that are uniquely optimized for detecting different classes of targets and separating them from the background. EX1001, 5:50-62.

29. The core insight of the '639 Patent is the use of target specific feature information—that is, features selected based on their statistical ability to distinguish a particular target class from background clutter. Any object that can be separated from the background may be considered as a target, and for each of those targets, target-specific feature information is automatically generated from the statistics of the input data. Claim 1 recites a structured method that begins by inputting data (step a), computing statistics from the data (step b), generating feature information from the statistics (step c), extracting the selected feature information (step d), using the extracted features to distinguish targets from

clutter (step e), and outputting both target and background clutter information (step f). In my opinion, this multi-step process defines an end-to-end discriminative architecture that departs materially from prior art systems, which generally treat all targets and non-targets using the same processing pipeline, and/or use predetermined features (not generated from the statistics), and/or use predetermined target classes.

30. In contrast to systems such as Barnard, which attempt to remove background clutter in an early analog preprocessing stage, the '639 Patent retains both target and background information for later-stage classification. This is an important distinction. The architecture claimed in the '639 Patent relies on the comparison of retained background signals against learned, target-specific features, rather than attempting to suppress background data altogether. As described in the Patent, the statistics, such as principal components, are computed from the input data in order to select target specific feature information which in turn is used to distinguish specific targets from background clutter. EX1001, 5:20-24.

31. The use of GHA, as originally described by Sanger (1989), provides the technical basis for this principal component learning. The GHA enables a neural network to compute an ordered set of eigenvectors—i.e., principal components—from unlabeled input data, which in this case are image patches

containing examples of the target class. As the Patent explains (e.g., EX1001, 7: 46–62), the network learns filters that correspond to the most informative statistical features of the target class, such as intensity gradients, edge orientations, or spatial frequency patterns. These learned filters are then convolved across the input image, and their response magnitudes—particularly variances—are used to determine whether the scene contains features consistent with the target class that can be separated from the background clutter.

32. A notable technical advantage of this approach is that it allows for the extraction of highly discriminative features even when targets appear at different ranges or orientations, and even if the targets are partially occluded or they resemble background clutter (EX1001, 7:35-37). The Patent discloses scaling techniques that adjust sampling density based on estimated target range, allowing consistent feature representation across variable resolutions (EX1001, 9:25-40). This kind of multiscale processing anticipates modern hierarchical and scale-invariant feature extraction methods used in deep learning.

33. In terms of output, the '639 Patent discloses that both target and background information are explicitly preserved and made available for downstream processing (see EX1001, Fig 10, 5:28-31). This is crucial for applications where maintaining context (e.g., target location relative to terrain or other entities) is important for situational awareness or sensor fusion. Prior

systems like Barnard, by contrast, discard background information during early filtering, thereby losing valuable contextual cues that could aid classification or decision-making.

34. From a systems engineering perspective, the '639 Patent also describes hardware implementations using operational transconductance amplifiers (OTAs) and resistive networks, allowing for analog realization of the neural network (see EX1001, FIG. 6–9). However, the claims are not limited to analog hardware and are readily implemented in digital software environments as well. The underlying architecture—a feedforward neural network trained using unsupervised Hebbian learning—is equally applicable in software and hardware domains.

35. In summary, the '639 Patent discloses a biologically inspired, statistically grounded method for detecting specific target classes within complex backgrounds. The approach is adaptive, target-specific, and class-discriminative, rather than generic or one-size-fits-all. The system selects features tailored to a particular target based on statistical properties of representative data, uses those features to extract discriminative signals from new input, and classifies based on learned distinctions between target and background. This architecture was technically advanced at the time of invention, and in my opinion, remains foundational to several principles now common in machine learning and

computer vision.

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

36. I have reviewed Terence D. Sanger's 1989 publication titled "Optimal Unsupervised Learning in a Single-Layer Linear Feedforward Neural Network" (EX2006, 459–473), which introduces what is now widely known as the Generalized Hebbian Algorithm (GHA). This work provides both the theoretical foundation and algorithmic structure for training a neural network to compute the principal components of an input distribution using only unsupervised, biologically plausible learning rules. Sanger's contribution is of particular significance to the '639 Patent because the Patent builds upon this learning framework to derive class-specific features for automatic target recognition.

37. The central contribution of Sanger (1989) is the formulation and proof of convergence for a learning rule that enables a single-layer feedforward network to discover the eigenvectors of the input correlation matrix solely through local Hebbian-like updates. The GHA is shown to yield a weight matrix whose rows converge to the first M eigenvectors of the input autocorrelation matrix, ordered by descending eigenvalue. This provides a biologically inspired and computationally efficient method for performing principal component analysis (PCA), or the Karhunen–Loève Transform (KLT), directly from data

without needing to compute or store the full correlation matrix. (EX2006, 460)

38. Sanger's optimality principle is grounded in the notion of preserving maximal information across a compressed set of outputs. Specifically, he defines optimal unsupervised learning as the process of enabling the best possible linear reconstruction of input data using fewer output dimensions—equivalent to minimizing the mean-squared reconstruction error. This criterion is met when the outputs correspond to projections onto the principal eigenvectors of the data distribution. Notably, this aligns with classical results in statistics and signal processing, but Sanger demonstrates that such behavior can be learned dynamically using biologically plausible neural mechanisms.

39. Sanger further demonstrates that the GHA can be implemented using only local operations—each weight is updated based solely on the activities of its pre- and post-synaptic units and, crucially, a modified form of the input vector that excludes the contributions of previously learned eigenvectors. This supports a layered, bottom-up training paradigm consistent with cortical processing models. Additionally, the GHA operates sequentially, allowing each output neuron to learn a distinct principal component without global coordination or centralized normalization.

40. Sanger validates his algorithm through applications to image coding, texture segmentation, and biologically relevant feature extraction (EX2006, 467-

469). The trained networks produce filters that resemble receptive fields found in the primate visual system, including center-surround and oriented edge detectors (EX2006, 470). These results reinforce the idea that unsupervised Hebbian learning can give rise to structures and functions observed in biological vision, and serve as compelling evidence that the learned filters correspond to statistically significant features in the data.

41. In summary, Sanger (1989) provides the theoretical and algorithmic basis for data-driven, unsupervised feature extraction through principal component analysis using a biologically plausible neural network. The Generalized Hebbian Algorithm introduced therein is directly relied upon by the '639 Patent as the mechanism for generating class-specific feature information from radar, infrared, or other sensor data. The applicability of GHA to high-dimensional inputs, and its capacity to produce compact, information-preserving representations, make it uniquely suited for the ATR tasks addressed by the '639 Patent.

42. Accordingly, 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).

VII. The Claims 1-7 Of The '639 Patent Would Not Have Been Obvious

43. Petitioner challenges claims 1-7 (the "Challenged Claims") of the '639 Patent based on several grounds.

44. In my opinion, none of the claims of the '639 Patent would have been obvious over Petitioner's prior art, for reasons I explain below. I will first review the Petitioner's prior art. Then I will address each of the grounds.

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

45. I have reviewed U.S. Patent No. 5,027,413 to Barnard, which describes a target detection system designed to identify objects based on variations in infrared (IR) radiation emitted from a scene. The system employs a rotating, line-scanning IR sensor that captures analog radiance signals across a 360-degree field of view (EX1005, 3:15-24). These analog signals are subjected to standard preprocessing techniques—including prewhitening and bandpass filtering—intended to remove detector artifacts and suppress background clutter (EX1005, 3:42-51). This filtering stage is designed to attenuate signal components associated with the expected background, such as sky and sea clutter, prior to digitization.

46. After analog preprocessing, the surviving signals are digitized and stored for further processing (EX1005, 3:51-54). Barnard's system then analyzes the stored signals to detect clusters of high-intensity pixels, which may correspond to potential targets. Several hand-crafted features are computed for these pixel clusters, such as brightness (the value of the brightest pixel), size (the sum of values of adjacent pixels), and quietness (the sum of surrounding, non-adjacent pixels) (EX1005, 4:50-65). These features are used to characterize the shape and radiometric profile of the object, and are compared against locally defined thresholds (EX1005, 1:21-23, 1:6-63, 6:57-60) to determine whether the object warrants further consideration.

47. A core aspect of Barnard's approach is its use of statistical analysis to manage feature selection. Within each predefined sub-image region, the system accumulates feature statistics over time to compute means and variances for both background and target-like signals. Features that exhibit excessive statistical variability—either across multiple frames or within the current frame—are discarded (EX1005, 6:12-16). This results in a detection pipeline that functions as a general-purpose noise filter, eliminating data considered unreliable or inconsistent, but without regard to any specific target class.

48. Importantly, while Barnard acknowledges that targets may include diverse objects such as missiles, seagulls, or wave crests, it treats all such

potential sources uniformly. The same feature extraction and thresholding criteria are applied to all detected objects, regardless of their type. The system does not learn or adapt its filters or decision rules based on the statistical characteristics of a particular class of target. Nor does it use any form of training data specific to known targets to guide feature generation or selection. Instead, it relies on fixed, global feature definitions and statistical consistency measures to detect anomalies or outliers in the scene.

49. In contrast to the challenged claims of the ‘639 Patent, Barnard does not disclose or suggest any mechanism for selecting features based on their discriminative power for particular target types. There is no use of principal component analysis, no learning of target-specific filters from training data, and no architecture for distinguishing between multiple target classes based on class-conditional statistics. Rather, Barnard's system aims to reduce false alarms and improve detection probability through adaptive thresholding within local image regions, but it does so using globally defined, generic features and without tailoring its detection strategy to any specific target identity.

50. In summary, Barnard discloses a system for general-purpose target detection based on standard analog preprocessing, digitization, and uniform application of hand-engineered features and statistical thresholds. While this may improve detection in non-uniform background conditions, it does not teach or

suggest the adaptive, class-specific, data-driven feature selection process that lies at the heart of the ‘639 Patent’s claimed invention.

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

51. I have reviewed International Publication No. WO 1990/16038 (“Lawrence”), titled “Continuous Bayesian Estimation with a Neural Network Architecture.” This reference discloses a neural network-based estimation system referred to as a “parametric avalanche” (PA), which implements continuous Bayesian filtering by modeling the state of a dynamic system over time. The architecture is composed of two recurrent neural subsystems: a “novum,” which compares incoming observations to predicted signals and outputs a novelty or prediction error, and an “Infinitesimal Generator” (IG), which generates state estimates based on a lattice of neurons encoding spatial patterns of prior observations (EX1006, 11:10-16). Lawrence primarily addresses the problem of estimating system state under uncertainty using an internal dynamic model that adapts over time to minimize prediction error.

52. The core function of the Lawrence system is to track temporal sequences and anticipate the future state of an observed system using a continuous, adaptive estimation process. The IG produces state estimates that are fed back into the novum, which compares those estimates to incoming sensory data. The novelty signal—the difference between the predicted and actual

input—is then used to update the IG's internal model using Hebbian learning (EX1006, 6:10-16). Meanwhile, the novum itself adapts using contra-Hebbian learning to minimize prediction error over time (EX1006, 6:28-32). The combined system thereby converges toward an internal model that accurately forecasts system behavior across time steps.

53. While Lawrence incorporates neural learning principles and Bayesian estimation theory, it does not disclose or suggest a method for selecting or applying target-specific features based on training data labeled with a particular target class. For example, 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.

54. Furthermore, Lawrence's architecture does not include a mechanism for using class-specific training data to derive a set of features optimized for distinguishing one type of target from background clutter. It operates without any explicit classification module. Unlike the '639 Patent, which generates filters via principal component analysis for target recognition and separation from background, Lawrence does not teach or suggest statistical feature selection for a

target recognition task. The IG in Lawrence learns to encode the overall structure of temporal sequences, and the novum functions as a residual calculator rather than a discriminative classifier.

55. In summary, while Lawrence describes learning mechanisms based on Hebbian and contra-Hebbian rules, it does not disclose or suggest adaptive feature selection based on class-conditional training data or the use of learned filters to distinguish targets from background clutter. Thus, Lawrence is fundamentally directed to time-series prediction and system modeling—not to adaptive, target-specific classification as claimed in the '639 Patent.

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

56. Knecht discloses a system for automatic image classification, particularly for use in a missile-based targeting application, in which a scanned two-dimensional image is reduced to a low-dimensional feature vector for real-time classification. The system collapses the digitized raster image along one axis to produce a one-dimensional signal profile, then applies a discrete Fourier transform (DFT) to extract frequency-domain coefficients representing the power spectrum of the signal (EX1016, 5:40-43, 8:17-21). A subset of these coefficients—specifically the squared magnitudes of the lowest non-zero frequencies—constitutes the feature vector used for classification. Decision rules for identifying object classes (e.g., types of ships) are precomputed from training

data and stored in memory, and real-time classification is performed by comparing the extracted feature vector against these stored rules using standard statistical methods such as Bayes classification. While Knecht employs signal transformation and statistical classification, it does not teach or suggest any adaptive learning of features based on target-specific training data or separate target from the background, nor does it use unsupervised learning techniques such as principal component analysis or Hebbian learning to optimize feature extraction for discriminating between different target classes.

D. Ground 1: The Challenged Claims Would Not Have Been Obvious In View of Barnard.

57. The Petition relies heavily on Barnard as the primary reference allegedly disclosing the core limitations of the challenged claims. In particular, Petitioner contends that Barnard teaches (i) the selection of "target specific feature information to distinguish specific targets from background clutter," and (ii) the step of "outputting target and background clutter information." In my expert opinion, Barnard discloses neither. Instead, the cited reference describes a fundamentally different system—one that performs generic statistical filtering using a fixed set of hand-engineered features and removes background clutter during analog preprocessing, prior to any feature calculation or classification.

58. As explained in detail below, Barnard applies the same set of features uniformly to all detected signals, without regard to the identity or class

of the object. There is no discussion or suggestion in Barnard of tailoring feature selection to improve discrimination between different types of targets—such as missiles, birds, or environmental clutter—nor any use of class-labeled training data to guide such selection. Nevertheless, Petitioner's expert attempts to reinterpret Barnard's general-purpose filtering as if it included adaptive, target-specific feature selection. In my view, this interpretation misrepresents the reference and improperly inserts functionality that is neither described nor implied.

59. Moreover, Barnard's architecture precludes the very operations that the challenged claims require. Barnard removes background clutter at the analog stage, before any digital signal processing or feature analysis occurs. This means that the system never analyzes background data alongside target information and cannot distinguish one from the other using target-specific features. It also means that Barnard cannot "output[] target and background clutter information," because the clutter has already been filtered out before reaching the digital detection stage.

1. Barnard Fails to Disclose Selection of Target-Specific Feature Information

60. The Petition asserts that Barnard discloses or suggests the claim limitation of "select[ing] target specific feature information to distinguish specific targets from background clutter," as recited in step (b) of claim 1 of the

‘639 Patent. In my expert opinion, this assertion is technically inaccurate and unsupported by the cited reference. Barnard describes a general-purpose target detection system that applies a fixed set of features—such as brightness, size, and quietness (EX1005, 4:50-65)—to all detected signals, regardless of the nature or class of the target. The system does not select features based on their ability to discriminate between different target types, nor does it use training data labeled by target class to generate or refine those features. Instead, Barnard uses statistical thresholds to discard features that exhibit excessive variability, a technique that may help reduce noise but is fundamentally different from the class-specific feature selection required by the challenged claims.

61. Despite the absence of any disclosure of target-specific feature selection in Barnard, Petitioner’s expert attempts to fill this gap by recasting Barnard’s generic filtering operation as if it involved discriminative, class-based processing. In my opinion, this is a post hoc reinterpretation that introduces functionality nowhere described or suggested in the reference. A person of ordinary skill in the art would not have understood Barnard to disclose the use of target-specific feature information, nor would they read into Barnard the architectural capacity to tailor feature selection based on a particular target class. The reliance on conclusory expert assertions to bridge this missing limitation is, in my view, improper.

62. The following subsections explain why Barnard neither teaches nor suggests the use of target-specific feature information. First, I address the Petition's general mischaracterization of Barnard's system and the expert's effort to equate generic filtering with adaptive feature selection (Section a). I then explain why Petitioner's reliance on Figure 6 and the so-called "hypersurface" does not support the claimed limitation (Section b), followed by an analogy that highlights the fundamental difference between Barnard's architecture and the class-specific approach claimed in the '639 Patent (Section c). Finally, I explain why Barnard's system is incapable of distinguishing among different target classes and therefore fails to satisfy the claim's multi-target discrimination requirement (Section d).

a. Barnard Does Not Disclose Target-Specific Feature Selection, and Petitioner Improperly Relied on Expert Opinion to Supply a Missing Limitation

63. I have reviewed Barnard and the portions of the Petition that allege Barnard discloses the claimed limitation of "select[ing] target specific feature information to distinguish specific targets from background clutter," as recited in, for example, step (b) of claim 1 of the '639 Patent. In my expert opinion, Barnard does not disclose, suggest, or imply this limitation. Further, Petitioner's expert mischaracterizes Barnard's teachings by conflating generic statistical filtering with the adaptive, class-specific feature selection that the '639 Patent requires.

64. Technically speaking, Barnard is directed to a general-purpose target detection system that relies on analog preprocessing and statistical thresholding to identify potential targets in infrared imagery. The system applies conventional filters such as prewhitening and bandpass filters (EX1005, 3:42-51) to suppress low-frequency background clutter and sensor artifacts. It then analyzes the preprocessed signals using a set of hand-engineered features—such as brightness, size, and quietness (EX1005, 4:50-65)—and retains or discards candidate detections based on statistical variance and distribution width. This feature evaluation process is applied uniformly to all detected objects, without regard to the nature or identity of the potential target.

65. Crucially, Barnard does not disclose any mechanism for selecting features based on their statistical discriminability for a *particular class* of target. It treats all possible sources of infrared radiation—missiles, birds, wave crests, etc.—using the same global feature definitions and thresholding logic. There is no training phase in which features are selected or ranked based on how well they distinguish one class of target from another. Nor is there any suggestion that Barnard's system is capable of adapting its feature selection criteria based on the unique characteristics of a specific target type. In contrast, the '639 Patent expressly teaches selecting feature information that is statistically tailored to a class of target, using principal component analysis learned from target-specific

training data. That class-specific selection process is a fundamental innovation and is entirely absent from Barnard.

66. Specifically, Petitioner's expert alleges that in "Fig. 2, Barnard provides the specific example of distinguishing specific targets, such as a point source 15 and a sea-skimming source 16 (e.g., a sea-skimming missile), from background clutter, such as wave crests 17." EX1003, ¶70, citing EX1005,1:24-36, 3:34-41.

67. However, as shown below, Barnard at 2:28-36.and 3:34-41 (reproduced below) offers no example or description that target specific features are selected to distinguish the point source 15. Similarly, the cited portions are silent with regard to selection of target specific features to distinguish the sea-skimming source 16.

> "A target detection system in accordance with the invention may be characterised in that means are provided to calculate the width of the statistical distributions of the background and target features and to discard a feature as a threshold parameter if the width of the statistical distribution of that feature exceeds a predetermined amount, or if the feature mean varies by more than a preset amount over a succession of scene images. EX1005, 2:28-36.

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> "As shown in FIG. 2, 30 mr above the horizon and 45 mr below the horizon are 35 covered. Thus a point source 15 some 5 mr above the horizon is seen against a sky background and a closer sea-skimming source 16 some 10 mr below the horizon is seen against a sea background. Wave crests 17

> closer to the apparatus can also constitute point sources of 40 radiation, as can a seagull 18." EX1005, 3:34-41.

68. While the above passages (and Barnard as a whole) refer to identification of generic target features (such as edges), there is no mention of "target specific" features, e.g., ones tailored to a particular target type or class.

69. Despite this, Petitioner's expert asserts that Barnard satisfies the target-specific feature selection limitation based on Barnard's use of "statistical measures" to retain features with low variability. In my opinion, this conflation is scientifically and technically inaccurate. The statistical filters in Barnard are not applied to distinguish one target class from another, but to eliminate noisy or inconsistent detections across time or space. In effect, Barnard performs *generic signal conditioning*, not *class-specific feature selection*. As such, Petitioner's expert is not identifying a teaching present in Barnard itself but is instead offering an interpretation that inserts an entirely new function into Barnard's system—namely, the ability to select features based on class-conditional variance or discriminability.

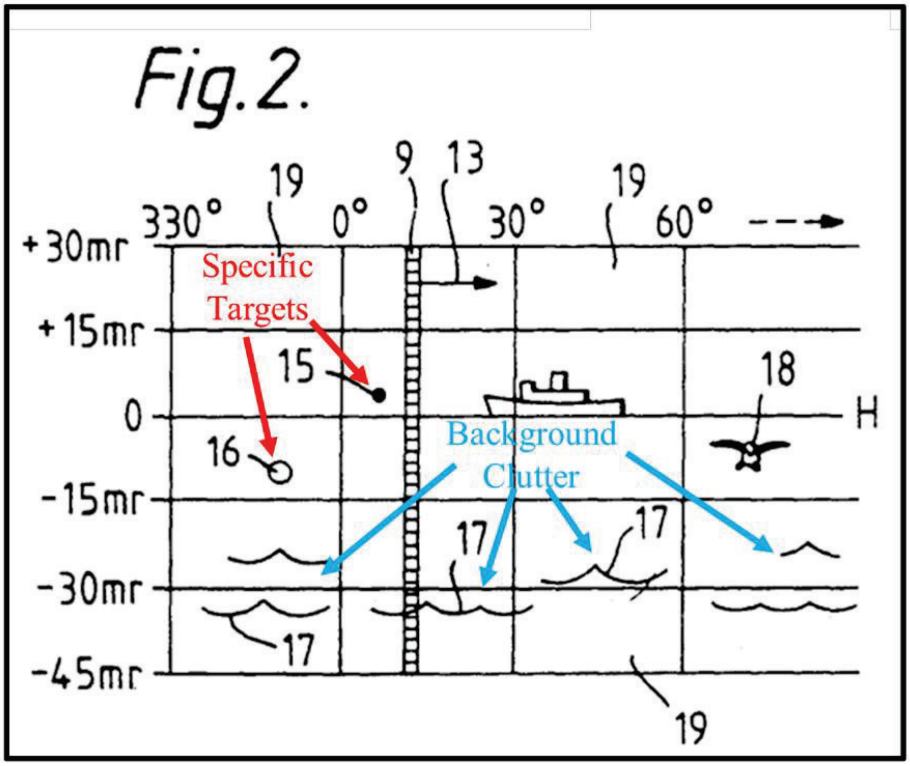
70. From a technical perspective, this amounts to an attempt to fill a material gap in the prior art through unsupported expert opinion. While it is appropriate for a technical expert to explain how a reference would be understood by a person of ordinary skill in the art, it is improper to rewrite the content of a

reference or to attribute capabilities to a system that are neither described nor suggested in the original disclosure. Barnard never mentions, and would not have been understood by a skilled artisan to disclose, a system capable of tailoring its feature selection process to specific target classes based on statistical training.

71. Indeed, Petitioner's expert does not contend—and cannot demonstrate—that Barnard teaches selecting different features to distinguish a seagull from a missile or a point source. Barnard contains no discussion of how any such target-specific feature selection would be performed, nor does it disclose generating feature information from training data tailored to a particular target class. At most, Barnard describes applying a fixed set of features uniformly across all potential targets and then filtering out those features that exhibit excessive statistical variance. This is not the same as selecting features based on their discriminative power for specific target classes, as required by the claims.

72. To the contrary, Figure 2 (below as annotated by the Petitioner) of Barnard illustrates the infrared radiation received—measured in milliradians—from multiple sources, including a point source (15), a sea-skimming missile (16), wave crests (17), and a seagull (18). Nowhere does Petitioner's expert assert that the features applied to target 15 (a point source) differ in any way from those applied to target 16 (a missile) or target 18 (a seagull). Nor does the expert explain how Figure 2 evidences a selection of "target specific feature information

to distinguish specific targets from background clutter," as required by the challenged claims.



Barnard, Fig. 2 (annotated).

73. Accordingly, Petitioner's contention that Barnard discloses the claimed selection of "target specific feature information to distinguish specific targets from background clutter" is unsupported by the reference. The passages cited by Petitioner's expert merely describe a generic statistical filtering process in which features common to all target types are excluded based on their distributional variability. That is, Barnard describes a method for discarding noisy or inconsistent features—not for selecting discriminative, target-specific

ones. As a result Barnard is silent as to any selection of target specific features for the purpose of distinguishing targets such as the point source 15 or sea-skimming source 16 from background clutter.

74. In summary, Barnard does not disclose the claimed selection of target-specific feature information. It uses fixed, global features and applies them uniformly to all data, regardless of target identity. Petitioner's expert opinion does not bridge this gap but instead relies on an incorrect interpretation of Barnard's functionality. Therefore, in my opinion, Petitioner has failed to establish that Barnard teaches or renders obvious the adaptive, target-specific feature selection required by the challenged claims of the '639 Patent.

b. Petitioner's Reliance on Barnard's Figure 6 is Misplaced and Fails to Demonstrate Selection of Target-Specific Feature Information

75. I have reviewed Figure 6 of Barnard and the accompanying disclosure at column 5, lines 13–19, which Petitioner and its expert cite in an effort to show that Barnard teaches the selection of target-specific feature information. In my expert opinion, this reliance is misplaced and reflects a misunderstanding of both the function of the depicted "threshold hypersurface" and the nature of target-specific feature selection as required by the challenged claims.

76. Barnard EX1005, 5:13-19 says "A selection of features can usually be found in which it is possible to place a threshold hypersurface in the feature space which effectively separates target objects from background objects. FIG. 6 illustrates this known approach using only two features B and Q..". It is to be noted that Barnard concedes that this approach is well known, and here is shown as an example to explain that neither feature B nor Q alone can separate the target objects from (remaining) background artefacts, but a combination of features is required. (As noted in EX1005, 3:49-51 Barnard, as part of preprocessing, "remove[s] detector artefacts and the majority of the background clutter signals using a prewhitening filter such as a bandpass filter.") Specifically, FIG 6 does not show target-specific feature selection but use a combination of features to identify group of target objects. The hypersurface represents a thresholding surface in a multidimensional feature space composed of hand-engineered feature values such as brightness, size, and quietness (EX1005, 4:50-65). However, Petitioner's expert provides no explanation of how hypersurface 27 is a *target-specific feature*, e.g., one "associated with a particular target type or class"—as opposed to a generic boundary applied equally across all classes of potential targets. Petitioner does not assert, for example, that Barnard's hypersurface 27 is specifically selected for seagulls (element 18) as compared to sea-skimming missiles (element 16). That is because no such differentiation exists in the

reference.

77. In fact, Barnard discloses no mechanism for adapting the hypersurface or the underlying features based on the class of the target being detected. There is no suggestion that one hypersurface is used for detecting missiles, another for birds, or another for wave crests. Nor does Barnard disclose or imply that the selection of features is informed by training data labeled according to target class. Rather, the hypersurface shown in Figure 6 represents a *fixed* statistical boundary that applies uniformly to all detected signals, regardless of their type. Specifically, there is no disclosure that different hypersurfaces or feature sets are used for different types of targets—such as a seagull versus a sea-skimming missile. Moreover, Barnard is silent as to any selection of target specific features for the purpose of distinguishing targets such as the point source 15 or sea-skimming source 16 from background clutter.

78. Accordingly, Barnard's hypersurface does not constitute or involve "target specific feature information" within the meaning of the challenged claims. It is merely a static filtering boundary applied to generic feature vectors and applied to all target objects without distinction. Petitioner's expert fails to identify any disclosure in Barnard that teaches or suggests the use of different feature sets or decision boundaries tailored to particular target classes. Nor does the expert provide a technical rationale or evidentiary basis for interpreting the

hypersurface as target-specific. The reference lacks any indication that it performs feature selection driven by class-discriminative statistics learned from labeled training data.

c. The Claimed Feature Selection Process is Fundamentally Absent From Barnard's Architecture

79. The difference between Barnard's system and the claimed invention is analogous to the difference between using a generic noise filter and using a voice recognition system trained to identify a specific speaker.

80. Barnard's approach is akin to a system that removes background noise from an audio recording by discarding sounds that fluctuate too much or fall outside of an expected range—regardless of the source of those sounds. It treats all incoming signals the same and simply filters out the statistically inconsistent ones. While this may clean up the signal, it does not help identify who is speaking.

81. By contrast, the claimed invention is more like a system that is trained to recognize a particular speaker's voice—using recordings of that speaker to learn distinctive vocal patterns, and then selecting features tailored to that voice to distinguish it from other sounds. This speaker-specific system not only filters out irrelevant audio but affirmatively selects and uses features that are uniquely suited to recognizing the speaker of interest.

82. In technical terms, Petitioner attempts to equate Barnard's generic filtering system with the claimed target-specific selection process, but the two operate on fundamentally different principles. Barnard discards unreliable data based on variability, without regard to what kind of target is present. The '639 Patent, by contrast, selects features based on their ability to differentiate a particular class of target from clutter, using statistical information derived from representative target-only data. Just as a noise filter cannot substitute for a trained voice recognition system, Barnard's generic filtering cannot satisfy the claimed requirement of selecting target-specific feature information.

83. Petitioner's expert fails to bridge this gap, offering only conclusory assertions unsupported by the reference itself. There is no description in Barnard of using target-specific training data, no mention of class-based feature selection, and no indication that the system can adapt its decision criteria based on target identity. As a result, the Petition's reliance on Barnard—and particularly its use of Figure 6—rests on an impermissible attempt to retrofit the reference with functionality it does not possess. In my opinion, Barnard does not disclose, suggest, or render obvious the selection of target-specific feature information as required by the challenged claims.

d. Barnard is Limited to Single-Target Detection and Fails to Address the Multi-Target Distinction Required by The Challenged Claims

84. In addition to lacking any disclosure of target-specific feature selection, Barnard also fails to satisfy a distinct and critical limitation of the challenged claims: the requirement that the system be capable of distinguishing among different types or classes of targets. As I understand the claims, this requirement is embodied in the recitation of "using said target specific feature information to distinguish specific targets from background clutter." The term "specific targets," in this context, implies more than the mere detection of a generic object—it implies discrimination *among* targets of different classes, based on feature information tailored to particular target types.

85. In technical terms, a system that merely detects the presence of an object that exceeds a radiometric threshold—without distinguishing whether that object is a missile, a seagull, a flare, or another source of infrared radiation—cannot be said to distinguish "specific targets" as required. This limitation is further reinforced by the claim requirement that the feature information be "target specific"—i.e., that it be selected or generated based on its utility in identifying one class of target relative to others. In my opinion, this necessarily excludes detection systems that apply the same processing pipeline to all objects without any adaptation based on target identity.

86. Barnard, by contrast, is directed to detecting the presence of a single target based on high-contrast features. The system is designed to process infrared

imagery, identify bright clusters of pixels, and apply hand-engineered statistical tests—such as brightness, size, and quietness (EX1005, 4:50-65)—to determine whether an object is likely to be a valid detection. This pipeline is not equipped to distinguish a missile from a bird, a point source, or a wave crest; it is simply designed to flag the presence of *any* target-like object in a cluttered scene. There is no discussion in Barnard of feature selection strategies that vary depending on the class of object being detected.

87. This limitation is evident in the description of Barnard's Figure 2, which illustrates that the system treats all high-emission sources—such as a point source (15), a sea-skimming missile (16), wave crests (17), and a seagull (18)—in a uniform manner. As the Patent explains, the system attempts to filter out background clutter through thresholding and statistical screening, but it does not perform any selection or classification based on the nature or class of the target. There is no differentiation in feature use or decision logic based on whether the detected object is a missile or another infrared-emitting source.

88. In contrast, the system described in the '639 Patent is expressly designed to distinguish among classes of targets using data-driven, target-specific feature selection. Accordingly, the system disclosed in the '639 Patent does not merely detect the presence of any target—it learns and selects features that are optimal for identifying a specific class of target, such as a missile, while

suppressing responses to, or distinguishing it from, other infrared-emitting objects, such as seagulls or environmental clutter. This ability to distinguish one class of target from others—based on statistically significant differences in learned feature profiles—is a key innovation of the ‘639 Patent and is entirely absent from Barnard.

89. From a system architecture standpoint, Barnard implements a fixed, class-agnostic detection pipeline. It does not train on labeled target data, does not adapt its feature selection to particular classes, and does not output target classifications based on learned distinctions. Therefore, even aside from its failure to select target-specific features, Barnard cannot satisfy the claims' requirement of distinguishing "specific targets" because it lacks the capability to differentiate between different types of objects.

90. In conclusion, Barnard is fundamentally directed to a single-target detection model. It applies static thresholds and statistical rules to generic features, with no provision for tailoring feature sets or decision logic based on the class of target being detected. Petitioner's reliance on Barnard therefore fails not only due to the absence of target-specific feature selection, but also because Barnard lacks the architectural framework to distinguish among multiple target types in the manner required by the challenged claims. Accordingly, in my opinion, Barnard does not disclose or render obvious the multi-target

discrimination capabilities claimed in the ‘639 Patent.

2. Barnard Removed Background Clutter Prior to Feature Calculation and Therefore Cannot Distinguish or Output Target and Background Clutter Information

91. I have reviewed Barnard and the portions of the Petition that allege Barnard discloses the claim limitations requiring “using said target specific feature information to distinguish specific targets from background clutter” and “outputting target and background clutter information.” In my expert opinion, Barnard cannot satisfy these limitations because it removes background clutter from the analog signal during a preprocessing stage that occurs before any feature calculation or classification is performed.

92. As described in Barnard, the detection system operates on signals that have already been processed to remove clutter and noise. The reference explicitly states:

> “The target detection system in accordance with the invention is applied to the results of this prior processing, these results being contained in a store having a store location for each pixel in the whole horizon image. Each store location will contain the value of that pixel… Thus the present situation of each pixel and its neighbours are available to be subjected to the target detection processes to be described.”
>
> EX1005, 3:59–68.

93. This prior processing is described in greater detail in Barnard at column 3, lines 42–59:

> "… each detector in the linear array traces out a horizontal path in the scene at a constant angular elevation or depression and provides an analogue signal proportional to the infrared radiance of the scene details it encounters. Such line scanning thermal imaging apparatus is well known in the art of thermal target detection. Also well known is the processing of the output of each detector in the array to remove detector artefacts and the majority of the background clutter signals using a prewhitening filter such as a bandpass filter. Each detector output is then sampled to provide picture element (pixel) values, digitised, and a matched filter applied tailored to the expected target signal profile. A d.c. threshold is then usually applied to the matched filter output and the surviving pixel values retained in a store preserving their relative positions. These processes will not be described further since they are not relevant to the present invention and are well known in the art."

94. These passages make clear that Barnard's system applies analog filtering to suppress or remove background clutter *before* the signal is digitized and subjected to feature analysis. Technically, this makes sense because digitization of analog signals was computationally expensive in 1989, and therefore, a common goal was to decrease the amount of digital processing required. The design choice to remove clutter at the analog stage was a practical necessity of the era, but it has significant implications.

95. Specifically, the use of prewhitening and bandpass filters (EX1005, 3:42-59) to attenuate background components means that the digital signals processed by Barnard's feature detection system no longer contain the clutter information that the challenged claims require to be distinguished. Barnard

confirms this architectural choice again at column 3, lines 40–44:

> "The target detection system may be further characterised in that means are provided for applying a filter to the picture signals **before the features are calculated**, the filter being chosen to attenuate those signal frequencies characteristic of background signals."
>
> (Emphasis added.)

96. As a result Barnard removes background clutter from the analog signal before digitization and feature calculation; it does not—and cannot—perform the claimed step of using target specific feature information to distinguish targets from background clutter. Because Barnard's system intentionally removes background components prior to digital processing, it necessarily lacks the ability to use learned, class-specific features to distinguish targets from clutter. There is simply no clutter left in the signal to compare against.

97. Moreover, because the filtered signal passed to Barnard's detection system contains only surviving high-intensity components (i.e., presumed targets), there is no capacity to "output[] target and background clutter information," as further required by the challenged claims. In Barnard, clutter is discarded at the analog stage and never processed or retained. The remaining pixel values that reach the digital stage represent only those components that passed the matched filtering and thresholding tests. Accordingly, the system

cannot output background clutter information because that information has been explicitly suppressed and discarded.

98. In my expert opinion, this architectural separation—between analog preprocessing and digital feature analysis—is fundamentally incompatible with the requirements of the '639 Patent. The claims require a system that operates on a complete dataset, including both target and background signals, and uses class-specific features to distinguish between them. In Barnard, by contrast, the system is given only a pre-filtered signal that excludes the very background data the claims require to be analyzed and output.

99. This architectural choice reflects a reasonable engineering decision for the time but also forecloses any possibility that Barnard discloses the claimed functionality. This design choice also forecloses any possibility that Barnard's system could perform the type of target-specific discrimination required by the claims. Because Barnard lacks background clutter at the point of feature processing, it necessarily cannot 'use said target specific feature information to distinguish specific targets from background clutter,' nor can it 'output[] target and background clutter information,' as recited in the challenged claims.

100. For these reasons, Petitioner's reliance on Barnard to satisfy the limitations involving background clutter is unfounded. Barnard's system never analyzes background clutter in the manner required by the claims, and its analog

filtering stage ensures that no such data is available for classification or output. As a result, in my opinion, Barnard cannot disclose or render obvious the claim limitations requiring the use of target-specific feature information to distinguish specific targets from background clutter or the output of both target and background clutter information.

E. Ground 2-4: Suffer the Same Deficiencies of Ground 1

101. I have reviewed the Petition's Grounds 2, 3, and 4, which challenge the patentability of claim 7 based on combinations of Barnard with Knecht and/or Lawrence. In my opinion, these grounds are deficient for the same reasons that Petitioner has failed to establish the unpatentability of independent claim 1. Because claim 7 depends from claim 1 and incorporates its limitations—including the requirement of "using said target specific feature information to distinguish specific targets from background clutter"—any failure to demonstrate that Barnard satisfies the limitations of claim 1 necessarily defeats the challenge to claim 7.

102. As discussed above, Barnard does not disclose or suggest selecting features based on their ability to distinguish one class of target from another. Instead, Barnard applies a fixed set of statistical filters—such as brightness, size, and quietness (EX1005, 4:50-65)—uniformly to all detected signals, regardless of target identity. Barnard treats all possible sources of infrared radiation—

missiles, birds, wave crests, etc.—using the same global feature definitions and thresholding logic. There is no use of target-specific training data, no adaptation of features based on class membership, and no selection of features designed to optimize separation between different types of targets. Petitioner's expert attempts to fill this critical gap with conclusory testimony, but does not identify any passage in Barnard that describes or suggests "selecting features based on their discriminative power for specific target classes, as required by the claims."

103. Ground 2 adds Knecht as a secondary reference. However, I have reviewed Knecht and found that it does not cure the deficiencies in Barnard. Knecht describes a method for reducing two-dimensional infrared images to one-dimensional vectors, transforming them into power spectra using the Fourier transform, and applying decision rules for classification. However, Knecht's system does not select different feature sets for different target types. It applies the same transform and classification pipeline to all scanned images. There is no discussion in Knecht of tailoring the selection of features based on target class, of separating target from background clutter, or of adapting the feature set using training data specific to a particular type of target. Accordingly, because neither Barnard nor Knecht, alone or in combination, teaches or suggests selecting different feature sets for different target types to separate from background clutter, as required by the claims, the asserted combination fails to disclose the

full scope of claim 7.

104. Ground 3 combines Barnard with Lawrence in an effort to bolster Petitioner's challenge to all claims. In my opinion, this combination also fails for at least two independent reasons. First, as explained above, Barnard does not disclose or suggest the use of "target specific feature information" to distinguish specific targets from background clutter. Its detection system applies the same feature evaluation criteria to all detected objects, with no mechanism for class-based feature selection. Petitioner's expert does not point to any structure in Barnard capable of performing such a selection, and instead offers only generalized statements that do not reflect the actual teachings of the reference.

105. Second, Barnard is structurally incapable of performing the claimed functionality because it removes background clutter during analog preprocessing. As I previously explained, Barnard removes background clutter from the analog signal before digitization and feature calculation; it does not—and cannot—perform the claimed step of using target specific feature information to distinguish targets from background clutter. The background signal is eliminated using a prewhitening or bandpass filter before the signal is digitized and subjected to feature extraction. Thus, Barnard lacks access to background clutter at the feature analysis stage, which forecloses any possibility of performing the claimed comparison between target and background using class-specific features.

106. Lawrence does not remedy these deficiencies. I have reviewed Lawrence and found that it describes a predictive neural network system that learns temporal patterns and evaluates innovation signals, but it does not disclose or suggest selecting features based on target class. As I explained earlier, there is no discussion in Lawrence of how to generate or apply features differently depending on whether the target is, for example, a missile versus environmental clutter. Lawrence focuses on modeling temporal dynamics and does not provide any mechanism for learning or applying class-discriminative features.

107. Because neither Barnard nor Lawrence discloses or suggests the use of target-specific feature information—and because Barnard lacks the required background data at the stage where features are analyzed—the asserted combination fails to satisfy the limitations of the challenged claims. Ground 3 should therefore be rejected.

108. Ground 4 combines Barnard, Lawrence, and Knecht to challenge claim 7. However, as discussed above, Barnard lacks both target-specific feature selection and access to background clutter at the feature calculation stage. These are fundamental deficiencies that neither Lawrence nor Knecht addresses. Lawrence does not disclose selecting features based on target class, and Knecht applies spectral feature extraction uniformly across all targets without class-specific adaptation and does not process background clutter. Accordingly,

because the combination does not collectively teach or suggest the use of target-specific feature information to separate target from background clutter, Petitioner's challenge to claim 7 necessarily fails.

109. In my expert opinion, none of the references relied upon in Grounds 2–4 teaches or suggests selecting features based on their ability to distinguish a specific class of target from background clutter. Nor do the combinations remedy Barnard's architectural deficiency of removing clutter before feature processing. Because the asserted references fail to disclose core limitations of claim 7, and because claim 7 depends on claim 1, which itself has not been shown to be unpatentable, I conclude that Petitioner has failed to establish a prima facie case of obviousness for claim 7. Institution should therefore be denied with respect to Grounds 2, 3, and 4.

VIII. Summary

110. I have reviewed the Petition's Grounds 2, 3, and 4, which challenge the patentability of claim 7 based on combinations of Barnard with Knecht and/or Lawrence. In my opinion, these grounds are deficient for the same reasons that Petitioner has failed to establish the unpatentability of independent claim 1. Because claim 7 depends from claim 1 and incorporates its limitations—including the requirement of "using said target specific feature information to distinguish specific targets from background clutter"—any failure to demonstrate

that Barnard satisfies the limitations of claim 1 necessarily defeats the challenge to claim 7.

111. As discussed above, Barnard does not disclose or suggest selecting features based on their ability to distinguish one class of target from another. Instead, Barnard applies a fixed set of statistical filters—such as brightness, size, and quietness—uniformly to all detected signals, regardless of target identity. As I explained earlier, Barnard treats all possible sources of infrared radiation—missiles, birds, wave crests, etc.—using the same global feature definitions and thresholding logic. There is no use of target-specific training data, no adaptation of features based on class membership, and no selection of features designed to optimize separation between different types of targets. Petitioner's expert attempts to fill this critical gap with conclusory testimony, but does not identify any passage in Barnard that describes or suggests selecting features based on their discriminative power for specific target classes, as required by the claims.

112. Ground 2 adds Knecht as a secondary reference. However, I have reviewed Knecht and found that it does not cure the deficiencies in Barnard. Knecht describes a method for reducing two-dimensional infrared images to one-dimensional vectors, transforming them into power spectra using the Fourier transform, and applying decision rules for classification. However, Knecht's system does not select different feature sets for different target types nor does it

mention anything about background clutter. It applies the same transform and classification pipeline to all scanned images. There is no discussion in Knecht of tailoring the selection of features based on target class, or of adapting the feature set using training data specific to a particular type of target. Accordingly, because neither Barnard nor Knecht, alone or in combination, teaches or suggests selecting different feature sets for different target types and distinguishing them from background clutter, as required by the claims, the asserted combination fails to disclose the full scope of claim 7.

113. Ground 3 combines Barnard with Lawrence in an effort to bolster Petitioner's challenge to all claims. In my opinion, this combination also fails for at least two independent reasons. First, as explained above, Barnard does not disclose or suggest the use of "target specific feature information" to distinguish specific targets from background clutter. Its detection system applies the same feature evaluation criteria to all detected objects, with no mechanism for class-based feature selection. Petitioner's expert does not point to any structure in Barnard capable of performing such a selection, and instead offers only generalized statements that do not reflect the actual teachings of the reference.

114. Second, Barnard is structurally incapable of performing the claimed functionality because it removes background clutter during analog preprocessing. As I previously explained, "Barnard removes background clutter from the analog

signal before digitization and feature calculation; it does not—and cannot—perform the claimed step of using target specific feature information to distinguish targets from background clutter.” The background signal is eliminated using a prewhitening or bandpass filter (EX1005, 3:42-59) before the signal is digitized and subjected to feature extraction. Thus, Barnard lacks access to background clutter at the feature analysis stage, which forecloses any possibility of performing the claimed comparison between target and background using class-specific features.

115. Lawrence does not remedy these deficiencies. I have reviewed Lawrence and found that it describes a predictive neural network system that learns temporal patterns and evaluates innovation signals, but it does not disclose or suggest selecting features based on target class. As I explained earlier, there is no discussion in Lawrence of how to generate or apply features differently depending on whether the target is, for example, a missile versus environmental clutter. Lawrence focuses on modeling temporal dynamics and does not provide any mechanism for learning or applying class-discriminative features.

116. Because neither Barnard nor Lawrence discloses or suggests the use of target-specific feature information—and because Barnard lacks the required background clutter data at the stage where features are analyzed—the asserted combination fails to satisfy the limitations of the challenged claims. Ground 3

should therefore be rejected.

117. Ground 4 combines Barnard, Lawrence, and Knecht to challenge claim 7. However, as discussed above, Barnard lacks both target-specific feature selection and access to background clutter at the feature calculation stage. These are fundamental deficiencies that neither Lawrence nor Knecht addresses. Lawrence does not disclose selecting features based on target class, and Knecht applies spectral feature extraction uniformly across all targets without class-specific adaptation. Accordingly, because the combination does not collectively teach or suggest the use of target-specific feature information, Petitioner's challenge to claim 7 necessarily fails.

118. In my expert opinion, none of the references relied upon in Grounds 2–4 teaches or suggests selecting features based on their ability to distinguish a specific class of target from background clutter. Nor do the combinations remedy Barnard's architectural deficiency of removing clutter before feature processing. Because the asserted references fail to disclose core limitations of claim 7, and because claim 7 depends on claim 1, which itself has not been shown to be unpatentable, I conclude that Petitioner has failed to establish a prima facie case of obviousness for claim 7. Institution should therefore be denied with respect to Grounds 2, 3, and 4.

IX. Conclusion

119. For the foregoing reasons, it is my opinion that Claim 1 of the '639 Patent would not have been obvious over the prior art in Petitioner's Petition for *inter partes* review.

120. Since Claims 2-7 are dependent claims corresponding to Claim 1, they would not have been obvious over the prior art in Petitioner's Petition for *inter partes* review for the same reasons as discussed above.

121. All statements made herein of my own knowledge are true, and all statements made on information and belief are believed to be true. Further, I am aware that these statements are made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under 18 U.S.C. § 1001. I declare under penalty of perjury that the foregoing is true and correct.

Executed on May 27, 2025, in Irvine, California.

Aditi Majumder

_ Dr. Aditi Majumder