

UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

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

v.

AIRSPACE DEFENSE, INC.
Patent Owner

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

**PETITIONERS' OPPOSITION TO PATENT OWNER'S CONTINGENT-
IN-PART AND NON-CONTINGENT-IN-PART REVISED MOTION TO
AMEND**

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LIST OF EXHIBITS

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

¹ Citations to patents are made by column and line cite; citations to patent publications are made by paragraph number; citations to Exhibit 1002 are made with reference to the Bates-stamped pagination; citations to other exhibits are made to the page number of the document itself. Citations to EX1035 and 1036 are to the underlying publication page number.

1010	U.S. Patent Application Publication No. 2017/0059692 to Laufer <i>et al.</i> , “Mitigation of Small Unmanned Aircraft Systems Threats” (“Laufer”) filed August 26, 2016, published March 2, 2017
1011	U.S. Patent No. 8,874,283 to Cavote, “Drone for Inspection of Closed Space and Method Thereof” (“Cavote”) filed December 4, 2012, published October 28, 2014
1012	Internet Archive Wayback Machine screenshot of www.lauferradarsystems.com/technology , dated August 1, 2017
1013	Laufer Wind, Eagle Take Minimization System, Contract DE-EE0007884.0000, Final Technical Report, dated March 28, 2018
1014	U.S. Patent Application Publication No. 2003/0143524 to Lerner, “Method and System for Determining the Amount, Distribution and Confirmation of Genetic Material in a Cell” (“Lerner”) filed January 31, 2002, published July 31, 2003
1015	U.S. Provisional Application No. 62/405,972 to Bar-Nahum <i>et al.</i> , “Multimodal Sensor Empowered Awareness Engine for Target Recovery and Object Path Prediction” (“’972 Provisional”), filed October 9, 2016
1016	Quadrotor Helicopter Flight Dynamics and Control: Theory and Experiment, Hoffmann <i>et al.</i> , American Institute of Aeronautics and Astronautics
1017	DJI Spreading Wings S1000+ User Manual, Version 1.4, dated January 2016
1018	Excerpts from <i>Control Theory for Humans</i> , Jagacinski and Flach, 2003
1019	Excerpts from <i>Control Systems Engineering</i> , Nise, 2004
1020	Excerpts from <i>Modern Control Systems</i> , Dorf and Bishop, 2005
1021	U.S. Patent Application Publication No. 2012/0106800 to Khan <i>at al.</i> , 3-D Model Based Method for Detecting and Classifying Vehicles in Aerial Imagery (“Khan”), filed October 28, 2010, published May 3, 2012
1022	PCT International Publication Number WO2017/123477 to Hogasten, Vehicle Based Radar Upsampling (“Hogasten”), filed January 6, 2017, published July 20, 2017, designating the U.S. and filed in English
1023	U.S. Provisional Application No. 62/277186 to Hogasten, “Vehicle Based Radar Upsampling” (“Hogasten Provisional”), filed January 11, 2016

1024	U.S. Patent Application Publication 2013/0301905 to Malecki et al., “System and Method for Determining an Orientation and Position of an Object” (“Malecki”), filed April 10, 2013, published November 14, 2013
1025	U.S. Patent Application Publication 2012/0004844 to Sahasrabudhe et al., “Formation Flying Method and System” (“Sahasrabudhe”), filed June 29, 2011, published January 5, 2012
1026	Claim Listing of Challenged Claims
1027	Siemens SIMATIC VS72X Manual, 2005
1028	<i>Command Limiting in Reconfigurable Flight Control</i> , Bodson et al., Journal of Guidance, Control, and Dynamics, Vol. 21, No. 4, July-August 1998
1029	Stipulation Email on May 29, 2025
1030	Second Declaration of Dr. William Singhose
1031	Definition of “autonomous” dated September 16, 2016
1032	Definition of “autopilot” dated September 22, 2015
1033	Transcript of Deposition of Dr. Nikolaos Papanikolopoulos in IPR2025-00629
1034	U.S. Patent No. 9,760,806 to Ning et al., “Method and System for Vision-Centric Deep-Learning-Based Road Situation Analysis” (“Ning”) filed May 11, 2016, published September 12, 2017
1035	Big/Little Deep Neural Network for Ultra Low Power Inference, Park et al., <i>2015 International Conference on Hardware/Software Codesign and System Synthesis Proceedings</i> , January 20, 2016 (“Park”)
1036	You Only Look Once: Unified, Real-Time Object Detection, Redmon et al., <i>2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Proceedings</i> , February 6, 2017 (“Redmon”)
1037	Declaration of Professor Hall-Ellis
1038	Transcript of Deposition of Dr. Nikolaos Papanikolopoulos for IPR2025-00530
1039	Third Declaration of Dr. William Singhose
1040	CV of Professor Hall-Ellis

I. SUBSTITUTE CLAIMS (SCS) 24, 25, AND 37 LACK § 112 SUPPORT

SC 37: [37.e1], [37.e3], [37.e4]: These require image-by-image decision-making

based on the *immediately preceding image* and the *current image*. RMTA, 21-25.

The specification is unsupportive. It describes switching between processing scheme groups, but not on a per-image basis where neural network (NN) choice for the *current* image depends on the NN applied to an *immediately preceding* image.

EX2019, ¶¶141-152; EX1039, ¶¶72-76. For ¶¶141 and 146-147, the only paragraphs cited for [37.e1], these describe processing video stream “frames,” examining processing schemes “from group to group,” and switching between groups. They do not disclose the granular requirements of [37.e1], [37.e3], [37.e4] that relate to an *immediately preceding image* and *current image*, and where NN selection for a current image depends on whether the *first* NN or *second* NN was applied to the *immediately preceding image*. RMTA, 21-25; EX2019, ¶112; EX1039, ¶77. PO cannot require obviousness to show possession. *L.A. Biomedical Rsch. Inst. v. Eli Lilly & Co.*, 849 F.3d 1049, 1057 (Fed. Cir. 2017). **[37.e3]:** These recite *a range defined by the first threshold and a second threshold greater than or equal to the first threshold*. RMTA, 24. PO relies on EX2019, ¶¶146, 147. RMTA, 24. ¶146

mentions no “range” or “threshold.” ¶147 references a “low threshold” and “range,” but such isolated words do not show possession of the specific range having two separate thresholds that can be equal. Nowhere in ¶¶146-147 or the rest of the

intrinsic record is a range defined by two separate thresholds, including separate thresholds that can be *equal*, collapsing the *range* into a single point. EX1039, ¶¶78-79. **[37.e4]**: This recites *selecting and applying* the *second* NN to a current image *when the confidence level is above the second threshold* that is greater than or equal to the *first threshold*, and the thresholds *define a range*. RMTA, 24-25. In the context of “low” threshold, the specification refers to confidence “fall[ing] outside” a range (EX2019, 147); it describes “high” confidence, “satisfy[ing]” a threshold, and confidence above “activation number.” *Id.*, 112, 116, 146-147. But *confidence level*, and using it in this way, is not supported as in [37.e4]. EX1039, ¶¶80-81. **SC 24**: EX2019, ¶¶94-95 describes classifying by “type” **or** “model,” not identifying “type” *based on* “classification.” RMTA, 9; EX1039, ¶¶82-83. **SC 25**: EX2019, ¶97 discloses “distance value,” “**distance**”-based factor, or “**speed**”-based factor, not *first* and *second speed adjustment* factors. RMTA, 6-10; EX1039, ¶¶84-85.

II. THE SCS ARE UNPATENTABLE

A. SCS 21-37 Are Not Enabled

The specification must supply novel aspects of an invention to be enabled. *Auto. Techs. Int'l, Inc. v. BMW of N. Am., Inc.*, 501 F.3d 1274, 1283 (Fed. Cir. 2007). PO amended the terms identified below into SCs 21, 36, and 37 during prosecution (EX1002, 215-229) or via its RMTA; it thus considers them novel aspects. As their meaning is not disclosed, the SCS are not enabled. **SC 21: /21.d/; SC 36: /36.c/; SC**

37: [37.d]: A POSITA cannot practice the SCs without undue experimentation due to the recited *speed adjustment factor*. RMTA, 6-7, 18, 21; EX1039, ¶¶86-90; *In re Wands*, 858 F.2d 731, 737 (Fed. Cir. 1988). **No direction/ guidance:** The specification says “[m]odifying the speed and/or acceleration...includes adjusting a factor used to control the speed...based on an amount of directional change....” EX2019, ¶99. It describes slower speeds are desirable for large directional changes and faster speeds for minor or no directional changes. *Id.* But this says nothing about how to determine a *speed adjustment factor*: no formula, algorithm, or procedure. EX1039, ¶90. The specification describes a “scaler” that multiplies a speed adjustment factor, and “plotting the scalar value” results in a bell curve or linear decrease. EX2019, ¶97-99. But this is a “scaler” multiplying a *speed adjustment factor*, not the factor itself. *Id.* Treating the scaler as the *factor*, these disclosures describe curve shape, not how to determine the scaler. EX1039, ¶¶91-92. A bell curve could represent any number of mathematical functions—the specification never identifies the standard deviation, parameters, or input and output ranges necessary. *Id.* Equations 7 and 8 and “speed factor” fare no better (EX2019, ¶106, Fig. 10); they involve constants “a, b, and c” that “may be the same value or they may be different values” and “may differ” based on how applied. *Id.* That is not guidance but an unknown choice. A POSITA has no direction on how to determine a *speed adjustment factor*. EX1039, ¶92. **No Working Examples:** The specification

contains zero working examples of the *speed adjustment factor*: No instance where a directional deviation used by a formula to produce a *speed adjustment factor*, nothing where constants “a, b, and c” are assigned actual numbers, and no demonstrations of how a bell curve or linear relationship is parameterized for any flight scenario. EX1039, ¶93. FIGS. 9 and 10 allegedly show “examples of functions utilized to adjust component values of a vector” and “example equations that can [be] utilized to scale/alter components values of a vector.” EX2019, ¶¶105-106, Figs. 9-10. But they do not determine any *speed adjustment factor*; they are abstractions containing undefined constants and are purely qualitative sketches. *Id.*; EX1039, ¶¶93-94. The specification further provides no experimental data, simulation results, or real-world demonstrations. *Id.* **Quantity of Experimentation:** A POSITA would have been forced to experiment across the entire space of possible functions relating directional deviation to a *speed adjustment factor*, parameter values (including the undefined constants a, b, and c discussed above), and saturation strategies (e.g., maximum limit), without any guidance. EX2019, ¶¶97-99, 105-106, Figs. 9-10; EX1039, ¶95. Quantity of experimentation is enormous. *Id.* **Nature of the invention:** The SCs involve flight control. EX1039, ¶96. An improperly determined *speed adjustment factor* could conceivably cause the vehicle to overshoot a target, oscillate, or crash. *Id.* The nature of the invention demands *more* specificity in the specification, yet the specification provides essentially *none*. *Id.* **State of the Prior**

Art: The specification points to no prior art teachings of how to determine a *speed adjustment factor* from a magnitude of *directional deviation*. EX1039, ¶97. **Level of Skill:** Even under PO's elevated POSITA definition (RMTA, 1-2), the specification's failures are not cured. EX1039, ¶98. The specification provides no methodology. *Id.* Skilled artisans, left to their own devices, would have to generate different functions (e.g., Gaussian, logistic, linear, etc.), select different parameters, determine different rate-of-change limits, and implement different saturation strategies. *Id.* The specification delegates invention to the reader. **Predictability of the Art:** The behavior of a *speed adjustment factor* depends on various variables unaddressed by the specification (e.g., vehicle dynamics, controller responsiveness, wind/turbulence, tracked target characteristics, natural frequencies), further demonstrating how experimentation would be undue. *Id.*; EX1039, ¶99. **Breadth of the claims:** SCs 21, 36, and 37 claim any *speed adjustment factor* determined from any *magnitude of deviation* of any *direction of the three-dimensional relative location* with respect to any *current flight direction* of the reference aerial vehicle but as discussed above, the specification does not teach how to determine such a factor. RMTA, 6-7, 18, 21; EX1039, ¶¶100-101. **Conclusion:** A POSITA attempting to practice SCs 21, 36, and 37 would have been forced into undue experimentation; SCs 21-37 are thus not enabled. *Id.* **SC 36: /36.d/; SC 37: /37.e2/:** These elements recite the terms *robustness*, *compute cost*, and *refresh rate*, and none are enabled.

RM.TA., 18-19, 22-23; EX1039, ¶¶102-104; *In re Wands*. **No direction or guidance: compute cost:** The specification says “[c]osts on all data inputs for the processing schemes can be pre-determined, estimated, or calculated.” EX2019, ¶142. Three verbs, zero instruction. It adds algorithm “cost [is] estimated” based on features (*id.*), but never says how or in what units—CPU cycles? Milliseconds? Floating point operations? Memory consumption? The specification observes “a negative relation between robustness of an algorithm and the cost” (EX2019, ¶109), but this teaches nothing about how to quantify *compute cost*. *Id.* The specification sorts processing schemes into “(i) High cost” “(ii) Medium cost,” and “(iii) Low cost” but never says what separates high, medium, and low. EX2019, ¶145. It further describes assigning processing schemes based on “determined” cost (*id.*, ¶144) without explaining how it is determined, by whom, or using what. The specification offers “as the number of features increases the cost can increase dramatically” (*id.*, ¶142)—an adverb doing the work of explanation that should have been included. None of this guides a POSITA. EX1039, ¶¶105-107. **robustness:** The specification says “[r]obustness of each algorithm [] can be compared by measuring a population of inputs that are selected as representative of sample conditions,” but fails to define what these inputs or sample conditions are, or what metric is used to measure—whether a number, score, percentage, letter grade, or something else. EX2019, ¶143; EX1039, ¶108. The specification describes algorithms having “high,” “average,” or

“low” robustness, or being “brittle” (EX2019, ¶¶110, 145-147, 150), yet provides no measurement methodology or baseline against which these qualitative labels are assessed. *Id.*; EX1039, ¶¶108-109. These are subjective opinions and not reproducible measurements of *robustness* a POSITA can apply. *Id.* **refresh rate:** *[R]efresh rate* appears in the specification as a parenthetical aside to “cost”—group (i) schemes are “[h]igh cost (low refresh rate)” while group (iii) are “[l]ow cost (high refresh rate)” —but the specification never defines the term, discloses its units, or says how to measure it. EX2019, ¶¶145-146, 150. Frames per second? Iterations per second? Cycles per time interval? Unknown. All a POSITA learns is direction—cheaper have a higher rate—but nothing about how to determine or quantify *refresh rate*. EX1039, ¶¶110-111. **No Working Examples:** The specification provides zero working examples of how to determine any of these three values. It provides examples of algorithms falling in groups (i), (ii), or (iii), which correspond to “high” or “low” *cost*, *robustness*, and *refresh rate*. EX2019, ¶¶145, 150-152. But mentioning these algorithms does not teach how to determine the *compute cost*, *robustness*, or *refresh rate* of any of them, grouping metrics, or what a “high” or “low” labels mean. EX1039, ¶112; EX2019, ¶¶145-152. **Quantity of experimentation:** A POSITA would need to independently devise a metric and measurement approach for *compute cost*, *robustness*, and *refresh rate*—an entire research program involving three undefined measurement problems requiring

independent resolutions. EX1039, ¶113. The quantity of experimentation is substantial. *Id.* **Level of skill**: Even under PO's elevated POSITA definition (RMATA, 1-2), the specification's failures are not cured. EX1039, ¶114. The claims require specific values for *compute cost*, *robustness*, and *refresh rate*; determining these depends on undefined metrics that would require undue experimentation under an elevated POSITA definition. *Id.* **State of the prior art**: The specification acknowledges known algorithms, but does not disclose a particular methodology for determining *compute cost*, *robustness*, and *refresh rate* for algorithms so that these values can be compared and determined as greater or less than each other. EX2019, ¶¶145-152; EX1039, ¶115. **Predictability of the art**: Algorithm *compute cost*, *robustness*, and *refresh rate* would depend on the hardware it runs on, its inputs, implementation, and the overall system. EX1039, ¶116; *see e.g.*, EX2019, ¶142. This demands specification guidance, yet the specification provides next to nothing. *Id.* **Breadth of the claims/ Nature of the alleged invention**: SCs 36 and 37 recite NNs having *compute cost*, *robustness*, and *refresh rate*, where some are greater or less than others, yet the specification does not teach how to assign **any** of these values to **any** algorithm, and the specification does not define how any of these parameters are determined or measured as discussed. EX1039, ¶¶117-119. **Conclusion**: A POSITA is unable to practice SCs 36-37 without undue experimentation. *Id.* **SC37: [37.e3]**: SC 37 is further not enabled as no guidance or examples of a *first threshold*

and *second threshold*, defining a *range*, set equal. *Id.*; RMTA, 24; Section I.

B. Substitute Claims 21-37 are Indefinite

SC 21: [21.d]; SC 36: [36.c], [36.d]; SC 37: [37.d], [37.e2]: These elements recite *speed adjustment factor*, *robustness*, *compute cost*, and *refresh rate* terms and they render the SCs indefinite. RMTA, 6-7, 18-24. It is unclear from the intrinsic record what the terms mean. Section II.A; EX1002; RMTA, 6-7, 18-24. A POSITA would not have known their boundaries. EX1039, ¶¶120-126. And the *robustness*, *compute cost*, and *refresh rate* terms have a comparative relationship where some are “greater” or “less” than others. RMTA, 6-7, 18-24. Without knowing their boundaries/how they are determined or measured, there is no way of comparing them to determine such a relationship. EX1039, ¶¶127-128. The SCs are thus indefinite. *Id.* SC 37: [37.e1], [37.e2], [37.e3], [37.e4]: These elements require network selection for a **current image** is *based on a confidence level for a detection of the target in the current image*. RMTA, 20-22. But if no network has yet been applied to the current image, the system cannot have a confidence level *for a detection of the target in the current image*, rendering the claim indefinite. EX1039, 129-133. The specification confirms this: confidence level is the output of applying a network—a “measure of quality for that prediction.” EX2019, ¶141. Within that specification context, the *confidence level* thus measures confidence for a prior prediction, not for a prediction for a *current image* that has not yet occurred.

EX1039, ¶133. Finally, SC 37 conditions on which NN *was applied to an immediately preceding image*. RMTA, 24-25. The specification never discusses such an image-by-image processing technique. Section I; EX2019, ¶¶34, 94, 112, 113, 116-118. 141, Fig. 12; EX1039, ¶134. And a POSITA cannot determine what *immediately preceding image* means. *Id.* It is unclear if this refers to the image one time-step before, the last image to which *any* NN was applied (which may differ from the temporally prior frame if processing is asynchronous), or the last image processed by the same NN pipeline. *Id.* As SC 37’s *first* and *second* NNs operate at different *refresh rates*, the *immediately preceding image* processed by the *first NN* may not be the same temporal frame as the *immediately preceding image* processed by the *second NN*. *Id.*; RMTA, 22-25. SC 37 is thus indefinite. *Id.*

C. Substitute Claims 21-36 are Obvious

Petitioners address SC limitations added via RMTA and relevant orig. limitations; unaddressed limitations are addressed in the Petition (Paper 1, “Pet.”). Elements unpatentable under §112 are addressed based on Petitioners’ understanding of PO’s position and as best understood by a POSITA. The SCs have priority issues acknowledged by the Board, and are not entitled to Oct. 9, 2016 priority. Pet., 3-4; ID (Paper 16), 11-12. Oct. 1, 2017 priority is assumed. PO didn’t contest. RMTA.

GND	SCs	Basis	Prior Art
23	21-27, 29, 31-33, 35	§103	Beard, Laufer, Pierce, Khan, Kumar
24	28	§103	Beard, Laufer, Malecki, Pierce, Khan, Kumar (“BLMPKK”)

25	30	§103	Beard, Laufer, Sahasrabudhe, Pierce, Khan, Kumar (“BLSPKK”)
26	34	§103	Beard, Laufer, Hogasten, Pierce, Khan, Kumar (“BLHPKK”)
27	36	§103	Beard, Laufer, Pierce, Ning
28	21, 23-26, 32	§103	Pierce, Kumar, Khan, Beard
29	22, 29, 35	§103	Pierce, Kumar, Khan, Beard, Laufer (PKKBL)
30	34	§103	Pierce, Kumar, Khan, Beard, Hogasten (PKKBH)
31	36	§103	Pierce, Kumar, Ning, Beard
32	21, 23-26, 31-33	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe (“PKKBS”)
33	22, 29, 35	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe, Laufer (“PKKBSL”)
34	34	§103	Pierce, Khan, Kumar, Beard, Sahasrabudhe, Hogasten (“PKKBSH”)
35	36	§103	Pierce, Kumar, Sahasrabudhe, Ning (“PKSN”)

Pierce, Khan, Kumar, Beard, and Ning (EX1034) are prior art to and in the same field of endeavor of the ’711 Patent, and reasonably pertinent to the particular problem the patent was trying to solve. Pet., 4-7; EX1034, Abstract, 4:29-6:14, 11:1-3, 12:55-13:16; EX1001, Abstract, 3:27-45; EX1039, ¶¶135-145. Ning (filed May 11, 2016, published Sept. 12, 2017) is §§102(a)(1), (a)(2) prior art.

1. Ground (“GND”) 23: SCs 21-27, 29, 31-33, 35

Motivation to Combine (“MTC”): A POSITA would have been motivated to combine Beard, Laufer, Pierce, Khan, and Kumar (the “BLPKK combination”) for the reasons of the Pet. for Beard and Laufer (Pet., 10-13), Beard, Laufer, and Khan (Pet., 36-38), and Beard, Laufer, and Kumar (Pet., 38-41). EX1039, ¶146. And a POSITA would have been motivated to combine Beard, Laufer, Khan, and Kumar (“BLKK”) with Pierce’s teachings of a drone having an on-board object tracking

module that implements NNs for object detection and tracking. *Id.*; EX1005, ¶¶0027, 0042, 0044-0046, Figs. 1, 6. Pierce provides implementation details for how a drone utilizes on-board NNs for object detection and tracking, furthering BLKK’s combined teachings for such concepts. *Id.*; Pet., 10-27, 36-41. Utilizing Pierce would have been applying a known technique (drone having on-board object identification and tracking capabilities that use NNs) to improve similar devices (drones that identify, track objects) in the same way, with the predictable result of Beard’s UAV performing on-board object identification and tracking using NNs. *Id.* For the reasons above, and overlap in subject matter between references and compatibility, there would have been a reasonable expectation of success. *Id.* **SC 21: [21.a]:** BLPKK combination teaches Beard’s image processor 234 “aboard UAV 100” receives and analyzes images captured by camera 210 and image sensor 212 aboard UAV 100 (*receiving at a processor at the reference aerial vehicle an image...*). Pet., 10-16; EX1009, 3:57-4:21, 7:13-53, Fig. 5; EX1039, ¶¶147-148. **[21.b]:** Pierce teaches “drone system 600 [that] may be drone 102,” where system 600 includes “object tracking module 615.” EX1005, ¶¶0027, 0042, 0044-0046, Figs. 1, 6. Images of the drone’s “surrounding area” include moving target objects, and on-board object tracking module 615 implements “various neural networks” that analyze the images “to identify and track the moving target” and estimate its position and velocity from the drone. *Id.*, ¶0045, Fig. 6. **Khan** discloses real-time classification of vehicle

model types in aerial imagery. EX1021, ¶0003. A computer on-board a UAV detects and classifies vehicle model types in images captured by image capturing devices of the UAV. *Id.*, ¶¶0037-0039. The computer processes captured images 700 by determining “salient features of a vehicle 702” in images; the features are “shape and appearance” features at feature locations 804, 806, and 808, located within a bounding box surrounding vehicle 702 shown by Figs. 7 and 8. *Id.*, 0045-0050, Figs. 7-8. These detected features are compared to 3D vehicle model features to determine a classification of vehicle type such as sedan or SUV. *Id.*, ¶¶0044-0063. Classification is performed by a “linear classifier” such as a “support vector machine classifier (SVM)” machine learning model. *Id.*, ¶0062; EX1039, ¶¶149-151. **Kumar** discloses “bounding boxes” around objects of interest in an image are output by a NN. EX1007, ¶0019; EX1008, ¶0029. A NN is a known type of machine learning model. EX1007, ¶0002; EX1008, ¶0001; EX1039, ¶152. The BLPKK combination thus teaches Beard’s on-board UAV image processor 234 detects a target 118 in image frames by applying a machine learning/NN algorithm to image frames to “identify potential target objects” 112a-d, which can be aircraft, “via bounding boxes” 116a-d that each surround a portion of an image including the potential target objects, where a target object is selected as target object 118 (*detecting at the reference aerial vehicle a target in the image including by applying at the reference aerial vehicle a machine learning model to the image, to identify a bounding box*

outlining a portion of the image). Pet., 15-16; EX1009, 3:9-4:21, 4:22-25, 2:2-8, 7:13-53, Figs. 1A-1C, 5; EX1003, ¶¶117-118; Section II.C.1 (MTC); EX1039, ¶153. In the combination, by performing the detecting of a target (*detecting at the reference aerial vehicle...*), the identified bounding boxes would have outlined detected “shape and appearance” features of potential target objects 112 (and thus the determined selected target object 118) as taught by Khan (*to identify a bounding box outlining a portion of the image that includes detected features of the target*). *Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7; EX1039, ¶154. And by performing detecting of a target (*detecting at the reference aerial vehicle...*), these features would have been used to classify selected target object 118 as a particular type of target as taught by Khan (*and to identify a classification of the detected target.*) *Id.* Additionally, under an alternative interpretation, by Beard’s on-board UAV image processor 234 applying machine learning/NN algorithm (*applying at the reference aerial vehicle a machine learning model...*) to generate the identified bounding boxes, these bounding boxes would outline detected “shape and appearance” features of potential target objects 112 (and thus the determined selected target object 118) as taught by Khan and Kumar (*to identify a bounding box outlining a portion of the image that includes detected features of the target*). *Id.*; EX1021, ¶¶0045-0063, Figs. 6, 7; EX1007, ¶¶0002, 0019; EX1008, ¶¶0001, 0029; EX1039, ¶155. Beard’s on-board UAV image processor 234 applying the machine learning/NN algorithm (*applying*

at the reference aerial vehicle a machine learning model...) would have classified selected target object 118 as a type of target based on the features as taught by Khan (*and to identify a classification of the detected target*). EX1021, 0045-0063, Figs. 6, 7; EX1007, ¶¶0002, 0019; EX1008, ¶¶0001, 0029; Section II.C.1 (MTC); EX1039, ¶155. [21.c]: The BLPKK combination teaches Beard's on-board UAV image processor 234 determines tracking parameters between the UAV and target 118 including distance, angle of elevation, and bearing (*determining at the reference aerial vehicle a three-dimensional relative location of the target...*). Pet., 16-18; EX1039, ¶¶156-157. The distance is "based on the pixel size of the target 118...relative to that of the frame" and specifically the area (i.e., the size) of bounding box 116 around a target, calculated by multiplying bounding box width of "γ pixels" with bounding box height of "δ pixels" (i.e., "γ*δ") (*determining...a three-dimensional relative location of the target...including by determining a distance to the target based at least in part on a size of the bounding box of the target detected within the image*). Pet., 16-18, 28-29; EX1039, ¶157. Further, Khan teaches classification of a target into a type (e.g., SUV, sedan) as discussed above for [21.b], and Kumar teaches a target tracking system that recognizes a target in captured images and produces a bounding box around the target. EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8; EX1007, ¶¶0020, 0035, Fig. 2; EX1008, ¶¶0018, 0030, Fig. 2. Kumar determines the relative position of a target to the camera capturing the

images based on the “known physical [bounding] box size of the object of interest’s type of object” and the “physical length of the diagonal across the [bounding] box for an average instance of the object.” EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, 14-15, 24-25, Fig. 3A; EX1003, ¶¶157-158. Thus, Khan teaches classifying a target in an image as a particular type, and Kumar teaches determining a relative position using a known physical size of such a type, and the BLPKK combination thus teaches the distance between Beard’s UAV 100 and target 118 would further have been based on a physical size (taught by Kumar) corresponding to the classified target object type identified in a captured image (taught by Khan) (*determining a distance to the target based at least in part on...and on a physical size corresponding to the classification of the target detected within the image*). EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1008, ¶¶0018-0023, 0032, claims 4-5, claims 14-15; claims 24-25, Fig. 3A; Pet., VIII.C; EX1003, ¶¶162-163; Section II.C.1 (MTC); EX1039, ¶158. [21.d]: Beard’s flight control operations controlling UAV rotors speed are on-board UAV 100 using attitude control system 232 (*performing at the reference aerial vehicle the flight control operation...*). Pet., 10-13, 18-27. Beard also discloses or at least renders obvious a *first speed adjustment factor* for the same reasons as in the Pet. *Id.*; EX1039, ¶¶159-161. SC 24: Khan teaches object classification into a model type (e.g., SUV, sedan). EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8. The BLPKK combination thus teaches

target detection by Beard’s on-board UAV image processor 234 applying a machine learning/NN algorithm to image frames, which includes identifying model type (e.g., vehicle model type: SUV, sedan) based on the classification of the target object as such a model type (*wherein detecting the target in the image including by applying at the reference aerial vehicle the machine leaning model to the image includes identifying a model type of the target based on the classification of the detected target*). Section II.C.1 (MTC, SC 21); Pet., 36-38; EX1039, ¶¶162-163. **SCs 22, 23, 25-27, 29, 31-33, 35**: obvious for the reasons discussed above for SC 21 and in the Pet. for claims 2, 3, 8-10, 12, 14-16, and 18, respectively. Pet., 27-43; EX1039, ¶164. Also, for **SC 25**, the combination teaches *second* speed adjustment factor for the reasons in the Pet. at 42-43. EX1039, ¶164.

2. GNDs 24, 25, and 26

BLMPKK (GND 24), BLSPKK (GND 25), and BLHPKK (GND 26) render obvious SCs 28, 30, and 34, respectively; a POSITA would have combined for the reasons above and in the Pet. for claims 11, 13, and 17. Pet., 43-50; EX1039, ¶¶165-168.

3. GND 27: SC 36

MTC: A POSITA would have been motivated to combine Beard, Laufer, Pierce, and Ning (the “BLPN combination”) for the reasons discussed for Beard, Laufer, and Pierce. Section II.C.1. And a POSITA would have been motivated to combine Beard, Laufer, and Pierce with Ning’s teachings of performing object detection using a

“You Only Look Once” (YOLO) and object tracking using an LSTM NN. EX1034, Abstract, 1:51-3:17, 4:38-5:54, 6:15-8:33, 8:41-9:4, 9:18-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 4-6, 8; Sections II.C.1 (MTC, [21.b], [21.c]); Pet., 10-13, 35-36; EX1039, ¶¶169-170. Ning’s YOLO and LSTM NNs provide “real time” object detection and tracking that is “efficient yet accurate,” enhancing Beard’s object detection and tracking. *Id.* The need for fast and accurate object detection in vehicle control was known, and using YOLO was a known favorable solution applicable to object recognition and tracking algorithms used by drones. EX1036, 779, 785-786; EX1039, ¶¶169-170. Ning’s system “can be amount[ed] on any suitable vehicle”—thus compatible with Beard-Laufer-Pierce. *Id.*; EX1034, 5:35-38. A POSITA would have thus combined, having the predictable result of Beard’s on-board UAV image processor 234 detecting target 118 in image frames by applying a YOLO NN and determining tracking parameters using a LSTM NN to predict and track location of a target in an analyzed image. *Supra* Section II.C.3; Pet., 35-36; EX1039, ¶170. There would have been a reasonable expectation of success: YOLO and LSTM were known object detection and tracking techniques well suited to use in vehicle applications due to their speed. *Id.*; EX1036, 779, 785-786. **SC 36: [36.b1], [36.b2], [36.c]:** BLPN combination teaches Beard’s on-board UAV image processor 234 detects target 118 in image frames by applying a machine learning/NN algorithm to frames and determines tracking parameters between the UAV and target of distance,

angle of elevation, and bearing (*processor configured to: detect at the reference aerial vehicle a target in the image; and determine at the reference aerial vehicle a three-dimensional relative location...*). Section II.C.1 ([21.b], [21.c]); Pet., 35-36. Attitude control system 232 aboard the UAV performs flight control operations of controlling UAV rotor speed (*a flight controller configured to perform a flight control operation...*). Sections II.C.1 ([21.d]), II.C.3 (MTC); Pet., 35-36; EX1039, ¶¶171-174. [36.d]: BLPN combination teaches Beard's on-board UAV image processor 234 detection of target 118 in image frames is by applying a "You Only Look Once" ("YOLO") NN having a high robustness and high compute cost (*wherein the detecting of the target in the image is performed by applying at the reference aerial vehicle a first neural network at a first robustness and a first compute cost*). EX1034, Abstract, 1:51-3:6, 4:38-54, 5:46-54, 6:15-43, 9:30-10:32, 10:55-11:13, 12:55-13:2, Figs. 2, 8; Sections II.C.1 (MTC, [21.b], [21.c]), II.C.3 (MTC); Pet., 35-36; EX1039, ¶¶175-176. The '711 Patent says YOLO NNs have a "high robustness" and "high cost," and Ning discloses a YOLO NN. *Id.*; EX1001, 27:54-56, 28:40-47. The patent says high cost and high robustness processing schemes "produce an object location estimation independent of historical information" and Ning's YOLO NN does this, performing object location estimates based only on a current full image. *Id.*; EX1036, 779-780, Figs. 1-2 (YOLO operates on single input image). The BLPN combination teaches Beard's on-board UAV

image processor 234 determines tracking parameters using an LSTM NN at a medium/low robustness and medium/low compute cost to predict and track location of a target in an analyzed image, where the prediction is continually updated (and the determining of the three-dimensional relative location of the target in the image comprises incrementally predicting the location of the target in the image by applying at the reference aerial vehicle a second neural network at a second robustness and a second compute cost). Sections II.C.1 (MTC, [21.b], [21.c]), II.C.3 (MTC); Pet., 35-36; EX1034, Abstract, 1:51-3:17, 4:55-5:3, 6:33-8:33, 8:41-9:4, 10:64-11:13, 12:55-13:2, Figs. 4-6; EX1039, ¶177. Ning teaches the LSTM NN “refin[ing]” its predicting and tracking of an object’s location, and repeating its object location predicting and tracking, and that a detected object is “follow[ed] over time,” thus teaching the object’s location is predicted *incrementally* as claimed. EX1034, 6:33-8:33, Figs. 1, 4, EX1039, ¶177. The ’711 Patent says medium robustness, medium cost algorithms use “last known location of the object location estimation” and low robustness, low-cost algorithms use a “known location of the object location estimation.” EX1001, 27:57-64. Ning’s LSTM NN aligns with both explanations, using previous known location predictions (e.g., “output of itself [the LSTM] from the last time step t-1, i.e., the location prediction”), memory cells “to store and output” information and thus “better discover long-range temporal relations,” and “learns from experience” to perform location prediction. EX1034,

4:55-5:3, 8:49-52, 10:50-54; EX1039, ¶¶177-178. The combination’s YOLO NN has “high robustness,” “high cost” (*the first robustness and the first compute cost being greater, respectively,*) and LSTM NN has “medium robustness,” “medium cost” or “low robustness,” “low cost” (*than the second robustness and the second compute cost*). *Id.*; Section II.C.3 (MTC, [SC 36], [36.d] *supra*).

4. GND 28: SCs 21, 23-26, 32

MTC: A POSITA would have been motivated to combine Pierce, Kumar, Khan, and Beard (the “PKKB combination”) for the reasons discussed in the Pet. for Pierce and Kumar (Pet., 50-53) and Pierce and Khan/Pierce, Kumar, and Khan (Pet., 72-73). EX1039, ¶179. A POSITA would have been motivated to combine Pierce, Kumar, and Khan with Beard’s teachings of a drone having an on-board control system that controls movement of the drone to track an object. *Id.*; EX1009, 4:60-63, 5:54-59, Fig. 5. This would have been applying a known technique (drone having on-board control system that controls movement of the drone) to improve similar devices (drones that control their movement) in the same way, with the predictable result of Pierce’s UAV implementing on-board flight control. *Id.*; Pet., 50-60, 72-73. A POSITA would have had a reasonable expectation of success. *Id.* **SC 21: [21.a]**: PKKB combination teaches a “drone system 600 [that] may be drone 102,” and system 600 includes “object tracking module 615.” EX1005, ¶¶0027, 0042-0046, Figs. 1, 6. This module would have been implemented on or as a processor on drone

102. EX1005, ¶¶0017, 0027, 0042-0046, Figs. 1, 6; EX1006, ¶0015; EX1039, ¶¶180-181. Drone 102's object tracking module 615 receives images of the drone's surrounding area captured by camera 104 (*receiving at a processor at the reference aerial vehicle an image...*). *Id.*; Pet., 50-54. **[21.b]**: To teach element [21.b], the teachings of Kumar and Khan of GND 23 ([21.b]) apply but would have been utilized by Pierce's on-board object tracking module 615 of drone 102 that detects an object (e.g., vehicle) in an image using a NN applied to the image. Section II.C.1 ([21.b]); Pet., 50-55; EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015; EX1021, ¶¶0045-0063, Figs. 6, 7; EX1039, ¶¶182-184. **[21.c]**: On-board object tracking module 615 of drone 102 determines relative position (x_0, x_1, x_2) of the object to the drone (*determining at the reference aerial vehicle a three-dimensional relative location of the target...*). Pet., 50-56; EX1005, ¶¶0017, 0027, 0042, 0044-0046, Figs. 1, 6; EX1006, ¶0015; EX1039, ¶¶185-186. This determination of relative location uses the "straight-line distance" value d , and this value d is determined using (1) a value A that represents the "area of the bounding box in pixels," specifying the area of a bounding box of a target object that is detected and tracked in the processed image, and (2) a value s that represents the "physical length of the diagonal across the box for an average instance of the object" (*determining...a three-dimensional relative location of the target...including by determining a distance to the target based at least in part on a size of the bounding*

box of the target detected within the image). Pet., 50-56; EX1039, ¶186. To teach *determining a distance to the target based at least in part on ...and on a physical size corresponding to the classification of the target detected within the image*, the teachings of Kumar and Khan of GND 23 ([21.c]) apply but would have been utilized by Pierce's on-board object tracking module 615 of drone 102 and would have been for the distance between Pierce's drone 102 and target object. Section II.C.4 (MTC); Section II.C.1 ([21.c]); EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8; EX1007, ¶¶0019-0025, 0035, 0037, Figs. 2, 3A; EX1008, ¶¶0018-0023, 0030, 0032, claims 4-5, 14-15, 24-25, Fig. 2, 3A; EX1007, ¶¶0019-0025, 0037, Fig. 3A; EX1003, ¶¶157-158, 162-163; Pet., 50-56, 72-73; EX1039, ¶187. [21.d]: Pierce describes controlling drone movement, and a POSITA would have understood or at least found obvious this occurs using processor 601 on-board drone 102 and/or a drone controller on-board drone 102 (*performing at the reference aerial vehicle the flight control operation...*). Pet., 50-53, 56-60; EX1005, ¶¶0017, 0019, 0025-0027, 0042, 0044-0046, Figs. 1, 6; EX1039, ¶¶188-189. PKKB teaches a control system on-board drone 102 performs flight control operations to move the drone to track an object (*performing at the reference aerial vehicle the flight control operation...*). *Id.*; Section II.C.4 (MTC); Pet., 50-53, 56-60; EX1005, ¶¶0017, 0019, 0025-0027, 0042, 0044-0046, Figs. 1, 6; EX1009, 4:60-63, 5:54-59, Fig. 5; EX1039, ¶¶188-189. Pierce/Pierce and Kumar also disclose or at least renders obvious a *first speed*

adjustment factor for the same reasons discussed in the Petition. *Id.* Pet., 50-53, 56-60. **SC 24:** Khan's GND 23 (SC 24) teachings apply but would have been utilized by Pierce's target detection by object tracker 615 on-board drone 102 applying NNs to image frames. EX1021, ¶¶0003, 0037-0039, 0044-0063, Figs. 7-8; Section II.C.1 (SC 24); Section II.C.4 (MTC, SC 21); Pet., 72-73; EX1039, ¶¶190-191. **SCs 23, 25, 26, 32:** obvious for the reasons discussed above and in Pet. for claims 3, 8, 9, and 15, respectively. Pet., 50-53, 60, 62-66. EX1039, ¶¶192-193. Further, for **SC 25,** the combination teaches the value $(x_t - _ (x_d))$ and value $P^*(x_t - _ (x_d))$, and each form a *second speed adjustment factor*. Pet., 62-64. EX1039, ¶193.

5. GNDs 29 and 30

GND 29: PKKBL renders obvious SCs 22, 29, and 35 (*see* discussion of SC 21; Pet. (clms. 2, 12, and 18 respectively)). Pet., 75-80. **GND 30:** PKKBL renders obvious SC 34 (*see* discussion of SC 21; Pet. (clm 17)). Pet., 68-75. A POSITA would have combined for each GND for the reasons of the Pet. *Id.*; EX1039, ¶¶194-196.

6. GND 31: SC 36

MTC: A POSITA would have combined Pierce, Kumar, Ning, and Beard for the reasons of Section II.C.3 (MTC) for Ning and Section II.C.4 (MTC) for Beard. The combination would have had the predictable result of Pierce's drone 102 performing on-board flight control and on-board tracking module 615 of drone 102 detecting an object (e.g., vehicle) in an image by applying a YOLO NN and determining the

object's relative location (x_0 , x_1 , x_2) using an LSTM NN to predict and track the location. Sections II.C.3 (MTC), II.C.4 (MTC); Pet. 50-60, 66-68; EX1039, ¶197. There would have been a reasonable expectation of success. *Id.*; Section II.C.3 (MTC). **SC 36:** [36.b1], [36.b2], [36.c]: Module 615 detects an object in images by applying NNs to images and determines relative location between the drone and an object. Flight control is performed on-board the drone. Sections II.C.3 ([36.b1], [36.b2], [36.c]), II.C.4 (MTC, SC 21); II.C.6 (MTC); EX1039, ¶¶198-201; Pet., 66-67. [36.d]: Drone 102 performs on-board flight control; module 615 detects an object in an image by applying YOLO NN and determines the object's relative location using LSTM NN. Sections II.C.3 (MTC), II.C.4 (MTC); II.C.6 (MTC); Pet. 50-60, 66-68; EX1039, ¶¶202-203. [36.d] is taught as in Section II.C.3 ([36.d]) for Ning. *Id.*

7. GNDs 32-35

GND 32: PKKBS renders obvious SCs 21, 23-26, and 32 (GND 28; Pet. (clms. 1, 3, 8, 9, and 15)), and SCs 31 and 33 (Pet. (clms. 14, 16)). Pet., 75-80. For SC 31, Pierce discloses or renders obvious *scaling the speed adjustment factor*: constant P multiplies value ($\alpha_t - \alpha_d$) that is *the speed adjustment factor*. Pet., 56-60, 79; EX1039, ¶204. **GND 33:** PKKBSL renders obvious SCs 22, 29, and 35 (GND 29; Pet. (claims 2, 12, and 18)). *Id.*, 80. **GND 34:** PKKBSH renders obvious SC 34 (GND 30; Pet. (clm. 17)). *Id.* **GND 35:** PKSN renders obvious SC 36 (GND 31). A POSITA would have combined as in Pet. at 75-80 and GNDs 28-31. EX1039, ¶¶205-208.

Respectfully submitted,

BAKER BOTTS L.L.P.

A handwritten signature in black ink, appearing to read "Chad C. Walters". The signature is fluid and cursive, with a long horizontal stroke extending to the right.

Chad C. Walters (Reg. No. 48,022)
Lead Counsel for Petitioners

Date: June 1, 2026

CERTIFICATE OF SERVICE

Pursuant to 37 C.F.R. § 42.6(e), I certify that on this 1st day of June, 2026, **Petitioners' Opposition To Patent Owner's Contingent-In-Part And Non-Contingent-In-Part Revised Motion To Amend and Exhibits 1039-1040** were served by email on the following counsel for Patent Owner:

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