

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

U.S. Patent No. 10,514,711

**PATENT OWNER REPLY TO OPPOSITION
TO REVISED MOTION TO AMEND**

TABLE OF CONTENTS

I.	SPECIFICATION FULLY SUPPORTS ALL PROPOSED SUBSTITUTE CLAIMS.....	1
A.	<i>Image-by-Image Selection of a Neural Network (NN).....</i>	<i>1</i>
B.	<i>Thresholds and Ranges and their Use in NN Selection</i>	<i>1</i>
C.	<i>Identifying Model Type Based on Target Classification</i>	<i>2</i>
D.	<i>Specification Supports Two Speed Adjustment Factors for SCs 21, 25</i>	<i>3</i>
II.	SCs 21-37 ARE ENABLED	3
III.	SCs 21-37 ARE NOT INDEFINITE	7
A.	<i>SAF and NN Parameter Terms of SCs 21, 36, and 37 Are Clear.....</i>	<i>7</i>
B.	<i>SC 37 Limitations Are Clear</i>	<i>8</i>
IV.	SCs 21-36 ARE PATENTABLE OVER ALL CITED COMBINATIONS.....	9
A.	<i>In all of Petitioners Grounds, Pierce’s Processor is Not On-board a Drone</i>	<i>9</i>
B.	<i>Pierce/Beard Cannot Be Straightforwardly Modified to Implement NNs</i>	<i>9</i>
C.	<i>A POSITA Would Not Have Made Any of the Proposed Combinations.....</i>	<i>10</i>
D.	<i>The combinations fail to show all limitations of SCs 21 and 36.....</i>	<i>11</i>

List of Patent Owner Exhibits

Exhibit No.	Description
EX2001	U.S. Army Contract No. W15QKN-17-9-1022
EX2002	Smithsonian, National Air and Space Museum Letter to Mr. Banga dated March 13, 2024
EX2003	Z. Yang and R. Sinnott, “Snake Detection and Classification using Deep Learning,” in Proceedings of Hawaii International Conference on System Sciences (2021), https://scholarspace.manoa.hawaii.edu/server/api/core/bitstreams/f9f2de4d-ddaa-4984-9fc3-9bbca4e27247/content
EX2004	Q. Ji, “Object Detection and Recognition,” https://sites.ecse.rpi.edu/~qji/CV/ObjectDetRecog2.pdf
EX2005	The National Science Foundation, “How to Radars Work?,” https://www.eol.ucar.edu/content/how-do-radars-work
EX2006	Principles of Doppler Radar, http://ww2010.atmos.uiuc.edu/(Gh)/guides/rs/rad/basics/dpmod.rxml
EX2007	https://developer.apple.com/documentation/corelocation/-configuring-your-app-to-use-location-services
EX2008	https://developer.apple.com/documentation/corelocation/-cllocation
EX2009	https://developer.android.com/develop/sensors-and-location/location/retrieve-current
EX2010	https://developer.android.com/reference/android/location-/Location
EX2011	https://www.merriam-webster.com/dictionary/autonomous

Exhibit No.	Description
EX2012	https://dictionary.cambridge.org/us/dictionary/english/-autonomous
EX2013	Declaration of Noah Moore
EX2014	Airspace Interceptor, Fully Autonomous Physical Mitigation System Designed to Detect, Capture or Ram Drone, https://www.airspace.co/airspace-interceptor/
EX2015	Smithsonian National Air and Space Museum, Donate a Personal Item, https://airandspace.si.edu/donate-item
EX2016	Smithsonian National Air and Space Museum, Roger Connor Bio, https://airandspace.si.edu/people/staff/roger-connor
EX2017	Smithsonian National Air and Space Museum, About the Collection, available at https://airandspace.si.edu/collections/about-collection (last visited July 14, 2025)
EX2018	Jointly Proposed Protective Order
EX2019	U.S. Patent App. No. 16/142,452 (from which U.S. Patent No. 10,514,711 issued), as filed
EX2020	Streaming, Definition of Streaming by Merriam-Webster (2016)
EX2021	Streaming definition and meaning, Collins English Dictionary (2018)
EX2022	R. Wang et al., “An Effective Image Denoising Method for UAV Images via Improved Generative Adversarial Networks,” <i>Sensors</i> vol. 18(7):1985 (2018), doi:10.3390/s18071985.
EX2023	A. Ahmad et al., “Noise and Restoration of UAV Remote Sensing Images.” <i>International Journal of Advanced Computer Science</i>

Exhibit No.	Description
	<i>and Applications</i> , vol. 11, no. 12 (2020) doi:10.14569/ijacsa.2020.0111222
EX2024	Curriculum Vitae of Dr. Nikolaos Papanikolopoulos
EX2025	Declaration of Nikolaos Papanikolopoulos, Ph.D. in Support of Patent Owner's Response and First Motion to Amend
EX2026 (Served; Not filed)	Frequently Asked Questions, About the Internet Archive Affidavit and the Wayback Machine, https://archive.org/legal/faq
EX2027 (Served; Not filed)	Supplemental Declaration of Nikolos Papaniklopoulos, Ph.D., in support of Patent Owner's Response and Motion to Amend
EX2028	<i>Number not used</i>
EX2029	<i>Number not used</i>
EX2030	<i>Number not used</i>
EX2031	Withdrawn
EX2032	Withdrawn
EX2033	Transcript of Deposition of Dr. Singhose (Apr. 15, 2026)
EX2034	E. Biediger and W. Singhose, "Formation Flying Satellite Control Utilizing Input Shaping," in AIAA/AAS Astrodynamics Specialist Conf., Big Sky, Montana (2003).
EX2035	Withdrawn
EX2036	Declaration of Nikolaos Papanikolopoulos, Ph.D. in Support of Reply to Opposition to Revised Motion to Amend
EX2037	Declaration of June Munford
EX2038	Curriculum Vitae of June Munford

Exhibit No.	Description
EX2039	Vanhoucke, Vincent, Andrew Senior, and Mark Z. Mao. "Improving the speed of neural networks on CPUs." <i>Proc. deep learning and unsupervised feature learning NIPS workshop</i> . Vol. 1. (2011)
EX2040	Intel, Intel® Instruction Set Extensions Technology, Support Knowledge Base, <i>available at</i> https://www.intel.com/content/www/us/en/support/articles/000005779/processors.html
EX2041	Raman, Srinivas K., Vladimir Pentkovski, and Jagannath Keshava. "Implementing streaming SIMD extensions on the Pentium III processor." <i>IEEE micro</i> 20.4 (2000): 47-57.
EX2042	Suleiman, Amr, et al. "Towards Closing the Energy Gap Between HOG and CNN Features for Embedded Vision." arXiv:1703.05853, arXiv, 17 Mar. 2017. <i>arXiv.org</i> , https://doi.org/10.48550/arXiv.1703.0585
EX2043	Ullah, Md Bahar. "CPU based YOLO: A real time object detection algorithm." <i>2020 IEEE region 10 symposium (TENSYP)</i> . IEEE (2020).
EX2044	Holleman, Matthijs, Real-time object detection with YOLO (2017), <i>available at</i> https://machinethink.net/blog/object-detection-with-yolo/
EX2045	Fang, Wei, Lin Wang, and Peiming Ren. "Tinier-YOLO: A real-time object detection method for constrained environments." <i>Ieee Access</i> 8 (2019): 1935-1944.
EX2046	Ren, Shaoqing, et al. "Faster R-CNN: Towards Real-Time Object

Exhibit No.	Description
	Detection with Region Proposal Networks.” arXiv:1506.01497, arXiv, 6 Jan. 2016. <i>arXiv.org</i> , https://doi.org/10.48550/arXiv.1506.01497 .
EX2047	Yang, Tianyu, and Antoni B. Chan. "Recurrent filter learning for visual tracking." <i>Proceedings of the IEEE international conference on computer vision workshops</i> (2017).
EX2048	Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." <i>The journal of machine learning research</i> 15.1 (2014): 1929-1958.
EX2049	Nakano, Reiichiro Christian S., et al. "Implementation of an artificial neural network in recognizing in-flight quadrotor images." <i>TENCON 2015-2015 IEEE Region 10 Conference</i> . IEEE (2015).
EX2050	Zhengj, Zejia, and Juyang Weng. "Mobile device based outdoor navigation with on-line learning neural network: A comparison with convolutional neural network." <i>Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops</i> (2016).
EX2051	Wong, Alexander, et al. "Yolo nano: A highly compact you only look once convolutional neural network for object detection. arxiv 2019." <i>arXiv preprint arXiv:1910.01271</i> 10 (2019).
EX2052	Apte, Maneesh, Simar Mangat, and Priyanka Sekhar. "YOLO Net on iOS." <i>CS231n. Stanford University</i> (2017).
EX2053	Jain, Vaibhav, and Dinesh Patel. "A GPU based implementation of robust face detection system." <i>Procedia Computer Science</i> 87

Exhibit No.	Description
	(2016): 156-163.
EX2054	Lu, Yongyi, Cewu Lu, and Chi-Keung Tang. "Online video object detection using association LSTM." <i>Proceedings of the IEEE international conference on computer vision</i> (2017).
EX2055	Apaza-Agüero, Karl, Luciano Silva, and O. R. Bellon. "Mesh segmentation with connecting parts for 3D object prototyping." <i>2015 IEEE International Conference on Image Processing (ICIP)</i> (2015).
EX2056	Watanabe, Kouki, and Alexander G. Belyaev. "Detection of salient curvature features on polygonal surfaces." <i>Computer Graphics Forum</i> . Vol. 20. No. 3. Oxford, UK and Boston, USA: Blackwell Publishers Ltd (2001).
EX2057	Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." <i>2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)</i> . Vol. 1. IEEE (2005).
EX2058	Nvidia, GeForce GTX Titan X Specifications, <i>available at</i> https://www.nvidia.com/en-us/geforce/graphics-cards/geforce-gtx-titan-x/specifications/
EX2059	Nvidia, CUDA, https://www.nvidia.com/en-us/geforce/technologies/cuda/
EX2060	Excerpts of Mohri, Mehryar, Afshin Rostamizadeh, and Ameet Talwalkar. <i>Foundations of machine learning</i> . MIT press (2018).
EX2061	Redmon, Joseph, et al. "You Only Look Once: Unified, Real-Time Object Detection." arXiv:1506.02640, arXiv, 9 May

Exhibit No.	Description
	2016. <i>arXiv.org</i> , https://doi.org/10.48550/arXiv.1506.02640 .
EX2062	Iandola, Forrest N., et al. "SqueezeNet: AlexNet-Level Accuracy with 50x Fewer Parameters and <0.5MB Model Size." <i>arXiv:1602.07360</i> , <i>arXiv</i> , 4 Nov. 2016. <i>arXiv.org</i> , https://doi.org/10.48550/arXiv.1602.07360 .
EX2063	Vanhoucke, Vincent, Andrew Senior, and Mark Z. Mao. "Improving the speed of neural networks on CPUs.", <i>available at</i> https://web.archive.org/web/20120130220632/http://static.googleusercontent.com/external_content/untrusted_dlcp/research.google.com/en/us/pubs/archive/37631.pdf .
EX2064	Intel, Intel® Instruction Set Extensions Technology, Support Knowledge Base, <i>available at</i> https://web.archive.org/web/20190119075515/https://www.intel.com/content/www/us/en/support/articles/000005779/processors.html
EX2065	A library catalog MARC record for <i>IEEE Micro</i> , <i>available from Penn State University Library at</i> https://catalog.libraries.psu.edu/catalog/51599008 .
EX2066	Raman, Srinivas K., Vladimir Pentkovski, and Jagannath Keshava. "Implementing streaming SIMD extensions on the Pentium III processor." <i>IEEE Micro</i> 20.4 (2000): 47-57, <i>as sourced from the Penn State University Library's collection</i> .
EX2067	A library catalog MARC record for <i>Proceedings of 2017 International Symposium on Circuits and Systems</i> , <i>available from Penn State University Library at</i>

Exhibit No.	Description
	https://catalog.libraries.psu.edu/catalog/22871497
EX2068	Suleiman, Amr, et al. "Towards Closing the Energy Gap Between HOG and CNN Features for Embedded Vision," <i>Proceedings of 2017 International Symposium on Circuits and Systems</i> , as sourced from the Penn State University Library's collection.
EX2069	A library catalog MARC record for <i>Proceedings of the 2020 IEEE Region 10 Symposium</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/32192556
EX2070	Ullah, Md Bahar. "CPU based YOLO: A real time object detection algorithm." <i>2020 IEEE region 10 symposium (TENSYP)</i> . IEEE (2020), as sourced from the Penn State University Library's collection.
EX2071	Holleman, Matthijs, Real-time object detection with YOLO (2017), available at https://web.archive.org/web/20170526072201/https://machinethink.net/blog/object-detection-with-yolo/
EX2072	A library catalog MARC record for <i>IEEE Access</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/51598571
EX2073	Fang, Wei, Lin Wang, and Peiming Ren. "Tinier-YOLO: A real-time object detection method for constrained environments." <i>Ieee Access</i> 8 (2019): 1935-1944, as sourced from the Penn State University Library's collection.
EX2074	A library catalog MARC record for <i>IEEE Transactions on Pattern Analysis and Machine Intelligence</i> , available from Penn State

Exhibit No.	Description
	<i>University Library at</i> https://catalog.libraries.psu.edu/catalog/51599284
EX2075	Ren, Shaoqing, et al. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," <i>IEEE Transactions on Pattern Analysis and Machine Intelligence</i> , as sourced from the Penn State University Library's collection.
EX2076	A library catalog MARC record for <i>Proceedings of the IEEE International Conference on Computer Vision Workshops</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/51598764
EX2077	Yang, Tianyu, and Antoni B. Chan. "Recurrent filter learning for visual tracking." Proceedings of the IEEE international conference on computer vision workshops (2017), as sourced from the Penn State University Library's collection.
EX2078	A library catalog MARC record for <i>Journal of Machine Learning Research</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/51620909
EX2079	Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." The journal of machine learning research 15.1 (2014): 1929-1958, as sourced from the Penn State University Library's collection.
EX2080	A library catalog MARC record for <i>Proceedings of the IEEE Region Ten Conference</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/51718430
EX2081	Nakano, Reiichiro Christian S., et al. "Implementation of an

Exhibit No.	Description
	artificial neural network in recognizing in-flight quadrotor images." TENCON 2015-2015 IEEE Region 10 Conference. IEEE (2015), <i>as sourced from the Penn State University Library's collection.</i>
EX2082	A library catalog MARC record for <i>Proceedings of the IEEE Conference on Computer Vision Workshops</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/51598764
EX2083	Zheng, Zejia, and Juyang Weng. "Mobile device based outdoor navigation with on-line learning neural network: A comparison with convolutional neural network." <i>Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (2016)</i> , <i>as sourced from the Penn State University Library's collection.</i>
EX2084	A library catalog MARC record for <i>Proceedings of the 5th Workshop on Energy Efficient Machine Learning and Cognitive Computing</i> , available from Penn State University Library at https://mit.primo.exlibrisgroup.com/discovery/fulldisplay?context=L&vid=01MIT_INST:MIT&search_scope=all&tab=all&lang=en&docid=alma9935203535606761
EX2085	Wong, Alexander, et al. "Yolo nano: A highly compact you only look once convolutional neural network for object detection. 2019," <i>Proceedings of the 5th Workshop on Energy Efficient Machine Learning and Cognitive Computing</i> , available at https://ieeexplore.ieee.org/document/9463524

Exhibit No.	Description
EX2086	Apte, Maneesh, Simar Mangat, and Priyanka Sekhar. "YOLO Net on iOS." CS231n. Stanford University (2017), <i>available at</i> https://web.archive.org/web/20171118092245/https://cs231n.stanford.edu/reports/2017/pdfs/135.pdf
EX2087	A library catalog MARC record for <i>Procedia Computer Science</i> , <i>available from Penn State University Library at</i> https://catalog.libraries.psu.edu/catalog/51678444
EX2088	Jain, Vaibhav, and Dinesh Patel. "A GPU based implementation of robust face detection system." <i>Procedia Computer Science</i> 87 (2016): 156-163, <i>as sourced from the Penn State University Library's collection.</i>
EX2089	A library catalog MARC record for <i>Proceedings of the 2017 IEEE International Conference on Computer Vision</i> , <i>available from Penn State University Library at</i> https://catalog.libraries.psu.edu/catalog/22615741
EX2090	Lu, Yongyi, Cewu Lu, and Chi-Keung Tang. "Online video object detection using association LSTM." <i>Proceedings of the IEEE international conference on computer vision</i> (2017), <i>as sourced from the Penn State University Library's collection.</i>
EX2091	A library catalog MARC record for <i>Proceedings of 2015 IEEE International Conference on Image Processing</i> , <i>available from Penn State University Library at</i> https://catalog.libraries.psu.edu/catalog/27695350
EX2092	Apaza-Agüero, Karl, Luciano Silva, and O. R. Bellon. "Mesh segmentation with connecting parts for 3D object prototyping."

Exhibit No.	Description
	2015 IEEE International Conference on Image Processing (ICIP) (2015), <i>as sourced from the Penn State University Library's collection.</i>
EX2093	A library catalog MARC record for <i>Computer Graphics Forum</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/51545295
EX2094	Watanabe, Kouki, and Alexander G. Belyaev. "Detection of salient curvature features on polygonal surfaces." <i>Computer Graphics Forum</i> . Vol. 20. No. 3. Oxford, UK and Boston, USA: Blackwell Publishers Ltd (2001), <i>as sourced from the Penn State University Library's collection.</i>
EX2095	A library catalog MARC record for <i>Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/39331403
EX2096	Dalal, Navneet, and Bill Triggs. "Histograms of oriented gradients for human detection." 2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05). Vol. 1. IEEE (2005), <i>as sourced from the Penn State University Library's collection.</i>
EX2097	Nvidia, GeForce GTX Titan X Specifications, <i>available at</i> https://web.archive.org/web/20200809205411/https://www.nvidia.com/en-us/geforce/graphics-cards/geforce-gtx-titan-x/specifications/
EX2098	Nvidia, CUDA, <i>available at</i>

Exhibit No.	Description
	https://web.archive.org/web/20200809115603/https://www.nvidia.com/en-us/geforce/technologies/cuda/
EX2099	A library catalog MARC record for <i>Foundations of Machine Learning</i> , available from Penn State University Library at https://catalog.libraries.psu.edu/catalog/9618647
EX2100	Selections from Mohri, Mehryar, Afshin Rostamizadeh, and Ameet Talwalkar. <i>Foundations of machine learning</i> . MIT press (2018).
EX2101	Redmon, Joseph, et al. “You Only Look Once: Unified, Real-Time Object Detection”, available at https://web.archive.org/web/20150922103408/http://pjreddie.com/media/files/papers/yolo.pdf
EX2102	Iandola, Forrest N., et al. “SqueezeNet: AlexNet-Level Accuracy with 50x Fewer Parameters and <0.5MB Model Size”, available at https://web.archive.org/web/20170128054438/https://arxiv.org/pdf/1602.07360v4.pdf
EX2103	Shi, Xingjian, et al. “Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting.”
EX2104	Hu, Wen-Shuai, et al. “Spatial-Spectral Feature Extraction via Deep ConvLSTM Neural Networks for Hyperspectral Image Classification.” <i>IEEE Transactions on Geoscience and Remote Sensing</i> . Volume 58, Issue 6 (June 2020)
EX2105	Shi, Xingjian, et al. “Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting.”, available at https://web.archive.org/web/20200915014241/https://arxiv.org/pdf/1506.04214v2.pdf .

Exhibit No.	Description
EX2106	Hu, Wen-Shuai, et al. “Spatial-Spectral Feature Extraction via Deep ConvLSTM Neural Networks for Hyperspectral Image Classification.”, <i>available at</i> https://web.archive.org/web/20220508083912/https://arxiv.org/pdf/1905.03577.pdf https://web.archive.org/web/20220508083912/https://arxiv.org/pdf/1905.03577.pdf .
EX2107	U.S. Patent App. Ser. No. 62/261,260

I. SPECIFICATION FULLY SUPPORTS ALL PROPOSED SUBSTITUTE CLAIMS

A. Specification Supports Image-by-Image Selection of a Neural Network (NN)

SC 37 requires selecting an NN for processing a current image, based on a confidence level obtained from processing the immediately preceding image. The specification teaches that this trade off occurs on a per frame (i.e., image) basis. EX2019, ¶109 (“negative relation between robustness” and “cost and/or latency of the algorithm *per spacio-temporal frame*”). The NNs are selected to “achieve[] high *combined frame rate* with higher quality.” *Id.* “The “processing schemes [NNs] produce a prediction of objects *within the video frame, as well as a confidence number.*” *Id.* ¶141. This informs that *in each frame / image*, a target is detected and a corresponding confidence number is used to select the best NN for the next frame / image to be processed. Several NNs disclosed in the specification use an image as the input. The “groups,” *see* Opp. at 1, are groups of NNs, not of frames/images. EX2019, ¶¶145-152. The NN selection does not depend on the NN used for the immediately preceding frame; it is based on the confidence level, as indicated by the “otherwise” limitations of [37.e3], [37.e4]. EX2036, § VII.A.1; *see id.* §§ V, VI.

B. Specification Supports Thresholds and Ranges and their Use in NN Selection

Per the specification, “a set of processing schemes ... are examined from group to group, and the *process cycles* through the processing schemes” where “if the *confidence number is higher than an activation number* ... stop or change a running group (i) and select or switch to group (ii).” “If the confidence is *below low*

threshold, falls outside of a range, ... group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied.” EX2019, ¶¶146-147. Group (i) contains high robustness/cost, low refresh rate NNs; Groups (i) and (iii) contain medium/low robustness/cost, high refresh rate NNs. An NN is selected from the group chosen based on the confidence. *Id.* ¶¶146 (“select a cheaper processing scheme from the group [] (ii)”), 150-152 (listing NNs for different groups). Thus, “Low threshold”/“activation number” are the first/second thresholds, respectively, defining a range. *Id.* ¶¶146-47; *see id.* ¶¶112-113 (“[i]n response to the performance score of the active processing scheme *failing to satisfy a threshold*, the method selects another processing scheme” where “the threshold can be based on available computing resources associated with the mobile capture device”). Thus, the range can be a point range, i.e., a single threshold. Switching to Group (ii) and selecting an NN therefrom when the confidence is “higher than an activation number” (second threshold) or applying a Group (iii) algorithm (second NN) when the confidence is high, teaches [37.e3] and [37.e4]. Thus the specification supports SC 37. EX2036, § VII.A.2-3.

C. Specification Supports Identifying Model Type Based on Target Classification

SC 21 recites “identify a classification,” and SC 24 recites “identifying a model type based on the classification.” But these are not necessarily two separate sequential steps – they are two different kinds of classifications: a coarse-grained

one where the target is classified as “a UAV” or “not a UAV,” EX2019 ¶50, and a fine-grained one determining the “type, model, class, manufacturer, size, etc.” EX2019 ¶94; EX2036 § VII.B.1; Paper 30 at 6-7.

D. Specification Supports Two Speed Adjustment Factors for SCs 21, 25

[21.d] and SC 25 recite “first” and “second” “speed adjustment factor[s]” (SAFs), respectively. The first SAF ([21.d]) is based on a magnitude of deviation and the second SAF (SC 25) is based on a distance. SC 25 thus does not require two SAFs that are both based on distances. For SC 21, the specification states: “[m]odifying the speed and/or acceleration associated with [a] vector includes adjusting a factor used to control the speed “based on an *amount of directional change*”; the “speed ... factor is multiplied by one or more scalar values that change in magnitude based on a directional deviation.” EX2019 ¶99. For SC 25, the SAF in the vector is defined “using a distance and/or speed value,” where “the distance value determined [based on image analysis] is mapped to a desired speed of travel to reach the target.” *Id.* ¶97. The SAF can be modified and redefined at different times such that the first factor is provided at one time and the second factor at another. *See* EX2019 ¶¶91, 97; EX2036, § VII.B.2. Thus, the specification supports SCs 21, 24, 25.

II. SCs 21-37 ARE ENABLED

Regarding the SAF, Petitioners’ arguments are inconsistent. They argue undue experimentation is needed to set them, but then Dr. Singhose says they are simply

going faster/slower depending on whether turning/flying straight. EX1039, ¶90. Petitioners allege “[n]o formula” is provided but then criticize the formula, saying actual values for the constants of the formula are not provided. Opp. at 3-4. A “*speed adjustment factor*” is simply a vector element value used to control, i.e., adjust speed. EX2019, ¶99 (“[m]odifying the speed ... associated with the vector includes adjusting a factor used to control the speed ... of the interceptor aerial vehicle”); *see* EX2036 § VII.B.2.a. The meaning of **robustness** in the NN context is the same as its ordinary meaning – strength/effectiveness in adverse conditions, e.g., noise. A POSITA would have known that robustness can be determined in terms of failure rate or frequency. *See e.g.* EX2043 at 7; EX2044 at 9; EX2034, Abstract.

Compute cost is simply the cost of computations, which can be expressed as the number of computations, computation time, etc. The ’711 patent clearly and consistently associates high cost with high robustness/low refresh rate, and low cost with low robustness/high refresh rate. EX2019 ¶¶145, 146, 150. Dr. Singhose agrees. EX2033 at 37:6-16. A POSITA would have known that **refresh rate** is the rate at which new images/frames of a video can be analyzed. EX2045 at 5; EX2046 at 2, Figure 2, 8. A POSITA would also have known that a low refresh rate means more compute time per image, i.e., high cost. *See* EX2019 ¶¶145, 146, 150. Thus, for all terms that Petitioners identified, a POSITA would have known their meanings and how to determine them, because those terms were well-established in the art, *In re*

Wands, 858 F.2d 737. The '711 patent additionally describes how those terms were used, so that a POSITA would know how to determine these quantities.

For SAF, *In re Wands* **Factors 2 and 3** are favorable. An SAF can be adjusted using a scalar relating to “a directional deviation” per a “bell curve” or a linear curve. EX2019, ¶99. Equations 7, 8, which a POSITA would have readily recognized as sigmoid functions, describe how “speedfactors can be computed.” *Id.* FIG. 10. Specific curves and equation constant values are not provided because they would not help a POSITA. The choice of a curve/equation constants would depend on the attributes (e.g., size, weight, top-speed) of a UAV using them, rendering them production details. For robustness, compute cost, and refresh rate (“**NN Parameters**”), the '711 patent provides specific, representative NNs associated with high/low robustness, high/low cost, and high/low refresh rate, as well as specific image sizes, and scenarios for speed adjustment. *See* EX2019 ¶¶97, 99, 150-152. Also, the '711 patent consistently states that high robustness equates to high cost and low refresh rate. Dr. Singhose agrees. EX2033 at 37:6-16. Hence, knowledge of only the cost or refresh rate enables NN selection.

For the low and high thresholds used in NN selection (“**Thresholds**”) the provided guidance is adequate because: (i) those thresholds are akin to several everyday examples including heating and cooling limits on a thermostat, and (ii) example actual threshold values would be unhelpful because they are production

details for which knowledge of the UAV, and its environment's attributes are highly beneficial, if not essential. *Wands* **Factor 1** for **SAF** is not high, as discussed for Factors 2-3. The selection of SAFs is related to the conventional mechanics of UAV flight and not to using ML/NN on-board a UAV for image analysis, meaning any necessary experimentation was routine. For **NN Parameters**, SCs 36 and 37 are directed to *scheduling* high and low cost (refresh rate) NNs that are chosen from known NNs whose NN Parameters were widely published. EX2047 at 7; EX2048 at 9; EX2042, Abstract; EX2049 at 5; EX2050 at 2, Figure 2, at 8. Therefore, the experimentation necessary to determine the NN parameters was also routine. Hence, a high quantity of experimentation may be tolerated for SAF and NN Parameters. For **Thresholds**, **Factor 1** is minimal because NNs report their confidence levels upon execution, which informs threshold selection. Selection of the best threshold(s) is a production-level optimization.

Factor 4 is complex, but the selection of the **SAFs** is related to conventional mechanics of UAV flight. For **NN Parameters**, the disclosed specific examples of NNs and explicit guidance about relative NN parameters mitigates the need for experimentation. For **Thresholds**, undue experimentation is unnecessary as discussed for Factor 1. **Factors 5 and 7** are favorable for SAFs; cited prior art teaches the use of SAFs. EX1009, 3:25-30; EX1025, ¶17. Likewise, **NN Parameters** for different types of NNs were known and published. EX1036 at 48; EX2054 at 7-

8; EX2047 at 7. **Factor 6**, “the relative skill of those in the art,” is high, which suggests only a reasonable amount of required experimentation. **Factor 8**, “the breadth of the claims,” overall is narrow: SCs 21, 36, and 37 require ML-NNs having particular functionalities and relative characteristics. EX2036, § VIII.A.

III. SCs 21-37 ARE NOT INDEFINITE

A. SAF and NN Parameter Terms of SCs 21, 36, and 37 Are Clear

The meaning of SAF, a vector element value used to adjust speed, would have been clear to a POSITA. EX2036 § VII.B.2. The meanings of the NN Parameters would have also been clear; these terms were well understood and the specification uses them in the same way as in the literature. Additional guidance and examples in the specification explain the use and meaning of these terms. EX2036 § VIII.A.2. Petitioners’ allegation, of “no way of comparing” NN Parameters without knowing how they are measured,” Opp. at 9, is a § 112(1) argument, not a § 112(2) issue.

A POSITA would have known how to measure NN Parameters. Supra II. For example, the specification teaches that the NN cost Parameter can be estimated based on the number of visual features in a frame. EX2019, ¶142. Because the cost is directly proportional to robustness and inversely to refresh rate, EX2019 ¶¶145-150; EX2033 at 37:6-16, the cost estimates of NNs based on visual features would have informed a POSITA of their relative NN Parameter values. Additionally, the specification groups NNs by the NN Parameters and also identifies NNs belonging

to each respective group. EX2019, ¶¶145-153. Thus, even without knowing the actual values of NN Parameters, a POSITA would know how two NNs are related with respect to NN Parameters such as cost for at least some NNs. Thus, these terms are clear and do not render the SCs indefinite. EX2036, § VIII.B.1

B. SC 37 Limitations Are Clear

Contrary to Petitioners' claim, SC 37 does not require an NN to be applied to a current frame in order to obtain a confidence level for use in selecting an NN for the current frame. *See* Opp. at 9-10. The “confidence level *for* a detection” in the current image is not a confidence level *based on/derived* from a detection in the current image. Rather, the confidence level obtained from the detection in the immediately preceding image is used to select an NN for application to the current image. *See supra* § I.A; EX2036 § VII.A.1. As such SC 37 does not have a circular dependence. The specification fully describes image-by-image processing. *Supra* § I.A.

The different refresh rates of the two NNs also do not create ambiguity. In fact, combining such different rates is an important goal of SC 37: “*combining multiple algorithms* in a way that achieves high *combined frame rate* with higher quality prediction.” EX2019, ¶109. Associating different refresh rates with two NNs is not ambiguous because SC 37 recites applying “only one of the first and the second neural networks” to an image. Thus, for each image in a sequence, the two NNs are applied in a mutually exclusive manner so that there is only a single immediately

preceding image for a current image. The selection of an NN for a given image does not depend on the refresh rate of the NN applied to the immediately preceding image. Thus, the different refresh rates of the first and second NNs that SC 37 recites do not render the claim ambiguous, unclear, or inoperative. EX2036, § VIII.B.2

IV. SCS 21-36¹ ARE PATENTABLE OVER ALL CITED COMBINATIONS

A. In all of Petitioners’ Grounds, Pierce’s Processor is Not On-board a Drone

Petitioners allege Pierce’s “FIG. 6 illustrates one example of a drone system 600” that includes the object tracking module 615 which includes an NN; and that in “various embodiments, drone system 600 may be drone 102.” EX1005 ¶42. But Pierce never discloses any embodiments in which system 600 is both a drone and includes the module 615. Pierce also states: “in *other embodiments*, various elements of drone system 600 may correspond to *separate components*, including drone 102, *a server*,” and that the “object tracking module 615” may “process a neural network detection system” – a “neural network system 500” that “operates as a *streaming server*.” *Id.* ¶¶38, 42, 45. Thus, a POSITA would have understood the module 615 as the neural network system 500, which is on a *separate* server, and not on-board the drone. *See* EX2036 §§ V, VI, VIII.C-J.

B. Pierce/Beard Cannot Be Straightforwardly Modified to Implement NNs

A POSITA would not implement an NN on Beard’s or Pierce’s processors. Beard

¹ No prior art grounds are asserted against SC 37.

and Pierce do not disclose any processors suitable for NN execution (GPUs, multi-core, etc.). Before 2017 and even later, it was well understood that implementing an NN on non-GPU processors, including any generic processor, let alone Beard's conventional image processor (e.g., a digital signal processor (DSP)), requires a *three-step reconfiguration*: (i) providing SIMD extensions; (ii) selecting a suitable framework from a choice of at least 6; and (iii) translating/tuning NN parameters for the selected framework by creating custom scripts / deriving math. This was reported as "really [] complex," yielding "terrible" results, and requiring "a bit of math." Hence, a POSITA would have known that implementing an NN on a generic processor was far from using known methods. To the contrary, a POSITA would have known this to be a significant challenge, and would not have implemented any NN on Pierce's or Beard's on-board processor. EX2036 §§ VIII.E.1, F.1, H.1.

C. A POSITA Would Not Have Made Any of the Proposed Combinations

All combinations require implementing at least one NN on Beard's or Pierce's processors, which involves the aforementioned three-step reconfiguration well outside a POSITA's scope. *Supra* § IV.B. All combinations also render Beard/Pierce inoperable for their intended real-time operation purposes. Executing NNs used for image analysis on a generic processor as opposed to on GPUs was known not to achieve real-time performance. *See* EX2045 at 1-2; EX2051 at 1-2; EX2052 at 3; EX2044 at 6-7. **BLPKK, PKKB** additionally result in *duplicative computations*

because Khan requires feature² generation using a conventional HoG algorithm, but an NN from Laufer, Pierce, Kumar automatically extracts its own features that are not HoG features and are not usable by Khan, resulting in duplicative feature extraction. Therefore, a POSITA would not make any of Petitioners' combinations. Petitioner alleges for BLPN that Ning's YOLO and LSTM are the first and second NNs, respectively. But the cost of YOLO is less than LSTM's, so BLPN does not teach two NNs having the required cost relation of SC 36. EX2036 §§ VIII.[C-F].1.

D. The combinations fail to show all limitations of SCs 21 and 36

Pierce's processor is not on-board a drone, and Beard's/Pierce's processors cannot be readily modified to implement an NN, per SCs 21,³ 36. *Supra* §§ IV.A-IV.B. For SC 21, the combinations do not teach/suggest an ML model "to identify a bounding box outlining ... detected features," because Beard is silent on ML model and Laufer/Pierce/Kumar are silent on detected features. In fact, Khan's bounding in FIG. 7 is provided by a human document illustrator, and not an ML system. Even for feature identification, Khan uses the HoG signal processing algorithm and not any ML system. An ML system is a customized, trained system, and cannot be straightforwardly adapted to provide new functionality, e.g., supplying HoG

² This is an image feature used by ML-NN – not a feature of a target.

³ SC 21 recites an ML mode to determine a bounding box; the only ML model that Laufer/Pierce/Kumar disclose is an NN.

features. Accordingly, the combinations do not teach/suggest the above limitation.

For SC 36, the combinations do not teach/suggest two NNs having the cost relationship recited in claim element [36.d]. Ning's LSTM (or any LSTM) cannot meaningfully process an image without the convolutional layers of an NN, e.g., Ning's YOLO. EX1034, 10:34-37, 12:66-13:2, FIG. 8; EX2105 at 3, 8; EX2104 at 3. Therefore, Ning's LSTM is inextricably coupled to Ning's YOLO, and cannot commence its processing of a frame until the YOLO first processes the frame and provides the required inputs to the LSTM. Ning's YOLO also depends on the LSTM's output, forming a dependence loop for processing a single image, EX1034, and hence, the YOLO and LSTN may not even be considered two separate NNs. Moreover, the per-image cost (latency) of Ning's LSTM includes the cost incurred by the YOLO in prior processing the image. This makes YOLO's cost less than LSTM's, and not "greater" as [36.d] recites. EX2054 at 7; EX1036 at 48.

SC 36 also recites "incrementally predicting the location of the target in the image using a second neural network." The second NN thus processes image frames. EX2019 ¶110 (a "background tracker may incrementally predict the location of a target **in the frame** with low compute cost"). In contrast, Ning's LSTM (alleged second NN) does not process images/frames, and instead, receives inputs only from the preceding YOLO. Accordingly, the combinations do not teach or suggest the above-identified limitation. EX2036 §§ VIII.[C-F].2; *see id.* §§ VIII.C-J, IX.

Respectfully submitted,

/ Suhrid Wadekar /

Suhrid Wadekar, Ph.D., Esq.
Registration No. 65,595
Counsel for Patent Owner
Airspace Defense, Inc.

Dated: June 22, 2026

CERTIFICATE OF SERVICE

Pursuant to 37 C.F.R. § 42.6(e), I hereby certify that on June 22, 2026, a copy of the foregoing Patent Owner's Reply to Petitioners' Opposition to Patent Owner's Revised Motion to Amend, and its exhibits, is being served electronically (per counsel's consent) to lead and backup counsel of record for Petitioners as follows:

DLAxonDedroneIPRs@bakerbotts.com

chad.walters@bakerbotts.com

harrison.rich@bakerbotts.com

ellyar.barazesh@bakerbotts.com

/ Suhrid Wadekar /

Suhrid Wadekar (Reg. No. 65,595)

PRINCE LOBEL TYE LLP

One International Place, Suite 3700

Boston, MA 02110

Tel: (617) 456-8000

Email: swadekar@princelobel.com