

Petitioners Axon Enterprise, Inc.,
Dedrone Holdings, Inc., and Skydio, Inc.
Hearing Presentation for IPR2025-00629
U.S. Patent No. 10,514,711

Outline of Arguments: IPR2025-00629 ('711 Patent)

- I. Overview of the '711 Patent and Procedural History**
- II. Obviousness of Original Claim 12**
- III. Dispute Overview – Original Claim 12**
- IV. Claim Construction and Obviousness of Original Claim 12 as Construed**
- V. Dispute Overview – Motion to Amend**
- VI. Substitute Claims 24, 25, and 37 Lack Written Description**
- VII. Substitute Claims 21-37 are Not Enabled**
- VIII. Substitute Claims 21-37 are Indefinite**
- IX. Substitute Claims 21-37 are Obvious**

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(12) United States Patent Bar-Nahum et al.	(10) Patent No.: US 10,514,711 B2 (45) Date of Patent: Dec. 24, 2019																																				
(54) FLIGHT CONTROL USING COMPUTER VISION (71) Applicant: Airspace Systems, Inc., San Leandro, CA (US) (72) Inventors: Guy Bar-Nahum, Sausalito, CA (US); Hong-Bin Yoon, San Leandro, CA (US); Karthik Govindaswamy, Milpitas, CA (US); Hoang Anh Nguyen, San Mateo, CA (US) (73) Assignee: Airspace Systems, Inc., San Leandro, CA (US) (*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days. (21) Appl. No.: 16/142,452 (22) Filed: Sep. 26, 2018 (65) Prior Publication Data US 2019/0025858 A1 Jan. 24, 2019 Related U.S. Application Data (63) Continuation-in-part of application No. 15/729,581, filed on Oct. 10, 2017. (60) Provisional application No. 62/566,449, filed on Oct. 1, 2017, provisional application No. 62/405,972, filed on Oct. 9, 2016. (51) Int. Cl. G06K 9/00 (2006.01) G05D 1/12 (2006.01) G08G 5/00 (2006.01) G08D 1/00 (2006.01) B64C 39/02 (2006.01) G08D 1/10 (2006.01) B64D 47/08 (2006.01)	(52) U.S. CL. CPC G05D 1/12 (2013.01); B64C 39/02 (2013.01); B64D 47/08 (2013.01); G05D 1/0088 (2013.01); G05D 1/101 (2013.01); G06K 9/0063 (2013.01); G08G 5/0013 (2013.01); G08G 5/0069 (2013.01); G08G 5/0078 (2013.01); B64C 22/01/141 (2013.01) (58) Field of Classification Search None See application file for complete search history. (56) References Cited U.S. PATENT DOCUMENTS <table border="0"> <tr> <td>7,995,794 B2 *</td> <td>8/2011</td> <td>Hope</td> <td>G03B 17/38</td> </tr> <tr> <td>9,031,280 B2 *</td> <td>5/2015</td> <td>Pakulski</td> <td>382/103</td> </tr> <tr> <td>9,412,278 B1 *</td> <td>8/2016</td> <td>Gong</td> <td>G06T 7/254</td> </tr> <tr> <td>2002/0196330 A1</td> <td>12/2002</td> <td>Park</td> <td>382/103</td> </tr> <tr> <td>2005/0021282 A1 *</td> <td>1/2005</td> <td>Sammot</td> <td>H04L 63/101</td> </tr> <tr> <td>2007/0098218 A1 *</td> <td>5/2007</td> <td>Zhang</td> <td>F41G 1/38</td> </tr> <tr> <td></td> <td></td> <td></td> <td>702/150</td> </tr> <tr> <td></td> <td></td> <td></td> <td>G06K 9/00238</td> </tr> <tr> <td></td> <td></td> <td></td> <td>382/103</td> </tr> </table> (Continued) <i>Primary Examiner</i>—Randolph I Chu (74) <i>Attorney, Agent, or Firm</i>—Van Pelt, Yi & James LLP (57) ABSTRACT A flight control operation of a reference aerial vehicle is performed. For example, an image captured by an image sensor of the reference aerial vehicle is received. A target is detected in the image. A three-dimensional relative location of the target with respect to the reference aerial vehicle is determined based on the image. The flight control operation is performed based on the three-dimensional relative location of the target with respect to the reference aerial vehicle. 20 Claims, 25 Drawing Sheets	7,995,794 B2 *	8/2011	Hope	G03B 17/38	9,031,280 B2 *	5/2015	Pakulski	382/103	9,412,278 B1 *	8/2016	Gong	G06T 7/254	2002/0196330 A1	12/2002	Park	382/103	2005/0021282 A1 *	1/2005	Sammot	H04L 63/101	2007/0098218 A1 *	5/2007	Zhang	F41G 1/38				702/150				G06K 9/00238				382/103
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Patent Owner cites the '452 application to support the substitute claims

'711 Patent: Overview of Original Independent Claim 1

A method of performing a flight control operation of a reference aerial vehicle, comprising:

receiving an image captured by an image sensor of the reference aerial vehicle;

detecting a target in the image including by applying a machine learning model to the image to identify a portion of the image that includes the target;

determining a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image including by determining a distance to the target based at least in part on a size of the target detected within the image; and

performing the flight control operation based on the three - dimensional relative location of the target with respect to the reference aerial vehicle , wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

Procedural History: '711 Patent

- The Petition (Paper 1) challenged claims 1-20 of the '711 Patent over the following grounds:

Ground	Claim(s)	Basis	References
1	1-3, 5, 6, 9, 10, 12, 14-16, 18-20	103	Beard, Laufer
2	4	103	Beard, Laufer, Khan
3	7, 8	103	Beard, Laufer, Kumar
4	11	103	Beard, Laufer, Malecki
5	13	103	Beard, Laufer, Sahasrabudhe
6	17	103	Beard, Laufer, Hogasten
7	1, 3, 5-9, 15, 19, 20	102	Pierce
8	1, 3, 5-9, 15, 19, 20	103	Pierce, Kumar
9	2, 12, 18	103	Pierce, Laufer
10	2, 12, 18	103	Pierce, Kumar, Laufer
11	4	103	Pierce, Khan
12	4	103	Pierce, Kumar, Khan
13	17	103	Pierce, Hogasten
14	17	103	Pierce, Kumar, Hogasten
15	1, 3, 5-9, 14-16, 19-20	103	Pierce, Sahasrabudhe
16	1, 3, 5-9, 14-16, 19-20	103	Pierce, Kumar, Sahasrabudhe
17	2, 12, 18	103	Pierce, Sahasrabudhe, Laufer
18	2, 12, 18	103	Pierce, Kumar, Sahasrabudhe, Laufer
19	4	103	Pierce, Sahasrabudhe, Khan
20	4	103	Pierce, Kumar, Sahasrabudhe, Khan
21	17	103	Pierce, Sahasrabudhe, Hogasten
22	17	103	Pierce, Kumar, Sahasrabudhe, Hogasten

- Patent Owner filed a Preliminary Response (POPR) (Paper 11)

Procedural History: '711 Patent

- The Board instituted trial (Paper 16)
 - The Board agreed that the '711 Patent is not entitled to a priority date prior to October 1, 2017
 - The Board agreed that Ground 1 (Beard and Laufer) demonstrated a reasonable likelihood of success that claim 1 is unpatentable, and further instituted Grounds 2-22.

Procedural History: '711 Patent

- Patent Owner filed a Patent Owner's Response (Paper 20)
 - Patent Owner's arguments focused exclusively on original dependent claim 12
- Patent Owner filed a Contingent-In-Part and Non-Contingent-In-Part Motion to Amend (Paper 21) presenting Substitute Claims 21-37
 - Contingent as to original claim 12; non-contingent as to original claims 1-4, 8-11 and 13-20; canceled original claims 5-7
- Petitioners filed a Reply (Paper 28)
- Petitioners filed an Opposition to the Motion to Amend (Paper 27)
- The Board issued Preliminary Guidance (Paper 30) finding that Petitioner showed a reasonable likelihood that the proposed substitute claims 21-37 were obvious, and substitute claim 33 was indefinite

Procedural History: '711 Patent

- Patent Owner filed a Contingent-In-Part and Non-Contingent-In-Part Revised Motion to Amend (Paper 37) presenting a revised Substitute Claims 21-37
 - Contingent as to original claim 12; non-contingent as to original claims 1-4, 8-11 and 13-20; canceled original claims 5-7
- Petitioners filed an Opposition to Revised Motion to Amend (Paper 46)
- Patent Owner filed a Reply to the Opposition (Paper 48)
- Petitioners filed a Sur-Reply to the Reply (Paper 50)

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A method of performing a flight control operation of a reference aerial vehicle, comprising:

receiving an image captured by an image sensor of the reference aerial vehicle;

detecting a target in the image including by applying a machine learning model to the image to identify a portion of the image that includes the target;

determining a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image including by determining a distance to the target based at least in part on a size of the target detected within the image; and

performing the flight control operation based on the three - dimensional relative location of the target with respect to the reference aerial vehicle , wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

'711 Patent: Overview of Original Dependent Claim 12

The method of claim 1, further comprising:

receiving a geographical location associated with the target detected at least in part using a ground-based sensor;

autonomously navigating the reference aerial vehicle towards the received geographical location; and

determining to allow image-based navigation

Petitioners Demonstrated that Original Claim 1 is Unpatentable

- Petitioners demonstrated that original independent claim 1 is rendered obvious by:
 - Beard and Laufer (Ground 1)
 - Pierce (Ground 7)
 - Pierce and Kumar (Ground 8)
 - Pierce and Sahasrabudhe (Ground 15)
 - Pierce, Kumar, and Sahasrabudhe (Ground 16)
- **PO does not dispute that claim 1 is obvious over these grounds.**

Petitioners Demonstrated that Original Claim 12 is Unpatentable

- Petitioners further demonstrated that original dependent claim 12 is rendered obvious by:
 - Beard and Laufer (Ground 1)
 - Pierce and Laufer (Ground 9)
 - Pierce, Kumar, and Laufer (Ground 10)
 - Pierce, Sahasrabudhe, and Laufer (Ground 17)
 - Pierce, Kumar, Sahasrabudhe, and Laufer (Ground 18)

Beard describes a flight control system where an "unmanned aerial vehicle (UAV) selects a target based on a reference image captured by an onboard camera" and "image processing determines a desired orientation of the target to the UAV, by which the UAV can track the target and provide streaming video images from the desired orientation."



(19) **United States**
(12) **Patent Application Publication**
Pierce et al.

(10) Pub. No.: US 2017/0160751 A1
(43) Pub. Date: Jun. 8, 2017

AXON EXHIBIT 1005, Page 1

Pierce describes “controlling drone movement for object tracking.” For instance, Pierce explains that a “drone 102 includes a camera 104 to record images as input,” and those images are used by a “drone control algorithm” so that the drone can track or follow a moving target.

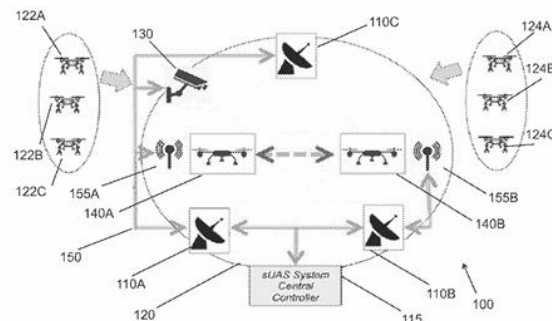
(19) **United States**
(12) **Patent Application Publication**
Laufer et al. (10) Pub. No.: US 2017/0059692 A1
(43) Pub. Date: Mar. 2, 2017

(54) MITIGATION OF SMALL UNMANNED AIRCRAFT SYSTEMS THREATS		Publication Classification	
(71) Applicant: Laufer Wind Group LLC, New York, NY (US)	(51) Int. Cl.		
	G01S 7/38	(2006.01)	
	(52) U.S. CL.		
	CPC	G01S 7/38 (2013.01)	

(22) Filed: **Aug. 26, 2016**

Related U.S. Application Data

(60) Provisional application No. 62/211,319, filed on Aug. 28, 2015, provisional application No. 62/352,728, filed on Jun. 21, 2016.



AXON EXHIBIT 1010, Page 1

A POSITA would have been Motivated to Combine Beard and Laufer (Ground 1)

- As combined, Beard's UAV would be brought to within an imaging range of the target using a radar-generated interception location and autopilot commands and use image-based flight control when within the imaging range, as taught by Laufer.
- The combination would have been applying a **known technique** (Laufer's machine learning object detection and use of radar) to **improve similar devices** (Beard's drone flight control system) **in the same way**.

Beard and Laufer Render Obvious Claim 12

The method of claim 1, further comprising:
receiving a geographical location associated with the target detected at least in part using a ground-based sensor;
autonomously navigating the reference aerial vehicle towards the received geographical location; and
determining to allow image-based navigation

- Doppler radar signals generated by ground-based doppler radars are used to determine, and thereby receive, an “interception location” where UAV 100 and the target will intercept (*receiving a geographical location associated with the target detected at least in part using a ground-based sensor*).
- UAV 100 is brought to within an imaging range of the target using the interception location and autopilot commands (*autonomously navigating the reference aerial vehicle towards the received geographical location*).
- When the target is within an adequate range of UAV 100's camera, UAV 100 is controlled using captured image/video data to track the target (*and determining to allow image-based navigation*).

A POSITA would have been Motivated to Combine Pierce and Laufer (Ground 9)

- Pierce's drone would be brought to within an imaging range of a target aircraft using a radar-generated interception location and autopilot commands, and the drone would use image-based flight control when within the imaging range, as taught by Laufer
- Pierce addresses a "need for better and more efficient drone tracking systems."

[0003] Drones are very useful tools for tracking objects remotely. However, most drone tracking systems are inefficient and provide for "jerky" drone flying movements, especially with a moving target. Thus, there is a need for better and more efficient drone tracking systems that provide smooth object tracking.

- Laufer furthers Pierce's teachings, providing tracking techniques for when a target is not within visual range.

Pierce and Laufer Render Obvious Claim 12

The method of claim 1, further comprising:
 receiving a geographical location associated with the target detected at least in part using a ground-based sensor;
 autonomously navigating the reference aerial vehicle towards the received geographical location; and
 determining to allow image-based navigation

- The substance of the Pierce-Laufer ground is the same as the Beard-Laufer ground, except Pierce's drone 102 is the *reference aerial vehicle*.

Grounds 10, 17, and 18 Render Obvious Claim 12

- Pierce, Kumar, and Laufer (Ground 10), Pierce, Sahasrabudhe, and Laufer (Ground 17), and Pierce, Kumar, Sahasrabudhe, and Laufer (Ground 18) render obvious original claim 12 for the same reasons as Grounds 1 and 9.

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Dispute Overview – Original Claim 12

- PO Disputes:
 - Construction of *autonomously navigating the reference aerial vehicle* recited in original claim 12.
 - Whether, in view of PO's proposed construction, a POSITA would have combined:
 - 1) Beard and Laufer,
 - 2) Pierce and Laufer,
 - 3) Pierce, Kumar, and Laufer,
 - 4) Pierce, Shahasrabudhe, and Laufer, and
 - 5) Pierce, Kumar, Shahasrabudhe, and Laufer
 - Whether the combinations teach claim 12 as construed by PO

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'711 Patent: Overview of Original Independent Claim 1

A method of performing a flight control operation of a reference aerial vehicle, comprising:

receiving an image captured by an image sensor of the reference aerial vehicle;

detecting a target in the image including by applying a machine learning model to the image to identify a portion of the image that includes the target;

determining a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image including by determining a distance to the target based at least in part on a size of the target detected within the image; and

performing the flight control operation based on the three - dimensional relative location of the target with respect to the reference aerial vehicle , wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

'711 Patent: Overview of Original Dependent Claim 12

The method of claim 1, further comprising:

receiving a geographical location associated with the target detected at least in part using a ground-based sensor;

autonomously navigating the reference aerial vehicle towards the received geographical location; and

determining to allow image-based navigation

PO's Proposes an Overly Narrow and Unsupported Construction of *Autonomously Navigating*

- PO argues the “**plain and ordinary meaning**” of *autonomously navigating the reference aerial vehicle towards the received geographical location* is:
 - “**making navigation decisions by the reference aerial vehicle by-itself, without outside control.**”
- PO's narrowing interpretation is **not the plain and ordinary meaning** and is contradicted by the specification.
- And even if PO's incorrect construction is adopted, **the Laufer-based combinations still render claim 12 obvious.**

PO's Inconsistent Interpretations Throughout this IPR Show that its New Interpretation is not the Plain and Ordinary Meaning

- PO's **proposed plain and ordinary meaning** of “autonomously navigating” has **shifted throughout this IPR**.

– POR at 10-11:

“receive[s] a geographical location” of the target. Also per Claim 12, the plain, ordinary, and customary meaning of “*autonomously navigating*” is **performing navigation by the reference UAV itself**. See EX2011 (defining “autonomous” as “undertaken or carried on without outside control”); EX2012 (defining autonomous as “independent and having the power to make your own decisions”).

as “independent and having the power to **make your own decisions**.” In light of these definitions and the specification of the '711 patent, the plain and ordinary / customary” meaning of “autonomously navigating the reference aerial vehicle” is **making navigation decisions by the reference aerial vehicle by-itself, without outside control**. EX2025 § IX.

51. Thus, a POSITA would have understood that “autonomously navigating” the reference UAV means **making flight decisions by a component of the reference UAV itself**, so as to direct the reference UAV towards a “*geographic location*” “*received*” by the reference UAV.

PO's Inconsistent Interpretations Throughout this IPR Show that its New Interpretation is not the Plain and Ordinary Meaning

- PO's expert concedes that PO's current proposal is not the same as PO's prior proposals.
 - EX2025 at 87 (FN2):

² I note that the POPR presented not the same but a similar meaning. Paper 11 at 30 (“the plain, ordinary, and customary meaning of ‘autonomously navigating’ is performing navigation by the reference UAV itself”). It is my understanding that

The Board has Already Rejected PO's Attempt to Limit the Performance of Method Steps to Onboard the Aerial Vehicle

- In the POPR, PO argued for a claim interpretation that required **steps performed “aboard the reference UAV.”**

Claims 1 and 20 recite “*detecting a target in the image including by applying a machine learning model to the image,*” and Claim 19 recites “*detect a target in the image.*” As explained below, these terms are properly interpreted as “applying aboard the reference UAV a machine learning model to the captured image for: (i) identifying a target in the captured image, (ii) identifying a bounding box for the identified target, and (iii) classifying the identified target, including identifying a type of the target.”

The Board has Already Rejected PO's Attempt to Limit the Performance of Method Steps to Onboard the Aerial Vehicle

- The Board rejected that interpretation.
 - ID at 8-9.

But the Detecting Limitations of claims 1, 19, and 20, merely require that a target be “detected.” The Detecting Limitations do not require that target detection be performed “aboard the reference UAV,” and claim 19 does not recite or require “machine learning.” Moreover, the Specification makes clear that the claims should not be limited to aspects of the disclosed embodiments, as Patent Owner proposes to do here. *See, e.g.*, Ex. 1001, 2:56–59 (“The invention is described in connection with such embodiments, but the invention is not limited to any embodiment. The scope of the invention is limited only by the claims”) Patent Owner additionally fails to cite any lexicographic definition or clear and unambiguous disclaimer of claim scope sufficient to limit the claims in the manner it proposes. We, thus, are not persuaded that the Detecting Limitations require “applying aboard the reference UAV a machine learning model to the capture image for: (i) identifying a target in the captured image.”

The Board has Already Rejected PO's Attempt to Limit the Performance of Method Steps to Onboard the Aerial Vehicle

- PO's interpretation of "*autonomously navigating*" **again improperly seeks to import limitations from the specification into the claims.**
 - The step must be performed **onboard the reference aerial vehicle**
 - The step must be performed **"by the reference aerial vehicle by-itself, without outside control."**
- The Board's logic in rejecting the onboard performance of the "detecting" limitations **applies equally to PO's even narrower interpretation** of "*autonomously navigating*"
 - No intrinsic or extrinsic evidence warrants the interpretation.

The Claims Do Not Support PO's Interpretation.

- **No claim elements** require the aerial vehicle to perform the step of "*autonomously navigating*" by-itself, without any outside control.
 - The step itself **does not recite where the step is performed** and **does not exclude** performance or involvement by another component.
- The **context of the claim also does not limit performance** to the aerial vehicle.
 - Claim 12 is a "**method** of performing a flight control operation of a reference aerial vehicle"
 - The claim does **not recite where that method is performed** or **require that it is performed** on the aerial vehicle alone without outside control.
 - *This is exactly what the Board recognized in rejecting PO's construction of the "Detecting Limitations" in the ID.*

The Specification Does Not Support PO's Interpretation.

- The specification **does not support PO's interpretation**.
 - PO's improperly attempts to limit to aspects of disclosed embodiments; PO's cited portions use permissive language and are example embodiments.

- EX1001, 9:38-43

311. The CPU may be configured to perform one or more flight decisions for the UAV. For example, the CPU may provide one or more flight commands to a flight controller module. For example, a flight command may include a specified speed for the UAV, a specified flight height for the UAV, a particular flight path for the UAV, etc. In response to

- *Id.*, 9:7-10

FIG. 3A is a diagram illustrating a front view of a UAV in accordance with some embodiments. Unmanned aerial vehicle 301 is an example of UAV 200 of FIG. 2 and/or aerial vehicle 102 of FIG. 1

- *Id.*, 9:49-51

a manner that is consistent with the flight commands. In some embodiments, the CPU is configured to receive flight instructions from a remote command center. In other embodiments, the CPU is configured to autonomously fly UAV 301.

- *Id.*, 15:28-31

FIG. 4 is a flowchart illustrating an embodiment of a process for automatically controlling flight of a vehicle. In some embodiments, the process of FIG. 4 is performed by interceptor aerial vehicle 102 of FIG. 1, UAV 200 of FIG. 2, and/or UAV 301 of FIGS. 3A and 3B.

The Specification Does Not Support PO's Interpretation.

- The **Board acknowledged** in the ID that importing these type of example embodiments is improper.
 - ID at 8-9

does not recite or require “machine learning.” Moreover, the Specification makes clear that the **claims should not be limited to aspects of the disclosed embodiments**, as Patent Owner proposes to do here. *See, e.g.*, Ex. 1001, 2:56–59 (“The invention is described in connection with such embodiments, but the **invention is not limited to any embodiment**. The scope of the invention is limited only by the claims”) Patent Owner additionally

- **None** of PO's citations includes a **lexicographic definition** of “*autonomously navigating*” or a **clear and unambiguous disclaimer** that would justify limiting the term to performance solely on the aerial vehicle without any outside control.

The Specification Does Not Support PO's Interpretation.

- EX1001 at 9:25-27 deals with generic CPU functionality for a UAV.

Computing chassis 302 is configured to protect the CPU of UAV 301. The CPU is configured to control the overall operation of UAV 301. The CPU may be coupled to a plurality of computing modules. For example, the plurality

- This portion says nothing about the UAV making “navigation decisions” without “outside control” and does not preclude outside control.

The Specification Does Not Support PO's Interpretation.

- PO states that the CPU “**performs** one or more flight decisions for the UAV” by **providing** ‘one or more flight commands.’” POR at 11; EX1001 at 9:38-43.

311. The CPU may be configured to perform one or more flight decisions for the UAV. For example, the CPU may provide one or more flight commands to a flight controller module. For example, a flight command may include a specified speed for the UAV, a specified flight height for the UAV, a particular flight path for the UAV, etc. In response to

- A CPU **performing flight decisions** by **providing commands to a controller** does not require the CPU to **actually make flight decisions** (let alone “navigation decisions”) **by itself or preclude** the UAV from receiving **any outside control**

The Specification Does Not Support PO's Interpretation.

- EX1001 at 9:49-51:
 - **says nothing** about how the UAV flies autonomously,
 - **does not describe** the UAV making any "navigation decisions,"
 - **does not describe** what "navigation decisions" are,
 - **does not describe** that such decisions are made by the reference vehicle itself "without outside control."

a manner that is consistent with the flight commands. In some embodiments, the CPU is configured to receive flight instructions from a remote command center. In other embodiments, the CPU is configured to autonomously fly UAV 301.

The Specification Does Not Support PO's Interpretation.

- EX1001 at 16:49-55 is unrelated to claim 12, because it concerns flight direction and speed based on a captured image.
 - This happens **after an aerial vehicle has navigated to a received location** and is capturing images of the target.

At 408, a flight operation is performed based on the detected relative location of the target. For example, a flight direction and/or speed of an interceptor aerial vehicle are automatically and autonomously adjusted based on a location and size of the target within the captured image (e.g., adjust direction to center the target within subsequently captured images). This allows the flight path of the inter-

- This portion also **does not limit** performance of that action **on the aerial vehicle itself** or **preclude all outside control**.

PO's Interpretation Improperly Excludes Embodiments

- *"autonomously navigating the reference aerial vehicle towards the received geographical location"* by its own terms occurs with **outside control** by virtue of **continually new or updated locations and navigation commands received from a ground-based sensor**.
- Requiring the limitation to mean "making navigation decisions by the reference aerial vehicle by-itself, without outside control" **would conflict with and even exclude the relevant portions of the specification**, weighing against PO's interpretation.

PO's Interpretation Improperly Excludes Embodiments

- The specification describes that a ground station “manage[s] interceptor aerial vehicle 102.”
 - EX1001, 3:43-61

target aerial vehicle (e.g., target aerial vehicle 110). Ground station 104 is used to manage interceptor aerial vehicle 102. Ground station 104 is in communication with interceptor aerial vehicle 102. For example, ground station 104 provides instructions, commands, sensor data, and/or other data that can be used by interceptor aerial vehicle 102 to monitor an airspace and/or navigate to and/or capture a target aerial vehicle. Interceptor aerial vehicle 102 may provide status

PO's Interpretation Improperly Excludes Embodiments

- The aerial vehicle continually receives “new” or “updated” location data from ground-based sensors as a “stream of locations.”
 - EX1001 at 4:14-22, 15:50-63.

The detected location of target aerial vehicle 110 may be provided to interceptor aerial vehicle 102 to allow it to automatically and autonomously fly towards the direction of the detected location. However, once interceptor aerial vehicle 102 is near target aerial vehicle 110, the location data from ground-based sensors may not be accurate or updated fast enough for interceptor aerial vehicle 102 to get close enough to the moving target aerial vehicle 110 to reliably deploy a capture mechanism. Interceptor aerial vehicle 102

reduce noise and inaccuracies. The filter may take into account a model of a target vehicle and its movement/flight properties and capabilities to determine the location based on a series of sensor measures over time. The location of the target may be updated and continually received as a new or updated location of the target is determined. For example, the received location is a part of a stream of locations tracked for the target.

PO's Interpretation Improperly Excludes Embodiments

- The “received location is utilized to navigate towards the received location” and the ground station communicates in “real time” with the aerial vehicle and can “redirect” the aerial vehicle.
 - EX1001, 15:64-16:3, 4:34-37

At **404**, the received location is utilized to navigate towards the received location. For example, the location is received at a navigation component and/or a flight controller of an interceptor aerial vehicle and the direction and/or

In some embodiments, ground station **104** is able to communicate in real time with the interceptor aerial vehicle **102** to be able to monitor, and if necessary, redirect detection and tracking based on security or threat level. In the example implementation, the telecommunications structure of ground station **104** is configured to receive and transmit signals.

The Prosecution History Does Not Support PO's Interpretation.

- PO also **does not cite** to any prosecution history defining "*autonomously navigating*" or otherwise disclaiming or disavowing subject matter in a way that would compel PO's interpretation.
 - The prosecution history is unresponsive.

Intrinsic Evidence Supports Petitioners' Correct Interpretation of Claim 12

- The '711 Patent's purported invention addresses issues in the background art associated with "flight controllers **manually operated by a human user.**"

- EX1001 at 1:27-34:

Typically unmanned aerial vehicles and drones are controlled using flight controllers manually operated by a human user. This requires the human user to have a visual sight of the aerial vehicle and/or an image captured by the aerial vehicle. However, this may be challenging in circumstances where a trained human user is unavailable or unable to react quickly enough to perform a desired flight maneuver. Additionally if communication between the aerial

- The patent states that "it may not be desirable to **manually control** the interceptor aerial vehicle to follow the target UAV."

- EX1001 at 3:24-26:

location). However, because the target UAV can move, the interceptor aerial vehicle needs to be able to follow the target UAV and get close enough until the target UAV is within range of a capture system. For at least the previously mentioned reasons, it may not be desirable to manually control the interceptor aerial vehicle to follow the target UAV. In some embodiments, the interceptor aerial vehicle is able to autonomously track and fly to the target UAV using machine vision based on images captured by a camera of the interceptor aerial vehicle.

Intrinsic Evidence Supports Petitioners' Correct Interpretation of Claim 12

- This interpretation also is consistent with, and does not exclude, the '711 Patent's embodiments describing that the ground station provides commands to the reference aerial vehicle, including to navigate the aerial vehicle towards the target location.

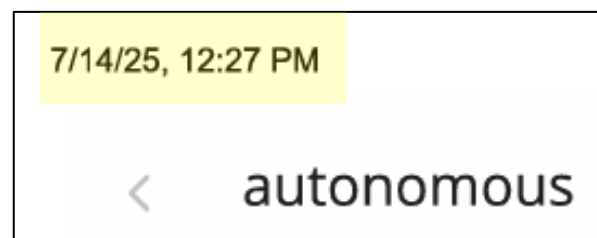
- EX1001 at 3:54-61: target aerial vehicle (e.g., target aerial vehicle 110). Ground station 104 is used to manage interceptor aerial vehicle 102. Ground station 104 is in communication with interceptor aerial vehicle 102. For example, ground station 104 provides instructions, commands, sensor data, and/or other data that can be used by interceptor aerial vehicle 102 to monitor an airspace and/or navigate to and/or capture a target aerial vehicle. Interceptor aerial vehicle 102 may provide status

- *Id.*, 4:34-37: In some embodiments, ground station 104 is able to communicate in real time with the interceptor aerial vehicle 102 to be able to monitor, and if necessary, redirect detection and tracking based on security or threat level. In the example implementation, the telecommunications structure of ground station 104 is configured to receive and transmit signals.

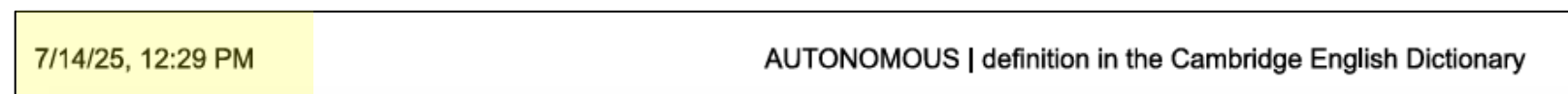
PO's extrinsic dictionary definitions are temporally irrelevant, and PO cites its conclusory expert declaration once.

- PO cites dictionaries dated in 2025—almost 9 years after the '711 Patent's earliest priority date.

– EX2011



– EX2012



- These definitions **should not be afforded any weight**, as PO has not shown that they reflect the meaning of "*autonomous*" to POSITAs **as of the '711 Patent's effective filing date**.
- Almost all of PO's statements are **unsupported attorney argument**. See POR at 10-12.
 - Regardless, that declaration does nothing to support PO's interpretation. Compare EX2025, ¶¶84-87, with POR at 10-12.

Extrinsic Evidence Supports Petitioners' Correct Interpretation of Claim 12

- Regardless of timing, PO's Cambridge dictionary definition (EX2012) **supports Petitioners correct interpretation** as well.
 - EX2012:

an autonomous machine or system is able to operate without being controlled directly by humans:

- **autonomous vehicle**

The Correct Interpretation of Claim 12

- If any construction is necessary, the plain and ordinary meaning of “autonomously navigating the reference aerial vehicle towards the received geographical location” is:
 - **navigating the reference aerial vehicle towards the received geographical location without human control.**
- This meaning is fully supported by the intrinsic record and extrinsic sources.

Extrinsic Evidence Supports Petitioners' Correct Interpretation of Claim 12

- Petitioners provide a dictionary definition (EX1031) from before the '711 Patent's effective filing date that supports Petitioners' interpretation.
 - EX1031, 5:

autonomous 

[aw-**ton**-uh-muh s]

[Examples](#) [Word Origin](#)

[See more synonyms on Thesaurus.com](#)

adjective

- Government.*
 - self-governing; independent; subject to its own laws only.
 - pertaining to an **autonomy**, or a self-governing community.
- having autonomy; not subject to control from outside; independent:
a subsidiary that functioned as an autonomous unit.
- (of a vehicle) navigated and maneuvered by a computer, without a need for human control or intervention under normal road conditions:
autonomous vehicle.
- Biology.*
 - existing and functioning as an independent organism.
 - growing naturally or spontaneously, without cultivation.

PO’s Expert Testified in Support of Petitioners’ Correct Interpretation of Claim 12

- PO’s expert distinguished levels of autonomy **based on level of human involvement** and further **confirmed that in 2015 “complete autonomy” meant no human involvement:**
 - EX1038, 22:9-14, 23:8-13

9	Q What would be an example of autonomy 2
10	versus autonomy 3 versus autonomy 4?
11	A As you increase the autonomy, you take the
12	human more and more out. So for example, if we're
13	looking at higher numbers, the human is completely
14	out of the loop. If you look at autonomy 2 and 3,

8	Q Were there people in 2015 that had the
9	opinion that complete autonomy meant there is no
10	human involved?
11	A Yeah, this goes back -- it is not only
12	2015. Discussions were going back to the darker
13	projects in the 1980s with NavLab. When I was a

Claim 12 is Obvious Under Petitioners' Correct Interpretation and PO's Erroneous Interpretation

- Under Petitioners' correct interpretation, claim 12 is obvious.
- **All of PO's patentability arguments are cabined to its erroneous interpretation.**
- Rejecting PO's interpretation results in rejection of all of PO's patentability arguments.
- But **even under PO's erroneous interpretation**, the grounds still render claim 12 obvious.

Claim 12 is Unpatentable Under the Correct Interpretation

- The Beard-Laufer combination teaches UAV 100 is brought to within an imaging range of the target using an interception location and autopilot commands (*autonomously navigating the reference aerial vehicle towards the received geographical location*).
 - PO does not contest that Beard and Laufer teach the other elements of claim 12.
- Because UAV 100 **utilizes the autopilot commands to control its flight**, UAV 100 is navigating itself towards the interception location **autonomously, without any human control**.

Claim 12 is Unpatentable Under the Correct Interpretation

- Laufer teaches that the **autopilot commands “pilot” the aircraft**, include yaw, pitch, and motor speed **commands**, and commands are used by the **aircraft flight controller**.
 - EX1010, ¶¶0040-0041:

to interception location 425. The set of autopilot aircraft commands 445 can include, for example, a yaw command, pitch command, and/or motor speed commands. In some embodiments, autopilot command module 440 can solve for the set of autopilot aircraft commands 445 to pilot an interceptor aircraft to interception location 425 using a matrix-type approach to determine all of the commands

aircraft in an upright position. Inner stability loop 450 uses command summer 470 which sums autopilot aircraft commands 445 and stability aircraft commands 465 to generate aircraft control commands 475. Aircraft control commands 475 are used by interceptor aircraft flight controller 480 to pilot the interceptor aircraft toward interception location 425, for example, as in step 330.

- Autopilot commands are generated by an “**autopilot command module**” based on the interception location and an “interceptor aircraft dynamics model.”
 - EX1010, ¶0040:

[0040] Central controller 115 uses autopilot command module 440 to generate autopilot aircraft commands 445 based on interception location 425 and the interceptor aircraft dynamics model. Central controller 115 uses autopilot command module 440 to solve for the set of autopilot aircraft commands 445 to cause the interceptor aircraft to fly to interception location 425. The set of autopilot aircraft

Claim 12 is Unpatentable Under the Correct Interpretation

- Laufer also distinguishes its autopilot commands from human control, explaining a human can manually override flight controls.

– EX1010, ¶¶0026, 0031, 0037

yaw) of interceptor aircraft 140A-140B. Interceptor aircraft 140A-140B can receive command data via a wireless connection from central controller 115. In some embodiments, a user can manually override control of interceptor aircraft 140A-140B by central controller 115 and pilot interceptor aircraft 140A-140B via manual input.

face (“GUI”) 210. GUI 210 can display real-time tracking maps and information based on, for example, signals and information received from radars 110A-110C, fixed camera 130, and/or cameras mounted on interceptor aircraft 140A-140B. GUI 210 can accept user input, for example where a user desires to manually override flight controls of interceptor aircraft 140A-140B. Central controller 115 includes

to interceptor aircraft 140A-140B. In other embodiments, a user monitoring interdiction method 300 can manually override the controls of interceptor aircraft 140A-140B by an interface through central controller 115, for example through GUI 210.

- PO acknowledges how Laufer’s autopilot commands are separate from human control:

– POR, 14:

Laufer’s autopilot commands may not be provided by a human, and may instead be generated by a computer, such as one provided in Laufer’s autopilot command module. But, those autopilot commands are generated by the central controller and

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- PO wrongly argues against **Laufer individually**. See POR at 12-16.
 - *In re Keller*, 642 F.2d 413, 208 USPQ 871 (CCPA 1981)
 - *In re Merck & Co., Inc.*, 800 F.2d 1091, 231 USPQ 375 (Fed. Cir. 1986).
- PO's statements amount to nothing more than **unsupported attorney argument**.
 - PO only cites to its expert declaration (EX2025) to support the **generic allegation** that "claim 12 is patentable." See POR at 18.
 - PO's specific arguments, including its arguments regarding a **POSITA's motivation to combine prior art and expectation of success, are unsupported**. See POR at 12-18.

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

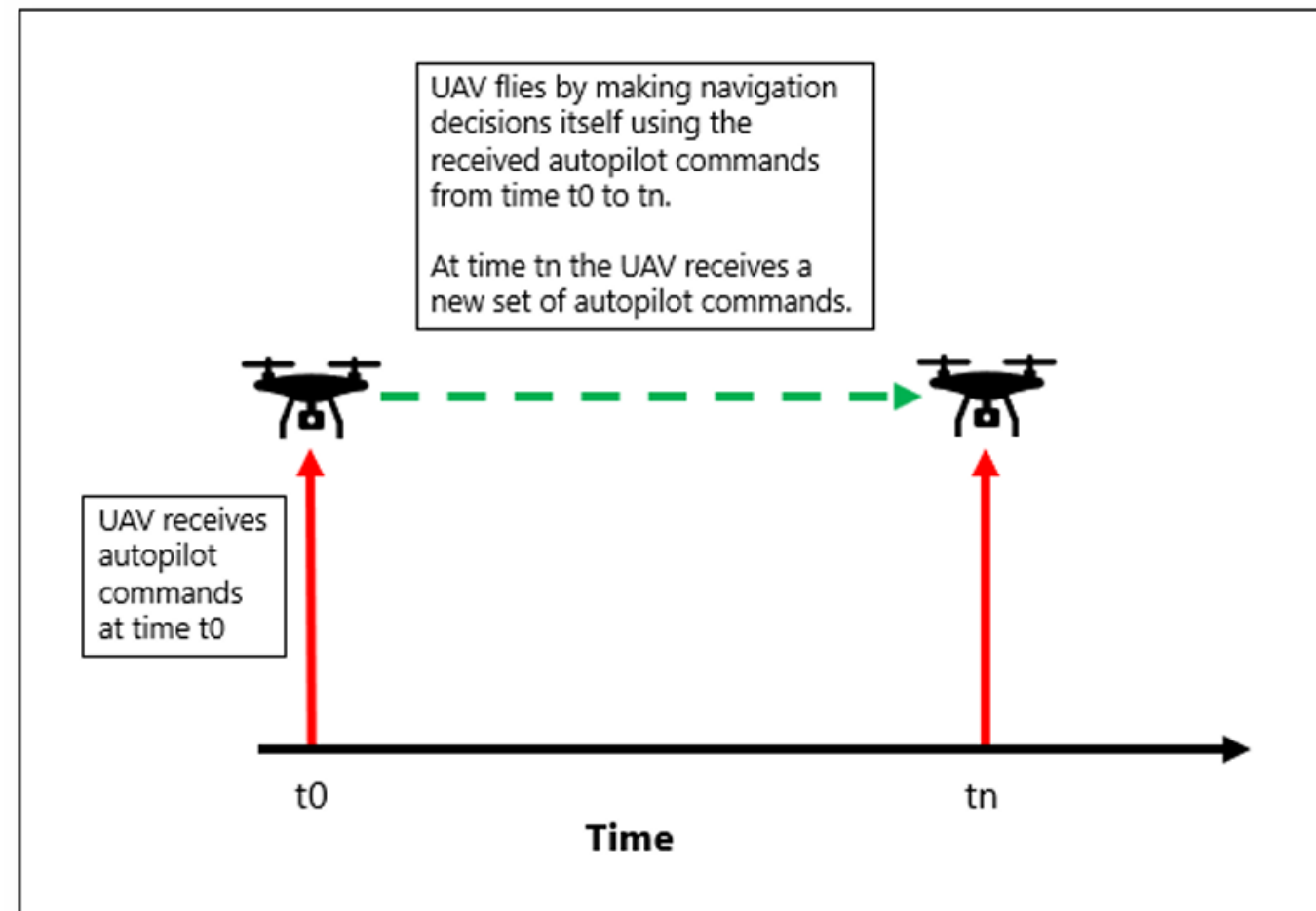
- PO argues a POSITA would not have “combined Beard and Laufer” because “the proposed combination does not provide a reasonable expectation of achieving autonomous navigation of an aerial vehicle, and thus the claimed invention of claim 12.”
- PO focuses on how Laufer purportedly describes that its central controller 115 is “not on-board a UAV” and autopilot commands are not generated by the UAV, and that Laufer’s UAV thus “does not navigate itself.”
 - Claim 12 includes **no requirement of on-board autonomous navigation** and PO’s interpretation **conflicts with claim 12 itself and the specification**, which makes PO’s entire argument inapposite.

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- Regardless of whether or not autopilot commands are determined on board UAV 100 in the Beard-Laufer combination,
 - the combination teaches that **UAV 100 uses the autopilot commands to control itself toward the received interception location.**

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- A POSITA would have understood that during the time period in which UAV 100 uses autopilot commands, it is making navigation decisions by itself, without any outside control.



Timeline Illustration

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- The use of **autopilot commands by UAV 100** means that **UAV 100 is autonomously controlling itself** (e.g., controlling its **yaw, pitch, and/or motor speed**) according to the **autopilot commands** and **without any other external or outside control**.
 - This is what it means for a vehicle to be controlled via “autopilot.”
 - EX1010, ¶¶0040:

[0040] Central controller 115 uses autopilot command module 440 to generate autopilot aircraft commands 445 based on interception location 425 and the interceptor aircraft dynamics model. Central controller 115 uses autopilot command module 440 to solve for the set of autopilot aircraft commands 445 to cause the interceptor aircraft to fly to interception location 425. The set of autopilot aircraft

to interception location 425. The set of autopilot aircraft commands 445 can include, for example, a yaw command, pitch command, and/or motor speed commands. In some embodiments, autopilot command module 440 can solve for the set of autopilot aircraft commands 445 to pilot an interceptor aircraft to interception location 425 using a matrix-type approach to determine all of the commands collectively. In other embodiments, autopilot command

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- PO's own expert confirmed that **changing speed and pitch in response to a speed command/pitch command is a "navigation decision"**

– EX1033, 124:7-9:

7	Q.	Is changing speed in response
8	to a speed command	a navigation decision?
9	A.	Yes.

– *Id.*, 127:2-5:

2	Q.	Is changing pitch in response
3	to a pitch command	a navigation decision?
4	A.	It's a possibility. It's the
5		execution of the navigation command.

- This is what the combination's UAV would be doing in the **time period it is using autopilot commands—changing speed and pitch in response to commands—even if the autopilot commands were received from the ground.**

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- PO's expert thus confirmed that the Beard-Laufer combination's autopilot commands that change UAV speed and pitch is a **navigation decision** which would **satisfy PO's interpretation**.
- Beard and Laufer thus teach "**making navigation decisions by the reference aerial vehicle by itself, without outside control**," teaching PO's erroneous interpretation.
 - PO does not contest that Beard and Laufer teach the other elements of claim 12.

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- PO never addresses how autopilot commands are **used** by the Beard-Laufer combination's drone to effectuate flight, and how their **use would involve navigation decisions without external control**.
 - PO Sur Reply at 23-24

Claim 12 is Unpatentable Under PO's Incorrect Interpretation

- PO attempts to differentiate between “implementing” and “making” navigation decisions
 - *Id.* at 24:

Thus, while Beard's UAV **implements** navigation decisions, that UAV is not “autonomously navigating” because it does not **make** navigation decisions, e.g., decide at what speed to fly, at what height to fly, etc. Thus, the Beard-Laufer

- But the 711 Patent never describes to “**make navigation decisions;**”

Claim 12 is Unpatentable Over Grounds 9, 10, 17, and 18

- Pierce and Laufer (Ground 9), Pierce, Kumar, and Laufer (Ground 10), Pierce, Sahasrabudhe, and Laufer (Ground 17), and Pierce, Kumar, Sahasrabudhe, and Laufer (Ground 18):
 - render obvious Claim 12 for the same reasons discussed for Beard and Laufer (Ground 1).

Outline of Arguments: IPR2025-00629 ('711 Patent)

- I. Overview of the '711 Patent and Procedural History
- II. Obviousness of Original Claim 12
- III. Dispute Overview – Original Claim 12
- IV. Claim Construction and Obviousness of Original Claim 12 as Construed
- V. Dispute Overview – Motion to Amend**
- VI. Substitute Claims 24, 25, and 37 Lack Written Description
- VII. Substitute Claims 21-37 are Not Enabled
- VIII. Substitute Claims 21-37 are Indefinite
- IX. Substitute Claims 21-37 are Obvious

Substitute Claim 24 requires “identifying a model type of the target based on the classification of the detected target”

[[1]]21.[pre] A method of performing a flight control operation of a reference aerial vehicle, comprising:

[21.a] receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle;

[21.b] 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 that includes detected features of the target, and to identify a classification of the detected target;

[21.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image 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 and on a physical size corresponding to the classification of the target detected within the image; and

[21.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a first speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

24. The method of claim 21, wherein detecting the target in the image including by applying at the reference aerial vehicle the machine learning model to the image includes identifying a model type of the target based on the classification of the detected target.

Substitute Claim 36

[[19]]36.[pre] A reference aerial vehicle, comprising:

[36.a] an image sensor configured to capture an image;

[36.b1] a processor configured to: detect at the reference aerial vehicle a target in the image; and

[36.b2] determine at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image; and

[36.c] a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to determine a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[[.]].

[36.d] 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, 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, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.

Substitute Claim 37

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.].

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

Dispute Overview – Motion to Amend

- PO Disputes:
 - Whether Substitute Claims 24, 25, and 37 **lack written description support**
 - Whether Substitute Claims 21-37 **are enabled**
 - Whether Substitute Claims 21-37 **are indefinite**
 - Substitute Claims 21-36 **are obvious**

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- VIII. Substitute Claims 21-37 are Indefinite
- IX. Substitute Claims 21-37 are Obvious

Substitute Claim 37 requires image-by-image decision-making based on the “immediately preceding image” and the “current image” ([37.e1], [37.e3], [37.e4])

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.].

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

No Written-Description Support Exists for Elements [37.e1], [37.e3], and [37.e4]

- Elements [37.e1], [37.e3], and [37.e4] require **image-by-image decision-making based on the immediately preceding image and the current image**, but the specification does not support this concept.

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and

PO Mischaracterizes Substitute Claim 37

- PO says the neural network selection does not depend on the neural network used for the immediately preceding frame

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.

- PO’s statement is **false** and **PO’s expert agrees**.
 - EX1041, 18:15-18, 20:18-21,,

15	Q.	And this e3 limitation only applies when
16		the second neural network was selected and applied
17		to the immediately preceding image, correct?
18	A.	That's correct.

18	Q.	37 -- the 37.e4 limitation only applies
19		when the first neural network was selected and
20		applied to the immediately preceding image, correct?
21	A.	That's correct.

No Written-Description Support Exists for Elements [37.e1], [37.e3], and [37.e4]

- PO's cited paragraphs for support only describe generally processing "frames," examining processing schemes "from group to group," and switching between groups.
 - EX2019:

[00141] An example aspect includes optimized video processing scheme scheduling. In an example implementation, processing schemes include localization algorithms that process video frames of one or more video data streams. The processing schemes produce a prediction of objects within the video frame, as well as a confidence number that is a measure of quality for

[00146] In an example implementation, a set of processing schemes (e.g., algorithms) are examined from group to group, and the process cycles through the processing schemes to produce a detection of an object. According to the example implementations, if the confidence

[00147] According to an example implementation, a voting system is provided that fuses estimations from high confidence results, and validates the result with an independent validation method. If the confidence is below low threshold, falls outside of a range, or the validation method fails, group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied to optimize resources. Different Groups of algorithms (e.g.,

No Written-Description Support Exists for Elements [37.e1], [37.e3], and [37.e4]

- PO **does not show support** for the specific requirements of [37.e1], [37.e3], [37.e4] regarding **an immediately preceding image and current image**,
 - where NN selection for a current image depends on **whether** the **first NN or second NN** was applied to the immediately preceding image.
- PO **cannot require obviousness to show possession**.
 - *L.A. Biomedical Rsch. Inst. v. Eli Lilly & Co.*, 849 F.3d 1049, 1057 (Fed. Cir. 2017).

No Written-Description Support Exists for Elements [37.e1], [37.e3], and [37.e4]

- PO points to EX2019, ¶109 and ¶141, but these portions (as PO admits) disclose algorithms have a “**cost and/or latency**” associated with a frame and confidence levels are for a **frame that has been processed**
 - No disclosure regarding predictions of an object **in a subsequent frame that has not yet been processed.**
 - EX2019 at ¶109 and ¶141

[00109] On a fixed compute budget there is a negative relation between robustness of an algorithm and the cost and/or latency of the algorithm per spacio-temporal frame. Tight

frames of one or more video data streams. The processing schemes produce a prediction of objects within the video fame, as well as a confidence number that is a measure of quality for that prediction. The confidence number can be normalized to a canonical range (0-1) and used to compare the confidence of each different processing scheme to track an item of interest.

PO resorts to bare attorney argument

- PO's assertion that a confidence "informs" how to select the neural network for the next frame is **bare attorney argument lacking specification or expert support**.

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

Substitute Claim 37 requires a “range defined by the first threshold and a second threshold greater than or equal to the first threshold” ([37.e3])

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.].

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

No Written-Description Support Exists for Element [37.e3]

- Element [37.e3] requires a **range** defined by a **first threshold** and a **second threshold greater than or equal to the first threshold**.

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

No Written-Description Support Exists for Element [37.e3]

- PO relies on EX2019 at ¶¶146, 147, but these portions (as well as the rest of the intrinsic record) **do not show possession** of the **specific range** defined by **two separate thresholds** that **can be equal**.

[00146] In an example implementation, a set of processing schemes (e.g., algorithms) are examined from group to group, and the process cycles through the processing schemes to produce a detection of an object. According to the example implementations, if the confidence number is higher than an activation number, an action is performed to stop or change a running group (i) and select or switch to group (ii). For example, a processing scheme from the group of

[00147] According to an example implementation, a voting system is provided that fuses estimations from high confidence results, and validates the result with an independent validation method. If the confidence is below low threshold, falls outside of a range, or the validation method fails, group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied to optimize resources. Different Groups of algorithms (e.g.,

PO's "point range" argument does not support [37.e3]

- PO argues that "the range can be a point range, i.e., a single threshold."
 - But a "single threshold" is different from, and insufficient to support, **two separate thresholds that can be equal, as required by SC 37.**
 - EX1041, 21:7-9, 21:14-18, 21:22-22:2

7	Q.	This limitation requires both a first
8		threshold and a second threshold, correct?
9	A.	That's correct.

14	Q.	For a prior art reference to invalidate
15		this claim, both a first threshold and a second
16		threshold must be shown in the art?
17	A.	More than that, because we need all the
18		claim terms.

22	Q.	You at least need to show a first
1		threshold and a second threshold, correct?
2	A.	Among all the claim terms in 37.e3.

PO's "point range" argument does not support [37.e3]

- PO **does not otherwise address** SC 37's requirement of two thresholds that can be set equal to each other.
- PO patches together **separate thresholds** ("low threshold"/"activation number"), but **none of those are disclosed as two separate thresholds, that can be equal, defining a range.**

[00146] In an example implementation, a set of processing schemes (e.g., algorithms) are examined from group to group, and the process cycles through the processing schemes to produce a detection of an object. According to the example implementations, if the confidence number is higher than an activation number, an action is performed to stop or change a running group (i) and select or switch to group (ii). For example, a processing scheme from the group of

[00147] According to an example implementation, a voting system is provided that fuses estimations from high confidence results, and validates the result with an independent validation method. If the confidence is below low threshold, falls outside of a range, or the validation method fails, group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied to optimize resources. Different Groups of algorithms (e.g.,

Substitute Claim 37 requires “selecting and applying the second neural network to the current image when the confidence level is above the second threshold” ([37.e4])

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.].

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

No Written-Description Support Exists for Element [37.e4]

- Element [37.e4] requires 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.

No Written-Description Support Exists for Element [37.e4]

- The specification is not supportive of using a confidence level as claimed:
 - EX2019, ¶¶112, 116, 146-147

performance score from the set of processing schemes. In response to the performance score of the active processing scheme failing to satisfy a threshold, the method selects another processing scheme to process the video data stream. Processing the video data stream can include

highest performance score from the set of processing schemes. In response to the performance score of the active processing scheme failing to satisfy a threshold, the one or more processors select another processing scheme to process the video data stream.

[00146] In an example implementation, a set of processing schemes (e.g., algorithms) are examined from group to group, and the process cycles through the processing schemes to produce a detection of an object. According to the example implementations, if the confidence number is higher than an activation number, an action is performed to stop or change a running group (i) and select or switch to group (ii). For example, a processing scheme from the group of

[00147] According to an example implementation, a voting system is provided that fuses estimations from high confidence results, and validates the result with an independent validation method. If the confidence is below low threshold, falls outside of a range, or the validation method fails, group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied to optimize resources. Different Groups of algorithms (e.g.,

No Written-Description Support Exists for Element [37.e4]

- PO argues switching between groups when confidence is higher than an activation number and a “high” confidence supports [37.e4].
 - But the specification **does not disclose an “activation number” forms a second threshold defining a range as claimed**, and just because a confidence is “high” does not support it being greater than **the second threshold of the range**.

[00146] In an example implementation, a set of processing schemes (e.g., algorithms) are examined from group to group, and the process cycles through the processing schemes to produce a detection of an object. According to the example implementations, if the confidence number is higher than an activation number, an action is performed to stop or change a running group (i) and select or switch to group (ii). For example, a processing scheme from the group of

[00147] According to an example implementation, a voting system is provided that fuses estimations from high confidence results, and validates the result with an independent validation method. If the confidence is below low threshold, falls outside of a range, or the validation method fails, group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied to optimize resources. Different Groups of algorithms (e.g.,

Substitute Claim 24 requires “identifying a model type of the target based on the classification of the detected target”

[[1]]21.[pre] A method of performing a flight control operation of a reference aerial vehicle, comprising:

[21.a] receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle;

[21.b] 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 that includes detected features of the target, and to identify a classification of the detected target;

[21.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image 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 and on a physical size corresponding to the classification of the target detected within the image; and

[21.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a first speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

24. The method of claim 21, wherein detecting the target in the image including by applying at the reference aerial vehicle the machine learning model to the image includes identifying a model type of the target based on the classification of the detected target.

Substitute Claim 25 requires “determining a second speed adjustment factor based on the determined distance to the target”

[[1]]21.[pre] A method of performing a flight control operation of a reference aerial vehicle, comprising:

[21.a] receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle;

[21.b] 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 that includes detected features of the target, and to identify a classification of the detected target;

[21.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image 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 and on a physical size corresponding to the classification of the target detected within the image; and

[21.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a first speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

[[8]]25. The method of claim [[7]]21 wherein performing the flight control operation includes determining a second speed adjustment factor based on the determined distance to the target.

Outline of Arguments: IPR2025-00629 ('711 Patent)

- I. Overview of the '711 Patent and Procedural History
- II. Obviousness of Original Claim 12
- III. Dispute Overview – Original Claim 12
- IV. Claim Construction and Obviousness of Original Claim 12 as Construed
- V. Dispute Overview – Motion to Amend
- VI. Substitute Claims 24, 25, and 37 Lack Written Description
- VII. Substitute Claims 21-37 are Not Enabled**
- VIII. Substitute Claims 21-37 are Indefinite
- IX. Substitute Claims 21-37 are Obvious

Substitute Claims 21, 36, and 37 require *determining/determine a speed adjustment factor* (elements [21.d], [36.c], [37.d])

[[1]]21.[pre] A method of performing a flight control operation of a reference aerial vehicle, comprising:

[21.a] receiving at a processor at the reference aerial vehicle an image captured by an image sensor of the reference aerial vehicle;

[21.b] 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 that includes detected features of the target, and to identify a classification of the detected target;

[21.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image 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 and on a physical size corresponding to the classification of the target detected within the image; and

[21.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a first speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle.

Substitute Claims 21, 36, and 37 require *determining/determine a speed adjustment factor* (elements [21.d], [36.c], [37.d])

[[19]]36.[pre] A reference aerial vehicle, comprising:

[36.a] an image sensor configured to capture an image;

[36.b1] a processor configured to: detect at the reference aerial vehicle a target in the image; and

[36.b2] determine at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image; and

[36.c] a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to **determine a speed adjustment factor** based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[[.]].

[36.d] 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, 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, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.

Substitute Claims 21, 36, and 37 require *determining/determine a speed adjustment factor* (elements [21.d], [36.c], [37.d])

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes **determining a speed adjustment factor** based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.],

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

A POSITA cannot practice SCs 21-37 without undue experimentation due to the recited *determining a speed adjustment factor*

- The *Wands* factors demonstrate that SCs 21-37 are not enabled due to the claimed requirement of *determining a speed adjustment factor*
 - *In re Wands*, 858 F.2d 731, 737 (Fed. Cir. 1988)
- The specification references a *speed adjustment factor* but **does not say how to *determine the speed adjustment factor***

No Direction or Guidance, and No Working Examples

- The specification's "scaler" **multiplies a *speed adjustment factor*** and is **not** the *factor* itself
 - EX2019, ¶¶97-99

correction) and the length of the vector is based on the determined distance and/or speed. In one example, the vector is defined by the azimuth angle, the altitude angle, and a factor based on an associated distance or speed. In some embodiments, the vector is defined by three-dimensional coordinate-based values and the vector is to be provided along with the associated distance and/or speed.

minor directional change is required. In some embodiments, the speed and/or acceleration factor is multiplied by one or more scalar values that change in magnitude based on a directional deviation of the vector from a current direction of movement (e.g., deviation of the target in the image from the center of the image representing the current heading direction of the interceptor aerial vehicle). For example, plotting the scalar value with respect to a directional deviation

[0098] At 508, the vector is scaled. In some embodiments, scaling the vector includes modifying a speed and/or acceleration associated with the vector as well as smoothing and limiting the rate of change associated with the vector. In some embodiments, the scaling the vector includes modifying one or more directional component values of the vector.

No Direction or Guidance, and No Working Examples

- If the scaler is treated as the *factor*, these disclosures describe **curve shape and relative relationships, not how to *determine* the scaler.**
 - EX2019, ¶¶97-99

aerial vehicle). For example, plotting the scalar value with respect to a directional deviation results in a bell curve where the highest scalar value is associated with the center of the graph corresponding to no change in directional deviation (e.g., the directional deviation given by a component value of the vector) and the scalar value decreases exponentially on either side of the center as the directional deviation increases. In other examples, the scalar value may decrease

- A bell curve could represent any number of mathematical functions—the **specification never identifies the standard deviation, parameters, or input and output ranges necessary**

No Direction or Guidance, and No Working Examples

- Equations 7 and 8 relate to “speed factor” equations including constants a, b, and c, but **no guidance or examples are provided on how to select these constants**
 - EX2019 at ¶106, Fig. 10

[00106] Figure 10 shows example equations that can utilized to scale/alter components values of a vector. For example, a logistical smoother alters the vector to stabilize the motion of

be a constant. Equations 7 and 8 may both be applied when determining the speed factor for Equations 5 and 6. In other embodiments, each vector component may utilize a specific component of speed factor (e.g., either Equation 7 or Equation 8). The constants a, b, and c depicted in Equations 7 and 8 may be the same value or they may be different values. That is,

$$\text{speedfactor}(\text{deg}X) = a / (1 + bc^{-\text{deg}X})$$

Equation 7

$$\text{speedfactor}(\text{deg}Y) = a / (1 + bc^{-\text{deg}Y})$$

Equation 8

FIG. 10

No Direction or Guidance, and No Working Examples

- The specification provides **no examples of:**
 - directional deviation used by a formula to **produce a speed adjustment factor;**
 - **what constants “a, b, and c” represent;** or
 - how a **bell curve or linear relationship is parameterized** for any flight scenario for a scaler

No Direction or Guidance, and No Working Examples

- EX2019 at ¶¶105-106, FIGS. 9 and 10:

[00105] Figure 9 is an illustration illustrating examples of functions utilized to adjust component values of a vector. Logic smoothing functions 900 comprises an x-axis logic

[00106] Figure 10 shows example equations that can utilized to scale/alter components values of a vector. For example, a logistical smoother alters the vector to stabilize the motion of

- These portions **do not determine any speed adjustment factor**; they are abstractions containing undefined constants and are purely qualitative sketches.
- The specification provides **no experimental data, simulation results, or real-world demonstrations.**

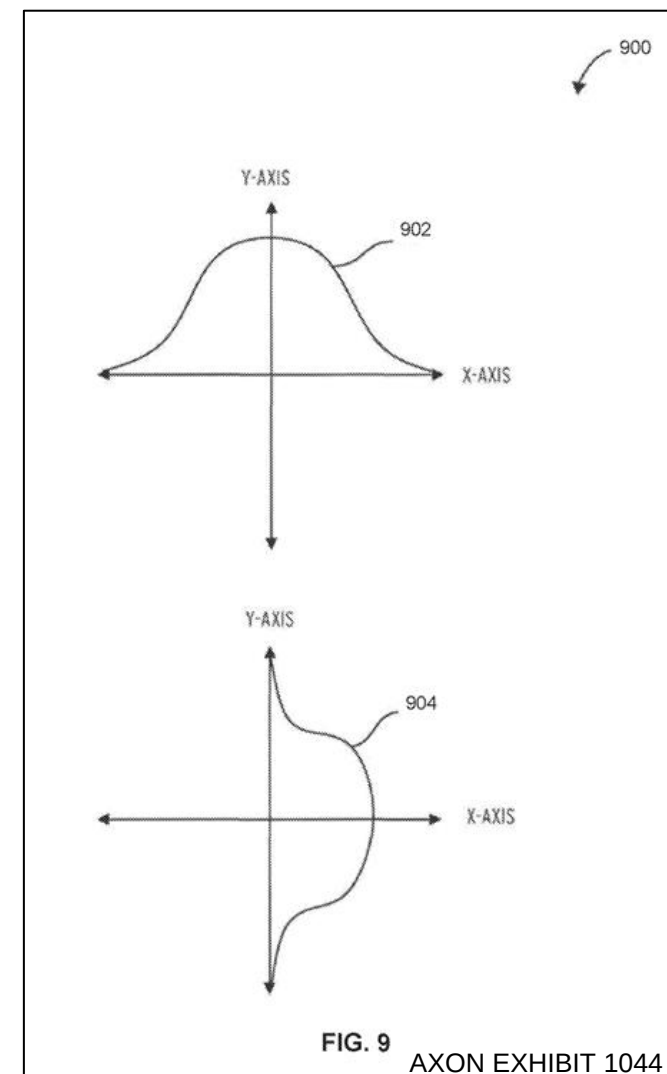
$$\text{speedfactor}(\text{degX}) = a / (1 + bc^{-\text{degX}})$$

Equation 7

$$\text{speedfactor}(\text{degY}) = a / (1 + bc^{-\text{degY}})$$

Equation 8

FIG. 10



PO's Scaler and Sigmoid Arguments are Erroneous

- Adjusting a speed adjustment factor with a scaler **does not explain how the speed adjustment factor was determined in the first place.**
-
- EX2019 at ¶99 and Fig. 10 say nothing about how to select the values needed to **compute a speed adjustment factor** and do **not explain how the Figure 10 equations would be recognized as sigmoids.**

minor directional change is required. In some embodiments, the speed and/or acceleration factor is multiplied by one or more scalar values that change in magnitude based on a directional deviation of the vector from a current direction of movement (e.g., deviation of the target in the image from the center of the image representing the current heading direction of the interceptor aerial vehicle). For example, plotting the scalar value with respect to a directional deviation

$$\text{speedfactor}(\text{deg}X) = a / (1 + bc^{-\text{deg}X})$$

Equation 7

$$\text{speedfactor}(\text{deg}Y) = a / (1 + bc^{-\text{deg}Y})$$

Equation 8

FIG. 10

AXON EXHIBIT 1044

The Specification Provides No Guidance or Examples of How Curves or Constants are Selected

- PO admits curve and constant choice (a, b, c) for determining a *speed adjustment factor* depends on “aircraft attributes”

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

- But the specification provides **no guidance or examples on how curves or constants are selected to account for such attributes.**

Equations 7 and 8 of Figure 10 do not describe how *speed adjustment factors* are determined

- The constants (a, b, c) of equations 7 and 8 are undefined by the specification—all we know is that they “**may be the same value or they may be different values**” and “**may differ**” between equations 7 and 8.
 - EX2019 at ¶106

component of speed factor (e.g., either Equation 7 or Equation 8). The constants a, b, and c depicted in Equations 7 and 8 may be the same value or they may be different values. That is, each constant for speed factor with respect to degX may be different, and the constant may differ

- **That is not guidance but an unknown choice.**

$$\text{speedfactor}(\text{degX}) = a / (1 + bc^{-\text{degX}})$$

Equation 7

$$\text{speedfactor}(\text{degY}) = a / (1 + bc^{-\text{degY}})$$

Equation 8

FIG. 10

AXON EXHIBIT 1044

Specific Curves and Constants Would Help a POSITA

- PO says that “[s]pecific curves and equation constant values are not provided” in the specification as they would not be helpful

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

- The missing specific example curves and constants **would help guide a POSITA if they explained (or even provided a single example of) how the constants were chosen in relation to the “attributes (e.g., size, weight, top-speed) of a UAV using them.”**

PO's Expert says Specific Constants “Vary Substantially” From Aircraft to Aircraft

- EX2036, ¶122:

airspace of an airport. On the basis of a selected curve shape, selecting a particular curve, or choosing the specific constants of the equation used to compute the speed adjustment factor is an optimization problem that would vary substantially from RAV to RAV and from one usage scenario to another. As such, any specific curves and/or equation constant values provided in the specification would generally not be applicable or even meaningful to RAVs at large.

PO's Expert says Constant Selection Depends on “Specifics” of the Aircraft and its Operating Environment

- EX2036, ¶123:

123. On the other hand, such curve and equation constants selection can be readily accomplished when the specifics about the RAV (e.g., its size, weight, shape, maximum speed, maximum altitude, etc.) and specifics about the environment in which the RAV would operate, e.g., the type of GPU, the nature of the terrain (e.g., mountainous, wooded, urban, etc.) are known and taken into account. The use of this information in choosing specific curves / constant values would be highly beneficial, and may even be invaluable. This would involve only a

PO and the Specification Never Address How the Constants (a, b, c) of Equations 7 and 8 Are Selected to Account for Aircraft Parameters

- PO's expert says the constants (a, b, c) depend on several parameters and are "drone specific"
 - EX1041, 36:15-37:14.

15	Q. Are A, B and C in equations 7 and 8
16	constants?
17	A. Are selected in general or can be part of
18	a lookup table or something which is associated.
19	There is a whole set of things associated with the
20	drone mechanics and the dynamical and kinematical
21	models that may tell you the proper selection of A
22	and B.

5	Q. Would a POSITA need to use all three
6	constants, A, B and C, when determining a speed
7	adjustment factor?
8	A. They can use all of them or they can have
9	fixed some of them and then play -- depending -- it
10	depends if they know the mass and the distribution
11	of the mass and the kinematic and dynamic model of
12	the drone.
13	It's drone specific. Let's put it this
14	way.

- PO and the specification **do not say how the constants would be selected to account for such parameters or a specific drone.**

No Direction or Guidance, and No Working Examples

- The **specification is not enabling as it lacks:**
- (1) **example constants or curves** demonstrating how they are chosen in relation to PO's identified aircraft attributes, as well as
- (2) any guidance on how the curves and constants would be selected so they account for these attributes.

Quantity of Experimentation is **Enormous**

- A POSITA would have been forced to **experiment, without any guidance, across:**
 - 1) **the entire space of possible functions** relating directional deviation to a speed adjustment factor,
 - 2) parameter values (including the **undefined constants a, b, and c**), and
 - 3) saturation strategies (e.g., **maximum limit**)

Quantity of Experimentation is **Enormous**

- An **enormous amount of experimentation** is required to determine the constants a , b , and c and, in turn, *determine a speed adjustment factor*.
- PO's statement that experimentation is "not high" and "routine" due to "conventional mechanics of UAV flight" **does not address any of the deficiencies raised by Petitioners and is thus unresponsive**.

Substitute Claims 36 and 37 require *robustness, compute cost, and/or refresh rate* (elements [36.d], [37.e2])

[[19]]36.[pre] A reference aerial vehicle, comprising:

[36.a] an image sensor configured to capture an image;

[36.b1] a processor configured to: detect at the reference aerial vehicle a target in the image; and

[36.b2] determine at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the image; and

[36.c] a flight controller configured to perform a flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein the flight controller is configured to perform the flight control operation including by being configured to determine a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[[.]].

[36.d] 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, 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, the first robustness and the first compute cost being greater, respectively, than the second robustness and the second compute cost.

Substitute Claims 36 and 37 require *robustness, compute cost, and/or refresh rate* (elements [36.d], [37.e2])

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.].

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

A POSITA cannot practice SCs 36-37 without undue experimentation due to the recited *robustness, compute cost, and/or refresh rate*

- The *Wands* factors demonstrate that SCs 36 and 37 are not enabled due to the claimed requirements of *robustness, compute cost, and/or refresh rate*
 - *In re Wands*, 858 F.2d 731, 737 (Fed. Cir. 1988)

No Direction or Guidance: *compute cost*

- The specification provides **no instruction on what** a *compute cost* is or **how to quantify it**.

- EX2019 at ¶142

[00142] Costs on all data inputs for the processing schemes can be pre-determined, estimated, or calculated. For example, a type of algorithm that operates on visual "features" can be dependent on the number of features in the video frame, and its cost estimated based on the number of features. As the number of features increases the cost can increase dramatically.

- **How or in what units is cost estimated?**

- CPU cycles?
- Milliseconds?
- Floating point operations?
- Memory consumption?

No Direction or Guidance: *compute cost*

- “A negative relation between robustness of an algorithm and the cost” teaches nothing about how to **quantify** *compute cost*.
 - EX2019 at ¶109

[00109] On a fixed compute budget there is a negative relation between robustness of an algorithm and the cost and/or latency of the algorithm per spacio-temporal frame. Tight restrictions on available compute cycles limit the responsiveness of the system, especially on autonomous or semi-autonomous drones. By combining multiple algorithms in a way that

No Direction or Guidance: *compute cost*

- The specification describes **assigning processing schemes based on “determined” cost and sorting processing schemes into high, medium, and low cost**
 - No guidance on how to determine cost or what separates high, medium, and low.
 - EX2019 at ¶¶144-145

[00144] The example implementation can statically assign each processing scheme in a set of processing schemes to a group based on each processing scheme's determined cost and/or robustness estimations on the selected input group.

- (i) High cost (low refresh rate), high robustness algorithm (e.g., processing schemes that produce an object location estimation independent of historical information);
- (ii) Medium cost, medium robustness algorithms (e.g., processing schemes that use a last known location of the object location estimation and/or use a fast validation method to validate the estimation); or
- (iii) Low cost (high refresh rate), low robustness algorithms (e.g., processing schemes that use a known location of the object location estimation and or a fast validation method to validate the estimation).

No Direction or Guidance: *compute cost*

- “[A]s the number of features increases the cost can increase dramatically” provides a **relative relationship without guiding how *compute cost* is determined.**
 - EX2019, ¶142.

[00142] Costs on all data inputs for the processing schemes can be pre-determined, estimated, or calculated. For example, a type of algorithm that operates on visual "features" can be dependent on the number of features in the video frame, and its cost estimated based on the number of features. As the number of features increases the cost can increase dramatically.

No Direction or Guidance: *robustness*

- The specification **fails to define** the inputs or sample conditions relevant to *robustness*, or **what metric is used to measure robustness**
 - EX2019 at ¶143

[00143] According to other examples, algorithms may differ in their effectiveness based on the type of input received. Robustness of each algorithm (e.g., processing scheme) can be compared by measuring a population of inputs that are selected as representative of sample conditions (e.g., real-life data sets) and prioritized by application requirements.

No Direction or Guidance: *robustness*

- The specification describes algorithms having “**high,**” “**average,**” or “**low**” **robustness**, or being “**brittle,**” yet provides **no measurement methodology or baseline against which these qualitative labels are assessed.**
 - EX2019 at ¶¶110, 145-147, 150

maintains lock on the target. Applying different tracking algorithms and DNN based detections of a target in the video frame provides **robustness at a high compute cost**. A reduced resource background tracker may incrementally predict the location of a target in the frame with low compute cost and **average robustness**. This optimization enables the coexistent application of advanced machine vision algorithms in addition specialized lower cost algorithms.

optimize local computing resources. For example, group (iii) algorithms may operate like group (ii) with a similar validation method but have secondary factors such as faster and **more brittle performance**.

- (i) **High cost (low refresh rate), high robustness algorithm** (e.g., processing schemes that produce an object location estimation independent of historical information);
- (ii) **Medium cost, medium robustness algorithms** (e.g., processing schemes that use a last known location of the object location estimation and/or use a fast validation method to validate the estimation); or
- (iii) **Low cost (high refresh rate), low robustness algorithms** (e.g., processing schemes that use a known location of the object location estimation and or a fast validation method to validate the estimation).

- These are **subjective opinions** and **not reproducible measurements of robustness** a POSITA can apply.

No Direction or Guidance: *refresh rate*

- [R]efresh rate appears in the specification **as a parenthetical aside to “cost”**
 - EX2019 at ¶¶145-146, 150

(i) High cost (low refresh rate), high robustness algorithm (e.g., processing schemes that produce an object location estimation independent of historical information);

(ii) Medium cost, medium robustness algorithms (e.g., processing schemes that use a last known location of the object location estimation and/or use a fast validation method to validate the estimation); or

(iii) Low cost (high refresh rate), low robustness algorithms (e.g., processing schemes that use a known location of the object location estimation and or a fast validation method to validate the estimation).

(i) High cost (low refresh rate), high robustness algorithm can select a cheaper processing scheme from the group of (ii) Medium cost, medium robustness algorithms. Medium cost algorithms can be run from group (ii) in higher refresh rate, while monitoring the confidence level of the result.

[00150] Processing scheme examples for a group (i) High cost (low refresh rate) - high robustness can include modified tiny You only look once (YOLO) Convolutional Neural Networks (CNN) on 448 pixels input tiles in the frame; a modified SSD (Single Shot Detection) CNN on 300 pixels multi-scale classification; a modified Faster R-CNN (Region Proposal Networks), segmentation analysis of the frame + classifier for each candidate, etc.

- The specification **never defines the term, discloses its units, or says how to measure it.**
- A POSITA learns direction—cheaper have a higher rate—but **nothing about how to determine or quantify refresh rate.**

PO's Arguments Demonstrate a Lack of Guidance

- Representative neural networks and the **relative relationship** between *robustness*, *compute cost*, and *refresh rate* does **not provide guidance or direction** with respect to the claims
 - The specification lacks **any objective measurement or metric on how to determine *robustness*, *compute cost*, or *refresh rate* for the claimed neural networks** and compare them—how to know a *first neural network* has a *first robustness*, *compute cost*, or *refresh rate* that is *greater* than a *second robustness*, *compute cost*, or *refresh rate* of a *second neural network* as claimed by SC 36 or SC 37.

No Working Examples

- The specification provides **zero working examples** of how to determine *robustness*, *compute cost*, and *refresh rate*.
- All that is disclosed is the **relative relationship of high, low, and medium/average**, but this is insufficient guidance for a POSITA
- Mentioning specific algorithms does not teach how to determine the *compute cost*, *robustness*, or *refresh rate* of any of them, metrics for these terms, or what the "high" or "low" labels mean.

Quantity of Experimentation is Substantial

- A POSITA would need to **independently devise a metric and measurement approach** for *compute cost, robustness, and refresh rate*.
 - This is an **entire research program** involving **three undefined measurement problems requiring independent resolutions**.

Substitute Claim 37 requires a *first threshold* and *second threshold*, defining a *range*, set equal to each other (element [37.e3])

[[20]]37.[pre] A computer program product for performing a flight control operation of a reference aerial vehicle, the computer program product being embodied in a non-transitory computer readable storage medium housed in a reference aerial vehicle and comprising computer instructions for:

[37.a] receiving a current image captured by an image sensor of the reference aerial vehicle;

[37.b] detecting at the reference aerial vehicle a target in the current image including by applying a machine learning model to the current image to identify a portion of the current image that includes the target;

[37.c] determining at the reference aerial vehicle a three-dimensional relative location of the target with respect to the reference aerial vehicle based on the current image including by determining a distance to the target based at least in part on a size of the target detected within the current image; and

[37.d] performing at the reference aerial vehicle the flight control operation based on the three-dimensional relative location of the target with respect to the reference aerial vehicle, wherein performing the flight control operation includes determining a speed adjustment factor based on a magnitude of deviation of a direction of the three-dimensional relative location with respect to a current flight direction of the reference aerial vehicle[.],

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

[37.e2] wherein the first neural network has a first robustness and a first refresh rate, and the second neural network has a second robustness and a second refresh rate, the first robustness being greater than the second robustness and the first refresh rate being less than the second refresh rate, and

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the

confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

A POSITA cannot practice SCs 36-37 without undue experimentation due to the recited a *first threshold* and *second threshold*, defining a *range*, set equal to each other

- The *Wands* factors demonstrate that SCs 36 and 37 are not enabled due to the claimed requirements a *first threshold* and *second threshold*, defining a *range*, set equal to each other
 - *In re Wands*, 858 F.2d 731, 737 (Fed. Cir. 1988)
- SC 37 is further not enabled as **no guidance or examples** of a first threshold and second threshold, defining a range, set equal.

A POSITA cannot practice SCs 36-37 without undue experimentation due to the recited *a first threshold and second threshold*, defining a *range*, set equal to each other

- The specification provides **no guidance or examples** of the **specific range** defined by **two separate thresholds** that **can be equal**.
 - EX2019 at ¶¶146, 147

[00146] In an example implementation, a set of processing schemes (e.g., algorithms) are examined from group to group, and the process cycles through the processing schemes to produce a detection of an object. According to the example implementations, if the confidence number is higher than an activation number, an action is performed to stop or change a running group (i) and select or switch to group (ii). For example, a processing scheme from the group of

[00147] According to an example implementation, a voting system is provided that fuses estimations from high confidence results, and validates the result with an independent validation method. If the confidence is below low threshold, falls outside of a range, or the validation method fails, group (i) processing is performed. If the confidence is determined to be high, then group (iii) algorithms can be applied to optimize resources. Different Groups of algorithms (e.g.,

PO Does Not Confront Petitioners' Arguments

- PO makes irrelevant and unsupported arguments regarding thermostats, says confidence levels “inform threshold selection,” and otherwise relies on analysis of other terms.
- Petitioners' **enablement argument is thus un rebutted.**

Outline of Arguments: IPR2025-00629 ('711 Patent)

- I. Overview of the '711 Patent and Procedural History
- II. Obviousness of Original Claim 12
- III. Dispute Overview – Original Claim 12
- IV. Claim Construction and Obviousness of Original Claim 12 as Construed
- V. Dispute Overview – Motion to Amend
- VI. Substitute Claims 24, 25, and 37 Lack Written Description
- VII. Substitute Claims 21-37 are Not Enabled
- VIII. Substitute Claims 21-37 are Indefinite**
- IX. Substitute Claims 21-37 are Obvious

SCs 21-37 are Indefinite (SC 21: [21.d]; SC 36: [36.c], [36.d]; SC 37: [37.d], [37.e2])

- SCs 21, 36, and 37 recite *speed adjustment factor, robustness, compute cost, and/or refresh rate*.
 - It is **unclear from the intrinsic record** what the terms mean and a POSITA **would not have known their boundaries**.

PO does not address Petitioner's argument ([21.d])

- The boundaries of how a *speed adjustment factor* is *determined* is unclear
- PO argues "[t]he meaning of SAF, a vector element value used to adjust speed, would have been clear to a POSITA," but this is unresponsive.

PO does not explain the boundaries of *robustness*, *compute cost*, and *refresh rate*, or how these terms are determined or measured ([36.c], [36.d]; SC 37: [37.d], [37.e2])

- PO's failure precludes any way of knowing their claimed **comparative relationship** in which some are "greater" or "less" than others.
- PO's expert acknowledged there are **several different ways** in which *robustness*, *compute cost*, and *refresh rate* may be measured.
 - EX1041, 40:2-15

Q. How does one measure robustness?

A. I just mentioned two metrics, precision and recall.

Q. What is the objective way to measure robustness?

A. We want to see how accurate our method is.

Q. Is there an objective way to determine how accurate the method is?

A. There are many metrics that can be used, depending on your particular interest.

PO does not explain the boundaries of *robustness*, *compute cost*, and *refresh rate*, or how these terms are determined or measured

– EX2036, ¶133:

can be expressed using many parameters, individually, or in combination. For example, compute cost can simply be the total number of computations, or the number of floating-point computations. It can also be the size of hardware and/or software used for the computation, power consumed by the computation, and time taken by the computation. The '711 patent associates cost with robustness and

PO's "Proportional" Argument is Wrong

- PO wrongly concludes a "POSITA would have known how to measure" *robustness*, *compute cost*, and *refresh rate* because cost is allegedly proportional to robustness and refresh rate
 - But even if true, the specification **does not say how such a cost is classified as being a high, medium, or low**; the specification provides **no guideposts or boundaries**
 - There would thus be **no way to know whether the algorithm's *robustness* and *refresh rate* is high, medium, or low** based on **cost**

PO’s “Grouping” Argument is Undercut by PO’s Expert

- PO argues that the specification’s groupings of neural networks “grouped” as high/low/medium *robustness*, *compute cost*, and *refresh rate* shows how networks are related with respect to these parameters.
- But PO’s expert admits different algorithm versions in a **single group** (e.g., “tiny YOLO” v1, v2) can have **differing compute costs, breaking the “relative” relationship** relied on by PO.
 - EX1041, 49:10-12, 51:11-15, 53:4-6, 54:19-21

10Q. Can two different Tiny-YOLOs have

11different compute costs?

12A. No.

11Q. Your statement in paragraph 133 that the

12compute costs can be the size of hardware and/or

13software used for the computation, does that refer

14to the model size of the YOLO?

15A. Yes.

TABLE 7. Performance of BFLOP/s and model size.					
	YOLO-V1	YOLO-V2	Tiny-YOLO-V2	Tiny-YOLO-V3	Tinier-YOLO
Size	1.1G	202.7MB	63.4MB	34.9MB	8.9MB
BFLOP/s	40.19	34.9	6.97	5.474	2.563

4Q. Tiny-YOLO-V2 has a size of 63.4 megabytes

5and Tiny-YOLO-V3 has a size of 34.9 megabytes?

6A. That's true.

19Q. The different versions of Tiny-YOLOs can

20have different compute costs?

21A. Yes.

SCs 36-37 are Indefinite ([36.c], [36.d]; [37.d], [37.e2])

- *Robustness, compute cost, and refresh rate* have a comparative relationship where some are “greater” or “less” than others.
 - Without knowing their boundaries/how they are determined or measured, **there is no way of comparing them to determine such a relationship.**

SC 37 is indefinite: [37.e1], [37.e2], [37.e3], [37.e4]

- SC 37 requires **neural network selection for a current image** based on a confidence level **for a detection of the target in the current image**.

image further comprises making a selection, from between the first and the second neural networks, of only one of the first and the second neural networks, based on a confidence level for a detection of the target in the current image;

immediately preceding image, making the selection comprises: (i) selecting and applying the first neural network to the current image when the confidence level is below a first threshold of a range defined by the first threshold and a second threshold greater than or equal to the first threshold, and otherwise (ii) selecting and applying the second neural network to the current image, and

immediately preceding image, making the selection comprises: (i) selecting and applying the second neural network to the current image when the confidence level is above the second threshold, and otherwise (ii) selecting and applying the first neural network to the current image.

- 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.

SC 37 is indefinite: [37.e1], [37.e2], [37.e3], [37.e4]

- The specification describes that the confidence level is the **output of applying a neural network to an image** and indicates the “quality” of prediction in that image
 - EX2019 at ¶141

frames of one or more video data streams. The processing schemes produce a prediction of objects within the video frame, as well as a confidence number that is a measure of quality for that prediction. The confidence number can be normalized to a canonical range (0-1) and used to compare the confidence of each different processing scheme to track an item of interest.

- Within that specification context, the confidence level thus **measures confidence for a prediction that has occurred and is not a confidence for a prediction that has not yet occurred.**

PO's Argument Changes the Meaning of *Confidence Level for a Detection of the Target in the Current Image*

- PO says the limitation means a **“confidence level obtained from the detection in the immediately preceding image [that] is used to select an NN for application to the current image.”**
 - PO's argument is **unsupported**; the claim and specification do **not** say this
 - By its own terms, the claim relates to **detection in the current image** but if **no neural network has yet been applied to the current image, a confidence level for such detection cannot exist**, rendering the claim indefinite.

SC 37 is indefinite: [37.e1], [37.e2], [37.e3], [37.e4]

- SC 37 conditions on which neural was applied to an *immediately preceding image*.

[37.e1] wherein a first neural network or a second neural network was applied to an immediately preceding image, and the detecting of the target in the current image further comprises making a selection, from between the first and the

[37.e3] when the second neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and

[37.e4] when the first neural network was selected and applied to the immediately preceding image, making the selection comprises: (i) selecting and

- The specification never describes such an image-by-image processing technique.
- A POSITA **cannot determine what *immediately preceding image*** means.
 - image one time-step before?
 - the last image to which any neural network was applied?
 - the last image processed by the same neural network pipeline?

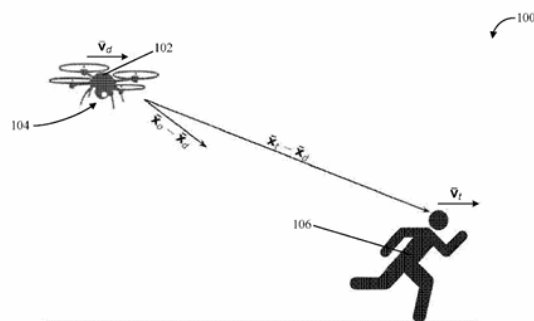
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- IX. Substitute Claims 21-37 are Obvious**

Obviousness of Substitute Claims 21-36

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”)

(19) United States	
(12) Patent Application Publication	(110) Pub. No.: US 2017/0160751 A1
Pierce et al.	(43) Pub. Date: Jun. 8, 2017
(54) SYSTEM AND METHOD FOR CONTROLLING DRONE MOVEMENT FOR OBJECT TRACKING USING ESTIMATED RELATIVE DISTANCES AND DRONE SENSOR INPUTS	Related U.S. Application Data (60) Provisional application No. 62/263,510, filed on Dec. 4, 2015.
(71) Applicant: Pilot AI Labs, Inc. , Sunnyvale, CA (US)	Publication Classification (51) Int. Cl. <i>G05D 1/10</i> (2006.01) <i>B64C 39/02</i> (2006.01) (52) U.S. Cl. <i>CPC</i> <i>G05D 1/101</i> (2013.01); <i>B64C 39/02A</i> (2013.01); <i>B64C 2201/127</i> (2013.01)
(72) Inventors: Brian Pierce , Santa Clara, CA (US); Elliot English , Stanford, CA (US); Ankit Kumar , San Diego, CA (US); Jonathan Su , San Jose, CA (US)	ABSTRACT (57) According to various embodiments, a method for controlling drone movement for object tracking is provided. The method comprises: receiving a position and a velocity of a target; receiving sensor input from a drone; determining an angular velocity and a linear velocity for the drone; and controlling movement of the drone to track the target using the determined angular velocity and linear velocity.
(73) Assignee: Pilot AI Labs, Inc. , Sunnyvale, CA (US)	
(21) Appl. No.: 15/569,733	
(22) Filed: Dec. 5, 2016	



Pierce describes “controlling drone movement for object tracking.” For instance, Pierce explains that a “drone 102 includes a camera 104 to record images as input,” and those images are used by a “drone control algorithm” so that the drone can track or follow a moving target.

(19) **United States**

(54) 3-D MODEL BASED METHOD FOR
DETECTING AND CLASSIFYING VEHICLES
IN AERIAL IMAGERY

(22) Filed: **Oct. 28, 2010**

Related U.S. Application Data

(60) Provisional application No. 61/256,113, filed on Oct. 29, 2009.

US 20120106800A1

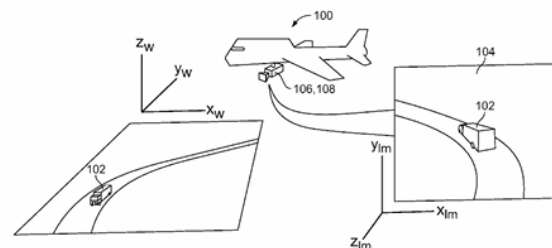
Publication Classification

(51) **Int. Cl.** *G06K 9/68* (2006.01)

(52) **U.S. Cl.** *382/104*

(57) ABSTRACT

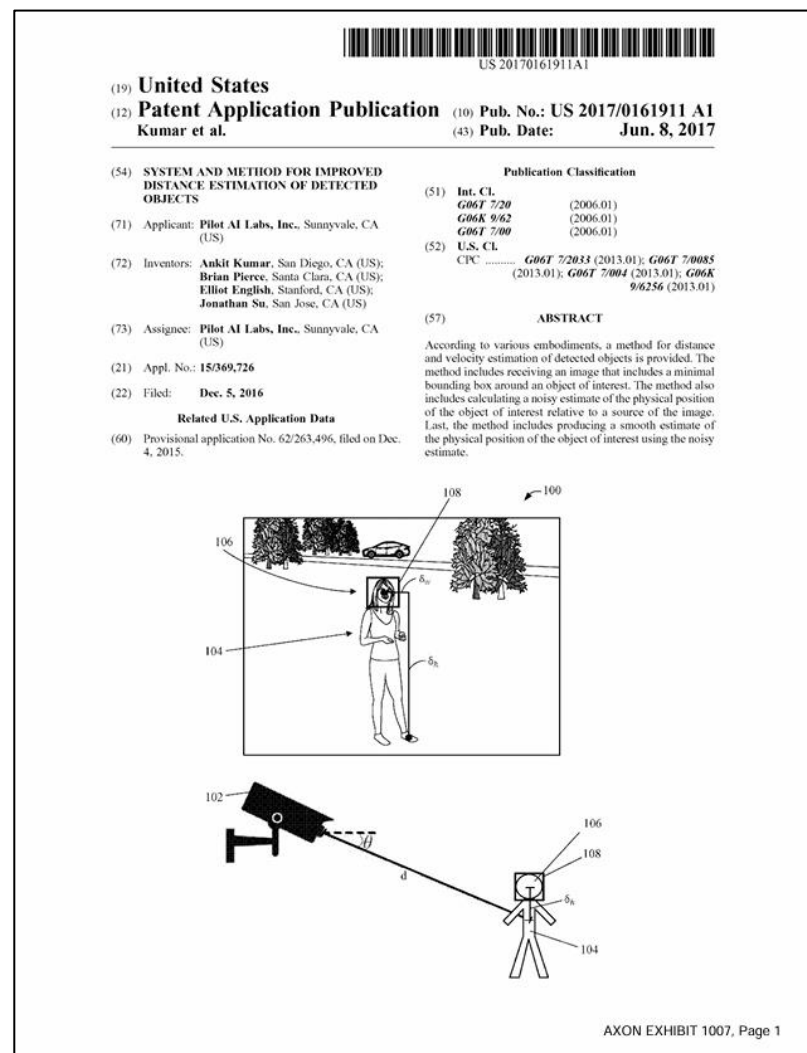
A computer implemented method for determining a vehicle type of a vehicle detected in an image is disclosed. An image having a detected vehicle is received. A number of vehicle models having salient feature points is projected on the detected vehicle. A first set of features derived from each of the salient feature locations of the vehicle models is compared to a second set of features derived from corresponding salient feature locations of the detected vehicle to form a set of positive match scores (*p*-scores) and a set of negative match scores (*n*-scores). The detected vehicle is classified as one of the vehicle models models based at least in part on the set of *n*-scores and the set of *p*-scores.



AXON EXHIBIT 1021, Page 1

Khan teaches a computer vision system used by UAVs that detects vehicle target objects in captured images and classifies them by "vehicle model type."

Overview of Kumar (EX1007)



Kumar is directed to a "method for distance and velocity estimation of detected objects." Kumar's system obtains an image and detects an "object of interest" within the image by, for example, using a neural network. A "bounding box" is produced around the detected object of interest within the image.

(12) United States Patent
Ning et al.

(10) Patent No.: US 9,760,806 B1
(45) Date of Patent: Sep. 12, 2017

(54) METHOD AND SYSTEM FOR VISION-CENTRIC DEEP-LEARNING-BASED ROAD SITUATION ANALYSIS

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(73) Assignee: TCL RESEARCH AMERICA INC.,
San Jose, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 21 days.

(21) Appl. No.: 15/152,094

(22) Filed: May 11, 2016

(51) Int. Cl.
G06K 9/00 (2006.01)
G06K 9/66 (2006.01)
G06T 7/00 (2017.01)
G06T 7/20 (2017.01)
B60W 50/14 (2012.01)

(52) U.S. Cl.
CPC G06K 9/66 (2013.01); B60W 50/14 (2013.01); G06K 9/00798 (2013.01); G06K 9/00805 (2013.01); G06K 9/00818 (2013.01); G06K 9/00825 (2013.01); G06T 7/0001 (2013.01); G06T 7/2013 (2013.01); G06T 7/2093 (2013.01); B60W 2050/146 (2013.01); G06T 2207/20001 (2013.01); G06T 2207/20236 (2013.01); G06T 2207/20241 (2013.01); G06T 2207/20261 (2013.01)

(58) Field of Classification Search
CPC .. G06K 9/66; G06K 9/00805; G06K 9/00798; G06K 9/00818; G06K 9/00825; G06T

7/0001; G06T 7/2033; G06T 2207/20226; G06T 2207/20261; G06T 2207/20241; G06T 2207/20081; B60W 2050/146; B60W 50/14

USPC 382/103, 104, 106, 107
See application file for complete search history.

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(Continued)

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ABSTRACT

In accordance with various embodiments of the disclosed subject matter, a method and a system for vision-centric deep-learning-based road situation analysis are provided. The method can include: receiving real-time traffic environment visual input from a camera; determining, using a ROI-O engine, at least one initial region of interest from the real-time traffic environment visual input by using a CNN training method; verifying the at least one initial region of interest to determine if a detected object in the at least one initial region of interest is a candidate object to be tracked; using LSTMs to track the detected object based on the real-time traffic environment visual input, and predicting a future status of the detected object by using the CNN training method; and determining if a warning signal is to be presented to a driver of a vehicle based on the predicted future status of the detected object.

20 Claims, 6 Drawing Sheets

FIG. 1

FIG. 2

FIG. 3

FIG. 4

AXON EXHIBIT 1034, Page 1

Axon Enterprises, Inc., Dedrone Holdings, Inc., and Skydio, Inc. v. Airspace Systems, Inc., IPR2025-00629

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The Opposition Demonstrated that a POSITA would have Combined the Cited References

- **Substitute Claim 21**

- 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 neural networks (NNs) for object detection and tracking**.
 - 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.
 - 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**.
- **Predictable Result:** Beard's UAV performing on-board object identification and tracking using NNs.

PO Wrongly Argues that Pierce Does Not Teach a Drone Implementing On-Board Neural Networks

- Pierce teaches a **drone** having an **on-board object tracking module** that implements **neural networks**
 - EX1005, ¶¶0042, 0045

one or more embodiments. In various embodiments, drone system 600 may be drone 102 previously described with reference to FIG. 1. However, in other embodiments, various

[0045] Drone system 600 may further include camera 605, global position system 607, velocity detector 613, object tracking module 615, and laser tracking module 617. In some embodiments, camera 605 may be camera 104 which may be used to capture a series of images of the surrounding area of drone 102. The series of images may include an object, such as a moving target. In some embodiments, the captured images may be input into various neural networks and/or computational systems, which may be implemented by object tracking module 615. For example, object tracking module may be configured to process a neural network detection system, a tracking system, and/or a position estimation system, as previously described in the various patent applications, incorporated by reference herein, to identify and track the moving target, and thereby estimate its position and velocity from drone 102. Such position and velocity of the moving target may be utilized by various steps in method 400, such as step 401.

- PO's reference to "separate components" is for "other embodiments" in Pierce and irrelevant.

PO's "Three Step Reconfiguration" Argument is Wrong

- The combinations rely on Pierce's teachings of a drone having an on-board object tracking module implementing NNs for object detection and tracking.
- For GNDs 23-27 (Beard-based grounds), the predictable results would have been **Beard's UAV performing on-board object identification and tracking using NNs.**
- PO's "three-step reconfiguration" and "inoperable" arguments ignore the combinations and Pierce's clear on-board disclosure.

PO's "Three Step Reconfiguration" Argument is Wrong

- The claims and specification contradict PO.
 - SCs 21 and 36 recite a **non-GPU processor with no "three-step reconfiguration."**
- PO says a DSP is insufficient to implement a NN, but its own specification discloses using a DSP without "reconfiguration."
 - EX2019, ¶¶134-135, 159

these components. The drone operation logic 2000 will typically comprise memory 2008 which may be utilized by the main controller 2004 and other components (e.g., the DSP 2026 and/or the GPU 2022) to read and write instructions (commands) and data (operands for the instructions).

[00159] Several portions of the subject matter described herein may be implemented via Application Specific Integrated Circuits (ASICs), Field Programmable Gate Arrays (FPGAs), digital signal processors (DSPs), or other integrated formats. However, those skilled in the art

The image processing 2018 may further utilize a navigation board 2002 and/or DSP 2026 toward these ends. Images and video stored in the memory 2008 may also be read and processed by the main controller 2004, DSP 2026, and/or the GPU 2022. The drone operation logic 2000 may

- Grounds 28-35 utilize Pierce as the primary reference, meaning **PO's arguments are irrelevant for those Grounds.**

The Opposition Demonstrated that a POSITA would have Combined the Cited References

- **Substitute Claim 21**

- **Khan** teaches to the combination real-time classification of vehicle model types in aerial imagery.
 - Khan's computer on-board a UAV detects and classifies vehicle model types in images captured by image capturing devices of the UAV.
 - 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.
 - These detected features are compared to 3D vehicle model features to determine a classification of vehicle type such as sedan or SUV.
 - Classification is performed by a "linear classifier" such as a "support vector machine classifier (SVM)" machine learning model.
- **Kumar** discloses "bounding boxes" around objects of interest in an image are output by a neural network, which is a known type of machine learning model.

The BLPKK Combination Teaches Element [21.b]

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...

- 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
- This is performed to "identify potential target objects" 112a-d "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

The BLPKK Combination Teaches Element [21.b]

to identify a bounding box outlining a portion of the image that includes detected features of the target, and to identify a classification of the detected target

- 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*).
- 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*.)

The BLPKK Combination Teaches Element [21.b]

- 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*).
- 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*).

PO's Arguments Regarding Khan and Kumar are Erroneous

- PO's arguments regarding the BLPKK (GND 23) and PKKB (GND 28) combinations misstate the combinations, rely on bodily incorporation, and are unsupported attorney argument.
- The combinations involve **Khan's teachings of classification by model type involving "shape and appearance features"** and **Kumar's teachings to use bounding boxes**, and the Opposition demonstrated how the combinations meet the SCs.

The Opposition Demonstrated that a POSITA would have Combined the Cited References

- **Substitute Claim 36**

- A POSITA would have been motivated to combine Beard, Laufer, and Pierce/Pierce, Kumar, Ning, and Beard with Ning's teachings of performing object detection using a "You Only Look Once" (YOLO) and object tracking using an LSTM NN.
 - Ning's YOLO and LSTM NNs provide "real time" object detection and tracking that is "efficient yet accurate," enhancing Beard's and Pierce's object detection and tracking.
 - 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.
 - Ning's system "**can be amounted on any suitable vehicle**"— thus compatible with the cited references.
- **Predictable result:** On-board UAV/Drone detection of a target 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.

The Ning-Based Combinations Teach Element [36.d]

- As combined, the Beard/Pierce UAV/Drone performs on-board flight control, in which an object in an image is detected by applying Ning's YOLO NN and determines the object's relative location using Ning's LSTM NN.
- 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*)

PO's Substitute 36 Arguments are Unsupported and Erroneous

- PO asserts “the cost of YOLO is less than LSTM’s” and cites to 70 pages of its expert declaration as support.
 - This is improper incorporation by reference. 37 C.F.R. § 42.24(a); *3M Company v. Evergreen Adhesives, Inc.*, 860 Fed. Appx. 724, 725-28 (Fed. Cir. 2021).
 - Regardless, **PO never shows how the YOLO has a lower cost**, and it does not as the **YOLO and LSTM are separate NNs in which the YOLO’s cost is higher**, where the LSTM performs incremental prediction as claimed as it determines tracking parameters that predicts and tracks an object’s location in an image frame over time.

Backup Slides

No Written-Description Support Exists for Substitute Claim 24

- EX2019 at ¶¶94-95 describes **classifying** by “type” or “model”
 - **NOT identifying “type” based on “classification.”**

bounding box outlines the minimum sized box that includes detected features of the target) and/or a classification of the detected target (e.g., type, model, class, manufacturer, size, etc. of the detected target).

using the target size within the image as a proxy for relative distance. In some embodiments, the machine learning model has been trained using different examples of types of aerial vehicles (e.g., different models, types, manufacturers, sizes, etc.) to be able to classify and identify the specific type of the detected target aerial vehicle and a corresponding size profile corresponding to the specific type. If a specific type of the target cannot be reliably determined, a default size

PO Wrongly Argues Substitute Claim 24 Requires “Two Different Kinds of Classifications” to Manufacture Support

- SC 24 recites **model type identification *based on the classification***
- SC 21 provides antecedent basis, reciting to ***identify a classification***.
 - SC 21 classification occurs first
 - SC 24 identifies model type based on SC 21's classification
 - **This concept is unsupported**

- EX2019 at ¶94 discloses a lone classification.

bounding box outlines the minimum sized box that includes detected features of the target) and/or a classification of the detected target (e.g., type, model, class, manufacturer, size, etc. of the detected target).

- Combining with EX2019 at ¶150 impermissibly requires obviousness.

and a set of negative examples. For example, the set of positive examples may include a plurality of feature vectors that indicate the detected object is a UAV. The set of negative

No Written-Description Support Exists for Substitute Claim 25

- EX2019 at ¶97 describes a “distance value,” “distance”-based factor, or “speed”-based factor, **not first and second speed adjustment factors**.

components are utilized to determine the vector. In some embodiments, the vector is at least in part defined using a distance and/or speed value. For example, the distance value determined in 502 is mapped to a desired speed of travel to reach the target (e.g., greater speed desired for further distance and slower speed desired for shorter distance to allow more time for direction

correction) and the length of the vector is based on the determined distance and/or speed. In one example, the vector is defined by the azimuth angle, the altitude angle, and a factor based on an associated distance or speed. In some embodiments, the vector is defined by three-dimensional

PO Points to Unrelated “Desired Speed”

- The distance and speed values referred to by PO relate to **desired speed** and **not speed adjustment**, let alone a *second speed adjustment factor* based on *distance*
 - EX2019, ¶¶90, 91, 97

the target. For example, a flight direction and/or speed of an interceptor aerial vehicle are automatically and autonomously adjusted based on a location and size of the target within the captured image (e.g., adjust direction to center the target within subsequently captured images).

of the three-dimensional vector. For example, the three-dimensional vector specifies directional and speed/acceleration changes to be performed by the interceptor aerial vehicle to direct the flight path of the interceptor aerial vehicle at a desired rate of change towards the target aerial vehicle.

specified by an azimuth angle and an altitude angle. A distance value to the target and/or desired speed/acceleration may also be specified for the relative location. In some embodiments, the

part defined using a distance and/or speed value. For example, the distance value determined in 502 is mapped to a desired speed of travel to reach the target (e.g., greater speed desired for further distance and slower speed desired for shorter distance to allow more time for direction correction) and the length of the vector is based on the determined distance and/or speed. In one

PO's "Modified and Redefined" Speed Adjustment Factor Argument is Unsupported and Erroneous

- SC 25 requires **flight control operation performance** includes **determining first and second speed adjustment factors**.

reference aerial vehicle, wherein performing the flight control operation includes determining a first speed adjustment factor based on a magnitude of deviation of

[[8]]25. The method of claim [[7]]21 wherein performing the flight control operation includes determining a second speed adjustment factor based on the determined distance to the target.

- PO leaves **unexplained** how these factors "**modified and redefined at different times**" would allow such a ***flight control operation***.
- EX2019, ¶91 and ¶97 do not disclose determining multiple speed adjustment factors for a **flight control operation**.

The Nature of the Alleged Invention Demands More Specificity (SAF)

- SCs 21-37 involve flight control.
- An improperly determined *speed adjustment factor* could conceivably cause the vehicle to overshoot a target, oscillate, or crash.
- The nature of the invention **demands more specificity in the specification**, yet the **specification provides essentially none**.

PO Admits Nature of the Invention is “Complex,” Favoring Petitioners (SAF)

- PO admits nature of the invention is “**complex**,” favoring Petitioners
- PO’s statement that “SAFs is [sic] related to conventional mechanics of UAV flight” is **unsupported, irrelevant, and does not address Petitioner’s argument** that showed invention nature **requires more specificity in the specification**
 - An improperly determined *speed adjustment factor* could be disastrous

State of the Prior Art Demonstrates Lack of Enablement (SAF)

- The specification points to **no prior art teachings** of how to determine a speed adjustment factor from a magnitude of directional deviation.

State of the Prior Art Demonstrates Lack of Enablement (SAF)

- PO acknowledges the prior art “teaches the use” of *speed adjustment factors*
 - PO **does not address** how the specification **lacks relevant guidance** on determining a *speed adjustment factor* based on various variables or UAV attributes, which PO itself admits.

Level of Skill in the Art Demonstrates Lack of Enablement (SAF)

- Even under PO's **elevated POSITA definition** the specification's failures are not cured.
- The specification provides **no methodology** for **determining a speed adjustment factor**.
 - 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.
- **The specification delegates invention to the reader.**

II. LEVEL OF ORDINARY SKILL IN THE ART

At the time of invention of the '711 patent, a POSITA would have had either:

(1)(a) at least a bachelor of science in mechanical engineering, electrical engineering, aerospace engineering, or an equivalent field, or (b) at least four years of experience in any of the above disciplines, and (2)(a) at least a bachelor's degree in computer science, or (b) at least four years of experience in the software industry in the field of artificial intelligence / machine learning. EX2025, § VI, 1044

RM TA at 1

PO Does Not Address Petitioners' Argument (SAF)

- PO asserts, without support, that "'relative skill of those in the art' is high."

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

- PO **does not explain why and does not address Petitioners' reasoning** that even under PO's elevated POSITA definition, the specification's failures are not cured.

Predictability of the Art Demonstrates Lack of Enablement (SAF)

- The **behavior** of a *speed adjustment factor* **depends on various variables unaddressed by the specification:**
 - vehicle dynamics
 - controller responsiveness
 - wind/turbulence
 - tracked target characteristics
 - natural frequencies
- These **unaddressed variables** demonstrate how **experimentation would be undue.**

Breadth of the Claims Demonstrates Lack of Enablement (SAF)

- 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*
- The specification **does not teach how to *determine* such a factor.**

PO Does Not Address Petitioners' Argument (SAF)

- PO generically says claim breadth is “narrow” and irrelevantly points to “ML-NNs” rather than anything regarding a *speed adjustment factor*.

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.

- PO **does not address** Petitioner's argument, rendering it **unrebutted**.

State of the Prior Art Demonstrates Lack of Enablement

- 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

[00150] Processing scheme examples for a group (i) High cost (low refresh rate) - high robustness can include modified tiny You only look once (YOLO) Convolutional Neural Networks (CNN) on 448 pixels input tiles in the frame; a modified SSD (Single Shot Detection) CNN on 300 pixels multi-scale classification; a modified Faster R-CNN (Region Proposal Networks), segmentation analysis of the frame + classifier for each candidate, etc.

a part of the score for the result estimation. Group (ii) Medium cost - medium robustness processing scheme examples can include: color-based tracking - hue, saturation, value (HSV) channel statistical modeling; feature based tracking - Oriented FAST and rotated BRIEF (ORB) features + descriptors, consensus of movement of keypoints (optical flow); movement based tracking - ego-motion compensation and background subtraction, etc.

detect a failure. Group (iii) Low-cost - low robustness processing scheme examples can include: extrapolation of location of object from past locations (e.g., no confidence measure (always max), depend on validation method to reject estimation, etc.); SqueezeNet super fast rejection CNN; template matching to the last known object appearance based on past detections, etc.

Level of Skill in the Art Demonstrates Lack of Enablement

- Even under PO's elevated POSITA definition the specification's failures are not cured.
- 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.**
 - RMTA at 1:

II. LEVEL OF ORDINARY SKILL IN THE ART

At the time of invention of the '711 patent, a POSITA would have had either:

(1)(a) at least a bachelor of science in mechanical engineering, electrical engineering, aerospace engineering, or an equivalent field, or (b) at least four years of experience in any of the above disciplines, and (2)(a) at least a bachelor's degree in computer science, or (b) at least four years of experience in the software industry in the field of artificial intelligence / machine learning. EX2025 § VI.

Predictability of the Art Demonstrates Lack of Enablement

- Algorithm *compute cost*, *robustness*, and *refresh rate* would depend on the hardware it runs on, its inputs, implementation, and the overall system.
 - This demands specification guidance, **yet the specification provides next to nothing.**

Breadth of the Claims/Nature of the Alleged Invention Demonstrates Lack of Enablement

- SCs 36 and 37 recite NNs having *compute cost*, *robustness*, and *refresh rate*, where some are greater or less than others.
 - 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.

PO Does Not Address Petitioners' Arguments

- PO admits nature of the invention is "complex," favoring Petitioners.
- PO's unsupported statement that examples and "guidance about relative NN parameters mitigates the need for experimentation" is undercut by Petitioners' showing with respect to guidance and examples, discussed previously.