

**MICROSOFT CORPORATION,
Petitioner,
v.
REALD SPARK, LLC,
Patent Owner.**

**IPR2023-01046
Patent 10,740,985 B2**

US Patent No. 10,740,985 (“’985 Patent”)

Title: “ADJUSTING A DIGITAL REPRESENTATION OF A HEAD REGION”

Abstract: “Methods and devices for generating reference data for adjusting a digital representation of a head region, and methods and devices for adjusting the digital representation of a head region are disclosed. In some arrangements, **training data** are received. A first machine learning algorithm generates first reference data using the training data. A second machine learning algorithm generates second reference data using the same training data and the first reference data by the first machine learning algorithm.”

Ex. 1001 (emphasis added)

IPR2023-01046 Sept. 20, 2024 Oral Argument
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Overview of the '985 Patent

Each of Independent Claims 1, 16, 17, 18, and 19*:

- Either a method or device for “generating reference data for adjusting a digital representation of a head region” (Ex. 1001 at Claim 1, 16, 17, 18, 19).
- “receiving **training data** comprising . . . a set of input patches . . . and a set of output patches in one-to-one correspondence with the input patches” (*Id.* at Claim 1[A]–[C]; Claim 16[A]–[C]; Claim 17[A]–[C]; Claim 18[A]–[C]; Claim 19[A]–[C]).
- The input patches are the “before” (Ex. 2008 at ¶ 46).
- The output patches are the “after” (Ex. 2008 at ¶ 46).

* Independent Claim 15 is not at issue in the instant IPR, and thus, is not addressed herein.

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

Overview of the '985 Patent

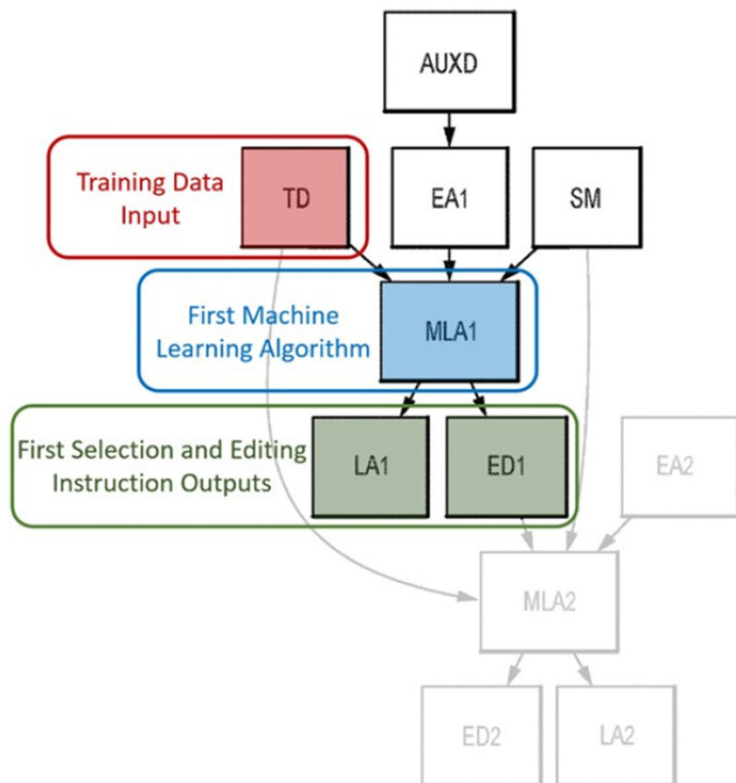
Each of Independent Claims 1, 16, 17, 18, and 19:

- “using a **first machine learning algorithm** to generate **first reference data** using the **training data**” (Ex. 1001 at Claim 1[D], Claim 16[D], Claim 17[D], Claim 18[D], Claim 19[D]).
- “using a **second machine learning algorithm** to generate **second reference data** using the **same training data** as the first machine learning algorithm” (Ex. 1001 at Claim 1[E], Claim 16[E], Claim 17[E], Claim 18[E], Claim 19[E]).

Overview of the '985 Patent – MLA 1

The **first machine learning algorithm (“MLA1”)** receives **training data** and then generates **first reference data**.

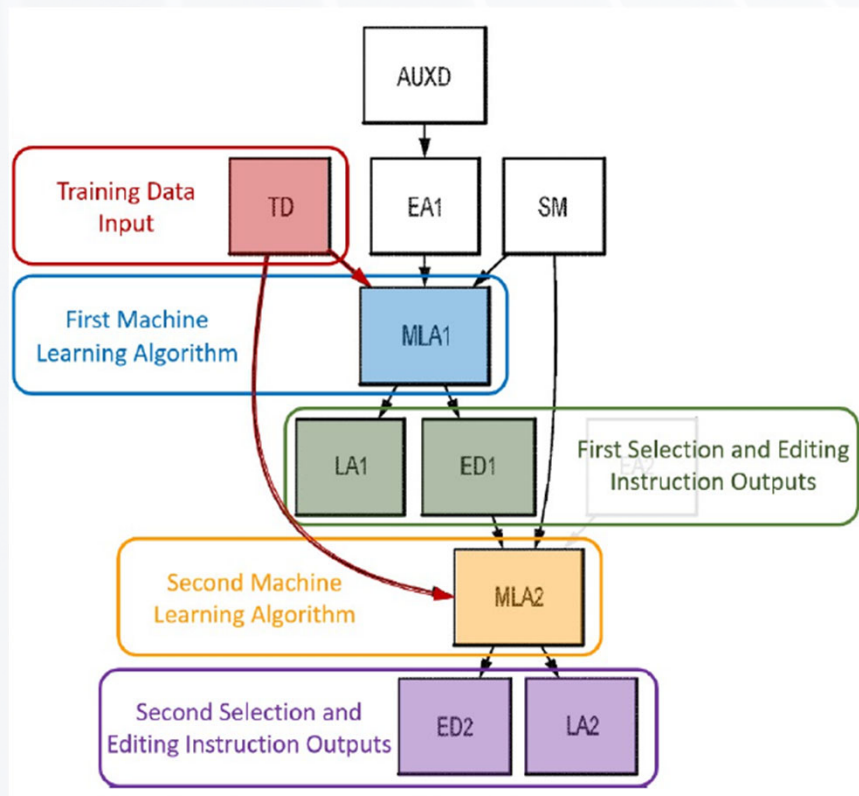
The **first reference data** includes one or both of the **first selection instructions** and **first editing instructions** for determining how the head region is to be adjusted.



Ex. 2008 at p. 21

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

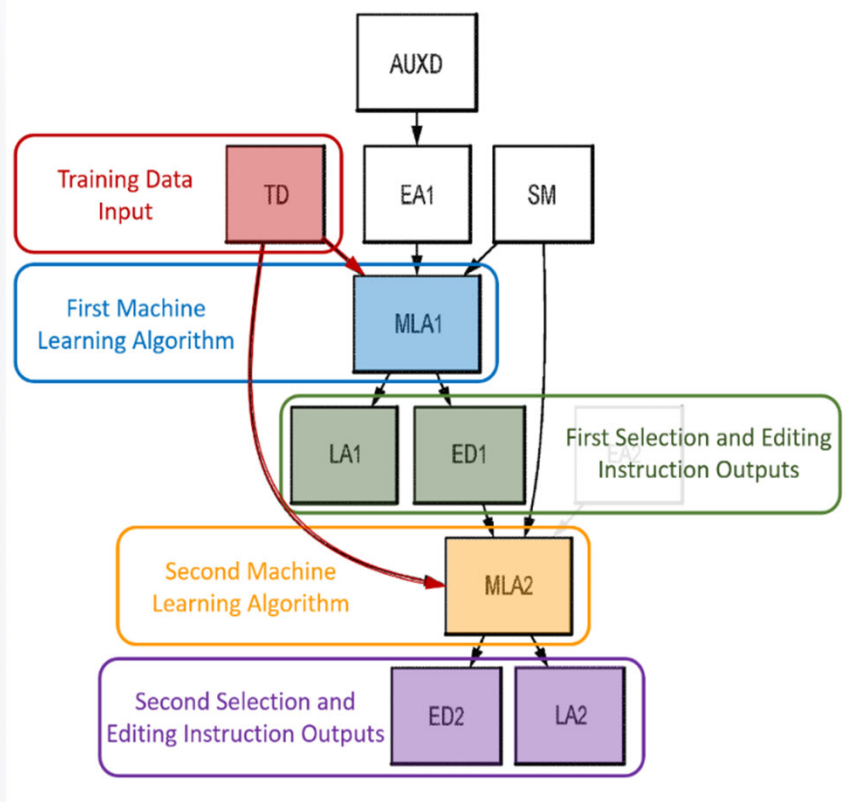
Overview of the '985 Patent – MLA 2



The **second machine learning algorithm ("MLA2")** receives **training data** and the **first reference data (first selection and/or first editing instructions)** output from the first machine learning algorithm.

MLA2 outputs **second selection instructions and/or second editing instructions** for determining how the head region is to be adjusted.

Overview of the '985 Patent – Key Features

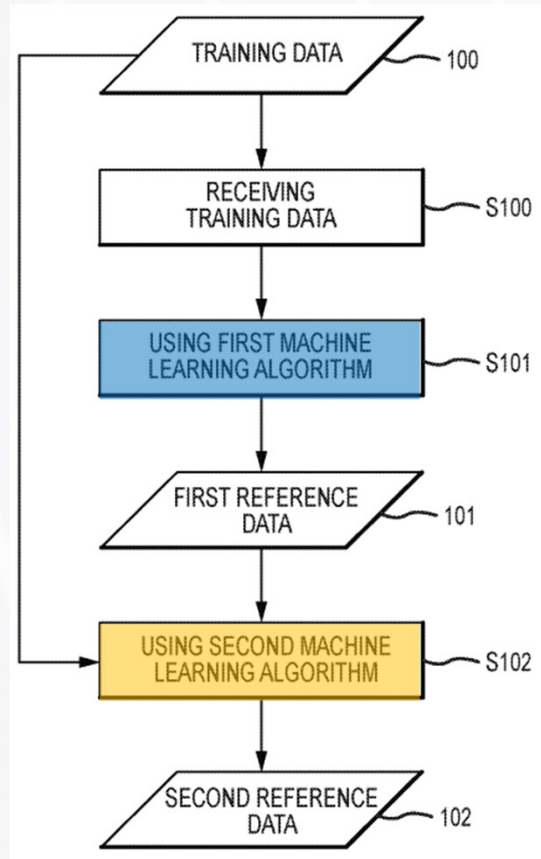


1. Two Machine Learning Algorithms (**MLA1** and **MLA2**)
2. **MLA1** and **MLA2** receive the same **training data**
3. **MLA2** receives and uses the **First Reference Data**
4. **The First Reference Data** $\neq$ **The Second Reference Data**

Ex. 2008 at pp. 21-22

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

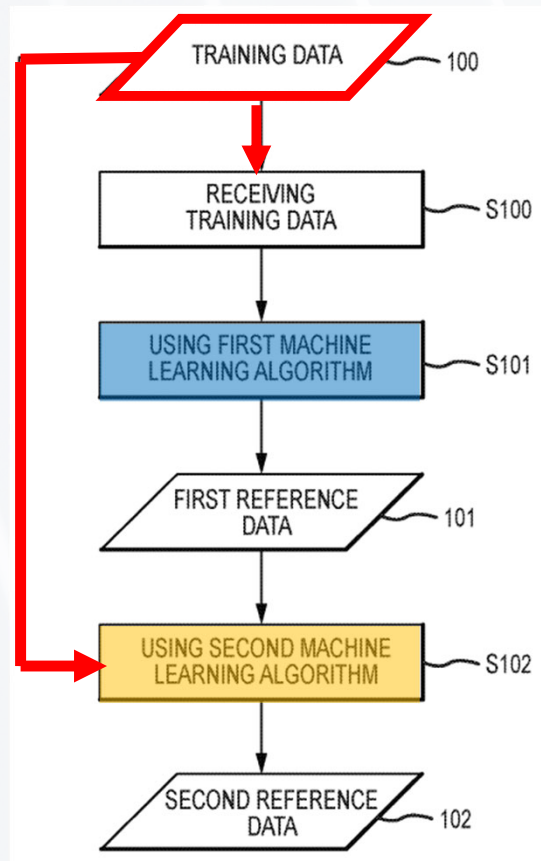
Another View – '985 Patent Fig. 8



Ex. 1001 at Fig. 8

1. Two Machine Learning Algorithms
(**MLA1** and **MLA2**)

Another View – '985 Patent Fig. 8

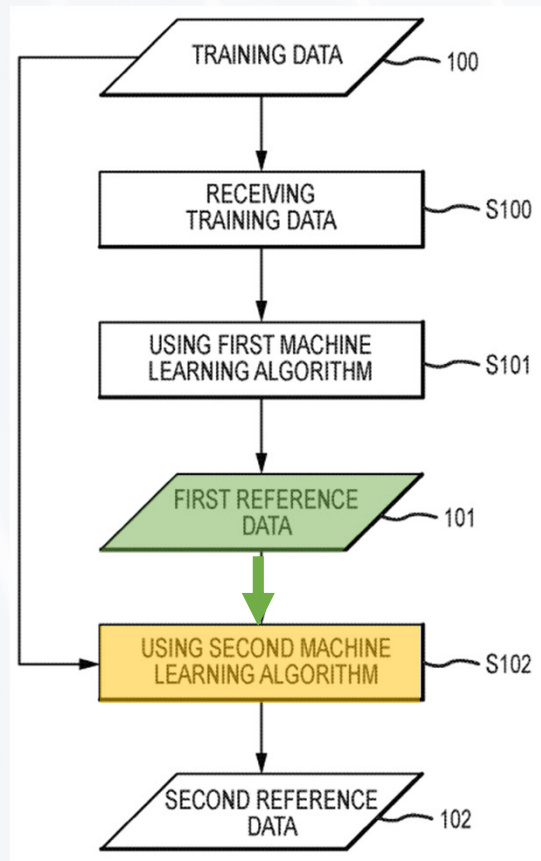


Ex. 1001 at Fig. 8

1. Two Machine Learning Algorithms
(**MLA1** and **MLA2**)

2. **MLA1** and **MLA2** receive the same
training data

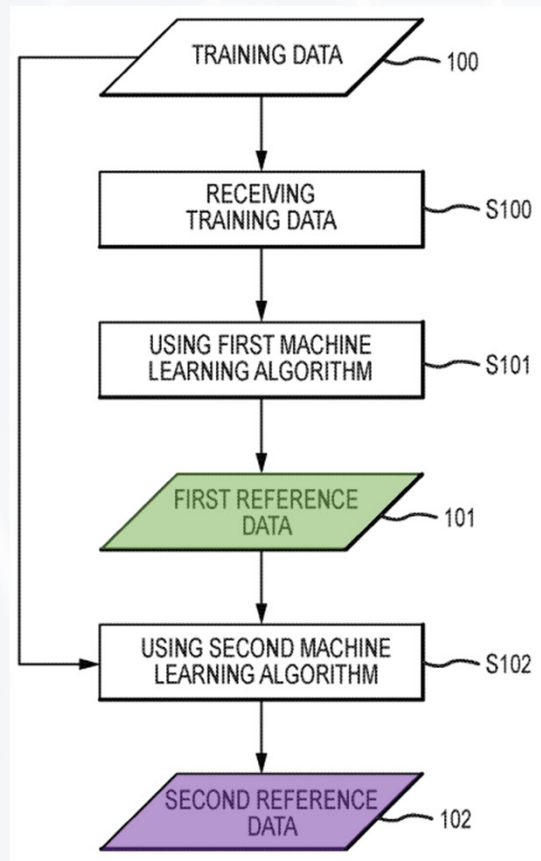
Another View – '985 Patent Fig. 8



Ex. 1001 at Fig. 8

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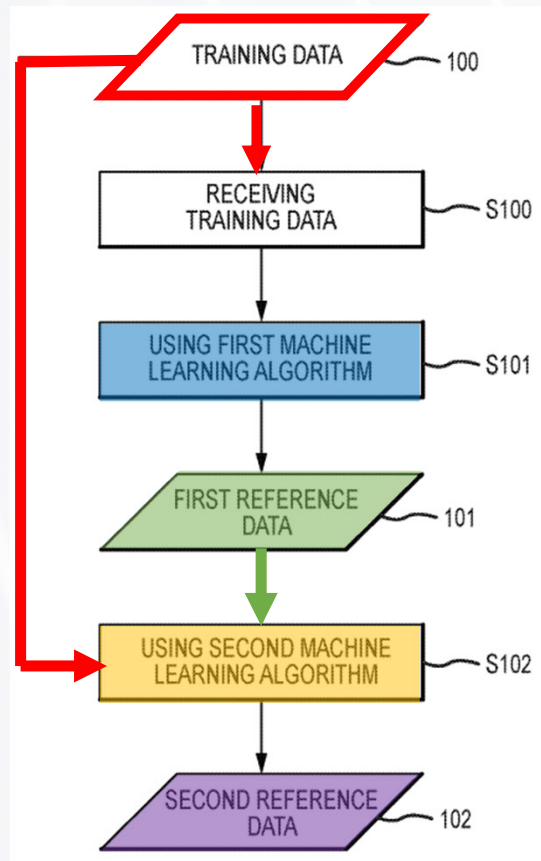
Another View – '985 Patent Fig. 8



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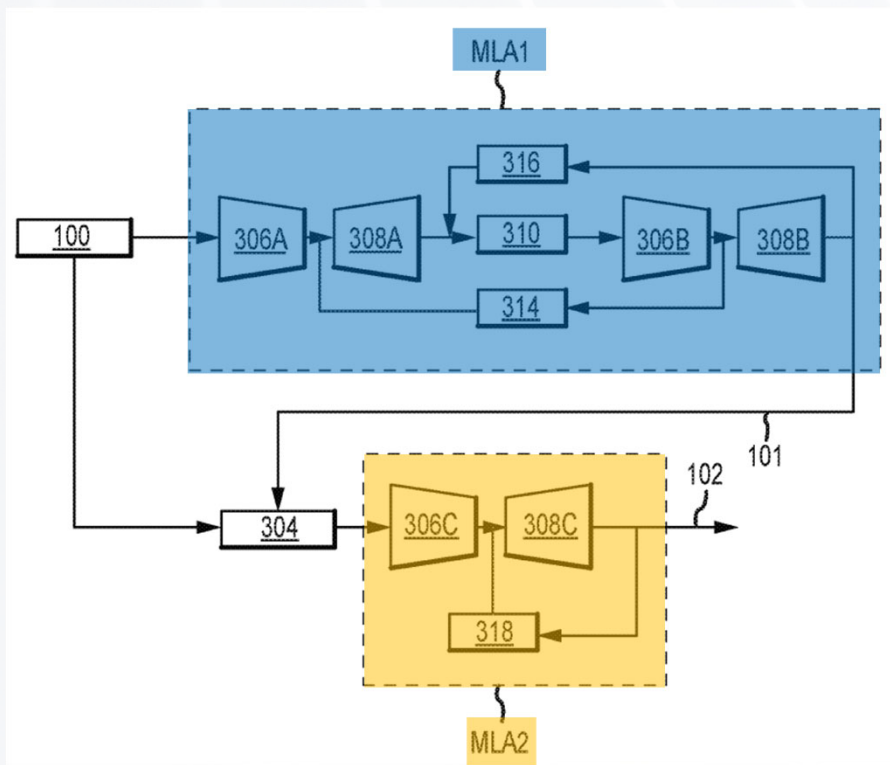
Another View – '985 Patent Fig. 8



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Another View – '985 Patent Fig. 14

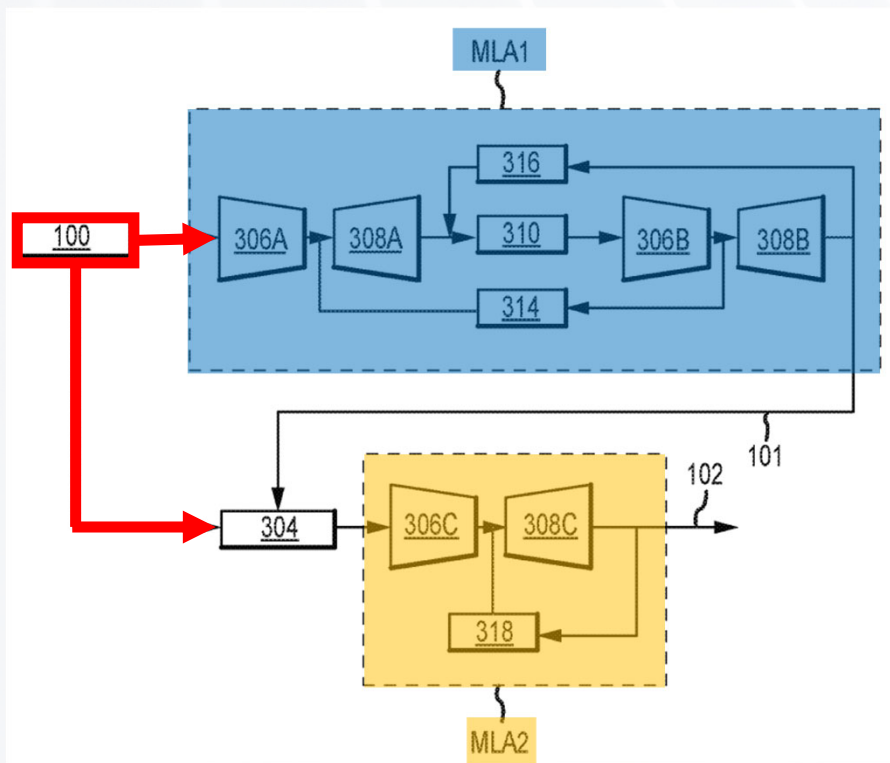


1. Two Machine Learning Algorithms
(**MLA1** and **MLA2**)

Ex. 1001 at Fig. 14

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

Another View – '985 Patent Fig. 14

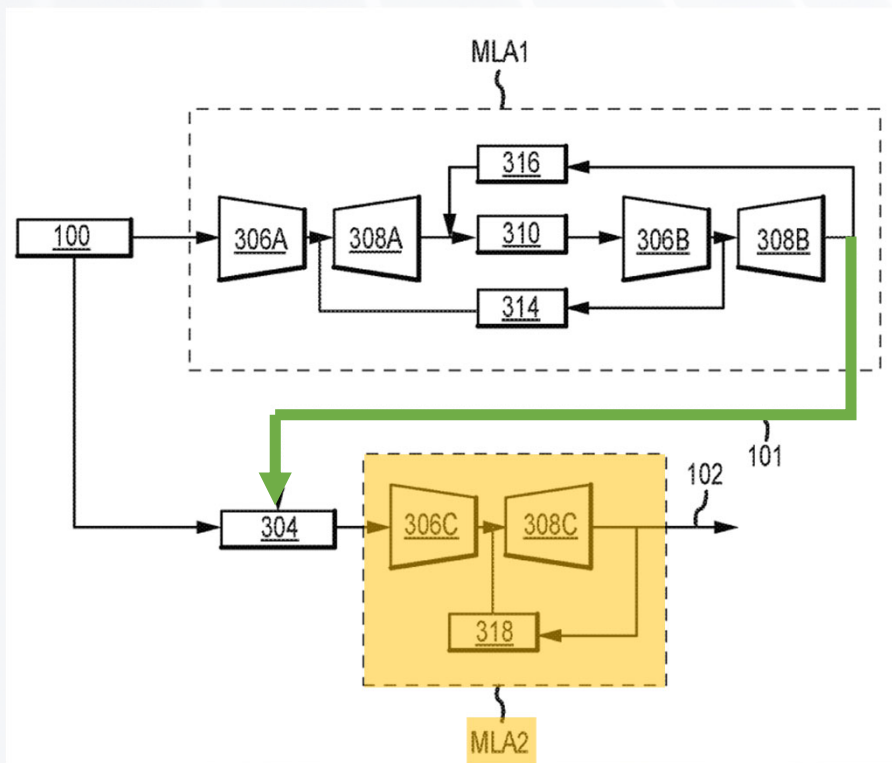


1. Two Machine Learning Algorithms (**MLA1** and **MLA2**)
2. **MLA1** and **MLA2** receive the same **training data**

Ex. 1001 at Fig. 14

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

Another View – '985 Patent Fig. 14



1. Two Machine Learning Algorithms
(**MLA1** and **MLA2**)

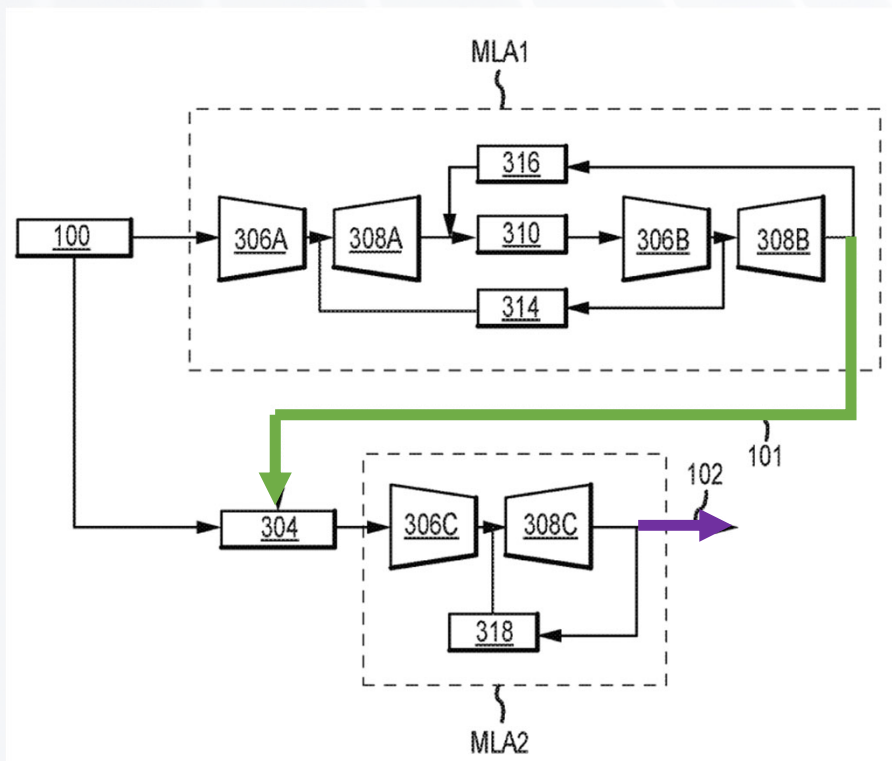
2. **MLA1** and **MLA2** receive the same
training data

3. **MLA2** receives and uses the **First
Reference Data**

Ex. 1001 at Fig. 14

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

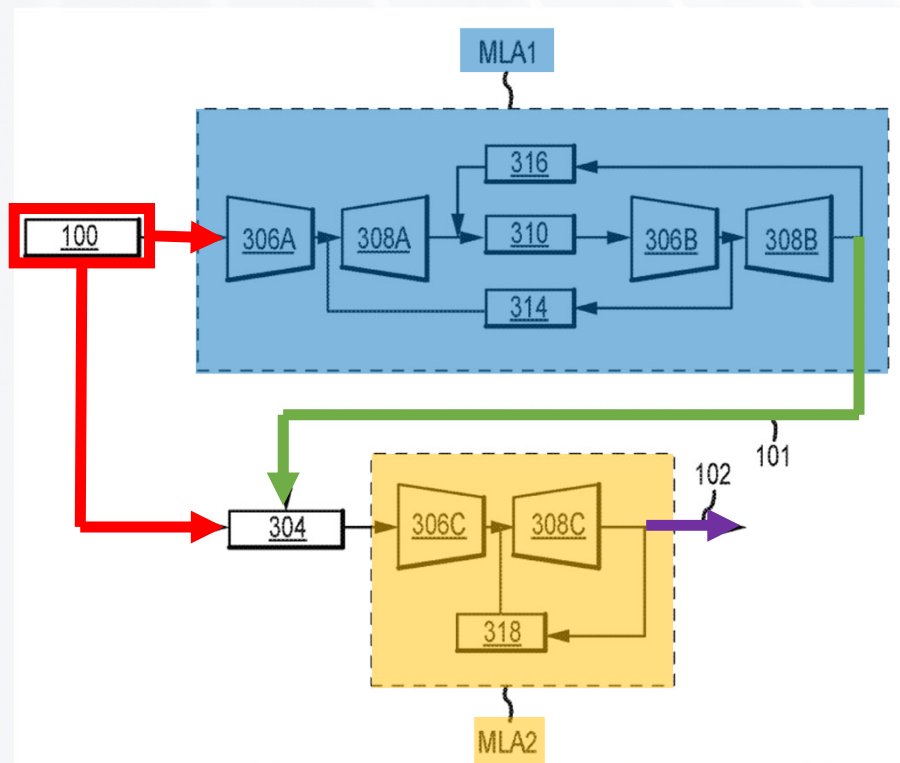
Another View – '985 Patent Fig. 14



Ex. 1001 at Fig. 14

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Another View – '985 Patent Fig. 14



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Ex. 1001 at Fig. 14

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

IPR Ground 1: 35 U.S.C. § 102 Anticipation by Ganin

“Petitioner argues that claims 1–3, 5, 10, 12–14, and 18 are anticipated by Ganin.”
(Decision Granting Institution of *Inter Partes* Review at p. 41).

“Under 35 U.S.C. § 102 a claim is anticipated ‘if each and every limitation is found either expressly or inherently in a single prior art reference.’” *King Pharms., Inc. v. Eon Laby’s, Inc.*, 616 F.3d 1267, 1274 (Fed. Cir. 2010) (*quoting Celeritas Techs. Ltd. v. Rockwell Int’l Corp.*, 150 F.3d 1354, 1360 (Fed. Cir. 1998) (emphasis added)).

IPR Ground 1: Ganin Does Not Anticipate The Independent Claims of the '985 Patent

Independent Claims 1 and 18 (and thus, dependent claims 2, 3, 5, 10, 12-14 which each depend from independent Claim 1) are not anticipated by Ganin for two reasons:

- 1) Ganin does not disclose the “second machine learning algorithm” and related elements
- 2) Ganin’s alleged algorithms do not use “the same training data”

Overview of Ganin

Ganin relates to “the task of generating highly-realistic images of a given face with a redirected gaze” using a neural network. (Ex. 1006 at p. 1).

Ganin provides a “deep feed-forward architecture that combines several principles of operation (coarse-to-fine processing, image warping, intensity correction)” and “is trained end-to-end in a supervised way using a specially collected dataset that depicts the change of the appearance under gaze redirection in real life.” (*Id.* at 2).

Overview of Ganin – Fig. 2

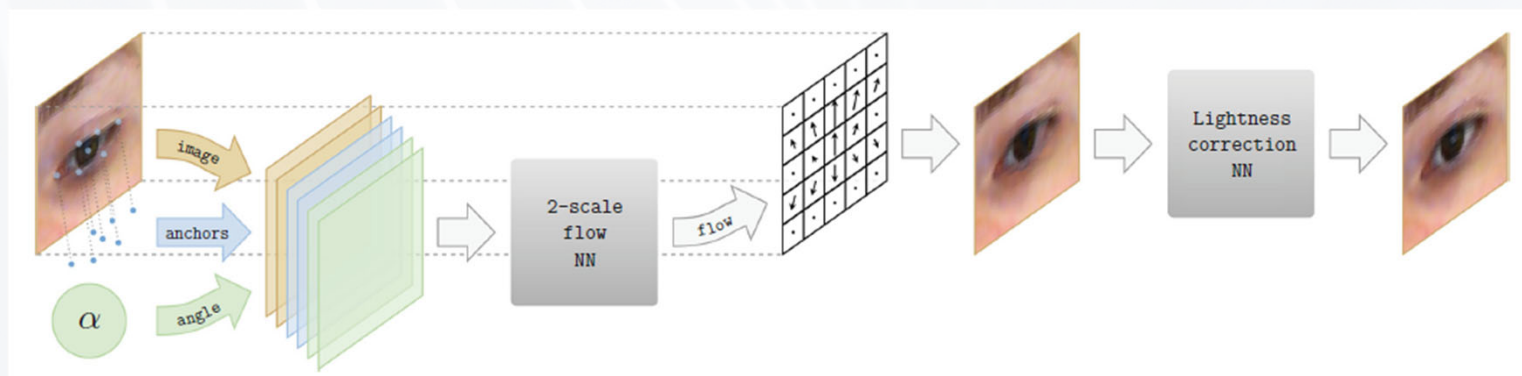
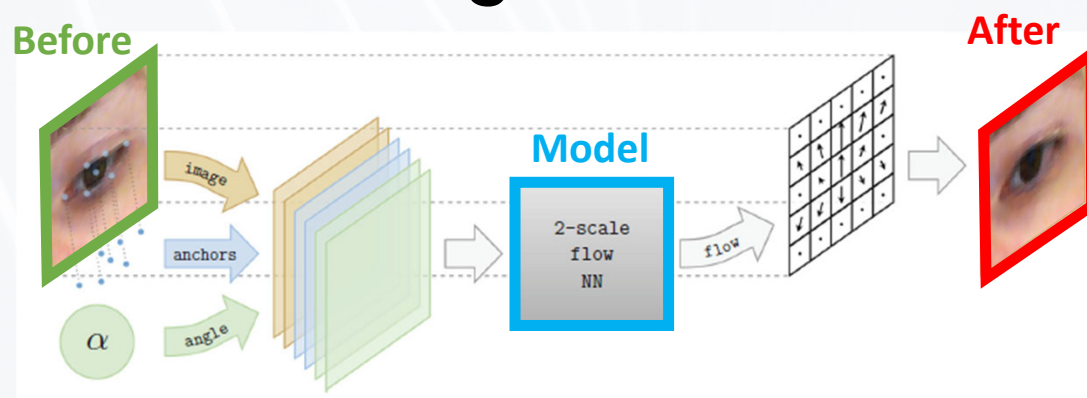


Figure 2 is a flow chart depicting Ganin's proposed system, which "takes an input eye region, feature points (anchors) as well as a correction angle α and sends them to the multi-scale neural network . . . predicting a flow field. The flow field is then applied to the input image to produce an image of a redirected eye. Finally, the output is enhanced by processing with the lightness correction neural network" (Ex. 1006 (corrected) at p. 4 (emphasis and citations omitted)).

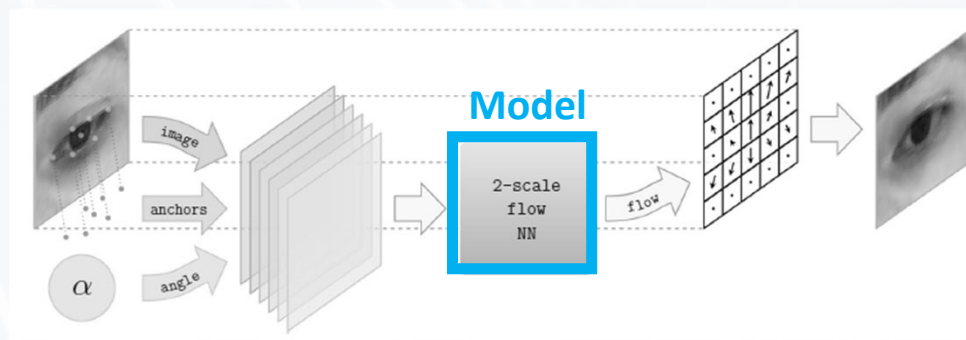
Overview of Ganin – Fig. 2



Ganin provides a “training pair” of one before and one after image. (Ex. 2008 at ¶ 79).

The input is the before image (in green). That input is sent to one algorithm (shown in blue as the “2-scale flow N[eu]ral N[et]work”), and the output is the after image (in red). (Ex. 2008 at ¶ 79).

Overview of Ganin – Fig. 2



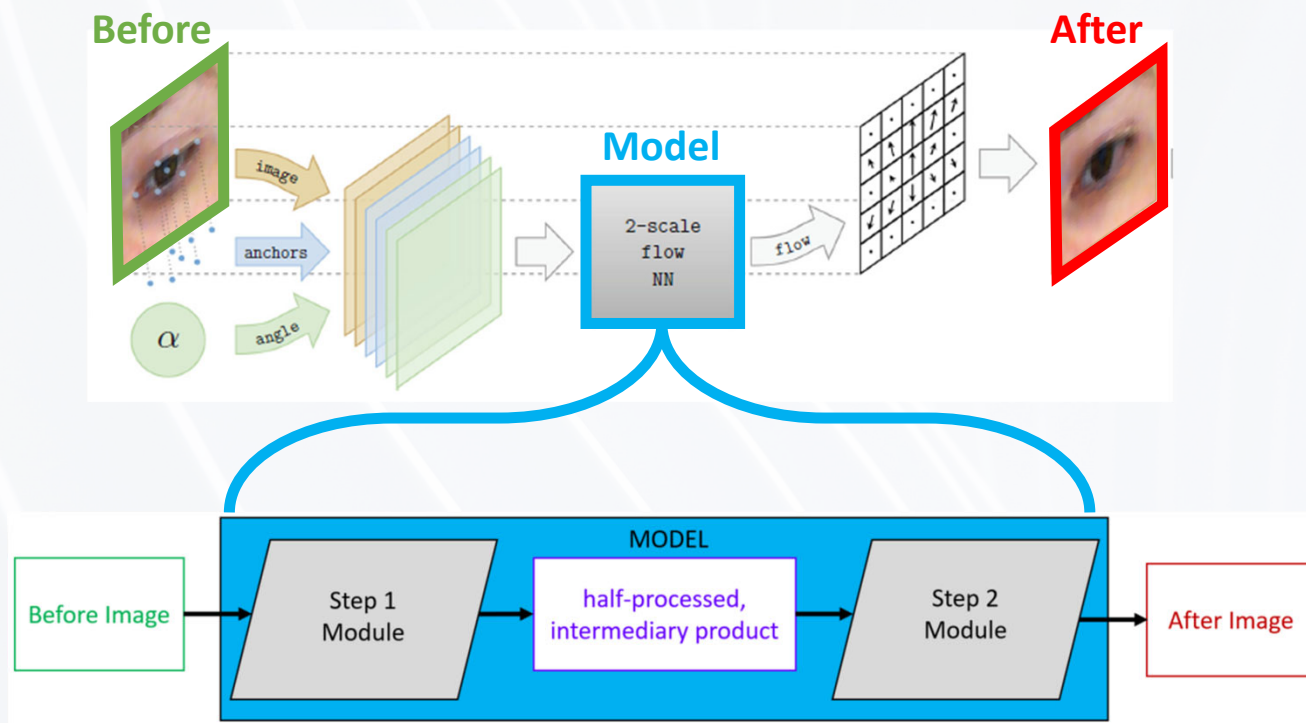
Ganin's **2-scale flow N[eu]ral N[et]work** is a single architecture with two steps: "the network . . . predict[s] [the gaze redirection] in two stages in a coarse-to-fine manner." (Ex. 1006 at p. 4).

Ganin's first "coarse" step provides a coarse adjustment to the image. Then that semi-adjusted image is passed to the second "fine" step to adjust the image on, for example, a pixel-by-pixel basis so that the eyelashes, pupil, and iris are rendered correctly. (Ex. 1006 at p. 4).

Ex. 2008 at pp. 34-35

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

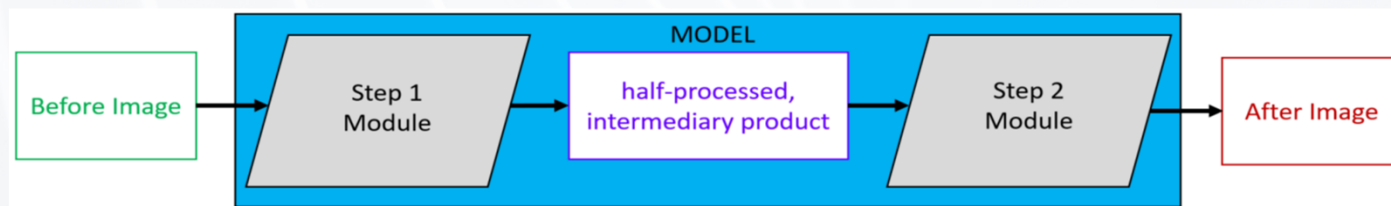
Overview of Ganin – More Detailed View of Fig. 2



Ex. 2008 at pp. 34-35

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

Overview of Ganin – More Detailed View of Fig. 2

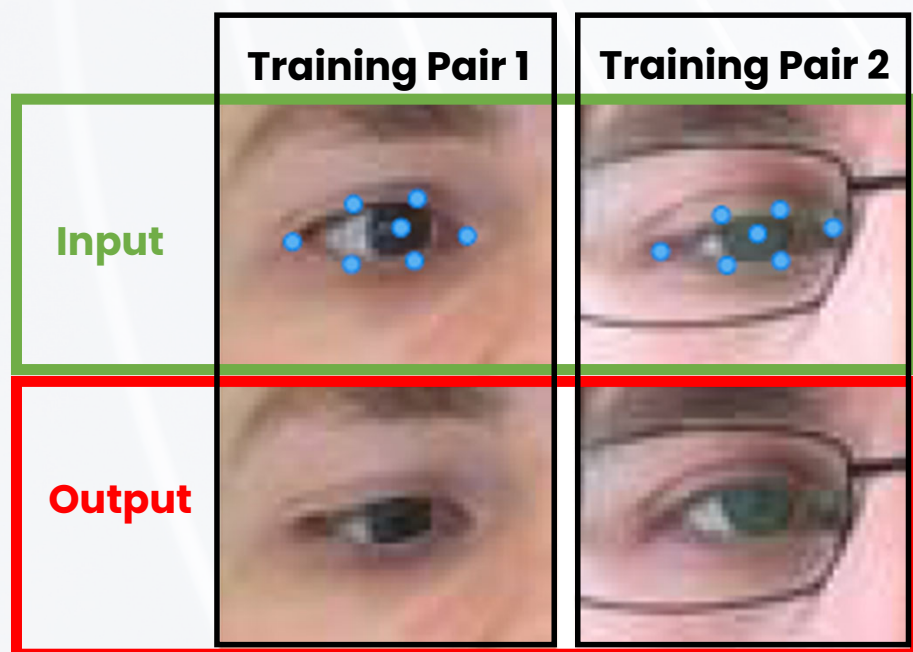


The Step 1 Module is Ganin’s first “coarse” step (also referred to as the half-scale warping module)

The Step 2 Module is Ganin’s second “fine” step (also referred to as the original scale warping module)

The before image is input into the “Coarse” step, which provides a coarse adjustment and then passes along that coarse adjustment via half-processed, intermediary product to the “Fine” step.

Ganin Does Not Disclose Two MLAs



Ganin has one set of training data

Ganin Figure 4 shows a training pair for two people where the top image is an “**input**” image with superimposed feature points on top” and the bottom image is the “**output**” image”

There is only a single **input** image and a single **output** image per pair.

Ex. 1006 (corrected) at p. 8; Ex. 2008 at p. 37;
Patent Owner’s Response at pp. 11–12

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

Ganin Does Not Disclose Two MLAs

Ganin has one objective function and therefore one machine learning algorithm.

A machine learning algorithm can measure how well it has learned the task with an error calculation called an “objective function.” (See Ex. 2008 at ¶ 73).

A typical objective function is called an “ l_2 -distance” that measures how far away the actual output is from the desired output present in the training pair. (See Ex. 2008 at ¶ 99, n.1).

Ganin discloses a single objective function: “We used a regular l_2 -distance between the synthesized output O_{output} and the ground-truth O_{gt} as **the** objective function.” (Ex. 1006 at p. 8 (emphasis added)).

Ganin Does Not Disclose Two MLAs

Ganin's text repeatedly states it includes one machine learning algorithm, not two:

- “[a]ll these operations are performed in a feed-forward manner . . . **the** resulting **neural network** can synthesize images with manipulated gaze.” (Ex. 1006 at p. 1).
- “**a** new deep feed-forward **architecture** [] combines several principles of operation . . .” (*Id.* at p. 2).
- “[**t**]he proposed system takes [various] input[s] . . . and sends them to **the** multi-scale **neural network** . . .” (*Id.* at p. 4 (Figure 2)).
- “3. **The Model**” (*Id.* at p. 4 (heading)).
- “[i]n this section, we discuss **the architecture** of our deep model . . . **The model** is trained on pairs of images . . .” (*Id.* at p. 4).
- “[t]he task of **the network** is therefore the prediction of the warping field.” (*Id.*).
- “[a]ll operations . . . are implemented in a **single** feed-forward **architecture** . . .” (*Id.*).
- “[**t**]he **model** was trained end-to-end . . .” (*Id.* at p. 8 (emphasis added to all)).

Ganin does not disclose a First MLA and Second MLA that use “the same training data”

Ganin does not disclose two MLAs and thus does not disclose two MLAs that use the “same” training data.

Even if Ganin’s two step single architecture was instead one coarse MLA and one fine MLA, each of those MLA would use different training data.

- Each MLA would require its own training pairs: coarse input/output training pairs & fine input/output training pairs.
- Ganin’s training data is simply the before image and after image without any intermediary product images for training a second fine MLA.

Ganin does not disclose a First MLA and Second MLA that use “the same training data”

The Decision Granting Institution of *Inter Partes* Review confirms that Ganin’s coarse step does not use the same training data as the fine step:

“Ganin discloses the coarse warping module processes the received training data to produce the output reference data, which it [the coarse warping module] forwards to the fine warping module for *further* processing. . . . While the forwarded reference data produced by the coarse warping module is expressed as *a function of the training data*, . . . it does not constitute the training data itself.” (emphasis added).

IPR Grounds 2–5: 35 U.S.C. § 103(a) Obviousness

A patent claim is unpatentable under 35 U.S.C. § 103(a) if the differences between the claimed subject matter and the prior art are such that the subject matter, as a whole, would have been obvious at the time the invention was made to a person having ordinary skill in the art to which the subject matter pertains. *KSR Int'l Co. v. Teleflex Inc.*, 550 U.S. 398, 406 (2007).

IPR Ground 3: Claims 16 & 19 Are Not Rendered Obvious by Ganin in view of Liu

Because Ganin does not disclose two MLAs, its combination with Liu also fails to disclose two MLAs.

Petitioner relies on an argument that a PHOSITA would have been motivated to use Liu “to compress Ganin’s warping fields” as required by claims 16 and 19.

Liu does not remedy Ganin’s lacking disclosure as to the “second machine learning algorithm” or “same training data” and thus, the combination of Ganin and Liu cannot render claims 16 and 19 obvious.

Petition at p. 39;
Patent Owner’s Response at pp. 20–21

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

IPR Ground 4: Claims 1-3, 5-6, 8-14, 16-19 Are Not Rendered Obvious by Chalom in view of Aslan

- 1) A POSITA would not have been motivated to combine Chalom and Aslan.
- 2) Chalom-Aslan Does Not Disclose a Second Machine Learning Algorithm that Receives First Selection Instructions
- 3) Chalom-Aslan Fails to Disclose a Second Machine Learning Algorithm that Uses First Reference Data
- 4) Chalom-Aslan Does Not Disclose First Reference Data and Second Reference Data that are Different

Overview of Chalom & Aslan

Chalom teaches a single machine learning algorithm for gaze correction based on a camera's location.

Aslan is directed to training multiple machine learning models in parallel.

A POSITA Would Not Have Been Motivated to Combine Chalom and Aslan

- Petitioner's alleged motivation rests on the incorrect assumption that Chalom is not a limited-resource, low-power environment.
- Petitioner's alleged "accuracy and/or efficiency gains" do not motivate a POSITA to combine Chalom and Aslan
- Chalom's motion vector fields do not lend themselves to combination with Aslan

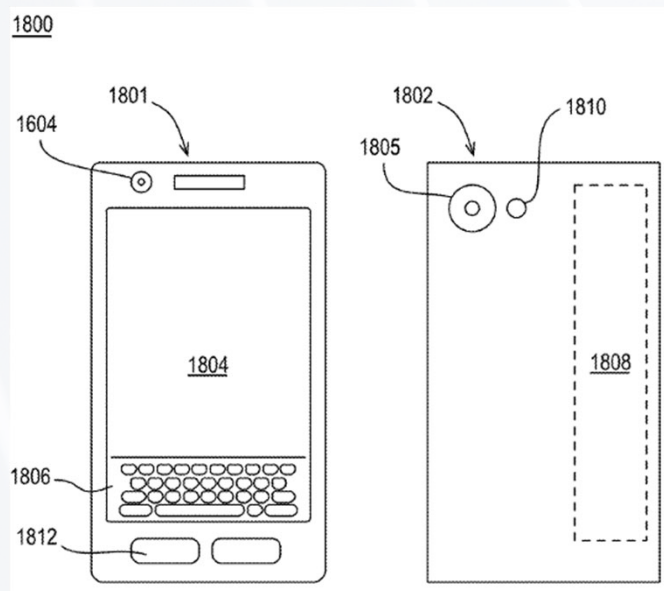
Chalom Discloses Performing in a Limited-Resource, Low-Power Environment

Petitioner asserts that “Chalom and Aslan are at least reasonably pertinent to a problem identified in the ’985 Patent of high accuracy MLAs often **consuming more computational resources** and being slower to run, as compared to efficient MLAs tending to provide less accurate predictions.” (Petition at p. 42)

Chalom discloses a system that performs perfectly well in a limited power, mobile device scenario.

Chalom discloses that its system “may be implemented as a mobile computing device A mobile computing device may refer to any device having a processing system and a mobile power source or supply, such as one or more batteries, for example.” (Ex. 1005 at 22:40–45; see *also* 19:1–14; 3:4–10; 22:46–55; 22:56–61).

Chalom Discloses Performing in a Limited-Resource, Low-Power Environment



“[S]ystem 1700 may be embodied in varying physical styles or form factors[,]” including a **“small form factor device 1800.”** (Ex. 1005 at 22:33–37 (emphasis added)).

There is No Motivation to Combine Chalom and Aslan For Accuracy or Efficiency Gains

Petitioner asserts that “Motivation also existed to incorporate Aslan’s teacher-student architecture into Chalom’s training of its RFC 306 *for accuracy and/or efficiency gains.*” (Petition at p. 42)

Chalom does not indicate that is its inaccurate or inefficient, and thus, there is no reason for a POSITA to look from to Aslan to correct these nonexistent problems with Chalom.

There is No Motivation to Combine Chalom and Aslan For Accuracy Gains

A POSITA would not look to adding another machine learning algorithm to yield higher accuracy.

Instead, Petitioner's expert identified ways to improve the accuracy of a poorly functioning MLA—none of which was to add another algorithm:

- (1) “running the training process through more iterations” (Ex. 2009 at 97:17–98:2);
- (2) “restarting the training with different . . . weight[s]” (*id.* at 98:3–7);
- (3) changing or tuning “the model hyperparameters” (*id.*);
- (4) “adding more layers” to the machine learning algorithm (*id.*); and
- (5) “using the right objective function” (*id.* at 99:18–24).

There is No Motivation to Combine Chalom and Aslan For Efficiency Gains

Combining Chalom and Aslan would result in a more complex, and thus *less efficient* system.

Adding Aslan's teacher-student system adds complexity by adding additional algorithms to Chalom's single algorithm system.

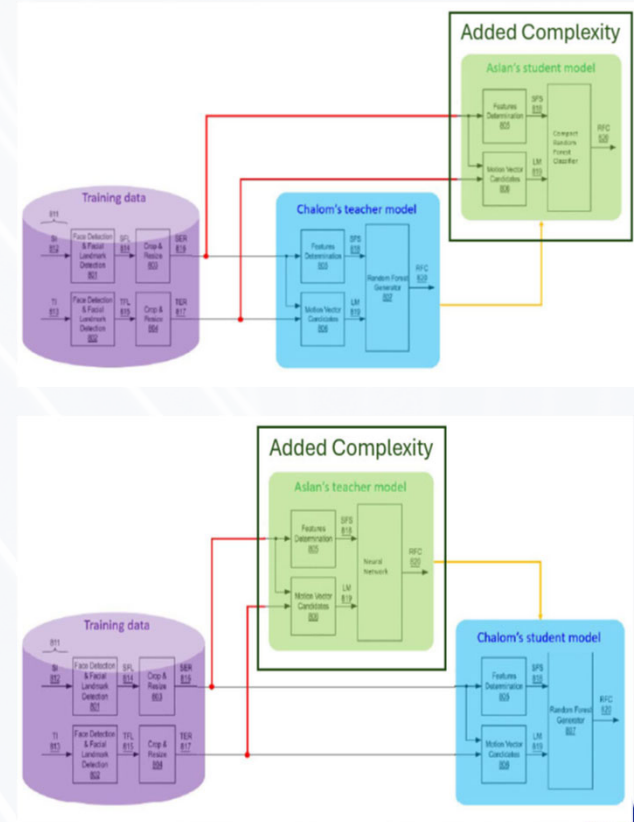
There is No Motivation to Combine Chalom and Aslan For Efficiency Gains

In either combination proposed by Petitioner, the Chalom – Aslan combination is more complex, and thus, less efficient.

Chalom alone would have the components highlighted in purple and blue.

Aslan's teacher-student element increases complexity by adding another model (in green) on top of the one presented in Chalom (in blue).

Patent Owner's Response at p. 25;
Ex. 2008 at ¶¶ 113–115



There is No Motivation to Combine Chalom and Aslan For Efficiency Gains

Chalom's gaze correction will be different depending on which direction the user is looking, so Chalom explains that the random forest classifier can choose a model that is particular to the appropriate camera orientation. (Ex. 1005 at 5:37-50).

Selecting the most appropriate model for the camera's location would provide Chalom's system with a more efficient operation, and would prevent a significant increase in complexity that would result from adding a second machine algorithm.

There is No Motivation to Combine Chalom and Aslan For Efficiency Gains

A POSITA looking to compress Chalom's random forest classifier (RFC) would not do so by adding a second machine learning algorithm.

Instead, a POSITA would seek to: (1) reduce the size of the RFC (i.e. fewer trees, fewer branches, etc.); (2) utilize the most probable trees/branches; or (3) create a smaller RFC for proper gaze adjustment.

Chalom's Motion Vector Fields Do Not Lend Themselves to Combination with Aslan

Chalom and Aslan use different techniques for different outcomes, and thus do not support combination.

Chalom performs a gaze correction task using motion vector fields that represent two-dimensional displacement vectors for a pixel in an image.

Aslan performs an image classification task using a class or label typically represented as an index number (e.g., class = 1, class = 2).

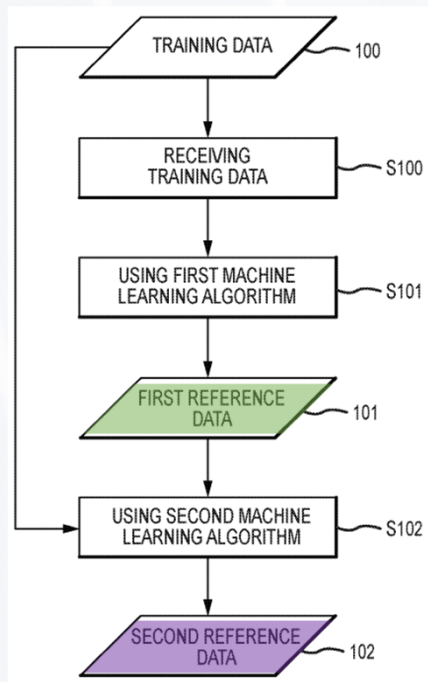
Chalom's Motion Vector Fields Do Not Lend Themselves to Combination with Aslan

Motion vector fields do not represent classes/labels

Motion vector fields represent **two-dimensional** displacement vectors (*i.e.* displacement in the x-direction dx and displacement in the y-direction dy) for a pixel located at (i,j) in given frame. (See Ex. 2010 at p. 76).

Classes/labels are usually integers (such as a number or index) and represent **one** dimension.

Chalom-Aslan Does Not Disclose a Second Machine Learning Algorithm that Receives First Selection Instructions



Patent Owner's Response at pp. 28-30;
Surreply at pp. 16-19

Claim 1 of the '985 requires that the "first reference data comprise[s] first editing instructions . . . **and** first selection instructions." (Ex. 1001 at 26:58-60 (emphasis added)).

The '985 Patent's description of Figure 8 explains that, in one embodiment, "the first reference data 101 comprises first editing instructions . . . **and first selection instructions** . . . for a particular input patch." (Ex. 1001 at 15:1-11 (emphasis added)).

Chalom-Aslan Fails to Disclose a Second Machine Learning Algorithm that Uses First Reference Data

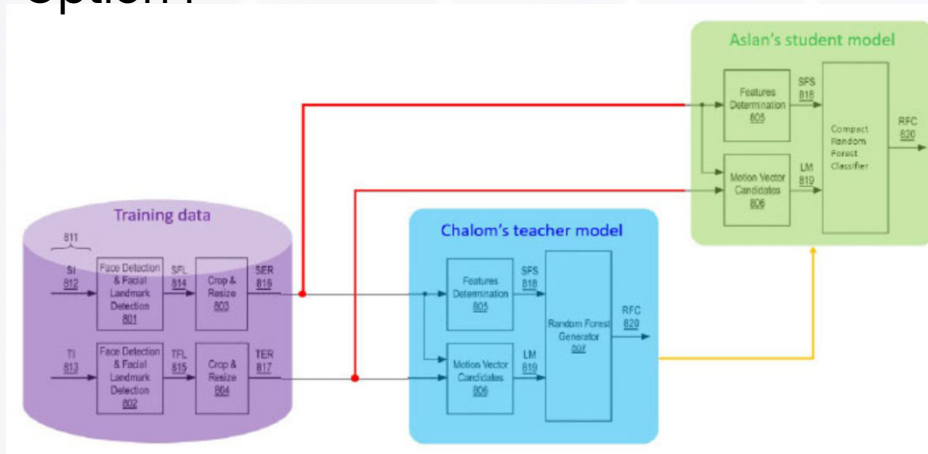
The independent claims require a second machine learning algorithm that uses the editing instructions from the first machine learning algorithm.

Petitioner contends that a POSITA would need only “follow the instructions provided in Aslan” (Petition at pp. 45, 47).

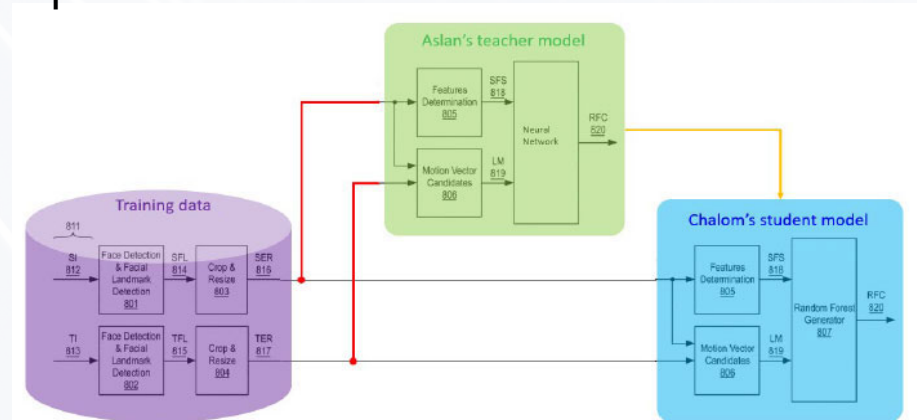
Chalom-Aslan Fails to Disclose a Second Machine Learning Algorithm that Uses First Reference Data

Petitioner's summary suggestion that Aslan can combined with Chalom fails to provide any of the requisite details.

Option 1



Option 2



Patent Owner's Response at pp. 30-34;
Surreply at pp. 19-23; Ex. 2008 at p. 57

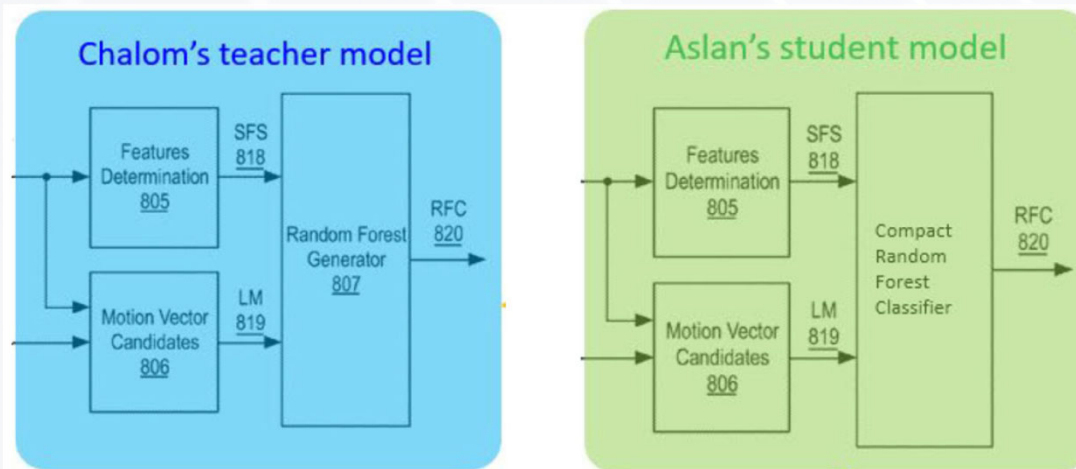
IPR2023-01046 Sept. 20, 2024 Oral Argument
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Chalom-Aslan Does Not Disclose First Reference Data and Second Reference Data that are Different

The '985 claims require that the “first reference data” be different from the “second reference data”

Chalom-Aslan combination uses the same inputs, provided to the same modules, which would return the same outputs (i.e., the same “reference data”).

Chalom-Aslan Does Not Disclose First Reference Data and Second Reference Data that are Different



Petitioner's proposed combination uses the same features determination modules and the same motion vector candidate modules.

Chalom-Aslan also uses a random forest for both the teacher and student models.

The resulting teacher model and student model would have the same outputs.

IPR Ground 4: 35 U.S.C. § 103(a) Obviousness of Claim 4 by Chalom in view of Aslan and Grau

Because the Chalom and Aslan combination do not teach or disclose the elements of independent claim 1, from which claim 4 depends, their combination similarly does not render claim 4 obvious.

Petitioner relies on an argument that Grau discloses that “the editing instructions comprise a filter field, a brightness adjustment field, or a texture blending field,” as required by claim 4.

Grau does not remedy Chalom and Aslan’s lacking disclosures addressed in relation to IPR Ground 3 and thus, the combination of Chalom, Aslan, and Grau cannot render claim 4 obvious.

Petition at p. 80;
Patent Owner’s Response at p. 37

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE

IPR Ground 5: 35 U.S.C. § 103(a) Obviousness of Claim 7 by Chalom in view of Aslan and Pace

Because the Chalom and Aslan combination do not teach or disclose the elements of independent claim 1, from which claim 7 depends, their combination similarly does not render claim 7 obvious.

Petitioner relies on an argument that Pace discloses “us[ing] wavelet transformation for compressing the editing instructions” as required by claim 7.

Pace does not remedy Chalom and Aslan’s lacking disclosures addressed in relation to IPR Ground 3 and thus, the combination of Chalom, Aslan, and Grau cannot render claim 7 obvious.

Petition at p. 83;
Patent Owner’s Response at pp. 37–38

IPR2023-01046 Sept. 20, 2024 Oral Argument
DEMONSTRATIVE EXHIBIT – NOT EVIDENCE