

UNITED STATES DISTRICT COURT
WESTERN DISTRICT OF WASHINGTON
AT SEATTLE

REALD SPARK, LLC,

Plaintiff,

v.

MICROSOFT CORPORATION,

Defendant.

Case No. 2:22-cv-00942-TL

**DEFENDANT'S ANSWERING CLAIM
CONSTRUCTION BRIEF**

JURY DEMANDED

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Microsoft Corporation v. RealD Spark, LLC
IPR2023-01046 - U.S. Patent No. 10,740,985

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1 **I. INTRODUCTION**

2 Defendant Microsoft Corporation provides its Answering Claim Construction Brief
3 regarding U.S. Patent No. 10,740,985 (“the 985 Patent”).¹

4 **II. BACKGROUND AND TECHNOLOGY OVERVIEW**

5 **a. The Desirability of Maintaining Eye Contact**

6 Eye contact is an important component of human interaction. During human conversation,
7 eye contact conveys non-verbal and subconscious information. In normal conversation, it can be
8 distracting when one person looks away from another’s eyes and appears to be focused on
9 something else. The desire for appearance of consistent eye contact during videoconferencing is
10 the motivating factor behind the ’985 Patent, which is directed to methods for training algorithms
11 to perform eye gaze correction (or adjustment of other facial features). When these algorithms are
12 used in production, after they are trained using the claimed methods, they adjust eye gaze to create
13 the appearance of direct eye contact between the participants in a video conference, even when a
14 user’s eyes are not looking directly into the camera.
15

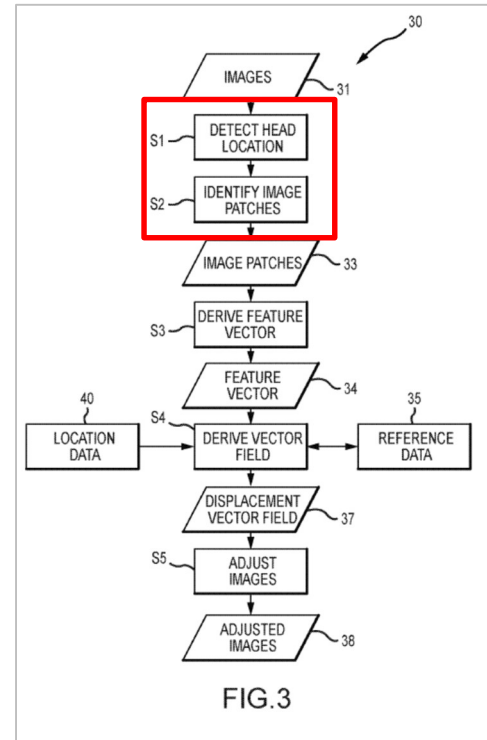
16 **b. Eye Gaze Correction**

17 The goal of “eye gaze correction”—as the phrase suggests—is to adjust (“correct”) a user’s
18 “gaze” so that it appears that the user is looking directly at the camera, and therefore directly at
19 the person or people on the other end of the call. To accomplish this, a system first recognizes
20 where a user is looking and—if they are not looking directly at the camera (*e.g.*, they are looking
21 at their computer monitor or elsewhere)—the system adjusts/edits the gaze of the user’s eyes to
22 make it appear that they are looking directly at the camera. This is sometimes called “warping”
23
24
25

26 ¹ Citations to the ’985 Patent below are provided in column:line format. For example, ’985 Patent, column 4, lines 1-5 is provided as 4:1-5.

the eye regions, or as characterized in the '985 Patent, "eye patches."²

There are a number of preliminary processes to accomplish this "warping," including head detection (*e.g.*, recognizing there is a head in the camera's view), face detection (*e.g.*, recognizing where a user's face is), and feature detection (*e.g.*, recognizing the location of features of a user's face, like the eyes, ears, nose, etc.). These techniques were well-known in the art and any of the known techniques could be used for these detections in the '985 Patent. *See, e.g.*, 6:40-46 ("In step S1, the stereoscopic pair of images 31 are analyzed to detect the location of the head and in particular the eyes of the source observer 14 within the stereoscopic pair of images 31. This is performed by detecting presence of a head, tracking the head, and localizing the eyes of the head. **Step S1 may be performed using a variety of techniques that are known in the art.**") (emphasis added); '985 Patent incorporating *Kononenko* by reference.³



The '985 Patent describes (but does not claim) the eye gaze *correction* process in Figure 3 (above). 3:55-56 ("FIG. 3 is a flow chart of a method of adjusting a stereoscopic pair of images"). As shown, the pre-adjustment steps noted above (and others) are performed in steps S1 through S4, and the images are adjusted in step S5.⁴ The end result of the eye gaze correction process is an adjusted image (*e.g.*, warped eyes looking at the participant). 11:65-12:3 ("In step S5, each

² A "patch" can be considered any area of a user's head, including the nose, mouth, etc. For ease of reference, Microsoft refers primarily to the "eye" region as it is region of interest for eye gaze correction. However, other regions or facial features can also be targeted for adjustment.

³ 10:61-67, incorporating *Kononenko et al.*, "Learning to Look Up: Realtime Monocular Gaze Correction Using Machine Learning," *Computer Vision and Pattern Recognition*, pp. 4667-4675 (2015), ReaID 00003898-3907, at 2: "Gaze Correction" and "3.1. Gaze Redirection. Eye Localization" (attached as Exhibit 1).

⁴ 5:18-19 ("FIG. 3 illustrates a method of adjusting multi-view images in response to eye gaze data").

1 image 31 of the stereoscopic pair is adjusted by transforming the image patches containing the left
2 and right eyes of the head in accordance with the derived displacement vector fields 37. This
3 produces an adjusted stereoscopic pair of images 38 as shown in FIG. 4, in which the gaze has
4 been corrected.”).⁵

5 c. Overview of Asserted Claims of the '985 Patent

6 The asserted claims of the '985 Patent are training claims—directed to the training of
7 algorithms for generating reference data for later adjustment of facial features (*e.g.*, eye gaze
8 correction)—and not to the use of such algorithms for actual editing/adjustment of user’s facial
9 features in videoconferencing software. This is clear from the language of the asserted claims, all
10 of which require the algorithm to be provided two sets of training inputs: input patches and
11 corresponding output patches. The claimed algorithms then learn, using known machine learning
12 techniques, to generate “reference data” that “are to be applied to an input patch to derive an output
13 patch.” 15:46-55. In other words, the result of the claims is a “trained machine learning model”
14 which is later “stored and operated” in videoconferencing applications for adjustment (editing) of
15 the desired facial feature or region of interest. 21:43-45.

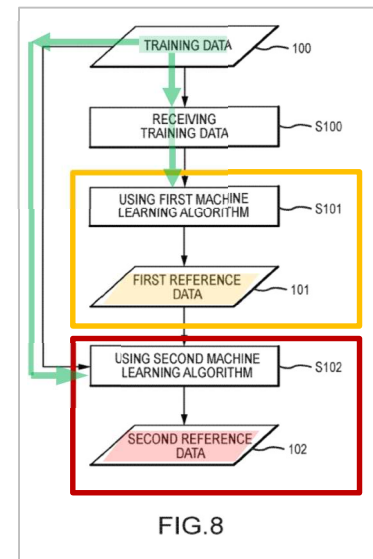
17 During prosecution of the '985 Patent application, the patentee opted to claim only the
18 training process for generating this reference data and declined to pursue separate claims directed
19 to later “adjusting” or “editing” the region of interest. More specifically, the patentees elected
20 during prosecution to pursue only training claims directed to generating what they called
21 “reference data” that included, *inter alia*, the instruction to “warp” a user’s eyes, and not electing
22 to prosecute claims directed to performance of the actual editing/warping.⁶

25 ⁵ Although not relevant to the asserted claims, the various methods and processes for the actual warping of the eyes
(or other facial features) are described in Figures 5-7, and the corresponding text in the '985 Patent.

26 ⁶ See Exhibit 2, File History, Restriction Notice, Aug. 15, 2019 (RealdD_00006037-6041), Response to Restriction
Notice, Oct. 15, 2019 (RealdD_00006043-6056).

1 The disputed claim limitations revolve around the central concept of using the recited
2 “**training** data” in a machine learning process to generate the “reference data.” That trained model
3 can be used later—and outside the scope of the ’85 Patent claims—for actual adjustment of the
4 regions of interest (*e.g.*, for eye gaze correction).⁷

5 As shown in Figure 8 of the ’85 Patent (reflecting the
6 first substantive claim limitation), the asserted claims start
7 with receiving **training data**. This training data is used by two
8 separate machine learning algorithms (**first machine learning**
9 **algorithm** and **second machine learning algorithm**) that
10 generate the claimed “reference data” (**first reference data** and
11 **second reference data**).
12



13 A natural question at this juncture would be: why do the claims require two machine
14 learning algorithms for generating two sets of reference data? The answer to this question goes to
15 the purported point of novelty of the ’85 Patent.

16 **d. The Requirement for *Two* Machine Learning Algorithms and *Two* Sets of**
17 **Reference Data / Editing Instructions.**

18 The ’85 Patent claims were intended to address the constraints of computer processing
19 power at the time of the patent application as applied to the computationally intensive requirements
20 of machine learning algorithms (“MLAs”). Specifically, as the ’85 patent recognizes, there
21 existed at the time a need to balance “between accuracy of the adjustment process and speed of
22 execution.” 2:17-19. In other words, devices at the time lacked computer power to use a full-scale
23 pre-trained MLA to “provide results at or near input data frame rate or user feedback
24

25
26 ⁷ The parties do not dispute that “reference data” includes, among other things, the editing instructions used to warp the eyes.

requirements.”⁸ 1:54-55.

To address hardware and other limitations that existed at the time the '985 Patent was filed, the patentees claimed an approach incorporating a second MLA that relies on the same training data and the reference data (editing instructions) generated by the first MLA. *See, e.g.*, claim 1 (“using a second machine learning algorithm to generate second reference data using the same training data as the first machine learning algorithm and the first reference data generated by the first machine learning algorithm”). In the art, this is known as the “teacher-student” approach to machine learning because the first MLA (the teacher) “teaches” the second MLA (student) how to approximate the desired result.⁹ 17:14-15 (“The second machine learning algorithm MLA2 thus gets the editing instructions to match or to approximate.”). The advantage of this model is that the second—less computationally intensive—MLA is deployed to production devices where it approximates the accuracy the first—highly intensive MLA—in generating image editing instructions. *See* Exhibit 3, U.S. Provisional Application 62/542,661 (MSFT_00003136) (“Machine Learning Algorithm 2 (MLA2), where the accuracy of ML algorithm 2 is not necessarily as good as using MLA1. However, MLA2 performs faster, and can approximate the accuracy of MLA1 with more training data.”). The '985 Patent specification succinctly describes this purportedly novel, two MLA method:

The described use of two machine learning algorithms allows an improved balance to be achieved between accuracy of the adjustment process and speed of execution. The first machine learning algorithm can be configured to provide highly detailed first reference data, which provides high accuracy. **Use of this first reference data directly** in a processing technique (e.g. image processing technique) to adjust a

⁸ One consequence is called the “uncanny valley” effect, which is the sense of irritation evoked by realistic renderings of humans with noticeable visual artifacts. *See, e.g.*, Ex. 3, '661 Provisional (MSFT_00003134) (“It is desirable to bridge the ‘uncanny valley’.”); Ex. 1, Learning to Look Up, RealD_00003989).

⁹ *See, e.g.*, Exhibit 4, Adriana Romero *et al.*, Fitnets: Hints for Thin Deep Nets (2014), at Abstract (“The recently proposed knowledge distillation approach is aimed at obtaining small and fast-to-execute models, and it has shown that a student network could imitate the soft output of a larger teacher network or ensemble of networks. In this paper we extend this idea to allow the training of a student that is deeper and thinner than the teacher, using not only the outputs but also the intermediate representations learned by the teacher as hints to improve the training process and final performance of the student.”).

1 digital representation (e.g. image or three-dimensional geometrical representation)
2 of a head region **would be relatively expensive in terms of computational**
3 **resources** because of the high level of detail. By arranging instead for the first
4 reference data to be provided to a second machine learning algorithm, which
5 provides, based on the first reference data and the original training data, the
6 reference data (**the second reference data**) that is to be used for the adjustment of
7 the digital representation of the head region, it is possible to benefit to an extent
8 from the high accuracy of the first machine learning algorithm whilst also
9 providing reference data that **is less detailed and thus easier to process**
10 **efficiently when performing the adjustment** of the digital representation of the
11 head region. The quality of the reference data provided by **the second machine**
12 **learning algorithm is found to be significantly improved when** the second
13 machine learning algorithm is **provided with both the first reference data and**
14 **the training data** in comparison to when the second machine learning algorithm
15 is provided only with the training data.

16 2:17-43 (emphasis added).

17 In short, during the training phase, which occurs offline and usually on powerful
18 computers, the first MLA builds a computationally complex model that allows it to generate first
19 reference data/editing instructions that are robust and accurate. The second MLA is then taught to
20 generate second reference data/editing instructions that approximates the accuracy of the first
21 MLA, but in a more efficient way. The second MLA can then be deployed to run on every day,
22 less powerful hardware.

23 e. The Heart of The Two MLAs: Training Data

24 For a machine learning algorithm to “learn,” it must be provided with *training data*. In the
25 ’985 Patent, the training data includes the pairs of *before* and *after* images that are used to
26 iteratively train the two MLAs. 7:65-8:5 (“The training input to the machine learning technique
is two sets of images (or image patches) ... [e]ach set may comprise images of the head of the
same group of individuals but captured from cameras in different locations relative to the gaze so
that the perceived gaze differs as between them (in the case where gaze is to be corrected)”). The
training images consist of “before” images (8:6-8 (“images of each individual with an incorrect
gaze”)) and “after” images (8:15-17 (“images of each individual with correct gaze”)) for a user.



Training image—incorrect gaze

Image of individual with an incorrect gaze.



Training image—correct gaze

Image of same individual with correct gaze.

The inner workings of the MLAs are known in the art and not part of the purported invention, but the essence of the training is that the MLAs go through numerous iterations of evaluating all of the training data, *i.e.*, all pairs of “before” and “after” images, and train themselves to adjust the pixels of the “before” images to provide the desired gaze correction of the “after” images. In the first iteration, the MLA would evaluate the first “before” image in the training data and attempt to generate editing instructions for correcting the gaze. It would then compare the result of adjusting the “before” image with those instructions and the desired “after” image. In the early stages of training, the resulting corrected images would not be very close to the desired “after” image, but at each training iteration the MLA learns to minimize errors it has made before. And so, with many training cycles through numerous “before” and “after” image pairs, the MLA is able to produce editing instructions that adjust “before” training images closer and closer to the desired “after” images in the training set. *See generally*, 8:47-9:12. The more training data that is provided to the MLA, the better the trained MLA will be at producing the appropriate editing instructions, not only to the images in the training set, but also to images of faces that the algorithm has never seen before.

The '985 Patent envisions training both claimed MLAs in this iterative learning process. However, whereas the first MLA requires lots of computational complexity to learn the interplay between “before” and “after” images, the second MLA essentially learns how to take a shortcut.

1 Specifically, the second MLA is fed the same before/after images that the first MLA is given as
2 well as *the output of the first MLA, i.e.,* the full set of reference data (editing instructions)
3 generated by the first MLA. *See, e.g.,* Fig. 8 (*infra*), Fig. 9, and supporting text (16:45-17:13).
4 The second MLA thereby learns how to efficiently select the appropriate set of editing instructions
5 for a given “before” image but does *not* need to perform the computationally intensive calculations
6 to generate those editing instructions. 17:14-17. The full advantage of this approach is not in the
7 efficiency of the training; instead, it exhibits itself when the second MLA is deployed to real use-
8 cases like videoconferences. At the time of the ’985 Patent, a typical phone or computer running
9 videoconference apps did not have sufficient hardware and software capabilities to run the full
10 computations of the first MLA. This problem can be avoided if the end user is provided with the
11 second MLA that has learned to approximate the accuracy of the first MLA while using
12 significantly less processing power. *See, e.g.,* 2:27-44.

14 III. LEGAL STANDARD

15 Claim construction is a question of law exclusively for the court. *Markman v. Westview*
16 *Instruments, Inc.*, 52 F.3d 967, 977-79 (Fed. Cir. 1995) (*en banc*). “[A] claim construction analysis
17 must begin and remain centered on the claim language itself” *Innova/Pure Water, Inc. v. Safari*
18 *Water Filtration Sys., Inc.*, 381 F.3d 1111, 1116 (Fed. Cir. 2004); *Phillips*, 415 F.3d at 1314 (*en*
19 *banc*). “Claim terms are generally given their plain and ordinary meanings to one of skill in the
20 art when read in the context of the specification and prosecution history.” *Golden Bridge Tech.,*
21 *Inc. v. Apple Inc.*, 758 F.3d 1362, 1365 (Fed. Cir. 2014) (citing *Phillips*, 415 F.3d at 1313). This
22 meaning governs *unless* the specification reveals “a **special definition** given to a claim term by
23 the patentee that differs from the meaning it would otherwise possess.” *Phillips*, 415 F. 3d at 1316
24 (emphasis added). The specification is the “single best guide to the meaning of a disputed term.”

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1 *Id.* at 1315 (quoting *Vitronics Corp. v. Conceptronic, Inc.*, 90 F.3d 1576, 1582 (Fed. Cir. 1996)).
2 However, limitations from specific embodiments described in the specification should ordinarily
3 not be read into the claims unless it is clear the patentee intends for the claims and the embodiments
4 to be strictly coextensive. *Id.* at 1323. Courts “resort to extrinsic evidence to construe claims only
5 if it is consistent with the intrinsic evidence.” *Seabed Geosolutions (US) Inc. v. Magseis FF LLC*,
6 8 F.4th 1285, 1287 (Fed. Cir. 2021) (cleaned up).

7 8 **IV. DISPUTED CLAIM TERMS**

9 Only four terms are disputed and each will be addressed in turn.

10 **a. “machine learning algorithm” (Claims 1, 16, 18, and 19)**

11 Microsoft’s Proposed Construction	RealD’s Proposed Construction
12 iterative algorithm that trains itself to produce output in response to a given input	an algorithm that is able to learn from data

13 The parties propose substantially similar constructions for the term “machine learning
14 algorithm.” The dispute is as to which proposed construction would better aid a jury’s
15 understanding of the term. *See, e.g., Avid Tech., Inc. v. Harmonic, Inc.*, 812 F.3d 1040, 1050 (Fed.
16 Cir. 2016) (“the aim of claim construction—to give the finder of fact an understandable
17 interpretation of claim scope to apply to the accused systems”); *In re Papst Licensing Digital*
18 *Camera Patent Litigation*, 778 F.3d 1255, 1261 (Fed. Cir. 2015) (the purpose of claim construction
19 is to “clarify[] the scope of [the] claims for the finder of fact.”). Microsoft’s proposed construction
20 adds helpful clarity for a jury, while RealD’s proposal merely rephrases the words of the term.

21 Unlike humans, machines do not use reason to come up with a solution. Instead, machine
22 learning algorithms “learn” from processing training data that is provided to them. Abstract (“A
23 first machine learning algorithm generates first reference data using the training data.”); ’985

1 Patent, incorporating *Kononenko et al.*, by reference¹⁰ (“We revisit the well-known problem of
2 gaze correction and present a solution based on supervised machine learning. At training time,
3 our system observes pairs of images, where each pair contains the face of the same person with a
4 fixed angular difference in gaze direction. It then learns to synthesize the second image of a pair
5 from the first one.”). The patentees were clear that they did not invent machine learning, nor did
6 they re-define the term “machine learning algorithm”— they merely incorporated into their patent
7 “any suitable learning machine learning technique.” 10:49; 11:21.¹¹
8

9 The ’985 Patent claims are directed exclusively to the training of their recited two machine
10 learning algorithms. The MLAs are trained with both (1) portions of images “prior to adjustment”
11 and (2) portions of the same images “after adjustment.” The MLAs use these training data pairs to
12 learn how to generate reference data that includes the editing instructions to get from (1) to (2).
13 *See, e.g.*, claim 1. In other words, the MLA is able to train itself to determine the necessary editing
14 instructions to translate specific “prior to adjustment” patches into corresponding “after
15 adjustment” patches. Conversely, when operated in a videoconferencing application, the
16 previously trained model would not be given the desired “after adjustment” patches. Instead, the
17 MLA would take patches from the actual video, use the model to compute instructions which
18 modify the actual input and then apply those instructions to correct the image.
19

20 The parties appear to agree that the term “machine learning algorithm” is used consistently
21 with its general understanding in the art. For example, both sides agree that a “machine learning
22 algorithm” is type of algorithm. The parties also agree that this algorithm is self-learning—
23 Microsoft phrases this the MLA iteratively training itself, while RealD uses the word “learn.” The
24 parties also agree that the algorithm processes some sort of “input” or “data.” It does not appear
25

26 ¹⁰ Ex. 1, RealD_00003898, Abstract.

¹¹ *See also*, examples of existing machine learning techniques incorporated into the prior art, e.g., U.S. Patent No. 10,740,985.

1 that there is a significant substantive dispute between the constructions—the “algorithm” [“trains
2 itself” / “learns”] by analyzing [“input” / “data”]. However, RealD’s proposed construction could
3 potentially broaden the meaning of the asserted claims beyond merely training the algorithms.
4 Microsoft’s proposed construction is meant to clarify to the fact finder that the claims are directed
5 only at the training of MLAs.

6
7 **i. Whether the “machine learning algorithm” is iterative?**

8 RealD exaggerates greatly by suggesting that Microsoft’s proposal for an iterative
9 algorithm is a “cardinal sin” of claim construction. Microsoft believes the iterative nature of the
10 MLAs in the asserted claims is required by the claims as well as by the disclosure in the ’985
11 Patent. However, the dispute over the word “iterative” is not critical to the parties’ invalidity or
12 non-infringement disputes. Therefore, Microsoft is amenable to dropping the word “iterative”
13 from its construction so long as the construction is clear that the asserted claims are **training**
14 claims—*i.e.*, the MLAs train themselves based on input data (the “receiv[ed] training data” that is
15 recited at the outset of each asserted independent claim).

16 Microsoft believes that “training” may be a disputed issue based on RealD’s infringement
17 contentions, accusing of infringement end-user devices that do no training or learning at all. If
18 RealD disputes that the asserted claims are training claims, as opposed to adjustment claims, RealD
19 should be clear about this position during the claim construction process so that the issue can be
20 resolved. *See, e.g.*, § II.c and Ex. 2 (Response to Restriction Notice).

21
22 **ii. Whether the “machine learning algorithm” must train itself to
23 produce output in response to a given input?**

24 Microsoft’s proposal reflects that the MLA does more than just learn—it builds something
25 based on its learning. As claimed in the ’985 Patent, the result of training the MLA is the
26 generation of reference data as its output. *See, e.g.*, asserted claims 1, 16, 18, 19 (“A method

1 of]/[device for] generating reference data"; "using a first machine learning algorithm to generate
2 first reference data"; "using a second machine learning algorithm to generate second reference
3 data using the same training data"). As claimed, the MLA learns to generate this reference data
4 by processing training data. *Id.* Thus, there can be no reasonable dispute that the claimed MLAs
5 generate some type of output.

6 The first limitation of all of the asserted independent claims requires the MLAs to
7 "receiving training data" as the training input. Thus, there can also be no reasonable dispute that
8 the MLAs generate output in response to this (training) input. *See, e.g.*, claim 1 ("A method of
9 generating reference data [*i.e.*, output of the machine learning algorithm] ... receiving training data
10 [*i.e.*, input to the machine learning algorithm]"); same for other independent claims. RealD does
11 not and cannot credibly dispute these points. Microsoft submits that it would be helpful to a fact
12 finder to clarify that the MLA trains itself to produce output in response to a given input.

13
14 **iii. "Able to" learn is ambiguous and incorrect.**

15 RealD's position is that the MLA "is able to learn." Therefore, RealD's construction
16 provides that the MLA has the *capacity* to learn but allows for the possibility that such learning
17 occurs outside of the claimed process—in other words, RealD may be once again trying to expand
18 the scope into something other than just the training of the MLAs. This would be improper. If,
19 however, RealD agrees that the asserted claims are directed only to training, Microsoft is willing
20 to accept a variation of RealD's proposed construction such as: "an algorithm that learns from data
21 to produce output in response to a given input."

22
23 Lastly, RealD argues that Microsoft's construction may create confusion because of the
24 words "input" and "output" are used elsewhere in the claims. However, the terms "input patches"
25 and "output patches" are independent phrases that are the subject of their own constructions.
26 Any potential ambiguity regarding those terms would likely be clarified during the

claim construction process, as set forth below.

b. “input patches” and “output patches” (Claims 1, 16, 18, and 19)

Term	Microsoft’s Proposed Construction	RealD’s Proposed Construction
“input patches”	patches of the original image	Plain and ordinary meaning
“output patches”	patches of the desired image	Plain and ordinary meaning

It is not clear whether the parties have a substantive dispute regarding the meaning of the terms “input patches” and “output patches.” RealD did not explain what it thinks these terms mean during the meet and confer process under Local Patent Rules 130–131. This continues in RealD’s brief, where RealD criticizes Microsoft’s proposed constructions without stating what RealD believes these terms mean.

This is a frequently used tactic by patent plaintiffs which is—appropriately—drawing increasing ire of the courts tasked with resolving claim construction disputes. *See, e.g., Volterra Semiconductor LLC v. Monolithic Power Systems, Inc.*, C.A. No. 19-2240-CFC-SRF, at 22:22-23:7 (D. Del. Nov. 12, 2021) (transcript) (Chief Judge Connolly expressing concern with parties who offer “plain and ordinary meaning” constructions without explaining what that meaning is: “I am tempted to say the next time I get this situation [where] one side, the plaintiff[,], says, oh, plain and ordinary meaning and offers no alternative definition and all it does is criticize the defendant[’s construction], ... I’m just going with the defendant. I was really tempted to do that in this case. So get the word out.”); *see also O2 Micro International Ltd. v. Beyond Innovation Technology Co., Ltd.*, 521 F.3d 1351, 1360-61 (Fed. Cir. 2008) (“[w]hen the parties raise an actual dispute regarding the proper scope of these claims, the court, not the jury, must resolve that dispute. ... “A determination that a claim term ‘needs no construction’ or has the ‘plain and ordinary meaning’ may be inadequate when a term has more than one ‘ordinary’ meaning or when reliance on a term’s

1 ‘ordinary’ meaning does not resolve the parties’ dispute.”).

2 The reason that Microsoft proposed these terms for construction is that they have the
3 potential to be very confusing to a fact finder. Because the ’985 Patent is directed to eye gaze
4 correction, the terms “input patches” and “output patches” might well suggest to an uninitiated
5 juror that these are the image patches before and after a machine learning algorithm adjusts the
6 images to correct a user’s eye gaze (*e.g.*, when the claimed second MLA is used during a live
7 videoconference). Although it would be understandable for a juror to have this impression, this is
8 **not** a proper understanding of the terms.

10 On the contrary, as set forth above (*supra* at §§ II.c-II.e), the asserted claims are exclusively
11 **training** claims. The machine learning algorithms in the claims are provided with **training data**
12 that includes **both** the “input patches” **and** their corresponding “output patches.” Each of the
13 asserted independent claims (claims 1, 16, 18 and 19) recite as follows:

Claim Language (Claims 1, 16, 18, and 19)	
receiving <u>training data</u> comprising:	
a set of <u>input patches</u> , each <u>input patch</u> comprising a target feature of a digital representation of a head region prior to adjustment of the digital representation of the head region, wherein the target feature is the same for each input patch; and	
a set of <u>output patches in one-to-one correspondence with the <u>input patches</u></u> , each <u>output patch</u> comprising the target feature of the digital representation of the head region after adjustment of the digital representation of the head region;	

19 The machine learning algorithms train themselves using all the above training data in order to
20 generate “reference data” (including “editing instructions”) that could be used in the future—and
21 outside the scope of the ’985 Patent claims—for adjusting a digital representation of a head region
22 (*e.g.*, for performing actual eye gaze correction). *See, e.g.*, § II.c and Ex. 2 (Response to Restriction
23 Notice); claims 1, 16, 18, and 19.

25 The critical point—and the basis for Microsoft’s proposed construction—is that the “input
26 patches” and “output patches” comprise pairs of before and after images that are used for training

1 but no actual adjustment of patches takes place to create the “output patches.” See claims 1, 16,
2 18 and 19. Rather, the “input patches” and “output patches” comprise the pairs of corresponding
3 patches, each pair including an original patch (e.g., eye patch with incorrect gaze) and desired
4 patch (e.g., eye patch with corrected gaze).¹²

5 “Training Data” in the ‘985 Patent Claims



7 “Input Patches”—incorrect gaze

8 Each “input patch” has a “one-to-one
correspondence” with its “output patch”

10 “Output Patches”—correct gaze

11 Each “output patch” has a “one-to-one
correspondence” with its “input patch”

12 By providing large sets of this recited “training data”—sets of “input patches” and “output
13 patches,” often including hundreds or thousands of these before/after pairs of images from
14 different people with varied gaze directions—the machine learning algorithms can iteratively train
15 themselves to create the “reference data” (including “editing instructions”) to perform later
16 adjustment of new user’s eyes (or other facial feature adjustment). However, the “output patches”
17 in the claims have had **no actual adjustment performed on them**. Rather, the “output patches”
18 in the claims are part of the training data pairs that enable the machine learning algorithms to train
19 themselves to perform actual adjustment at a later time (which is not the subject of the claims).
20

21 If this understanding is shared by the parties, the claim construction work will be simple.
22 The Court and parties can simply resolve on wording to capture the above concept and ensure that
23 a jury is not confused by the terms, particularly by the term “output patches”—which could easily
24 be misinterpreted to refer to patches that have actually been edited, which is not true. If RealD

25
26 ¹² The claim language “prior to adjustment” and “after adjustment” are alternate phrasings of Microsoft’s proposed
“original image” and “desired image” language.

1 disagrees with the above understanding and believes that “output patches” should encompass
2 patches that have actually been edited and output by the algorithm used in a videoconferencing
3 application, then RealD should come clean about that position now so that the claim construction
4 process can resolve the dispute. If RealD continues to refuse to offer its understanding of the
5 meaning of these terms (offering only “plain and ordinary meaning”), this likely reveals RealD’s
6 desire for confusion in order to advance an erroneous application of the claims.

7
8 A construction of “plain and ordinary meaning” is improper in view of the concerns
9 presented above. Indeed, the terms “input patches” and “output patches” do not have a plain and
10 ordinary meaning. Even if the terms “input,” “output,” and “patch” have plain and ordinary
11 meanings on their own, their combination into the phrases “input patch” and “output patch” are
12 neither plain nor ordinary in the context of the ’985 Patent. For example, “input” (by itself)
13 implies something that is provided to a computer or system. But is this keyboard input, data input,
14 file input, patch input, or some other input? Likewise, “output” could be the result of a program
15 or a video output to a screen. A “patch,” in the computer sense is typically a software repair (a
16 software patch), but the patent also uses “patch” with respect to images. Most importantly, as set
17 forth above, “output patches” might well suggest something that is “output” by a machine learning
18 algorithm, rather its proper recitation in the claims as part of the “training data” that is provided as
19 input to train the machine learning algorithms. Tellingly, RealD does not cite to any intrinsic or
20 extrinsic definition for “input patch” or “output patch,” confirming that these terms do not have a
21 plain and ordinary meaning. Accordingly, “input patches” and “output patches” should be
22 construed by the Court. *See O2 Micro*, 521 F.3d at 1360.

24 i. Alternate Construction

25 RealD takes issue with the term “image” in Microsoft’s proposed construction.
26 10. The word “image” is not critical to Microsoft’s construction of the claim.

- The output of the second MLA includes “image editing instructions,” and therefore the “digital representations of the head region” must flow from originating “image patches.” Claim 1 recites “second image editing instructions” and claim 6 recites a “second image editing algorithm.”
- RealD confirms that when the “patches” that are modified are images, the input is an “image.” Br. at 9; 13:37-45 (“A patch consists of a target portion of a digital representation of a head region. In a case where the digital representation comprises an image, the patch may be referred to as an image patch. Each input patch (e.g. input image patch) comprises a target feature of the digital representation (e.g. image) of the head region prior to adjustment of the digital representation (e.g. adjustment of the image to be displayed) of the head region.”).
- Figures 1, 2, 4, and 13 illustrate correcting a user’s “image,” and Figures 3, 5, 6, 7, and 11 refer to “images.” “Patches” are defined areas of images provided as training data. *E.g.*, 6:66-7-6. Images are transformed into “digital representations” of a head region. *E.g.*, 1:23-29, 1:45-48.

However, focusing on the word “image” is not essential and detracts from the more important issues presented at the outset of this section. If the word “image” is not preferable, Microsoft does not object to using alternative words. In view of RealD’s complaints about the word “image,” potential alternate versions of Microsoft’s proposed constructions would be: “patches of the original digital representation or image” and “patches of the desired digital representation or image.”

c. “target portion” (Claim 16)

Microsoft’s Proposed Construction	RealD’s Proposed Construction
<i>Indefinite</i> Alternatively: target feature	A portion of the digital representation of a head region

Microsoft originally proposed to RealD to treat this term as an obvious typographical error of the type that can be corrected during the claim construction process. However, RealD disagrees that this term reflects an obvious typographical error and instead insists on giving it a meaning which is not supported by the record. In fact, given the structure of the claim, if this term is not a correctable error, giving another meaning to it renders the claim indefinite, as set forth below.

i. “target portion” lacks antecedent basis and is indefinite

It is well established that a claim term written as “the [claim term]” must be referenced earlier in the claim. *Automed Techs., Inc. v. Microfil, LLC*, 244 Fed. App’x 354, 359 (Fed. Cir. 2007) (“[C]laim term employing definite article ‘the’ ... requir[es] an antecedent basis.” (citing *NTP, Inc. v. Research in Motion, Ltd.*, 418 F.3d 1282], 1306 (Fed. Cir. 2005)). For a claim term to have proper antecedent basis, an *indefinite* article (for instance, “a” or “an”) must precede the first use of the term in the claims and subsequent references to the term preceded by a *definite* article (for instance, “the” or “said”). See generally *Microprocessor Enhancement Corp. v. Texas Instruments Inc.*, 520 F.3d 1367, 1375-76 (Fed. Cir. 2008) (discussing the role of indefinite and definite articles in establishing proper antecedent basis). Antecedent basis is necessary so that those with skill in the art can ascertain the scope of a patent and its claimed inventions with “reasonable certainty.” *Nautilus, Inc. v. Biosig Instruments, Inc.*, 572 U.S. 898, 910 (2014).

As shown below, the first instance of “target portion” in claim 16 is preceded by the word “the.” Because the phrase “target portion” does not appear anywhere else in claim 16—or in any other claim of the ’985 Patent, for that matter—there can be no dispute that this term lacks

1 antecedent basis.

2 During the various meet and confers, Microsoft repeatedly indicated that the term “target
3 portion” appeared to be a typographical error which, when corrected to “target feature,” would
4 save the claim from lacking an antecedent basis. RealD rejected this position and continues to
5 propose a construction for “target portion.” However, this ignores the tenet of patent law that
6 “target portion” must have antecedent basis or the claim is indefinite. *See, e.g., Halliburton Energy*
7 *Servs., Inc. v. M-I LLC*, 514 F.3d 1244, 1249 (Fed. Cir. 2008) (a claim is “indefinite if a [claim]
8 term does not have proper antecedent basis”). RealD proposes no argument regarding proper
9 “antecedent basis” and the word “antecedent” does not even appear in RealD’s brief.
10

11 Thus, because RealD does not dispute that “target portion” lacks proper antecedent basis,
12 the phrase “the target portion” renders claim 16 indefinite. *Halliburton*, 514 F.3d at 1249.

13 **ii. Based on RealD’s position, claim 16 should not be corrected.**

14 In order to correct an obvious error in a patent, the error must be “evident from the face of
15 the patent,” *Grp. One, Ltd. v. Hallmark Cards, Inc.*, 407 F.3d 1297, 1303 (Fed. Cir. 2005). District
16 courts may only correct “obvious minor typographical and clerical errors in patents” when “(1) the
17 correction is not subject to reasonable debate based on consideration of the claim language and the
18 specification and (2) the prosecution history does not suggest a different interpretation of the
19 claims.” *Novo Indus., L.P. v. Micro Molds Corp.*, 350 F.3d 1348, 1354, 1357 (Fed. Cir. 2003).
20

21 Each of the independent claims includes substantively identical language repeating “target
22 feature,” except for the lone “target portion” recited in claim 16 (emphasis added below).

23 (Claim 1)

24 receive training data comprising:

25 a set of input patches, each input patch comprising a target feature of a
26 digital representation of a head region prior to adjustment of the digital
representation of the head region, wherein the target feature is the same for
each input patch; and

1 a set of output patches in one-to-one correspondence with the input
2 patches, each output patch comprising the target feature of the digital
3 representation of the head region after adjustment of the digital
4 representation of the head region;

5 (Claim 16)

6 receive training data comprising:

7 a set of input patches, each input patch comprising information about a
8 target feature of a digital representation of the head region prior to
9 adjustment of the digital representation of the head region, wherein the
10 target feature is the same for each input patch; and

11 a set of output patches in one-to-one correspondence with the input
12 patches, each output patch comprising the target portion of the digital
13 representation of the head region after adjustment of the digital
14 representation of the head region;

15 (Claim 18)

16 receive training data comprising:

17 a set of input patches, each input patch comprising a target feature of a
18 digital representation of a head region prior to adjustment of the digital
19 representation of the head region, wherein the target feature is the same for
20 each input patch; and

21 a set of output patches in one-to-one correspondence with the input
22 patches, each output patch comprising the target feature of the digital
23 representation of the head region after adjustment of the digital
24 representation of the head region;

25 (Claim 19)

26 receive training data comprising:

a set of input patches, each input patch comprising a target feature of a
digital representation of a head region prior to adjustment of the digital
representation of the head region, wherein the target feature is the same for
each input patch; and

a set of output patches in one-to-one correspondence with the input
patches, each output patch comprising the target feature of the digital
representation of the head region after adjustment of the digital
representation of the head region;

Based on this consistent use, Microsoft believed the patentees drafted claim 16 with a
typographical error. Microsoft's position was further supported because the use of "the target
portion" destroys the parallelism between the "set of input patches..." and "set of output
patches..." that are in "one-to-one correspondence" with each other. As shown above, in claims
1, 18, and 19, the "set of input patches" includes "a target feature of the digital representation of
the head." The "set of output patches" are in "one-to-one correspondence with the input patches

1 and include the same “target feature of the digital representation of the head.” Claim 16 breaks
2 this “one-to-one correspondence” by tying the “target feature” of the “input patches” to some
3 newly introduced and non-corresponding “target portion” in the “output patches.”

4 Despite being made aware of these problems in the meet and confer process, RealD
5 doubled down on its position that no correction is necessary, instead arguing that “target feature”
6 and “target portion” are *completely different limitations*. Br. at 12 (“different claim terms are
7 presumed to have different meanings”; Br. at 13 (“‘portion’ is a distinct term from ‘feature’”).
8 RealD then proposed a construction for the term “target portion” allegedly based on the intrinsic
9 record. Br. at 12 (“RealD’s Construction is Consistent with the Intrinsic Record and should be
10 Adopted.”). This means that the construction of “target portion” is the subject of reasonable
11 debate, and therefore that correction of the term is not appropriate. *Novo*, 350 F.3d at 1357.

13 This case is similar to *ORBCOMM* from the Eastern District of Texas. *Smith v.*
14 *ORBCOMM, Inc.*, No. 2:14-CV-666, 2015 WL 5302815 (E.D. Tex. Sept. 10, 2015) (Gilstrap, J.).
15 There, plaintiff argued that disputed term had a particular meaning or should be corrected as having
16 a typographical error. Because the plaintiff proposed a viable construction for the disputed term,
17 the EDTX court found that no evident error existed in the claim as drafted and, therefore, correction
18 was not available. *ORBCOMM*, 2015 WL 5302815, at *12-13 (“**If the error was evident from**
19 **the face of the patent, then Plaintiff would not continue to argue for an alternative**
20 **construction**”; “Simply stated [] the claims either include an obvious clerical error or they do not.
21 Plaintiff cannot have it both ways.”) (emphasis added). Because the term lacked antecedent basis
22 and no correction was available due to the plaintiff’s position, the claim was found indefinite. *Id.*

24 RealD’s claim construction position leads to the same conclusion as in *ORBCOMM*: “when
25 read in light of the intrinsic evidence, [claim 16] fail[s] to inform, with reason, the skilled artisan, of the
26

1 skilled in the art about the scope of the invention.” *Id.* Accordingly, claim 16 is “invalid for failing
2 to particularly point out and distinctly claim the subject matter regarded as the invention.” *Id.*¹³

3 **iii. Plaintiff’s proposed construction cannot be adopted**

4 Even if claim 16 is not deemed indefinite, RealD’s proposed construction cannot be
5 adopted. A substitution of RealD’s proposal into the claim yields a non-sensical claim limitation:

6 each output patch comprising [the target feature a portion of the digital
7 representation of a head region] of the digital representation of the head
8 region...

9 The repetition of the phrase “of the digital representation of the head region” makes no sense in
10 the claim and would likewise lead to indefiniteness. And, removing RealD’s repetitive phrase
11 from the proposed construction yields only “a portion.” This would eliminate the word “target”
12 from the construction and highlights plaintiff’s backdoor attempt to rewrite the claim to have
13 antecedent basis by changing the word “the” to “a.”

14 For these reasons, Plaintiff’s proposed construction should be rejected.

15 **iv. If the word “target portion” is amenable to any construction, it should**
16 **mean “target feature”**

17 As discussed above, Plaintiff’s arguments and proposed construction mean that “target
18 portion” is subject to reasonable debate, making it ineligible for judicial correction and in turn
19 rendering the claim indefinite. However, if this term can be construed at all, the only possible
20 construction would be “target feature.” *See*, § IV.c.ii, *infra*.

21 **V. CONCLUSION**

22 For the foregoing reasons, Microsoft’s proposed constructions should be adopted.

23
24
25 ¹³ *See also*, MPEP § 2173.05(e) *Lack of Antecedent Basis* (“A claim is indefinite when it contains words or phrases
26 whose meaning is unclear. *In re Packard*, 751 F.3d 1307, 1314 (Fed. Cir. 2014). The lack of clarity could arise where
a claim refers to “said lever” or “the lever,” where the claim contains no earlier recitation of a lever and
where it would be unclear as to what element the limitation was making reference to.”). *Id.*

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25 **RealD Exhibit 2003 - Page 27**
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26 **IPR2023-01046 - U.S. Patent No. 10,740,985**

CERTIFICATE OF SERVICE

I hereby certify that on the 28th day of July 2023, I served the foregoing Defendant's Preliminary Claim Constructions and Extrinsic Evidence via electronic mail to all counsel of record.

SIGNED THIS 28th day of July 2023 at Seattle, Washington.

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