UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.,

Petitioner,

v.

AUTONOMOUS DEVICES LLC,

Patent Owner

Case IPR2023-01054

U.S. Patent 10,452,974

Deposition of ELI SABER, PH.D.,

Conducted Remotely

Thursday, May 16, 2024

8:32 a.m.

Reported by: Matthew Goldstein, RMR, CRR

DIGITAL EVIDENCE GROUP

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1 Deposition of ELI SABER, PH.D., conducted
2 remotely:
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9 Pursuant to Notice, before Matthew Goldstein,
10 RMR, CRR, Notary Public in and for the State of
11 Maryland.
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1 A P P E A R A N C E S

2 ON BEHALF OF THE PETITIONER:

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11 ON BEHALF OF THE PATENT OWNER:

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1 C O N T E N T S

2 EXAMINATION OF ELI SABER, PH.D. PAGE

3

4 By MR. KHAN 5

5

6 E X H I B I T S

7 EXHIBIT PAGE

8

9 Exhibit 1004 United States Patent No. 159
10 9,604,359 B1
11 Exhibit 1001 United States Patent No. 8
12 10,452,974 B1
13 Exhibit 2007 Declaration of Dr. Eli Saber, 8
14 Ph.D.
15 Exhibit 2015 Curriculum Vitae of Dr. Eli 9
16 Saber

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1 P R O C E E D I N G S

2 Whereupon,

3 ELI SABER, PH.D.,

4 being first duly sworn or affirmed to testify to

5 the truth, the whole truth, and nothing but the

6 truth, was examined and testified as follows:

7 EXAMINATION BY COUNSEL FOR THE PETITIONER

8 BY MR. KHAN:

9 Q. Good morning, again.

10 A. Good morning.

11 Q. Well, thank you for making yourself

12 available today. I understand you have a sharp

13 cutoff at 5 o'clock. So I'll do my best to finish

14 before then. I think most likely we will.

15 Given our start time, we may take a few

16 breaks here and there. When you do need a break,

17 please let me know.

18 MR. KHAN: And same thing for Matt and

19 Arvind, if there's a break, just please let me

20 know.

21 BY MR. KHAN:

22 Q. I'll just request that you give me a

1 few minutes heads-up notice so I can finish up
2 that line of questioning.
3 Does that work for you?
4 A. That works fine.
5 Q. Great.
6 And when we do take those breaks, you
7 understand you're not allowed to discuss the
8 substance of your testimony today with opposing
9 counsel?
10 A. I do.
11 Q. And if you are approached by anyone at
12 any point during the cross-examination today
13 regarding your testimony or any feedback or
14 anything, will you let me know?
15 A. Of course.
16 Q. Thank you.
17 And, again, giving the timing, we may
18 take a lunch break in between. I'm happy to give
19 an extended lunch break as needed.
20 Do you agree that we are here today to
21 discuss your declaration which was submitted as
22 Exhibit 2007 in IPR proceeding IPR2023-01054,

1 which relates to U.S. Patent No. 10,452,974?
2 A. I do.
3 Q. For purposes of brevity, I'll refer to
4 the patent at issue as the '974 patent.
5 Is that okay?
6 A. That's perfectly fine.
7 Q. Do you understand that your testimony
8 today is sworn testimony taken under oath?
9 A. I do.
10 Q. And you understand that your oath you're
11 taking is as solemn as the oath you would be
12 taking if you were testifying at trial in court?
13 A. I do.
14 Q. Do you understand that the deposition
15 testimony today can be used at a trial and
16 subsequent briefs in this proceeding?
17 A. I do.
18 Q. Are you taking any medicine that would
19 prevent you from answering the questions
20 completely and truthfully to the best of your
21 ability?
22 A. No, I'm not.

1 Q. Is there anything else that would
2 prevent you from answering the questions
3 completely and truthfully to the best of your
4 ability today?
5 A. No.
6 Q. Do you have a clean copy of the
7 '974 patent, which is Exhibit 1001, and your
8 declaration, which is Exhibit 2007, with you
9 today?
10 A. I do.
11 Q. Okay.
12 A. But I also ask you to drop it in the
13 chat box.
14 Q. Sure.
15 A. Have you dropped it?
16 Q. I am in the process right now.
17 (Exhibit 1001 was marked for
18 identification and attached to the transcript.)
19 (Exhibit 2007 was marked for
20 identification and attached to the transcript.)
21 BY MR. KHAN:
22 Q. You should see the first document

1 loading pretty soon. Let me know when you have
2 that or you see that.
3 A. I do. Just one second.
4 I received the '974 document.
5 Q. Okay. The other one will take a little
6 bit longer. It's your declaration. So you should
7 be seeing it pretty soon.
8 A. Do you want me to go ahead -- I received
9 it. Do you want me to go ahead and open them?
10 Q. Yes, please. Thank you.
11 And while we're at it, I'll also put
12 your CV, which is Exhibit 2015, here in the chat.
13 A. Thank you.
14 (Exhibit 2015 was marked for
15 identification and attached to the transcript.)
16 BY MR. KHAN:
17 Q. You can let me know when you have the
18 three open.
19 A. I have all three of them open.
20 Q. Fantastic.
21 Okay. So just a few questions on your
22 background. Did you obtain your bachelor's in

1 1988 and your Ph.D. in 1996?
2 A. That is correct.
3 Q. Did your Ph.D. or graduate research
4 involve applying machine learning techniques?
5 A. To some extent, yes.
6 Q. Can you explain how?
7 A. Sure.
8 So my research was about -- if you look
9 at the title of my dissertation, automatic image
10 annotation and query by example using color shape
11 and texture information. So, essentially, what we
12 were doing at the time, we were building a system,
13 we called it Voogle, kind of like a visual Google
14 in a sense.
15 And the system was supposed to -- you
16 should be able to present the system with an
17 image, to show the system an image of a car, and
18 it should be able to go into a database of images
19 or videos and search for that particular object
20 based on shape, color, and texture information in
21 a series of images.
22 You know, the idea behind it is if you

1 went to Disney World, for instance, on a vacation
2 and you collected 10,000 images or something and
3 you came back home, you put them all in a
4 database, can you query them and search them, and
5 so on in a visual manner by giving examples to the
6 computer and have the computer go find what it's
7 looking for.
8 So that's the essence of the work in a
9 short, brief summary.
10 Q. And which part of this involved machine
11 learning?
12 A. Well, in a sense, the color and the
13 shape. Mostly the shape one involved more machine
14 learning than the color.
15 Q. When you say the color and the shape
16 involved machine learning, could you just clarify
17 what you mean by that?
18 A. Well, I mean, with the color stuff, we
19 were looking at examples. For instance, we were
20 looking at there are what we call memory colors,
21 say, you know, people's skin, green grass, blue
22 sky is something you would remember. And memory

1 color, you typically don't think of grass as red,
2 for instance.
3 So if you were showed the computer a
4 texture of a grass or a piece of grass, you know,
5 an example of a piece of grass, could the computer
6 go search the database and find this piece of
7 grass based on the color information. So we
8 designed some algorithms to do that, to do the
9 searching.
10 The same thing with shape, for instance,
11 a car, if you were able to provide the computer
12 with a template of a car, this is what a car shape
13 looks like, a sedan or an SUV or something, can
14 the computer go segment the images, you know, do
15 some segmentations and, say, frame by frame in a
16 video or just regular images, segment the images,
17 separate different things, and locate that shape,
18 which may be a collection of multiple regions.
19 Because when you segment a car, you
20 know, the glass is, let's say, white, the car is
21 red, the tires are black, so if you segment based
22 on color, you have multiple regions. You still

1 have to combine them in the hierarchical object
2 description to say this is the root node of a car
3 in a sense and then match to that object.
4 Q. You mentioned segmentation. Is that
5 required to do the comparison here? You have to
6 break out a picture and compare the segments, or
7 can you compare kind of images as a whole
8 one-to-one kind of thing?
9 MR. JAIRAM: Objection; form.
10 THE WITNESS: Essentially, it depends a
11 little bit of what exactly you're looking for, but
12 segmentation is usually the underlying foundation
13 for a lot of the algorithms. You'll need to
14 separate the images into a variety of regions,
15 typically.
16 Sometimes people do
17 foreground/background segmentations. Sometimes
18 people do, you know, multi-object segmentations.
19 So you need to have some understanding of the
20 objects in the image to do the queries.
21 Otherwise, you're probably doing, like, a brute
22 force type of approach.

1 BY MR. KHAN:
2 Q. What happens when there's only one
3 object in an image?
4 A. Well, you would still segment that frame
5 in a sense. You would find that object. You
6 might create -- you know, if a hierarchical
7 representation of the object, you might create a
8 root node that says this is the object and then
9 sub nodes under it that would say these are the
10 tires and this is the windows and this is the
11 fenders or whatever.
12 So you have the pieces of the object
13 under, let's say, the parent root node, if you
14 wish. And that would be your object versus the
15 background in the scene.
16 Q. And how does the computer know that
17 there's a particular object in a picture -- an
18 image, sorry?
19 A. Well, you would have to use some type of
20 a template. You would have to say, for instance,
21 I'm looking for an object that has this kind of
22 shape. So you'd have to provide a template --

1 you'd have a database of -- like a training set,
2 if you wish, a database of templates.
3 You might say, here's a shape of what a
4 car looks like. It's shaped in this fashion. So
5 as the computer is searching the image, it's
6 looking for regions or a combination of regions
7 that might match that particular shape, depending
8 on what shape matching algorithms you were using.
9 Q. And just so I understand, and once the
10 machine is trained -- let's just use your example
11 of a car. The machine understands that a certain
12 type of car has to have a certain type of shape.
13 What does it do with that information? Does it
14 store it, like, in a library, or what does it do
15 with that information?
16 A. Yeah, you would --
17 MR. JAIRAM: Objection; form.
18 THE WITNESS: Yeah, you would
19 basically -- I mean, if you're looking at the
20 single image, for instance, the single frame of
21 video and you have segmented this frame for the
22 very first time, let's say, and you have a bunch

1 of regions and the car may be ten regions.
2 And as you search that image for a car
3 and you've provided this shape and it happens to
4 find those ten regions put together match that
5 shape, you would have a record of that.
6 So now you have, like, an accompanying
7 record in a sense of the image stored in a
8 database with that image, like some type of a
9 connection or a correlation that would indicate
10 that this particular, you know, group of ten
11 regions matches that particular template. So the
12 next time you search that image, you have some
13 prior knowledge.
14 BY MR. KHAN:
15 Q. So is this -- the shape, it's
16 essentially -- is it, like, a certain type of
17 pixel orientation? How does it determine the --
18 how does the computer determine the shape?
19 A. Well --
20 MR. JAIRAM: Objection; form.
21 THE WITNESS: -- it's essentially the
22 boundary -- one way to look at the shape is the

1 boundary of the cohesive region. So you're
2 looking at regions that have to be neighboring,
3 for instance, and you have a boundary of those
4 regions or the subregions. Those boundaries would
5 define, in a sense, the shape.
6 You do have to be cognizant of the scale
7 variations and, you know, rotations and
8 translations. Typically, translations are easier,
9 but rotations in the image plane are much easier
10 than rotations in and out of the image plane.
11 BY MR. KHAN:
12 Q. So in storing this information, once the
13 computer learns to associate a shape with a
14 certain object, so the certain shape, for example,
15 associated with a car --
16 A. Yep.
17 Q. -- then in its database it stores that
18 shape information along with a label, such as this
19 is a car; is that correct?
20 MR. JAIRAM: Objection; form.
21 THE WITNESS: I mean, more or less, yes.
22 I mean, your -- general summary, yes.

1 BY MR. KHAN:
2 Q. And along with that information there
3 could be additional information such as a
4 scalability factor or perhaps variations in color?
5 MR. JAIRAM: Objection; form.
6 THE WITNESS: Yeah, I mean, it would
7 recognize, you know, these group of regions is the
8 car. If you do some color matching on that, you
9 would say, okay, this is a red car.
10 So as you search, you will learn more
11 and you augment, in a sense, your database. So
12 you would create a root node it, for instance, for
13 where the car is and put under that root node the
14 subregions of the car. And each of them would
15 have, you know, a proper kind of metadata-type
16 things. It would say, you know, this has the
17 color red and the tires are black and, you know,
18 et cetera.
19 BY MR. KHAN:
20 Q. And this whole machine learning
21 algorithm that we're just discussing, this is part
22 of your Ph.D. thesis?

1 A. Yes. This was part of my Ph.D. work,
2 and you could see that published in my CV. So if
3 you go to my CV -- I'm just going to hit the
4 journal papers, but if you'll look at the first
5 five journal papers, the ones that are labeled 35
6 through 39, and the corresponding conference
7 papers, those published the work directly from my
8 Ph.D. work.
9 And then after that, you know, once I
10 completed my Ph.D., I started working with a
11 student, Yaowu Xu, who you see named in the
12 remaining papers after that. That continued a lot
13 of this work until he graduated.
14 Q. On page 11 of your CV, you also have a
15 list of patents, patent applications, and
16 publications; is that right?
17 A. That is correct.
18 Q. So there's a list of 12 --
19 A. Yeah.
20 Q. -- documents; is that right?
21 A. That is correct.
22 Q. Were you involved in the prosecution

1 work for these patents in any way?
2 MR. JAIRAM: Objection; form.
3 THE WITNESS: I don't know what you mean
4 by "prosecution work." I was involved in
5 providing the attorney with the technical aspects
6 of the patents. You know, the ones at Xerox --
7 that were done at Xerox, you know, Xerox has
8 attorneys that would handle all the legal stuff of
9 the patents. You know, we provide the technical
10 stuff.
11 So they would sit with us on multiple
12 meetings and they would ask all the technical
13 details and read any papers that we might have put
14 together that weren't published yet and et cetera,
15 you know, write flowcharts.
16 And we walk them through all the
17 technical stuff, and then they would follow up
18 with the patent office and do all the legal stuff
19 that needs to be done, you know, write the claims,
20 for instance, and that type of thing and prosecute
21 the patent, as you would say, to achieve the
22 patent.

1 MR. JAIRAM: I'll caution the witness
2 not to reveal the substance of any third-party
3 confidential information, including any
4 confidential information of Xerox or any other
5 party.
6 BY MR. KHAN:
7 Q. Are you familiar with the term "office
8 action"?
9 A. I am, yes.
10 Q. Did you work on any office action
11 responses for any of the patent applications that
12 you were named an inventor for?
13 A. No, I have not. You know, the attorneys
14 would come back to us and ask additional
15 questions. It's probably related, you know, to
16 some responses that they would receive. So it's
17 not just one meeting, and you're done. So it's
18 kind of an iterative -- collaborative and
19 iterative process. But they would come back and
20 ask questions, and then we'd provide more details
21 as needed.
22 Q. Okay. Now, you mentioned you were at

1 Xerox. You were at Xerox for about 16 years; is
2 that correct?
3 A. That is correct.
4 Q. Is it fair to say that was one place
5 where you were for the longest part of your
6 career?
7 A. No, that would not be correct.
8 Q. Which other place have you been longer
9 than your period at Xerox?
10 A. So I started at RIT in 1998 as an
11 adjunct faculty. If you look at my CV, you would
12 notice I was an adjunct faculty at the University
13 of Rochester -- well, I would say a part-time
14 faculty at the University of Rochester, because I
15 had also research funding together with the
16 faculty there and I had teaching responsibilities,
17 versus at RIT I was just an adjunct faculty,
18 because I didn't have any research
19 responsibilities.
20 So I started at RIT in 1998 as an
21 adjunct faculty. And in 2004, I joined full-time
22 as faculty. And today we're 2024. So my

1 full-time period, in this August it would be
2 20 years, and obviously before that, I've had
3 six years or so of adjunct.
4 Q. And at the time you were at Xerox, were
5 you teaching full-time?
6 A. No. When I was working for Xerox, I was
7 working for Xerox full-time, and I was teaching
8 part-time at the University of Rochester and
9 teaching part-time at the Rochester Institute of
10 Technology.
11 At the U of R, I also had a research
12 grant with a Professor Murat Tekalp. We had a
13 GOALI -- NSF GOALI grant, which is essentially the
14 grants they would give to somebody where you have
15 a faculty from a university, a representative from
16 industry, that was me, and a student that's being
17 guided by both the faculty and the industry
18 personnel.
19 Q. During the course of your education or
20 subsequent professional experience, did you learn
21 how to code?
22 A. Oh, yes. Oh, yes, most of the stuff

1 that I coded at the time -- well, initially, I
2 learned to code in Fortran, because I guess I'm
3 getting older these days, but I learned to code in
4 Fortran in the '80s. In the '90's, I learned to
5 code in C and then C++ and MATLAB, because these
6 became much more available at the university
7 settings.
8 I continued to code a lot with MATLAB
9 for my coursework and some of my research, but the
10 coursework a lot of times, you know, you want to
11 demonstrate something for the students or create
12 an algorithm or show how something would take
13 place.
14 MATLAB is a really great place to do
15 that, because, one, it has all the supporting
16 functions underneath it. You don't have to
17 create, you know, a least squared algorithm and
18 create multiplication or whatever. All those
19 functions are available. They're well organized.
20 It's free to all students and faculty. So
21 students can access it freely. They don't have to
22 download and do stuff.

1 Q. How many languages would you say you
2 know?
3 A. You mean computer languages?
4 Q. Sorry, computer languages.
5 A. Yes. So I used to know Fortran. It's
6 been a long time since I've coded in Fortran. I
7 actually started coding in basic, excuse me, back
8 at my engineering science part -- degree. So I
9 used to know basic, probably don't know it much
10 anymore.
11 I used to know Fortran -- or have coded
12 in Fortran. C and C++ are the primary ones I have
13 used over the years, as I was doing my Ph.D. work
14 and subsequent to that. But then, also, we use
15 MATLAB more extensively, because it's available
16 for us freely at the university.
17 MR. JAIRAM: And may I suggest,
18 Dr. Saber, if you refer to any technical acronyms,
19 such as Fortran, MATLAB, et cetera, please spell
20 it out to ease it for the court reporter?
21 THE WITNESS: Okay.
22

1 BY MR. KHAN:
2 Q. Dr. Saber, do you know that the
3 petitioner in this case is Tesla?
4 A. Is what?
5 Q. Tesla?
6 A. Yes.
7 Q. I'm sorry, can you give me a moment,
8 please?
9 A. Sure, take your time.
10 (Recess from the record.)
11 BY MR. KHAN:
12 Q. So I asked you whether you know that the
13 petitioner in this case is Tesla?
14 A. Yes.
15 Q. Do you own a Tesla vehicle?
16 A. No, I do not.
17 Q. Is there a reason you do not?
18 A. I like, actually, trucks, believe it or
19 not. So I own a Dodge Ram 1500, and then I -- you
20 will probably never find me driving a car. I
21 haven't driven a car since 2010.
22 Q. I see.

1 A few moments ago we were talking about
2 your patents. Are there specific ones that are
3 related to machine learning?
4 MR. JAIRAM: Objection; form.
5 THE WITNESS: Let me take a peek here
6 for a second.
7 The one that has to do with Unsupervised
8 Color Image Segmentation by Dynamic Color Gradient
9 Thresholding has -- well, it's not exactly machine
10 learning, but it has some of the fundamentals that
11 you would use for, you know, a machine learning
12 immigrate.
13 The one on Image Segmentation using
14 Dynamic Color Gradient Threshold would also have,
15 you know, the fundamental pieces that we would be
16 using. I mean, these were basically algorithms
17 that we used in some of our machine learning work.
18 BY MR. KHAN:
19 Q. Just to be clear, you're referring to
20 Items 4 and 5 in your patent list on page 11 of
21 your CV?
22 A. I'm referring to -- sorry, I think -- I

1 was referring to 5 and 7, but 4 provides a
2 different methodology of doing the similar thing,
3 because we were doing multi-resolution. You know,
4 this way you can take large images and work as a
5 pyramid.
6 And the last one that HP filed, so the
7 one -- No. 1, 2, 3, I think, were filed by HP. I
8 was doing some work for HP on a number of grants.
9 HP funded my lab for a number of years. Those
10 were filed by HP.
11 The last one obviously has to do with
12 CNN, convolutional neural networks. I don't know
13 what the status of that is from HP. I don't
14 know -- I haven't followed up on it.
15 Q. I wanted to turn to Exhibit 2007, which
16 is your declaration. And if you could, please,
17 let me know when you have that in front of you.
18 A. I have my declaration in front of me.
19 Q. And can you turn to paragraph 32?
20 A. Yes, just one second.
21 Yes, I'm at paragraph 32.
22 Q. In paragraph 32, you refer to a person

1 of ordinary skill in the art; is that right?
2 A. Yes.
3 Q. For purposes of our discussion, I'll
4 refer to person of ordinary skill in the art as a
5 POSITA.
6 Is that okay?
7 A. That's fantastic. Thank you.
8 Q. So who is a POSITA?
9 A. Well, as you see in paragraph 32, this
10 is kind of the legal description of a POSITA. And
11 in my declaration on page 16, we define the POSITA
12 for this particular declaration. When you hear me
13 flip, I have a hard copy here in front of me that
14 counsel has provided.
15 Q. I'll just repeat my question.
16 Who is a POSITA?
17 A. Well, as you see in paragraph 32, that's
18 the legal definition of a POSITA. I understand
19 it's a person of ordinary skill -- having ordinary
20 skill in the art may be defined by factors, such
21 as the levels of education and experience of the
22 inventor or other persons actively involved in the

1 field, the type of problems encountered in the
2 field, prior art solutions to those problems, you
3 know, rapidity with which innovations are made and
4 sophistication of the technology.
5 So that's the legal definition, to my
6 understanding. Obviously, I'm not a lawyer, but
7 that's the legal definition that I was provided
8 for a POSITA.
9 Q. So in paragraph 32, I understand you
10 mentioned the factors that you used to define a
11 POSITA.
12 A. Right.
13 Q. But it doesn't tell me who a POSITA is.
14 For example, you have factors of levels of
15 education or types of problems encountered in the
16 field, but you haven't specified what those types
17 of problems are.
18 So, again, who is a POSITA?
19 A. So if you go to page 16 of my
20 declaration, on paragraph 45, it defines the
21 POSITA for this particular declaration. You know,
22 in that paragraph we call him a POSA, but I'm sure

1 it's the same thing.
2 So the definition that I've used is I
3 believe a person of ordinary skill in the art at
4 the time of the alleged invention would have had
5 at least a bachelor's degree in electrical
6 engineering, computer engineering, computer
7 science, systems engineering, or a similar
8 technical field with at least three years of
9 experience in the fields of computer vision, image
10 video processing, and/or machine learning.
11 And, obviously, there's an alternative,
12 one, if you have a master's. So that defines, in
13 a sense, the POSITA for this declaration.
14 Q. This definition was -- sorry, was this
15 definition something that you developed?
16 A. I don't remember exactly how this
17 definition came about, but this definition
18 obviously is something that I follow -- you know,
19 we collaboratively developed and followed.
20 Q. When you comment on what would have been
21 or what would not have been obvious to a POSITA,
22 what's the criteria you use to make your

1 conclusion?
2 A. Well, obviously, I've been working in
3 the field for many years. I worked with
4 engineers, colleagues, students, professionals of
5 various types. So -- and I've worked with people
6 that are experts in the field. I've worked with
7 people that are practitioners in the field and at
8 variety levels.
9 So I'm well-versed in the knowledge of
10 the field and what a person of ordinary skill in
11 the art would know at the time of the invention.
12 Q. How does someone like yourself who
13 received a bachelor's and master's in the '90's
14 understand what would have been obvious to a
15 POSITA in the year 2016?
16 A. Well, I received my bachelor's,
17 master's, and doctorate, you know, obviously, as
18 you know, in the late '80s and '90's. And I've
19 been -- since that time, I've been teaching in the
20 field, doing research in the field.
21 You know, I started teaching in the
22 field in 1997, as my first teaching assignment at

1 the University of Rochester, and also had a grant
2 with Professor Tekalp from U of R.
3 I started teaching at RIT in 1998, as an
4 adjunct faculty, as I mentioned earlier. And I've
5 worked in this field ever since. I mean, we've
6 done a lot of work in various aspects of this
7 field.
8 We've had multiple grants from the
9 Department of Defense, I think five of them, if my
10 memory serves me right. I've had multiple grants
11 from Hewlett Packard and other industrial partners
12 to do a variety of different things. So I've
13 worked in this field for many, many years.
14 Q. You mentioned that a POSITA would have a
15 bachelor's degree in electrical engineering,
16 computer engineering, computer science, systems
17 engineering, or a similar technical field with at
18 least three years of experience; is that correct?
19 A. That's correct.
20 Q. Of the students that you have had who
21 achieved a bachelor's degree and obtained
22 three years of experience, are you in touch with

1 any one of them?
2 A. Well, some of them, obviously, worked
3 for me doing an MS/Ph.D. So they got their
4 bachelor's, and then they worked under me doing an
5 MS/Ph.D. type of work with me. Some of them went
6 to industry, like HP and others.
7 The ones that have -- you know, that
8 I've worked with, professionals from HP, not just
9 my students, but others that also -- at different
10 paces of their careers. Some of them were on
11 let's say the first five years of their career, so
12 to speak. Others were more advanced in their
13 careers.
14 So I've worked with a variety of
15 different engine- -- at Xerox, for instance, I've
16 hired engineers. You know, towards the end of my
17 career at Xerox, I was a senior scientist and
18 manager. So I've hired engineers of various --
19 you know, various degrees.
20 Some had a BS in engine science. Others
21 had a BS in electrical engineering. And, you
22 know, I've coached them and obviously mentored

1 them. So I'm very familiar with, you know, their
2 knowledge.
3 MR. KHAN: Matthew, we're joined by
4 Nicholas Stephens. He might be joining in and out
5 today. He's a colleague of mine at Fish &
6 Richardson. We both represent petitioner, just
7 for the record.
8 BY MR. KHAN:
9 Q. Dr. Saber, you mentioned that you have
10 some of your students doing MS after your -- after
11 their bachelor's.
12 Does that MS take more than three years?
13 A. Well, it depends sometimes on the
14 student. Occasionally, some do. Most usually
15 complete in two years or so. Occasionally, a
16 student will spill into the three-year format.
17 And once they complete the MS, you know, some of
18 them have taken my advice and gone on for a Ph.D.
19 at RIT and continued from there.
20 I also think that that POSITA definition
21 here is I think very much similar definition to
22 what Tesla had in their petition, if I'm not

1 mistaken.
2 Q. So why did you think that experience in
3 computer vision, image video processing, and/or
4 machine learning is necessary for a POSITA?
5 A. Well, I mean, if you think about the
6 field of, let's say, autonomous driving, you have
7 the vehicle. The vehicle has sensors on it.
8 Those sensors can be LiDAR, it could be cameras.
9 You know, cameras and LiDAR are probably the
10 primary most used sensors.
11 Cameras acquire imagery. So that
12 imagery has to be analyzed for the vehicle,
13 obviously, to properly operate. And you could
14 acquire imagery from all around the vehicle. So
15 it has to be analyzed in the proper context of
16 where you are in the vehicle, and it has to be
17 analyzed so you know what's in the front, what is
18 in the back type of thing.
19 So you need a lot of computer vision
20 techniques to be able to handle all that analysis
21 in, obviously, a realtime situation, if you're
22 driving.

1 You need image and video processing
2 knowledge because you're going to be acquiring
3 videos, not still images. You're going to be
4 acquiring frames of videos at, say, 30 frames a
5 second. So you'll need a lot of tracking
6 knowledge and video type of knowledge.
7 And you need machine learning knowledge
8 because you're going to be making decisions on,
9 you know, what the vehicle should do within a
10 limited amount of time. That has to be done in
11 near-realtime or realtime-type situations.
12 So you have to have some way of
13 absorbing all this imagery, dissecting what's
14 important, and providing, you know, output to the
15 vehicle so the vehicle can do what needs to be
16 done. So you have to have some control knowledge
17 of how to control the vehicle, you know, start,
18 stop, move, turn, et cetera.
19 Q. Did you write the declaration yourself?
20 A. So, typically, I usually -- obviously, I
21 read the patents and the prior art in the petition
22 in this case very carefully. I have discussions,

1 obviously, with counsel.
2 I provide a first draft for the
3 declaration, and then it becomes a collaborative
4 and iterative effort between myself and counsel
5 until the final document is finalized. I review
6 that extremely carefully. I read every word of
7 the document and I approve it and I sign it.
8 Q. So I -- my question was not what you
9 typically did. It was specifically for this
10 particular declaration.
11 For this particular declaration, did you
12 write the first draft?
13 A. I wrote the first draft of this
14 declaration, that is correct.
15 Q. And then you engaged in the
16 back-and-forth process with opposing counsel?
17 A. It's a collaborative -- as I mentioned,
18 it's a collaborative and iterative effort, you
19 know, back and forth.
20 MR. JAIRAM: I'll instruct the witness
21 not to reveal the substance of any privileged
22 communications with counsel.

1 BY MR. KHAN:
2 Q. Are you familiar with the term "claim
3 construction"?
4 A. Obviously, I'm not an attorney, but yes,
5 I am familiar with the term.
6 Q. What does that mean to you? Sorry, I
7 should be clear, what does claim construction mean
8 to you?
9 A. Well -- so if -- so if you go to
10 paragraph 55 of my declarations, that defines
11 claim construction.
12 Q. And what is the definition of "claim
13 construction"?
14 A. Well, as you can see on the first
15 sentence of paragraph 55, I understand that claim
16 terms are typically given their ordinary and
17 customary meaning as would have been understood by
18 a POSITA at the time of the alleged invention.
19 Q. Are you involved in the co-pending
20 district court proceedings for this patent?
21 A. I don't believe so, no. I'm just
22 involved in the IPR process.

1 Q. Now, in your declaration, you offered a
2 construction for the term "connection"; is that
3 correct?
4 A. That is correct.
5 Q. And how did you develop this
6 construction?
7 A. Well, as you can see in paragraph 55,
8 the second sentence is what I've applied,
9 obviously. In considering the meaning of the
10 claims, I also understand that one must consider
11 the claim language, the specification, prosecution
12 history, and the knowledge of a POSITA at the
13 relevant time.
14 So if you look at paragraph 57 of my
15 declaration, I provide my opinion. So it says, in
16 my opinion, in the context of Claim 7 of the
17 '974 patent, including in light of the claims,
18 specifications, drawings, and obviously
19 prosecution history of this patent, a connection
20 should be construed as a relationship that
21 includes a link. And that's supported by the
22 claims, the specs, the drawings, and the intrinsic

1 record as a whole.
2 Q. Can you explain to me how you applied
3 the prosecution history in developing your
4 construction for the term "connection"?
5 A. Well, I mean, I've looked at the
6 prosecution history, I looked at the '974 patent,
7 I looked at the specification, I looked at the
8 drawings, not just one document. I looked at the
9 claims to try to understand what does the owner of
10 the patent mean with the term "connection" and,
11 based on that, generated this construction.
12 Q. Can you tell me which part of the
13 prosecution history informed your opinion on what
14 the construction for "connection" should be?
15 A. I don't remember off the top of my head,
16 sitting here today. It's been a while. I don't
17 remember off the top of my head. But I looked at
18 all those things I just mentioned.
19 Q. Is it fair to say that whatever
20 information you considered in developing your
21 construction for the term "connection" was cited
22 in paragraphs 56 to 62 of your declaration?

1 A. Well, I mean, obviously, this is the
2 summary in a sense of how this was arrived at and
3 explained here. But I certainly looked at the
4 claims by the patents. I looked at the
5 specifications, the drawings of the patent itself.
6 As I mentioned, the prosecution history
7 and my knowledge of the word "connection" and what
8 does it entail in this particular setting. And
9 based on that, we -- that -- you know, that
10 definition came about.
11 Q. Is it correct to say that in
12 paragraphs 56 to 62, you did not have a single
13 citation to the prosecution history?
14 A. I don't recall. I would have to check
15 all those, but I don't recall off the top of my
16 head. I would have to check.
17 Q. It's about seven paragraphs. You can
18 check, and then you can let me know.
19 (Witness peruses the exhibit.)
20 THE WITNESS: Yes, I do not see a direct
21 citation to the prosecution history in
22 paragraphs 57 to 62.

1 BY MR. KHAN:
2 Q. So I just wanted to understand. In
3 paragraph 55, you noted that you must consider the
4 prosecution history in formulating your
5 construction, but in paragraphs 56 to 62, when you
6 adopted -- or when you specified your
7 construction, you did not include any mention of
8 the prosecution history; is that correct?
9 A. I hear some discussion in the
10 background.
11 So I did not include a citation to the
12 prosecution history in those paragraphs, but
13 obviously, I included many citations to the patent
14 itself and where -- in each of the paragraphs, you
15 know, where the knowledge came about.
16 Q. We've hit the one-hour mark. So maybe
17 we can take a short break here. How does
18 ten minutes sound to you?
19 A. It sounds fine to me.
20 MR. JAIRAM: Dr. Saber, do you want to
21 do five minutes so that we can make sure that we,
22 like, you know, get everything done in the time

1 frame? We can do ten if you want, but I suggest
2 doing five for the breaks to keep things moving
3 along.
4 THE WITNESS: It's up to counsel. I'm
5 happy to take five. I'm happy to take ten, as
6 long as we're done by 5 o'clock.
7 MR. KHAN: Yeah. Well, I think we'll be
8 fine. We can take a ten-minute break. And we can
9 come back at 9:40?
10 THE WITNESS: 9:40. I have 9:30 on my
11 clock. I'll be back in my seat at 9:40.
12 MR. KHAN: Thank you.
13 THE WITNESS: Thank you very much.
14 (Recess from the record.)
15 BY MR. KHAN:
16 Q. Dr. Saber, can we turn to Exhibit 1001,
17 which is the '974 patent? When you have that
18 open, can you let me know, please?
19 A. Yes, I have that open.
20 Q. How would you describe the '974 patent?
21 MR. JAIRAM: Objection; form.
22 THE WITNESS: Well, it's a long patent.

1 So it's -- but as you obviously can see, if you
2 look at the title of the patent and the abstract
3 of the patent, it provides a decent description.
4 And I also have a description in my declaration, a
5 brief description in the declaration.
6 BY MR. KHAN:
7 Q. Can you turn to Figure 1, please. And
8 just let me know when you're there.
9 A. Figure 1.
10 Q. Figure 1 of the '974 patent.
11 A. Yes, sir.
12 Q. Can you describe to me your
13 understanding of Figure 1?
14 A. Well, obviously, Figure 1 provides an
15 overview, essentially, of the invention. It
16 provides kind of an overview, like, where you
17 would follow a block diagram or, you know, an
18 architectural kind of block diagram of the
19 invention.
20 The description on the patent of the
21 figure says it's "a block diagram of a Computing
22 Device 70 that can provide processing capabilities

1 used in some of the disclosed embodiments."
2 Q. Do you believe that the '974 patent has
3 an alleged innovative feature?
4 A. Of course.
5 Q. Which block in Figure 1 has that
6 innovative feature, whatever that may be?
7 A. Well, it's not -- you can't point to a
8 single block, because it's obviously integrated
9 knowledge. So it's not just in a single block. I
10 mean, you have a human machine interface in
11 block 23. You have memory in block 16.
12 You know, I/O devices are probably not
13 going to have some of that stuff, but you have a
14 processor there that's going to have software
15 that's going to do a variety of things that the
16 patent describes.
17 You have storage, where you have, you
18 know, the information that's being stored, the
19 connections that we're talking about, the
20 correlations, the mixed knowledge base. So it's
21 not in a single box of that figure or
22 architectural diagram.

1 Q. Can you tell me which boxes it is in?
2 A. I'm sorry?
3 Q. Can you tell me which boxes the
4 innovative features are in?
5 MR. JAIRAM: Objection; form.
6 THE WITNESS: As I mentioned to you, you
7 know, it's not in a specific box of these boxes.
8 I mean, it's -- you know, the invention,
9 obviously, you have algorithms, you have knowledge
10 base. So it's not in a single one of these boxes.
11 It's going to be, you know, dependent on what
12 piece of it is going to be in various places of
13 these boxes.
14 BY MR. KHAN:
15 Q. The display device 21, is there
16 something different that this display device does,
17 compared to other display devices?
18 A. Probably not in a display device. I
19 mean, I'm assuming it's just a -- you know, it's a
20 display device like we have here. So it's going
21 to be -- it's going to display some of the
22 connectivity and stuff.

1 There may be interfaces there, like a
2 graphical user interface that's being displayed.
3 So it's -- you know, you can't say well, this box
4 has and this box has not. This is just an overall
5 architecture diagram. But the invention will
6 probably be -- will have pieces on all the boxes.
7 Q. What's the human machine interface 23 in
8 Figure 1?
9 A. Well, I mean, it is described in the
10 patent. So if you look at the patent, on
11 Column 58 of the patent, it will describe the
12 human machine interface that you were asking
13 about.
14 So it states there in Column 58,
15 Computing Device 70, which is the device of this
16 whole figure here, via bus 5, which you see that
17 bus going across the figure -- sorry, I read the
18 wrong line. This was a mistake. Let me back up.
19 Computing Device 70 may also include --
20 I'm reading the wrong line again. One second.
21 So Computing Device 70 may also include
22 Human interface -- machine interface 23, which is

1 what you're asking about, such as a keyboard, a
2 pointing device, a mouse, a touchscreen, joystick,
3 remote controller, and/or other input device.
4 And then there's -- in other
5 implementations, it discusses more the
6 Human-machine interface.
7 Q. Thank you.
8 Can you turn to Figure 2 of the
9 '974 patent?
10 A. Yes.
11 Q. What's your understanding of Figure 2?
12 Well, sorry, what's your understanding
13 of what Figure 2 depicts?
14 A. Well, let's look at the description in
15 the patent. So if you look at the patent itself,
16 so the patent states, Figure 2 illustrates an
17 embodiment of Device 98. So -- and that's what it
18 labels there, Device 98 -- comprising unit for
19 learning and/or Using a Device's Circumstances for
20 Autonomous Device Operation. And it calls that a
21 DCADO Unit 100. Essentially, that's one of their
22 devices.

1 Q. Is device 98 in Figure 2 the same as
2 device 70 in Figure 1?
3 A. Well, it's not the same as device 70.
4 Device 70 is the overall kind of description, in a
5 sense an overall architectural diagram, you know,
6 a block diagram, as we discussed.
7 Device 98 kind of talks about the pieces
8 that have to do with, you know, the learning
9 and/or using a device's circumstances for
10 autonomous device operation. So it's talking
11 specific about that piece of it. It's not
12 something you can pick up and drop into the other
13 piece.
14 Q. So is device 98 not the same as
15 device 70 in Figure 1?
16 A. Well, device 70, as I said, in Figure 1,
17 provides the processing capabilities used in some
18 of the disclosed embodiments. It's just a block
19 diagram that kind of gives you the overall
20 processing capabilities of the disclosed
21 embodiments in this particular patent.
22 Device 98 focuses more on the autonomous

1 device operation unit, as I described.
2 Q. Are there any embodiments that are
3 implemented by the device in Figure 2 -- device 98
4 in Figure 2 that -- I'm sorry.
5 Are there certain embodiments in
6 device 70 in Figure 1 that are not implemented in
7 device 98 in Figure 2?
8 A. And I'm not sure what you're asking. I
9 mean, device 98 in Figure 2 talks about -- you
10 know, illustrates an embodiment -- Figure 2
11 illustrates an embodiment of device 98 comprising
12 a unit for learning and/or using a device's
13 circumstances for autonomous device operation. So
14 it talks about one embodiment.
15 Q. I understand that. I guess what I'm
16 trying to understand is whether Figure --
17 device 98 in Figure 2 is the same or different
18 from device 70 in Figure 1. And I haven't got an
19 answer from you.
20 So, I mean, can you indicate, is
21 device 70 the same or different than device 98?
22 A. Well, I just described to you what they

1 are. Device 70 provides a block diagram of a
2 computing device. So this is a block diagram, and
3 it talks about the processing capabilities. So,
4 essentially, it lays out a bit of the hardware
5 kind of description of this computing device in a
6 sense.
7 You know, it talks about the I/O ports,
8 the processor, memory. So it lays out in a sense
9 the hardware type of description as a block
10 diagram architecture.
11 Device 98 talks more about an embodiment
12 for learning and/or using a device's
13 circumstances. So device 98 gets into one of his
14 embodiments of this particular invention.
15 Q. So I can appreciate the description of
16 each one of these devices that you're providing,
17 but that was not my question. My question was not
18 asking you to describe these devices.
19 The question was: Is device 98 in
20 Figure 2 the same or different than device 70 in
21 Figure 1?
22 A. Well, they're different functionality.

1 I mean, device 70 is a block diagram architecture
2 of essentially laying out the hardware as one
3 would use in a system.
4 Device 98 is talking more about this
5 DCADO unit that the inventor has proposed. So
6 they're not -- they don't define the same things.
7 Q. Thank you.
8 So you mentioned the D-C-A-D-O. I'll
9 refer to that as DCADO, if that's okay.
10 Is that okay?
11 A. Yeah, that's fine.
12 Q. Thank you.
13 What is the DCADO unit used for?
14 A. Well, as you can see from the figure,
15 right, it provides all the pieces, right. In this
16 particular embodiment we're talking about, it
17 provides the pieces that you would need for
18 autonomous driving.
19 Q. And when you say the pieces that you
20 would need for autonomous driving, you're
21 referring to things like machine learning and
22 training; is that correct?

1 A. Well, all the fundamental pieces. Like,
2 if you look at Column 66 of the patent, it starts
3 to describe referring to Figure 2. And it
4 describes the DCADO unit that is illustrated in
5 Figure 2. It talks about the various pieces of
6 it.
7 Q. What does the artificial intelligence
8 unit 110 do?
9 A. Well, just what it says. I mean, that's
10 where probably -- that's where his artificial
11 intelligence, say algorithms or whatever, are
12 comprised. So if you look, for instance -- so if
13 you look on Column 67, starting at line, say, 14
14 or so, you can see a description of the artificial
15 intelligence unit. And it's a long description.
16 So I'm not going to read all of it, but it starts
17 on line 67. There's a good description starting
18 on line, say, 13, 14.
19 Q. The artificial intelligence unit is
20 connected to the object processing unit 93 in
21 Figure 2.
22 Do you see that?

1 A. Yes.
2 Q. What does the object processing unit 93
3 do?
4 A. So if you look at Figure 3A to 3E, it
5 kind of provides some high-level descriptions of
6 various sensors that feed into the object
7 processing units. So you have sensors, like, you
8 know, a camera, microphone, et cetera, feed into
9 the object processing unit. Sorry.
10 And if you look at Column 71, so
11 Column 71 starts to describe the object processing
12 unit. And starting at line 38, it talks about the
13 description of the object processing unit.
14 Q. Going back to the DCADO unit, the DCADO
15 unit has a modification interface 130.
16 What does a modification interface do?
17 A. So if you look at Column 139 of the
18 patent, starting on line 64, it describes the
19 modification interface. And there's also a
20 description on line -- on Column 140, starting on
21 line 42.
22 Q. So -- and I've asked you a few different

1 components and you've pointed to me in the spec
2 where they're mentioned, but, you know, I can read
3 the spec. I would like to understand what your
4 understanding is.
5 So can you tell me what your
6 understanding of the modification interface 130
7 is?
8 A. So if you look at Column 139, for
9 instance, towards the bottom, it says,
10 "Modification Interface 130 comprises the
11 functionality for modifying execution and/or
12 functionality of Application Program 18,
13 Processor 11," et cetera.
14 On Column 140, starting at line 9 or 8,
15 Modification Interface comprises the functionality
16 to access, modify, and/or perform other
17 manipulations on runtime, engine/environment,
18 virtual machine, operating machine, et cetera,
19 compiler, et cetera, et cetera.
20 And later on, it will say, comprise the
21 functionality to access, modify, or perform other
22 manipulations. Essentially, that's the purpose of

1 it.
2 Q. So in systems such as the one in the
3 '974 patent, when, as you just described, there is
4 a modification of the execution and/or
5 functionality of application programs, how is such
6 modification implemented?
7 A. Well, some will be implemented in
8 hardware. Some will be implemented in software.
9 So it depends on, you know, how the system
10 essentially is designed. Some of them could be
11 implemented in hardware, some software.
12 Q. And so when you are -- when we're
13 talking about -- and maybe I should clarify my
14 question. We're talking about specifically
15 Column 140, where it's talking about modification
16 involving modifying execution and/or functionality
17 of application program. That's what you had just
18 mentioned earlier.
19 How is the application program execution
20 functionality modified?
21 MR. JAIRAM: Objection; form.
22 Objection; scope.

1 THE WITNESS: I'm not sure I understand
2 what you're asking.
3 BY MR. KHAN:
4 Q. Well, what I'm asking is that
5 Column 140 -- just an explanation of what this
6 means really. In Column 140 you just pointed to
7 is talking about the modification interface
8 comprises the functionality for modifying
9 execution and/or functionality of application
10 program 18, that's in Column 140, lines 1 through
11 3 which you had just pointed me to and I'm trying
12 to understand better what that means and what that
13 would entail. So that's what I'm asking.
14 What does modify -- how does the
15 modifying of the execution functionality of
16 application program actually accomplished?
17 A. Well, if you look at that same column,
18 starting at line, let's say, 35, you'll see,
19 "Modification Interface 130 comprises the
20 functionality to access, create, delete, modify,
21 and/or perform other manipulations on values,
22 variables, parameters, and/or other data or

1 information."
2 Then the next line will say,
3 Modification Interface comprises any features,
4 functionalities, and embodiment of Acquisition
5 Interface 120, and vice versa, and other disclosed
6 functionalities.
7 So, essentially, the modification
8 interface has the functionality, I'm reading at
9 line 35, to access, create, delete, modify, and/or
10 perform other manipulations on values, variables,
11 and parameters.
12 So you have an application program that
13 has values, variables, parameters, and the
14 modification interface will go in and make a
15 change and say, you know, I see a person running
16 quickly to my car, you know, it's going to hit the
17 car or do something.
18 So it will change variables, modify, you
19 know, parameters in the application program to
20 make the proper changes.
21 Q. And these changes occur during the
22 course of machine learning; is that correct?

1 MR. JAIRAM: Objection; form.
2 THE WITNESS: Well, I think your
3 question is extremely broad, and I'm not sure I
4 understand what you mean. But you typically have
5 machine learning algorithms. You have a training,
6 essentially, dataset. In a typical machine
7 learning application, you have training datasets,
8 you have test datasets.
9 So I'm not sure what you're asking. I'm
10 not sure what your question is about.
11 BY MR. KHAN:
12 Q. I'll try to be a little clearer to the
13 extent I can so hopefully it will be helpful.
14 Is it correct that the DCADO unit is a
15 unit for learning and/or using a device's
16 circumstances?
17 MR. JAIRAM: Objection; form.
18 THE WITNESS: So let's be precise and
19 accurate. Let's look at the description. So if
20 you look at Figure 2 description, it says,
21 "illustrates an embodiment of Device 98 comprising
22 Unit for Learning and/or Using a Device's

1 Circumstances for Autonomous Device Operation."
2 So that's the precise description.
3 BY MR. KHAN:
4 Q. Okay. That wasn't my question. Again,
5 I'm going to ask you to answer the question
6 specifically.
7 Is it correct that the DCADO unit is a
8 unit for learning and/or using a device's
9 circumstances?
10 MR. JAIRAM: Objection; form.
11 THE WITNESS: That's -- I mean, if you
12 look at Figure 2 description, I think I have
13 answered your question. So you have a device 98
14 comprising unit for learning and/or using a
15 device's circumstances for autonomous device
16 operation. So it's using the device's
17 circumstances for autonomous operation.
18 So I'm not sure I understand your
19 question, but that's the description.
20 BY MR. KHAN:
21 Q. Well, I'm asking you about learning
22 and/or so using a device's circumstances, and your

1 response does not indicate -- in your response
2 you're saying it's using a device's circumstances
3 for autonomous operations. You're not answering
4 the question. And I can repeat the question.
5 Is it correct that the DCADO unit is a
6 unit for learning and/or using a device's
7 circumstances?
8 A. I think I've answered your question.
9 Q. You haven't, and I can ask it again.
10 A. I mean, if we go back to Column 66,
11 that's the starting description of Figure 2, it
12 describes the DCADO unit comprises interconnected
13 AI, Artificial Intelligence Unit, et cetera, et
14 cetera. So it describes the DCADO unit, which is
15 this whole Figure 2 that we're talking about.
16 So, obviously, it's going to do all
17 these pieces that you see in this diagram in
18 Figure 2. It's got a Human-machine interface.
19 It's got an object processing unit. It's got
20 sensors. It's got an AI unit.
21 I guess I'm not sure what you're asking.
22 Q. Okay. We can move on. We can go back,

1 actually, to modification interface. You had
2 pointed me to the description of the modification
3 interface in Column 140, I believe it was lines 26
4 to 30, where it states, "Modification Interface
5 comprises the functionality to access, create,
6 delete, modify, and/or perform other manipulations
7 on functions, methods, procedures, routines,
8 subroutines, and/or other elements of Application
9 Program 18"; is that correct?
10 A. What was the column you just mentioned?
11 Q. Column 140, approximately lines 26 to
12 30.
13 A. Column 140. Yes. So -- yes, this is
14 the description. I mean, it describes it,
15 obviously, starting -- the description starts on
16 Column 139, on line 64, and goes into Column 40.
17 But, yes.
18 Q. So can you give me one example of the
19 functionality of deleting function, method, or
20 procedure of application program 18?
21 A. Are you reading?
22 Q. It's that same section. I'm just asking

1 for an example of the description.
2 A. So can you point me to which line are
3 you reading so we can be on the same page?
4 Q. Yeah, it's, again, lines 26 to 30,
5 Column 140, with the same --
6 A. Okay.
7 Q. Yeah. You see it says, to access,
8 create, delete, modify, and/or perform other
9 manipulations on functions, methods, procedures,
10 et cetera, of application program 18.
11 So I was looking at that and trying to
12 understand that better, and I was asking if you
13 could give an example of when some -- you know,
14 there's a deleting of a function method procedure
15 routine of application program 18?
16 A. Well, I mean --
17 MR. JAIRAM: Objection; form.
18 THE WITNESS: I mean, you're asking a
19 very obviously general question. You would have
20 to look at the software carefully. But generally
21 speaking, and I'm speaking now in very general
22 terms, I mean, let's say you have an application

1 program that's -- maybe it's slowing down the
2 vehicle.
3 So you have a program that's going to
4 slow down the vehicle and come to a stop, let's
5 just say. And that program is slowing it too
6 abruptly, so where the -- potentially a passenger
7 sitting in the car is being rocked forward too
8 fast or something.
9 Then, obviously, this modification
10 interface, as you do some training, you would
11 access those variables, and you would say, okay,
12 put it slower, a slower time constant on this.
13 Let's slow down so the deceleration is being
14 slowed down so you're not rocking the person
15 inside or you're not accelerating abruptly from
16 where you are.
17 So you're modifying, i.e., the function,
18 perhaps. Maybe you put a filter on some of these
19 variables or, you know, time charts or you're
20 deleting perhaps one and putting a whole new one
21 or you're accessing some of the variable time
22 constants or whatever and you're changing them,

1 you're slowing things down so you don't overshoot,
2 that type of thing. So those are some examples.
3 BY MR. KHAN:
4 Q. Thank you. I appreciate that.
5 A. You're welcome.
6 Q. You mentioned the example of a car and a
7 passenger sitting in the car. When a car is
8 traveling on a new road that may not be, you know,
9 on the driving app, road map, how does the system
10 learning modify its knowledge of the road
11 structure?
12 A. I --
13 MR. JAIRAM: Objection; form.
14 THE WITNESS: I'm not sure I follow your
15 question, sir.
16 BY MR. KHAN:
17 Q. So in your last example you talked about
18 a car traveling on a road, coming to a stop sign,
19 something like that.
20 A. Yes.
21 Q. So I'm just asking, going along with
22 that example, when you have a car, let's say the

1 car is now on a road that's not there in the
2 application map, right --
3 A. So you have a car on a road that it is
4 not part of any of the maps in the car?
5 Q. That's right. That's right.
6 Does the application then -- if it's,
7 like, a mapping application, does it update its
8 records to reflect that there's a new road here?
9 MR. JAIRAM: Objection; form.
10 Objection; scope.
11 THE WITNESS: Well, I'm not sure exactly
12 what you're asking. But you're obviously asking a
13 very hypothetical question, and it's very hard to
14 constrain all the details. So I will try to give
15 you some answers with the understanding that
16 you're asking a very open-ended, a very
17 hypothetical question that's essentially -- you
18 know, it's hard to constrain all the pieces.
19 But if you put a car on a road that the
20 car has never seen before and the road doesn't
21 exist in the road application map of the vehicle,
22 the vehicle would have to rely on its sensors at

1 that point, just like you would if you were -- if
2 you were to pick me up and put me in Johannesburg,
3 South Africa, where I've never been and put me on
4 a road there that I've never seen before.
5 So the car would have to rely on its
6 sensors, cameras, Lidars, et cetera, to do the
7 automation, you know, to do the driving. So
8 you'll have to ingest the videos and/or
9 information from all the sensors, process that in
10 realtime, and provide controls to the vehicle.
11 You know, obviously, there are some
12 things you would use from its machine learning,
13 you know, artificial intelligence unit, but you
14 will need to do realtime processing of sensors
15 right then and there.
16 So I'm not sure about -- if this is
17 addressing what you're asking, but you're asking a
18 very open-ended, hypothetical question that's --
19 without knowing all the constraints, without
20 knowing all the pieces, without seeing the road,
21 it's hard to answer such questions like that.
22

1 BY MR. KHAN:
2 Q. Thanks for the explanation.
3 In what circumstances does the
4 modification interface 130 access the functions,
5 methods, procedures, routines of the application
6 program 18?
7 A. I'm not sure I could answer that
8 question without -- you know, you'd have to go
9 through the code specifically to really answer
10 exactly in what circumstances that happens.
11 But I would assume you'd have access to
12 the application programs, you know, on a regular
13 basis, because you have to be able to interact.
14 You're doing this in realtime in a sense. You
15 have to be able to interact with those application
16 programs readily.
17 Q. And when the system is -- I'm sorry,
18 when the modification interface is accessing this
19 application program, does that involve accessing
20 the corresponding memory locations of the
21 application program?
22 A. Well, it's got to access -- see, if you

1 look and see -- I'm going back to 140, Column 140,
2 the lines that you mentioned, lines 26 to 30. So
3 Modification Interface comprises a functionality
4 to access, create, delete, modify, and/or perform
5 other manipulations on functions, methods,
6 procedures, routines, subroutines, and/or other
7 elements of Application Program.
8 So it has the capability to do all these
9 things. Now, does it do that every single time,
10 every single one of them? It depends on what's --
11 what it's seeing, what it's receiving, what's the
12 input. But it has the ability to do all these
13 things.
14 Q. Yeah, and I'm actually just asking --
15 you know, given that you're the expert, I'm asking
16 what the -- exactly this disclosure, how it would
17 be done and what it means. And that's why I had
18 asked earlier about, you know, deleting.
19 And now I'm asking about access. Like,
20 how does it do the accessing; right? We can just
21 stick to the sentence, right, and that's fine.
22 I'm trying to understand how this is done.

1 So in the context of the '974 patent,
2 right, nothing abstract, nothing -- like in the
3 context of the '974 patent, when we're talking
4 about the modification interface accessing the
5 function methods of the procedures, et cetera, as
6 noted in lines 26 to 30 of Column 140, right, of
7 the application program, how is that done. And
8 I'm just trying to understand that.
9 So is this access done? Is it done --
10 my previous question was: Is it done by
11 referencing memory locations that are --
12 correspond to application program 18, or is there
13 something else?
14 So if you could explain -- the question
15 here, to be clear, is: How is the accessing, as
16 noted in lines 27 of Column 140, how is that
17 access done?
18 A. Well, to answer this question very
19 specifically, how is it done, you would have to
20 look at the software, you know, exactly and/or the
21 hardware design to really answer that.
22 But I will give you a generic answer,

1 you know, not the exact specific how, but a
2 generic answer. You know, the modification
3 interface, let's assume -- I'm making assumptions
4 here.
5 So we'll assume that the modification
6 interface is a software program that is handling
7 this -- all these type of things. So it's kind of
8 like an overall programming, you know, software
9 application here.
10 It would have to access the variables in
11 the application program. It would have to access
12 various memory locations there. It would have to
13 access, you know, some of the classes and
14 different things to be able to make changes and
15 delete and modify stuff.
16 It would have to access some of the
17 functions and provide, you know -- because the
18 functions will have input variables. It would
19 have to update the values of all these input
20 variables so the functions can then process that
21 information.
22 So it has to have -- be able to do all

1 this. So it's got to access all these different
2 things for it to be able to provide the proper
3 input into the application programs.
4 Q. And, again, that list of verbs, access,
5 create, delete, modify, and perform -- there's
6 also perform. And I'm referencing lines 26 to 30,
7 Column 140, the '974 patent.
8 When the patent talks about the
9 modification interface performing these functions,
10 methods, of the application program 18, does that
11 include performing the instructions -- the
12 instruction sets that are also part of the
13 disclosure in the '974 patent?
14 A. Well, it's performing other
15 manipulations on functions, methods, procedures,
16 routines, subroutines. So it's going to perform,
17 you know, manipulations there. It may, you know,
18 change case. For instance, if you see this, do
19 this or -- you know, you're familiar with C,
20 probably. You have like this case -- case-case
21 type of calls. So it's going to affect some of
22 that. So it's going to perform these type of

1 manipulations on functions.
2 There may be multiple functions that do
3 a specific item. It's going to select which one
4 of these functions should be run in a sense.
5 There may be calls within the functions that, you
6 know, use -- and I'm being generic now and making
7 assumptions and being hypothetical and really just
8 providing a simplistic example here.
9 But, you know, for instance, it may say,
10 well, why don't we use a least square algorithm
11 instead of an absolute value algorithm to do this
12 and that.
13 So it's going to depend a lot on what's
14 being -- what it's seeing and what's being done.
15 It's very hard to answer such generic questions,
16 very hypothetical.
17 Q. Well, just to be clear, there's no
18 hypothetical here, because I'm just asking you to
19 explain what the patent means when it's making
20 these statements. And this is within the context
21 of the '974 patent.
22 I'm not providing any hypothetical here.

1 I'm just asking you to explain, based on your
2 knowledge as an expert, how these things are done
3 or what they mean, right. I'm just pointing to
4 the same statement.
5 And so along those lines, when we're
6 talking about performing, deleting, or creating,
7 modifying these functions, methods, procedures,
8 routines, subroutines, and other elements of the
9 application program, would this involve modifying,
10 deleting, adding instruction sets, as well, that
11 are part of this application program 18?
12 A. Well, it will involve whatever is needed
13 to obviously perform the activity that's being
14 programmed by the software -- you know, that's put
15 forth by the hardware and/or program by the
16 software of this particular application.
17 Q. Did these instruction sets that might be
18 stored as part of the functions of an application
19 program, are they typically stored in a memory
20 location associated with the application program?
21 A. Well, I mean, for instance, if you look
22 at -- if you look at that same column, 140, let's

1 go to line 42.
2 For instance, you can see it talks about
3 various techniques for modifying, execution or
4 functionality of the application program,
5 processor, et cetera. Some aspects, some of the
6 previously described techniques and/or tools can
7 be utilized. Code instrumentation, for instance,
8 may involve inserting additional code, overwriting
9 or rewriting existing code, and/or branching to
10 separate segments of code.
11 So it has to be able to access all these
12 different locations to do these type of things.
13 So code is typically stored, you know, in memory
14 locations and/or hard drives somewhere in this
15 particular application. It's got to be able to
16 access that in the appropriate timing for the
17 activity that you're doing.
18 Q. I see.
19 So along the lines of what it says here,
20 lines 45 to 51 in Column 140, the addition of code
21 or overwriting or rewriting existing code would be
22 part of the modification performed by the

1 modification interface --
2 A. Yeah. Yes, I mean, obviously, that's
3 what it describes. It gives you a little example,
4 like, Device1.moveLeft type of thing or whatever.
5 So you have some example -- a small example there.
6 But it has to be able to access whatever
7 the application that's being accessed and do these
8 type of things to effect the situation at hand.
9 Because you can't possibly program every possible
10 situation you're going to see out there in the
11 world. So it has to make decisions more or less
12 on the fly.
13 Q. I see.
14 Can I ask you to turn to Column 80,
15 line 50, of the '974 patent?
16 A. Column 80, line 50.
17 Q. If you can let me know when you're
18 there.
19 A. I am there.
20 Q. Could you read that sentence starting at
21 line 50?
22 A. Yes. So referring now to the DCADO

1 Unit 100, DCADO Unit 100 comprises any hardware,
2 programs, or a combination thereof.
3 Q. Based on this sentence, is it your
4 understanding that in some cases the DCADO unit
5 can be just hardware?
6 A. The DCADO unit comprises any hardware,
7 programs, or a combination thereof. So it
8 would -- it has obviously hardware. It's got to
9 have memories and processing units and so on.
10 It's got to have software programs that are going
11 to do the various things, and you're going to be
12 able to change those on the fly in a sense, you
13 know, make changes to those. And it's got to have
14 a combination between them to be able to do what
15 it needs to do.
16 Q. So is your understanding of this
17 statement that the DCADO unit must have a
18 combination of hardware and programs?
19 A. It comprises any hardware, programs, or
20 a combination thereof. So it's got to have the
21 proper hardware, the proper software, and
22 combinations of those where it's needed.

1 Q. So you just said "and a combination
2 where needed." Does that sentence say "and" or
3 "or"?
4 A. Well, it specifically says "or a
5 combination thereof." But, you know, you have to
6 understand, I mean, this unit has -- it's got to
7 have hardware, it's got to have programs that are
8 functioning onto this hardware, and obviously a
9 combination was needed to do what it needs to do.
10 Q. And when you say it must have hardware,
11 can you point to me where in the patent it says
12 that it must have hardware?
13 A. Well, this is a pretty large patent. I
14 mean, I can do some searching if you want, but
15 obviously, it says it comprises any hardware,
16 programs, or a combination thereof. So it has all
17 those pieces. It has the ability to have all
18 those pieces.
19 Q. So does it have all the pieces or the
20 ability to have all those pieces?
21 MR. JAIRAM: Objection; form.
22 THE WITNESS: I guess I'm not sure what

1 you're asking, but the DCADO unit that we're
2 talking about here comprises any hardware,
3 programs, or a combination thereof. So it has
4 hardware, it has programs, and combinations is
5 needed.
6 BY MR. KHAN:
7 Q. Okay. We're hitting about the one-hour
8 mark. So we can take another ten-minute break.
9 That would be great.
10 Does that work for you?
11 A. That works fine for me.
12 Q. Great.
13 MR. KHAN: If that's okay with everyone
14 else, then we'll see you back at 10:50 a.m., okay,
15 Eastern.
16 THE WITNESS: Thank you very much.
17 (Recess from the record.)
18 BY MR. KHAN:
19 Q. Dr. Saber, can you turn to Figures 4A
20 and 4B of the '974 patent. And let me know when
21 you're there, please.
22 A. Yes, I have Figure 4A and 4B in front of

1 me.
2 Q. Great.
3 In your words, can you describe what's
4 depicted in Figures 4A and 4B?
5 A. Well, if you go to Column 79 of the
6 patent, it talks about the description in 4A. And
7 Column 80 talks about the description in 4B.
8 So if you take a look at the figure, as
9 he's describing, so you see it's an example in
10 Figure 4A, you have an object 615a, which is -- in
11 this case is a cat -- it looks like a cat. Object
12 may be detected at a distance of 6 meters from the
13 device. It shows a bearing angle, and it provides
14 a description. So do you want me to read the
15 section on 4A, or is this sufficient?
16 Q. Well, the question was to describe
17 Figures 4A and 4B in your words. I'm familiar
18 with the patent. I've read the patent. So, you
19 know, when I ask those questions, I'd
20 appreciate -- of course, answer how you'd like,
21 but if you can answer in your own words when
22 asked, that would be great, instead of reading

1 from the patent, because I think we've all done
2 that already.
3 So in future, if I ask you that, then
4 please note that what I'm asking is not to, you
5 know, read off of the patent, just to describe in
6 your own words what your opinions are.
7 A. I would like to be as precise and
8 accurate for the deposition, and that's why I
9 think it's important to look at them. So it's a
10 very precise description and not just a generic
11 thing.
12 Q. Yeah, I can understand that. I
13 appreciate that.
14 A. Sure.
15 Q. Thank you.
16 Would you agree that in Figure 4A,
17 there's three objects -- I'm sorry, there's -- the
18 device 98 detects three objects, which is the --
19 object 615a, b, and c; is that right?
20 A. That would be correct, yes.
21 Q. And object 615c is a person, 615a is a
22 cat, 615b is a tree; is that correct?

1 A. That is correct.
2 Q. How does the device know that the
3 person, 615c, is John Doe?
4 A. Well, I mean, in this diagram they just
5 have a label there so they can refer to it. But
6 this is -- I mean, for this particular figure,
7 this is just a label there so you can refer to it.
8 You know, now, if you look at the
9 description here, it describes basically -- in the
10 patent, it says, Object 16C [sic] is also
11 detected. Object 16C may be recognized as a
12 person. Object 16C may be identified as John Doe.
13 So you would have to have, obviously,
14 the proper object tracking and recognition
15 algorithms to recognize a person and facial
16 recognition to determine that person is John Doe.
17 Q. So I guess I'm asking exactly about this
18 object tracking and recognition algorithms that
19 you've referred to in your answer.
20 How does that work? Can you explain to
21 me in the context of the '974 patent, how is that
22 object recognition and tracking performed so that

1 the system can determine that this person is John
2 Doe?
3 A. Well, it talks about that a little bit
4 earlier. So if you go to Column 75, for instance.
5 If you look at the top of Column 75,
6 even a little bit earlier, but 75 I think will be
7 a good place to start just for the discussion and
8 the question that you asked.
9 So if you look at Column 75, starting at
10 the beginning, you have a picture recognition
11 techniques, analyze features, lines, edges,
12 ridges, corners, et cetera.
13 A few lines below that, he refers to
14 artificial intelligence unit 110. I'm on line 10
15 now. Line 11 talks about facial recognition
16 techniques that would obviously do facial
17 recognitions. Line 17, some aspects, facial
18 recognition techniques and/or tools involve
19 identifying and/or analyzing facial features. So
20 you're looking at a variety of facial features to
21 be able to obviously recognize the person.
22 So you have to have appropriate facial

1 recognition techniques that can do this.
2 Q. I see.
3 And so putting that disclosure that you
4 just pointed to in the frame of Figure 4A, for
5 instance, the system performs object recognition
6 and determines that there's an object that matches
7 the -- I guess the records related to a John Doe,
8 and, therefore, it identifies that person -- that
9 object as John Doe; is that right?
10 A. So you cut out a little bit, but you
11 obviously -- the device has to recognize there is
12 an object. So you have object detection. Then
13 you have object recognition. So you're going to
14 detect the object. There is an object over here.
15 You have to recognize this is a human, cat, tree,
16 whatever. Because some objects move, others
17 don't. Like a tree hopefully is not moving.
18 But the person may be walking across a
19 crosswalk. So there's object recognition in terms
20 of recognizing this is a person versus another,
21 you know, vehicle or something.
22 And then there's also the recognition of

1 if it is a person, is this John Doe? And then
2 there's -- obviously, it would be tracking where
3 you would track that object throughout the frames.
4 So in this case, you know, you're
5 recognizing John Doe. So you have to have facial
6 recognition and something in your database that
7 says this is John Doe.
8 Q. And then is it fair to say then that
9 this information, the data that's recognized, is
10 then stored as part of a collection of object
11 representations that you see in Figure 4B?
12 A. Well, if you look at the description in
13 Figure 4B, I'm looking at Column 80, starting at
14 line 16. And if you look at that, it's referring
15 to object processing unit 93. And that's the
16 label that you see on Figure 4B of that big --
17 that largest box there, object processing unit.
18 And within that, you have a collection
19 of object representations, and those are
20 essentially -- if you look at the description,
21 starting on line 16, you have object processing
22 unit may generate -- may create or generate

1 collection of object representations. And he
2 gives a bunch of examples of that.
3 And he gives an instance -- for
4 instance, you talked about the cat, you have a
5 type, you have a distance, and so on. So you have
6 descriptions of each of the objects in these
7 object representations.
8 Q. So when an image, such as the one shown
9 in Figure 4A, is processed in the '974 system, the
10 system will determine that there's these three
11 objects and then add in the collection of object
12 representations the data corresponding to these
13 objects. And that data is in the form of, for
14 example, the object representation shown in
15 Figure 4B.
16 Did I get that right?
17 A. Well, close. I mean, you obviously
18 identify an object. You would create an object
19 representation with various categories. He gives
20 an example here of the type, the distance, the
21 bearing.
22 But, obviously, the example continues --

1 he also states -- line 34, Column 80, also states,
2 any number of object representations and/or other
3 elements or information can be included in
4 collection of object representation.
5 So, you know, you identified a cat. You
6 might want to say, you know, the size of the cat
7 or where it is located in the frame of the video.
8 You know, there's other pieces that you would need
9 for you to track that particular object through
10 the video that you're collecting.
11 Q. In the object representation, we see
12 that the labels of John Doe, cat, tree, they're
13 captured in that stored object representation.
14 Let's just say you come across another cat --
15 A. Yeah.
16 Q. -- you know, you're having a stream of
17 pictures. How does the system figure out whether
18 it's the same cat or a different cat?
19 A. Well, you obviously have to do object
20 detection. So you have a video -- let's say
21 you're capturing a video. So I'm talking now a
22 little bit hypothetically speaking.

1 You're capturing a video with your
2 camera. There's two cats out there, one on the
3 right side, one on the left side. So they're in
4 different spatial locations in the video. Cat 1
5 is, you know, on bearing angle whatever,
6 56 degrees. And cat 2 is at bearing angle
7 287 degrees.
8 So they're at two different locations in
9 the video. They have two different motions.
10 Maybe the sizes are different. So you would have
11 to capture that information.
12 Q. I see.
13 So you have this video, let's say images
14 coming in from a video. And initially you have
15 these three objects, as shown in Figure 4A. And
16 maybe in a subsequent image there's another cat,
17 and so the object -- the collection of object
18 representations would then be updated or modified
19 to include the description of the additional cat
20 once it enters the images.
21 And so the object representations would
22 include, for example, a label of cat 1 at a

1 distance of 6 meters at a bearing 56 degrees
2 angle, and then another object representation with
3 a label of, for example, cat 2 and a distance
4 varying corresponding to the location of cat 2; is
5 that right?
6 A. That's generally correct, yes. You
7 would have obviously different representation for
8 each of the objects dynamically through the
9 system.
10 Q. Could I ask you to turn to Figure 32,
11 please, of the '974 patent?
12 And please let me know when you're
13 there.
14 A. Yes, I am there.
15 Q. Figure 32, Step 9105, that step says
16 that there's a "receiving a first collection of
17 object representations."
18 Do you see that?
19 A. Yes.
20 Q. What are object representations?
21 A. Well, we just described that earlier.
22 We just talked about that a few minutes ago in the

1 other Figure 4B.
2 Q. Okay. I see.
3 And so the collection of object
4 representations is that collection that we see in
5 Figure 4B, is that --
6 A. Yeah, go ahead. Sorry, I --
7 Q. Yeah, so I just want to clarify.
8 So one example of receiving a first
9 collection of object representations would be when
10 we receive data that is similar to what was shown
11 in Figure 4B; is that correct?
12 A. Yeah, I mean, that's what it says. If
13 you look at Figure 4B, Item 525, it says,
14 collection of object representations, and it gives
15 three examples.
16 Q. And then Step 9110 says, "receiving a
17 first one or more instruction sets for operating a
18 device."
19 Do you see that?
20 A. I do.
21 Q. How is this receiving in Step 9110
22 accomplished?

1 A. What do you mean how is it accomplished?
2 Q. How does it receive the sets for
3 operating a device?
4 A. Well, it has, obviously, instruction
5 sets. You've done some training. You've created
6 some instruction sets. Those instruction sets are
7 in the system. So all you're doing the training
8 as we speak, and you're creating instruction set.
9 It depends on what the application is.
10 Q. So the instruction sets are a result of
11 the training; is that right?
12 A. Well, yeah, you would -- I mean, you're
13 doing some type of training, and you are creating,
14 you know, instruction sets as a result of your
15 training.
16 Q. And there would be -- I'm sorry, were
17 you finished or --
18 A. Yeah, I'm not sure I understand what
19 you're asking, but you have -- you know, as you do
20 some training, you provide -- you receive
21 instruction sets. You create instruction sets.
22 Q. And is there generally just one type of

1 training, or can there be multiple types of
2 trainings?
3 A. Well, such a big generic question.
4 Obviously, you have different ways of doing
5 training, depending on the activity that's being
6 trained.
7 Q. In the context of the '974 patent, is
8 the device performing one type of training or
9 multiple types of training?
10 A. Well, I mean, it's going to perform
11 training, obviously, dependent on different types
12 of objects that we're talking about here.
13 Q. Can you clarify that? I just want to
14 understand. You said that it performs training
15 depending on different types of objects.
16 So does that mean that the training for
17 a cat would be different from the training of a
18 person?
19 A. Well, I mean, if I'm doing -- let's say
20 I'm doing training for facial recognition. So,
21 obviously, I'm going to be training -- I'm not
22 going to be using a cat to train on human facial

1 recognition. I'm going to be using faces of,
2 let's say, humans. You might interject other
3 things there to see if the system can do things
4 accurately.
5 So if I'm training on, for instance,
6 recognizing the shape of an animal, my training
7 database is going to be -- has different sets of,
8 you know, training imagery. It's such a big
9 topic. It's hard to define what you're asking.
10 But training has to be customized or tailored to
11 what you are trying to train.
12 Q. Okay. Just so I can understand, maybe
13 in the context of this somewhat relatable example,
14 I guess. In the context of, for instance,
15 security situations, you mentioned facial
16 recognition. So I could go to one camera and
17 there could be a facial recognition algorithm
18 that's performed and that data is used for
19 training.
20 So then when I go to another airport and
21 they also perform a facial recognition. As a
22 result of the training of the first camera, the

1 system -- the security system would be able to
2 determine that I'm the same person; is that right?
3 A. I think you're mixing up --
4 MR. JAIRAM: Objection to form.
5 THE WITNESS: I think you're mixing up a
6 lot of things. It's kind of hard to follow what
7 you're saying. But let's say, for instance --
8 I'll give you an example.
9 Say, for instance, I have a company with
10 100 employees, and, obviously, they all look
11 different. And I want to train a camera system to
12 open the door when only one of my employees show
13 up.
14 Okay. So I have pictures of the 100
15 employees. I may have pictures of profiles versus
16 head on versus different angles and slightly
17 different scales, perhaps. I have all these
18 pictures in, say, some kind of what we call a
19 training database.
20 So then I will train my neural network
21 or my machine learning algorithm, I would
22 construct an algorithm with neural nets and

1 multiple layers, whatever, CNN, whatever you
2 construct. You're going to train that algorithm
3 on all these various imageries, and then you're
4 going to provide images that are these people, as
5 well as others, to test on. Because if there's
6 somebody that's not your employee, it shouldn't
7 open the door, right.
8 So you're going to test it on unknown
9 subjects, and you're going to test it on your
10 employees. You have perhaps a test database and
11 you determine its level of accuracy and you tweak
12 and make changes.
13 So the training will take place on, you
14 know, whatever -- in this case, the facial
15 recognition that you're trying to do. So when an
16 employee walks up to the door, the camera now
17 executing -- you're not training anymore. You're
18 just executing now.
19 It will see the employee walking up. It
20 will take a snapshot, let's say, or take a look at
21 the video, track the person as they're coming
22 towards the door, and then do facial recognition

1 and say, yes, this is Tom, open the door, and this
2 is an unknown, don't open the door. So this is
3 kind of a simplified illustration, example type of
4 thing.
5 BY MR. KHAN:
6 Q. I see.
7 And so in that example, let's go with
8 that example, the training is, I guess, data
9 that's related to the facial features of your
10 employee and then the instruction set would, for
11 instance, be if the facial scan matches whatever
12 is in the database, then allow the door to open,
13 and if it doesn't, then don't allow the door to
14 open?
15 A. So that would be, you know, obviously, a
16 simplified illustrative example, but, yeah, that's
17 the idea. So you have facial pictures of your
18 employees at various angles and scales and so on.
19 You've trained this neural network to recognize
20 them.
21 So now when a person walks up, the
22 neural network is going to run facial recognition

1 on that person. It's going to say, that's Tom.
2 Then the computer system is going to say, yep,
3 this is one of our employees, unlock the door,
4 take a picture of the person walking in, maybe
5 they have a suitcase in their hand, whatever.
6 I mean, you have an instruction set that
7 you want -- the company wants to follow in the
8 right protocol for that employee.
9 Now, if somebody comes in -- comes over
10 that's not an employee, maybe they're holding a
11 weapon or whatever, then you're going to see that
12 person, you're going to determine they're holding
13 a weapon, and maybe the instruction says, call
14 911, they're holding a weapon.
15 So, yes, you have instruction sets that
16 you're going to do dependent on what you see in
17 this particular illustrative generic example.
18 Q. And let's say I grow some facial hair --
19 or sorry, let's say your employee grows some
20 facial hair and comes in the following day. Would
21 that additional facial hair then be part of the
22 training data for that particular employee so that

1 in future when that employee again grows some
2 facial hair, that it still matched to that
3 employee?
4 MR. JAIRAM: Objection; form.
5 THE WITNESS: Again, I mean, we're still
6 talking in this illustrative hypothetical type of
7 example. But typically, when you're doing facial
8 recognition, you kind of weight the recognition
9 algorithms to more of the center of the face.
10 Like, you know, I could -- you could
11 shave your entire head, right. So all your hair
12 has disappeared. You know, you could obviously
13 grow a beard, as you have mentioned.
14 So the outside portion of your face,
15 which is generally referring to your hair on your
16 head and your beard and so on, are very easy to
17 change. But the interior part of your face, your
18 eyes, your nose, your mouth, and the location of
19 those, you know, require plastic surgery to
20 change. So they're much more difficult to do.
21 So you typically weight facial
22 recognition algorithms on more the inside -- let's

1 say, the inside two-third of the face. If you
2 look at the face as an ellipse, for instance,
3 you're looking at the inside two-third of that
4 face as the heavier weighting versus the outside
5 of the face.
6 Now, if you still don't recognize the
7 person because your algorithms were not -- you
8 know, let's say they're wearing sunglasses that
9 are very strong, and you can't see the eyes. Then
10 you would just say, I don't recognize this person,
11 and the door doesn't open. And then the person
12 would have to call security, and security would
13 have to say, You need to remove your glasses and
14 come again.
15 You know, so things of that sort. I
16 mean, it's not -- obviously, these systems are not
17 100 percent perfect.
18 BY MR. KHAN:
19 Q. And the images that you obtained for the
20 employee as part of the training or part of the
21 collection of the object representations, does
22 that have to be from one camera, or can it be from

1 multiple cameras?
2 A. Well, it can be -- it can be from
3 multiple cameras. It's typically -- and you do
4 some type of what you call feature normalization.
5 So you have to do some type of -- because the
6 picture could be taken on a sunny day. The next
7 day it's a shady day or whatever. So you have to
8 do some type of normalizations. It's not just a
9 straight ingestion of it. And, two, there's
10 dynamic updating.
11 You know, like the employee obviously
12 gets older, right, year after year after year.
13 You're not going to use the same picture from
14 25 years ago. If you looked at me 25 years ago, I
15 had a full head of hair when I joined RIT. So
16 things change over time.
17 So as the employee continues to come,
18 right, you continue to update -- you know, you're
19 collecting imagery from that employee. You may
20 set a certain update cycle in a sense in your
21 database and continue to update that. You know,
22 for different objects, the cycle will be

1 different.
2 Q. I see.
3 And then the instruction sets -- going
4 back to Step 9110, Figure 32, the instruction sets
5 that are received, who are these -- or where or
6 who are these instruction sets received from?
7 A. So your system -- you know, you've done
8 some training -- you know, in the case of the
9 employee walking into the company, as we've been
10 talking, you've done some training, and you've
11 determined that Tom is an employee. You've done
12 some face recognition. And then you've created an
13 instruction set that basically says, Open the door
14 for Tom when he's coming in.
15 But maybe John is an employee in a
16 wheelchair. So -- and let's say that particular
17 door has steps, but there's a different door where
18 that particular person in a wheelchair can roll
19 across the ramp. So for that person, you're going
20 to open a different door.
21 So there's a different instruction set
22 for John, we know John is in a wheelchair. So

1 open door 2 instead of door 1. So the instruction
2 set would be tailored, you know, to the objects in
3 a sense or the circumstance that's taking place.
4 Q. That tailoring that you're talking
5 about, is that what's referred to in Step 9115 as
6 the "correlating"?
7 A. I mean, generally speaking, yes, that's
8 obviously correlating the instruction set with the
9 collection of object representation.
10 Q. And so who -- again, I guess who
11 provides instruction sets? Is it, like, the
12 employer or, you know, an organization of the
13 building? Like who is providing the -- this
14 feature says, receiving a first one -- sorry, this
15 Step 9110 says, "receiving a first one or more
16 instruction sets for operating a device."
17 Where is the instruction set being
18 received from?
19 A. Well, I mean, I'm going to give you a
20 generic answer. Typically, the instruction sets
21 would be created as part of the training. So you
22 would, you know, create that as part of the

1 training and obviously modify them as part of the
2 training.
3 Q. Okay. Thanks.
4 I can appreciate that, but my question,
5 though, is: Where is the instruction sets being
6 received from?
7 A. That's what I said. When you're doing
8 the training for what other activity that you're
9 doing, you are going to create some instruction
10 sets for that particular training. So if I see a
11 person walking in a crosswalk while the car is
12 coming up a crosswalk, you are going to provide
13 certain instruction sets so that would take place
14 to do what needs to be done.
15 Q. And who is doing the providing?
16 A. Well, as part of your training, that
17 could be done by some human interaction. It could
18 also be done with the machine -- you know,
19 artificial intelligence algorithms. You're asking
20 me a very generic question. It depends on the
21 particular thing that you're doing.
22 Q. I'm just trying to understand the figure

1 and what it entails. So, you know, any
2 explanation you can provide is helpful. Thanks.
3 You know, with respect to -- you know,
4 you mentioned that there's -- you mentioned that
5 the instruction sets are created as part of the
6 training. And so these instruction sets, can they
7 be different for different objects and different
8 for -- I'm sorry, let me ask one question at a
9 time.
10 The instruction sets that are created,
11 can they be different for the different objects?
12 A. I mean, generally speaking, yes, of
13 course. I mean, you have different objects. You
14 know, the instruction sets would be different --
15 could be different. It depends on -- it's hard to
16 answer that. But, you know, if I have a person
17 walking in a crosswalk versus an incoming vehicle
18 coming from the other side and -- you know, the
19 instruction sets would be different.
20 Q. And can the instruction sets be
21 different depending on the sensor that's being
22 used to obtain the image?

1 A. Well, I mean, if you're capturing, let's
2 say, imagery with a camera versus you're capturing
3 LiDAR information with a sensor, the
4 instructions -- or you're doing multimodal, so you
5 have camera and LiDAR and, you know, other
6 sensors, yeah, the instruction sets would have to
7 accommodate whatever the input that you have.
8 Q. And moving to Step 9115, when the object
9 representations are correlated to the instruction
10 sets, what does the system do to correlate the
11 object representations with the instruction sets?
12 A. Well, that would be, in essence, the
13 part of your training, right. So if you have a
14 person walking in a crosswalk and you would like
15 the car to come to a stop so you don't run over
16 the person, so you have imagery that show a person
17 coming through the crosswalk, you've done some
18 object recognition in tracking, et cetera, and
19 you've defined that basically situation, you now
20 have to define instruction sets for the vehicle to
21 slow down and come to a stop so that the person
22 can, you know, clear the crosswalk.

1 And you would correlate that
2 circumstance of a person walking through a
3 crosswalk with the vehicle coming to a -- you
4 know, slowing down and potentially coming to a
5 stop, depending on where it's at in relation to
6 the crosswalk.
7 Q. But is that something like a -- in terms
8 of implementation, does that look like an if-then
9 statement, sort of, like, if certain circumstances
10 are there, then perform operation X?
11 A. Well, it's not quite that. I mean,
12 that's what -- you know, you have a machine
13 learning neural net. It's not an if-then set of
14 instructions. It's more of you have machine
15 learning algorithms that are going to have --
16 you've trained the algorithm, let's say supervised
17 learning, you've trained the algorithm. You
18 provide a set of input imagery, and the algorithm
19 will do something.
20 And you basically say, This is what I
21 would like you to do. You did this. You really
22 should do this. So you define an error, you know,

1 we call that a loss function or a cost function.
2 You quantify the difference between them. You
3 essentially back propagate that difference through
4 the network. You update all the potential
5 parameters and hyperparameters of the network, and
6 then you continue the training process. You
7 provide another sequence.
8 And then you keep this up for a while.
9 You know, training could take several hours, days
10 sometimes, depending on what you're doing, what
11 you're training, until you have a satisfactory
12 situation with the accuracy that you're looking
13 for.
14 And if you don't have enough data, you
15 need to get more data and so on and so forth. So
16 there's a lot to it. You're, I think,
17 oversimplifying it extensively.
18 Q. Yeah, pardon my lack of experience in
19 the area. So maybe my questions will be
20 oversimplified, but bear with me while I can,
21 please.
22 You mentioned sometimes this case of --

1 you know, you might have in some cases hours of
2 data, in some cases not so much. And I suppose in
3 situations like security systems maybe that are
4 monitoring certain premises, you can have hours of
5 data that are being recorded.
6 A. Yeah.
7 Q. And in these sets of situations when you
8 have so much data and volume, what does the system
9 do in terms of training storage when, you know,
10 there's no more space left for the data?
11 A. Well, you obviously have to organize the
12 data. I mean, you, for instance -- I'm going to
13 take a billion image of me and put that in your
14 database. You know, you're going to take enough
15 images of me so you can -- so the accuracy of your
16 training is beyond the point where you want it.
17 Let's say I'm looking for 99 percent
18 accuracy or 95 percent accuracy, right. And I
19 find that ten images of me will provide 95 percent
20 accuracy of me when I walk up to the camera. Then
21 I may store 10 or 15 images. I'm not going to
22 store a thousand images.

1 You know, and the same thing with the
2 video collections, you know. If you have --
3 you're not going to store a billion videos of
4 people walking in crosswalks. You're going to
5 store enough -- you're going to -- this is what we
6 call data augmentation. You're going to have
7 enough data to ensure an accuracy that you're
8 willing to accept for this particular application.
9 And each application is different.
10 Like the employees walking in the
11 company, the accuracy doesn't have to be that
12 high. Because the worse that can happen is, No,
13 I'm not going to open the door for you, and you'll
14 have to call security and security will come over
15 and open the door once they verify you're an
16 employee.
17 But if this is a medical imaging
18 application where you may be doing a spinal
19 surgery, you can't afford a 95 percent accuracy.
20 You know, you may have to have 99.9 or better than
21 any possible doctor can possibly do.
22 So it depends on the application how you

1 would approach the storage of the data and how
2 much of the data and how frequent of the data and
3 how dynamically do you update the data and you
4 retrain.
5 Q. So this part I wanted to get a little
6 bit more detail in terms of better understanding
7 the storage and the training of -- and the storage
8 of training data.
9 When you get an image and it's being
10 stored for training purposes, what exactly is
11 stored? Is it, like, pixel values? Is it shape
12 and size?
13 What is the information that's stored?
14 A. I think you should take my course at
15 RIT.
16 Q. You know, one day I might, but if you
17 give --
18 A. Yes, I have an advanced graduate course
19 on this that would teach you all these aspect of
20 it.
21 But, typically, in images -- let's say
22 we're looking at images, facial recognition.

1 You're going to store pictures of Eli. And, you
2 know, you may take a head shot. You may take a
3 shot at this angle, that angle. You're going to
4 store enough pictures.
5 And each picture, obviously, is going to
6 be in color, let's say. So it's got an RGB
7 component to it. Each RGB has a value of pixel
8 between 0 and 255. And you have images, you know,
9 mug shots of me at various angles, maybe even all
10 the way around your head.
11 So you may store -- depending on the
12 accuracy that you're looking for, you're going to
13 store images. You may store images with tilted
14 heads or, you know, where the head is tilted one
15 way or the other, tilted backward or forward.
16 That's called rotations in and out of the image
17 plane, when it's tilted backward and forward or
18 right and left. Or if I'm tilting this way, those
19 are rotations within the image plane that are much
20 easier to handle than rotations in and out of the
21 image plane.
22 So you're going to store -- you know,

1 you might start by storing, let's say, three or
2 four or five mug shots of me. And then when you
3 do your training, you'll discover that, you know,
4 it's not -- it's not generalizing.
5 You know, when I say "generalizing" for
6 a network means does the network -- if I would
7 have you shown a network, a database that it's
8 never seen, would it perform at the same accuracy
9 as my training. So that's what we call
10 generalizing.
11 So if I collect three or four pictures
12 of me and then all these other people and the
13 accuracy is only 67 percent, it's not doing it,
14 then I have to change some network parameters.
15 I may add more layers. I may have more
16 nodes per layers. I may change the convolutional
17 aspect of the network. And if it's still not
18 doing it, then I have to do maybe data
19 augmentation.
20 And I may say, well, instead of having
21 four pictures per person, let's go to six. We're
22 going to get more precision, more resolution on

1 the angles, you know, more rotations.
2 So you start to augment your dataset
3 until you get the training accuracy that you're
4 looking for or you're happy with on your training
5 dataset. Then at that point you test that on a
6 test dataset, which you have of these people that
7 you've never trained on, to see if they generalize
8 it.
9 Will it get the accuracy on the test
10 dataset at the same value as the accuracy of the
11 training dataset? If the answer is yes, then
12 you're doing a great job. If the answer is no,
13 then you need to do changes to your training.
14 You should take my course at RIT.
15 Q. It sounds fascinating.
16 So the -- when you're taking a bunch of
17 these pictures, and you mentioned like the subject
18 might be at different angles, like tilting
19 backward or straight or, you know, a side face or
20 front face. Those pictures are then -- I guess
21 there's a label that's assigned to them, this is
22 front face or this is tilted, and then that is

1 stored?
2 A. You can.
3 Q. Okay.
4 A. I mean, you don't really -- it depends
5 on the objective. If your objective is to
6 recognize a person, as long as you have different
7 pictures of it -- of the person on the database
8 you trained on and I arrived to the door -- let's
9 say I'm that person and I'm talking to my friend
10 as I'm walking to the door, so I'm slightly on an
11 angle. The camera is able to pick me up and say,
12 Yes, this is Dr. Saber, then you're successful.
13 Q. Yeah.
14 A. The camera picks you up and says, I
15 don't know who that is, then you're not so
16 successful.
17 Q. Yeah, I mean, is there a way to
18 understand -- for the system to know, for
19 instance, whether this is the front of my face, or
20 this is the front of my face?
21 A. Yeah, I mean, you can train that. You
22 can train that to say, okay, these are profiles,

1 pictures versus frontal pictures. You can train
2 all of that.
3 Q. I see.
4 And so when you are -- I forgot the
5 exact term you used, but once you've done some
6 training, you test it again, so sort of a -- I
7 guess a test database, and you see what the
8 results are. If it's good enough, then you know
9 you're good. If it's not good enough, then you
10 have to augment; is that right?
11 A. Well, you may have to do other things,
12 but typically, we do three -- there's three things
13 that are done. There's a training database;
14 there's a validation database, typically, and
15 there's a test database. And there are ways of
16 doing all these things, you know, what we call,
17 you know, like different ways of capturing
18 randomly samples from the database.
19 But let's -- without getting into those
20 details, so you have a training database. Let's
21 say I have 100,000 images in that database of my
22 employees, you know, a thousand per employee, and

1 I have 100 of them.
2 And then you have a validation database
3 that has pictures of those employees, but not the
4 same ones from the training database.
5 And then you have a test database that
6 also has pictures from your employees, but not the
7 same one in the other two databases.
8 So they're basically three distinct
9 databases. You do your training on the training
10 database. So you -- you know, you do the various
11 things you want to do to the network on your
12 training database.
13 You then use the validation database to
14 tweak the hyperparameters. You know, you want
15 more regularization or you want smaller
16 regularization parameter, you want different
17 nodes, you want to do a dropout, whatever. You
18 fiddle around with the parameters of the network.
19 You use the validation database to validate each
20 of these parameters to find the right one.
21 Finally, when you're done, you say,
22 okay, now I'm ready -- and you keep an accuracy

1 value, right. You keep, you know, with your best
2 training. Finally, when you've tweaked
3 everything, your accuracy is 95 percent.
4 Then you go to your test database. You
5 say, okay, here's a database the network has never
6 seen. Put that into the network and give me, you
7 know, the accuracy measurements.
8 And if the accuracy comes out to be
9 95 percent, then you've done a great job. If the
10 accuracy comes out to be 10 percent, then
11 obviously your network isn't generalizing properly
12 to data it hasn't seen. You need to make changes.
13 That could be data augmentation. That
14 could be different ways of training. That could
15 be selecting differently randomly from the
16 database. It could be feature normalization,
17 upfront you're not doing -- it could be
18 normalizing at every layer in the network. It
19 could be changing templates of the CNN algorithms.
20 There's a lot of things you have to do -- you
21 could do.
22 Q. I see. And --

1 A. This is a big, big area, sir. That's
2 why I have one course on this, advanced. You
3 know, it's a course for MS -- second-year MS and
4 first-year Ph.D. students that RIT actually asked
5 me to create. So we created part one. I'm in the
6 process of creating part two for this particular
7 course. Part one was just taught this spring, and
8 then I'm in the process of creating part two.
9 This goes through all the mathematics,
10 every details of supervised learning and all the
11 pieces of it and gets into the math, like going
12 into the back propagation algorithms, all the
13 mathematics of it, every step. So a graduate
14 student, like a Ph.D. student, can pick that up,
15 learn, and then go and create original research.
16 Q. Yeah. I mean, I'm sure your students
17 are not going to be bored any day. So this is
18 really cool stuff. It's very interesting.
19 You know, just to follow up on that, one
20 of the things I'm not clear about, if you could
21 explain is, when these images are obtained, how
22 does the system know which memory locations to go

1 to?
2 So, for example, there's, you know,
3 subject X, right, that John Doe we saw in
4 Figure 4A. How does the system know which
5 locations in the memory to go to for John Doe and
6 update the information on John Doe?
7 MR. JAIRAM: Objection; scope.
8 THE WITNESS: Well, I'm not sure exactly
9 what you're asking, but if I'm creating the
10 employees thing that we're talking about, you're
11 going to create some type of database, and you
12 have a structure in that database. So you're
13 going to put employee A in, let's say, folder A,
14 employee B in folder B, employee C in folder C.
15 And employee A, I have ten pictures of,
16 employee B, I only have five, and employee C, I
17 have 15. So you're going to have some
18 organization of how your data is organized. It
19 could be as simple as dumping it all in one big
20 database or more of a structured database. It
21 depends on your application and the complexity of
22 the application.

1 BY MR. KHAN:
2 Q. So using the example that you're saying,
3 let's just say you're an organization with 100
4 employees, and so you have presumably some images
5 for your 100 employees. Now, let's say that you
6 want to update the training, your training the
7 images for employee John Doe, right.
8 Then does the system know, for instance,
9 okay, there are certain memory allocated for
10 John Doe, so I need to go to that memory and
11 update it? Is that kind of how it works?
12 A. It depends on how you've structured
13 the data -- how you designed and structured the
14 database for your system. So if, for instance,
15 your database is, let's say, a set of folders and
16 subfolders. So John Doe has a subfolder. Tom X
17 has a different subfolder.
18 So John Doe's subfolder has 10 images of
19 John Doe. If that's not enough for your training
20 and you acquired three more, you're going to put
21 those in the John Doe folder, and now you have 13.
22 So it could be as simple as something

1 like that, where you have allocated different
2 memory locations to different people. It could
3 also be interconnected, depending on the
4 application that you're looking at. So it's not a
5 simple thing to do. It depends on how -- what the
6 application is, how the database is structured,
7 et cetera.
8 Q. So what happens when the allocated
9 memory for these images is filled up? So let's
10 say you've -- you have a certain amount of space,
11 it's already used up. Then do you have to delete
12 stuff and then add the new stuff -- so I should be
13 more clear, I'm sorry. Let me rephrase that.
14 When you're running out of memory when
15 you're training these systems, and you may now
16 have memory to update your training database, then
17 what does the training database do? Does it
18 remove data that's stored in the training base to
19 add the new data?
20 MR. JAIRAM: Objection; form.
21 Objection; scope.
22 THE WITNESS: Well, memory is cheap

1 these days, just buy more memory. You know, if
2 your disk drive is, you know, I don't know
3 1 trillion or 1 terabyte and it's not big enough,
4 you get another one.
5 BY MR. KHAN:
6 Q. Yeah, I understand that, but, you know
7 do you --
8 A. If your disk drive is limited, then you
9 do some what we call pruning. So you will -- if I
10 have 50 pictures of John Doe and they're all front
11 pictures and I'll pick the best ten and I remove
12 the rest.
13 Q. I see.
14 So you would select information -- you
15 would be -- essentially, you'd filter out the new
16 information, you wouldn't add it, and you'd keep
17 the old information and you'd filter out the new
18 information?
19 A. That's not what I said. So --
20 Q. Okay.
21 A. -- if I have 100 pictures of John Doe in
22 my database, okay, and 30 of those pictures are

1 just straight on John Doe, so there's 30 of them.
2 It's really redundant, and I find that in my
3 training if I were to remove 25 of those 30, my
4 accuracy hasn't changed.
5 So I get 95 percent accuracy in
6 recognizing John Doe with only five of the 30 or
7 30 of the 30, then obviously the other 25 are
8 redundant. So I would remove the other 25 and
9 store them somewhere else for now and just keep
10 the five.
11 So this is sometimes what we call
12 principal component analysis. So you try to do
13 some analysis on your database to remove
14 situations that are 100 percent redundant or have
15 a high degree of redundancy that you don't need
16 because that could speed up your training process.
17 But with today's memory being so cheap
18 and disk space being so cheap, typically, that's
19 not a big problem. The problem is the time to
20 train more so than the storage.
21 Q. And what do you do with training
22 information that is out of date? So let's see

1 just say, for example, there's a vehicle --
2 there's a road, and that road is now -- you know,
3 doesn't exist anymore. There's a building, that
4 building doesn't exist anymore.
5 What happens in those situations for the
6 training data?
7 MR. JAIRAM: Objection; form.
8 Objection; scope.
9 THE WITNESS: Well, you would
10 potentially prune some of that out. Like, you
11 know, I look different today than I looked
12 40 years ago. So, you know, my -- a picture of me
13 40 years ago may not be as relevant to recognize
14 me today, right. So you would prune some of that
15 out or make dynamic updates to your database.
16 So every so often you may have to do
17 some retraining. You have to collect new data and
18 update. You know, do you ever see the Google car
19 or whatever driving around and taking pictures of
20 the streets or whatever, doing some updates?
21 A new neighborhood comes in, it's not on
22 Google Maps and, you know, they send a car around

1 and it kind of takes pictures and then all of a
2 sudden it shows up on Google Maps.
3 So you have to do some -- I mean, it's
4 not a perfect science. You have to do some
5 updates over time. You have to add things and
6 delete things and prune things.
7 There are some things that remain more
8 constant, like somebody walking in a crosswalk.
9 Crosswalks are still going to be there, say,
10 ten years from now. So those are more of a
11 constant. But if a street no longer exists, for
12 instance, or a type of object no longer exists,
13 then that would change.
14 BY MR. KHAN:
15 Q. Right. Okay. Yeah, I think that's
16 conceptually easier to understand, that you have,
17 for example, a Google vehicle moving around, it
18 captures some images.
19 Now, let's say there's a new building
20 around the corner. It will then go to the
21 database -- the training database, modify it by
22 adding information about that building --

1 A. Yeah.
2 Q. -- and then the whole sort of
3 Google Maps' database updates, and whenever you
4 see the road, then you can see the picture of that
5 building?
6 A. Yeah, I mean, you know, you have to
7 continuously make updates. And obviously as
8 you -- as vehicles drive autonomously and you have
9 more of that database, obviously, you're
10 collecting information. So that database can be
11 dynamically updated on a regular basis.
12 Q. Okay. We are close to lunchtime now.
13 So -- and we've been just about an hour. So if
14 it's all right, I suggest maybe a 45-minute break
15 for lunch.
16 Does that work?
17 A. It works for me. So I will be back in
18 my chair at 12:45 Eastern.
19 Q. Excellent.
20 MR. JAIRAM: Okay.
21 MR. KHAN: Thank you.
22 (Recess from the record.)

1 BY MR. KHAN:
2 Q. Dr. Saber, thanks.
3 During the lunchtime, did you have any
4 contact with counsel for Autonomous Devices?
5 A. No, I have not.
6 Q. Great.
7 Before the break, we were discussing
8 Figure 32 of the '974 patent.
9 A. Yes.
10 Q. If you don't mind going back there,
11 we'll sort of continue where we left off.
12 A. No, no problem.
13 Q. Great.
14 And for this conversation, I might jump
15 between Figure 32 and 33.
16 Do you agree the first two steps are
17 essentially identical?
18 A. Yes.
19 Q. In Figure 32, Step 9125 and 9130,
20 there's a receiving of new collection of object
21 representations and comparing the new collection
22 with the first collection of object

1 representations.
2 Do you see that?
3 A. Yes.
4 Q. Okay.
5 A. It says 9125 and 9130?
6 Q. Yes, that's right.
7 A. Yeah.
8 Q. What does the system do when it's
9 comparing the collection of object
10 representations -- the two collection of object
11 representations?
12 A. Well, it's going to, obviously, do some
13 comparisons. Let me take you to that section.
14 So if you go to Column 154, starting at
15 line 42, it discusses this particular step.
16 Q. So my understanding is lines 42 onwards,
17 beginning with line 44, it states, "Comparing one
18 collection of object representations with another
19 collection of object representations may include
20 comparing at least a portion of one collection of
21 object representations with at least a portion of
22 the other collection"?

1 A. Yes.
2 Q. Do you see that?
3 A. Yes.
4 Q. Yeah, so I guess that's my question, is
5 how does it do the comparing?
6 A. Well, it depends a little bit on the
7 object, obviously, and it depends what kind of
8 object it is. But if you'll continue reading
9 there, it's going to give you some description.
10 You know, like on line 54, it will say, "comparing
11 of object representations may include comparing
12 one or more object properties of one object
13 representation with one or more object properties
14 of another object representation."
15 For instance, I'm looking at the shape
16 of a cat, and I'm comparing the shape of a cat
17 from object one with the shape of the cat from
18 object two to see if both shapes are very similar
19 or not. So you're looking at object properties
20 and/or elements of a particular object.
21 Q. In Figure 33, there is a similar
22 receiving Step 9220.

1 Do you see that?
2 A. 9220 is the method. 9205 is the
3 receiving.
4 Q. No, in Step 9220, there's receiving a
5 new collection.
6 A. Oh, yes.
7 Q. That's the same as Step 9125 in
8 Figure 32?
9 A. Yes, they both state, "receiving a new
10 collection of object representations." So they
11 both state the same exact thing.
12 Q. Yeah. And Figure 33, Step 9225 that
13 follows Step 9220, there's an anticipating step,
14 anticipating the instructions --
15 A. Yes.
16 Q. -- based on at least a partial match.
17 Can you explain to me how that is
18 implemented? How do you anticipate the
19 instructions based on the partial match?
20 A. So if you go to Column 159, it obviously
21 talks about that step of anticipating based on at
22 least a partial match. And, essentially, what

1 it's referring to here is if you have a partial --
2 let's say you have a collection of images of which
3 the object has been tracked into in your training
4 database, and you receive a new collection of
5 object representation. And the old collection,
6 for instance, had -- you know, I'm giving you here
7 an example.
8 The old collection, for instance, was
9 taken on the street in -- I don't know, in
10 downtown Beijing, and a new collection may be
11 taken in a different street somewhere else where
12 some of the background might be different, but the
13 object -- objects may be the same or similar.
14 You have a partial match of objects,
15 which then you can anticipate. I see a crosswalk.
16 I see a person walking in the crosswalk, and
17 whether they're walking in the crosswalk in
18 Beijing or in downtown Nashville, your reaction
19 should be the same.
20 So if you've been trained on the object
21 that's walking through the crosswalk in Beijing,
22 you would anticipate when you see the object

1 walking across the crosswalk in Nashville to
2 perform the proper instruction, which would be,
3 obviously, slow down and stop. It's just kind of
4 an illustration in a sense or, you know, a
5 simplification of this description.
6 Q. We talked about the -- based on at least
7 the partial match between the two object
8 collections. So that at least a partial match,
9 that would include matches between some of the
10 objects in object representations or all of the
11 object representations; is that right?
12 A. I didn't understand your question.
13 Q. The step of comparing the two object
14 collections --
15 A. Yes.
16 Q. -- or collections of objects -- I'm
17 sorry, the step of comparing the collection of
18 object representations, right --
19 A. Yes.
20 Q. -- and determining whether there's at
21 least a partial match between the --
22 A. Yes.

1 Q. -- two collection of object
2 representations --
3 A. Yes.
4 Q. -- that could encompass a match of some
5 of the object representations in the two
6 collections or all of the object representations
7 in the two collections; is that right?
8 A. We have at least a partial match. So
9 you could have a partial match of the object
10 because -- I mean, there are different situations.
11 You have a person walking in a crosswalk. The
12 background is downtown Washington, D.C. You have
13 another person walking in a crosswalk and the
14 background in Nashville.
15 So there are different backgrounds, but
16 the partial matching would recognize the person
17 walking in the crosswalk. Even though the
18 backgrounds don't match, the object representation
19 in the situation does match.
20 Now, if you happen to get a person
21 walking in the same exact -- downtown in Nashville
22 in the same exact crosswalk, then the matching

1 will be a lot higher. Typically, ideally you
2 would probably never get an exact full match, but
3 you'll be very high.
4 Q. Yeah. And so these comparisons involve
5 comparing like -- comparing an entire image or
6 portions of the image; right?
7 A. Or collection of images. I mean, you're
8 going to have typically a series of video frames.
9 So you're comparing not just a single image, but
10 you're comparing -- you're finding the object,
11 you're identifying the object, you're tracking the
12 object in the video frames, and you're comparing
13 to whatever you've been trained on. So the
14 comparisons usually are done on the video frames.
15 Q. I see.
16 A. It's not just a single image comparison
17 is what I'm saying.
18 Q. I see.
19 And then in response to determining that
20 there's a partial match, the system will execute
21 the first one or more instruction sets that are
22 correlated with that first collection of object

1 representations. That's Step 9140 and Step 9230
2 in Figure 32 and 33.
3 Do you see that?
4 A. Yes, you read it directly.
5 Q. Okay. So how does it perform this
6 execution? What does the system have to do to
7 figure out which -- how to execute these
8 instruction sets?
9 A. So, again, I'll give you a simplistic
10 example here just to illustrate. So if you had a
11 person walking through the crosswalk that you've
12 trained your vehicle to come to a stop on and that
13 person was 6'5 tall. Okay.
14 And today I have a person that's
15 4 foot 3, walking through the crosswalk in
16 Nashville versus the training was done, let's say,
17 in Rochester, New York. Okay. So the training
18 was done in Rochester, New York, on a 6'5 person.
19 I have a person walking through in Nashville, and
20 they're 4'6 or whatever.
21 So that's receiving a new collection of
22 object representation. So you've segmented the

1 video, you found the object, you've tracked it,
2 all this type of thing. You compared the new
3 collection of object representation with the first
4 collection. So you've compared that with what
5 your training has been done and you've recognized
6 that this is a crosswalk and there's a person
7 walking in the crosswalk.
8 You've created a partial match. So you
9 understand that this is a crosswalk circumstance
10 situation. You now execute the instructions that
11 you've been trained on in Rochester here in
12 Nashville, because you expect that the vehicle
13 comes to a stop regardless whether a person is 4'3
14 or 6'5.
15 So you would execute the instructions.
16 So you would let the vehicle know that you need to
17 come to a stop. Now, the vehicle might be
18 600 feet away, the vehicle might be 10 meters
19 away, the vehicle might be 60 meters away. So you
20 have to adjust, obviously, that appropriately to
21 where the vehicle is in relation to this
22 crosswalk.

1 Q. What's the difference between executing
2 the instruction sets and performing operations
3 defined by the instruction sets?
4 A. Where --
5 Q. That's the Steps 9140 and Step 9145 in
6 Figure 32, Step 9230 and 9235 in Figure 33.
7 A. So if you look at Column 158, starting
8 at line 26, it describes obviously the Step 9145.
9 And if you read through this section, it says the
10 one or more operations may be performed in
11 response to the aforementioned executing, which is
12 obviously mentioned in the previous step.
13 So, essentially, the operations are kind
14 of like subsections, if you would, or subpieces of
15 the entire instruction, because you may not need
16 the entire instruction.
17 You know, in our illustration example,
18 for instance, the person may be walking in the
19 crosswalk, but the car is 60 meters away. So you
20 don't need to come to a full stop. You can
21 execute the instruction of slowing down. So the
22 operation is slowing down and slowly decelerating

1 and et cetera.
2 And as you're paying attention to the
3 crosswalk, the person has cleared the crosswalk so
4 you now can proceed without having to come to a
5 complete stop. So the instruction may have all of
6 those pieces in it, all these different
7 operations, but you don't have to execute them all
8 for every situation.
9 Excuse me for one minute. I'm just
10 going to mute my audio because I'm hearing noise
11 from upstairs. Just one second.
12 Q. Sure.
13 A. I'm sorry, please go ahead.
14 Q. No problem.
15 A. I think there's some phone calls going
16 on upstairs.
17 Q. Can you turn to Figure 17, please, in
18 the '974 patent?
19 And let me know when you're there,
20 please.
21 A. Yeah, one second.
22 Yes, sir, I am there.

1 Q. Can you describe to me in your words
2 what Figure 17 is showing?
3 A. So according to the patent, Figure 17
4 illustrates various artificial intelligence
5 methods, systems, and/or models that can utilized
6 in a DCADO unit. So it's essentially showing you
7 different, you know, articulations of -- you know,
8 you have Model A, Model B, Model C, Model D. It
9 shows different interconnectivity of various,
10 let's say, nodes in this AI unit.
11 Q. When you say "nodes," do you mean the
12 circular structures 852, like we see in these
13 models?
14 A. Yes. And you can see that on
15 Column 103. If you go down to line 51, it will
16 say, Node 52 can store any data, object, data
17 structure, blah, blah, blah.
18 So it refers to it as node 52. And 853,
19 obviously, is the connection.
20 Q. What do these nodes represent?
21 A. Well, if we look at Column 103, I'm on
22 line, roughly, 46-ish. You can see it starts with

1 a little bit of description, As such, machine
2 learning, knowledge structuring or representation,
3 decision making, pattern recognition, and/or other
4 AI functionality may include a network of nodes
5 (also referred to as neurons) and connections
6 similar to that of a brain.
7 So you use typical nodes, is usually
8 what we use in neural nets. Sometimes people
9 refer to them as neurons, sometimes people refer
10 to them as nodes, but they're typically kind of a
11 package where you hold various things. Like, you
12 can have biases there, offsets, data structures.
13 It depends on the design of your system,
14 activation functions, et cetera.
15 In this case, the author says node 852
16 can store any data, object, data structure, and/or
17 other item or reference thereto. And in the
18 description after that -- so you can hold a data
19 structure there, you know, object structure in a
20 sense.
21 The next line, starting at line 53, may
22 include a function for transforming or

1 manipulating the data. Typically, we call those
2 sometimes activation functions. So input to the
3 node maybe 45, and then you have a sigmoid that
4 would be applied to the 45 or will give you some
5 kind of an output.
6 And he gives examples of that. Like, on
7 line 55, he'll say, Example of such transformation
8 functions include mathematical transformations,
9 et cetera.
10 Q. So that section you described is a
11 little technically heavy. So I might ask some
12 very basic questions, if that's okay.
13 This section, you know, it speaks to
14 Model A, right, I think you were describing. This
15 is a section in Column 103, lines 42 onwards --
16 A. Yeah.
17 Q. -- you were just referring to.
18 A. Yeah.
19 Q. It mentions here that the Model A, for
20 instance -- in Model A, the disclosed artificially
21 intelligent devices, systems, methods for learning
22 and/or using a device's circumstances for

1 autonomous device operation may include a neural
2 network (also referred to as artificial neural
3 network).
4 And then I think early on you had
5 mentioned something about the connections similar
6 to that of a brain.
7 A. Well --
8 Q. Why are -- I guess just from a
9 high-level perspective, why are these networks
10 called neural networks?
11 A. I don't know. Was there a question
12 there, sir? I guess --
13 Q. Oh, I'm sorry, you didn't hear my
14 question?
15 A. No.
16 Q. My question was -- I'm sorry.
17 My question is: Why are these networks
18 called neural networks?
19 A. Well, I mean, you have to go back way in
20 history to, like, the first initial units which
21 appeared, I think, I don't know, in the '40s or
22 '50s or something. This is way back now. So

1 people were trying to look at the brain and
2 connectivity of the brain and say, Can I create an
3 artificial neural network that kind of re-creates
4 or try to mimic this type of activity?
5 So there's some initial research on
6 that, I think I forgot, in the '40s. And then
7 there's the McCulloch cells and whatever. You
8 know, I think McCulloch and Pitts or something
9 published a paper many years back, maybe '40s or
10 '50s. It's one of the initial papers on that.
11 And, you know, how you would try to create some
12 kind of artificial neural nets. So they adopted
13 those names from back then.
14 Q. And is the idea of these, like, models
15 that they created, so these nodes and connections
16 is to kind of like mimic a model of what your
17 higher brain might be thinking or processing this
18 information.
19 Is that the general idea or something
20 else?
21 A. Are you familiar with neural nets at
22 all?

1 Q. Not too much; hence, my questions to
2 you. So --
3 A. Maybe you should take my course.
4 But the idea is, you know, neural nets
5 typically you have -- with artificial neural nets,
6 you have a series of nodes. Each layer may
7 contain a series of nodes, and the
8 interconnectivity between the nodes is typically
9 done in a nonlinear fashion.
10 Because if you were to do it all
11 linearly, you can actually collapse the entire
12 network to just two layers. You can show
13 mathematically, and I have shown mathematically,
14 that that could be the case. So you want some
15 nonlinear connectivity between the layers of the
16 neurons.
17 And supposedly, obviously with this
18 nonlinear connectivity and all these different
19 neurons, you can fit any particular space or any
20 function in the space. So you can fit any
21 nonlinear-type function. So if you had a
22 nonlinear function of various kind, you can say,

1 well, if I add enough neurons, I can fit the
2 nonlinearity of that function without having to
3 create an equation.
4 You know, for instance, if you had a
5 parabola, you know, Y equals AX squared would
6 define a parabola. So you don't need to fit an
7 equation to every point on the parabola, because Y
8 equals X squared or, let's say, AX squared would
9 define a parabola equation.
10 But if I give you a nonlinear function
11 that has basically many different peaks and so on
12 and so forth, you can't create a function -- an
13 equation for that function; but if you add enough
14 neurons, you can fit that function with the
15 nonlinear description of the neural nets.
16 That's essentially one of their
17 attraction, is the ability to fit to any
18 nonlinearity in the space, which is not easily
19 comprehended by equations; hence, the attraction.
20 Q. I see.
21 So the neural networks are a means of
22 modeling the nonlinearity of a particular

1 situation.
2 Did I capture that right or --
3 A. Is that a question or a statement, sir?
4 Q. I'm trying to see if I captured that
5 correctly or not.
6 A. Well, if you -- let's say, for instance,
7 you've done an experiment, X and Y. You've
8 collected points X and Y. And let's assume your
9 points fit exactly on a straight line, perfect
10 line. Then you don't need a neural net for this.
11 You can just say, Y equals 2X plus 3 is the exact
12 model for this experiment, right, because they fit
13 perfectly on this line.
14 Well, that rarely ever happens in real
15 life. You know, most of the things in real life
16 and most of the systems are nonlinear in nature.
17 So the responses are very nonlinear in nature. So
18 you don't have an equation to fit this particular
19 line. So now you have to try to fit every small
20 portion of that function with some kind of
21 equation. And people have done that with these
22 lines or other things.

1 But one way to comprehend a nonlinearity
2 and basically have an ability to manage a
3 nonlinearity is through the use of neural nets,
4 where you can allow the weighted connections
5 between the neurons, as well as the content of
6 each neurons, biases, offsets, whatever you put in
7 there, to comprehend a nonlinearity of the space.
8 And as long as you have data on the
9 input, training data on the input and
10 corresponding output -- like, for instance, you
11 say when I show you this, this is a cat. When I
12 show you this, this is a dog.
13 So as long as you have that training
14 dataset that is accurate in nature, you can
15 hypothetically train the network and adjust these
16 biases and these weighted connections and these
17 activation functions and these hyperparameters to
18 basically get the network to fit to the
19 nonlinearity of the space. So that's typically
20 the idea.
21 Now, sometimes it overfits, and that's
22 what we call overfitting. Essentially, you're

1 fitting to the noise in the data, and you're not
2 comprehending the model anymore. That's called
3 overfitting.
4 Q. So thanks for the explanation.
5 I guess -- I still want to go back to my
6 original question, which was: Why are these
7 called neural networks?
8 I mean, why -- you know, you mentioned
9 stuff about nonlinearities, I understand, but
10 they're not called nonlinear networks or nonlinear
11 models. They're called neural networks.
12 A. Yes.
13 Q. So why they chose neural networks?
14 A. Because you essentially create a neuron,
15 a single neuron, which the neuron has -- if you
16 look back in the 1940s or '50s -- and I'm drawing
17 back on memory now from many years back,
18 obviously, you know, where people have created the
19 initial neuron cell. You know they had a cell,
20 for instance, within some type of an activation
21 like, let's say, a sigmoid activation or something
22 of that sort or hard limiter.

1 So you have an input to that, there's
2 some kind of bias, and the cell would give you an
3 output. So that by itself, you call that a neuron
4 or a node. Now, you're going to replicate that --
5 because one by itself cannot fit a high -- there's
6 only so much one cell can fit. You can fit so
7 much with -- especially if the cell, let's say, is
8 a bias plus weight times input, times -- you know,
9 going through an activation function.
10 So you can only fit so much nonlinearity
11 with one cell. So then if you copy and paste the
12 cell, now you have two cells, you can fit more
13 nonlinearity. And if you copy and paste that
14 more, you can fit more nonlinearity, and that's
15 how you end up with a network, you know, multiple
16 layers.
17 Now, in each layer you can actually
18 duplicate the neuron, as well, so you have more
19 flexibility per layer and connectivity to multiple
20 layers, which essentially can fit higher and
21 higher degrees of nonlinearity.
22 The problem with that is you also have

1 to have more time to train -- the bigger you make
2 it, the more time it takes to train and get it to
3 converge to what you're looking for.
4 Q. I see. Okay.
5 A. And the more data you need and the more
6 iterations you need and the more time you need
7 and -- bigger takes much more, usually.
8 Q. So these nodes are essentially models
9 of, like, brain cells, like neurons; right?
10 They're essentially models of that; is that right?
11 A. Well, they try to say that, but it's
12 essentially more what we call artificial neural
13 nets. So we don't really know exactly how a
14 neuron in your brain exactly functions. You know,
15 that's really not the interesting part of this.
16 It's just you've created an artificial node that
17 has a certain nonlinearity associated with it.
18 And that's essentially what McCulloch
19 and Pitts initially tried to create with the
20 initial cells. And then the Perceptron algorithms
21 came about and added more to that and so on.
22 There's a whole history of this of how these

1 things progressed.
2 Q. I see.
3 A. There's probably good tutorial papers on
4 them. There's a tutorial paper by Lippmann in the
5 signal -- IEEE Signal Processing Magazine that
6 would give you a pretty good overview of some of
7 the neural nets.
8 Q. Nice.
9 A. I think it's published in 1988, I think.
10 Q. Okay. Thank you. That's helpful.
11 And so these nodes are then -- they're
12 connected by -- so they're associated with each
13 other with some sort of relationship, and that
14 relationship has this bias and weights that's
15 specified by these connections; is that right?
16 A. Well, the connections -- the biases are
17 typically within the node itself. So within the
18 node, you have certain biases, perhaps certain
19 offsets that you define for the node. And then
20 you have a connectivity between the node and
21 another node that you define. This could be a
22 weighted connectivity. This could be some

1 function of one node to the other.
2 So you define what that connectivity is.
3 It could be as simple as -- you know, a weighted
4 connectivity could have more structure to it. It
5 depends on how much training and stuff you want to
6 do and how much data you have.
7 Because the more difficult you make the
8 connectivity, the more parameters you add, the
9 more you need to train and when you copy and paste
10 that over an entire network.
11 So if two neurons are connected by one
12 connection that has ten parameters and you copy
13 and paste that 100 times, obviously, you're going
14 to now have 1,000 parameters that you have to
15 train. Yeah, so --
16 Q. And so how complex or simple the model
17 is will also determine the complexity of the
18 connection, as well; right?
19 A. Yeah, so the amount of layers -- the
20 number of neurons per layer and the number of
21 layers and that's the term -- you know, the term
22 "deep learning"?

1 Deep learning, basically, you're getting
2 more deeper -- more layers, right. Instead of
3 just one layer or two layers, which we call, you
4 know, shallow networks sometimes, I may have 50
5 layers.
6 So the more layers you add, the more
7 nonlinearity and complexity you have, and the more
8 difficult it is to train. Because as you back
9 propagate the error using gradients, which is
10 typically what we do, that -- as you back
11 propagate through the layers, that gradient starts
12 to vanish, because it's getting smaller and
13 smaller. And pretty soon it's only .0001 by the
14 time it gets to the first layer. So you would
15 need to train many, many, many, many more
16 iterations to get it to move anything.
17 So the more layers you add, the more
18 complexity you're adding to the system. So you
19 typically want to try to manage the complexity to
20 the complexity of the problem.
21 Q. All right.
22 A. Yeah.

1 Q. Okay.
2 A. So if I'm recognizing apples from
3 oranges, I don't need a 50-layer neural net with
4 500 nodes per layer to do that. You know, two
5 layers with maybe ten nodes each may do it.
6 Q. Okay. Sorry, just give me a minute.
7 A. Take your time. I may step away for one
8 minute. Is that okay?
9 Q. Yeah, that's fine.
10 A. Okay. Let me step away for one minute.
11 I'll be back.
12 (Recess from the record.)
13 THE WITNESS: Okay, I'm back. Thank
14 you.
15 BY MR. KHAN:
16 Q. The connections that we see in this --
17 in these models, are they -- in a particular
18 model, so let's just say all the nodes -- sorry,
19 all the connections in Model A, do they all have
20 the same length, are they like -- yeah, do they
21 all have the same length or is that -- sorry. Let
22 me just stop there.

1 Does it have the same length?
2 A. Well, I don't know what you mean by
3 length. These are not physical like you can't
4 take a measuring stick and measure them. They're
5 not -- they're virtual connections, right.
6 They're not -- it's not like you have a node on
7 the ground and 1 meter later you have another node
8 and you just got to measure them. They're --
9 Q. I see.
10 A. Yeah.
11 Q. So it's more like they're -- when you
12 say "virtual connections," do you mean, like,
13 they're not actual, like, physical connections,
14 but they're more like logical connections? It's
15 like when you're going from one node to another?
16 A. Yeah, they're not like a string between
17 the two nodes, right. They're -- so you know this
18 node is connected to this other node, and there's
19 some type of a function that connect those nodes.
20 So it's not a physical -- you know, in the neural
21 net, it's not a physical string. You know, this
22 is not like a truss in a bridge, you know what I

1 mean.
2 Q. I see.
3 So even though, like, Model A, Model B,
4 Model C, D, these are showing -- they're showing
5 different lengths, but the length is not
6 important. They might just be indicative of some
7 type of a relationship between the different nodes
8 that the connections are connecting?
9 A. Those are not length. They're different
10 configurations.
11 Q. Okay.
12 A. So Model A could be what we call fully
13 connected. A fully connected network means every
14 node in layer I is connected to every node in
15 layer I plus one. You don't have to have it fully
16 connected. You can have certain connections not
17 available or not needed. And you could also have
18 connections that connect back on itself. So there
19 are different ways of configuring them.
20 Q. I see.
21 A. Yeah, and then you can have feedback.
22 And it's a very complicated subject. That's why I

1 have a two-course series on this at the graduate
2 level with all the mathematics.
3 Q. Look out for my name one of these days.
4 I might need to sign up.
5 Let's see. Okay. Maybe we will turn to
6 the Grotmol reference. But we are coming up to
7 the hour mark. So maybe it's a good time to take
8 a short break. Would five minutes work for you?
9 A. It works fine for me.
10 Q. Okay.
11 MR. KHAN: Arvind, is five minutes is
12 good for you?
13 MR. JAIRAM: Yes, thank you.
14 THE WITNESS: Should I turn to Grotmol?
15 MR. KHAN: Yeah, when we come back, we
16 can turn to Grotmol. So maybe at 1:45, we can
17 reconvene.
18 THE WITNESS: Perfect.
19 MR. KHAN: Okay.
20 THE WITNESS: I'll be back in my seat at
21 1:45.
22 MR. KHAN: Great.

1 (Recess from the record.)
2 (Exhibit 1004 was marked for
3 identification and attached to the transcript.)
4 BY MR. KHAN:
5 Q. So while we were on break, I uploaded
6 the Grotmol reference to the chat. If you'd like
7 to open it that way, you can. Grotmol is
8 Exhibit 1004 in this proceeding.
9 So please let me know when you have that
10 open.
11 A. I am working on it.
12 Q. Great.
13 A. Okay. I have it open.
14 Q. Thank you.
15 And so Grotmol -- if you'd like to turn
16 to Grotmol's Figure 1. Figure 1 -- oh, sorry,
17 please let me know when you're there.
18 A. Yes, Figure 1, Grotmol.
19 Q. Great.
20 Figure 1 of Grotmol shows a robot 160
21 moving in direction 164, and there's a sensor
22 component 166 that provides a view 168.

1 Do you agree with that?
2 A. Yes.
3 Q. And the sensor can include a camera; is
4 that right?
5 A. Yes.
6 Q. And do you agree that the images
7 obtained through this camera sensor would have
8 data, including pixel values that are associated
9 with objects and features in the frames and images
10 captured by the camera sensor?
11 A. I'm not sure that I understood exactly
12 your question.
13 Q. The question is basically the data
14 that's captured by the camera, that data
15 includes --
16 A. They're images.
17 Q. Yeah, the images.
18 A. So they're images captured by the
19 camera. So they would basically be RGB images or
20 gray scale images with pixel values, accordingly.
21 Q. Yeah.
22 A. Assuming it's a camera.

1 Q. Yeah.
2 And do you agree that Grotmol also
3 discloses object recognition and classification?
4 A. Which section of Grotmol are you
5 referring to?
6 Q. Well, I'm assuming you've reviewed
7 Grotmol; is that correct?
8 A. Yes. I mean, Grotmol does talk about
9 object recognition, but is there a specific
10 section that you're referring to?
11 Q. Not at the moment. I might get into
12 some more specifics right now, but I just wanted
13 to see if at least we're on the same wavelength
14 there that there is disclosure of object
15 recognition and classification in Grotmol.
16 If it helps, I can also point to
17 Column 9, lines 40 to 43 of Grotmol.
18 A. Yeah.
19 Q. Do you agree that it says there, "In one
20 or more implementations, object recognition and/or
21 classification may be implemented using a spiking
22 neuron classifier..."?

1 A. Yeah.
2 Q. And can you turn to Figure 2?
3 A. Yes.
4 Q. And Figure 2 shows a number of features,
5 specifically 1 to n?
6 A. Yes.
7 Q. That a part of the sensory context
8 provided to predictor; is that right?
9 A. Yes.
10 Q. The features that are pointed to here,
11 what are they referring to, Feature 1 to n?
12 A. Well, you know, it could be certain
13 features.
14 Q. I'm sorry, are you done with your
15 answer, or are you still continuing?
16 A. I'm not sure what you're asking. It
17 could be, you know, features, you know, corners,
18 or be detecting, you know, certain colors of
19 certain pixels. Is there something specific that
20 you're asking? I mean, yes, it says Features 1
21 through n.
22 Q. Okay. And these features are provided

1 in the Grotmol system for training purposes; is
2 that right?
3 A. Yeah, presumably, training and/or
4 operation purposes.
5 Q. On the point of features, could you turn
6 to Figure 10A and 10B. Let me know when you're
7 there.
8 A. 10A and 10B.
9 Q. Yeah.
10 A. Okay.
11 Q. Maybe we could start with Figure 10B.
12 In Figure 10B, you see that there's a
13 box with feature extractors, and you see Feature
14 extractor 1 to N?
15 A. Yes.
16 Q. And then there's a box, the Behavior 1,
17 Adaptive controller 1; another one, Behavior 2,
18 Adaptive controller 2.
19 Do you see that?
20 A. Yes. Yes.
21 Q. And then there's output 1 to output N.
22 Do you see that?

1 A. I do.
2 Q. Okay. Great.
3 What's the role of the adaptive
4 controllers in Grotmol's system?
5 A. Well, he describes it a little bit with
6 reference to Figure, you know, 4A, but it's a
7 similar description. So if you look at Column 15,
8 for instance, in Grotmol, he says, Figure 4A
9 illustrates an implementation of adaptive control
10 system 400.
11 So if you look at Figure 4A -- wait a
12 minute. Yeah, this whole adaptive control system.
13 So the adaptive control system may comprise a
14 corrector, an adaptive predictor. So he has
15 basically a description of it here.
16 There's also another description.
17 Q. Sorry, were you done with your answer,
18 or are you --
19 A. Yeah, I mean, he describes it basically
20 where I just mentioned. I'm going back there.
21 Just give me one second.
22 So Figure 15 -- Column 15, as I said,

1 starting at line 18-ish or so, he describes, the
2 adaptive control may comprise, you have a
3 corrector. I mean, he's obviously talking about
4 Figure 4A and Figure 4B later on, but...
5 So, essentially, you have a controller.
6 You have basically an adaptive predictor, a
7 combiner, and a controller robotic platform. And
8 you have a learning process of the adaptive
9 predictor.
10 And he talks about a supervised learning
11 process, as we talked earlier, supervised
12 learning, potentially enforcement learning. So
13 that's the description that Grotmol offers.
14 Q. Okay. So these components you see in
15 Figure 4A or 4B, these are the ones you would find
16 in the adaptive controller in Figure 10B?
17 A. Generally speaking, yes. I mean, you
18 would -- obviously, in the Figure 10B, it's
19 showing you you have some user commands that you
20 would provide. The controller is going to take on
21 certain features. And then you have certain
22 behaviors and then provide outputs. And you can

1 see in his Figure 4A, he gives a little bit of
2 description of that.
3 Q. So Figure 10B, the adaptive controller,
4 there's a line that goes diagonally across the
5 adaptive controller, it says "user commands."
6 Do you see that?
7 A. Yes.
8 Q. And there's another one for adaptive
9 controller 2, also have user commands; is that
10 right?
11 A. Yes.
12 Q. And so these adaptive controllers can
13 receive commands from different users and then
14 have the outputs; is that right?
15 A. That's correct. I mean, you receive
16 commands from different users to change a certain
17 behavior or control a certain behavior or adjust
18 it.
19 Q. And so in Figure 10A, you see, like, one
20 adaptive controller behavior. In Figure 10B, you
21 see two. In Figure 10C, you see N1s of these.
22 That basically means that you can sort of have as

1 many adaptive controllers or a flexible number of
2 adaptive controllers in Grotmol's system; is that
3 right?
4 A. Yeah, that's the idea. So you have --
5 instead of just one big unit, you may have one
6 unit that's dedicated to moving forward and
7 backward, one unit dedicated to going right and
8 left, you know. That's not what he says, but I'm
9 just giving you an example of the idea.
10 Q. I'd just like to turn to Column 21,
11 Grotmol, please. And let me know when you're
12 there.
13 A. Column 21.
14 Q. 21, yes.
15 A. Yes, sir.
16 Q. Okay. Do you see Table 1, 2, and 3
17 there?
18 A. Yes.
19 Q. Okay. And right below Table 2, in
20 lines 47, you see the sentence starting, "Training
21 apparatus"?
22 A. Yes.

1 Q. Great.
2 At the end of that paragraph, there's
3 line 50 to 55 talking about training and that
4 depending on the type of robot, the task, state of
5 training, and other information, the teacher may
6 switch from one teaching mode to another one to
7 teach a behavior that's in the most effective
8 manner.
9 Do you see that?
10 A. I do.
11 Q. Okay. And so this training that's
12 involved in Grotmol, it could vary depending on
13 the type of robot; is that right?
14 A. Yeah, so it states, "Depending on one or
15 more of the type of robot, the task, the state of
16 training, and/or other information, the teacher
17 may switch between one teaching mode to
18 another..."
19 Q. I see.
20 So if you have one robot as one type of
21 robot and there's another type of robot, you can
22 configure them for different types of training and

1 the different modes; is that right?
2 A. Essentially. I mean, what's this
3 saying? You know, if you have a robot, for
4 instance, that has a higher resolution camera on
5 it, another one that doesn't have a camera or it
6 has, you know, maybe just LiDAR on it, you
7 obviously can configure your training
8 appropriately.
9 Q. And then in Table 3, we have a list.
10 And Table 3 is in Column 22.
11 Do you see that?
12 A. I do.
13 Q. Okay. In that we have different modes.
14 There's a control mode, listen mode, override
15 mode, correct, an autonomous mode?
16 Do you see that?
17 A. I do.
18 Q. If it's not too much to ask, would you
19 be able to give an example of when, like, a
20 robot -- when a robot in Grotmol would perform
21 each one of these modes or engage in these modes?
22 MR. JAIRAM: Objection; form.

1 THE WITNESS: Yeah, I'm not quite sure
2 what exactly you're asking. But let's say I have
3 a robot --
4 BY MR. KHAN:
5 Q. I'm sorry, I don't mean to interrupt.
6 Can I clarify the question?
7 A. Please. Please do.
8 Q. Okay. Sure. Yeah, my apologies, it's
9 probably not the clearest question.
10 So in Table 3, we see that there's a
11 control mode. In the control mode, the action
12 that is taken, it states, "Executes the action in
13 accordance with the training input."
14 A. Yes.
15 Q. Okay.
16 A. Does not learn association.
17 Q. Yes.
18 And then we have a listen mode. In the
19 listen mode, the robot executes the action in
20 accordance with the training input?
21 A. Yes.
22 Q. And the difference between the control

1 and the listen mode is that in the control mode,
2 the robot is not learning the association, but in
3 the listen mode, it is learning the association;
4 is that right?
5 A. Correct. You read it correctly.
6 Q. And then in the override mode, the robot
7 executes the action in accordance with the
8 training input and learns the association?
9 A. Yes.
10 Q. What's the difference in the listen and
11 the override mode?
12 A. Well, in the listen mode, you have a
13 training input, let's say, and you've provided
14 some type of control to the robot. So the robot
15 is going to execute the action in accordance with
16 the training input, and it's going to learn that
17 association.
18 Like when you see a table in front of
19 you, slow down, come to a stop. So learn that.
20 When you see an obstacle in front of you, when you
21 see a table in front of you, whatever, come to a
22 stop.

1 Override mode is you're going to
2 override the action. Because the robot may be
3 going, and it's going to hit the table. So
4 perhaps the prior learning wasn't done 100 percent
5 effective.
6 So you're going to provide an override
7 and say, Well, you really need to stop before you
8 hit the table about a meter away. I don't want
9 you to stopping just 1 centimeter away. I want
10 you stopping a meter away.
11 So you're going to override what the
12 robot is doing, because the robot may stop
13 1 centimeter away or it may be stopping but
14 speeding too abruptly and then going to come to a
15 stop too abruptly. You're going to override that
16 and provide additional -- different instructions.
17 Q. The override, can that happen by a user
18 input?
19 A. Typically, that's what you provide. You
20 provide an override input that essentially
21 corrects the incorrect activity that the robot is
22 doing. You're going to override that input and

1 correct it supposedly. So the next time the robot
2 sees the table, it slows down, starts to slow down
3 earlier, and stops 1 meter away instead of
4 1 centimeter away. There's a little description
5 of that on Column 23.
6 So if you go to Column 23, Grotmol
7 describes -- well, it starting, actually, in
8 Column 22, and he goes through the descriptions.
9 In the control mode -- the bottom of Column 22, it
10 talks about the control mode. And then in
11 Column 23, he talks about the listen mode.
12 And at the end of that, you see once
13 enough examples have been provided and the robot
14 has learned something, the override mode may be
15 used. And then there's a description of the
16 override mode starting at line 12 to, say, 22.
17 Q. So they -- going back to Table 3,
18 there's a reference of the training input --
19 sorry, the description includes discussion of
20 training input and the prediction.
21 And in the autonomous mode, the robot
22 ignores the teaching input and executes an action

1 in accordance with the prediction.
2 When they refer to the prediction, what
3 are they referring to?
4 A. What it predicts to what it's seeing.
5 So if the robot is processing, let's say, imagery,
6 it sees a table. So there's a prediction in its
7 system based on what it has learned that when you
8 see a table, you should start steering away from
9 it. So it's being given basically -- so the
10 systems of the robot are looking ahead in a sense
11 of predicting what the next action is going to be.
12 Q. Is that prediction based on the
13 training, as well?
14 A. Well, typically, yes.
15 Q. Could you turn to Column 33, please?
16 And let me know when you're there.
17 A. Column 33?
18 Q. Yes.
19 A. Yeah, I'm there.
20 Q. Line 13 says, "Apparatus and methods for
21 behavior undo during training of robots are
22 disclosed herein..."

1 What does it mean by "behavior undo"?
2 A. If you go to Column 34, starting at
3 line 18, it describes -- there's some capital
4 UNDOS there, but it prescribes the undo. I mean,
5 it probably -- a good description may be, if you
6 look at line 22, "user indication may be used to
7 trigger an UNDO operation. In some
8 implementations, the UNDO operation may comprise
9 loading of the previously saved configuration."
10 So -- and on line 32, you can see one or
11 more undo indications may be utilized in order to
12 remove multiple behaviors, basically correcting an
13 erroneous behavior that you may have accidentally
14 trained perhaps or erroneously trained.
15 Q. I see.
16 So you can implement an undo operation
17 if you want to correct or remove certain behaviors
18 of the robot; is that right?
19 A. Yeah, I mean, look at line 25, By
20 loading at time t1 the configuration saved at time
21 T0 less than t1, so a prior configuration, the
22 robot controller effectively "forgets" what it

1 learned in time interval t0 to t1.
2 So you did something between t0 and t1,
3 it wasn't effective, you didn't train the right
4 behavior, you want to undo it and start again,
5 essentially.
6 Q. I see.
7 And so then you could say -- you could
8 load another configuration, and then that would
9 effectively come in place of the configuration
10 that's forgotten?
11 A. Well, you go back to a prior state, and
12 then you will train from there. Kind of like you
13 do when you're typing. You're typing text or say
14 you created something and you cut and paste text
15 and then you hit the undo. It just takes it away
16 and brings you back to the previous configuration.
17 Q. Okay. I guess in this case -- in this
18 case, when you're doing the undo operation, it
19 loads the previously saved configuration, but
20 forgets about it; is that right? That's at
21 Column 34, lines 22 is 27?
22 A. I don't think you have it correct,

1 accurately. So you have a configuration up to
2 time t0. Okay. So up to time t0 you have done
3 some training. Let's say you have a configuration
4 up to that time.
5 Between time t0 and time t1, you added
6 some things. You told the robot to do a
7 handstand. So between t0 and t1, the robot,
8 instead of doing a handstand, fell on its face and
9 broke the camera.
10 Then you're going to say, Well, I guess
11 this didn't work. Let me undo this operation, go
12 back to time zero, and I'm going to start over by
13 doing something different, training it in a
14 different way or putting safety guards in place so
15 it doesn't break the camera while it's doing a
16 handstand.
17 I'm exaggerating obviously, but...
18 Q. Yeah, I see.
19 So like in Column 34, lines 18 to 21,
20 right before this, where it talks about high level
21 that the software platform -- BrainOS software
22 platform, it allows these multiple users to

1 selectively remove a learned behavior through the
2 undo or time machine operation.
3 And that's what you're saying then, that
4 once you're at a -- after time t0, if you ask the
5 robot to do something and it doesn't do it
6 properly, then you have the option to go back --
7 sorry, to undo the configuration; is that right?
8 A. More or less, yeah. Yes. To undo what
9 you've done between t0 and t1 and go back to t0
10 and then restart over again with the training.
11 Q. I see.
12 And so the robot is constantly basically
13 loading these different configurations based off
14 of, you know, what may be -- so, yeah, sorry, let
15 me correct.
16 So the robot is loading these
17 configurations at different times; is that right?
18 A. Well, the robot is loading -- it depends
19 on which mode it's in, but the robot is loading --
20 so if the robot is navigating forward, it sees a
21 couch, and it hasn't been -- it's been trained on
22 when it sees an obstacle to slow down and move to

1 the left, to the right, whatever, it's going to
2 basically load that configuration and do what it's
3 been trained to do. If there's never been any
4 training, then obviously it's going to either come
5 to a stop or hit the couch.
6 Q. Okay. So using -- sorry, I'm just
7 reading your comments.
8 So using the example you gave with the
9 couch, for instance, if the robot has a
10 configuration that's been loaded, and when it
11 comes up against a couch if that configuration
12 says, you know, turn left, then it will turn left.
13 But, you know, let's say there's, like,
14 water when you turn left, so it failed. And so
15 you could then load another configuration and tell
16 the robot to, well, when you come up to a couch
17 turn right, so that the next time the robot
18 approaches that couch, it will make a right turn
19 because of that newly loaded configuration; is
20 that right?
21 A. Well, close, but, I mean, like, if you
22 look, for instance, at the -- look at Column 34,

1 towards the end of -- say between lines 28 and 36,
2 37. Do you see it says, By -- towards the end of
3 that, let's say line 34, By a way of an
4 illustration, pressing control plus Z in a MS Word
5 may effectuate UNDO of successive edits.
6 So you would hit undo on your edits.
7 Similarly, providing a plurality of UNDO
8 indicating -- it should say indications, but it's
9 a typo -- may cause removal of multiple learned
10 associations.
11 So you've taught the robot something up
12 to t0. And between t0 and t1, you taught it
13 something. Then between t1 and t2, you taught it
14 more some more things. And between t2 and T3, you
15 taught it some more things. And you discovered
16 that it's failing, or it's not doing it right.
17 You say, Okay, I'm going to go back to the
18 beginning and start over again with my training.
19 So you're going to undo the t2 to t3,
20 undo the t1 to t2, undo the t0 to t1, and then go
21 back to t0 and say, Okay, I'm going to retrain it.
22 I'm going to do it a little differently, or I'm

1 going to change the speed or whatever. So that's
2 essentially what -- the idea behind it.
3 Q. I see.
4 And so with these different robots and
5 users, you could have a situation where, according
6 to Grotmol, you have a robot that -- one robot
7 that comes up against this couch, makes a left
8 turn, fails, another robot that makes a right turn
9 but doesn't fail, and then by virtue of learning
10 from each other, the first robot could then -- if
11 it learns from the second robot, would then also
12 make a right turn when it --
13 MR. JAIRAM: Objection --
14 BY MR. KHAN:
15 Q. -- reaches that couch the next time; is
16 that right?
17 MR. JAIRAM: Objection; form.
18 Objection; scope.
19 THE WITNESS: I think you're
20 misunderstanding this whole operation. In
21 Grotmol, there is one user training one robot in a
22 sense. That configuration -- so I have a user

1 training a robot in one learning process. That
2 configuration can be loaded on a second robot, but
3 there's no mixed training of robots. That is not
4 discussed at all.
5 So I have one user training one robot I
6 can undo different things and retrain the robot
7 and undo something and retrain the robot. And
8 when I'm done, so to speak, I have some trained
9 configuration of this robot. I can load that onto
10 a second robot.
11 BY MR. KHAN:
12 Q. Can you point to me a disclosure in
13 Grotmol that says only one user can train one
14 robot?
15 A. Well, I mean, if you read the
16 description of Grotmol, it's essentially that's
17 what I was talking about.
18 Q. That's kind of what I'm asking, is can
19 you point me to a disclosure in Grotmol that says
20 only one user can train one robot?
21 A. So you can start -- you know, look at
22 the background, for instance, Column 1, line 62,

1 63, "conventional approaches, given a task in
2 which a user wants to train a robot to navigate
3 along a path," and it talks about that. So that's
4 starting with the background. So you can get an
5 idea what Grotmol was trying to do with the
6 motivation behind Grotmol.
7 So the user may first control the robot
8 one time or multiple times to move along. And if
9 you look at Column 10, starting on line 45, you
10 see, In some implementations a user may train the
11 system to switch between tasks based on sensory
12 inputs.
13 And later on at line 50, it talks about
14 a predictor may assign priorities, blah, blah,
15 blah -- may assign priorities to the available
16 tasks based on the sensory context. The
17 priorities may be trained by the user via a
18 corrector plus combiner scheme.
19 So later on in that same column, it
20 talks about from the user, line 61.
21 Column 11, line 10, The user may correct
22 the system by providing an indication as to which

1 task the system should be performing.
2 Line 17, In some context the user may
3 want to signify.
4 Line 26, The user corrections may be
5 processed.
6 I mean, it's clearly describing a
7 user -- essentially, one user operating one device
8 in one learning process and creating that learning
9 activity.
10 Q. So your conclusion that Grotmol teaches
11 one user per one robot is because in the
12 description, Grotmol says "a user" when it's
13 referring to the interaction with the training of
14 the robot; is that right?
15 A. Well, Grotmol -- as I mentioned
16 obviously in my analysis of the claims in my
17 declaration, Grotmol discloses one user operating
18 one device in one learning process. So you have
19 one user, you're operating a device, you learn
20 something, you operate that device, you learn
21 something, and that learning -- that knowledge can
22 be propagated onto a second robot.

1 But there's no description in Grotmol of
2 multiple users operating multiple robots and
3 having mixed knowledge of any kind. That is not
4 discussed or disclosed in Grotmol. One user, one
5 device, and one learning process.
6 Q. In these sections that you pointed to,
7 does it say "one user"?
8 A. Well, it's talking a user, the user, a
9 user, the user. I mean, we can keep going.
10 You'll see that throughout Grotmol.
11 Q. So your conclusion that only one user is
12 using the robot here portrayed is based on the
13 explicit recitation of "a user" or "the user"?
14 A. No, my conclusion is based on reading
15 Grotmol and obviously understanding what Grotmol
16 is doing. Grotmol has one user operating one
17 device in one learning process. And when you read
18 the description of Grotmol and you read the
19 specification carefully, you would come to that
20 conclusion.
21 Q. Can you point to me anyplace in Grotmol
22 that has one user, that recites explicitly one

1 user?
2 A. Well, I'm not sure the word "one user"
3 is recited in Grotmol, but as I mentioned to you
4 when you read -- when you read Grotmol, you would
5 come to that conclusion. Grotmol has one user
6 operating one device in one learning process.
7 Q. Can you point to me -- and, again,
8 please just answer the question.
9 Can you point to me any place in Grotmol
10 that recites only one user?
11 A. I don't --
12 Q. I'm sorry. I'm sorry, let me rephrase
13 that.
14 Can you point to me anyplace in Grotmol
15 that explicitly recites that only one user can use
16 a robot?
17 A. I don't think those words explicitly are
18 in Grotmol, but what I've said to you is when you
19 read the context of Grotmol, you read the
20 specification, you look at the drawings, you read
21 the details, you understand what Grotmol is doing,
22 you come to that conclusion. You have one user

1 operating one device in one training process or
2 learning process.
3 Q. Okay. I think it's -- we just hit the
4 one-hour mark. You want to take a five-minute
5 break?
6 A. Sure, I'll be back in my seat at 1 -- at
7 2:50 Eastern.
8 Q. Okay.
9 (Recess from the record.)
10 MR. KHAN: I have no further questions.
11 So the witness is yours.
12 MR. JAIRAM: Okay. Let's just go off
13 the record, just take a five-minute break.
14 (Recess from the record.)
15 MR. JAIRAM: I have no questions. This
16 concludes the deposition. Thank you.
17 Go off the record.
18 (Off the record at 3:16 p.m.)
19
20
21
22

1 STATE OF MARYLAND)
2 ss:
3 COUNTY OF MONTGOMERY)
4 I, Matthew Goldstein, Notary Public
5 within and for the State of Maryland, do hereby
6 certify:
7 That I reported the proceedings in the
8 within entitled matter, and that the within
9 transcript is a true record of said proceedings.
10 I further certify that I am not related
11 to any of the parties to the action by blood or
12 marriage, and that I am in no way interested in
13 the outcome of this matter.
14 IN WITNESS WHEREOF, I have hereunto set
15 my hand this 21st day of May, 2024.
16
17
18
19
20
21
22 Matthew Goldstein, RMR, CRR

1 Eli Saber, Ph.D., c/o
2 McKOOL SMITH P.C.
3 1999 K Street, NW, Suite 600
4 Washington, D.C. 20006
5
6 Case: Tesla, Inc. v. Autonomous Devices LLC
7 Date of deposition: May 16, 2024
8 Deponent: Eli Saber, Ph.D.
9
10 Please be advised that the transcript in the above
referenced matter is now complete and ready for signature.
11 The deponent may come to this office to sign the transcript,
a copy may be purchased for the witness to review and sign,
12 or the deponent and/or counsel may waive the option of
signing. Please advise us of the option selected.
13 Please forward the errata sheet and the original signed
signature page to counsel noticing the deposition, noting the
14 applicable time period allowed for such by the governing
Rules of Procedure. If you have any questions, please do
15 not hesitate to call our office at (202)-232-0646.
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8 Witness Name: Eli Saber, Ph.D.
9 Deposition Date: May 16, 2024
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11 I do hereby acknowledge that I have read
12 and examined the foregoing pages
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13
14 (Check appropriate box):
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15 complete transcription of the answers given by
me to the questions therein recorded.
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9 Witness Name: Eli Saber, Ph.D.
10 Deposition Date: May 16, 2024
11 Page No. Line No. Change
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