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Transcript of Eli Saber, Ph.D.

Date: May 30, 2024

Case: Meta Platforms, Inc., et al. -v- VL Collective IP LLC (PTAB)

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Meta 1051
Meta v. VL Collective
IPR2023-00924

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Conducted on May 30, 2024

1 (1 to 4)

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1 UNITED STATES PATENT AND TRADEMARK OFFICE	1 A P P E A R A N C E S
2 BEFORE THE PATENT TRIAL AND APPEAL BOARD	2 ON BEHALF OF THE PETITIONER:
3 - - - - - X	3 TODD BAKER, ESQUIRE
4 META PLATFORMS, INC., :	4 KIRKLAND & ELLIS LLP
5 INSTAGRAM, INC., : IPR2023-00923	5 1301 Pennsylvania Avenue, N.W..
6 WHATSAPP LLC, META : Patent 7,266,682	6 Washington, D.C. 20004
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8 TECHNOLOGIES, LLC, : IPR2023-00924	8
9 and GIPHY, INC. : Patent 7,436,980	9 ON BEHALF OF THE PATENT OWNER:
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11 v. :	11 REICHMAN JORGENSEN LEHMAN & FELDBERG
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15	15
16 Deposition of ELI SABER, PH.D.	16 ALSO PRESENT:
17 New York, New York	17 Chandrajit Bajaj, Ph.D. (via teleconference)
18 Thursday, May 30, 2024	18
19 8:07 A.M.	19
20 Job No.: 534494	20
21 Pages: 1 - 299	21
22 Reported By: Anita M. Trombetta, RMR, CRR	22
2	4
1 Deposition of ELI SABER, Ph.D., held at the	1 -----I N D E X-----
2 offices of:	2 WITNESS
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4	4 EXAMINATION BY Page
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9	9 (Previously marked.) Page
10	10 Exhibit 6
11 Pursuant to notice, before Anita M. Trombetta,	11 Exhibit 2005 26
12 RMR, CRR, Notary Public in and for the State of	12 Exhibit 1001 28
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5 1 PROCEEDINGS 2 ATTORNEY BAKER: Good morning, Dr. Saber, 3 I am Todd Baker, and I am here on behalf of 4 petitioner Meta. And... 5 ATTORNEY EKLEM: Philip Eklem with 6 Reichman Jorgensen Lehman & Feldberg on behalf of 7 VL Collective IP, LLC, the patent owner, and the 8 witness. 9 ELI SABER, Ph.D., 10 called as a witness, having been duly 11 sworn by a Notary Public, was examined and 12 testified as follows: 13 EXAMINATION BY 14 ATTORNEY BAKER: 15 Q So, Dr. Saber, I understand this is not 16 your first deposition; is that correct? 17 A That is correct. 18 Q So you understand I'm going to ask you a 19 series of questions. To the extent you can, 20 you're going to answer those questions, correct? 21 A That's correct. 22 Q If you don't understand my question or if	7 1 A Yes. My specialty is in signal image view 2 processing, computer vision, pattern recognition, 3 machine learning. 4 Q And you've been an expert on a number of 5 inter partes reviews; is that correct? 6 A That is correct. 7 Q Approximately how many IPRs have you been 8 involved with? 9 A More than 40, less than maybe 60. 10 Somewhere between 45 and 55. 11 Q And have all of those IPRs involved video 12 processing? 13 A I think so, yeah. Most of them involved 14 either image, video processing or machine 15 learning, or some type of pattern recognition 16 stuff. Something within my -- within my 17 expertise. 18 Q And is it fair to say you represent both 19 petitioners and patent owners? 20 A I have. 21 Q Do you roughly have an idea of how many -- 22 A No.
6 1 you think it needs to be clarified, please let me 2 know. Direct that inquiry to me, not to your 3 counsel. Is that agreed to? 4 A Agreed. 5 Q I'm going to hand you what has been 6 previously marked as Exhibit 2005. 7 A Yes, sir. 8 Q Are you familiar with this document? 9 A I am. 10 Q And this document is your CV? 11 A It is. 12 Q When was the last time you updated your 13 CV? 14 A Maybe a month ago, month and a half ago. 15 Q Do you recall what you added or what you 16 amended? 17 A Off the top of my head, no. 18 Q And you have a Ph.D. in electrical 19 engineering; is that correct? 20 A That is correct. 21 Q And do you have a concentration or a 22 speciality within electrical engineering?	8 1 Q Is it 50/50 or does it lean one way or the 2 other? 3 A I don't remember off the top of my head. 4 Probably more towards petitioner than patent 5 owner, probably, but I'm not 100 percent. 6 Q In any of the IPRs where you've been 7 serving as an expert, have you been opposite 8 Dr. Chandrajit Bajaj? 9 A I have. I don't remember if it is two or 10 three times. I have, yes. 11 Q Did at least one of those IPRs involve 12 3Shape versus Dental Imaging Technologies? 13 A I think so. I don't remember off the top 14 of my head, but I believe so. 15 Q Do you list your IPRs on your CV? 16 A I don't list them on my CV. I have a 17 separate document that lists all my legal 18 engagements. 19 Q As you likely anticipate, we're going to 20 have a lot of discussions directed to 21 spatiotemporal models. 22 A Of course.

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9 1 Q Have you written any papers on that topic? 2 A Sure. I mean, I've published a lot of 3 papers. 4 Q You have. I was wondering if any of them 5 specifically focused on a spatiotemporal model, 6 and in particular one that may involve a graphical 7 model. 8 A Yes. We have published papers that have 9 to do with graphical models as far back as my 10 Ph.D. work, because I was doing work with shape 11 recognition that involved graphical models to 12 represent, you know, shapes and objects and 13 multiple layers of objects. And I've worked since 14 then extensively in digital video processing. I 15 actually started the digital video processing 16 course at RIT. 17 Just to give you a little bit of 18 background, so I -- obviously, as you know from my 19 CV, I joined Xerox in 1988. And then in 1993 I 20 went back to the University of Rochester to do my 21 graduate work with a scholarship from Xerox. And 22 when I went back to U of R, I started taking	11 1 So I reestablished their pattern 2 recognition course. They used to have it on the 3 books, but they haven't taught it for several 4 years. So I reestablished the course for them. 5 And I also started a digital video processing 6 course in the department. They didn't have such a 7 course. They had signal processing course and an 8 image processing course, but they didn't have a 9 video processing course. 10 So just to give you some background, the 11 signal processing course usually do the 12 one-dimensional signal processing, like acoustics. 13 The digital image processing course usually 14 handles the two-dimensional, you know, 15 multi-dimensional image processing, basically. 16 And the digital video processing courses usually 17 handle images as a function of time, and that's 18 where the spatiotemporal models come in. 19 So one of the first things we teach is the 20 spatiotemporal modeling and how do you model a 21 sequence of frames. So I established that course 22 at RIT and I've taught it for many, many years,
10 1 graduate courses, and some of those graduate 2 courses, most of them were in the area of signal 3 processing and computer vision. 4 I took a course from Dr. Ballard, 5 Professor Dana Ballard, in computer vision at 6 U of R; I took a course from -- several courses of 7 Professor Tekalp in digital image processing, 8 digital video processing, pattern recognition. So 9 that's when I started basically falling in love 10 with the area, and I did a lot of my Ph.D. work in 11 the digital imaging, video processing area and in 12 computer vision work. 13 When I finished my Ph.D., I was invited 14 back to U of R in 1997 to join as kind of an 15 adjunct part-time faculty because I had an NSF 16 grant together with Dr. Tekalp. So I joined as a 17 part-time faculty. I started teaching courses for 18 him in the areas of pattern recognition, 19 communications, you know, signal processing, 20 linear systems. And in 1998, I was invited by RIT 21 to join as an adjunct faculty and teach courses 22 for them as well.	12 1 and I obviously continue doing research in that 2 area. 3 In 2004, I designed -- I left Xerox and 4 joined RIT full-time. So I left the University of 5 Rochester at that time and became a full-time 6 faculty at RIT, and then continued, essentially, 7 that work. 8 Q So you indicated that digital video 9 processing courses usually handle images as a 10 function of time, and that's where spatiotemporal 11 models come in, correct? 12 A Well, we teach -- I mean, digital video 13 processing, obviously, as you know, it's frames as 14 a function of time. So there is a lot of modeling 15 that goes on with these functions of times. It 16 depends on how many applications. 17 So spatiotemporal models, you know, the 18 mathematics behind them, you know, start -- get 19 introduced to the students at that point, and, you 20 know, you're starting to develop basically motion 21 estimations and, you know, teach chapters on 22 motion estimation and segmentation, you know, a

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13 1 variety of applications that build on top of that 2 with different types of spatiotemporal models. 3 And then we get into -- later part of the 4 course, into compression, image and video 5 compression, and you get into the JPEG and the 6 MPEG type of stuff. 7 Q And you teach these classes at a bachelor 8 level, master's, Ph.D. or all of the above? 9 A They are graduate courses, so they're 10 meant for -- the digital video processing class is 11 meant for the student that's coming in to do a 12 master's and/or doctorate. And they have to take 13 the digital signal processing course first, then 14 the digital image processing course next - so 15 they're prerequisites - and then they can take the 16 digital video processing. Because it builds on 17 from the 1D, to the 2D to the 2D Plus-Plus to get 18 into the video, essentially. 19 Q And did you work on object tracking as 20 part of this video processing? 21 A Oh, absolutely. Many times, for many 22 years. I had five -- I've had five Department of	15 1 the late '90s. Then, when I joined RIT full-time, 2 shortly after that, we got a grant from 3 Department of Defense National 4 Geospatial-Intelligence Agency at RIT. You know, 5 RIT have the Center for Imaging Science, and I'm 6 also an extended faculty at -- 7 (Reporter clarification.) 8 A So RIT has a Center for Imaging Science, 9 and I'm a faculty -- I'm an extended faculty, so I 10 have a second appointment in that center for 11 imaging science. And, you know, the center 12 is well-known internationally for imaging, 13 basically, applications, remote sensing, that kind 14 of applications. 15 So I've had five grants from the 16 Department of Defense and the National 17 Geospatial-Intelligence Agency, and through my 18 role as a primary faculty at the electrical and 19 computer -- electrical engineering department, 20 electrical and microelectronic engineering 21 department, and as an extended faculty for the 22 center of imaging science.
14 1 Defense grants that had to do with object 2 tracking, object recognition, object detection, 3 three-dimensional scenery construction, change 4 detection, remote sensing, and tracking objects. 5 And, yes, we've been doing that for years. 6 Q And what was the earliest defense contract 7 you received for doing that, approximately? 8 A Well, I had an NSF GOALI grant together 9 with Dr. Tekalp at the U of R, I want to say in 10 the late '90s. Because at that time I was in 11 industry, I was in Xerox, so you can't obviously 12 get an NSF directly at Xerox. So we have -- 13 there's this GOALI program where a professor from 14 the academia and then an industry person and a 15 student, so you kind of like have a triangle. You 16 have the professor from academia serving on the 17 grant, which typically is the primary principal 18 investigator; you have the industry person serving 19 on the grant as the industry liaison, in a sense; 20 and you have the Ph.D. student working on the 21 grant together. 22 So my first grant was during that time in	16 1 Q So when did you start teaching object 2 tracking as a faculty member? 3 A We started -- I started teaching that -- 4 when we teach pattern recognition, those topics 5 come under essentially a pattern recognition 6 course. And I started teaching that in the late 7 '90s, maybe '98, '99, 2000 time frame, when I 8 joined, basically, the U of R as an adjunct at 9 RIT. 10 And then the digital video processing 11 course I started teaching at RIT, I want to say 12 late '90s, early 2000. And I'm -- you know, I've 13 taught it for many, many years. 14 Q So you can teach pattern recognition on a 15 single frame or image, correct? 16 A And -- and video frames. 17 Q And then you can extend those teachings -- 18 A Of course. 19 Q -- to apply to a video? 20 A Of course. 21 ATTORNEY EKLEM: Objection to form. 22 A I mean, you know, we teach basically -- so

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17 1 when we teach pattern recognition course, 2 typically the course is organized into three 3 primary modules. The statistical module talks 4 about the base, the Markov models, and Bayesian 5 estimations, map, maximum a posteriori 6 probability, maximum likelihood, Neyman-Pearson 7 classifiers, classifiers that are based on 8 statistical foundations. 9 The second module is a structural type of 10 module where you're teaching based on templates 11 and convolutions and that type of things. So it's 12 a structural type of pattern recognition. 13 The third part, the third module is built 14 on neural. So that's when you're doing like the 15 machine learning, the neural nets, and, you know, 16 this convolution of neural nets and that type of 17 pattern recognition. 18 But all three talk about images and video 19 type of applications, multimedia applications. 20 Q So in that primary module that involves 21 statistics, would you teach probabilistic 22 analysis?	19 1 objects and connectivity between layers and 2 between components. So those are usually done in 3 the structural part. And obviously they involve 4 probabilities, and, you know, that type of thing 5 as well. 6 Q And for pattern matching, there are 7 different approaches. There is a contour-based 8 approach; is that correct? 9 A There are contour-based approaches; there 10 are, you know, region-based approaches; there are 11 clustering based approaches; there are, you know, 12 template matching based approaches. There is a 13 lot of different ways. There are very large books 14 on this stuff. 15 Q What about wavelength-based approach? 16 What is that? 17 A We also talk about -- wavelength is 18 essentially a multifrequency kind of 19 decomposition, like subband composition, where you 20 would take, let's say, an image or a frame, and 21 instead of doing a 48 transform and getting the 22 frequency domain in one map, you would say, okay,
18 1 A Oh, absolutely. I mean, that's -- 2 essentially the primary part of that module is 3 Bayesian type, statistical foundations, like 4 maximum likelihood, maximum a posteriori 5 probability classifiers, Neyman-Pearson 6 classifiers, likelihood ratio tests, receiver 7 operating curves, characteristic curves. All 8 those statistical type of stuff apply to object 9 tracking, face recognition, you know, variety of 10 applications that you can apply these to in a 11 statistical foundation. 12 You know, Markov models, I did Markov 13 models and Markov random fields in my Ph.D. thesis 14 work, Markov and Gibbs random fields. 15 Q In which module would you teach these 16 graphical models? 17 ATTORNEY EKLEM: Objection to form. 18 A Well, the graphical models typically come 19 in into the structural type of -- part of the 20 course, we get into, you know, structures and 21 layers. And, you know, you have essentially a 22 graphical model that models objects and layers of	20 1 well, show me in this image -- and I'm putting it 2 in simplistic terms a little bit. 3 Q Please. 4 A Show me in this image the low frequency 5 components in both directions, which we call 6 low-low, let's say. 7 Q Okay. 8 A So you would use the proper filter and the 9 proper wavelength to see the low-low frequency 10 part. 11 And then in the next piece, the subband, 12 let's say, you say, show me the ones that are low 13 in this direction but high in this direction. So 14 we would say that's low-high. And then, show me 15 the ones that are low in this direction and high 16 in this direction, and we get the high-low. And 17 then the high-high would be, give me the high 18 frequency content in both directions. 19 So to relate it to what you're asking 20 would be like, you know, like you're -- you know, 21 typical, let's say, skin on the forehead would be 22 a low-low because it's a low -- it doesn't change

21 1 a lot. 2 Q Okay. 3 A Versus straight edges that, say -- let's 4 say straight edges on somebody's face or let's say 5 your shirt, like my pocket shirt, straight edges, 6 would be low in one direction, high in the other 7 direction. So it's high frequency content as you 8 transfer from here to here, but low as you go 9 across the edge; versus like my tie would be 10 high-high because a lot of changes in both 11 directions. 12 Q Would you use that high and low frequency 13 information to identify edges? Or how is it used 14 for detection? 15 A Typically what you do is you do subband 16 decompositions and you look at the energy in the 17 subbands. Like you would say, okay, I'm looking 18 for a low frequency content in this image. I'm 19 trying to classify skin; you know, nice patches of 20 skin, or a blue shirt like yourself. So you would 21 look at the energy within the subband and do the 22 classification on that.	23 1 A So that jacket, right? So if I did a 2 subband decomposition, a wavelength decomposition 3 of grass, I would see the energy in a given 4 subband, versus your jacket might be the energy 5 and it's a total different subband. So I -- for 6 instance, say, if I'm classifying grass from your 7 jacket, I can say, well, I'm seeing the energy in 8 subband alpha - I'm giving it a number just for 9 illustration - there is a lot of energy there, and 10 this is usually what grass is, versus that jacket, 11 it's at subband beta. Do you see what I mean? 12 Q Okay. And you could use that on a 13 person's face as well? You could distinguish 14 their forehead from their nose? 15 A Well, you would try -- you're 16 distinguishing frequency content. So your nose 17 has low frequency content and ridges on it. 18 Q Okay. 19 A Right? So it's not just taking parts and 20 distinguishing them, it's more looking at the 21 frequency content of the image. 22 Q How would you know the ridge from the
22 1 You know, texture is a great example on 2 that. There's been some good papers on texture 3 classification using wavelength decompositions. 4 Q So you're using the energy to identify 5 components of an image effectively? 6 A Yeah, you would use essentially the energy 7 in the subband. You would say, for instance -- 8 now, you could go more than what I just said. 9 This was just an example. You could have more 10 than four subbands. But you could divide it in 11 much more than. This is why we get the multi 12 resolution decomposition. 13 So you, for instance, say, I want to know 14 how much energy there is in this subband here, 15 between this frequency and that frequency. So you 16 would look at the energy of the subband. To give 17 you an example to relate it to practice, like, you 18 know, grass, for instance, has a texture to it. 19 Q Okay. 20 A Right? So is that jacket that you're 21 wearing, behind you. Yeah, that's your jacket. 22 Q I had it.	24 1 frequency content? 2 A Well, the ridge would come in as high 3 frequency in one subband and maybe low in another 4 subband. 5 Q Okay. 6 A If there's a vertical edge, it will be -- 7 the edge is, say, vertical, it would be low in 8 this direction because it's the same value. But 9 when you're going -- so it's low in the vertical 10 direction but high in the horizontal direction, if 11 it is a vertical edge, let's say. 12 Q So identifying a ridge is similar to 13 identifying a contour? 14 ATTORNEY EKLEM: Objection to form. 15 A Not quite. Not quite. 16 Q What's the difference? 17 A Well, the contours aren't straight 18 verticals and horizontals, so they obviously loop 19 all over the image. So trying to identify a 20 contour is a different type of, you know, 21 application in a sense, and it requires different 22 type of algorithms.

25 1 Q Let's return to your CV, Exhibit 2005. 2 A Yes, sir. 3 Q Page 1, I believe you mention receiving 4 external funding. 5 A Yes, sir. 6 Q Has any of that funding come from 7 VL Collective? 8 A No. 9 Q Has any of that funding come from Meta? 10 A No. 11 Q I always forget how to say this, Giphy, or 12 Jiphy? 13 A No. 14 Q WhatsApp? 15 A No. 16 Q Instagram? 17 A No. 18 Q Okay. Do you have stock in any of those 19 companies? 20 A No. I don't have any direct stock. I 21 have mutual funds that may invest in them, I don't 22 know.	27 1 matter, were you familiar with any of their 2 papers? 3 A Not that I recall off the top of my head. 4 I mean, I see a lot of papers. I don't remember 5 each paper, who wrote it. 6 Q Understood. You indicated that you have 7 taught classes that involve probabilistic 8 analysis. Do you have any journal articles on 9 that topic? 10 A Oh, yes. I mean, I also taught a class at 11 RIT, and I taught it many times, called random 12 signal and noise. Essentially the class is on 13 probability, random variables, random processes, 14 linear systems. So that class used to be in the 15 program, but I've picked it up – and it's a 16 graduate class. I picked it up and taught it for 17 a number of years. So – as well. 18 But yes, we have published papers that 19 involve probabilistic models. 20 Q How about papers on Bayesian similarity 21 measures? 22 A I don't remember off the top of my head,
26 1 Q Understood. 2 A I don't look. But I don't have any direct 3 stock in any of these companies. 4 Q Do you attend computer-vision-related 5 conferences? 6 A Yes, I do. 7 Q Regularly? 8 A Regularly from '93 until COVID. I've 9 attended more online since COVID. I think this 10 year I'm planning to go to some machine learning 11 conferences, and maybe the international 12 conference on image processing – an international 13 conference on image processing, which I think is 14 in Abu Dhabi. 15 Q I'm going to hand you what's been 16 previously marked as Meta Exhibit 1001. 17 Are you familiar with this exhibit? 18 A Yes, I am. 19 Q Do you know any of the named inventors of 20 the '980 patent? 21 A No, I do not. 22 Q Before being engaged as an expert in this	28 1 but yes, we have published papers that involve 2 probability models, Bayesian type models. I 3 published those early in my career as well. My 4 Ph.D. work had to do with Markov and Gibbs random 5 fields, which obviously use a Bayesian framework 6 to do -- you know, to do the estimations and the 7 probabilities and all this type of stuff. And 8 I've used that in applications for segmentation, 9 shape matching, shape recognition, motion 10 estimation, that kind of stuff. 11 Q So as part of my review of the materials, 12 I see discussions on probabilities and discussions 13 on likelihoods. Are those synonymous? 14 ATTORNEY EKLEM: Objection to form. 15 A I mean, you're asking a very good 16 question. It's really -- I would have to see some 17 details to be able to tell you if that is. 18 Q I'm going to hand you what's been 19 previously marked as Exhibit 2004. Are you 20 familiar with this document? 21 A I am. 22 Q And can you please identify for the record

29 1 what this document is? 2 A Yes, this document is "Declaration of 3 Eli Saber, Ph.D. in Support of Patent Owner's 4 Response." And the patent that we're talking 5 about is the '980. 6 Q And will you confirm on Page 112 that 7 that's your signature? 8 A Yes, that is my signature. 9 Q And will you turn to your appendix, 10 please. 11 A Yes. 12 Q And you have a list of materials 13 considered? 14 A Yes, sir. 15 Q Are there any materials that you 16 considered which are not listed here? 17 A There are materials cited throughout this 18 declaration, obviously. You know, I obviously 19 relied on my knowledge in the field. I may have 20 looked at some other things. I don't remember off 21 the top of my head. 22 Q One of the exhibits you list is	31 1 nonobviousness? 2 A Not that I -- not that I recall off the 3 top of my head. Not that I recall. I don't think 4 so. 5 Q Can you turn to Paragraph 44 of your 6 declaration. 7 A Yes, sir. 8 Q In Paragraph 44 you referenced the level 9 of ordinary skill of a POSITA as described by 10 Dr. Bajaj. Do you agree with that definition? 11 A Yes, I do. 12 Q And for any future questions, when I'm 13 asking you about the knowledge of a POSITA in the 14 relevant time frame, can we agree that that time 15 frame is the 2004 time frame? 16 A Yes. May 27, 2004. 17 Q And as part of your preparation in writing 18 this declaration, you reviewed the claims of the 19 '980 patent, correct? 20 A That is correct. 21 Q And you formed an understanding of what 22 those claims mean, correct?
30 1 Exhibit -- strike that. 2 In preparing your declaration, did you 3 review Dr. Bajaj's declaration, Exhibit 1004? 4 A Yes, I have. 5 Q And did you review all of the references 6 discussed in that declaration? 7 A Yes, as needed to render my opinions. 8 Q In rendering your opinions as provided in 9 Exhibit 2004, did you have discussions with anyone 10 other than counsel for VL Collective? 11 A No. 12 Q Can you take a second to review the table 13 of contents, your declaration. 14 A (Document review.) 15 Yes. 16 Q Do you know what secondary considerations 17 of nonobviousness are? 18 A I generally understand the idea of this, 19 but I'm not an attorney, obviously, so I can't put 20 it in the proper legal language. 21 Q In your declaration, did you provide any 22 opinions as to secondary considerations of	32 1 A Yes, that is correct. 2 Q And that meaning is in accordance with the 3 understanding of a POSITA, correct? 4 A That is correct. 5 Q And when you analyzed the prior art that 6 is discussed in your declaration, you did that 7 from the perspective of a POSITA, correct? 8 A That is correct. 9 Q And I plan on taking a break roughly every 10 hour. 11 A That's perfectly fine. 12 Q If at any point you need to stop, please 13 let me know. 14 A That's fine. Every hour is perfect. That 15 would be very nice. 16 Q I'm going to hand you Exhibit 1003. 17 Are you familiar with this document? 18 A Yes, I am. 19 Q What is this document? 20 A It's -- it's the provision -- provisional 21 patent application. 22 Q And do you understand how the provisional

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33 1 application relates to the '980 patent? 2 A I do. I have a section on that in my 3 declaration. 4 Q Do you want to give me an explanation for 5 how the two relate? Feel free to review your dec. 6 ATTORNEY EKLEM: Objection to form. 7 A What's -- what's your question? 8 Q Does the '980 patent incorporate by 9 reference the teachings of the provisional 10 application? 11 ATTORNEY EKLEM: Objection to form. 12 A There is a section labeled "Section D, 13 Priority Date of the '980 Patent," in my 14 declaration, starting on page 16, that discusses 15 how each of the claim elements and their 16 relationship to the provisional patent, and where 17 they are disclosed in the provisional patent 18 application. It's Page 16, 1-6. 19 Q Do you have Exhibit 1002 in front of you, 20 the '980 patent? 21 A That's 1001 in my -- the one I have. 22 '980, right?	35 1 patent, according to Item Number 22, was filed on 2 May 23rd, 2005. 3 Q Thank you. 4 And looking at your declaration, 5 Exhibit 2004, can we turn to Paragraph 31. 6 A Yes, sir. 7 Q You state in Paragraph 31, at the very 8 end, on Page 17, that, "A POSITA would have 9 understood that the inventors were in possession 10 of this element." 11 A Yes. 12 Q What do you mean when you state, "The 13 inventors were in possession of this element"? 14 A So obviously this paragraph is talking 15 about, you know, the provisional application 16 conveys to a POSITA that the inventors had 17 possession of element 19, 19 pre -- sorry, my 18 mistake. 19 So essentially what it's talking about is 20 the '980, Exhibit 1001, and the "pre" that we are 21 discussing here is for -- I'll just talk about 22 Claim 1, but it's the copy and paste for Claim 9
34 1 Q Yes. 2 A 1001. 3 Q I apologize, correct. 1001. 4 A Yes, I do. 5 Q Can you turn to column 1, line 4 of 6 Exhibit 1001. 7 A Column 1, line 4, yes, sir. 8 Q So do you understand what it means where 9 it states, "The application claims priority to 10 U.S. provisional application serial 11 number 60/574,799?" 12 A "Filed on May 27, 2004, which is here 13 incorporated by reference in its entirety." 14 Q Yes. Do you have an understanding of what 15 that sentence means? 16 A Well, I'm not an attorney, but this 17 application of -- the '980 application, when they 18 filed this application, claims priority to the 19 provisional application where the inventors, you 20 know, initially disclosed their inventions. And 21 the serial number is the one you just read. And 22 this is filed on May 27, 2004, because the '980	36 1 same idea. 2 Q Understood. 3 A Would that be okay? 4 Q Yes. 5 A So for Claim 1, the pre is "The 6 computer-implemented method for object detection 7 comprising, semicolon." So that's the pre. And 8 this paragraph discusses that the provisional 9 application would convey to a POSITA. So when I'm 10 reading this from the eyes of a POSITA, I would 11 understand that that pre is disclosed in this 12 application in the provisional application, and 13 the support for that is in this paragraph that we 14 can read through if you like. 15 Q Thank you. And "pre" is short for 16 preamble, correct? 17 A Correct. 18 Q So let's make sure I understand the 19 process. You reviewed the preamble for Claim 1 20 and you also reviewed the provisional to determine 21 whether a POSITA would have concluded that the 22 inventors were in possession of the subject matter

37 1 recited in the preamble? 2 A That's generally correct, yes. I reviewed 3 the patent, the '980; I read the claims very 4 carefully. I studied them, I studied the 5 specification. I reviewed the provisional 6 application very carefully, and then in this 7 section that's titled "D, Priority Date of the 8 '980 Patent," I describe where each of these 9 elements of Claim 1 are found or supported in the 10 provisional application from the eyes of a POSITA 11 reading that application. 12 Q Did you compare the provisional 13 application description to the description 14 provided by the '980 patent? 15 A Yeah, I looked at the technical 16 description. I read through the provisional 17 application, read through the technical 18 description, and obviously I read through the '980 19 patent, and that's how these paragraphs are laid 20 out. 21 So if you look, for instance, at 22 Paragraph 31 -- and I'll just give you a quick	39 1 take a quick break, maybe? 2 Q Absolutely. 3 ATTORNEY BAKER: Let's take our first 4 10-minute break. 5 (Recess.) 6 Q Dr. Saber, we were going to look at the 7 '980 patent. 8 A Yes, sir. 9 Q And the '980 patent has five figures, 10 correct? 11 A Yes. 12 Q And the brief description of the drawings 13 of the '980 patent indicates that Figure 5 is a, 14 "Flowchart of a method according to an embodiment 15 of the present disclosure," correct? 16 A You read that correctly, yes. 17 Q And in column 7 of the '980 patent, there 18 is a description of Figure 5? 19 A That is correct. Starting on line 45. 20 Q Does the provisional include Figure 5? 21 ATTORNEY EKLEM: Objection to form. 22 A Well, the figure is not literally present
38 1 illustration. So Paragraph 31 essentially targets 2 the preamble, as you mentioned, right, and it's 3 quoted there, "Computer-Implemented Method For 4 Object Detection." Paragraph 32 targets 5 Element 1A, which is the next element in that 6 claim, and where that is supported in the 7 provisional. And then paragraph after paragraph, 8 the same thing. 9 Q And during this review, did you notice any 10 differences in the disclosures of the provisional 11 application and the '980 patent? 12 ATTORNEY EKLEM: Objection to the form. 13 A I don't know what you mean by 14 "differences." 15 Q So let's look at the '980 patent. 16 A Okay. 17 Q Actually, for ease of this discussion, can 18 you have the '980 patent out and the provisional? 19 A That would be fine. 20 Q We'll turn our attention first to the '980 21 patent. 22 A Before we jump into this, is it okay to	40 1 in the provisional, but the descriptions, when you 2 read the provisional, you would understand that 3 these functionalities are present in the 4 provisional. 5 Q So column 7, lines 53 to 55, recite 6 "detecting the object in any image upon comparing 7 the probabilities for each image to a threshold 8 for detecting the object 505;" is that correct? 9 A You read it correctly. 10 Q Where is that functionality described in 11 the provisional? 12 A So if you go to my declaration, starting 13 on Page 22, Paragraph 36, and you read through 14 that Paragraph 36, 37 -- no, sorry, 36, not 37. 15 You notice that Paragraph 36 states, "The 16 provisional application conveys to a POSITA that 17 the inventors had possession of Element 1/9E." 18 And if you look at Element 9E in -- or 1E. 19 I'm only going to talk about 1, as we agreed. The 20 element says, "Detecting the object in any image 21 upon comparing the probability for each image to a 22 threshold for detecting the object," which is that

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41 1 same sentence you read from column 7. 2 Now, if you continue reading through this 3 paragraph, it will give you the support from the 4 eyes of the POSITA of where that is found in the 5 provisional application. And we can go through 6 that paragraph if you'd like. 7 Q Could we, please. 8 A Sure. So, the next sentence in that 9 paragraph says, "In addition to the disclosures 10 for Elements 1/9D, the provisional application 11 further states in the abstract" - so if you look 12 at the abstract - "that object detection and 13 tracking is then formulated as an inference over 14 directed loopy graph and is solved with 15 nonparametric belief propagation that uses a 16 variation of particle filtering." 17 And this continues. The quote continues, 18 "This type of an object model allows object 19 detection to make use of temporal consistency 20 (over an arbitrary sized temporal window) and 21 provides mechanism for simultaneous robust 22 tracking of the object."	43 1 typically requires probabilities, and -- that uses 2 a variation of particle filtering. 3 So -- now, to get -- to continue all the 4 support for this thing, we would have to go 5 through the remaining part of the paragraph. 6 Q Okay. 7 A So you see in Section 1, labeled 8 "Introduction" in the provisional, "The 9 provisional application further states that object 10 detection can be made" -- it's a typo -- "can be 11 made more reliable by considering the consistency 12 of the detection over time." And that, "object 13 detection and tracking are formulated as inference 14 over a two-layer graphical model in which objects 15 and components are connected via learned spatial 16 and temporal probabilistic constraints." 17 So you have probabilistic constraints that 18 you've connected these components with. And that 19 is on Page 4 of the provisional. 20 Q Okay. 21 A Now -- 22 Q Can we pause there?
42 1 That's in Exhibit 3, which is the 2 provisional, at Page 3. 3 We continue in Section 1 -- 4 Q If you don't mind, can we do it piecemeal? 5 Or do you want to go through each one of them 6 before -- 7 A Whichever you prefer. 8 Q So, if you don't mind, let's do it 9 piecemeal. 10 How does that first description show that 11 the inventors were in possession of comparing the 12 probabilities for each image to a threshold for 13 detecting the object? 14 ATTORNEY EKLEM: Objection to form. 15 A Well, I mean, this is initially the 16 abstract, which typically summarizes the 17 invention, right? So you have object detection 18 and tracking in the abstract. It's formulated as 19 an inference over direct loopy graphs. So 20 inference is kind of like reasoning, getting to 21 some type of, you know, reasoning, and is solved 22 with nonparametric belief propagation, which	44 1 A Yes. 2 Q Going back, did the patent inventors 3 develop nonparametric belief propagation? Is that 4 their invention? 5 ATTORNEY EKLEM: Objection to form. 6 A They utilized nonparametric belief 7 propagation to accomplish their invention. It 8 would be like utilizing calculus derivatives to do 9 your work. You didn't invent the derivative, but 10 you're using the derivative to compute rates for 11 something or other. 12 Q And how would you characterize what their 13 invention is? 14 A Well, I mean, if you look at the abstract 15 of the provisional, it gives the summary in a 16 sense of what the invention is. And the 17 introduction provides more work -- more 18 description of that invention. 19 And if you look at Section 1.1 of the 20 provisional, and I'm looking on Page 5, the 21 paragraph above the figure, Page 5 provisional, 22 paragraph above the figure, so you see it

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45 1 says, "Here we present a novel approach for object 2 detection and tracking that builds on top of, 3 improves, and extends the standard AdaBoost." 4 And then in that paragraph he describes 5 what they basically introduce as novel content; 6 what is their invention, you know, what are the 7 primary points of their invention, and compare to 8 prior art. And that's typical what we do in 9 papers and publications. 10 Q And what is AdaBoost? 11 A Oh, AdaBoost -- are you familiar with 12 machine learning? 13 Q I am. 14 A Oh, good. So AdaBoost stands for adaptive 15 boosting. That's the AdaBoost. So the idea 16 behind it, and I'll just be -- kind of give you an 17 overview, in a sense. 18 Say you have a classifier, let's call it 19 Classifier A, okay? And it's a weak classifier. 20 So let's say you're doing face -- facial 21 detection, and the classifier classifies, let's 22 say, eyes, "find eyes." But it's not a strong	47 1 stronger classifier as a combination of the weaker 2 ones. 3 Q So by adding up the likelihood of these 4 components, you have a better understanding of the 5 likelihood of the overall object; is that 6 accurate? 7 A You improve the accuracy over all objects. 8 So like if you look at the patent on -- I'm 9 looking at '980 -- 10 Q Okay. 11 A -- column 5, line 45. '980, column 5, 12 line 45. 13 Q Give me one second. 14 A Take your time. 15 Q Column 5, line 45? 16 A Line 45. 17 Q I'm there. 18 A Do you see that formulation there? H of I 19 equals sum alpha K HK of I? 20 Q Yes. 21 A So the HK of I, think of that as your weak 22 classifier.
46 1 classifier. It doesn't to do it with high 2 accuracy. Maybe the accuracy is 60 percent. And 3 I'm making these numbers up to illustrate the 4 point. 5 Q Okay. 6 A So we call that a weak classifier. So 7 instead of trying to work on it to make it 8 stronger, and say, well, what if I bring in 9 another weak classifier, what if I classify a 10 classifier that would find the nose, maybe with 11 60 percent or 55 percent, and find another 12 classifier that will pick up the ears, maybe 50 or 13 60 percent, and find another classifier that will 14 find the mouth, maybe it's -- or find one that 15 does skin tone. 16 Now, when I put them together, integrate 17 them in a linear or nonlinear framework, the 18 combination of all the weaknesses will get 19 stronger because now you have essentially a 20 correlation between them. Right? You have to 21 have eyes and nose and mouth and ears, you know. 22 So when you start adding this up, you get a	48 1 Q Okay. 2 A And you have capital K of them? Do you 3 see that summation K equals one, the capital K? 4 Q I do. 5 A So you have capital K of them. Let's say 6 capital K is 10 for the purposes of this 7 discussion. So you're combining HK of I times 8 alpha I, which is a weighting, because you might 9 weight the eyes more than, let's say, the ears, 10 and you combine them linearly in this case to 11 produce H of I, which is your stronger classifier, 12 hoping to get a stronger classifier. 13 Q And the stronger classifier is for the 14 overall object? 15 ATTORNEY EKLEM: Objection to form. 16 A For whichever application you're doing, 17 it's essentially a stronger classifier is going to 18 improve the accuracy of your -- so if you're going 19 face detection, HK -- H1 might have been the eyes 20 and H2 might have been the nose and H3 might have 21 been the mouth, and you've combined them together, 22 H might be the face. So I'm getting a better

49 1 classification on face by combining multiple weak 2 classifiers together. 3 Q And this is AdaBoost, right? 4 A This is the principle behind it. I mean, 5 AdaBoost is an algorithm because you have to 6 train -- obviously you have to find the right 7 alphas, right? So you have to do multiple things. 8 One, you have to train the classifiers. So your 9 weak classifier, you have to get it as strong as 10 you can get it, right? So you have to train it. 11 So each of the weak classifiers need 12 training, and then the combination, like why would 13 you pick -- how would you combine the eyes with 14 the nose? You know, do you want more weight on 15 the eyes or more weight on the nose? So that 16 weighting has to be trained to get the best 17 scenario, in a sense, on some kind of a training 18 set. And once you have done that, then -- so the 19 algorithm does that, essentially. 20 Q Okay. What about the last equation at the 21 bottom of column 5? What is that? 22 A So that's essentially -- so if you read	51 1 right HKI. So do I want to use this classifier to 2 do the eye or maybe this one is a little bit 3 better. Do I want to look at the entire eye or 4 just the pupil? I mean, you have to work with a 5 classifier to get it as best as possible. Even 6 though it's weak, you want the strongest of the 7 weakness. 8 Q So you select which classifiers to train, 9 and you typically select the strongest 10 classifiers? 11 A So you design a classifier for a 12 particular feature. Now, when you design the 13 classifier for the feature, let's say it's 14 classifying at 45 percent. I'm making this up. 15 So you might tweak the classifier a little bit to 16 get it up to 50 percent or maybe 51 percent. So 17 you're going to play with the classifier to get it 18 as strong as you can possibly get it by itself. 19 Then you're going to do another classifier 20 for feature two, the nose, let's say, and do the 21 same thing. Now you have to train the 22 combination; like do I use alpha one as .1, do I
50 1 what it says there -- and so I'm reading on 2 column 5, line 59, "The output of the AdaBoost 3 classifier is a confidence HKI" -- "is a 4 confidence HKI that the given pattern I is of the 5 desired class," right? So the pattern I is your 6 eye, let's say, or your nose, right? And the HKI 7 is the classifier designed for that. 8 "An object is considered present if HI," 9 which is computed above as the summation, "is 10 greater than one-half times this" -- this 11 combination of the weights. 12 Q And is this also a principle of AdaBoost? 13 A So this is -- AdaBoost does the training, 14 right? So AdaBoost is the -- how do I say it? So 15 AdaBoost, if you look at the equation 45, okay? 16 Q Mm-hmm. 17 A I'm sorry, the equation on column 5, 18 line 45. 19 Q Okay. Understood. 20 A Okay. So if you look at that equation, 21 that equation has multiple pieces that need 22 training ahead of time. So you need to find the	52 1 use alpha two as .2? How would I combine them? 2 Which one of those classifiers do I give more 3 weighting for? 4 So that training has to take place to find 5 those alphas. 6 Q Got it. From there you get the -- 7 A That's the AdaBoost. 8 Q Sorry. Okay. 9 A That's the AdaBoost. 10 Q That's line 45? 11 A So that's -- column 5, line 45 is 12 essentially the algorithm that will find the best 13 feature classifier and the ideal combination of 14 the weak classifier to get the strong HI, the 15 strongest you can get. 16 Q Does the machine learning do the weighting 17 or does the programmer do the weighting? 18 ATTORNEY EKLEM: Objection to form. 19 A Well, the weighting is typically done 20 through, like, supervised learning. So you 21 present something, you know the output, and you 22 adjust the variables. So it's essentially done

53 1 through trial and error, which – you know, 2 supervised learning approach. So it's not just 3 randomly. 4 You have a training set and you would 5 present the input, see what the output is, and do 6 the training to get – to get it as strong as 7 possible feature-wise and then combination-wise. 8 Once you've done that, then essentially the 9 AdaBoost is now – you've done the algorithm. 10 You're now going to use the output of the 11 algorithm to do the classifier. And that's 12 column 5, line 65. 13 Q So column 5, line 65 is the classifier 14 itself via AdaBoost? 15 ATTORNEY EKLEM: Objection to form. 16 A So you see it says there, I'm reading 17 column 5, line 60 – 59. 58, 59. "The output of 18 the AdaBoost" - the output - "of the AdaBoost 19 classifier is a confidence HKI for a given pattern 20 I." So that HKI is that weak classifier that you 21 made it as strong as possible. "For a pattern 22 eye," which is your feature, let's say the eyes or	55 1 formulate a formula and I do a second derivative. 2 You add a second – I know how to do a second 3 derivative from calculus, but the formula is what 4 I've invented, right? 5 So the AdaBoost algorithm steps are known. 6 The application to what you are doing, finding 7 those weak classifiers, designing each one of 8 them, HKI, H1I, H2I, for your application is 9 something you have to do. The algorithm doesn't 10 design them; you have to design how that 11 classifier is going to work, then train them to be 12 as strong as possible among their weakness. 13 And then, how do I linearly combine them 14 to get the best potential output, is something you 15 have to do for your patterns that you're doing 16 that. So that's where your contribution is. Even 17 though you're using the algorithm as the 18 foundation, that's where your knowledge comes in. 19 So if I handed you an AdaBoost and say, 20 Mr. Baker, could you do autonomous driving with 21 the AdaBoost? It's probably – you know, unless 22 you're an autonomous driving expert, it may not
54 1 the nose, "of the desired class." So if I'm doing 2 face recognition, maybe it's the eyes, the class 3 that I'm looking for. 4 "An object is considered present" - so I 5 have a face - "if H of I is greater than one-half 6 times the summation." 7 Q Got it. So everything we've just 8 discussed, though, was known through AdaBoost, 9 correct? 10 ATTORNEY EKLEM: Objection to form. 11 A I think you're misrepresenting what's 12 going on. 13 Q What have the inventors extended from 14 AdaBoost in the equations from column 5, line 45 15 and column 5, line 65? What have the inventors 16 added? 17 ATTORNEY EKLEM: Objection to form. 18 A So let me give you a small example to 19 start. So we know from calculus that you can do 20 first and second derivatives, right? 21 Q Mm-hmm. 22 A So I have an application here that I	56 1 work. 2 Q Well, if I understand you correctly, what 3 you're adding is the training to be used in 4 AdaBoost, correct? 5 ATTORNEY EKLEM: Objection to form. 6 A No, that's not what I said. That's part 7 of what I said. 8 So you have to design the weak classifier 9 first, right? How do I find the eye, okay? So 10 you have to design that classifier. So you have 11 to do some image processing, some video 12 processing, whatever you're going to do to 13 essentially figure out what that classifier is. 14 You have to analyze it: How weak is it, what's 15 the best accuracy I can get out of it? It is it 16 50 percent, is it 52 percent? So you have to 17 train it. All right. You have to change its 18 parameters, fiddle around with its parameters 19 until you get it to be as strong as possible. 20 Then you have to design the next 21 classifier for your nose, right, and do the same 22 thing. And now you have to group them together

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57 1 using that summation. So you need alpha 1, 2 alpha 2, alpha 3. So you have to find those. You 3 don't just pick them out of the sky. So you've 4 got to train this combination of classifiers to 5 find the right combination that's going to give 6 you the best accuracy. Right? 7 Q Does the '980 describe how to design a 8 classifier to find an eye, for example? 9 A Well, I mean, it's talking about -- you 10 know, this example I'm giving you is about face 11 recognition, right? This is not -- this patent 12 isn't about face recognition, so... 13 Q Does the '980 describe how to design a 14 classifier to find a limb? 15 A Yes. I mean, that's essentially what is 16 it's describing. It's describing -- it's got 17 probabilities, equations. It's describing a 18 process of how you would do, you know, object 19 detection and tracking. 20 Q Do the claims recite designing a 21 classifier? 22 ATTORNEY EKLEM: Objection to form.	59 1 five elements there. First element is, "Providing 2 a spatiotemporal model for an object to be 3 detected." So you need a spatiotemporal model. 4 You're providing a model for an object so you can 5 detect the object. 6 Q And that was well-known, correct? 7 ATTORNEY EKLEM: Objection. 8 Q The step of providing a spatiotemporal 9 model for an object to be detected. 10 ATTORNEY EKLEM: Objection to form. 11 A Why would you say it was -- I mean, he's 12 providing model, the spatiotemporal model, in his 13 patent to do that. 14 Q But didn't you tell me you were teaching 15 spatiotemporal models in the late '90s and the 16 early 2000s? 17 A Oh, I think you're misrepresenting what 18 I'm saying. So spatiotemporal model isn't just 19 one model that does everything. So its 20 application dependent of how you create this 21 model. So it's not the same model you would 22 create for autonomous driving that you would
58 1 A So -- well, we can go through the first 2 claim if you like. 3 Q I'm happy for you to give an explanation, 4 but answer my question and then you can explain. 5 So do the claims require designing a 6 classifier? 7 ATTORNEY EKLEM: Objection to form. 8 Q And I'm happy for you to go "yes" or "no" 9 and then explain. 10 A Well, the word "classifier" isn't printed 11 in, let's say, Claim 1. And I'm specifically 12 talking about Claim 1. I would have to look at 13 the other ones to see if the word "classifier" is 14 there. But the word "classifier" isn't in 15 Claim 1. But when you read Claim 1 as a POSITA, 16 you would understand that that's what the 17 invention is trying to do, is doing the object 18 detection and tracking. 19 So if I were to go through Claim 1, for 20 instance, it says, "A computer-implemented method 21 for object detection." So the method is for 22 object detection, and it comprises, and there is	60 1 create, let's say, for facial recognition or 2 object tracking. 3 So the model is just the overview 4 description, but the details of the model is what 5 you are creating in this patent. 6 Q But Claim 1 is just directed to a method 7 for object detection, correct? 8 ATTORNEY EKLEM: Objection to form. 9 A Well, it says, "A computer-implemented 10 method for object detection comprising," yes. 11 Q So the use of a spatiotemporal model to 12 detect an object, was that well-known in the 2004 13 time frame? 14 ATTORNEY EKLEM: Objection to form. 15 A Again, I think you're misunderstanding 16 what I'm saying, perhaps. So he's -- in the '980 17 patent, he's providing -- the authors are 18 providing a spatiotemporal model to do this 19 detection. It's part of their contribution. 20 There may be other authors that have a different 21 kind of spatiotemporal model, but these -- the 22 spatiotemporal model that's provided in this

61 1 patent is – is part of their contribution. 2 Q So they have a specific spatiotemporal 3 model described, correct? 4 ATTORNEY EKLEM: Objection to form. 5 A Well, they described in their patent a 6 spatiotemporal model that's essentially designed 7 to do object detection, for an object to be 8 detected. And if you look at the next element, 9 it's providing a video comprising a plurality of 10 images, including the object. 11 Q So that's well understood: Have a 12 video -- 13 A You have a video -- 14 Q -- the video -- multiple frames has an 15 object, correct? 16 ATTORNEY EKLEM: Objection to form. 17 A Well, it's providing a video comprising 18 the plurality of images, which would include the 19 object because you're trying to do object 20 detection. 21 Q Okay. 22 A And the next one says, "Measuring the	63 1 object, so that object is the "an object" you 2 started with, "in any image," those images that 3 you arrived at with video, "upon comparing the 4 probabilities." 5 So you are detecting the object that you 6 created the spatiotemporal model for an object to 7 be detected, you're detecting the object in any 8 image upon comparing the probabilities for each 9 image to a threshold for detecting the object. 10 So that's essentially what's in Claim 1 as 11 a whole. 12 Q So let's just go back to Step D for a 13 second. 14 A Step D, "Determining." 15 Q "Determining a probability that the object 16 is in each image." 17 A Right. 18 Q And if we go to column 5, lines 59 to the 19 end, it says that, "The output of the AdaBoost 20 classifier is a confidence that the given pattern 21 is of the desired class." And then it concludes, 22 "An object is considered present if."
62 1 object as a collection of components in each 2 frame" – "in each image." So you have the object 3 and you have a collection of components that make 4 up the object. Kind of like, as an illustration, 5 if you look at Figure 2A or something, you can see 6 that collection of components. 7 And then you have the next thing. So 8 measuring the object is talking about the object 9 from 1A, which is the "an object to be detected." 10 You see that connection. So then you have, 11 "determining a probability that the object," which 12 is the, "an object to be detected," is in each 13 image. 14 Q Is that completed using AdaBoost? 15 ATTORNEY EKLEM: Objection to form. 16 A Well, you're determining a probability at 17 this point. You're determining a probability that 18 the object is in each image. 19 Q Do you accomplish that using AdaBoost? 20 ATTORNEY EKLEM: Objection to form. 21 A I think you're mixing concepts here. And 22 let me finish the 1E. You're now detecting the	64 1 A Yes. 2 Q Is that how you determine a probability 3 that the object is in each image, using that -- 4 ATTORNEY EKLEM: Objection to form. 5 Q -- disclosure? 6 A Well, it's more than that. That's part of 7 the process, it's not the whole process. So if 8 you continue reading on column 6, it describes the 9 details. So this is just part of the process. 10 Q What's the additional part that you 11 believe to be the inventor's contribution that's 12 recited in Claim 1? 13 ATTORNEY EKLEM: Objection to form. 14 A So, I mean, again, if you continue reading 15 on column 6, it says, "This confidence is 16 converted into a likelihood function by 17 normalizing the alphas so that HI is between 0 and 18 1." Because you're trying to make -- the reason 19 you went it between 0 and 1 is because it's now 20 getting into a probability scenario. 21 Probabilities are between 0 and 1. 22 And in exponentiating -- and this is

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65 1 essentially your likelihood function. And if you 2 look back at the equations from the previous 3 column 3 or so, you'll see those likelihood 4 functions there, where T is a temperature 5 parameter that controls the smoothness of the 6 likelihood function, and with smaller values of T 7 leading to a peakier, more peak, peakier 8 distribution. 9 So this distribution that we're talking 10 about, those are about probability distributions. 11 Q Weren't these likelihood computations you 12 just discussed well-known in the relevant time 13 frame? 14 ATTORNEY EKLEM: Objection to form. 15 A No, this is not -- I mean, if we go back 16 to -- if you look at column 3, towards the bottom 17 of column 3, I'm looking at line 47 where it talks 18 about graphical object models, so this is part of 19 their contribution. So they propose this 20 spatiotemporal model. They have these 21 probabilities. You see "probability of," etc. 22 They have -- excuse me, they have likelihood	67 1 A Well, he says obviously here he's using a 2 nonparametric belief propagation, which is kind of 3 a generalization of particle filtering. So you 4 see it says, "The approach is a generalization of 5 particle filtering," and then continues on. I'm 6 reading on line 30 in column 6. 7 Q Would you also agree that the graphical 8 model -- use of the graphical model was well-known 9 as well? 10 ATTORNEY EKLEM: Objection to form. 11 A So again, I think you're mixing concepts 12 here. So derivatives in calculus are well-known, 13 but applying a derivative into my modeling 14 equation is not well-known. So it's -- it's -- 15 Q So are you saying the modeling equation is 16 the contribution of the inventors? 17 A Well, the inventors proposed a graphical 18 model that includes the objects and its 19 components, right? Different people might have 20 proposed a different -- a graphical model do 21 something else. So how you construct the 22 graphical model is something that you would
66 1 functions and they have temporal compatibility 2 functions that they introduce there. These are 3 introduced by them. These are not found in the 4 field. These are introduced in this patent. 5 They introduce the temporal connectivity 6 compatibility functions, they introduce local 7 evidence functions, which are the phis that you 8 see there, and I denote the local evidence. And 9 that's part of their formulation. 10 And then they describe how to compute 11 these compatibility functions and how to formulate 12 their likelihood functions and how do it the 13 classification as you continue reading column 4, 14 5, and 6, and maybe 7. 15 Q Can I turn your attention to column 6, 16 line 24. Can you go ahead and read that to the 17 end of the paragraph, read to yourself. 18 A (Document review.) 19 Yes, what is your question? 20 Q So doesn't this reflect that particle 21 filtering was well-known? 22 ATTORNEY EKLEM: Objection to form.	68 1 propose. 2 Now, you could propose a graphical model 3 that is only top down, so if I have the object and 4 the components but there is no connectivity to the 5 object, there is just object to components. So in 6 their case they proposed a graphical model that 7 has two layers, the object and the components, and 8 the components are interconnected. 9 So that's part of their contribution in 10 terms of what they're proposing. And then how you 11 interconnect them with probabilities is part of 12 your contribution of how you would make this 13 happen. 14 Q Does Claim 1 require a graphical model? 15 ATTORNEY EKLEM: Objection to form. 16 A Well Claim 1, you're providing a 17 spatiotemporal model for an object to be detected, 18 so you have a spatial -- it requires a 19 spatiotemporal model for the object, and if you 20 look two below, "measuring the object as a 21 collection of components in each image." So now 22 you're looking at the object in a collection of

69 1 components, so you have a graphical model as 2 they're describing it in the specification. 3 Q But does the claim require the model to be 4 graphical? 5 A Well, when you read the claim in light of 6 the specification, as a POSITA I'm reading the 7 claim, you have an object as a collection of 8 components, so you have components that make up 9 the object, how you're putting these components 10 together in light of the specification, they 11 propose this graphical, two-layer model. 12 Q Does the claim require a two-layer model? 13 ATTORNEY EKLEM: Objection to form. 14 Q Claim 1. 15 ATTORNEY EKLEM: Object to the form. 16 A Again, when you read the claim in light of 17 the specification, a POSITA would understand that 18 you are formulating the object, measuring the 19 object as a collection of components in each 20 image. So you have that essentially design that's 21 being proposed in this patent. 22 Q Doesn't column 4, lines 42 to 44,	71 1 because you can talk about the object by itself - 2 "and reduce the complexity of the graphical model 3 by allowing the assumption of the conditional 4 independence of components." Because then you can 5 get into the components part of the object. So 6 there is an advantage for doing the two-layer 7 model as they're proposing. 8 Alternatively, he says you can have a 9 single layer model. But obviously what they're 10 proposing is they're giving you the justification 11 why a two-layer model would be more beneficial. 12 Q But they also explain that in some 13 scenarios a single layer model would be 14 beneficial. Let's turn your attention to 15 column 6. 16 A Yes, sir. 17 Q Starting at line 15, doesn't the '980 18 explain that if the whole appearance of an object 19 is too complicated to model as a whole and can 20 only be modeled in terms of components, a uniform 21 likelihood can be assumed. So doesn't that teach 22 a single layer model?
70 1 contemplate a single object layer model? 2 A I lost where you are -- 3 Q Column 4, lines 42 to 44 or 42 to 45, 4 "Alternatively." 5 A Yeah, so that's an alternative potential. 6 But if you read before that, you can see, "To 7 integrate temporal constraints, the spatial 8 graphical models are extended over time to an 9 arbitrary length temporal window." 10 So you have a spatial graphical model and 11 you're doing a temporal thing, as you see in 12 Figure 2 of the patent. 13 "The resulting spatiotemporal graphical 14 models are shown in Figure 2A and 2B." And if you 15 look at those figures, you'll see essentially a 16 time axes on top, and with time going from left to 17 right, and then you see the object layer and the 18 components layer, and essentially illustrating a 19 graphical model that's temporally built. 20 "Having a two-layer graphical model allows 21 the inference process to reason explicitly about 22 the object as a whole" - e.g., two or three,	72 1 ATTORNEY EKLEM: Objection to form. 2 A No, I think you're misunderstanding what 3 it's saying. 4 Q What is it saying? 5 A So what he's trying to say is, depending 6 on the object, one may or may not have a 7 likelihood or a proposal project for the object 8 layer nodes. Okay? So if the object is too 9 complicated, you may not have a likelihood for it 10 that you can arrive at through training easily, 11 because it may be too complex to train, for 12 instance. 13 Q Okay. 14 A "So, for example, if the whole appearance 15 of an object is too complicated to model as a 16 whole." 17 Q Mm-hmm. Then what? 18 A So let's say you have hundreds of ridges 19 in the object or whatever, I mean, something very 20 complicated that you -- to model as a whole, and 21 can only be modeled in terms of components, the 22 pieces of the object. "Then a uniform likelihood

73 1 can be assumed over the object state space." 2 So instead of saying for the object state, 3 it's -- it's -- you're more likely to have arms, 4 let's say, than to have a blue shirt, okay? 5 Instead of having my object state space 6 distribution be more biased towards arms and a 7 blue shirt, you can say, I'm just going to assume 8 that to be uniform, where both are equally likely 9 to appear. A uniform distribution means 10 everything is equally likely, right? Just like 11 tossing a coin, right? Half the time you get, you 12 know, heads, half the time you get tails. It's 13 equally likely to assume it's a fair coin. 14 So that's what this is saying. It's not 15 saying that I'm not going to model the two layers, 16 it's just saying for the object layer, instead of 17 having to come up with the specialized 18 distribution, I'll just assume it's a uniform 19 distribution because it's too complicated to train 20 in that specific instance. 21 Q How do you have two layers if you can't 22 model the object as a whole?	75 1 bullhorns on the top? So there are a few of those 2 cars, right? This is very, very unlikely that you 3 see a car with bullhorns on the top, right? 4 So if that object is a car with bullhorns 5 on the front, right, so you'd have -- that piece 6 is in this distribution of the object with very, 7 very, very unlikely scenario, like one car in, I 8 don't know, 10,000. I'm making this up. I don't 9 know exact amount. Okay? 10 So that's the point he's saying. So if 11 you can't figure out how these components -- how 12 this object distribution is laid out over these 13 components, you can just assume it's uniform. 14 Essentially you're saying, I'll assume every car 15 out there has bullhorns on there. 16 Q Okay. 17 A Which is obviously unlikely, but -- you 18 wouldn't do that in this particular scenario, but 19 I'm just making this up as an illustration to help 20 you see what's going on. 21 Q Did the inventors make any contribution to 22 building the graphical model as described in
74 1 ATTORNEY EKLEM: Objection to form. 2 A Well, you can model the object as a whole. 3 What he's talking about here is the potential 4 distribution of the object over its components. I 5 think you're misunderstanding the concept. 6 Q But -- are you saying that the object 7 detection requires detection of each component? 8 ATTORNEY EKLEM: Objection to form. 9 A So in the model that he's proposing, he's 10 basically saying, I'm going to take my object, a 11 car, a human, whatever, and that object has a 12 collection of components. A car has tires and 13 wide windows and fenders and doors, the collection 14 of components that I find from the image that I 15 have. Okay? 16 Now, I have to come up with a likelihood, 17 with a distribution for the object, and how well 18 does this distribution distribute on these 19 components. I'm more likely to see, for instance, 20 normal door handles than I would see a fancy door 21 handle or I would see bullhorns on the top of the 22 fender. You know, you see that cars with	76 1 column 4? 2 ATTORNEY EKLEM: Objection to form. 3 A I don't understand what you're saying. 4 Q Is what's disclosed in column 4, was that 5 well-known or did the inventors make some type of 6 inventor contribution? 7 ATTORNEY EKLEM: Objection to form. 8 A That's what their contribution is about, 9 this patent, right? This patent documents their 10 invention, right? 11 Q But you would agree that the disclosure, 12 some of it relates to things that were well-known, 13 AdaBoost, and some things may allegedly be their 14 contribution. And I'm trying to distinguish 15 between what they acknowledge to be well-known and 16 what they believe to be their invention. 17 ATTORNEY EKLEM: Objection to form. 18 A Again, I think you're mixing things a 19 little bit. Like I said, derivatives in calculus 20 are well-known, but when I come up with a new 21 formula that I introduce into, let's say, the 22 technical market or the technical community, I

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77 1 introduce this new formula and I differentiate it 2 twice, that doesn't mean it's well-known when I 3 get it second derivatives. Because I introduced 4 this formula. Yes, the process of differentiating 5 is well-known, but the formula that I introduced 6 and how it's utilized in my algorithms is not -- 7 is part of my invention. 8 So the algorithm of AdaBoost is known, but 9 that's just a framework of taking weak classifiers 10 and making them stronger. You have to design the 11 weak classifiers for your application, you have to 12 design how you integrate them together to make 13 them stronger, you have to determine what is the 14 best integration, what's the optimum integration 15 setup. Is it a linear summation, is it a 16 multiplication? How are you going to integrate 17 them? 18 You're going to have to do that over a 19 training set. You're going to have to classify 20 the accuracy of that, look at it over many 21 different training sets, do all this work to 22 essentially -- so think of the AdaBoost as your	79 1 your declaration, did you read this paper? 2 A I -- I don't recall if I looked at it or 3 not. 4 Q Is the description in column 6 of PAMPAS 5 accurate? 6 ATTORNEY EKLEM: Objection to form. 7 Q To your knowledge. 8 A Well, I mean, this is a summarization, but 9 I would have to look at the paper in detail to 10 give you an accurate description of it. 11 Q Is the summary of PAMPAS, to your 12 knowledge, accurate? 13 ATTORNEY EKLEM: Objection to form. 14 A It seems -- I mean, again, I would have to 15 look at the paper carefully, but this seems -- 16 seems reasonable, yes. 17 THE WITNESS: Do you think we can do a 18 five-minute? 19 ATTORNEY BAKER: Yeah, let's do a break 20 now. It's a good time. Let's go off the record. 21 (Recess.) 22 Q Let's turn to your declaration briefly.
78 1 derivative for calculus and your stuff as that 2 formulation that you've created. So you have to 3 distinguish those two a little bit. 4 Q Okay. I want to return our attention to 5 the discussion of -- am I saying it correct, 6 PAMPAS, P-A-M-P-A-S? 7 A That's good enough for me. 8 Q Before your work on this IPR, were you 9 familiar with PAMPAS? 10 A I mean, I see a lot of stuff. I read a 11 lot of papers, so I'm sure I've come across these 12 type of things at one point or other. It's 13 published in a good conference. So computer 14 vision and pattern recognition is a good 15 conference. 16 Q Does PAMPAS disclose a graphical model 17 joint probability distribution formula? 18 A I don't remember off the top of my head, 19 sitting here today, what exactly is disclosed in 20 that paper. I couldn't tell you that sitting here 21 today. I would have to see the paper. 22 Q As part of your preparation for writing	80 1 A Yes, sir. 2 Q And I just want to go over the scope of 3 your opinions. So Section 9, and either you can 4 go to Section 9, which is on page... 5 A 73. 6 Q 73, or you can look at the table of 7 contents if that's easier for you. 8 A Yeah, it's probably easier to start with 9 the table of contents. 10 Q Did you provide any opinion regarding 11 Ground 1, that Element 1 or 9 for the preamble was 12 not disclosed or rendered obvious by Zhou? 13 ATTORNEY EKLEM: Objection to form. 14 A Well, my opinions are obviously listed -- 15 the section -- the parts of the claims that I 16 provided opinions on are listed, you know, in a 17 summary group to illustrate purposes in this table 18 of content. But as -- while you're describing 19 some of these things, there are discussions of 20 other pieces of the claim. But the focus was 21 these claim elements that you see there for 22 claims.

81 1 Q Does Zhou disclose a computer-implemented 2 method for object detection? 3 A I mean, I need...I didn't provide any 4 opinion on that particular one specifically. But 5 I provided opinions on Claim 1E, 9E, and the 6 description of Dr. Bajaj and why Zhou does not 7 disclose or render obvious Elements 1E, 9E. 8 Q And for Ground 2, did you limit your 9 discussion to Claim Elements 1D, 9D, and Claim 10 Elements 1E and 9E? 11 ATTORNEY EKLEM: Objection to form. 12 Q Is that correct? 13 A I mean, those are the elements that I've 14 rendered opinions on. But as you're rendering 15 those opinions, obviously you are discussing the 16 claim as a whole and how the opinions are 17 developed, so you have to look at the claim as a 18 whole not just a single element of the claim. 19 Q And the same question for Ground 3. Did 20 you limit your opinion or discussion to Claim 21 Element 1E and 9E? 22 ATTORNEY EKLEM: Objection to form.	83 1 A So three-frame means three frames from a 2 video sequence, and spatiotemporal, so spatial 3 obviously is an abbreviation of spatial; temporal 4 is the time, spatial is the space. And you have a 5 model, and in this particular sentence it 6 says, "We use a three-frame spatiotemporal model," 7 so it's extended over three frames. 8 Q So the model is extended over three frames 9 or is the model applied to three frames? 10 ATTORNEY EKLEM: Objection to form. 11 A Well, it's -- 12 Q I'm not sure if -- it's just my clarity. 13 A Yeah, so, I mean, you have a 14 spatiotemporal model that you would model in 15 general. In this case you're applying it over 16 three -- so you're using a window of three frames 17 to apply it on. You could apply it on five frames 18 or seven frames. The more frames you include, the 19 more complexity you start to get, typically. 20 Q Do you have the provisional in front of 21 you, Exhibit 1003? 22 A Yes, I do.
82 1 A And again, the same answer is, as I'm -- 2 as I'm rendering my opinion on that, I'm looking 3 at the claim as a whole, and what's described in 4 the claim as a whole from the eyes of the POSITA 5 was described in the specification -- you know, in 6 light of the specification, as I rendered my 7 opinions. 8 Q If we can turn to Page 18 of your 9 declaration, we're looking at the end of 10 Paragraph 32. 11 A Yes. 12 Q And you reference that the provisional 13 states that, "We use a three-frame spatiotemporal 14 model." 15 Do you see that? 16 A The third sentence from the bottom? 17 Q Yes. 18 A Yes, I see. You read that correctly. 19 Q Do you have an understanding of what is 20 meant by a three-frame spatiotemporal model? 21 A Yes. 22 Q What is your understanding?	84 1 Q Turning to Section 3.1, I believe that's 2 on Page 10. 3 A Yes, sir. 4 Q And Section 3.1 is entitled, "Vehicle 5 Spatiotemporal Tracking," correct? 6 A You read that correctly. 7 Q And that section discusses Figure 4, 8 correct? 9 A Yes, it references Figure 4 in that second 10 line of the paragraph. 11 Q Can you turn your attention to Figure 4. 12 A Yes. 13 Q Do you have an understanding of what the 14 initialization proposal distribution is shown in 15 Figure 4A? 16 ATTORNEY EKLEM: Objection to form. 17 A So, yes, I do have an understanding of 18 that. 19 Q What is that understanding? 20 A So when you're applying models - I'm just 21 talking in general - on a video sequence, let's 22 say I have a sequence of a thousand frames, okay,

85 1 and I just received the first frame. 2 Q Okay. 3 A So when I receive the first frame, there 4 is no frames before it, right? It's the very 5 first one. So I need to initialize the process. 6 So I need to get the -- you know, initialize the 7 process to the sequence, you know, or the imagery 8 that I'm receiving and so on. As I start the 9 initialization process and I move in, let's say, 10 three, four frames later, and now I can start 11 applying, you know, whatever models I've 12 developed. It's kind of like a kick-start. 13 Q So when we look at Figure 4, that upper 14 left corner frame is the initial frame for the 15 frames in the column that follow below? 16 ATTORNEY EKLEM: Objection to form. 17 Q Is that accurate? 18 A Well, it's -- I mean, I don't -- you can't 19 see much in this figure if you look at it. 20 Q Yeah. 21 A You can't see much in this figure, so I 22 don't remember exactly off the top of my head.	87 1 component. It's not the same thing. So you might 2 see a component in the frame, you may not see it 3 in a frame. 4 Q Okay. 5 A So it depends on -- so it's not exactly 6 the same. 7 Q If we could return for a moment to 8 Figure 4A and the initialization process. Do you 9 have an understanding of what is accomplished 10 during the initialization process? 11 A You would typically -- I mean, in a 12 typical initialization process, you might do the 13 segmentations or do what's needed to get your 14 spatiotemporal model focused on the objects that 15 are in these frames. 16 So, you know, you're going to see an 17 object in the frame, you need to focus on the 18 object, get your -- get your graphical models, 19 whatever, focused on the object, where it is in 20 the image, and now you can begin the tracking 21 across the frames. 22 Q And in Figure 4A, what is the proposal
86 1 But... 2 So the figure is labeled "Vehicle Object 3 Detection and Tracking." Part A shows the 4 initialization proposal distribution. So that's 5 essentially what you're initializing for the 6 process, right? And Part B show -- it says, "30 7 samples taken from the belief for each of the four 8 components and an object." 9 Q So are the four components TL, TR, BR, and 10 BL? 11 A Yes. 12 Q Okay. 13 A Yes, essentially. 14 Q The provisional uses the term "sample." 15 Are samples and frames the same thing? 16 ATTORNEY EKLEM: Objection to form. 17 A Well, I would have to see where exactly 18 you are talking about. 19 Q I'm looking at the caption for Figure 4B. 20 A So these are samples taken from the belief 21 for each of the four components of an object. So 22 these would be like samples for that particular	88 1 distribution? 2 ATTORNEY EKLEM: Objection to form. 3 A Well, the distributions that it discusses 4 in the provisional. 5 Q Discusses where? 6 A Well, I mean, if you look at the -- you 7 know, the provisional patent like you have, for 8 instance, you have equation five provides those 9 likelihood functions. Right? 10 So I'll just give you an example here. 11 I'm looking at Page 10, equation five, and just 12 below it. So with smaller values of T, T is a 13 parameter that changes, leading to peakier 14 distribution. Right? So these essentially -- you 15 have some distributions that you initialize once 16 you find the object in the first frame, so then 17 you can start the tracking process. 18 So you model things with distributions. 19 You model the object with a distribution, you 20 model the components. You have essentially 21 conditional distributions of probability density 22 functions or distributions.

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89 1 Q And is it a human or the program that does 2 the initialization and proposal distribution? 3 A Typically it's done by the program. I 4 mean, you've designed the program to -- to find 5 the object, so once you've trained it and you've 6 got it working, it's going to -- you've now 7 presented a sequence of video frames; it's going 8 to go to the first frame, find the object, detect 9 it, and then apply -- update the distributions for 10 that particular object. Because that object will 11 be a car and the next object could be a human. So 12 they're not the same object. 13 And then you track it throughout the 14 frames, and as you're going throughout the frames, 15 you start to move your track. 16 Q So the first step is detecting the object 17 and then you track? 18 A Yes, you need to detect to track. Because 19 maybe the first 10 frames there is no car, right? 20 Let's say you have a camera looking outside and 21 the street is empty right now, so there is nothing 22 to track. And then at some point a vehicle comes	91 1 Q So you have to detect the object in each 2 frame? 3 A Yeah, you would need to look -- you know, 4 detect the object in the frames and do the 5 tracking. It's usually done like a -- it's a kind 6 of an integrated model. Like you don't do one 7 then the other. It's part of -- because, you 8 know, if I know the object is a car and it's 9 moving at a certain speed - I'm simplifying now, 10 right - I can say, in the next frame I think it's 11 going to be here. 12 Q Because it has a constant velocity? 13 A Because it has a constant velocity or I 14 know the acceleration or whatever. So I can 15 predict where it's going to be. When I go to the 16 next frame, I'm going to look for it there, and 17 once I establish, then I have this track. So it's 18 part of the model. 19 Q Is that the temporal component of the 20 model? 21 ATTORNEY EKLEM: Objection to form. 22 A So the temporal component obviously
90 1 into the street, so you pick that up and then you 2 start to track it. 3 Q Is there any distinction between detecting 4 and tracking? 5 ATTORNEY EKLEM: Objection to form. 6 A I'm not sure what you mean. But object 7 detection is detecting the object; object tracking 8 is tracking the object through the frames, 9 typically. 10 Q So Figure 4 says it's "Vehicle Object 11 Detection and Tracking." 12 A Yes. 13 Q Is the detection Figure 4A, and is the 14 tracking done at 4B? 15 A Well, you would do the tracking throughout 16 the frames. So you would -- you're doing it in 17 Figure 4 -- 4B as well. You're detecting -- so 18 every time you go to a new frame, you have to 19 detect the object and correspond with the previous 20 frames to say, okay, used to be here, it's now 21 here, it's now here, right? So you have to find 22 it and establish the track.	92 1 addresses how you would look at the object 2 tracking over time. The spatial component is 3 looking at the object within the frame, and the 4 integration of the two together gives you 5 obviously the best typical performance. 6 Q So detection occurs before tracking in 7 each frame? 8 A Well, I don't know if you could say 9 before, but it occurs -- they both have to occur. 10 So you would need -- because I can predict where 11 it's going to be in the next frame, right? So I 12 already have a track, in a sense, based on prior 13 knowledge, right? I know where it's going to be. 14 So I go there, I detect it, I confirm, and 15 then I continue. I'm simplifying extensively for 16 just the illustration here. But that's the idea. 17 So it's not done like the Step 1, Step 2. 18 Typically it's done as an integrated model. 19 Q But the detection is simplified if you can 20 make some assumptions about either -- for example, 21 you said acceleration. If you know what the 22 acceleration is, that will help with detection in

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93 1 a future frame. That was one example, correct? 2 ATTORNEY EKLEM: Objection to form. 3 A In that particular example, you can 4 simplify the search in the frame by using 5 predictions from prior frames. 6 Q And in that example, acceleration is used? 7 A Let's say. 8 Q That's one? 9 A Yes. 10 Q I think you mentioned a constant linear 11 velocity? 12 A Perhaps, yeah. 13 Q How about a constant angular velocity? 14 A If it applies, yes. But again, these were 15 illustrations just to discuss the concepts. 16 Q Understood. But just to confirm, the very 17 first frame, the initial frame, there you have no 18 velocity or acceleration to use as part of the 19 detection or tracking, correct? 20 A In the illustration that we've been 21 discussing. So let me simplify it maybe a little 22 bit.	95 1 contour recognition or wavelength recognition, you 2 have to use one of your techniques, right? 3 A Well, you have to do -- 4 ATTORNEY EKLEM: Objection to form. 5 A You have to do object detection. And it 6 depends on the application and what the inventors 7 have designed that to be. 8 Q What are some various ways you can do 9 object detection of a car, for example? 10 A Well, you could do segmentation of the 11 frame, for instance, and try to find -- you know, 12 do some template matching to find, you know, here 13 is what a car looks like. You may have to do that 14 at different scales and rotations and that type of 15 thing, because a car doesn't always come in this 16 way; it may come in this way or something else, 17 right? But it's not going to be coming in 18 rolling, for instance. Hopefully not. 19 Q Hopefully not. 20 A Hopefully not. So you could do other 21 things. You know, you could do -- you know, look 22 at the color, for instance, if you're looking for
94 1 Let's say I have a camera looking at the 2 street downstairs, and it's empty, there is 3 nothing there. So the camera is watching the 4 street, there is nothing on the street. A car 5 comes in -- comes into the view of the camera. 6 You pick up the first frame, you see the car, 7 right? 8 Q Yeah. 9 A So you detect it. You don't have a 10 velocity at that point because you only have one 11 frame. And let's say you're capturing that 30 12 frames a second. So I just have a first frame. 13 Now I see it in the next frame, I start to 14 establish, okay, it looks like it's moving at 15 60 miles an hour. So I start to establish a 16 rapport, right? And as you see it more and more 17 frames, your models become more and more accurate 18 in tracking the object because you're -- you have 19 historical information from prior frames. 20 Q But that first frame, when the car first 21 comes into the view of the camera, you detect the 22 car, you have to -- you have to do some type of	96 1 red cars or something like that. You could look 2 at contours, that's another option. There are 3 many different ways to detect object. 4 It depends also on the object that you're 5 trying to detect. Is the object rigid or is it a 6 more deformable object? Like a car is a rigid 7 object. It doesn't deform, right? Hopefully not, 8 right? So it's going down the road, it remains in 9 its rigid form. 10 A human is a deformable object, right? 11 Your arms move, you may stretch or jump or 12 whatever, so you're more of a deformable object 13 and harder to find. 14 Q But in the '980, the detection relates to 15 an object that has many components, correct? 16 A Yeah, I mean, the object -- you have an 17 object layer and you have components that are part 18 of that object. Yes, your lens and whatever, your 19 head. 20 Q So then you're detecting each of the 21 components as part of the object detection, 22 correct?

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97 1 A And the object, yeah. You have to detect 2 the components and the object. 3 Q How do you detect the object separately? 4 A Well, if I'm looking, for instance, for 5 cars as one object, I know a car -- a sedan, let's 6 say, has a certain shape. So I would be looking 7 for objects that have that shape under certain 8 transformations. 9 Q How about for a human? 10 A I know a human has a certain shape, but 11 they're harder because they're deformable so 12 you're going to have to address different parts of 13 that. Because your arms move, right? You're not 14 in the same spot. 15 Q So in that case you look for the 16 components? 17 A Well, you look for the -- you have some 18 object detection using some, you know, template 19 matching, let's say, for instance, or using some 20 Bayesian techniques. And then you also look for 21 components, you know, like if this is a human, 22 where is the arms, you know.	99 1 ATTORNEY EKLEM: This is what we're using. 2 This is what's of record. 3 ATTORNEY BAKER: That's fine. We can 4 continue. 5 THE WITNESS: Okay. 6 Q Section 3.2 discusses Figure 5, correct? 7 A That is correct. 8 Q And Section 3.2 is directed to pedestrian 9 spatiotemporal tracking, correct? 10 A You read that correctly. 11 Q So, like, Figure 4 and Figure 5, the 12 frames shown in 5A are the initialization frames; 13 is that accurate? 14 A That's what it says. A, it shows the 15 initialization/proposal distribution, and B is the 16 other ones. 17 Q What are the other ones? 18 A The mean of 30 samples taken from the 19 belief for each of the four components of an 20 object. 21 Q And in 5B you have an object which is a 22 collection of the four components, HD, LUB, RUB,
98 1 So kind of one essentially improves the 2 other, right? If I can find the components, I 3 have more confidence in the detection of the 4 object, and back and forth. 5 Q All right. Let's go to the Section 3.2, 6 which I think we're already at. Are were we in 7 3.1 before? 8 A In my declaration? 9 Q In the provisional. 10 A Provisional. Okay. 11 Yes. 12 ATTORNEY BAKER: Let me ask your counsel 13 one question. Is there any chance we can have a 14 better copy of this provisional, or is this as 15 good as it gets? And not today, later. I didn't 16 know if there was a way to get a better copy of 17 record. 18 ATTORNEY EKLEM: I don't know what -- I 19 mean, I can look into that. 20 ATTORNEY BAKER: This is what you're 21 using. Right? What you have is no better than 22 this?	100 1 and LB, correct? 2 A Yes, sir. HD would probably be head, left 3 upper body, right upper body, and lower body. 4 Q Does the provisional describe a way to 5 detect the object before detecting the components? 6 ATTORNEY EKLEM: Objection to form. 7 A I'm not sure. I mean, it describes 8 obviously -- so if you go to provisional Page 5, 9 you have a section "Geographical Object Models." 10 So it describes how it models the object, right? 11 And it provides equation one on Page 6 to model 12 the -- the potentials, potential functions of the 13 object, and then gives some details of that. 14 And building a graphical model goes to the 15 next section. And then learning spatial and 16 temporal constraints in the next section is for 17 the particular object that you're working on. And 18 then putting it into a nonparametric belief 19 propagation graph. 20 So it's an integrated part. It's not like 21 this or that type of thing. It's kind of an 22 integrated thing.

101 1 Q So the object is modeled as a graph of its 2 components, right? 3 A It's an object and a graph of its 4 component, right? If you look at the -- so if you 5 look at Figure 2, you see it's giving an 6 illustration, in, let's say, Figure A of a 7 pedestrian, and Figure B. So A is the vehicle and 8 B is the pedestrian, and then C and D give the 9 corresponding spatiotemporal counterparts. 10 Q But there is no probability formula for 11 the object by itself, correct? 12 ATTORNEY EKLEM: Objection to form. 13 A I don't know what you mean by that. 14 Q Isn't the object probability the joint 15 probability of its components? 16 A And the object. I mean, you would have 17 the object and its component jointly modeled. I 18 mean, otherwise you don't -- you lose the 19 connectivity between the object and the 20 components. 21 Q Where is that shown? 22 A Well, it's described in --	103 1 circle. 2 A You see "OT." And then below that OT, do 3 you see "CHD," which is not very readable, but I 4 can tell what it is just because I've read this 5 thing. So it's CHD; C left, supposedly upper body 6 or something; C right; and then C lower. 7 So those are the components, and they're 8 connected to the object itself. And when you see 9 that connectivity with those straight lines, that 10 indicates the connectivity between them. So the 11 components have interconnectivity and the object 12 has connection to them. 13 Q But you agree there is no disclosure other 14 than this figure of a probability distribution of 15 the object by itself? 16 ATTORNEY EKLEM: Objection. Form. 17 A Well, I mean, there isn't -- you know, 18 when you read the provisional, you come to those 19 understandings, right, because you're formulating 20 essentially the model. Do you see those potential 21 functions on equation one? You're formulating the 22 model.
102 1 Q Or described. 2 A So the description starts on Page 5, 3 "Graphical Object Models." So you see the first 4 sentence says, "We model an object as a 5 spatiotemporal directed graphical model." Then it 6 gets into, "Each node in this graphical" -- "in 7 this graph represents an object or a component of 8 an object at time T." Do you see that, "each node 9 in this graph." 10 So if you look at Figure 2, for instance, 11 let's just look at 2C, you see the object nodes on 12 top that serve that big circle with the "OT" 13 inside of it. So those are the object nodes, and 14 they're interconnected to the component nodes that 15 are below them that -- labeled "C" below them. 16 Like let's look at Figure D, for instance, 17 just for an example. So if you see in Figure D, 18 I'm looking at the middle one, in the middle. 19 Q Mm-hmm. 20 A You see the "OT" in that circle? You need 21 a big pair of glasses, yes. 22 Q Yes, I see "OT" and then the little	104 1 I'll give you an example. If you look at 2 formula one on Page 6, do you see that formula? 3 Q Yes. 4 A Do you see where it says "XI" and "XJ"? 5 Q Yes. 6 A Now, if you go back to the previous page, 7 do you see where it says "Each node has an 8 associated state vector X equal xys." 9 Do you see that? 10 Q Mm-hmm. 11 A So that each node is essentially referring 12 to -- if you look at the sentence before that, the 13 second sentence in that paragraph, it says, "Each 14 node in this graph represents an object or a 15 component of an object." 16 Do you see that? 17 Q Yeah. But the sentence you were reading, 18 "Each node has an associated state vector," it 19 says it's defining the component's position. It 20 doesn't say it's defining the object's position. 21 A Yes. But also, that X has to also define 22 the object because you have to know where the

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105 1 object is related to its component. Because 2 otherwise, how would you connect the two together? 3 Like, for instance, look at Figure 2D. Do 4 you see that Figure 2D again? 5 Q 2D, yes. 6 A Look at the middle figure in 2D. Do you 7 see where it says "CHD," and at the bottom it 8 says, "C," I think "LG" or something. I can't 9 read it. 10 Q That bottom component and the lower -- 11 A Yeah, the bottom component says something 12 "lower," right? It's like lower body and a head. 13 Do you see that? 14 Q Mm-hmm. 15 A Do you see that the head has no connection 16 to the lower body? 17 Q Direct. No direct connection? 18 A Yes. Because obviously your head isn't 19 connected to your legs directly. 20 Q Except to the hip bone. 21 A Or connected, right, through your body, 22 right, to the other pieces. So that connectivity	107 1 references on Page 12 of the provisional. 2 A Yes, sir. 3 Q And do you see reference 2? 4 A Yes, sir. 5 Q Are you familiar with reference 2? 6 A Yeah. That's TLP in our discussions here, 7 right? 8 Q Right. 9 A That's the one labeled "TLP" in my -- I 10 think in Dr. Bajaj's declaration and my response 11 here. 12 Q I believe so. Do you believe it's the 13 same reference? 14 A It seems -- it seems that way. 15 Q So you mentioned Section 2, "Graphical 16 Object Models," in the provisional? 17 A Yes. 18 Q So do you agree that the provisional 19 follows the framework of TLP? 20 ATTORNEY EKLEM: Objection to form. 21 A Now you're getting into a whole different 22 arena that -- so my analysis of the '980 in
106 1 has got to be described correctly for the correct 2 object that you're modeling. Because if you put a 3 connection between the head and the legs directly, 4 then your model has to go find that connection. 5 It's not going to find it because your head is 6 never going to be sitting on top of your leg. So 7 you're going to have errors in your model. 8 Q Errors in the model? 9 A Errors, yeah, obviously. Because your 10 head isn't attached directly to your legs, right? 11 Q Isn't it true from the provisional and the 12 '980 that the object probability is always the 13 joint probability of its components? 14 ATTORNEY EKLEM: Objection to form. 15 A I -- I mean, I just explained to you that 16 you have to have -- you have to have the 17 probability of the object and you have the 18 probability of the components, and you have the 19 joint distribution that puts the whole model 20 together, in a sense. So you've got to have all 21 of that. 22 Q Let's turn your attention to the list of	108 1 relation to TLP is described in my declaration. 2 My opinions that are rendered there starting at 3 Page 102. 4 Q I'm going to get there as well. But the 5 provisional directly cites TLP, correct? 6 A Well -- 7 ATTORNEY EKLEM: Objection to form. 8 A Do you have TLP? 9 Q I do. 10 ATTORNEY BAKER: I'm going to hand the 11 witness a copy of Meta Exhibit 1009. 12 A Yes. 13 Q So my question is whether the provisional 14 cites TLP in Section 2. 15 ATTORNEY EKLEM: Objection to form. 16 A I mean, that citation appears on 17 Reference 2. It seems to me be. 18 Q The provisional indicates that the 19 graphical object model follows the framework of 20 TLP, correct? 21 ATTORNEY EKLEM: Objection to form. 22 A So the devil is usually in the details.

109 1 So if you go to the provisional, Page 6, they 2 obviously cite Reference 2 that we're talking 3 about. And if you read that sentence, it 4 says, "Unlike the model presented in 2, having a 5 second layer also allows us to assume conditional 6 independence of components over time given the 7 whole appearance, hence, reducing the complexity 8 of the overall graphical model." 9 So what's being introduced in the 10 provisional is not the same as what's being 11 described in TLP, or in reference to TLP. 12 Q So does that passage indicate to you and 13 to a POSITA that the difference between the 14 provisional and TLP is the use of a two-layer 15 graphical model in lieu of a single layer model? 16 ATTORNEY EKLEM: Objection to form. 17 A I mean, when you read that sentence, 18 right, it says, "Unlike the model presented in 2," 19 that reference that we're talking about, "having a 20 second layer also allows us to assume conditional 21 independence." 22 So you have two layers in the provisional	111 1 So obviously I disagree. "Dr. Bajaj 2 provides no explanation as to how this, 3 'probabilistic method,' which determines a limb 4 likelihood, i.e., component likelihood, is 5 'equivalent,' to determining the probability that 6 the object is in each image." 7 The next paragraph is where the analysis 8 begins. 9 Q I'm sorry, please continue. 10 A So the next paragraph is where the 11 analysis begins. It says, "TLP makes clear to a 12 POSITA in its model, 'each node in the graphical 13 model represents...' it's a whole description 14 here, "'a limb,'" we show that in Figure 1 in TLP, 15 "i.e., component," and this quote is from 16 Exhibit 9 at 1. 17 And the next paragraph says, "A POSITA 18 would have understood that TLP's model does not 19 include nodes that represent the object, only 20 components referred to as limbs or parts." 21 So I think that answers your question. 22 Q I'm not sure it does. You are jumping
110 1 model. 2 Q Mm-hmm. 3 A So if you go to my declaration starting on 4 Page 102, where I've rendered my opinions, 5 starting on -- I'll wait until you get there. 6 Q Paragraph 102, right? 7 A Page 102, Paragraph 155. 8 Q I'm there. 9 A Okay. So this is where I started to 10 render my opinions with regards to Ground 4, which 11 discusses the claims in view of TLP. 12 So you see in Paragraph 155, I set the 13 stage: "Dr. Bajaj argues that TLP, 'discloses or 14 at least rendered this limitation obvious,'" 15 we're talking about limitation 1D and 9D, "'based 16 on TLP's inference model,' which defines the fee 17 to be the likelihood of observing any measurements 18 conditioned on the pose of limb i." 19 Then the next sentence says, "Dr. Bajaj 20 argues that this is, 'equivalent to determining a 21 probability an object is in each image.'" And it 22 cites the paragraph that Dr. Bajaj has written.	112 1 into the grounds of TLP and Dr. Bajaj's opinion. 2 I wanted to look at the provisional and see how 3 the inventors themselves characterize TLP. 4 So you're correct, there is a discussion 5 regarding TLP, Reference 2 in Section 2.1. 6 A Yes, sir. 7 Q Can we agree that the distinction made by 8 the inventors in Section 2.1 as relates to 9 Reference 2, TLP, is that the provisional 10 discusses a second layer to its graphical model, 11 correct? 12 A Yes. "Having a second layer also allows 13 us to assume conditional independence of 14 components over time, given the whole appearance 15 of the object itself." 16 Q So that's one distinction that they make 17 regarding TLP. But do you also agree that in 18 Section 2, that the inventors indicate that they 19 are following the framework of TLP when modeling 20 the object? 21 ATTORNEY EKLEM: Objection to form. 22 A Which sentence are you referring to?

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113 1 Q Page 5, Exhibit 1003, first sentence of 2 Section 2. 3 A Well, this is kind of a general statement 4 that they're making, and this is typically -- you 5 know, it's done in the literature. It's said, 6 "Following the framework of 1, 2" - 2 is our 7 discussion here - "we model an object as a 8 spatiotemporal directed graphical model." 9 So this is a general statement that you're 10 following the framework, you're going to create 11 the spatiotemporal temporal directed graphical 12 model. It doesn't mean the model is exactly the 13 same as the other one, it's just saying we're 14 following the same general framework. 15 And then he discusses the framework, 16 discusses the equation, and distinguishes from 2 17 by saying, well, in our framework we're using two 18 layers; in this Reference 2, there is only a 19 single layer. And this is our reasoning for using 20 two layers, because it does this in this manner. 21 Q In the two-layer discussed in the 22 provisional the first layer is just one node,	115 1 A So you have an image, you can look at this 2 image at a given scale or you can, let's say, 3 subsample it, look at it at a different scale, 4 subsample it, look at it at a different scale. So 5 those are -- see, think of the image as a frame in 6 the video, and you're just using different scales 7 of it, for a training process, essentially. 8 Q So for each scale, do you determine 9 whether a component -- the likelihood of a 10 component's existence is above a threshold? Is 11 that the process? 12 A Well, you are -- essentially you're kind 13 of performing your proposal distribution and 14 training, essentially, your classifiers, right? 15 So you have to assume that the object isn't going 16 to always appear at this scale in the image, 17 right? Sometimes it's going to be over here and 18 it's going to be a lot smaller. 19 Q Okay. 20 A So you have to try to train at the 21 appropriate scales that you think you're going to 22 observe in the application that you are applying
114 1 correct? 2 A Yeah, typically the first layer 3 comprehends the object as a whole. 4 Q And you agree that there is no formula 5 disclosed in the provisional for a single node for 6 the object by itself, correct? 7 ATTORNEY EKLEM: Objection to form. 8 A I think you've already gone through this 9 question before, right? The provisional obviously 10 discloses, you know, formula one that we've been 11 talking about here. It discloses -- you have the 12 object node, you have component nodes; discloses 13 how it's creating these potential functions. 14 So it is disclosing how the model is being 15 built as a two-layer model. 16 Q Can you turn to Section 2.5 of the 17 provisional. Do you see in Section 2.5 where the 18 provisional states that the, "AdaBoost detector is 19 run over an image at a number of scales to produce 20 a set of detection results"? 21 A Yes. 22 Q What is meant by that?	116 1 this object in, or applying these algorithms in. 2 Q Let's look at the claims of the '980. 3 A Yes. 4 Q And you briefly have done this. I just 5 want to walk through it to make sure I understand. 6 1D, the determining step, requires 7 determining a probability -- 8 A Yeah. 9 Q -- for an object in each image, correct? 10 A It states, "Determining a probability that 11 the object" -- that is -- I guess you guys call 12 this antecedent basis, being the "an object" in 13 1A. That object is in each image. 14 Q So you understand the concept of 15 antecedent basis? 16 A Well, I'm not an attorney. But the point 17 is, the object that's discussed in 1D is the "an 18 object" discussed in 1A. 19 Q Okay. So what is "the probabilities" in 20 1E? What is its antecedent basis? 21 A So you can see, like, the whole claim kind 22 of flows, right? You're providing -- so in 1A

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117 1 you're providing a spatiotemporal model for an 2 object to be detected. So that spatiotemporal 3 model comprehends the object spatially, 4 temporally, and the proper probabilities for that 5 object as described in the patent. 6 Then you're providing a video comprising a 7 plurality of images including the object. So now 8 you have a series of images, you have a series of 9 frames where the object is present. You're 10 measuring the object as a collection of components 11 in each frame, so you're looking at the object and 12 you're looking at its components. That's where 13 the graphical models come in. You're determining 14 a probability that the object is in each image. 15 So that -- determining the probability that the 16 object is in each image is obviously based on the 17 spatiotemporal model that you have created for 18 this object. 19 And then you're detecting the object in 20 any image upon comparing the probabilities, 21 because you determined a probability so now you're 22 comparing the probabilities for each image to a	119 1 probabilities for each image that you've computed 2 from this spatiotemporal model to a threshold for 3 detecting the object. 4 Q Wouldn't Step E make more sense if you 5 read it to state, "detecting the object in any 6 image upon comparing the probabilities of the 7 components for each image to a threshold for 8 detecting the object"? 9 ATTORNEY EKLEM: Object to form. 10 A No. 11 Q Why not? 12 A Because, I mean, as a POSITA reading this, 13 I'm just reading plain and ordinary reading of 14 what I'm reading. I've created a spatiotemporal 15 model for the object, so that spatiotemporal model 16 comprehends the object, comprehends its 17 components, and comprehends that spatially and 18 temporally. So I have that. 19 Then I've provided a video that contains a 20 bunch of images that have the object appear in 21 them. I measure the object as a collection of 22 components. So I have the object and I have the
118 1 threshold for detecting the object. 2 Q But what confuses me is that in D, you 3 determine a probability that the object is in each 4 image, then in E you're referring to "the 5 probabilities" for each image. So I don't 6 understand how you go from a probability to the 7 probabilities. I don't understand the antecedent 8 basis there. 9 Do you have an understanding? 10 A I mean, I'm not an attorney. I'm just 11 reading this as a POSITA. So just like you have 12 an object and the object, right, you have 13 determining a probability that the object is in 14 each image. So you're going to determine that 15 probability that the object is in each image, and 16 then you're going to detect the object in any 17 image upon comparing the probabilities for each 18 image to a threshold for detecting the object. 19 So that sentence, "detecting the object in 20 any instance," is essentially using the 21 spatiotemporal model that you have created, and 22 you are doing that based on comparing the	120 1 components of the object in each of those images. 2 So that's the graphical models that we've been 3 talking about. 4 Then I determine a probability that the 5 object is in each image. So using my 6 spatiotemporal model that I have created - 7 otherwise, what's the purpose of it - created this 8 model, I'm going to now use that model to 9 determine that the object is in each image. 10 And then I'm going to detect the object in 11 any image of those images that I acquired for 12 video upon comparing the probabilities for each 13 image to a threshold for detecting the object. 14 Q But again, in Step D you're determining a 15 probability that the object is in each image; in 16 Step E, you're comparing the probabilities for 17 each image. I don't see the antecedent basis 18 there. 19 Let me try again. Wouldn't Step E make 20 more sense if it read, "detecting the object in 21 any image upon comparing the probabilities for the 22 collection of components for each image to a

121 1 threshold for detecting the object?" 2 ATTORNEY EKLEM: Objection to form and 3 scope. 4 Q Especially since Step C says, "measuring 5 the object as a collection of components?" 6 ATTORNEY EKLEM: Same objection. 7 A Well, I think I've explained to you 8 already this answer. So you've created a 9 spatiotemporal model for the object. So you have 10 a spatial model, you have a temporal model, you 11 have -- you have an object, and you understand 12 that in a spatiotemporal way. And obviously the 13 specification, you know, provides the details. 14 Then you provide a video comprising a 15 plurality of images and a series of images that 16 include the object, you measure the object as a 17 collection of components. So you do have the 18 object. You don't just get rid of it. You have 19 the object as part of your spatiotemporal model. 20 That's why you have the two-layer graphical model. 21 Q You also have the components? 22 A You have the object and you also have the	123 1 Q Probabilities. What are the probabilities 2 for each image? 3 ATTORNEY EKLEM: Objection to form. 4 A Well, for each image you have a 5 probability. You have all these images, so each 6 of them has a probability. 7 Q But the claim says, "comparing the 8 probabilities for each image." 9 What are those probabilities for each 10 image? 11 ATTORNEY EKLEM: Objection to form. Asked 12 and answered. 13 A So you determine in a probability that the 14 object is in each image. So you have a 15 probability for this image. 16 Q A singular probability. 17 A The next image you have another 18 probability. That's two of them now. 19 Q Okay. 20 A So there are more than one probability, 21 because you have a temporal model, right? So I 22 have a probability for image one, I have a
122 1 components. 2 The next step is, you're determining the 3 probability that the object is in each image. 4 That probability is based on the spatiotemporal 5 model that you have created in those graphical 6 two-layer models. It's not just based on one 7 component. 8 So you have a spatiotemporal model, you 9 have a two-layer graphical model. You're going to 10 use that to determine the probability that the 11 object is in each image, because that's the only 12 thing would make sense to a POSITA. 13 And then you detect the object in any 14 image of those video, collection of images, 15 plurality of images, based on comparing the 16 probabilities for each image to a threshold for 17 detecting the object. 18 Q So what are the probabilities? Which 19 probabilities are we talking about for each image? 20 A Well, you have -- for each image, you 21 have -- you determine the probability that the 22 object is in each image.	124 1 probability for image two, I have a probability 2 for image three. That's three probabilities. 3 That's probabilities. 4 Q Mm-hmm. 5 A Right? 6 Q Mm-hmm. Where is that described in the 7 provisional? 8 A Well, I mean, it's described in those 9 equations that we've been talking about. 10 Q Those equations describe having three 11 probabilities, a probability for each image, and 12 comparing those probabilities relative to a 13 threshold? That's described in the provisional? 14 A Well, I mean, if you read the provisional, 15 you're obviously building a graphical model that 16 has two layers, you've connected the object as 17 components, you've created this graphical model 18 distributions and everything we've been talking 19 about. 20 Q Correct. 21 A You've created the potential functions and 22 the likelihoods and all this type of stuff.

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125 1 So now you have this spatiotemporal model 2 that includes those two layers. You're going to 3 use that to compute the probabilities for images. 4 Q Where does it teach computing the 5 probabilities for the multiple images and 6 comparing those against the threshold? Where in 7 the provisional is that taught? 8 A Well, I mean, you have to read the 9 provisional application in the entirety. But if 10 you look, for instance, at the Section -- Page 9, 11 Section 2.4, right, you are -- I'll let you get 12 there. Provisional Page 9, Section 2.4. Are you 13 there? 14 Q Yes. 15 A So you see in the first sentence, it 16 says, "The inference algorithm applied in the 17 previous section requires probabilistic image 18 likelihood model Φ_i." So those probabilistic 19 likelihood models are described obviously earlier; 20 in this case, the next page: "This likelihood 21 model is the likelihood of observing the image 22 conditioned on the state of Node I and," etc.,	127 1 So AdaBoost -- AdaBoost is an algorithm, as we 2 described -- as I described earlier. It's an 3 algorithm to do the training so you can find the 4 weak classifiers and the stronger classifiers, 5 right? That's AdaBoost. 6 Now, the weak classifiers require the 7 probability models for you to be able to do the 8 classification. That's not AdaBoost, that's the 9 weak -- those weak classifiers you have to design 10 based on your models. 11 So for me to find the eye of a face, it's 12 not AdaBoost, it's -- you've got to design that 13 classifier, H_1, H_2, H_3. AdaBoost helps you 14 find -- helps you tune it to be more accurate, but 15 you've got to design it, and it has to be based on 16 something. 17 And these -- obviously in this provisional 18 it's based on these graphical models and the 19 probabilities that they have developed. 20 Q So how do you get from there to the 21 provisional teaching comparing for each frame the 22 probability that an object is present relative to
126 1 etc. 2 See, down below, skip a paragraph down 3 below do you see where it says, "Given a set of 4 labeled patterns, AdaBoost procedure learns a 5 weighted combination of base weak classifiers." 6 So those classifiers are going to be using 7 these "likelihood models," this H_1, H_2, blah, 8 blah, blah, and the combination is going to be 9 creating H_I, which is your classifier. So you're 10 going to be using those probabilities to do these 11 classifications; otherwise, how would you do the 12 classification? 13 Q So that's all AdaBoost. We discussed that 14 earlier. 15 ATTORNEY EKLEM: Objection to form. 16 Q Correct? 17 A No, I think you're mixing apples and 18 oranges. 19 Q Aren't you just describing what AdaBoost 20 teaches? 21 ATTORNEY EKLEM: Objection to form. 22 A I think you're mixing apples and oranges.	128 1 some threshold? Where does that leap come from? 2 ATTORNEY EKLEM: Objection to form. 3 A It's not a leap, it's -- the provisional 4 describes a two-layer graphical model with 5 likelihood functions and potential functions that 6 models this model. So you have an object, the 7 nodes, the connectivity, and all this kind of 8 stuff. And the probability distributions of this 9 whole thing is comprehended. 10 So now you are going to design classifiers 11 to find that object in a given image. So H_1, you 12 have to design that; how are we going to find the 13 object based on some probabilistic distributions. 14 Then H_2 is going to be a different probabilistic 15 distribution. Because H_1 is looking for the eye, 16 H_2 is looking for the nose. So they're different 17 type of classifiers. They have different 18 probability distributions. 19 AdaBoost is going to say, for H_1, you can 20 try these parameters or these parameters or these 21 parameters. The training is going to tell you 22 which is the ideal set of optimized parameters.

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129 1 Then AdaBoost is going to say, well, when you put 2 these three classifiers together, should we add 3 them uniformly or should we put more weight on the 4 eye versus the nose? AdaBoost is going to help 5 you select the proper weighting between them. So 6 you might want to put more emphasis on the eyes 7 and the nose versus the ears. 8 That's -- but the classifiers still have 9 to use the probabilities to do the work. AdaBoost 10 just helps you combine them together in a more 11 optimized fashion. So you're mixing two things 12 together, I think. 13 Q Everything you just stated in your answer 14 is applicable to a single frame, W equals 1. It 15 has nothing to do with each frame having a 16 separate probability, and comparing each one of 17 those probabilities to a threshold, correct? 18 ATTORNEY EKLEM: Objection to form. 19 A Totally incorrect. Absolutely incorrect. 20 Q Well, let's do it piecemeal. What did you 21 just say that's inapplicable to a single frame? 22 ATTORNEY EKLEM: Objection to form.	131 1 A You would need to collect -- because you 2 have to initialize the spatiotemporal model. You 3 have a model that has spatial parameters and 4 probabilities and temporal parameters and 5 probabilities. So you can't just say, well, I'll 6 just get my image, one image, and I'll do this. 7 You're going to collect a series of images 10, 15 8 frames, whatever. You're going to collect a 9 series of images. You're going to initialize your 10 model in those images, and then start basically 11 moving it as you add more images into -- into your 12 sequence. 13 Q Didn't you testify earlier that you have 14 to detect and track in each frame? 15 ATTORNEY EKLEM: Objection to form. 16 A You have to detect and track, but you need 17 the spatiotemporal modeling to do that. It's not 18 just a frame by frame in the vacuum. I think 19 you're mixing -- 20 Q But isn't the temporal part of it the 21 messaging between nodes? 22 ATTORNEY EKLEM: Objection to form.
130 1 A Well, you have a graphical model that's 2 spatiotemporal, right? So you have defined the 3 graphical model if you've defined the 4 spatiotemporal apportionment. That by itself, 5 that temporal, is more than one frame. 6 Q How about the initialization? 7 A Well, the initialization, you initialize 8 it on the first, let's say two or three frames 9 that you've receive, but you still need the 10 temporal aspect of it. 11 Q For the initialization you need the 12 temporal aspect? 13 A Even with the initialization. So you're 14 going to get the first, say, series of frames, you 15 get first four, five, six; you initialize the 16 spatiotemporal model. You need to collect -- 17 buffer a few frames to do the spatiotemporal 18 model. 19 Q So the initialization can't be based on 20 pattern recognition and scaling on the first 21 image? 22 ATTORNEY EKLEM: Objection to form.	132 1 Q Does that implement the temporal component 2 of the spatiographical model? 3 A No, you're mixing -- you're mixing a lot 4 of concepts, sir. 5 So the messaging between nodes, you have a 6 graphical model, right? So I have a node and 7 node, right? So I'm messaging between nodes with 8 probabilities and messages, right? 9 Q Sure. 10 A And then I also have a temporal model, 11 right? And I have another graphical model here 12 for the object in the next frame, and that is 13 messaging between nodes, right? But I also have 14 messaging across frames between the graphical 15 models. 16 Q So when you message across frames, what 17 does -- 18 A The likelihoods and the potentials, you 19 know, the probabilities that we use spatiotemporal 20 model. 21 Q And is that based on the assumptions of, 22 for example, acceleration or constant velocity?

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133 1 ATTORNEY EKLEM: Objection to form. 2 A It depends, obviously, how you've 3 created – it depends how you've created the model 4 in – in this provisional, it's based on the 5 graphical models, the two layers, the connectivity 6 of the object, all this kind of stuff. 7 So this model is not the same as, say, 8 somebody else's model that may be – that 9 description I was using before is just an 10 illustration to help – to help, you know, 11 communicate what's going on. 12 Do you think we could do a quick break? 13 Q Let's wrap up this thing on the 14 provisional, if you don't mind, another 10 15 minutes, and then we'll do it. 16 Does the patent, the '980 patent or 17 provisional, discuss initializing a spatiotemporal 18 model? 19 A Of course it does. 20 Q Where does it state that? 21 A I would have to search it, but... 22 So you see, for instance, when he's	135 1 Like if you look at the description on 2 Page 10, 3.1, "We have tested the system on 3 sequences of moving vehicles collected using a 4 mounted moving camera." 5 Figure 4 shows the results for the 6 55-frame long sequence. So it has 55 frames, long 7 sequence, that he does his testing on. "We use a 8 three-frame spatiotemporal model," so you have 9 three frames, "that is shifted in a tracking 10 centric," so it's going to be tracking, obviously, 11 the vehicle that you're doing, "way through time." 12 "The results are very encouraging," and etc. 13 So he's using a spatiotemporal model; he 14 has to initialize that model, and shows you that 15 in Figure 4, in Part A, initializes the 16 spatiotemporal model, and then applies it on a 17 three-frame basis throughout the 55-frame 18 sequence. 19 Q But isn't the initialization discussed in 20 those figures the initialization of the proposal 21 distribution? 22 A Which is part of the model. Those
134 1 presenting his results in the provisional – I'm 2 on Page 11. In Figure 4 and Figure 5 he talks 3 about obviously the spatiotemporal object 4 detection. 5 So Figure 5, "Pedestrian component-based 6 spatiotemporal object detection A shows the 7 initialization proposal distribution." The same 8 thing for Figure 4. One is a vehicle and one is a 9 pedestrian. 10 So you have an initialization process, and 11 you have to have an initialization process. 12 Q For a spatiotemporal model? 13 A For the spatiotemporal model. 14 Q And, I'm sorry, where were you again? 15 Where were you pointing to? 16 A So I'm looking at the provisional, 17 Figure 4 and Figure 5. So if you look at 18 Figure 4, you see it says, "Vehicle object 19 detection and tracking A shows the initialization 20 proposal distribution." So you have an 21 initialization process that takes place, and then 22 you apply this temporally through the sequence.	136 1 distributions are part of your model. 2 Q Just a couple more questions before we 3 take a break. 4 A Sure. 5 Q What's the space or dimension of the 6 spatiotemporal temporal model? 7 ATTORNEY EKLEM: Objection to form. 8 A What do you mean, what's the space and 9 dimensions? You have a spatiotemporal model, so 10 you have a spatial model, you know, that kind of 11 models the spatial components of your model. You 12 have a temporal model, so you have the time 13 aspect, but you have a graphical two-layer 14 decomposition. 15 So it's not – it's not like an XYZ 16 dimension. It's not that. You have to comprehend 17 the two-layer graph model that's moving over time, 18 and you have the temporal connectivity among – 19 Q Of the frames? 20 A Among the frames and among the nodes, both 21 spatially and temporally. 22 ATTORNEY BAKER: Let's take our break.

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137 1 (Recess.) 2 Q Dr. Saber, let's go to Paragraph 48 of 3 your declaration. 4 A Paragraph 48. 5 Q Talking about the '980 patent, correct? 6 A That is correct. That's the heading of 7 the section. 8 Q And in Paragraph 48, you state that, "To a 9 POSITA, the patent's object model explicitly 10 models the object (as a distinct entity from its 11 components)." 12 Do you see that? 13 A Not yet. I'm looking. I'm on 14 Paragraph 48, right? 15 Q Let me make sure I find it. Look above 16 the figure on Page 37. 17 A Okay. Okay. So... 18 Q It says, "This indicates to a POSITA." 19 A Yes. 20 Q Do you see that sentence above -- 21 A Yes. 22 Q Okay. What do you mean when you state	139 1 Q But does distinct mean separate from the 2 components? You say it's a distinct entity. 3 A Well, I mean, it's not -- the point is, 4 it's a separate node from the component nodes. So 5 you have the object node and the component nodes. 6 That's what I mean. 7 Q What does a node capture? 8 ATTORNEY EKLEM: Objection to form. 9 A Well, if you look at the patent, 10 column 3 -- 11 Q Okay. 12 A -- and my Paragraph 50 in the declaration, 13 they're kind of synonymous in a sense. 14 Q Okay. 15 A So you see my Paragraph 50 in the 16 declaration says, "The '980 patent further 17 explains that an object...is modeled as a 18 spatiotemporal directed graphical model." 19 So if you look at the disclosure or the 20 citation there at the end of that sentence, you 21 see it's citing column 3, lines 47 to 53? 22 Q Yes.
138 1 that, "the object model is a distinct entity from 2 its components"? 3 ATTORNEY EKLEM: Objection to form. 4 A So if you look at the figure, right, you 5 have the item that's circled in red. That's your 6 OT. So the sentence reads, "This indicates to a 7 POSITA that the patent's object model explicitly 8 models the object as well as the object's 9 corresponding components in the same model for a 10 given point in time." So you have that same 11 graphical model. 12 Now, the part in parentheses, it's 13 basically saying that you have a distinct entity 14 between the object itself, the circle in red, and 15 the circles in blue that essentially are the 16 components. So that's where you get the two 17 layers. 18 And if you look at the figure, you see the 19 figure labels, "Object 203," and you have the 20 objects essentially at the -- across the top. And 21 the next 201 labels the components, which are the 22 22 components of the given object.	140 1 A So if you look at those lines, you can see 2 on line 47 is the beginning of the discussion, 3 "Graphical object models." And then it starts, 4 "An object such as an automobile, see Figure 2B, 5 is modeled as a spatiotemporal directed graphical 6 model." That's the quotes that we have in this 7 paragraph. "Each node in the graph represents 8 either the object or a component of the object at 9 Time T. Nodes have an associated state vector 10 (XYS) defining the component's real value position 11 and scale within an image," and then it continues 12 on. 13 Q And what is the probability associated to 14 a node? 15 ATTORNEY EKLEM: Objection to form. 16 A Well, you can see the equation below it 17 starts to get into the probabilities, the equation 18 on column 3, line 60. 19 Q That's the joint probability, correct? 20 A Yes. 21 Q So what is the probability for each node? 22 ATTORNEY EKLEM: Objection to form.

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141 1 A Well, it would be contained in the -- 2 obviously the joint probability model. Because 3 you see that joint probability models, you see, 4 like, probability of X0, X0, C0, X0, C1, blah, 5 blah, blah. 6 Do you see that in the equation? 7 Q Yes. 8 A So the 0 on the bottom is obviously 9 indicating the object. The one on top, the first 10 X0o is the object. That -- that's an O on top, 11 not really a 0. 12 Q Okay. 13 A The next one is X0c0, that's object 0, 14 component 0. 15 Q Got it. 16 A Then object 0, component 1, all the way to 17 object 0, component N. And then, comma, dot, dot, 18 dot, because it's got to comprehend all the 19 spatiotemporal stuff, right, all the way to, say, 20 Time T, and then you have, again, the object and 21 all the stuff that goes with it. 22 Q And this formula, is this also disclosed	143 1 would be the only difference? 2 ATTORNEY EKLEM: Objection to form. 3 A Well, it's more than just that. Because 4 when you model -- when you have a two-layer model, 5 right, you have connectivity between the object 6 and the proper components, right? That 7 connectivity has to be comprehended in the model. 8 So you have a one-layer model in TLP, you 9 just have components, connectivity, but no 10 connectivity to an object. And none of this 11 connectivity is comprehended. So when -- that 12 connectivity has to be comprehended in two-layer 13 models, which adds, obviously, complexity to the 14 model. 15 Q So looking at the equation on 43, 16 Paragraph 43, is it fair to say an object is 17 always a spatiotemporal graphical model and not a 18 separate distinct entity from its components? 19 ATTORNEY EKLEM: Objection to form. 20 A Well, it's modeled -- it's modeled by a 21 joint probability. You're looking at Equation 8. 22 Did I understand your question correctly?
142 1 in TLP, this joint probability? 2 A Well, we discuss that on -- the short 3 answer is yes, and the discussion starts on 4 Page 16. So Page 33 of my declaration, 5 Paragraph 43. 6 So if you look at that paragraph, that 7 paragraph is talking about Claim Element 8 -- 8 Claim 8, not claim element. Claim 8 and 16, which 9 are the same. So, "The provisional application 10 conveys to a POSITA that the inventor had 11 possession of Claim 8/16," and then the quote 12 basically quotes the claim itself. And you see 13 that formula is there. 14 And the discussion below that discusses 15 where in the provisional a POSITA would be -- 16 would -- would be led to believe that this is 17 described or comprehended in the provisional. 18 Q And I'm not sure, but I assume that in 19 TLP, it's the same joint probability distribution 20 except for there is no X0nod or Xnod0? 21 ATTORNEY EKLEM: Objection to form. 22 Q There is no X for the object in TLP. That	144 1 Q I'm looking at what you have on 43. 2 A Okay. So that equation there is a 3 joint -- joint probability distribution that 4 discusses the object and the components, and the 5 joint probability of that, in the spatiotemporal 6 model we're talking about. 7 See, if you look, for instance, at the 8 first -- you see where it has that psi IJ? 9 Q Yes. 10 A Do you see that's a multiplication? Kind 11 of like you have the sum -- 12 Q Okay. 13 A -- this is the multiplication version, 14 right? So do you see where it says, psi IJ, and 15 in parentheses, it has (XIOXJO). Do you see that 16 first term? 17 Q Mm-hmm. 18 A So that's obviously connecting the 19 potentials of object to object. That wouldn't be 20 in TLP because you don't have that object to 21 object. 22 Q But in TLP, when you define the

145 1 components, aren't you defining the object? 2 ATTORNEY EKLEM: Objection to form. 3 A No. So in TLP you would not have that 4 first multiplication because it's object to 5 object. 6 And then, if you go down to the next one, 7 you see where it goes object to components, you 8 have O to C? You wouldn't have that either in 9 TLP. So those two pieces would not be part of the 10 TLP because you don't have a two-layer model, you 11 don't have those connections. You don't have 12 object to object temporally and you don't have 13 object to component spatially. 14 Q You just have component to component in 15 TLP? 16 A You just have component to component. So 17 in this formulation, you would have the psi KL, in 18 a sense. Your third piece there, you would have 19 that. And obviously you would have phi XICK, 20 which is the component version. So you have to 21 add those other pieces when you add the complexity 22 of the two layers.	147 1 Q Does the spatiotemporal model have a 3D 2 geometry? 3 A Where are you? 4 Q Let's go to TLP. 5 A Okay. 6 Q Does TLP reflect that the spatiotemporal 7 model has a 3D geometry? 8 ATTORNEY EKLEM: Objection to form. 9 A I don't know what you mean by "3D 10 geometry." I mean, the components obviously have 11 a geometry to them. Like you see in TLP... 12 Q Look at Figure 2 of TLP. 13 A Yes. So I see what you're getting at. 14 So if you look at TLP Page 2, right 15 column, bottom, where it starts "Section 2." Are 16 you there? 17 Q Page 3 -- 18 A TLP Page 2. 19 Q Page 2. Okay. 20 A Right column, bottom section. 21 Q Yes. 22 A So you see it says, "So following the
146 1 Am I making sense? 2 Q You do. You're making sense. I'm 3 following. 4 Would you agree that in the '980 patent, 5 the spatiotemporal model is three-dimensional? 6 A What do you mean by three-dimensional? I 7 don't understand what you mean by 8 three-dimensional. Which sentence are you 9 referring to so I can get a better understanding 10 of what you're asking? Are we looking at TLP or 11 '980? 12 Q Well, remember, '980 claims priority to 13 the provisional and incorporates the provisional, 14 correct? 15 A Correct. 16 Q And the provisional builds on TLP, 17 correct? 18 ATTORNEY EKLEM: Objection to form. 19 A Well, the provisional describes something, 20 obviously. We went through this before, right? 21 But what is your question in regards to 22 dimensionality?	148 1 framework in 22," blah, blah, blah, and this talks 2 about Figure 1, where it's got the components. 3 Now, the next paragraph, you see it 4 says, "In order to describe the body parts in a 5 graphical model, we assume the variables in the 6 node are conditionally independent of those in 7 non-neighboring nodes, given the values of the 8 nodes' neighbors." 9 Then he says, "Each part/limb is modeled 10 by a tapered cylinder having five fixed and six 11 estimated parameters." 12 Do you see that? 13 Q Yes. 14 A So the fixed parameters, and he's using 15 the Greek letter, I think this is phi, is LI, WIP, 16 WID, OIB, and OID. 17 Do you see that? 18 Q Mm-hmm. 19 A And the description of that, so the first 20 one is -- the LI is the part length. If you look 21 on Figure 2 you can see the L on the figure. The 22 next part is WIP. P stands for proximal, which is

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149 1 closer to you; and I is for the part and W is the 2 weight. WID is -- D stands for distal, that's 3 away from you; and obviously W is the width. And 4 then you have OIP and OID, which are the offset. 5 And you can look -- you can see those in the 6 figure, offset from the -- likely kind of a center 7 of the joint, so to speak. 8 So that modeling of the part of this 9 tapered cylinder thing is how he's doing it in 10 TLP, and he's defined the geometry of the part. 11 Q And doesn't TLP say that this represents 12 the 3D position of the proximal joint? 13 ATTORNEY EKLEM: Objection to form. 14 Q Bottom line? 15 A Well, you -- so what I just described to 16 you are the fixed parts, right? So you've got a 17 tapered cylinder like this, let's say, for some 18 limb, your arm or something. You make it as a 19 tapered cylinder. 20 Now, if you continue and he shows you 21 that -- he says, okay -- he describes those fixed 22 parameters as shown in Figure 2, and you look at	151 1 respect to the X axis, the Y axis, and the 2 C axis. 3 Q Okay. 4 A So that's how he's defined his object in 5 TLP. 6 Q So isn't the spatiotemporal model then 7 here specified in three dimensions? 8 A Well, this is modeling a limb of this -- 9 of his object, right? You're modeling one limb. 10 That model, if you look at the limb, that limb is 11 moving in time, right? The spatiotemporal model 12 models the graphical object model as a function of 13 time, which obviously incorporates these limbs and 14 these pieces. 15 But the limb itself has got the geometry 16 and the orientation. The spatiotemporal model 17 covers the probabilities and the graphical 18 modeling temporally. So it's not quite as simple 19 as that. 20 Q Let's just stay with TLP for a little 21 longer. Can we take a look at Figure 3. 22 A Yes.
150 1 Figure 2, you see them. 2 Now, the estimated parameters -- remember 3 four, five sentences above that, it said the five 4 fixed and six estimated, do you see that? 5 Q Mm-hmm. 6 A "The estimated parameters," and he gives 7 them a vector notation, "capital XIT equals small 8 xi vector and theta i vector." 9 Do you see those two side by side? 10 Q I do. 11 A "Represent the configuration of Part A in 12 a global coordinated frame where xi belongs to 13 R3," because that's your -- basically XYZ. "And 14 theta i are the rotation angles." Because I can 15 represent the object, if you look here, as this is 16 XYZ, but can I also rotate it, right? 17 So I have to represent the location and 18 the rotation. 19 Q Is the rotation, in other words, for 20 orientation? 21 A In a sense, yes. Because obviously the 22 object can be oriented so you have the angles with	152 1 Q So do you agree that the spatiotemporal 2 model as shown in Figure 3 is defined and moves in 3 three dimensions? 4 ATTORNEY EKLEM: Objection to form. 5 A Well, Figure 3 describes the learned 6 spatial and temporal potentials. So that's 7 essentially those potentials that you're looking 8 at with the psi function. 9 Q What are the tapered cylinders? 10 A I'm sorry? 11 Q What are the tapered cylinders? 12 A Oh. So if you look at the limbs, you see, 13 like -- look at, for instance, where it 14 says "Spatial" on the left side, do you see that 15 arm? Look at the left arm. Do you see that 16 little kind of tapered cylinder between the green 17 dot and the red thing? That's a tapered cylinder 18 that's from Figure 2. 19 Q Okay. 20 A So that tapered cylinder in Figure 3 is 21 what he described in Figure 2 for that limb. 22 Q And what do the red dots reflect?

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153 1 A So if you read the description of the 2 figure, it says "Green spheres indicate the joint 3 position of a sample," so you have a joint 4 between, let's say, my lower -- this part of my 5 arm, this arm, right, so the green ones represent 6 the joint, "while the red spheres indicate the 7 distal end of the limb for each sample." So 8 distal means the away, right? So that's what the 9 red ones are. 10 Q So that means the joint positions and 11 orientations are all in three dimensions, right? 12 A Well, you're -- so as I went through 13 initially with the description, right, each one of 14 these tapered cylinders -- so if you look, for 15 instance, at the lower leg. Let's look at the 16 left lower leg of Figure 3A, okay? 17 If you look at the left lower leg, you 18 have essentially a tapered cylinder that's 19 comprehended by its XYZ components and its 20 rotational components as we discussed, right? 21 It's got a green dot joined to the upper tapered 22 cylinder, which represents your thigh. So you	155 1 model for the object to be detected comprises 2 providing detectors for each of the collection of 3 components." 4 Do you see that? 5 A Line 37 to 39? 6 Q Yes. 7 A Yes, I see that. You read it correctly. 8 Q And the '980 indicates that, "Fine layer 9 nodes represent multiple components of the 10 object." I think that's in column 2, lines 58 and 11 59? 12 A Yes, "Coarse layer node represents..." so 13 Figures -- so I think you're referring to lines 14 starting on line 55, right? "Referring to 15 Figures 2A and 2B, object detection and tracking 16 is formulated as an inference in a two-layer 17 graphical model," so that's what you see in 18 Figure 2A and 2B, obviously, "in which a coarse 19 layer node represents the whole object," so if you 20 look at Figure 2A, that's the OT on top, in the 21 big white circle, "and fine layer nodes represent 22 multiple components of the objects," and that's
154 1 have a thigh and then you have a calf. Do you see 2 the difference? So they're connected by the node. 3 Q Okay. 4 A The red part shows that the bottom part 5 can move, right? But the node part cannot move 6 like this, right, because it's -- they're 7 connected. So the node part has restrictions, so 8 there is a restriction on the space that you can 9 move it. The bottom red part can move more 10 freely, and that's what he shows you in the red 11 part. 12 Q Okay. 13 A Do you see that? 14 Q I do. Let's go to the '980 patent. 15 A Yes, sir. So we put TLP aside? 16 Q Yes. Let's put TLP aside for a moment. 17 A Give it a little rest. 18 Q Give it a little rest. 19 So let's go to column 1 of the '980. And 20 we're in the summary of the invention, correct? 21 A Yes, sir. 22 Q And it says, "Providing the spatiotemporal	156 1 what you see below the big white circle in the 2 figure, those small pieces we've been talking 3 about. 4 Q Let's go to column 4 of the '980, lines 34 5 to 36. 6 A Yes, sir. 7 Q There the '980 indicates that the temporal 8 aspect is achieved because, "each node in the 9 graph represents either the object" -- actually, 10 strike that. 11 "In order to integrate temporal 12 constraints, the two-layer model is extended over 13 time to some arbitrary length temporal window," 14 correct? 15 A You read that correctly. 16 ATTORNEY EKLEM: Objection to form. 17 A The -- so let's be clear on what we are 18 reading. "To integrate temporal constraints, the 19 spatial graphical models are extended over time to 20 an arbitrary length temporal window." 21 Q And the '980 indicates that, "The 22 arbitrarily set temporal window reduces the

157 1 complexity of the graphical model by allowing the 2 assumption of the conditional independence of 3 components over time," correct? 4 ATTORNEY EKLEM: Objection to form. 5 A Well, the second sentence -- well, the 6 sentence that you're reading says, "having a 7 two-layer graphical model allows the inference 8 process to reason explicitly about the object as a 9 whole," and if you look at the figure you were 10 talking about here, it's obviously labeled 203 in 11 the figure, "and reduce the complexity of the 12 graphical model by allowing the assumption of the 13 conditional independence of components," and 14 that's, e.g., 202 and 208 to 210. 15 So if you look at Figure 2A, you'll see 16 Component 202 and 208 and 210 in, let's say, one 17 of the graphics, over time, given the overall 18 object appearance. 19 Q Do you have an understanding of what is 20 meant by the conventional independence of 21 components? 22 A Where are you reading conventional?	159 1 essentially you're going to say, well, for 2 instance, the head is conditioned on -- you know, 3 should be above the body or the right arm or 4 whatever, but the head and the legs aren't going 5 to be on top of each other. So I can assume 6 conditional independence between these two because 7 I'm already comprehending it with the arms and the 8 body. I don't need to create one between the head 9 and the leg directly. 10 Q And by using a temporal constraint on the 11 size of that window, that allows you? 12 A By constraining the size of the window, 13 you don't track it over time endlessly, right? 14 Because as you track it over time, it becomes -- 15 essentially you're assuming an hour ago -- I'm 16 exaggerating a lot. Let's say an hour ago, or say 17 a few minutes ago, the component was over here, 18 right? The fact that three minutes later it's 19 over here isn't dependent on where it was five 20 minutes ago. It's more dependent on where it was 21 three, two, five seconds ago. 22 So that long-term dependence is not needed
158 1 Q I'm sorry. Conditional. 2 A Yes. 3 Q What does that mean? 4 A So conditional independence would be like 5 saying probability of A given B, C, for instance. 6 So probability of A given B, C, you can say, well, 7 I'm assuming that C doesn't really contribute to 8 A, so it's just going to be based on probability 9 of A given B, without integrating C. So you have 10 some conditional independence, so where you would 11 say I have the ability to construct the 12 probability model by multiplication. 13 Because if you have independence, 14 probability of A times B, AB is probability of A 15 times probability of B. When you're independent, 16 you multiply the probabilities. If there is 17 dependence between them, then you have to subtract 18 that dependence, which makes it harder to compute. 19 Q So is each component independent of each 20 other? 21 A No. I mean, this is talking about 22 conditional independence of components. So	160 1 anymore, if you know what I mean. Because time 2 has passed and things have changed. That's 3 typical in these type of systems, because 4 otherwise it would be untrackable to do all this 5 over, you know, a lot of time. 6 Q You're looking at Figure 2 of the 280 -- 7 I'm sorry, the '980 patent? 8 A Yes, sir. 9 Q Figure 2A, to be more precise. Let's use 10 that one. 11 A Sure. 12 Q Where there is a direct connection between 13 any two components, doesn't that reflect that 14 there is no independence, that the two components 15 are related? 16 A Well, you have a direct connection that 17 comprehends the potentials between them, but you 18 also -- so those two components are there, let's 19 say, 1/30th of a second earlier, and 2/30ths of a 20 second earlier. You know, I'm talking about 21 frames of video at 30 frames a second, right, 22 three frames earlier, or five frames. 100 frames

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161 1 earlier, I don't really need to know that because 2 it's too far back, right? But if I know, let's 3 say, the first three or five frames, I'm good 4 enough. I don't need more than that. 5 That's typical with Markov-type models, is 6 you condition on the previous state rather than on 7 the previous two states or previous three states 8 or previous 50 states. 9 So that's essentially the independence 10 that you're talking about here. You don't need to 11 go that far back. If you just go enough frames 12 back, you should be good enough. 13 Q It's good enough, and it also reduces 14 the complexities of -- 15 A Of operating and training. 16 Q Okay. 17 A Because, you know, if I'm going to 18 continue this instant in time on something that 19 happens three minutes ago, 60 frames earlier, I've 20 got to train all of that, right? So I have to 21 come up with all of those likelihoods and 22 probabilities, and that's just extensive. So you	163 1 Q -- and objects are within that window? 2 A Right. A window, yeah. 3 Q But part of that is based on the 4 assumptions, again, of something, either 5 acceleration, constant velocity. Does that allow 6 you to use that smaller temporal window? 7 A Well, on how you design the model -- 8 ATTORNEY EKLEM: Objection to form. 9 A On how you design your model. So your 10 spatiotemporal model has graphical connectivity, 11 right, between them. It's not just acceleration. 12 You have graphical connectivity between them. You 13 have spatial and temporal connectivity, and you've 14 done some training to compute all these 15 probabilities. You don't need that over, you 16 know, 60 frames ago. So if you did that over 17 three, four, five frames, it should be sufficient. 18 But the model ideally can model over as 19 many frames as you want. The question is, can you 20 get the training done so you can find all the 21 parameters. So typically, when you go to exercise 22 practicality, you would reduce your window to a
162 1 don't need all of that. 2 And it's also not -- because from 60 3 frames earlier, you could have gone in this 4 direction, right, or in this direction. There is 5 no reasoning to say you're going to be over here, 6 right? Because I can get that from just three 7 frames -- two or three frames earlier, I can know 8 where you're at. I don't need to see you 9 20 frames ago. 10 Q You know where the object is at or you 11 know where the components are at? 12 A Both. 13 Q From looking two or three frames before? 14 A Yeah, so as you look, let's say, at the 15 previous two or three frames, I can tell where the 16 object is going to be and where the component is 17 going to be. I don't -- 18 Q Again -- go ahead. 19 A I don't need to look 60 frames ago, right? 20 Q Two or three frames ago allows you to 21 predict where the components -- 22 A A window.	164 1 more reasonable, practical size. 2 Q So is the reasoning or inferencing that 3 we're talking about done in the frame space, which 4 is two-dimensional for a video, or in 3D 5 dimensions where the spatiotemporal model is 6 defined? 7 ATTORNEY EKLEM: Objection to form. 8 A You're mixing a lot of things, and that's 9 the problem. 10 Q What am I mixing? 11 A A lot of things. 12 Q Give me an example of how I'm mixing. 13 A So you have a spatiotemporal model, right? 14 The graphical representation, right, that is a 15 virtual spatiotemporal model, right? It's 16 graphical representation. Each node represents a 17 limb, let's say, or the object. Let's just say a 18 limb node. You have one node that represents the 19 limb in the frame. That representation of a node 20 in the frame is represented by XYZ in the 21 rotational angles, right? In the TLP it's done 22 with tapered cylinders.

165 1 Q Yes. 2 A In the '980, it's represented with, let's 3 say, points and angles and etc. 4 Q Okay. 5 A So positional information. Okay? 6 But the connectivity between them, that's 7 in the graph itself. So there is the spatial 8 information in the nodes, there is the 9 connectivity in the graph, and then there is the 10 temporal element from frame to frame. So they're 11 not all in the same dimensionality. 12 Q So how would a POSITA know XYZ in a frame 13 which is two-dimensional in space? 14 A Well, a POSITA would have the frame, 15 right, would have found the limb, and assuming you 16 found the limb in the frame. 17 Q Okay. 18 A So you know the -- the points where the 19 limb is. Okay? 20 Q I'm with you. 21 A And you have the rotational angles of this 22 limb, so that would be computed from the frame.	167 1 fulfillment of the requirements for the degree of 2 Doctor of Philosophy by Xian Zhou at Carnegie 3 Mellon University. And it's labeled Exhibit 1006. 4 Q Thank you. 5 Zhou is a little lengthy. Were you able 6 to read all of it in preparing your declaration? 7 A Absolutely. It's not that lengthy, 8 actually. 9 Q As dissertations go, is this of average 10 size? 11 A Yeah. I mean, they're double-spaced and 12 stuff, so... 13 Q So is it fair to say that you're not 14 disputing that Zhou discloses a spatiotemporal 15 model? Is that fair? 16 ATTORNEY EKLEM: Objection to form. 17 A No, that is not fair. 18 Q What is missing -- well, does Zhou 19 disclose a model for detecting and tracking 20 objects? 21 A Zhou discloses a probabilistic spatial 22 model for detecting objects. Zhou does not
166 1 ATTORNEY BAKER: If lunch is here, let's 2 go ahead and take a lunch break. 3 ATTORNEY EKLEM: It is, yes. 4 (Luncheon recess.) 5 ATTORNEY BAKER: I do want to make clear 6 for the record because I don't think I put it on 7 the record before. Dr. Chandrajit Bajaj is 8 listening to the depo. So I just want to make 9 sure that that's clear. 10 ATTORNEY EKLEM: Yeah, that's fine. 11 THE WITNESS: Say hello to Dr. Bajaj for 12 me. 13 ATTORNEY BAKER: He's listening. 14 THE WITNESS: Dr. Bajaj, hello. 15 Q All right. So let's put both your 16 declaration and Zhou Exhibit 1006 in front of you. 17 So I'll give you 1006. 18 Dr. Saber, will you identify what 19 Exhibit 1006 is. 20 A Yes, it's the -- it's title is "Dressed 21 Human Modeling Detection and Parts Localization." 22 It's a dissertation submitted in partial	168 1 disclose a spatiotemporal model using -- in the 2 context of the '980 as we are discussing for 3 modeling and tracking objects as we've been 4 discussing. In fact the word "spatiotemporal" 5 don't appear in Zhou. 6 Q Can Zhou's model be used to track an 7 object once it's been detected in an image? 8 A Well, once the object has been detected, 9 Zhou does disclose -- so if you go to my 10 declaration, on Page 73, it starts Section 9, 11 "Dr. Bajaj does not show that any challenged claim 12 would have been obvious," section, on Page 73. 13 Q Yes. 14 A And Part A is talking about Ground 1, 15 which is Zhou, and there is under Part A, 16 Section 1, and then there is Part A to Section 1 17 and Part B to Section 1. 18 So I'm going to jump ahead to the section 19 that addresses your question, or paragraph that 20 addresses your question, which is Paragraph 112 of 21 my declaration on Page 80. Let me know when you 22 are there.

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169 1 Q I am there. 2 A Okay. So if you -- if you see what I've 3 said there, "While Zhou states that motion 4 information" -- "While Zhou states that, 'motion 5 information obtained from previous frames can be 6 used to predict the orientations of the limbs and 7 to solve the ambiguity,' when limbs are misaligned 8 or confused, a POSITA would have understood that 9 such, 'motion information' does not include (nor 10 is it based on) the probability of the object (the 11 person) being present in another image or 12 comparing that probability to a detection 13 threshold." 14 And I'm referring to Exhibit 1006 at 15 Page 91, where the quote was taken from. 16 Q Thank you for that. But I think my 17 question was simpler. Can Zhou's model be used to 18 track an object once it's been detected in an 19 image? 20 A Well, the next sentence discloses that 21 exactly and answers your question. I'm on 22 Page 81, starting on the first full sentence with	171 1 mentions geometrical relationships and he mentions 2 space and size relationships as quoted. But there 3 is no description probabilities whatsoever. And 4 as you know, the context of the '980 is all about 5 probabilities spatially and temporally, as we've 6 been discussing all morning. 7 Q But at bottom, Zhou is using the motion 8 information to track the components of an object 9 from one frame to the next; isn't that correct? 10 ATTORNEY EKLEM: Objection to form. 11 A Well, as I said, while Zhou states that 12 motion information obtained from frames can be 13 used to predict the orientations of the limbs - 14 that's a quote directly from Zhou - Zhou doesn't 15 state how that motion information is -- there is 16 no equations, there is no description of that 17 motion information at all, besides the statement. 18 Zhou does reference geometrical 19 relationships and does reference space and size 20 relationships, as quoted in my declaration. There 21 is no description of probabilities of any kind or 22 the mentioning of a spatiotemporal model, and
170 1 the word "Indeed." So "Indeed" -- I'm on Page 81. 2 Q Okay. 3 A So, "Indeed, as explained above, that Zhou 4 teaches updating and predicting the parameters of 5 detected and undetected parts based on 6 'geometrical relationships' and 'spatial and size 7 relationships,' not based on the probability of 8 the object (the person) being present in other 9 images." 10 And he gives an example in the next 11 sentence about the left knee. So while he's doing 12 some motion estimation that's done in Zhou based 13 on geometrical relationships and spatial and size 14 relationships, there is no probability description 15 of any kind in his motion information. Actually, 16 there is no description of any motion information 17 details besides mentioning the word "motion." 18 Zhou doesn't describe in his thesis how that 19 motion is accomplished, doesn't state whether it's 20 block matching or face correlations. There is no 21 description of how that's done in Zhou. 22 And it's -- you know, obviously he	172 1 certainly not in the context of the '980 patent. 2 Q Is the use of Bayes' similarity, is that 3 using a probabilistic determination? 4 A The use of? 5 Q Is Bayes' similarity, is that 6 probabilistic? 7 A Is Bayes -- 8 Q Bayes, Bay-ez. I don't know how to say 9 it? 10 A Oh, Bayes. I'm sorry, I didn't understand 11 you. 12 So Bayes is essentially a formulation. 13 Like Bayes' theorem would be -- for instance, if 14 you would open a book on probability and look at 15 Bayes' theorem, you'll see two things; one is one 16 called total probability theorem, and the other 17 one is called Bayes' theorem. They're usually 18 side by side within a few pages. 19 Q Okay. 20 A Bayes' theorem essentially states - and 21 I'm stating simple here - probability of A given B 22 is equal to the probability of B given A, times

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173 1 probability of A divided by probability of B. 2 That's Bayes' theorem. Okay? So it's essentially 3 conditioning one element on the other. 4 Q Okay. 5 A In Zhou, the use of Bayes, Bayes' theorem, 6 is done in the spatial manner. There is no 7 temporal discussion or any formulation that talks 8 about the use of Bayes in a temporal manner, as 9 done in the '980 patent, and certainly not in the 10 context of the '980. So strictly a spatial domain 11 consideration. 12 Q Can you -- I'll give you a little reading 13 assignment, not too long. Can you read the 14 paragraph starting at the bottom -- this is to 15 yourself. Starting at the bottom of Page 92 of 16 Zhou, it starts, "To demonstrate," Page 92. 17 A Until? Yes. 18 Q You got it? 19 A Yeah. Until? 20 Q Until the end of the bottom of Page 93. 21 A Okay. 22 (Document review.)	175 1 Q Yes. 2 A Do you see where it says, "Problem 3 formulation"? 4 Q Yes. 5 A Okay. If you go down below, do you see 6 where it says, "According to Bayes' rule equation 7 3.1, 3.2." 8 Q Mm-hmm. 9 A And when you look at that equation, it 10 says "Argument" -- so it starts above that, 11 according to Bayes' rule. You see it says, 12 "Argument that maximizes the probability of H, C," 13 C stands for the contour, "given person." That 14 slash means given. 15 Do you see that? 16 Q Yes. 17 A Now, in the next equation below it, you 18 see that he has now used Bayes' theorem. So you 19 see the first part of Bayes' theorem. So he said, 20 "Probability of H, C given person is equal to 21 probability of C given H, person times probability 22 of H given person."
174 1 Okay. What was your question. 2 Q So the point I want to focus on, can you 3 read aloud the sentence that begins with, "Then." 4 It's about four lines down on Page 93. 5 A Yes. 6 Q Can you read that sentence aloud, please? 7 A Yeah. "Then the body parts are identified 8 based on the Bayesian similarity measure 9 illustrated in Chapter 3; the locations of the 10 joints are updated using the RCR algorithm 11 described in Chapter 4." 12 Q So doesn't that reflect that the Bayesian 13 similarity updates in time between frames? 14 A No, it does not. 15 Q What does that sentence mean to you? 16 A Well, if you go to Chapter 3, it will 17 describe it. 18 Okay. So if you go to Chapter 3, on 19 page -- Meta Page 54, not thesis page. Meta 20 Page 54 on the bottom, which are slightly 21 different page-wise. Do you see the section that 22 starts with 3.3.1?	176 1 That's part of the probability. Like 2 probability of A, B is probability of A given B 3 times probability of B. 4 Q Okay. 5 A Then the next step is now using Bayes' 6 theorem. He basically says, "The argument that 7 maximizes H of the probability of C given H, 8 person." So the first term is the same. 9 Do you see that? 10 Q I do. 11 A The next term, "Probability of H given 12 person became probability of person given H times 13 probability of H divided by probability of 14 person." 15 That's a direct application of Bayes' 16 theorem. Okay? 17 Q Okay. 18 A None of that has anything to do with time. 19 Q All right. So let's -- 20 A There is no timing component in all of 21 that. 22 Q Okay.

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177 1 A And then the formulation continues, you 2 know, with the BSN and all this, but there is no 3 time component of any kind in any of this. 4 Q Let's look at Figure 5.7. 5 A Okay. 6 Q Have you reviewed that figure? 7 A Yes, sir. 8 Q And let's also go back to Page 93. 9 A Yes, sir. 10 Q Can you read that next sentence after 11 where we stopped that starts with, "The results 12 shown." 13 A Yes, sir. "The results shown in 14 Figure 5.7," which is the figure you just referred 15 to that's titled -- the figure title is "Joint 16 Localization of Figure Skaters." 17 "The results shown in Figure 5.7 18 demonstrate that even if the skaters are in 19 various postures and wear skirts flying in the 20 air, the covered body parts can still be located 21 accurately using the dynamically assembled human 22 model, the Bayesian similarity measure, and the	179 1 has to do with the geometrical relationship and 2 the spatial and size relationships that we're 3 talking about. There is no probability, 4 connectivity from frame to frame at all in these 5 models. 6 Q But there is a temporal component? 7 A Well, as I mentioned here in my 8 declaration, see, in Paragraph 112, I state, "Zhou 9 states that ' motion information obtained from 10 previous frames can be used to predict the 11 orientation of the limbs and to solve the 12 ambiguity.' When limbs are misaligned or 13 confused, a POSITA would understand that such 14 motion information does not include or nor is 15 based on the probability of the object being 16 present in another image or comparing that 17 probability detection threshold." 18 So in the '980, there is a probability 19 component to the temporal model, to the 20 spatiotemporal model. So that's not in Zhou at 21 all. 22 Q So I haven't gotten to the probability
178 1 coarse-to-fine localization approach." 2 Q Does that have a time component? 3 A None of it -- 4 ATTORNEY EKLEM: Objection to form. 5 A None of it have a time component. That's 6 is done spatially on a frame-by-frame basis. 7 Q And how about the assumptions between the 8 frames that's discussed on Page 92, the 9 predictions? 10 A Which -- 11 ATTORNEY EKLEM: Objection to form. 12 A Which are you referring to exactly? 13 Q This is with reference to Figure 5.4, but 14 it says, "While in the second half of the cycle 15 the predictions from previous frames (constant 16 angular velocity is assumed) is used to get better 17 results of body part localization." 18 A Yes. 19 Q Does that have a time component? 20 A Well, that's the -- when I read my 21 declaration part to you, that's the part that have 22 to do with the geometrical -- that's the part that	180 1 aspect. 2 A Yes. 3 Q I'm trying to figure out, and if you 4 just -- see if we can agree on whether or not 5 there is a temporal component to Zhou's model. 6 A Well, Zhou, as I state in the next 7 sentence, which I think answers your question, 8 "Indeed, as explained above, Zhou teaches updating 9 and predicting the parameters of detecting an 10 undetected parts based on geometrical 11 relationships and spatial and size relationships 12 not based on the probability of the object." 13 So there is geometrical relationships 14 between the frames that Zhou is using to -- to 15 make -- to make the updates and predict the 16 parameters. "Zhou's example of considering 'how 17 the left knee angle changes with time' confirms to 18 a POSITA that Zhou's consideration of motion 19 information from previous frames" - so considering 20 the motion - "is based on geometrical and spatial 21 relationships, not on probabilities of any kind." 22 Q But does motion information infer a

181 1 temporal component to the analysis? 2 A Well, motion information would infer, you 3 know, difference between -- so it has, in essence, 4 a connectivity to temporal -- to the temporal 5 aspect, but that's not in the same context of the 6 '980 patent that we're talking about. The '980 7 patent temporal context contains probabilities 8 that are not here in Zhou at all. 9 Q Could I turn your focus to Page 93 of 10 Zhou. 11 A Yes, sir. 12 Q And about a little more than halfway down 13 in a passageway on -- passage on Page 93, do you 14 see the statement, "Dynamically assembled human 15 model"? 16 A Yes, sir. 17 Q Do you have an understanding of what that 18 means? 19 A Yes. I mean, Zhou describes that a little 20 bit. Like you see in the figure, you see how the 21 contours are changing. If you look at the 22 Figure 5.7, right, you see how he's got that	183 1 skaters are in various postures -- which reflects 2 multiple frames, correct? 3 ATTORNEY EKLEM: Objection to form. 4 A What's your question? 5 Q I'll read the sentence, then I'll ask you 6 the question. So Zhou states, "The results shown 7 in Figure 5.7 demonstrate that even if the skaters 8 are in various postures and wear skirts flying in 9 the air," does that suggest to a POSITA that you 10 are viewing more than one frame? 11 A Not yet. Because that says, in this 12 frame, the skater has a certain posture; in this 13 other frame, it may have a different posture. 14 So -- but you're looking at the frame 15 independently from the other frame. You're not 16 connecting the two frames together yet. 17 Q Doesn't it go on to say that the parts can 18 still be located accurately using the dynamically 19 assembled human model? 20 A Yes. 21 Q And what's the dynamic component? 22 A That's what you see when you've got the
182 1 little contour next to the image, and you see the 2 contour of the skater changing dynamically from 3 one to the other where the joints have obviously 4 moved? So that's what he's talking about. 5 Q And although the skater is moving and the 6 body parts are moving, the image of the skater can 7 still be located, correct? 8 ATTORNEY EKLEM: Objection to form. 9 A Well, I think you're mixing a few things. 10 So you have a frame, the skater. Zhou has a 11 contour algorithm to find the contour of that 12 skater, identify, you know, the body parts that 13 we've been talking about, like you see in the 14 stick figure next to the skater. 15 So if you look at the skater, you see a 16 skater in an image. Next to it you see like a 17 little contour where there is some red lines to 18 it, right? So he identifies the contour of the 19 skater, he finds the appropriate joints or 20 whatever of the skater, and that's what Zhou does 21 in a given frame. 22 Q Doesn't Zhou teach that even if the	184 1 whole contour and the pieces. Like, I know the 2 legs are here and the head is here, so you have 3 some dynamics between them. And then here, as he 4 states, there is motion -- you know, the use of 5 motion information based on geometrical and 6 spatial and size relationships to connect the 7 frame to frame, in a sense. There is no 8 probabilistic description at all. 9 Q Isn't this like the '980, in that for each 10 frame you detect the object and then you track it? 11 ATTORNEY EKLEM: Objection to form. 12 Q Doesn't Zhou do the same thing as the 13 '980? 14 A No -- 15 ATTORNEY EKLEM: Objection to form. 16 A -- not at all. 17 Q What is different? 18 A Well, Zhou does -- all the detection in 19 Zhou is done spatially. There is no probabilistic 20 formulation temporally at all in Zhou to do any 21 kind of object detection in a temporal sense at 22 all. The '980 has a joint probability density

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185 1 function, as I showed you in that formula, that 2 big huge formula, that has a spatial and a 3 temporal domain aspect to it. 4 That's all jointly developed. It's not 5 this then this, it's a joint model. It's a joint 6 spatiotemporal model that's based on probabilities 7 and likelihood and -- and then -- and potentials 8 and that kind of thing. We went through that 9 formula with you. 10 None of that is in Zhou. 11 Q Now, in the '980, you do agree that you 12 first detect the object and then you track the 13 object on a per-frame basis, correct? 14 ATTORNEY EKLEM: Objection to form. 15 A You jointly do that. You don't just 16 detect and then track. You have a joint -- you 17 have a joint distribution that has essentially a 18 joint model, so you do both of those in a sense 19 simultaneously. You don't detect -- it's not a 20 two-step process like you're thinking about. 21 Q Let's go through and discuss Figure 5.4 in 22 Zhou.	187 1 Q Okay. How would you describe Column C? 2 What does that illustrate? 3 A Identified body parts. 4 Q Per frame? 5 A For the given frame that it detected. 6 Like if you look across the top, you have the 7 image, the corresponding foreground object 8 detected from background subtraction, the 9 corresponding identified body parts, the updated 10 and predicted locations and outlines of the body 11 part, the edge image for that particular object, 12 and the aligned body parts. All that is done 13 spatially in the frame. 14 Q So how do you identify the body parts? 15 What's the process as taught by Zhou? 16 ATTORNEY EKLEM: Objection to form. 17 A So Zhou describes his model. It's a 18 long -- it's a description over a couple of chips. 19 But he describes the dressed human modeling in 20 Chapter 2, basically the translation, rotation and 21 scale, environment body model, and then talks 22 about the Bayesian similarity measure in Chapter 3
186 1 A Yes, sir. 2 Q Have you reviewed 5.4? 3 A Yes, sir. 4 Q Did you review it before preparing your 5 declaration? 6 A Yes, sir. 7 Q Did you review it in preparation for this 8 deposition? 9 A Yes, sir. 10 Q Okay. Column A in Figure 5.4 illustrates 11 a plurality of images of a walking person, 12 correct? 13 A That is correct. 14 Q Column B illustrates detecting the object, 15 the person, from the background. 16 ATTORNEY EKLEM: Objection to form. 17 Q Correct? 18 A Column B states it's "foreground object 19 detected from background subtraction." 20 Q What is the foreground object? 21 A The person that you see in white there, 22 essentially.	188 1 that we've been talking about. 2 And when you look at Chapter 4, it talks 3 about the recursive context reasoning algorithm, 4 and it uses to locate the body parts, and you 5 know, comprehend the contour and that type of 6 thing. And if you look on page -- Meta Page 17, 7 it gives you the steps of the contour, of the RCL 8 algorithm. 9 Q In Step D, when you update the predicted 10 locations and outlines of the body parts, that's 11 accomplished using motion information obtained 12 from previous frames, correct? 13 A It doesn't state that here, how it's done, 14 in this particular figure. But if there is any 15 motion information to be used, it's just basically 16 based on geometrical essentially relationships in 17 spatial and size. There is no probabilities at 18 all. 19 Q But there is a temporal component? 20 ATTORNEY EKLEM: Objection to form. 21 A Well, I prefer to call it a motion 22 information, because that's what Zhou states. And

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189 1 I want to make sure it's -- it's distinguished 2 from the context of the '980, which talks about 3 the spatiotemporal model that considers 4 probabilities. 5 Q How do you define motion without time? 6 A I didn't say you would define motion 7 without time, I just said you compute motion 8 information. But I want to distinguish the 9 wording, because the '980 defines a spatiotemporal 10 model as a model that consists of spatial and 11 temporal elements in the probabilistic framework 12 and has got a joint distribution and everything 13 else. I want to make sure those words are 14 distinctively different from what is in Zhou, 15 which is motion information that has nothing to do 16 with probabilities temporally of any kind. 17 Q Does motion information inherently have a 18 time component? 19 A So motion information would obviously be 20 looking at it from frame to frame, so you would be 21 looking -- as I mentioned in my declaration, you 22 would look at geometrical relationships between	191 1 here. There is no probabilities of any kind. 2 Q When we were discussing the '980, we 3 didn't discuss making assumptions based on either 4 acceleration or constant velocity? Didn't we 5 discuss that? 6 A We discussed -- but those are -- we're 7 talking in terms of -- well, some of those were 8 illustrations to -- there wasn't -- you know, not 9 all of them were in the context of the '980. Some 10 of them were just illustrations to illustrate the 11 point. 12 But in the '980, you have a joint 13 probability distribution that -- that basically 14 models the spatiotemporal framework of the '980. 15 That is clear in the '980, and that's not in Zhou. 16 Q '980 doesn't describe motion information, 17 does it? 18 A I don't know what you mean, "doesn't 19 describe motion information." '980 provides a 20 joint PDF, joint probability distribution 21 function, or probability density function, that 22 discusses -- basically that couples the temporal
190 1 frames. So this point on my arm is over here in 2 this frame and it's moved over here in that frame, 3 that constitutes motion information, geometrical 4 relationships between them. That has not -- it 5 has nothing to do with the spatiotemporal model as 6 described in the '980 in the context of 7 probabilities and joint distributions and 8 everything that we've been talking about. 9 So this -- there is a clear distinction 10 here. 11 Q Let's look at the passage below Figure 5.4 12 on Page 92 of Exhibit 1006. Doesn't Zhou teach -- 13 A Which passage are we talking about? 14 Q I'm going to quote it. "While in the 15 second half of this cycle, the prediction from 16 previous frames is used to get better results of 17 body part localization." 18 A Yes. Because -- and "(is constant angle 19 of velocity is assumed)." 20 So it's talking about essentially 21 geometrical relationships, spatial and size 22 relationships, and that's what is being discussed	192 1 domain. So it inherently it's talking about the 2 motion of the object across the frames. 3 Q All right. Let's go to Paragraph 100 of 4 your declaration. So you conclude in 5 Paragraph 100 that, "Zhou's human detection method 6 determines the probability that a human is in a 7 single image, and compares only that probability 8 to a threshold for detecting a human in that 9 image. The detection is not based on the 10 probability that the human is present in another 11 image;" is that accurate? 12 A You read it accurately. That is correct. 13 Q But Zhou does teach that it uses, "the 14 prediction from previous frames to get better 15 results in a later frame;" isn't that correct? 16 ATTORNEY EKLEM: Objection to form. 17 A Predictions are not probabilities. You're 18 confusing two concepts. 19 Q But you agree that Zhou teaches using 20 predictions to get better results in a later 21 frame? 22 ATTORNEY EKLEM: Objection to form.

193 1 A Well, as I read to you from my 2 Paragraph 112 on Page 81, and I'm reading from the 3 full sentence there, "Indeed, as explained above, 4 Zhou teaches updating and predicting the 5 parameters of detected and undetected parts based 6 on geometrical relationships and spatial and size 7 relationships." 8 So, yes, Zhou teaches updating and 9 predicting the parameters of detected and 10 undetected parts based on geometrical and spatial 11 and size relationships, not based on the 12 probability of the object being present in other 13 images. 14 So there is no temporal Zhou modeling of 15 any probability at all. The predictions are 16 basically based on geometrical and spatial type 17 relationship. And Zhou doesn't provide any 18 formulation for his motion estimation at all, 19 besides stating it. 20 Q Didn't you describe Zhou as providing a 21 probabilistic method? 22 A Zhou provides a probabilistic method	195 1 human model. Excuse me. 2 And if you look at the wording that goes 3 with the figure, I'm on Page 46 halfway down the 4 page, "This hierarchy provides a compact 5 representation of a coarse-to-fine modeling of 6 human shapes. See some examples given in 7 Figure 2.8." 8 These are different examples of how you 9 can model. You can model a whole body as an 10 ellipse on the left side of 2.8. You can model it 11 as kind of two ellipses sitting on top of a 12 rectangle. All the way to the right, you can 13 model it as, you know, you have the arms and you 14 have the legs and you have a head, and kind of 15 have an ellipse for the torso. 16 So he's basically using contour models. 17 Q Isn't that similar to the '980, which has 18 a two-layer model, a coarse layer, and a fine 19 layer? 20 ATTORNEY EKLEM: Objection to form. 21 A That's completely different from what the 22 '980 is doing.
194 1 within a given frame. So spatial. There is no 2 temporal aspect to it at all. 3 Q Let's turn to Figure 2.8 of Zhou. That's 4 on Page 46 of Exhibit 1006. 5 A Meta Page 46? 6 Q Meta Page 46. Yes, please. 7 A Okay. Figure 2.8. 8 Q Doesn't Figure 2.8 illustrate Zhou's 9 object model and the components of the object? 10 ATTORNEY EKLEM: Objection to form. 11 A So -- so the section starts with talking 12 about dressed human modeling. And essentially 13 Zhou is describing that, you know, "In contrast 14 with a model of a particular object, a model of an 15 object class should represent the generic shapes. 16 So obviously if you are talking about a 17 human being, you have a torso and you have legs 18 and you have arms. So you're trying to 19 essentially model that shape of a human being, in 20 a sense. 21 So in Figure 2.8, he's giving you an 22 illustration of assembling the human body -- the	196 1 Q Modeling-wise, it is? How is it 2 different? 3 A '980 has a graphical, graphical type 4 model. This is not a graphical kind of model, 5 this is a contour model and a spatial component. 6 Q Does it teach coarse-to-fine modeling? 7 A Yeah, but you're mixing -- you're talking 8 about apples and oranges here. This is -- the 9 coarse would be -- if you look at the left side of 10 that figure, you're looking at the coarse, right? 11 And as you go from left to right, you're looking 12 at fine. This is all in the context of a spatial 13 domain, and contour models in the spatial domain. 14 Q What is the hierarchy? 15 ATTORNEY EKLEM: Objection to form. 16 A In the context of a spatial domain that 17 we're talking about here. So you go to the '980, 18 you're talking about a graphical object model that 19 has directed edges and nodes. It's totally 20 different from what is here. That graphical model 21 isn't a spatial domain model like this one is. 22 Q Now, the probability provided on each

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197 1 node, isn't that the graphical model in Zhou? 2 ATTORNEY EKLEM: Objection to form. 3 A You're not providing the probability on 4 each node. You're providing -- so you see, I'm on 5 Page 54, Meta. Do you see it says, "Probability 6 of H, C," where C being the contour and H is the 7 hypotheses space, "given person." Right? 8 So he's modeling -- essentially his 9 probabilistic framework is based on contours 10 given -- so a person contour should look, let's 11 say, like this. So if you find a contour that 12 looks like the shape of a car, that probability 13 should be very low because it doesn't represent a 14 person. 15 That has nothing to do with the '980 16 modeling that we're talking about. Totally 17 different framework. 18 Q Can you turn to Page 56? 19 A Of? 20 Q Of Meta 1006, Zhou. 21 A Okay. 22 Q Can you explain the conditional	199 1 So, "According to the above observation, 2 the following formula is designed to estimate 3 probability of person given the hypothesis. 4 Probability of a person given a hypothesis is 5 equal to the sum over" -- he doesn't show it, but 6 it's over I, obviously, of DI, WI. So where DI 7 equals 0, if HI equals 0, that means the body -- 8 the model body part fi is not identified. 9 So if you have a body part and you can't 10 tell if it's not a leg or -- maybe it's a tire of 11 a car. So if you haven't identified it as a 12 human, you would assign it DI equal to 0. And a 13 DI is equal to 1 indicates if HI is not equal to 14 0. Okay? 15 Now, WI is a weight used to evaluate the 16 contribution of the identification of the body 17 parts. So, for instance, you said, I found the 18 right arm and I found the left arm, so you have a 19 weighted combination, but I see something down 20 here and I can't see if they're legs or not, 21 because assume the legs are, let's say, hidden 22 behind the wall. You see the upper torso.
198 1 probability calculation, which is equation 3.7, 2 and how that works. 3 A So that explanation kind of starts a 4 little bit higher than that. So if you look, it 5 says, "The conditional probability" -- I'm looking 6 at Page 56, second paragraph. "The conditional 7 probability P a person given H the hypotheses is 8 estimated based on the number of types of the 9 identified body parts." Okay? 10 The more body parts are identified, the 11 more likely the extracted contour as a person. So 12 if I'm spatially looking and I find, you know, two 13 arms and two legs, then I can say most likely 14 there is a person here. 15 "And the presence of a fine level body 16 part indicates a higher likelihood of the presence 17 of a person than the coarse level body part does." 18 Right? So if you look at Figure 3.1 above, you 19 see, like, the ellipse has a .55 above it, and you 20 see the .92 on the fourth one above it. So the 21 more distinctive the body parts are, the more 22 likely you say that's a human. Okay?	200 1 You can't see the legs, you see the right 2 arm and you see the left arm, so you have a 3 weighting that says, okay, I see those two, it's 4 going to improve your identification. 5 Now, if you see the two arms and the head, 6 then you're weighting those up, and more likely to 7 be a person. 8 Q Is it a weighting per component or is it 9 an overall weighting? It's a weighting per 10 component, correct? 11 A Yes. Because it's WI, DI, right? The 12 I -- so that summation is missing the I equals 1 13 to N, with N being the components that you found. 14 So that's missing in the summation. 15 So this summation is inaccurate. But 16 that's what it's trying to get at. 17 Q So these probabilities are for detecting 18 the presence of the object in the image, correct? 19 ATTORNEY EKLEM: Objection to form. 20 A Well, this DI and WR are not 21 probabilities. The probability of a person given 22 age is -- you're formulating that probability;

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201 1 what's a probability this is a person given this 2 hypothesis? Okay? That's what you formulate. 3 This is all in the spatial domain. There is no 4 temporal here of any kind. 5 Q But it is the probability detecting the 6 object in a frame, correct? 7 ATTORNEY EKLEM: Objection to form. 8 A It's a probability of the -- of stating 9 it's a person given, you know, the hypotheses that 10 we are talking about here, in a given image or 11 frame. No temporal situation here at all. 12 Q Let's go to Section 1.2.2 of Zhou. That's 13 on Page 22 of Exhibit 1006. 14 A Page 22 Meta of Zhou? 15 Q Yes, Meta 1006. 16 A Yes, sir. 17 Q So that section is entitled, "How to 18 Handle the Difficulties," correct? 19 A Yes, that he's referring to in the 20 previous paragraph, obviously. 21 Q Can you read out loud the passage 22 beginning on Page 23 of Meta 1006 at the bottom of	203 1 In the middle of -- the bottom of 2 Paragraph 115, the sentence reads, "Thus, the 3 claims specifically require detecting the object 4 in a current" - that is a first - "image according 5 to measurements of the object from a latter second 6 image and a latter third image." 7 A That's a typo. It should be from an 8 earlier second image and a latter third image. I 9 think that's a typo. 10 Q Do you want to confirm? 11 A Well, let's look at the claim. So we are 12 talking here about Claim 4 and 12, obviously, 13 which is the same thing. Or very, very similar. 14 So the claim states -- reads, "The 15 computer implemented method of Claim 1, wherein 16 determining the probability that the object is in 17 each image, comprises detecting the object" -- 18 excuse me. "In a current image according to 19 measurements of the object as a collection of 20 components determined from a prior image and a 21 later image relative to the current image." 22 So that sentence should say, "determined
202 1 that page, the sentence that begins with, "In this 2 dissertation, I develop." 3 A Yeah. So that sentence says, "In this 4 dissertation, I develop a TRS invariant 5 representation of the shapes of the body parts and 6 their size and spatial relationships." 7 Q The next sentence, please. 8 A "For the human model, the probability 9 distributions are used to handle the shape 10 variations between different people." 11 Q Do you understand what probability 12 distributions he's speaking of? 13 A Yes. 14 Q What are those? 15 A The spatial domain that we're talking 16 about. 17 Q Let's go to Paragraph 115 of your 18 declaration. 19 A 115. 20 Q I'm not sure that one sentence here is 21 accurate. I was going to ask you to read it and 22 tell me if there are any corrections.	204 1 from a prior image and a later image relative to 2 the current image. Thus, the claims specifically 3 require detecting the object in a current, a first 4 image" - that's the current image in the frame - 5 "according to measurements of the objects from a 6 prior image and a later image." So that shouldn't 7 say "later" and "later." That's a typo. Good 8 catch, though. 9 Q Thank you. 10 Do you agree with Dr. Bajaj that analyzing 11 data in image frames from video by using 12 measurements from adjacent frames, including 13 previous and later frames, was widespread and 14 commonly understood in the relevant time frame? 15 ATTORNEY EKLEM: Objection to form. 16 A Which -- which -- which sentence are you 17 referring to? What are you referring to? 18 Q I can take you to Dr. Bajaj's -- 19 A Please. And where in my declaration are 20 you referring to? 21 Q I am just asking, do you agree with 22 Dr. Bajaj. I can take you to his paragraph. I

205 1 think you discuss it, but I'll hand you Bajaj. 2 This is Exhibit -- 3 A Yes, sir. 4 Q -- 1004. And going to Paragraph 109. 5 A Dr. Bajaj. 6 Q Yes. Do you see the first sentence there 7 in Paragraph 109? 8 A Yes. 9 Q Do you agree with that statement? 10 A I mean, you've got to get into the 11 detail -- the devil is in the details. I mean, 12 it's a very general statement, "analyzing data and 13 video in image frames from video by using 14 measurements from adjacent frames including" -- 15 let me reread that. Let me start over. 16 "Notably, analyzing data and image frames 17 from video by using measurements from adjacent 18 frames, including previous and later frames, was 19 widespread and commonly understood in image 20 processing." 21 It's a very general statement. I mean, 22 video has motion estimation and analyzes	207 1 Q Did you review those references? 2 A Off the top of my head, I don't remember, 3 but I did briefly -- I did briefly look at them. 4 Yes, I'm familiar with, I think, one or two of 5 them. Yes. 6 Q And these references are directed to 7 detection and tracking of objects, correct? 8 A But again, we're talking apples and 9 oranges here. I mean, the '980 is talking about a 10 probabilistic models -- joint probabilistic 11 models, spatial and temporal. Andrew Blake and 12 Michael Isard are talking about active contours. 13 It's completely different from this thing over 14 here. 15 And Blake, Isard, and MacCormick are 16 talking about statistical models of visual shape 17 and motion. That's totally different from what 18 we're talking about here. So you're comparing 19 apples and oranges. It's just like saying MPEG 20 was published in 1993 and MPEG talks about motion; 21 therefore, anybody that does motion after that is 22 widely understood. That's total nonsense.
206 1 measurements. But in the context of the '980 is 2 not the same as what we're talking about here. In 3 the context of '980, you are using the probability 4 distribution function that is jointly defined 5 between spatially and temporally. That's not the 6 same thing. This is a very blanket general 7 statement. 8 Q Is it generally correct? 9 A I mean, it's a general statement. So, you 10 know, do video basically have motion estimation, 11 you know, measurements from adjacent frames? You 12 know, yes. I mean MPEG came out in 1993 and has 13 motion estimation. That's -- this is completely 14 out of context of what we're talking about in the 15 '980. 16 Q Dr. Bajaj does point to three references 17 to support that conclusion, correct? 18 A Yes, I see -- which references are you 19 referring to? 20 Q I think they're identified on Page 61 of 21 Meta 1004. 22 A Yes, yes.	208 1 Q But the concept of using a buffer to 2 collect the frames and to study a prior frame and 3 a latter frame to make the analysis of a current 4 frame that's being processed, conceptually, that 5 was known, correct? 6 A I think you're oversimplifying it. 7 Basically it's just like saying MPEG was 8 introduce -- MPEG-1 was introduced in 1993, does 9 motion estimation, therefore, everything after 10 1993 that does motion estimation is well-known. 11 No, that's totally incorrect. 12 Q I think my example is a little more 13 specific than MPEG. I was talking about the use 14 in object detection and tracking, use of a buffer 15 such that you can utilize the data of a prior 16 frame and a latter frame to make the analysis of a 17 current frame. 18 ATTORNEY EKLEM: Objection to form -- 19 A That's not what we're talking about here. 20 ATTORNEY EKLEM: -- scope. 21 A That's not what we're talking about in the 22 '980 at all. It's mixing apples and oranges.

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209 1 Q How does '980 use the prior frame? 2 A We've been talking about that all morning. 3 So '980 has a joint spatiotemporal model, right? 4 It has a joint distribution -- you look at that 5 big formula we talked about, has a joint 6 distribution that models the spatial aspect 7 probabilistically, models the temporal aspect 8 probabilistically in a joint framework, not 9 separate pieces in a buffer. This is in a joint 10 framework. That's not the same as talking about 11 motion estimation across two frames. 12 Q But '980 talks about using information 13 from a prior frame when analyzing the current 14 frame. 15 A Analyzing -- 16 ATTORNEY EKLEM: Objection to form. 17 Q Where does it talk about the later frame? 18 A I think I showed you that. 19 Q I'm not sure we discussed the later frame 20 part. 21 A Well, go to -- I mean, I'll just give you 22 an example. Go to the '980, column 3, line 60.	211 1 object. 2 Q Yes. 3 A And then the first one is X0, with an O on 4 top being the object. Do we agree on that? 5 Q Yes. 6 A Now do you see after X0, C, capital N, do 7 you see that like a few steps later? 8 Q Yes. 9 A After that there is a comma with three 10 dots, and then there is another comma, and then 11 you start X, capital T at the bottom, O on top. 12 Q Mm-hmm. 13 A That dot dot dot includes multiple time 14 indices. 15 Q Aren't they all labeled "T"? 16 A No. This would be like -- if you were 17 going to write them all out, you would say X10, 18 X1C0, X1C1, etc. Then X20, X2CO, XC21, etc., 19 until you reach X capital T being so many frames 20 later. 21 Q I would read this, and tell me if I'm 22 incorrect, that X0T, X for object at time T, X
210 1 Let me know when you're there. 2 Q I'm there. 3 A So do you see that probability and this 4 big formula we've been talking about? 5 Q Yes. 6 A Yes. Do you see where it says "X0," and 7 there is an X0 and there is an O on top? 8 Q That's for the object, right? That's the 9 probability of the object? 10 A The O on top -- the O on the top is the 11 object. 12 Q Yes. 13 A The 0 on the bottom is like the time 14 index, right? 15 Q Okay. Time. Okay. 16 A So, now, you see how it says the next one 17 is X0 at the bottom, CO on top? 18 Q Mm-hmm. 19 A The next one, X0 on the bottom, C1 on top. 20 Do you see that? 21 Q Mm-hmm. 22 A So those are the components of that	212 1 component 0 at time T, X component 1 at time T, 2 that all relates to a single time which I would 3 understand to be the earlier frame for T. 4 A No. 5 Q I don't see anywhere where it's T plus 1 6 or T minus 1. I just see a single T. 7 A I think the dot dot dot in between those 8 two, this is where all the time is comprehended. 9 He just didn't want to write them all out. 10 Q This shows forward and backward in time? 11 A Well, X0 would be like the first one, 12 right? And X capital T would be X many times -- 13 you know, X time later. 14 Q I would under X0 to be the current frame. 15 A No, I don't think you're understanding it 16 correctly. 17 See, look at the sentence below that. Do 18 you see where it says, where XtO -- at the bottom 19 of that formula, do you see where it says, "Where 20 XtO is the state of the object at time T." Do you 21 see that? "Respectively." 22 Q Yes.

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213 1 A "N belongs to 1, N, N being the number of 2 objects, and small t belongs to 1, T." 3 Do you see that? So one – 4 Q Lower T has a subset of either one or 5 capital T, right? Is that what that means? The 6 part bridging columns 3 and column 4? 7 A It's not 1, T being only those two. It's 8 1 all the way to T. Just like the one that says N 9 includes 1, N, it doesn't mean it's just 1 and the 10 N. That's just a mathematical notation that says 11 1, 2, 3, 4, all the way to, N. That's just a poor 12 way of noting it. He could have done a better job 13 by saying 1, 2,..., N, and it would be more clear. 14 But that's what it means. It's just not 1NN. It 15 wouldn't make any sense. 16 Q Can we take a look at Claim 8 of the '980? 17 A That's the one of the claims that explains 18 the formula. Yeah, that's basically this formula. 19 Q Isn't that for one time? 20 A What do you mean, one time? I don't know 21 what you're talking about. 22 See, it says, "The computer-implemented	215 1 right? You don't want to say this formula only 2 works for two frames, you want it to be as general 3 as possible. And then, when you implement the 4 formula, you have practical considerations that 5 you have to be – you know, you have to live with 6 because of the computational complexity of trying 7 to implement a formula across the same thousand 8 frames. 9 Q So this could be for T equals 1, right? 10 A No, it can't be for T equals 1. 11 Q Why can't it? 12 A Because it's a joint PDF with a 13 spatiotemporal. If you went to T equals 1, you 14 just dissolve the entire temporal aspect of it. 15 Q Is it also true for window equals 1? 16 A No, it's – it's a spatiotemporal model. 17 So you have to have multiple frames; otherwise, 18 there is no temporal. 19 Q So the first probabilities at X-naught, 20 does that mean -- is that the initial frame that's 21 being analyzed? 22 A Yes. So X-naught -- there is a 0 at the
214 1 method of Claim 1," so it's dependent from 2 Claim 1, "wherein a joint probability 3 distribution," joint not single, "for the 4 spatiotemporal model within N components," that 5 means N is 10, 20, whatever, "N components," so 6 for each of the objects, "is," and he gives you 7 this whole big formula. 8 And X0 is the time index 0; X1 would be, 9 let's say, the time index 1; X2 would be time 10 index 2; all the way to XT would be the last one 11 in the model, in a sense. So you have a joint 12 across – 13 Q How many Ts could you have? 14 A Well, that's – I mean, the formulation is 15 general, right, as you do. Then your window is 16 going to determine how many of those you're going 17 to use. So when you say "I'm going to use a 18 window of three," you have basically three of 19 them, essentially. 20 You may limit -- bring it down to 21 practical size, but you typically -- when you 22 write the formula, you want it to be general,	216 1 bottom and an O on top. 2 Q O is for the object, 0 is for? 3 A 0 is for time index. 4 Q Time -- yes. 5 A So X0 would be typically your first frame 6 or a first frame in a window of -- let's say I 7 took a window of five, so it would be the first 8 one in that window. And then X1, which is 9 included in those dot dot dots, would be the next 10 one, and so on. 11 Q So for X0 in the time index, because there 12 is no temporal component, you're only detecting 13 the object; is that accurate? 14 ATTORNEY EKLEM: Objection to form. 15 A What do you mean, there is no temporal? 16 Q It's the first frame. 17 A Yes. 18 Q So aren't you just detecting the object at 19 that point? 20 ATTORNEY EKLEM: Objection to form. 21 A I think you're mixing up a lot of stuff. 22 Q You have to detect, right? You have to --

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217 1 before you can track anything, you have to detect 2 it, correct? 3 ATTORNEY EKLEM: Objection to form. 4 A I think you're mixing a lot of things, so 5 let me -- let me try to explain. 6 So this formulation is a joint model. 7 This is -- 8 Q Probabilities of the components in the 9 object, yes. 10 A This is not detecting, this is just 11 modeling the spatiotemporal model. You're 12 modeling. You're basically saying, here is the 13 model I'm going to model in my space. Okay? I'm 14 modeling that as a spatiotemporal model. I'm 15 computing all these conditionals and likelihoods 16 or whatever and I'm formulating the model. I have 17 a training set, and I'm going to spend weeks 18 training this model, whatever, formulating the 19 model. This probability defines the model. 20 The detection happens in the equations 21 that we talked about earlier this morning with the 22 AdaBoost stuff or whatever. That happens later.	219 1 I'm going to model the distribution using a 2 Gaussian probability density function. Because 3 the Gaussian is modeled by an average in a 4 standard deviation or variants, right, if I'm 5 using one variable. 6 So the model is the Gaussian PDF. The 7 parameters are the mean and variance. So here, 8 the model is this probability of all these frames 9 together with the likelihoods and the conditions 10 that we're talking about. You now have to fill in 11 all these with a training so that you can say, 12 okay, for humans across various frames, and you 13 have to train these variables in the model, 14 compute the proper means, the proper co-variances, 15 create the Gaussian PDF's, and so on to compute 16 the model. 17 Now you have a model that you can apply to 18 a new video that arrives. 19 Q Okay. So you have this new video, and the 20 car just comes into the image, the first time the 21 car is shown -- 22 A Right.
218 1 But the model is defined by this big formula 2 you're looking at in Claim 8. 3 Q So how do you find the probability of the 4 object at time index naught? How do you do that? 5 A Well, obviously you have to develop the 6 model, right? So you have to perform some 7 training, develop these models and computer 8 probability distribution function, like you would 9 do if you were -- let's say I wanted to measure 10 the height of men, okay? So -- in the world. I 11 have, let's say, 5 billion men in the world, and I 12 want to measure their height. So I can measure 13 them all and spend my time measuring all 14 5 billion, and then put them all in a big Excel 15 sheet and look at a model, create a model, right? 16 Since I don't have time to measure all 17 5 billion, I'm going to take a sample of, say, 18 5,000, randomly, hopefully, selected, not all MBA 19 players. I'm going to take a random sampling of 20 the population of 5,000 or 10,000, I'm going to 21 measure their heights, I'm going to compute the 22 mean, I'm going to compute the variants, and then	220 1 Q -- in an image. 2 How do you calculate the probability of 3 that object at X-naught? 4 A Well, when the car comes into the image, 5 so you're going to look at a few frames of the 6 car. 7 Q In the future? 8 A Well, you've got a frame, you've got the 9 next frame, you've got the next frame, you've got 10 the next. You're going to collect, you know, 11 three, four, five frames. 12 Q In a buffer? 13 A In however you collect them. It doesn't 14 matter. You're going to have four, five frames, 15 10 frames, over. A window of frames. 16 Q Okay. 17 A Then to that window of frames you're going 18 to apply essentially your models that you have 19 created. You're going to say, here is the models, 20 here's what I'm applying to this frame, and then 21 use your classifiers to detect, okay, where is 22 these objects, and track them in the frames.

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221 1 So it's -- it's not a trivial thing. It's 2 not, like -- it's not a Step 1, Step 2 type of 3 thing. It's not that. 4 Q There is an algorithm for doing this in 5 the '980, correct? 6 ATTORNEY EKLEM: Objection to form. 7 A Doing what? 8 Q The computer-implemented method. 9 ATTORNEY EKLEM: Objection to form. 10 A Yeah, I mean, the '980 talks about how you 11 create the model, how you train the model, and how 12 you use the model to do the object detection and 13 tracking. 14 Q Claim 1 is directed to using the model. 15 We assume the model has been generated, right? 16 A Yeah. So Claim 1 is directed to the 17 computer-implemented method for object detection 18 comprising these five things. So it's a method to 19 detect objects, for object detection. 20 I'm reading it as a POSITA, obviously, not 21 as a lawyer. 22 Q Yeah. So, again, how do you begin	223 1 hundreds of thousands of frames. 2 Then the next step says, "While a W," a 3 window frame, "a W-frame windowed smoothing 4 algorithm is used," where W is an odd integer, 5 because you want to center it on the frame, "there 6 are two ways ones can do windowed smoothly, in an 7 object detection centric way or a tracking centric 8 way," and he continues from there on. 9 So essentially he says, instead of doing 10 this on the entire sequence and taking a long 11 time, I'm going to pick a window of so many frames 12 that I can actually do practically. 13 And then you can see later on he describes 14 the window XT minus W minus 1 divided by 2. So 15 obviously the T plus W minus 1 divided by 2. 16 So W is the window; say it states 5. 5 17 minus 1 would be 4, divided by two 2 would be 2. 18 So you would go from T minus 2 to T plus 2. So 19 essentially T minus 2, T minus 1, T, T plus 1, T 20 plus 2. So you have five frames. If your window 21 is 5, it's 5. 22 Q What does the '980 mean when it says, "In
222 1 tracking when you have the first frame in W equals 2 1? 3 ATTORNEY EKLEM: Objection to form. 4 A You don't. You wait until you have a 5 bunch of frames to do the tracking. You don't 6 just begin on the first one. 7 Q Is that taught in the '980, that you wait? 8 A Well, you're looking at the window, right? 9 You're looking at a window. See, look at -- yeah, 10 it's taught in the '980. 11 Look at Column 7. Do you see the sentence 12 that starts on Line 6, "While it is possible to 13 perform inference over the spatiotemporal model 14 defined for the entire image sequence, there are 15 many applications for which this is not an option 16 due to the lengthy offline processing needed." 17 So if I have a sequence of a thousand 18 frames, let's say, and I want to do this 19 theoretically on the thousand frames, and I have a 20 fast enough computer, I can do it. But 21 practically, it's saying, you know, you probably 22 don't have a computer fast enough to do this over	224 1 the tracking centric way, only the nodes 2 associated with the new frame are initialized?" 3 A Where is the sentence? 4 Q Column 7, line 15. 5 A Oh, yeah, I see it. "In the tracking 6 centric way, only the nodes associated with the 7 new frame are initialized, which tends to enforce 8 temporal consistency from before T minus W minus 1 9 divided by 2." 10 So when you bring in a new frame, right -- 11 you've got a series of frames, you've already done 12 all the detection and tracking here -- 13 (Reporter clarification.) 14 A You've already got a series of frames, 15 okay? Say you have 10. And you've done the 16 object detection and tracking in all those frames. 17 The new frame shows up, okay? So in this new 18 frame, you're going to say essentially, "In the 19 tracking centric way, only the nodes associated 20 with the new frame are initialized." 21 So you're going to -- you're going to do 22 some segmentation here or whatever to find where

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225 1 the object is in the nodes – 2 Q That's detecting, isn't it? 3 A Yes. But you're going to use this 4 information from here, you're not just going to do 5 it. That's why he says, "in a tracking centric 6 way," right? You're going to do it by using the 7 prior information from the joint spatiotemporal 8 model. 9 You're not going to do this in a vacuum. 10 You're going to use what you've learned to detect, 11 you're going to apply that and then essentially 12 continue your tracking. And now you get the next 13 frame, you do the same thing again. That's why it 14 says, "In a tracking centric way," because you 15 have the information from a prior frame. So 16 you're not just going to throw all that away and 17 just work on this in a vacuum. 18 Q The W frame windows smoothing algorithm, 19 does that work for W equals 1? 20 A That's not the intent of this. I mean, he 21 says at the bottom – see at Line 20, it says, 22 "Note that when W equals 1, the algorithm	227 1 A I think we've gone over that already a few 2 times. 3 Q It has to use spatial detecting; 4 otherwise, it couldn't be spatiotemporal, correct? 5 ATTORNEY EKLEM: Objection to form. 6 A I think you're mixing up different 7 concepts again, with all my due respect. 8 Q How am I mixing up concepts in that last 9 question? 10 A Well, as I've explained to you, the '980 11 has a joint distribution that is spatial 12 temporally done. It's not a spatial part and a 13 temporal part, it's a joint distribution. It's 14 not two single distributions put together, it's a 15 joint computation. It has proper information 16 spatially, information temporally that's all 17 correlated and brought in together into one 18 distribution. 19 It's just like saying, the height and 20 weight of men is not the height of men times the 21 weight of men. It's not one then the other put 22 together, it's the joint of the two. So you have
226 1 resembles single frame component-based fusion." 2 So it's basically giving you the 3 limitations. It's saying that if you make W equal 4 1, you get rid of all this temporal stuff and all 5 you're doing is just spatial. So that's just to 6 help you visualize or get an intuition of the 7 algorithm. 8 But that's not what the algorithm is 9 doing. It's not saying – you know, otherwise, 10 you lose all the temporal portion of it, and you 11 lose a large portion of the knowledge that you 12 built of this temporal model. It wouldn't make 13 any sense at all. 14 Q Spatial detection is within a single 15 frame, correct? 16 A Generally speaking, yes. But, I mean, 17 that's not what's happening here. But yes, 18 generally speaking, spatial, you're talking about 19 a single frame, generally speaking. We're not 20 talking about the context of the '980. 21 Q Isn't the '980 using spatial detecting? 22 ATTORNEY EKLEM: Objection to form.	228 1 a joint model that models spatially and temporally 2 at the same time. It's not two physical entities 3 put together. 4 Q Doesn't the '980 explicitly indicate that 5 W is an odd integer greater than or equal to 1? 6 And I'm in column 7, lines 9 and 10. 7 A Yes. It states, "A W-frame windowed 8 smoothing algorithm is used where W is an odd 9 integer greater or equal to 1." 10 ATTORNEY BAKER: Let's take a ten-minute 11 break. 12 ATTORNEY EKLEM: Okay. 13 (Recess.) 14 ATTORNEY BAKER: Back on the record, 15 please. 16 Q Let's go to Zhou again. That's 17 Exhibit 1006. 18 A Yes, sir. 19 Q Meta Page 24. Let me know when you're 20 there. 21 A I've got two more exhibits here. This is 22 Dr. Bajaj. I'm going to put that aside. Tell me

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229 1 that page again, please. 2 Q 24. 3 A Yes, sir. 4 Q So Figure 1.7 of Zhou illustrates 5 generating merged body parts, correct? 6 A That's what it says, "Generating Merged 7 Body Parts." That's the label of Figure 1.7. 8 Q And Zhou teaches, at the bottom of 9 Page 24, that, "locations of real body parts can 10 be inferred from the merged parts covering them." 11 Do you see that? 12 A Yes. 13 Q Is that inference based on probabilities? 14 A Spatially. So using the merged body 15 parts, various shape configurations can be built, 16 as shown in Figure 1.8. You look at 1.8 next 17 door, the next page, and the locations of the real 18 body parts can be inferred from the merged parts 19 covering them. And obviously he does that in his 20 dissertation using spatial modeling. 21 Q Let's now turn to Page 42 of Zhou. 22 A Yes, sir.	231 1 and limb components? 2 A Well, this description is talking about -- 3 so assuming that the human body model consists of 4 M body parts, right? M as in Mary, M body parts. 5 Parameterized with vectors F1 through FN. So F1 6 refers to body part 1, F2 refers to body part 2, 7 all the way to FM. 8 "Where fi for body part I is made up of AI, 9 LI, XI" -- excuse me, "and theta, then the human 10 body model is parameterized with four matrices," 11 and he describes those. 12 Q What are the four matrices? 13 A You've got the aspect ratio matrix A; the 14 length ratio, matrix S, and S is essentially this 15 length over this length; the relative position 16 vector X; and the orientation theta matrix. 17 Now, if you notice at the bottom of the 18 page he says, "I'm not using the orientation 19 matrix. In the future, the orientation constraint 20 data will be incorporated to form stronger 21 constraints." But he's not using it for the rest 22 of this thesis work.
230 1 Q Let's take a look at Figure 2.6. And that 2 describes modeling body parts with ribbons, 3 correct? 4 A Yes, sir. 5 Q Can you turn your attention to Page 29 of 6 Zhou. 7 A Page 29 or Page 43, Meta Page 43, it's 8 thesis Page 29. 9 Q Great question. I'm at Meta Page 43. My 10 apologies. 11 A No, problem I'm with you. I can see your 12 page right there. I'm anticipating every move. 13 Q Very good. So doesn't Zhou teach that the 14 human body model is parameterized with four model 15 matrices? 16 Do you see that? 17 A Where are you reading now? 18 Q First full paragraph on Page 43, Meta 19 Page 43. 20 A Yes. Yes. Yes. 21 Q So is this human body model the 22 hierarchical? Does it have an object component	232 1 (Reporter clarification.) 2 A To form stronger constraints in the 3 appearance of a person. 4 Q Again, let's return to Figure 3.1 for a 5 second, please, which is on Meta Page 56. 6 A Yes, sir. 7 Q Doesn't this reflect that when all 8 components of the human object are detected, the 9 probability is 1? 10 ATTORNEY EKLEM: Objection to form. 11 Q So let's start over. I'll strike that 12 question. 13 So in Figure 3.1, each drawing, if you 14 will -- 15 A Yes. 16 Q -- there are five drawings -- 17 A Yes. 18 Q -- they all reflect a single person, which 19 is the object, correct? 20 A Well, it's the grouping of object parts 21 where the first one just has one thing and the 22 next one has three and the next one has five. So

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233 1 just essentially it increases as you go all the 2 way to the right side, where you have the full 3 human body. 4 Q And the probability that the left drawing, 5 the oval, is a person is .55, correct? 6 A So those numbers on top aren't really 7 essentially probability in the probability sense, 8 like you see -- look at the next page, on Page 57. 9 So you see on the top of there it says, "For the 10 body parts who have subparts, NI is defined 11 recursively. NI is equal to alpha sum over NJ for 12 all FJ being the subpart of fi, where alpha less 13 than 1 is a degeneration factor used to punish the 14 ambiguity with the coarse level body parts so that 15 a contour that only matches a low resolution model 16 well does not get high similarity measure." 17 So this .55, .75, whatever, is kind of 18 like a similarity measure. So in essence it 19 represents a probability, but it's in the spatial 20 domain. There is no temporal of any kind here. 21 This is all essentially spatial. 22 Q But it's the probability that the object	235 1 Q Therefore there is a probability that the 2 object, including the three components, or 3 composed of the three components, the probability 4 that that is a human is .75, correct? 5 A Generally speaking, yes. 6 Q And then in the next picture, the system 7 has now detected five components, and therefore 8 the probability that that overall image is a human 9 is .84, and so on, correct? 10 A Yes. I mean, if you look at the caption 11 of the figure it says, "Examples of the calculated 12 probability of a person given the hypotheses." 13 Q Okay. Thank you. 14 A Right? "Given the degeneration factor 15 alpha equals .9 in the contour parts matching the 16 model parts exactly." Yes. 17 Q Doesn't Figure 3.1, doesn't the oval show 18 the first layer of the spatial model in Zhou? 19 ATTORNEY EKLEM: Objection. Objection to 20 form. 21 A No, that's not what it shows. That just 22 shows a contour of what you found in your image,
234 1 is in an image, correct? 2 A Well, it's -- essentially it's talking 3 about the contour and how well does the contour 4 matches that as, say, of a human, right? 5 Q Correct. 6 A So the contour that you're looking at, how 7 well does that match a person, if the person is 8 what I'm interested in? The closer it matches the 9 person, the higher this number gets. And the 10 lesser it matches a person -- like the ellipse on 11 the left, it obviously doesn't match a person very 12 well so he gave it a .55 weighting, indicating 13 that it's -- it's not very good, right? And 1 14 would be like it matches a person very well. 15 Q So doesn't it reflect that in the first 16 picture only one object is detected, the oval? 17 A Yes. 18 Q And therefore the probability that that 19 oval is a human is .55, correct? 20 A Generally speaking, yes. 21 Q And in the next picture, if you will -- 22 A It detected three components.	236 1 let's say. 2 So you're doing a segmentation and you're 3 doing whatever Zhou is doing, and the part is 4 just -- has this contour to it. You're going to 5 say, is this a person or not; you know, that 6 figure is saying, well, probably the person, given 7 the hypotheses is .55, so it's not really. It's 8 almost as good as random guessing, right, because 9 flipping a coin would be .5. 10 Q You can't flip a coin for the second 11 image, could you, for the three components? I'm 12 sorry, when there are three components, you're not 13 just flipping a coin, right? 14 A So when you go to the next one, you now 15 have three contours, and what you're saying is, 16 what's the probability of this being a person 17 given those three parts. That is .75 in this 18 case. And then you continue. 19 Q So there is not another layer -- 20 A That's not really -- 21 Q -- of a spatial model? 22 ATTORNEY EKLEM: Objection to form.

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237 1 A Well, first of all, that's not a layer, 2 and, two, it's definitely not a layer like we 3 discussed in the context of the '980 patent. So 4 those are completely distinct concepts. 5 Q Is Figure 2.7 of Zhou showing layers? 6 A Which page are we talking about? 7 Q Meta Page 45. 8 A That's just talking about the merged body 9 parts. That's not layers as in the context of the 10 '980. '980 has a graphical model. This is not a 11 graphical model. This is the spatial type of 12 model, right? You have the body and these pieces 13 together. This is -- this is kind of a spatial 14 model. 15 Q Can a spatial model have layers? 16 A Well, this doesn't. I mean, this is just 17 a spatial model. 18 Q Can a spatial model have layers? 19 A Depending on how you would construct it. 20 This is not constructed in this -- in this 21 fashion. 22 Q In Figure 3.1, aren't there probabilities	239 1 A Well, a POSITA would be -- you know, would 2 understand graphical models if they've worked in 3 computer vision. But you would have to read the 4 '980 to understand how the '980 has defined its 5 model. And you read something else, it defines it 6 differently. So it all depends on what -- the 7 context of what you're reading. 8 Q Do you believe that Claim 1 of the '980 is 9 limited to the graphical model provided in the 10 specification? 11 ATTORNEY EKLEM: Objection to form. 12 A I don't understand your question at all. 13 Q Claim 1 recites a spatiotemporal -- well, 14 not Claim 1. Bad question. I'll strike that. 15 And let's go to Claim 3. Claim 3 recites, 16 "Wherein the spatiotemporal model is a graphical 17 model comprising nodes corresponding to each of 18 the collection of components and to the object." 19 Do you see that? 20 A Yes. 21 Q Is that graphical model limited to the 22 graphical model described in the '980?
238 1 for each one of the nodes that constitute the 2 graphical model? 3 ATTORNEY EKLEM: Objection to form. 4 A I don't know what you're talking about. 5 There is no graphical model here. There's no 6 nodes here. This is just contours and spatial 7 contours. 8 Q What are the requirements of a graphical 9 model? 10 A Well, it depends on how you design it. It 11 depends on the applications. I mean, the '980 12 defines graphical model as being the object node 13 and component nodes. You could define it as 14 different object states. I mean, there's 15 different ways of defining it. '980 defines it as 16 object node, and you have components node that go 17 with the object and there is some linking between 18 them. This is completely different from that. 19 Q Would a POSITA have an independent 20 knowledge of what a graphical model is outside of 21 the '980 patent? 22 ATTORNEY EKLEM: Objection to form.	240 1 ATTORNEY EKLEM: Objection to form. 2 A I don't know what you mean. I mean -- 3 Q Could there be other graphical models that 4 meet those requirements that are not described by 5 the '980? 6 A Well, it says, "Wherein the spatiotemporal 7 model," this is the spatiotemporal -- this is -- 8 Claim 3 depends from Claim 1. Again, I'm not a 9 lawyer here, I'm just reading as a POSITA. So 10 Claim 3 depends from Claim 1, so it inherits all 11 the stuff from Claim 1. "Wherein the 12 spatiotemporal model that's talked about in 13 Claim 1 is a graphical model comprising nodes 14 corresponding to each of the collection of 15 components and to the object." 16 So this is saying you have a graphical 17 model, it's got nodes corresponding to each of the 18 collection of components. So for each component 19 you get a node, and you get one for the object. 20 So that's what this is claiming. So kind of like 21 what you see in Figure 2A, in a sense. 22 Q Can we turn to Section 2.4.1 of Zhou.

241 1 It's on Page 42. 2 A Meta Page 42? 3 Q Meta, yes. 4 A Yes, sir. 5 Q Do those pages describe Zhou's model? 6 A It describes a TRS invariant body model. 7 Q Which is Zhou's model, correct? 8 A Yes. 9 Q Does Figure 2.6 of Zhou reflect a 10 graphical model as defined by Claim 3 of the '980? 11 ATTORNEY EKLEM: Objection to form. 12 A No. 13 Q Why not? 14 A This is all spatial stuff. There is no -- 15 there is no nodes here. There is no nodes here, 16 there is no object node, there is no collection of 17 component nodes, there is no spatiotemporal model. 18 Q Could the torso be the object? 19 ATTORNEY EKLEM: Objection to form. 20 A Claim 3 says you have a spatiotemporal 21 model, so it has to be spatial and temporal. 22 There is no temporal here at all. It's a	243 1 A Yes, so, "However, the aspect ratio is too 2 ambiguous to be used alone to distinguish 3 different parts. For example, the head and the 4 torso have similar aspect ratios. Therefore, 5 besides the aspect ratios of the body parts, the 6 geometric relationship between them are also 7 modeled." 8 Do you want me to continue? 9 Q Yes, please. 10 A "To do so, a local coordinate frame is 11 associated to each body part. The origin of the 12 part frame is located at the joint connecting the 13 part to its parent in the 'connect to' hierarchy 14 as shown in Figure 2.6B, except that the torso 15 frame origin is located at the geometric center." 16 Q Can you keep reading, please. 17 A Sure. "The advantage of locating the 18 origin at the joint instead of the geometric 19 center of the body part is that the location of 20 the origin becomes invariant to the body part's 21 orientation. In summary, the body part is 22 parameterized with a vector, vector a, l, x, y,
242 1 graphical model. This is a spatial type of model, 2 not a graphical model, "comprising nodes," there 3 are no nodes here, these are just components, 4 essentially body parts, "corresponding to each of 5 the collection of components." 6 So this is -- this is -- this is a spatial 7 domain representation. This is not a graphical 8 representation as described in the '980, in the 9 context of the '980. This is a spatial domain 10 representation. So if you read those paragraphs, 11 you get that idea. He talks about the origins, 12 the geometric center, locating the origin, the 13 geometric relationships, the aspect ratios. 14 You're talking about a spatial modeling. It's 15 clear as day. 16 Q Okay. I'm returning to Page 42. I 17 apologize for bouncing back and forth. 18 A No problem. 19 Q Page 42 of Meta, 1006. 20 A Yeah. 21 Q Can you read out loud the paragraph 22 beginning with, "However."	244 1 theta, where A is equal to W divided by L is the 2 aspect ratio that captures the general shape of a 3 ribbon, X, Y are the coordinates of the origin in 4 the coordinate frame of the parent part, and theta 5 is the intersection angle between the major axes 6 of this part and its parent part." 7 Q What is the parent part? 8 A So, like, you look at Figure 2.6B, you see 9 that hierarchy there? You have, let's say, a left 10 thigh, left calf, so essentially the left thigh is 11 above the left calf, which is above the left foot. 12 So your left foot would essentially be -- so if 13 you would look at that sentence here on Page 43, 14 you would see the general shape of the ribbon, 15 "X, Y are the coordinates of the origin of the 16 coordinate frame of the parent part," like your 17 left calf, "and theta is the intersection angle 18 between the major axes of this part" your left 19 calf, and -- this part would be your left foot, 20 "and its parent part," your left calf. 21 Q So would a POSITA, after reading the 22 paragraph bridging pages 42 and 43 of Zhou, would

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245 1 they have understood that Zhou describes a full 2 human model with spatial parameters and joint 3 angles, and also a body model which has multiple 4 components? 5 A Well, a POSITA would understand what I 6 just read. You have essentially -- you have body 7 parts are represented by length, aspect ratios, 8 X-Y angles; you have relationship -- geometric 9 relationships between them; you've parameterized 10 them with a vector; and you have an origin of -- 11 you know, you put the origin at the joint so that 12 you have -- you know, you have a joint between the 13 left foot, let's say, and the left calf. So you 14 have a joint there and you place the origin at 15 that -- to essentially create some aspect of 16 invariance. 17 But all of that is in the spatial domain. 18 There's no -- this is all spatial information, 19 right? The length, the width, the coordinates, 20 the aspect ratios, everything you see here is 21 spatial. Nothing temporally at all. 22 Q What does Zhou mean by a "TRS invariant	247 1 translated -- if I were to take this bottle and 2 translate it in the image, would it remain the 3 same or would it change? So if you were to look 4 at the bottle -- if an algorithm is looking at the 5 bottle here and if I translate it to here, I want 6 the bottle to look the same regardless of where it 7 is in the image. So my classifier shouldn't look 8 any differently if it's over here. 9 Now, if I were to rotate the bottle, does 10 it look differently to my classifier as I rotate 11 it? So my model should have the ability to be 12 rotation invariant. I should be able to say "this 13 is a bottle," regardless of whether it's rotated. 14 And then if I scale it, because in the 15 image -- 16 (Reporter clarification.) 17 A So in the image, if I put the bottle back 18 here, it's going to look a lot smaller than if I 19 bring it way up here. Could my classifier 20 classify that independent of the scale? 21 So the three together is usually the 22 foundation for good pattern recognition
246 1 body model"? What does that mean? 2 A Well, the "T" stands for translation, the 3 "R" stands for rotation, and the "S" stands for 4 scaling. And he defines that in his dissertation 5 somewhere earlier. If you do a search on your 6 computer, you'll find it. It is defined someplace 7 in his dissertation. 8 Q No luck. Let me see if I can search for 9 it. 10 A Yeah, I can tell you, it's -- I've seen 11 it. 12 See, if you go to Page 41 Meta, and take a 13 look at that paragraph there, I'm looking to see 14 if he has a definition of TRS. I'm 100 percent 15 sure it's translation, rotation, and scale. And 16 he says it somewhere, I just have to find it. 17 Q Well, independent of the Zhou 18 dissertation, do you have an understanding of what 19 TRS invariance means? 20 A Of course. 21 Q What does it mean? 22 A Well, translation invariance means if you	248 1 algorithms. Because otherwise you would have to 2 do a brute force approach and search every 3 possible translation and every possible rotation 4 and every possible scale. 5 And a translation has two parameters, the 6 rotation has -- if you were out of the image 7 plane. We're not even talking outside. There's 8 one parameter for rotation, two for translation, 9 and scaling has got two parameters and you have a 10 sheer parameter. So it becomes what's known as a 11 fine transformation. And you don't want to 12 have -- you don't want to create a classifier that 13 is not independent of translation, rotation, and 14 scale, because otherwise you have to search a 15 six-dimensional space, which is not a good thing. 16 Q So due to Zhou having a TRS invariant 17 model, its object can be detected no matter what 18 posture or orientation it has in the image; is 19 that correct? 20 ATTORNEY EKLEM: Objection to form. 21 A Well, that's the motivation. Whether it 22 works 100 percent is a different story. But the

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249 1 motivation is, I'm going to try to model my object 2 such that it's translation, rotation, and scale 3 invariant. That's the motivation. 4 And you see when he starts talking on 5 Page 41, Meta, you see that top left page, it 6 says, "The human body can be represented directly 7 using 3D model or indirectly using a collection of 8 2D models," right? 9 And then he simplifies that. He 10 says, "Since the goal of this thesis is to detect 11 people in an image," they don't want to deal with 12 the 3D because it's too complicated, you have to 13 deal with in and out of rotations, "2D models are 14 preferred because the 2D model can be compared 15 directly with a 2D shape without projecting the 3D 16 model onto the image plane." So he doesn't want 17 to deal with the pose and orientation in 3D. He 18 wants to limit the work to 2D. 19 And then he continues on and discusses how 20 he models things, and introduces the TRS 21 notation -- the TRS model that he's talking about. 22 There is a footnote in his thesis	251 1 A Yes. So he would do this in a frame, then 2 he would do it in the next frame. So his model is 3 strictly a spatial model, so the detection happens 4 in a frame, in a 2D sense spatially. No temporal 5 detection. 6 Q And we agreed that Zhou's method of 7 detection is a probabilistic method? 8 A Spatially, in the spatial domain of a 9 given frame, it's based on probabilities, yes. 10 See, you look at -- so you see, like, I'm looking 11 on Page 54 of Meta, "probability of a contour 12 given age," right, so he is detecting -- 13 essentially, he's doing this spatial domain thing. 14 And you look at Page 64, Meta, you see 15 Formula 3.12. Page 64, Meta, says, "The 16 probability of a person given this contour," and 17 then he formulates it using Bayesian rule, and 18 then does the classification. 19 Q For each frame, correct? 20 A For each frame, frame by frame. There is 21 no temporal modeling of any kind. 22 Q If it's okay with you, let's turn to
250 1 somewhere. 2 Q Let me ask you this: So Zhou's method 3 using this TRS invariant body model can be used to 4 detect the human in each frame of a video, 5 correct? 6 ATTORNEY EKLEM: Objection to form. 7 A So his model is designed to detect using 8 contours in a specific frame; the probability of 9 the person given this contour, what's the 10 probability this is a person versus a rabbit 11 versus a car. That's what his algorithm is 12 designed on detecting. 13 Q In each frame, correct? 14 A I'm sorry? 15 Q That can be done in each frame, what you 16 discussed? 17 A Well, it's designed to detect it spatially 18 in a frame in a two-dimensional sense, because he 19 doesn't want to deal with the three-dimensional 20 models, as I showed you. 21 Q But again, that can be conducted in each 22 frame of a video?	252 1 Steffen. 2 A I don't have -- 3 Q I'll hand you Steffen. 4 A Are we done with Zhou? 5 Q I can't -- 6 A Promise that? 7 Q -- promise, but I'm hoping so. 8 I'm handing you a copy of what's been 9 previously marked as Meta Exhibit 1008. 10 A Yes, sir. That's not Steffen, that's 11 Ozer. 12 Q You can keep it but I'm going to give you 13 another one as well. 14 I'm also going to hand you what's been 15 previously marked as Meta Exhibit 1007, which 16 should be Steffen. You can confirm? 17 A I do confirm. 18 Q All right. So let's turn to column 9, 19 lines 1 through 4 of Steffen. 20 A Yes. This copy is kind of hard to read. 21 It's a lot of... see all these little... 22 Q Do you have a personal copy or --

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253 1 A I don't. 2 ATTORNEY BAKER: Is yours bad as well? 3 ATTORNEY EKLEM: I think it's -- the 4 of-record version has the black stuff on it. 5 That's what it is. 6 A This seems like worse than what I've seen, 7 but okay. 8 Q So does Steffen use a model graph for 9 finding a human face in an image? 10 A So that's what that first sentence states. 11 So he basically says -- Steffen says, "The model 12 graph 168," and he's referring to Figure 12 in the 13 patent, "that's particularly designed for finding 14 the human face in an image is shown in Figure 12." 15 Q And does it use similarity functions in 16 order to identify that human face? 17 A Yes, that's the general idea behind -- if 18 you look down on that column, he has computed -- 19 it's a normalized scalar product. 20 Q And with reference to Figure 14 of 21 Steffen. 22 A What about Figure 14?	255 1 would be the -- you would think that would be the 2 idea, you would get a coarse -- so you see the 3 next sentence it says, "After coarse landmark 4 finding has been achieved, higher precision 5 localization may be performed on higher resolution 6 images for precise finding of a particular facial 7 feature." 8 So you have a lower resolution image. You 9 might just think you've found the contour of the 10 face, let's just say. 11 Q And the face is the object? 12 ATTORNEY EKLEM: Objection to form. 13 A Assuming that's the case. 14 Q Okay. 15 A And then you go to the higher resolution 16 and you start to find the corners of the eyes and 17 the tip of the nose and whatever. 18 Q And those are the objects -- I'm sorry, 19 those are the components of the object, right? 20 ATTORNEY EKLEM: Objection to form. 21 A No, those are not components in the sense 22 of the '980 patent. Those are landmarks.
254 1 Q Does it teach a coarse-to-fine approach 2 for detecting a face? 3 A So on column 10 it says, "A course," and 4 it's misspelled. So, "A coarse-to-fine landmark 5 finding approach shown in Figure 14 uses graphs 6 having fewer nodes and kernel on lower resolution 7 images." 8 So that's what's displayed in Figure 14. 9 Q So the image including the female face, 10 that is the coarse analysis? 11 ATTORNEY EKLEM: Objection to form. 12 A The coarse-to-fine landmark finding 13 approach. 14 Q What does that mean to you? 15 A So you have landmarks, you know, different 16 places on the face. So you can have a coarse one 17 to a more finer version. You may have, you know, 18 five landmarks on the coarse one, and when you get 19 to the final, you may have 50 of them. 20 Q But isn't the first coarse to get the 21 whole outline of the face? 22 A Well, that would be the idea. But -- that	256 1 Q I didn't ask anything about the '980. I 2 said, looking at the '370 -- 3 A Yes. 4 Q -- and Figure 14 -- 5 A Yes. 6 Q -- and the first step is to get the -- 7 identify the coarse outline of the object. 8 ATTORNEY EKLEM: Objection. 9 Q And I use the term "outline" loosely. If 10 you want to use a different word, that's fine. 11 A Well, let's use what they use. 12 Q Let's use what they use. 13 A So it's not -- it's not what I think or 14 what you think, it's what they use. "A 15 coarse-to-fine landmark finding approach shown in 16 Figure 14 uses graphs having fewer nodes and 17 kernel on the lower resolution images. After 18 coarse landmark finding has been achieved," so 19 these are landmarks that you found, like important 20 points, corner points, or whatever, "higher 21 precision localization may be performed on higher 22 resolution images for precise finding of

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257 1 particular facial features." 2 So these are landmarks that you found, and 3 when you go to the higher resolution, you find 4 more landmarks. 5 Q They call them features? 6 A Particular facial features. So the 7 landmark is supposed to locate a facial feature, 8 like a corner of an eye or tip of the nose or 9 something. So the facial feature is your tip of 10 your nose. The landmark that will go across on 11 the figure is going to be hopefully pointing to 12 that location. That's your landmark. 13 And when the image has a coarse 14 resolution, you don't see the fine stuff. And 15 when you go to higher resolution, you get more 16 landmarks. 17 Q Does Steffen disclose a spatiotemporal 18 model? 19 A No, there is no spatiotemporal model here 20 disclosed, especially in the context of the '980. 21 Q I'm just asking about Steffen. 22 A Right. But you have to be careful that	259 1 and you have a landmark tracking. And then you 2 have an identifier. 3 So essentially you're doing -- you know, 4 like if you look at column 3, I'm on line 57, 5 "Depending on the nature of the image data, the 6 head detection model uses one of a variety of 7 visual pathways which are based on, for example, 8 motion, color, or size (stereo vision) topology or 9 pattern." 10 So it is potentially employing some motion 11 information, but that's completely different from 12 what's being discussed in the '980. It's not -- 13 it's not an apple-to-apple discussion or 14 comparison. 15 Q So you agree that column 10, lines 62 to 16 67 of Steffen discuss a tracking technique 17 involving linear motion prediction? 18 A Yes. 19 Q Okay. 20 A He says, "A first tracking technique 21 involving linear motion prediction." That's what 22 it says.
258 1 you're not, you know -- because you're using the 2 same terminology, and it's important to 3 distinguish it. 4 So his model essentially is doing -- you 5 know, if you see -- I mean, it's a different 6 approach. There is no probabilities here in 7 Steffen. It's a totally different approach than 8 what's disclosed in the '980. 9 Q I didn't ask for whether there was any 10 probabilities used at this point. I was just 11 asking, does Steffen employ a spatiotemporal 12 model? 13 ATTORNEY EKLEM: Objection to form. 14 A Well, I mean, it's important to 15 distinguish things. So it's -- it's -- you want 16 to be very clear. Steffen has essentially -- if 17 you look at Figure 1 of Steffen, you have a video 18 RAM 28 coming in, so you have video imagery coming 19 in; you have head detection and tracking in 14, 20 right, using a head detection and tracking 21 process; and then you have preselector; you have a 22 landmark finding that we've been talking about,	260 1 Q And any inferences made by Steffen is done 2 with video including a plurality of frames, 3 correct? 4 ATTORNEY EKLEM: Objection to form. 5 A Well, you have video input, obviously, and 6 Steffen is operating on these frames, you know, as 7 I just discussed. But that is completely 8 different from the context of the '980 that we've 9 been talking about. They're a totally different 10 world. 11 Q When you say that they are a "totally 12 different world," are you referring to the '980 13 specification and what it describes or the '980 14 claims and what is claimed there? 15 A Well, I'm referring to the '980 as a 16 whole. The '980 claims -- you know, the claims of 17 the '980 discusses spatiotemporal model, discuss, 18 you know, acquiring video, discuss measuring the 19 object as a collection of components that are 20 defined in the specification, determine 21 probabilities that the object is in each image, 22 and then detecting the object based on those

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261 1 probabilities that we've been discussing. 2 So it has a spatiotemporal model that has 3 a joint distribution with probabilities as we've 4 been discussing, and that's being used to do all 5 these things. The specification describes the 6 details, but those are the claims. 7 Q Does Claim 1 define a joint distribution? 8 A Well, defines a spatial -- 9 Q I mean probability. I'm sorry. 10 ATTORNEY EKLEM: Objection to form. 11 A So Claim 1 provides a spatiotemporal 12 model, right? And that spatiotemporal model is 13 described in the specification, this joint 14 distribution that we've been talking about. 15 Q And again, Claim 1 does not require a 16 two-layer graphical model, correct? 17 ATTORNEY EKLEM: Objection to form. 18 A Well, Claim 1 says you have the object as 19 a collection of components. So you have the 20 object and you have a collection of components. 21 And you have a spatiotemporal model. So that 22 spatiotemporal model is what we've been discussing	263 1 time -- do you see how he's got his figure and you 2 see that little white stuff on the figure? 3 Q Yes. 4 A And you see how it goes to the next one, 5 and as it goes to the one on the right? So you 6 have the initial graph and the final graph, you 7 get that SF, the similarity has gone up to .74. 8 And when you go to the next one in the rotations, 9 you see the graph, and the similarity goes up to 10 .96. And then that's for the left one and for the 11 right one. 12 So he's essentially doing a similarity 13 measure that's based on the scale of product. 14 There is no discussion of probabilities here at 15 all. 16 And you look at the formula, it will tell 17 you exactly that. So if you look at the formula 18 for -- look on column 9, line 55 or 50 -- or 63, 19 whatever. Either one of them. So he said, "The 20 similarity of two jets" -- so I'm reading the 21 sentence above it: "If the components of the 22 Jet G are written in the form with amplitude AJ
262 1 in the prior -- you know, prior discussions. And 2 if you look at Claim 2, for instance, it 3 says, "Wherein providing the spatiotemporal model 4 for the object to be detected comprises providing 5 detectors for each of the collection of 6 components." 7 So you have a spatiotemporal model for the 8 object, the object has components, this graphical 9 model that describes that. That graphical model 10 has a spatial and temporal aspect to it. There is 11 a joint distribution, probability distribution. 12 That's all described in the specification. None 13 of that is in Steffen. There is no probability in 14 Steffen at all. 15 Q Does Figure 21 of Steffen illustrate 16 matching and tracking of a face? 17 ATTORNEY EKLEM: Objection to form. 18 A So Figure 21, you see it has a 19 transformation into the Gabor space, which is 20 essentially like a wavelength decomposition, and 21 then you have a frontal bunch graph matching, 22 essentially, so you have graph matching each	264 1 and phase phi J, the similarity of two jets, J and 2 J', is the normalized scalar product of the 3 amplitude vector." 4 So you see S, J, J' is equal to the scalar 5 product of A, J, A, J' sum. And to normalize it 6 so it doesn't go beyond 1, he divides it by the 7 total sum of both of them, the total sum of the 8 square of the product of both of them. So this 9 way it's normalized. 10 But that's a similarity. That's like a 11 dot product. It's a scalar product, essentially. 12 That has nothing to do with probability at all. 13 Q What if the similarity is 1? 14 A Similarity has nothing do with 15 probability. There is no probability discussion 16 here. There is no probability in this whole 17 patent. I bet if you search on the word 18 "probability," it's not there. 19 Q Have you done that? Have you searched for 20 the word "probability"? 21 A I don't remember off the top of my head. 22 But I -- I read this very extensively, and there

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265 1 is no probability discussion in this patent. 2 There is no probability formulation in it of any 3 kind. There is no probability in this patent. 4 Q Is it fair to say the greater the 5 similarity, the more probable the object is -- 6 A The more similar. 7 Q The more similar? 8 A Not probable, more similar. 9 Q The greater the similarity, the higher the 10 similarity, the more probable that the object is a 11 face? 12 ATTORNEY EKLEM: Objection to form. 13 A The greater the similarity, the more 14 similar two jets are. So when I'm looking at the 15 similarity of Jet J to Jet J', the greater S -- 16 you understand how dot product works? Do you? 17 Q I do. 18 A So a dot product is essentially -- if you 19 have a vector and you have another vector, you dot 20 product the two vectors together. The more 21 aligned the two vectors are, the higher the dot 22 product. So if the two vectors are perpendicular,	267 1 object parts and recognize their activities in 2 compressed and uncompressed domains," correct? 3 A You read that correctly. 4 Q So the nonrigid object detection indicates 5 to a POSITA that the object is moving, correct? 6 A Is deformable, like a human being. 7 Q So it's deformable. In order to see the 8 deformation, you couldn't see that in a single 9 frame, right? That would take multiple frames, to 10 see a deformation? 11 A No, that's not how you would interpret 12 that. 13 Q Really? You can see a deformation in a 14 single frame? 15 A So what -- what this is talking about is 16 deformable, you know, nonrigid object. So you 17 have a human being, right, my arms are moving; 18 that's a nonrigid object, right? 19 Q So there is movement. 20 A But the point is, in the frame, your arms 21 can be above your head in a frame. I can still 22 detect a human in the frame, it's just the object
266 1 the dot product would be 0, the scalar product 2 would be 0. And if the two vectors are completely 3 aligned, then the scalar product would be one if 4 you normalized it. But that is just a similarity 5 measure. That's not a probability at all. 6 Q So if we take the similarity score and 7 normalize it, don't we have a probability between 8 0 and 1? 9 A No. That's a similarity measure, it's not 10 a probability. 11 ATTORNEY BAKER: Let's take a 10-minute 12 break. 13 (Recess.) 14 Q I previously handed you Meta Exhibit 1008. 15 Do you have that in front of you? 16 A Yes, the Ozer patent. 17 Q So let's turn our attention to column 3, 18 lines 55 to 57. 19 A Yes. 20 Q All right. So Ozer states that, "The 21 system of the present invention can detect 22 nonrigid, for example, human body, and rigid	268 1 is the nonrigid object. But I can still detect it 2 in the frame. 3 Q Even looking at the cover of Ozer, there 4 is a video input, correct? 5 A It's "Method And Apparatus For Automated 6 Video Activity Analysis." 7 Q Let's look at the exemplary figure at the 8 bottom. Do you see that? 9 A Yes, sir. 10 Q There is a video input 401? 11 A Yes, sir. 12 Q And there is a teaching of multiple frame 13 classification, correct? 14 A Yes, sir. 15 Q And there is nonrigid object detection 16 taught by Ozer as well? 17 A Well, there is a graph -- there is -- I 18 mean, it's a series of steps, right? He does 19 background illumination, then segmentation, then 20 contour generation, he fits an ellipse to the 21 contours, he does some object modeling, graph 22 matching, and multiple frame classification. But,

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269 1 you know, he's going after the activity, not the 2 object. It's an activity analysis. 3 Q Doesn't line 55 in column 3 say it's 4 detecting nonrigid and rigid object parts? 5 A Yes. "Can detect nonrigid and rigid 6 object parts and recognize their activity." 7 Q But that's an "and," right? It's not the 8 only thing it's detecting. 9 A It detects the object parts and recognize 10 the activity. The activity is done in the video. 11 The object parts are done in the frame. 12 Q So if you detect the rigid and nonrigid 13 object parts and recognize their activities, does 14 that infer a temporal component? 15 ATTORNEY EKLEM: Objection to form. 16 A Not in the context of the '980 at all. If 17 you see -- if you look at my declaration, Page 98, 18 Paragraph 148 and 149, I address that. 19 Q Well, I didn't ask you about whether it's 20 in the context of the '980. And because we are 21 getting low on time, I asked you, as relates to 22 Ozer, does the description at column 3 beginning	271 1 detect specific activities." 2 So you have two levels here that are being 3 discussed. The devil is always in the details. 4 It's not just a overview mapping like that. 5 Q So doesn't Ozer use hidden Markov models 6 for detection of object parts? 7 ATTORNEY EKLEM: Objection to form. 8 A So he's using hidden Markov models for the 9 activity recognition. So you look in column 4 and 10 it starts to discuss the process, right? So you 11 kind of go step by step. You go to column 3, it 12 starts the system, then, "low level part performs 13 object detection and extracts the parameters" that 14 we've been talking about. 15 Then column 4, you see on line 7, "The 16 system is capable of managing the segmentation 17 process by using object-based knowledge," and it 18 discusses that process. 19 Then the next paragraph, starting on 20 line 18, says, "The system is also capable of 2D 21 approximation of object parts by fitting close 22 curves, etc."
270 1 at line 55 teach a model which has a temporal 2 component? 3 A So what it's teaching is -- so you have 4 to -- the devil is in the details. You read one 5 sentence and you've got to get into the details of 6 what he's doing to really understand what's 7 happening. So he's detecting rigid and nonrigid 8 object parts in the frame, and then he's 9 classifying -- looking at the activity across 10 frames from the video. 11 So you see, as I say in Paragraph 148 of 12 my declaration, I'm reading halfway down the 13 paragraph, "Ozer makes clear that his technique 14 involves two separate processes, specifically, 'a 15 method with two levels,' namely low and high 16 levels, is used where, 'the low level part 17 performs object detection and extracts parameters 18 for the abstract graph representation of the image 19 being processed.'" So it's processing that one 20 image. And, "The high level part uses dynamic 21 programming to determine the activities of the 22 object parts, and uses a distance classifier to	272 1 Then the next paragraph starts on line 24, 2 "Object detection is achieved by matching the 3 relational graphs of objects with the reference 4 model. This method maps the attributes," etc. 5 There is no temporal yet. Nothing temporally. 6 Then, "After the detection of the object 7 parts, the system is ready to recognize the 8 activities for each" -- "of each object part and 9 the overall activity of the object." So now it 10 goes to the next piece. So it's done the object 11 detection; now it's ready for the activity 12 recognition. 13 Now it gives you an example. "If the 14 object is of interest is a human body, the system 15 will first detect different object parts," hands, 16 etc. "If the object is a rigid object," like 17 would be a car, for instance, "the system would 18 detect object parts and compare the attributes." 19 Then it talks about the high level. The 20 high level part uses a pattern classifier, namely 21 hidden Markov models, which classifies the 22 activity patterns of the body in a space-time" --

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273 1 "in space-time, and determines the movements of 2 the object parts." 3 So the object detection is done spatially. 4 The activity is modeled in a space-time scenario. 5 Q Isn't that a spatial-temporal scenario? 6 A Well, the object is spatial. There is no 7 temporal there. 8 Q What does "space-time" mean? 9 A Well, like as I said, the object is done 10 strictly spatially. There is no temporal. The 11 activity has a space and time, because in space 12 it's looking at the object, in time it's looking 13 at the activity. 14 Q Isn't that tracking an object? 15 ATTORNEY EKLEM: Objection to form. 16 A Well, it's looking at the activity of the 17 object. 18 Q Isn't that another way of saying you're 19 tracking the object? 20 A Well, I mean, you're looking at the 21 activity of the object, but that's not the 22 spatiotemporal process that we're talking about in	275 1 classifier, namely hidden Markov models, which 2 classifies activity patterns of the body parts in 3 space-time and determines the movements of the 4 object parts." 5 Q So isn't that using probabilities for 6 tracking? 7 A Well, this is completely different context 8 than what we were talking about with the '980, 9 where you have a joint -- I mean, that's the 10 point. You're using the same wording, and I want 11 to make sure that is a clear distinction here. 12 The wording is very important because of the 13 context that we're talking about. 14 Q So I'll ask again. In the context of the 15 '266, a POSITA reading the '266 -- 16 A Yes. 17 Q -- doesn't he teach using probabilities 18 via the hidden Markov models for tracking the 19 activities of an object? 20 A Well, I mean, the activity, you have 21 classification using probabilities for the 22 activity. But that's a different concept or
274 1 the '980. So context is completely different. 2 Q What does "activity" mean to you in the 3 context of the '266? 4 A Let's say a human is walking, right? 5 You've got activity, right? The human is walking. 6 So you're looking at the different location of the 7 hands to say, okay, it's walking, it's an 8 activity. 9 Q Over time? 10 A But the detection of the object is done in 11 the frame. You look at the next frame, you can 12 see the motion of the hand from one point to the 13 other geometric features. There is no probability 14 here. There is no discussion of probabilities in 15 this case. There is no -- 16 Q Isn't the hidden Markov model a 17 probability? 18 A Well, the hidden Markov model talks about 19 the different states of the activities, right? 20 Q Didn't you say the hidden Mark model 21 classifies the activity patterns? 22 A Yeah, "The high level part uses a pattern	276 1 different modeling scenario than what's discussed 2 in '980, complete apple and orange differences. 3 They're not the same thing. 4 This is a hidden Markov model that models 5 the states. That one over there is a joint 6 distribution that models the object in the graphs 7 and all this stuff. Completely apples and 8 oranges, total -- completely different. 9 Q But didn't I frame my question in the 10 context of the '266 as it would be understood by a 11 POSITA, and wasn't my question whether or not, 12 "Reading the '266, a POSITA would have understood 13 that Ozer teaches using a patent pattern 14 classifier, namely hidden Markov models, to 15 classify the activity patterns of body parts"? 16 A So look at column 7, starting on line 34. 17 Q Can you answer my question first? 18 A I'm going to answer it. I'm going to 19 answer it. Column 7, line 34, "Classifying over 20 multiple frames." See, this is what Ozer teaches. 21 "Output of the graph-matching algorithm is the 22 classified object parts." That's done in the

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277 1 frame. "The movement of the object parts are 2 described as a spatiotemporal sequence of feature 3 vectors," okay, "that consists of the direction of 4 the object part movements." So we're talking 5 about spatiotemporal sequence of feature vectors. 6 There is no probabilities here yet. 7 "The system checks direction of the 8 movements of the object parts for a number of 9 frames and calculates the probabilities of the 10 activities with the known activities by using a 11 hidden Markov model." 12 So now they're looking at the probability 13 of the objects. It's looking at the probability 14 of an activity. Like, what's the probability that 15 if I see hands doing this, the person is walking? 16 That's not the probability of an object, it's the 17 probability of an activity. "And chooses the 18 pattern with the highest probability," the pattern 19 of the activity. This is a human walking, this is 20 a human running versus a standing still or 21 whatever. 22 So he describes that description. You	279 1 So you have, "A pattern classifier, namely hidden 2 Markov models." So the hidden Mark models model 3 the state of walking, so this is how walking would 4 look like from state to state to state. "Which 5 classifies activity patterns," walking, standing, 6 running, "of the body parts in space-time, and 7 determines the movement of the object parts." 8 So that's what it means. 9 Q And how about, will you read the sentence 10 that begins at line 49? 11 A "For articulated objects like human body, 12 the system will find the activities of the body 13 part independently from each other and combine the 14 activities to find the gesture and overall 15 activity of the human body at a later stage by 16 using a quadratic distance classifier. 17 Q So doesn't that teach tracking each body 18 part independently? 19 ATTORNEY EKLEM: Objection to form. 20 A It's looking at the -- it's looking at the 21 activities of each body part. So what is this 22 body part doing? Your head is turning like this
278 1 know, he has a description here for it. That's 2 why I want to make sure it's clear that this 3 spatiotemporal sequence that he's talking about 4 has to do with feature vectors, not probabilities, 5 and it's the activity that has the probability, 6 not the object. 7 Q Can you read column 4, lines 44 to 47 out 8 loud, please. 9 A Column 4... 10 Q Lines 44 to 47. 11 A Okay. "The high level part uses a pattern 12 classifier, namely hidden Markov model, which 13 classifies activity patterns of the body parts in 14 space-time, and determines the movement of the 15 body" -- "of the object parts." 16 Q What does that sentence mean to you as an 17 expert? 18 A It uses the pattern classifier, like his 19 is what walking looks like. So you teach the 20 computer: A human walking would look like this. 21 This is what the activity -- this is what a 22 pattern of the human body walking would look like.	280 1 or your arms are moving like this. So it's the 2 activity that it's looking at, what is the meaning 3 of this activity, not essentially the object part, 4 independently from each other. 5 So you're looking at the leg -- right hand 6 is doing this, the left hand maybe is doing 7 something different. And combine the activities. 8 So now you can say, well, the right hand is 9 swinging this way and the left hand is swinging 10 that way; maybe this person is walking. "To find 11 the gesture and overall activity of the human body 12 at a later stage by using a quadratic distance 13 classifier," kind of like a Euclidian classifier 14 or a Mahalanobis classifier. 15 Q What's your understanding of what a 16 gesture is? 17 A You know, a gesture, like make a pose, 18 maybe, or walking, you jump over something. 19 Q What if I raise my eyebrows? Is that a 20 gesture? 21 A Probably, unpredictable. I don't know if 22 that's considered a gesture or more of a facial

281 1 expression. 2 Q Doesn't a gesture involve movement of body 3 parts? 4 A I mean, you're combining the activities to 5 find the gesture and overall activity of the human 6 body. So you're combining the left arm activities 7 with the right arm activity, you can say, well, 8 this looks like the swinging of arms so this guy 9 looks like he's walking. 10 ATTORNEY BAKER: Can we take a five-minute 11 break? 12 (Recess.) 13 Q I'm going to ask you about an exemplary 14 figure from the four prior art references, TLP 15 Ozer, Steffen, and Zhou. I'm going to just ask 16 you a couple of simple questions and we're going 17 to wrap it up, all right? 18 So let's start with TLP, which is 19 Exhibit 1009. Do you have it? I think you do. 20 A I do. 21 Q Can you turn to Figure 6? 22 A Figure 6, yes.	283 1 Q But you agree that each frame illustrates 2 detecting components of a human object, correct? 3 A very straightforward question. 4 A Yeah, he says, "Note that we use only 5 detectors for the head, upper arms, and calves." 6 So he's detecting head, upper arms, and calves. 7 And they give a rough relocation orientation of 8 the limbs, they cannot differentiate from left to 9 right, and it's a bottoms -- bottom-up detector. 10 And then he says, "After several 11 iterations of belief propagation, the algorithm 12 finds the limbs and has a reasonable distribution 13 over the limbs' poses," Measures 6C and 6D that 14 you see there, it's from different camera 15 viewpoints. 16 Q And then Figure 7, after you've done the 17 detecting of the figure, Figure 7 shows the 18 tracking over multiple frames, correct? 19 A It shows -- 20 ATTORNEY EKLEM: Objection to form. 21 A So Figure 7 shows the results of tracking 22 over 25 frames after automatic initialization.
282 1 Q So Figure 6 illustrates TLP processing 2 multiple image frames, correct? 3 A So Figure 6 talks about automatic 4 initialization from bottom-up detectors. 5 Q Doesn't it illustrate an object, multiple 6 frames each showing an object? 7 A Well, you've got to be careful with the 8 details of the discussion. So -- so let's look 9 at -- I'm looking at Page 6 of 1009, left column, 10 the description of Figure 8 -- Figure 6. It 11 says, "Figure 6A shows the automatic 12 initialization of the 3D body model using the 13 bottom-up part detectors. Note that we use only 14 detectors for the head, upper arms, and calves, 15 and that these detectors are very inaccurate. 16 While they give a rough 3D location and 17 orientation for the limbs, they cannot 18 differentiate left from right limbs reliably. 19 Note also that the right calf was not detected." 20 Because you see, if you look at Figure 6A, 21 the top one, you don't see anything on the right 22 calf.	284 1 Q And the initialization includes detecting 2 the components that you discussed, correct? 3 A Yes. So we see Figure 6A shows the 4 automatic initialization of the 3D body model 5 using bottom-up part detectors. So 6A provides 6 the initialization, and then you have the tracking 7 in Figure 7. 8 Q I was asking, does the initialization 9 include detecting the components of the human 10 body? 11 A Yes. So if you see, Figure 6A shows the 12 automatic initialization of the 3D body model 13 using bottom-up part detectors. 14 Q Okay. Let's go ahead and look at Ozer. 15 A Yes, sir. 16 Q Does Ozer also show detecting an object 17 and its components in each frame, and then 18 tracking the object across frames? 19 ATTORNEY EKLEM: Objection to form. 20 A I think we went over that, right? It 21 shows -- discusses that, detecting the object in 22 each frame, right? "So output of the

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285 1 graph-matching algorithm" -- I'm looking at Ozer, 2 column 7, lines 34. "Output of the graph-matching 3 algorithm is the classified object parts." So it 4 detects the object parts. "The movement of the 5 object parts are described as a spatiotemporal 6 sequence of feature vectors that consist of the 7 direction of the object part movement." So we're 8 looking at feature vectors. 9 "And the system checks direction of the 10 movements of the object parts for a number of 11 frames, and calculates the probability of the 12 activity with" -- "in known" -- "with the known 13 activities." So you have the known activities 14 that you have developed ahead of time: This is 15 what a walking activity would look like, this is 16 what a crawling activity would look like. So you 17 have that -- you have the hidden Markov models of 18 that training activity, and what you're doing here 19 is you're looking at the activities across the 20 frames and then essentially saying, is this guy 21 walking or is he crawling. 22 Q But you're tracking that activity, right,	287 1 entity over multiple frames. 2 Q Let's go to Steffen, Figure 21. 3 A Yes, sir. 4 Q Does Figure 21 illustrate a process 5 involving multiple image frames -- multiple 6 frames? Let's just use that. 7 A So, I mean, yes, you're looking at a 8 particular frame in the image; you know, I would 9 say a series of video frames. You're looking at 10 the frame and you're doing some graph 11 classification -- graph placement in the frame. 12 That's within the frame. There's no probability 13 here. This is strictly based on similarity. 14 Q Okay. But you're detecting the face in 15 each frame, correct? 16 A Well, let's look at the description of 17 Figure 21. 18 Q Doesn't each frame show the graph relative 19 to the face? Isn't that detecting? 20 A Well, essentially you're doing -- you're 21 using the similarity. But I want to look at the 22 language exactly, so that's why I'm trying to find
286 1 to use the parlance? 2 A Well, you're looking at the activity in a 3 space-time situation. 4 Q You're looking at it in order to track it? 5 A See, if you go back to column 4, the 6 sentence that you pointed out earlier, I'm on 7 sentence 44 -- line 44, column 4. "The high level 8 part uses a pattern classifier, namely hidden 9 Markov models, which classifies activity patterns 10 of the object parts," so are they crawling or are 11 they walking, "in space-time," so it's classifying 12 it in the space of the frame and looking at it 13 across time, "and determines the movements of the 14 object parts." 15 Q So when it's looking at it across time, 16 isn't that a form of tracking? 17 A It's looking at the activity across time. 18 Q Can you track an activity? 19 A Well, the activity itself is defined 20 across time with the hidden Markov model. So 21 you're not tracking the activity, you are defining 22 the activity. An activity is, by definition, an	288 1 the description of Figure 21. The problem is, 2 this is a little bit hard to read, some of it. 3 Okay. So if you go to column 14, starting 4 on line 48 or so, you see, "An example of such 5 pose estimation procedure is shown in Figure 21." 6 Do you see that? 7 Q Mm-hmm. 8 A "The first step of the pose estimation is 9 equivalent to that of the regular landmark 10 finding." 11 Q So that's the detecting, right? 12 A So you have landmarks in your -- this is 13 all spatially in the same frame. There is no 14 temporal here. 15 Q And you do that in each frame. You do 16 that detecting that you were just discussing in 17 each frame, correct? 18 ATTORNEY EKLEM: Objection to form. 19 A "So the image, Block 198," those original, 20 "is transformed" in order to use the graph 21 similarity functions that he defined for that 22 equation that we talked about. And then he says,

289 1 "Then, instead of the only one, a family of three 2 bunch graphs is used," because he's trying to hit 3 the pose. Because you may be looking straight, 4 and you look at the right, you maybe look on the 5 left. 6 "The first bunch graph contains only the 7 frontal pose faces, and the other two contain 8 quarter rotated faces." So he's completely 9 operating in the frame looking straight, right, 10 and left, and trying to detect the face. So he's 11 basically giving himself three degrees of freedom. 12 Q To detect? 13 A To detect the face. 14 Q And that's all I wanted to know. So there 15 is a detection of the face in each frame, correct? 16 And doesn't Steffen also teach tracking the face 17 across frames? 18 ATTORNEY EKLEM: Objection to form. 19 A So Steffen talked about face recognition 20 from video images. But there is no description of 21 probabilities or anything in Steffen at all. 22 Q I didn't ask about probabilities. I was	291 1 first at the coarse level and then proceeding at 2 the fine" -- "at the fine level." 3 Q Thank you. 4 ATTORNEY EKLEM: Todd, we're at just a 5 little over seven hours. If you've got like one 6 more -- 7 ATTORNEY BAKER: One last question. 8 Q It's going to be a two-parter, and I'm 9 going to ask it in one sentence and then I'll 10 leave it to you to answer. 11 Zhou, Figure 5.4, does that illustrate 12 detecting an object on a frame-by-frame basis and 13 then tracking that object across frames? 14 ATTORNEY EKLEM: Objection to form. 15 A Tell me again which figure. What page are 16 we talking about? 17 Q 5.4, Meta 1006, Page 92. 18 A So what was your question? 19 Q Does Figure 5.4 illustrate detecting an 20 object on a frame-by-frame basis and then tracking 21 that object across frames? 22 ATTORNEY EKLEM: Objection to form.
290 1 just asking, after detecting per frame, does it 2 track across frames? 3 A So it's tracking the landmarks across 4 essentially frames. He's using like a linear 5 motion model that may generate. So it's 6 essentially tracking -- you know, like you look at 7 column 11, for instance, line 22, "The tracking 8 technique based on a Gaussian image pyramid 9 applied to one dimension as illustrated in 10 Figure 19," that you see in that figure. 11 So to try to do -- to try to track -- 12 instead of -- "instead of using the original image 13 resolution, the image is down-sampled to create a 14 Gaussian pyramid." That's because you're trying 15 to speed up basically the process. 16 Q In order to do the tracking, correct? 17 A "So an image pyramid of four levels 18 results in a distance of," you know, whatever, "in 19 a distance of 24 pixels of the finest," and so on. 20 "Jets may be computed and compared at any level of 21 the pyramid. So tracking of a node on the 22 Gaussian image pyramid is generally performed	292 1 A So again, I think we went over Zhou 2 multiple times. So Zhou only detects -- looks at 3 the contours spatially within the frame, and talks 4 about using motion information essentially using 5 geometric entities or spatial and size 6 relationships to -- to go across the frames. 7 There is no probability discussions of going 8 across the frames at all. There is no 9 spatiotemporal models as discussed in the '980, in 10 the context of the '980. 11 ATTORNEY BAKER: No further questions. 12 ATTORNEY EKLEM: Just a couple quick ones. 13 Give me one second. 14 EXAMINATION BY 15 ATTORNEY EKLEM: 16 Q Dr. Saber, do you recall being asked about 17 the definition of -- do you recall being asked 18 about the definition of the person of ordinary 19 skill in the art? 20 A Yes. 21 Q Okay. In your declaration, did you 22 provide an independent -- your own independent

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293 1 analysis of what the definition of the person of 2 ordinary skill in the art should be? 3 A No, I did not provide an independent 4 definition. 5 Q Okay. Did you adopt the definition that 6 Dr. Bajaj provided for purposes of your 7 declaration? 8 A I did. 9 Q Okay. Do you remember being asked about 10 examples of detection that involve linear 11 velocity, acceleration, and angular velocity? 12 A Yes. 13 Q Okay. Is linear velocity, acceleration, 14 or angular velocity the probability that an object 15 is an image? 16 A No. 17 Q Last one here. Do you recall being asked 18 about -- in the '980 patent, do you recall being 19 asked about column 7, lines 9 through 10 that 20 mention W greater than or equal to 1? 21 A Yes. 22 Q Okay. Does Claim 1 of the '978 [sic]	295 1 Q I think I'm getting at the smoothing 2 window is different from the number of frames you 3 have in the video, right? So let's say you're 4 analyzing a video that has 10 frames. 5 A Yes. 6 Q Why can't you use a W-frame windowed 7 smoothing algorithm where W equals 1? 8 A Well, I mean, if you use a W equals 1, you 9 essentially took out the temporal situation of 10 your model. You basically reduce your model, your 11 spatial model, and that's not what you want to do. 12 So if you look at the last sentence of 13 column 7, it says, "Note that with W equals 1, the 14 algorithm resembles single frame component-based 15 fusion." That's essentially a simplification. 16 But your spatiotemporal model has a joint 17 probability that requires multiple frames for it 18 to function. You can't do that on a single frame. 19 Q When W is 1, you still process all the 20 frames, but you just do one frame at a time during 21 the processing, correct? 22 A No, that -- that -- that wouldn't work in
294 1 patent cover an embodiment of W equals 1? 2 A No. I mean Claim 1 requires the 3 collection -- a plurality of images. You have to 4 have "providing the video comprising a plurality 5 of images." So you have to have a plurality of 6 images to do what's being done in Claim 1. 7 ATTORNEY EKLEM: No further questions. 8 ATTORNEY BAKER: Give me two seconds to 9 chew on that last answer, then I think we're done. 10 EXAMINATION BY 11 ATTORNEY BAKER: 12 Q Dr. Saber, couldn't you use a W-frame 13 windowed smoothing algorithm for a video even when 14 W is set to 1? 15 A No. It wouldn't make sense. I mean, a 16 W-frame -- I mean, you look at column 7, "A 17 W-frame windowed smoothing algorithm is used where 18 W is an odd integer greater or equal to 1." 19 But -- so that's what it states there. So 20 what was your question? If you want it to be an 21 odd integer, it's got to be greater or equal to 1, 22 so it's 3, 5, 7, etc.	296 1 the context of the '980. You need multiple frames 2 to have your joint distribution. You wouldn't -- 3 you wouldn't -- it wouldn't work that way. 4 If you were to go to one frame, 5 essentially you're taking away all of your 6 temporal angle. You wouldn't want to do that. 7 There is no point creating a spatiotemporal model 8 so you don't -- so you're not using the temporal 9 part. 10 ATTORNEY BAKER: No further questions. I 11 appreciate your time. 12 (Time Noted: 4:47 P.M.) 13 14 15 16 17 18 19 20 21 22

297 1 ACKNOWLEDGMENT OF DEPONENT 2 I, ELI SABER PH.D., do hereby acknowledge 3 that I have read and examined the foregoing 4 testimony and the same is a true, correct, and 5 complete transcription of the testimony given by 6 me and any corrections appear on the attached 7 errata sheet signed by me. 8 9 _____ 10 (SIGNATURE) (DATE) 11 12 13 14 15 16 17 18 19 20 21 22	299 1 IN WITNESS WHEREOF, I have hereunto set my 2 hand and affixed my notarial seal this 11th day of 3 June, 2024. 4 My commission expires: 10.07.2025 5 6 7  8 _____ 9 ANITA M. TROMBETTA, RMR, CRR 10 11 12 13 14 15 16 17 18 19 20 21 22
298 1 CERTIFICATE OF SHORTHAND REPORTER-NOTARY PUBLIC 2 3 I, ANITA M. TROMBETTA, RMR, CRR the officer 4 before whom the foregoing deposition was taken, do 5 hereby certify that the foregoing transcript is a 6 true and correct record of the testimony given; 7 that said testimony was taken by me 8 stenographically and thereafter reduced to 9 typewriting under my direction; that reading and 10 signing was requested [or not requested, as 11 appropriate]; and that I am neither counsel for, 12 related to, nor employed by any of the parties to 13 this case and have no interest, financial or 14 otherwise, in its outcome. 15 I further certify that the adverse party was 16 represented by counsel at the deposition. 17 I further certify that the deposition of 18 ELI SABER PH.D., occurred at the offices of 19 Reichman Jorgensen Lehman & Feldberg, 20 400 Madison Avenue, Suite 14D, New York, NY 10017 21 on Thursday, May 30, 2024, commencing at 8:07 a.m. 22 to 4:07 p.m.	

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Date: 5/30/2024

Case: Meta Platforms, Inc., et al. -v- VL Collective IP LLC (PTAB)

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ACKNOWLEDGMENT OF DEPONENT

I, Eli Saber, Ph.D., do hereby acknowledge that I have read and examined the foregoing testimony, and the same is a true, correct and complete transcription of the testimony given by me and any corrections appear on the attached Errata sheet signed by me.

____6/15/2024____

(Date)



(Signature)