

IN THE UNITED STATES PATENT AND TRADEMARK OFFICE

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Title: VEHICLE DESTINATION PREDICTION

DECLARATION OF DR. VASSILIOS MORELLAS

I currently hold the opinions set expressed in this declaration. But my analysis may continue, and I may acquire additional information and/or attain supplemental insights that may result in added observations.

I hereby declare that all statements made of my own knowledge are true and that all statements made on information and belief are believed to be true. I further declare that these statements were made with the knowledge that willful false statements and the like so made are punishable by fine or imprisonment, or both, under Section 1001 of the Title 18 of the United States Code.

Dated: 01/25/2024

By: 
Vassilios Morellas

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I. QUALIFICATIONS AND BACKGROUND INFORMATION

1. My education and experience are described more fully in the attached curriculum vitae. For ease of reference, I have highlighted certain information below.

2. I am currently employed as a Research Professor of Electrical and Computer Engineering at the University of Minnesota, Twin Cities, Minnesota. I am currently also the Director of the National Science Foundation (“NSF”) Center on Robots & Sensors for Human Well Being at the University of Minnesota.

3. I believe that I am well qualified to serve as a technical expert in this matter based upon my educational and work experience.

4. I have been involved with the design and evaluation of computer vision systems, sensors, lasers for various automation tasks, for approximately 30 years. My academic research has been in the areas of computer vision, robotics, intelligent transportation systems, sensor networks, object recognition, and sensor-based control in transportation systems. I have also been involved in work since 1995 involving computer algorithms for vehicle tracking, camera calibration, inspection, object recognition, vehicle monitoring systems, and motion control devices. I have authored or co-authored a book and book chapters and numerous

peer-reviewed technical papers in these areas. My curriculum vitae details my degrees, employment history, teaching experience, publication list, scholarly accomplishments, professional contributions, grants, honors, and awards.

5. I received my Diploma of Engineering in Mechanical Engineering from the National Technical University of Athens in Greece in 1983. I obtained my Master of Science degree in Mechanical Engineering from the Columbia University in New York, New York in 1989. In 1995, I received my Ph.D. in Mechanical Engineering from the University of Minnesota. My research at the time was in robotics, computer vision and control, computer integrated manufacturing, and software engineering, and my Ph.D. thesis was titled “A Neuro-computational Mobile Robot Architecture for Mapping Localization and Navigation.” The work revolved around the use of neural networks and a suite of ultrasonic sensors to accomplish place recognition and autonomous navigation for a mobile robot.

6. After receiving my Doctorate degree, from 1995-1998, I was employed as a Research Associate at the Department of Mechanical Engineering at the University of Minnesota. My work as a research associate concerned autonomous driving of a tractor trailer using a combination of cameras, Differential Geographic Position Systems (DGPS), and magnetometers along with speed and steering control algorithms to achieve autonomous navigation. Autonomous driving of

this vehicle was successfully demonstrated at a testing facility of the Minnesota Department of Transportation (MnDOT).

7. Starting in 2003, and until 2014, I was an instructor at the Department of Mechanical Engineering at the University of Minnesota. As an instructor, I taught classes related to robotics and computer vision. I also conducted research and oversaw projects directed to camera-based security and surveillance. Network camera surveillance and tracking was field deployed at Philadelphia's train station.

8. From 2019 until the present, I have served as a Research Professor of Electrical and Computer Engineering at the University of Minnesota. While in this role, I have advised and mentored students related to image-based cancer recognition, precision agriculture automation, and vision-based techniques for early detection of autism spectrum disorders. I have mentored and advised student research related to Computer Vision, Artificial Intelligence, Algorithms and Data Structures, and Readings in Computational Vision. These cover a variety of topics that include 3D reconstruction, extraction of depth, inspection, tracking, light striping, lasers, structured light, structure from motion, occlusions, edge detection, and basic image processing. My academic research has continued in the fields of computer vision systems, sensors, and lasers, with primary specialties in robotics, intelligent transportation systems, and sensor-based control in transportation applications.

9. From 2006-2019, I was the Program Director of the Computer Science & Engineering of the University of Minnesota. While in this role, I continued research on various types of automation involving the integration of sensors of different modalities with electro-mechanical platforms.

10. I have received research grants for various projects involving computer vision as applied to the transportation industry, including the development of a camera-based solution to the Truck Parking Availability problem that uses 3D reconstruction of truck park stops.

11. In terms of my industrial experience, from 1998-2005, I was employed as a Principal Research Scientist, in the Advanced Technology Labs of Honeywell International Inc. From 2005-2006, I was employed as a Senior Principal Research Scientist, also in the Advanced Technology Labs of Honeywell. During my time at Honeywell, my work was primarily concerned with systems that enhanced security and surveillance. The pinnacle of this work was a demonstration of secure gate access of vehicles at a naval base, using a custom developed multi-spectrum camera and face recognition technologies.

12. From 2007-2014, I served as a Co-PI for the NSF Research Center on Safety, Security and Rescue at the University of Minnesota. While there, I was tasked with directing the University of Minnesota site research on various research

topics of interest to industrial partners that chose to join our center paying an annual fee.

13. From 2014 until the present, I have acted as the Director of the NSF center on Robots & Sensors for Human Well Being at the University of Minnesota. In this role, my work concerns organizing the center's activities attracting industrial financial support and directing research in intelligent transportation, medical research (cancer recognition, mental health disorders), precision agriculture, and robotics

14. I am listed as an inventor on numerous patents issued in the United States and foreign countries. My inventions concern technologies including computer and machine vision technologies. Examples of my issued U.S. patents include:

- US Pat. No. 9,858,816, titled "Determining Parking Space Occupancy Using a 3D Representation"
- US Pat. No. 7,907,750, titled "System and Method for Autonomous Object Tracking"
- US Pat. No. 7,602,942, titled "Infrared and Visible Fusion Face Recognition System"
- US Pat. No. 7,149,325, titled "Cooperative Camera Network"

- US Pat. No. 7,806,604, titled “Face Detection and Tracking in a Wide Field of View”
- US Pat. No. 7,606,425, titled “Unsupervised Learning of Events in a Video Sequence”

15. I have authored or co-authored over 130 articles or conference presentations, including numerous papers and presentations concerning computer or machine vision technologies. Of particular interest may be the following papers and presentations:

- Video Analytics for Security and Transportation Applications, Keynote talk at the 4th IEEE Computer Vision and Pattern Recognition Workshop on Object Tracking & Classification Beyond the Visible Spectrum (OTCBVS 2007), June 22, 2007
- Between the Lines: A Driver-Assistive Technology for Staying in the Lane, GPS World, Vol. 9, 1988
- Accurate 3D ground plane estimation from a single image, IEEE International Conference on Robotics and Automation, 2009

16. I have been actively involved in multiple technical communities, including the IEEE Society, and NSF Review panels. I have served in the organizing committee of many technical conferences, including, for example:

- Associate Editor, IEEE/RSJ International Conference on Intelligent Robots and Systems, 2019
- Technical Committee, 22nd International Conference on Pattern Recognition, ICPR 2014
- Program Area Chair, 5th IEEE International Conference on Advanced Video and Signal Based Surveillance, 2008

17. My research has been recognized by multiple organizations, universities, and institutions. The following is a small set of honors and awards that I have received:

- Center for Transportation Studies: CTS Research Partnership Award, 2016
- Best Student Paper Award, IEEE International Conference on Image Processing (ICIP), 2012
- Technical Achievement Award, for Technical Excellence in the area of “People Tracking in Camera Networks”, Highest Honorary Distinction from Automation and Control Solutions (ACS) of Honeywell International Inc., April 2003.

18. Overall, I have used my education, industry, teaching, writing, and membership and service experiences and my understanding of the knowledge, creativity, and experience of a person having ordinary skill in the art in forming the opinions.

19. My extensive experience in the transportation industry is applicable to analyzing the Asserted Patents.

20. I have been retained on behalf of Tesla, Inc. to offer technical opinions relating to U.S. Patent No. 10,829,002 (“the ’002 Patent”) and prior art references relating to its subject matter. I have reviewed the ’002 Patent, and relevant excerpts of the prosecution history of the ’002 Patent. I have also reviewed the following references:

- TESLA-1004 U.S. Pat. App. Pub. No. 2005/0251325 (“Kudo-325”)
- TESLA-1005 U.S. Pat. App. Pub. No. 2004/0128066 (“Kudo-066”)
- TESLA-1006 U.S. Pat. App. Pub. No. 2005/0228553 (“Tryon”)
- TESLA-1007 U.S. Patent No. 5,471,393 (“Bolger”)
- TESLA-1008 U.S. Pat. App. Pub. No. 2005/0125148 (“Van Buer”)
- TESLA-1009 U.S. Patent No. 6,484,096 (“Wong”)
- TESLA-1013 U.S. Patent No. 6,144,917 (“Walters”)
- TESLA-1014 European Pat. App. No. EP 0763712A1 (“Giras”)
- TESLA-1015 U.S. Pat. App. Pub. No. 2009/0037089 (“Tkachenko”)
- TESLA-1016 U.S. Patent No. 7,163,076 (“Seksaria”)
- TESLA-1017 U.S. Patent No. 6,076,623 (“Teraoka”)
- TESLA-1018 U.S. Patent No. 5,499,196 (“Pacheco”)

21. I have also reviewed various supporting references and other documentation as further noted in my opinions below.

22. Counsel has informed me that I should consider these materials through the lens of one of ordinary skill in the art related to the '002 Patent at the time of the earliest possible priority date of the '002 Patent, and I have done so during my review of these materials. The '002 Patent claims the benefit of priority to a series of applications dating to an earliest date of November 17, 2005 (“the Critical Date”). Counsel has informed me that the Critical Date represents the earliest possible priority date to which the challenged claims of '002 Patent are entitled, and I have therefore used that Critical Date in my analysis below.

23. I have no financial interest in the parties or in the outcome of this proceeding. I am being compensated for my work as an expert on an hourly basis. My compensation is not dependent on the outcome of these proceedings or the content of my opinions.

24. In writing this declaration, I have considered the following: my own knowledge and experience, including my work experience in the field of transportation systems; my experience in teaching those subjects; and my experience in working with others involved in those fields. In addition, I have analyzed various publications and materials, in addition to other materials I cite in my declaration.

25. My opinions, as explained below, are based on my education, experience, and expertise in the fields relating to the '002 Patent. Unless otherwise stated, my testimony below refers to the knowledge of one of ordinary skill in the art as of the Critical Date, or before. Any figures that appear within this document have been prepared with the assistance of Counsel and reflect my understanding of the '002 Patent and the prior art discussed below.

II. OVERVIEW OF CONCLUSIONS FORMED

26. This declaration explains the conclusions that I have formed based on my analysis. To summarize those conclusions, based upon my knowledge and experience and my review of the prior art publications listed above, I believe that:

- Claims 1-16 are obvious over Kudo-325 and Kudo-066;
- Claim 3 is obvious over Kudo-325, Kudo-066, and Bolger; and
- Claim 17 is obvious over Kudo-325, Kudo-066, and Tryon.

III. LEVEL OF ORDINARY SKILL IN THE ART

27. In my opinion, one of ordinary skill in the art relating to, and at the time of, the invention of the '002 Patent would have had a bachelor's degree in electrical engineering, computer engineering, mechanical engineering, civil engineering (transportation systems), physics, or a related field, and at least four years of experience (or the academic equivalent) in the field of transportation systems.

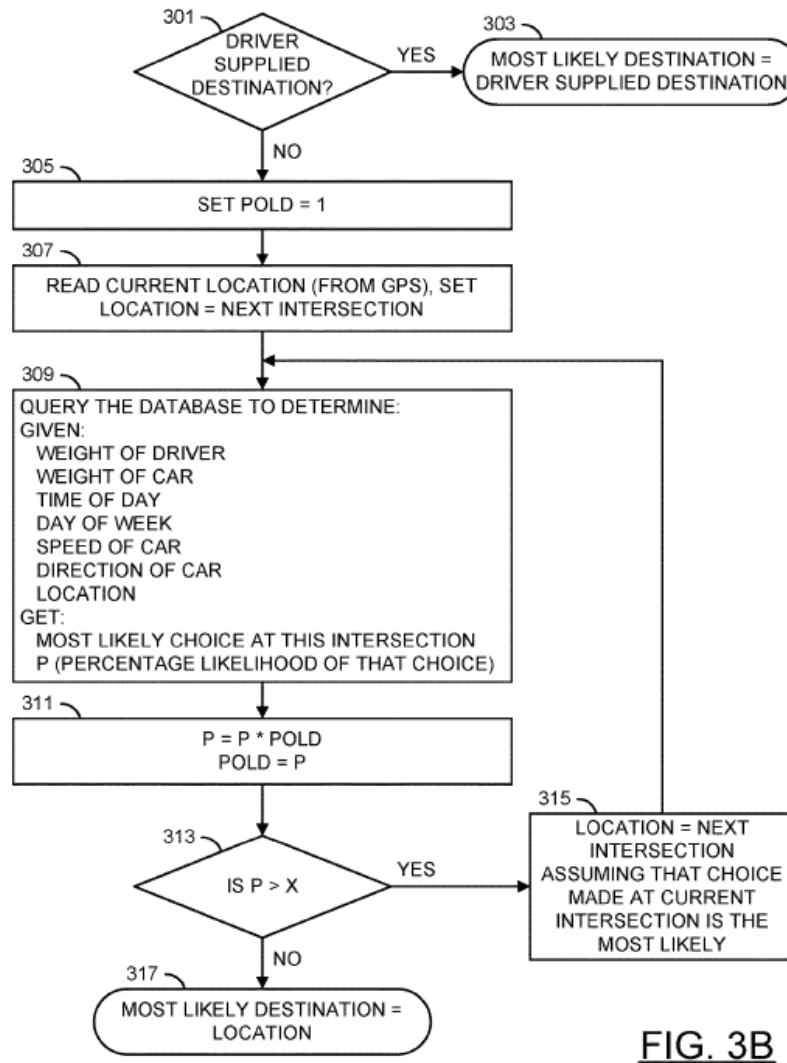
28. Based on my experiences, I have a good understanding of the capabilities of one of ordinary skill. Indeed, I have taught, participated in organizations, and worked closely with many such persons over the course of my career. Based on my knowledge, skill, and experience, I have an understanding of the capabilities of one of ordinary skill. Furthermore, I possess those capabilities myself.

IV. OVERVIEW OF THE '002 PATENT

29. The '002 Patent states that its “invention relates to devices, methods and systems for controlling power applied to a vehicle engine.” TESLA-1001 ('002 Patent), 1:15-16. The claims, though, specifically relate to an approach “predict[ing] a destination of a driver” in response to (1) a pattern detected by analyzing stored sensor data samples received during operation of the vehicle and (2) historical data associated with operation of the vehicle. *Id.*, 27:35-48. In light of the scope of the claims, and in view of related description (which I discuss in the following paragraphs), I characterize the field of endeavor of the '002 Patent as relating to vehicle navigation. *See* TESLA-1001 ('002 Patent), claim 1, 11:50-13:63.

30. In more detail, the '002 Patent describes “determin[ing] one (or more) most likely destinations based on information provided from environmental inputs, user command inputs, and vehicle operational status inputs.” TESLA-1001 ('002 PATENT), 12:3-9. These inputs include, *e.g.*, “the weight of the driver, the time of the day, the current location of the vehicle, the direction that the vehicle is facing

(or traveling in), the day of the week, and the speed of the vehicle” for the vehicle’s current trip. *Id.*, 12:12-18; *see* FIG. 3B, reproduced below (illustrating an example of statistical destination logic). A combination of one or more of these inputs for the current trip is used “to select among a record of destinations to which the vehicle has previously driven” to thereby “infer the vehicle’s destination” for its current trip. *Id.*, 12:20-25. For instance, “[t]he list of possible locations” (*e.g.*, possible destinations) “may be weighted by the statistical destination logic based on how closely the information inputs correspond to the associated information inputs for the destinations.” *Id.*, 12:47-56.



Excerpt from '002 Patent, FIG. 3B

31. With this context, I provide a brief summary of claim 1 of the '002 Patent. This claim relates to analyzing stored sensor data samples, including driver-related samples and telemetry data, that are received during operation of a vehicle. The stored sensor data samples are analyzed to detect a pattern, such as a pattern of characteristics of travel of the vehicle, such as a current trip of a vehicle. This pattern, in combination with historical data gathered from a driver's operation

of the vehicle during past trips, is used to predict the destination of the driver. *See* TESLA-1001 ('002 Patent), claim 1.

V. THE CHALLENGED CLAIMS ARE UNPATENTABLE

A. [GROUND 1A] – Claims 1-16 are rendered obvious by Kudo-325 and Kudo-066

1. Overview of Kudo-325

32. Kudo-325 describes “a technology for predicting a travel destination” of a vehicle. TESLA-1004 (Kudo-325), [0001]. Generally, Kudo-325’s approach involves “accumulating, as a travel history, a travel route obtained from the history of position information of the mobile body,” *e.g.*, the vehicle. *Id.*, [0013]. This travel history is used to “predict[] one or more travel destinations where the mobile body will advance,” taking into account factors such as “time, date, weather, driver, a fellow passenger, and the like.” *Id.*, [0013]-[0014]; *see* [0087] (“Accumulation of a travel history by segment from travel start to travel end enables prediction of a travel destination based on detailed route information”).

33. Kudo-325’s prediction technology is based on the concept of nodes, which can represent “intersections, landmarks, area names, and the like.” TESLA-1004 (Kudo-325), [0081]; *see* [0058]-[0059]. “[I]nformation relating to nodes,” such as “an ID number assigned to a node” and “information indicating the positions such as latitude/longitude information,” is stored in a “map information DB

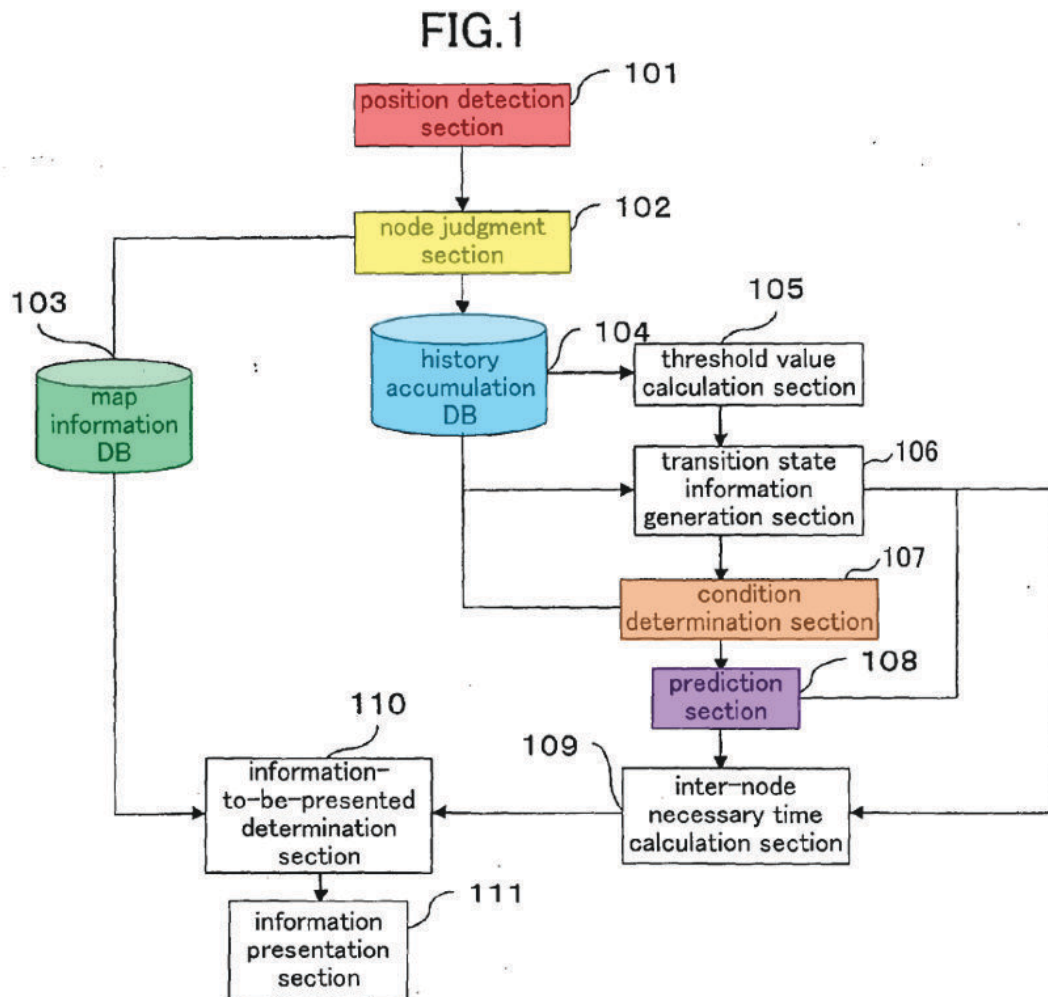
[database].” *Id.*, [0081]-[0082]. An example of a map information database storing “node relating information,” including node ID, node kind/name, and longitude/latitude coordinates, is illustrated in FIG. 2, reproduced below. *Id.*, [0021]. Each node ID number is “assigned to a node in one-to-one correspondence.” *Id.*, [0082]. In some cases, the latitude/longitude coordinates stored for a node are indicative of “representative points,” where the node encompasses a “range[] (radius of the representative point as a center, or the like)” around that point specified by the latitude/longitude coordinate pair. *Id.*

FIG.2

node number	kind/name	east longitude	north latitude
C1	intersection	135' 20"35.45"	34' 44"35.22"
C2	intersection	135' 24"35.74"	34' 44"86.5"
C3	intersection	135' 22"6.22"	34' 44"78.18"
C4	intersection	135' 22"10.4"	34' 45"60.75"
C5	intersection	135' 22"20.0"	34' 46"79.37"
C6	intersection	135' 20"42.76"	34' 46"70.48"
C7	intersection	135' 22"35.39"	34' 47"35.82"
.	.	.	.
L123	landmark (home)	135' 19"48.42"	34' 42"38.29"
L124	landmark (office)	135' 30"22.33"	35' 12"23.6"
.	.	.	.
A427	area (Umeda, North)	135' 29"51.9"	34' 41"57.0"
A428	area (Keihanna, Gakuentoshi)	135' 46"18.80"	34' 44"30.65"

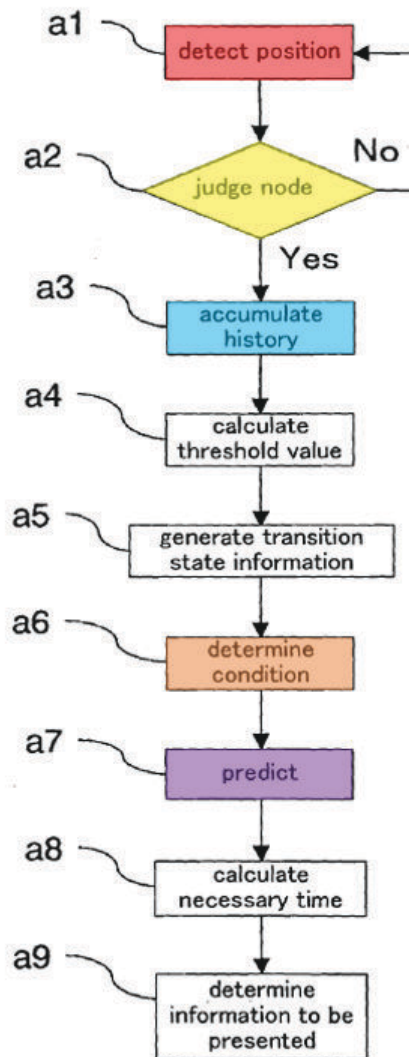
Kudo-325, FIG. 2 (annotated)

34. Kudo-325's "information acquisition system" for destination prediction is illustrated in FIG. 1, which I have reproduced and annotated below, and its operation is illustrated in the flow chart of FIG. 4, also reproduced and annotated below. In operation, "the current position of the car navigation system is detected" by a "position detection section 101" of the system (highlighted in red). TESLA-1004 (Kudo-325), [0077], [0090]; *see* block a1 of FIG. 4.



Kudo-325, FIG. 1 (annotated)

FIG.4



Kudo-325, FIG. 4 (annotated)

35. A node judgement section 102 (yellow) references the map information database 103 (green) to determine “whether the current position is a node or not.” *Id.*, [0090]; *see* block a2 of FIG. 4. If it is, “an ID number indicating the node is accumulated in the history accumulation DB 104 [blue].” *Id.*, [0090]; *see* block a3 of FIG. 4. Other information, such as “time, date, weather, and the like is

[also] accumulated” in the history accumulation DB. *Id.*, [0090]; *see* [0088] (“information on weather, a driver, or a fellow passenger may be stored”).

36. A condition determination section 107 (orange) and a prediction section 108 (purple) “perform[] prediction of a future travel destination” based on “information indicating the current state” of the trip, such as “the current position” of the vehicle, “a travel history from departure,” and “date and time conditions,” and also based on information characterizing past trips of the vehicle, as I discuss further below. *Id.*, [0079], [0096]; *see* blocks a6 and a7 of FIG. 4.

37. An example of travel data “accumulated in the history accumulation DB” is shown in FIG. 3, which I have reproduced and annotated below. TESLA-1004 (Kudo-325), [0087]. Notably, these travel data include both “information relating to the current travel” and “past history information” relating to previous trips of the vehicle. *Id.*, [0096]. The history accumulation database stores “pairs of the node numbers and times of passage therethrough” for the nodes passed by the vehicle during “segment unit[s],”¹ where each row of the tables in FIG. 3 corresponds

¹ A “segment unit” is, *e.g.*, “a unit of ‘segment from engine start (travel start) to engine stop (travel end),” a “unit of ‘segment from departure from home to going back home,”” or “a segment unit of ‘the same day.” TESLA-1004 (Kudo-325), [0087].

to one such node. *Id.*, [0087]. For instance, the first table of FIG. 3 stores travel route data for a segment unit in which, in part, “the vehicle departed from, passed through and stops at a node L6 at 8:05 a.m. on July 31, a node C8 at 8:06 a.m. on the same day, and a node C12 at 8:11 a.m. on the same day,” as indicated by the blue-highlighted rows. *Id.* Other information also can be stored in the history accumulation database, including “information on weather, a driver, or a fellow passenger.” *Id.*, [0088].

FIG.3

104

node number	time
L6	8:05 a.m. on July 31
C8	8:06 a.m. on July 31
C12	8:08 a.m. on July 31
C9	8:09 a.m. on July 31
C34	8:11 a.m. on July 31
.	.
L128	8:53 a.m. on July 31

(a)

node number	time
L128	12:25 p.m. on July 31
C140	12:29 p.m. on July 31
C125	12:36 p.m. on July 31
.	.
.	.
L68	1:33 p.m. on July 31

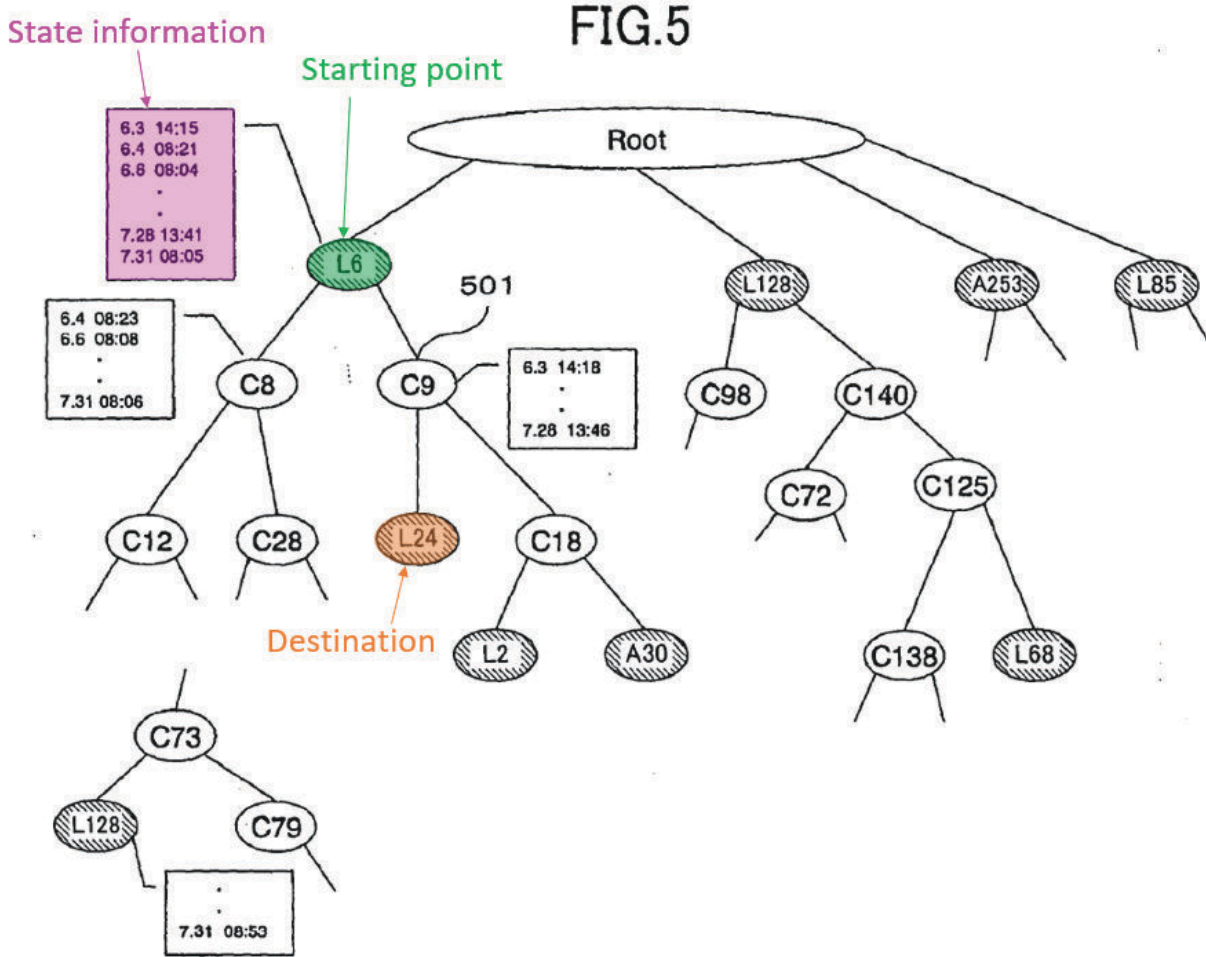
(b)

node number	time
L6	8:05 a.m. on July 31
C8	8:06 a.m. on July 31
C20	8:08 a.m. on July 31
L12	8:10 a.m. on July 31
L12	1:40 p.m. on July 31
C34	1:50 p.m. on July 31
.	.
.	.
L6	9:20 p.m. on July 31

Kudo-325, FIG. 3 (annotated)

38. Past travel data stored in the history accumulation database is used to develop “transition state information” characterizing that past travel. TESLA-1004 (Kudo-325), [0093]; *see* [0091]-[0092], [0109]. For instance, the transition state information has “a tree structure,” illustrated in FIG. 5, which I have reproduced and annotated below. *Id.*, [0093]. The “nodes (starting points) ... are arranged at

the uppermost level immediately below a root.” *Id.* “[H]istories of past node transition ... are expressed in a tree structure,” and the endpoints of travel “are located at the lowermost level of the respective branches.” *Id.* For instance, the tree structure of FIG. 5 indicates an example of past travel starting at node L6 (green), passing through node C9, and ending at node L24 (orange). State information (highlighted in pink for node L6), such as “the dates and times” at which the vehicle passed through each node and “information on a driver and a fellow passenger,” accompanies the nodes in the tree structure. *Id.*, [0093]-[0094]. “[T]he number of pieces of the accompanying state information” for a given node indicates the “frequencies of departure from, passing through and arrival at the node” by the vehicle. *Id.*, [0093]. As explained in the following paragraphs, this transition state information is used to predict the destination of a current trip of the vehicle.



Kudo-325, FIG. 5 (annotated)

39. To predict the destination of a current trip (*e.g.*, a trip in progress), a “condition determination section 107” (orange in FIG. 1 above) acquires, from the history accumulation database, “information relating to the current state” of the vehicle’s trip (*e.g.*, “the current position” and “the date and time”) as well as “the past history information” of the current trip (*e.g.*, “a route from departure to the current node”). TESLA-1004 (Kudo-325), [0096]; *see* block a6 of FIG. 4. One or

more relevant “conditions (categories)” (*e.g.*, ‘weekday,’ ‘afternoon,’ and ‘summer’) are identified that correspond to the retrieved trip information. *Id.*, [0096]; *see* [0014]. Some conditions are “extracted by referencing tables as indicated in FIG. 28,” reproduced below, which provide a mapping between trip information and conditions. TESLA-1004 (Kudo-325), [0096]. Other conditions are based on position information, *e.g.*, the current position or previously transited nodes. *See* TESLA-1004 (Kudo-325), [0097], [0102]. In a specific example, “the current position is a node ‘C9’; a travel history from departure is ‘L6 to C9; and the date and time is 2 a.m. on June 3,” and from this information and from the tables of FIG. 28, conditions including “weekday,” “afternoon,” “summer,” “C9,” and “L6 to C9” are identified.² *Id.*, [0096]-[0097], [0102].

² Based on the identification of “afternoon” as one of the conditions identified from the “2 a.m. on June 3” date/time information, and the tables of Kudo-325’s FIG. 28, a POSITA would have understood the date/time information to refer to 2 p.m. rather than 2 a.m.

FIG.28

date condition table

condition	month	date
holiday	June	1, 2, 8, 9, 15, 16, ...
	July	6, 7, 13, 14, 20, 21, ...
	.	.
weekday	the other days	

trip information

time condition table

condition	time
morning	5 a.m. to 11a.m.
afternoon	12 p.m. to 5 p.m.
evening	6 p.m. to 11 p.m.

conditions

season condition table

condition	month
spring	March to May
summer	June to August
autumn	September to November
winter	December to March

Excerpt from Kudo-325, FIG. 28 (annotated)

40. Combinations of the identified conditions for the current trip are used to calculate probabilities that the current trip will end at each of various nodes. *See* TESLA-1004 (Kudo-325), [0097]-[0103] *see* FIG. 6, reproduced and annotated below. Specifically, “a node satisfying” one combination of the identified conditions (“for example, ‘weekday and ‘C9’”) “is retrieved from the transition state information,” and “a probability of future transition” is calculated between this node and each of one or more of the “nodes located at the lowermost level” of the tree

structure (*e.g.*, the nodes representing destinations), taking into account the particular combination of conditions. *Id.*, [0097]-[0099]; *see* blocks b2-b6 of FIG. 6. For instance, the transition probability from one node (*e.g.*, the vehicle's current node C9) to a candidate node Ln under a particular set of conditions Cond is expressed as follows:

$$\frac{\text{Transition probability}}{\text{Freq}(C9|\text{Cond})} P(Ln|C9) = \text{Freq}(Ln|\text{Cond}) /$$

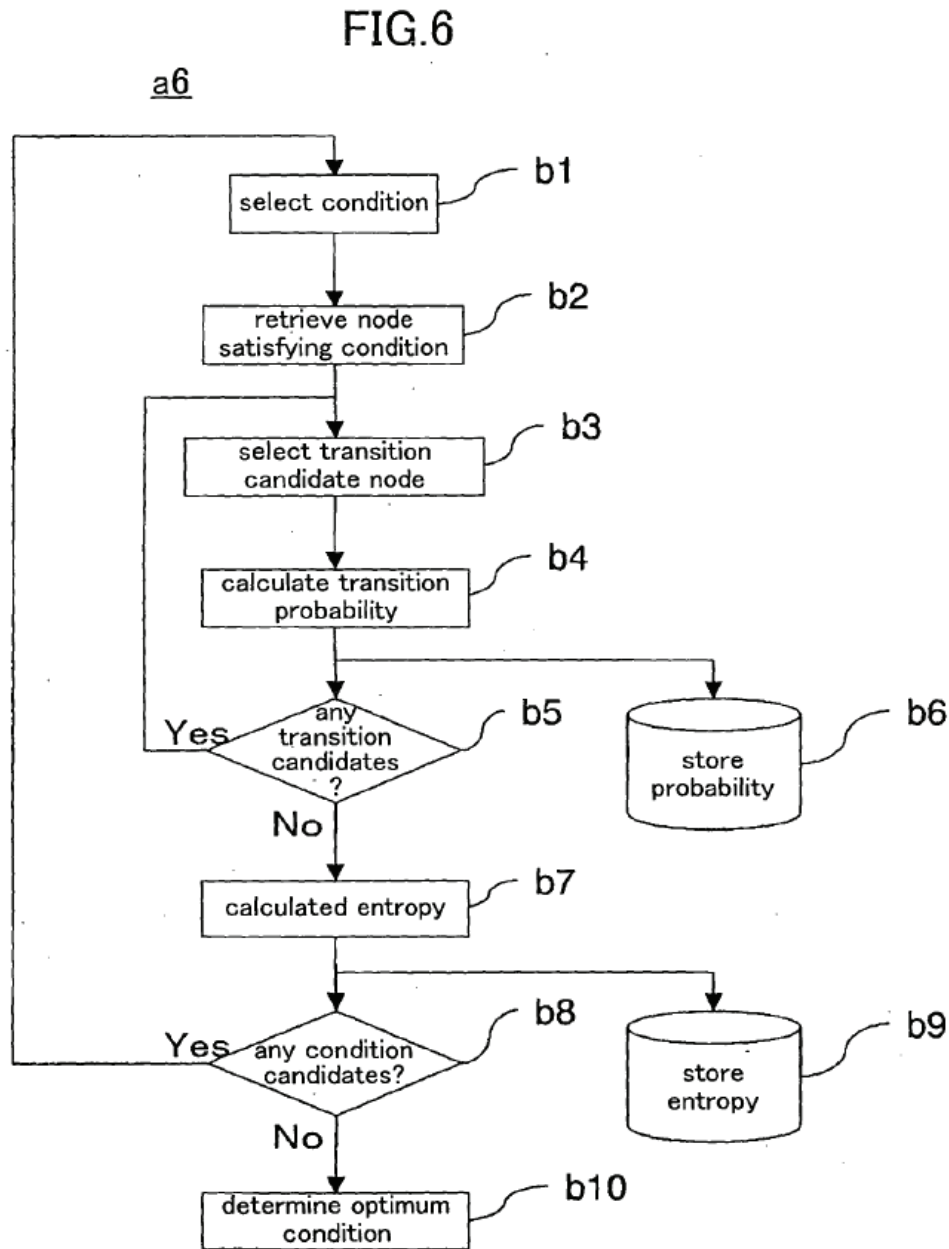
41. An entropy for that transition probability is then calculated. *See id.*, [0101], blocks b7-b9 of FIG. 6. For instance, the following expression indicates an “example of the entropy calculation method where a probability of a travel toward one Li of destinations where the driver has been in the past is Pi under a given condition.” *Id.*, [0101].

$$\sum P_i(-\log_2 P_i)$$

42. “[T]he same operation is repeated” for other combinations of the identified conditions (*e.g.*, “weekday and C9 and afternoon,” “weekday and ‘L6 to C9’ and summer”) to calculate additional probabilities for possible destination nodes and corresponding entropies. *Id.*, [0102]; *see* block b8 of FIG. 6. After all entropy calculations have been carried out, the set of combinations corresponding to the smallest entropy value is “determined as an optimum condition for retrieval,” *e.g.*,

“a kind and a category of a key used for retrieval of the travel history” is identified.

Id., [0103]; see block b10 of FIG. 6.



Excerpt from Kudo-325, FIG. 6

43. A “prediction section 108, purple in FIG. 1 above, “performs retrieval under the condition for retrieval” to “predict[] a travel destination where the automobile will advance based on the retrieval result.” *Id.*, [0104]. Specifically, the transition state information (*e.g.*, as illustrated in FIG. 5) is referenced to identify a “future transition destination node.” *Id.*; *see* block a7 of FIG. 4. The node can be identified in various ways, such as by “selecting the node having the highest prediction probability,” “selecting all nodes having probability values exceeding a predetermined value,” or “selecting a given number of nodes in order from the node having the highest probability value.” *Id.*.

44. Once the destination has been predicted, information related to the predicted destination node, such as “the name and other materials of the predicted node, and information relating to the estimate necessary time and the estimated arrival time.” TESLA-1004 (Kudo-325), [0106]; *see* elements 110 and 111 of FIG. 1 and blocks a8-a9 of FIG. 4. This information “may be acquired via a network.” *Id.*, [0107]. For instance, “information indicating a predicted travel destination or travel route is uploaded to a server on the network from the car navigation system, the relating information is selected by the server, and then, only information selected in the server is received by the car navigation system.” *Id.*.

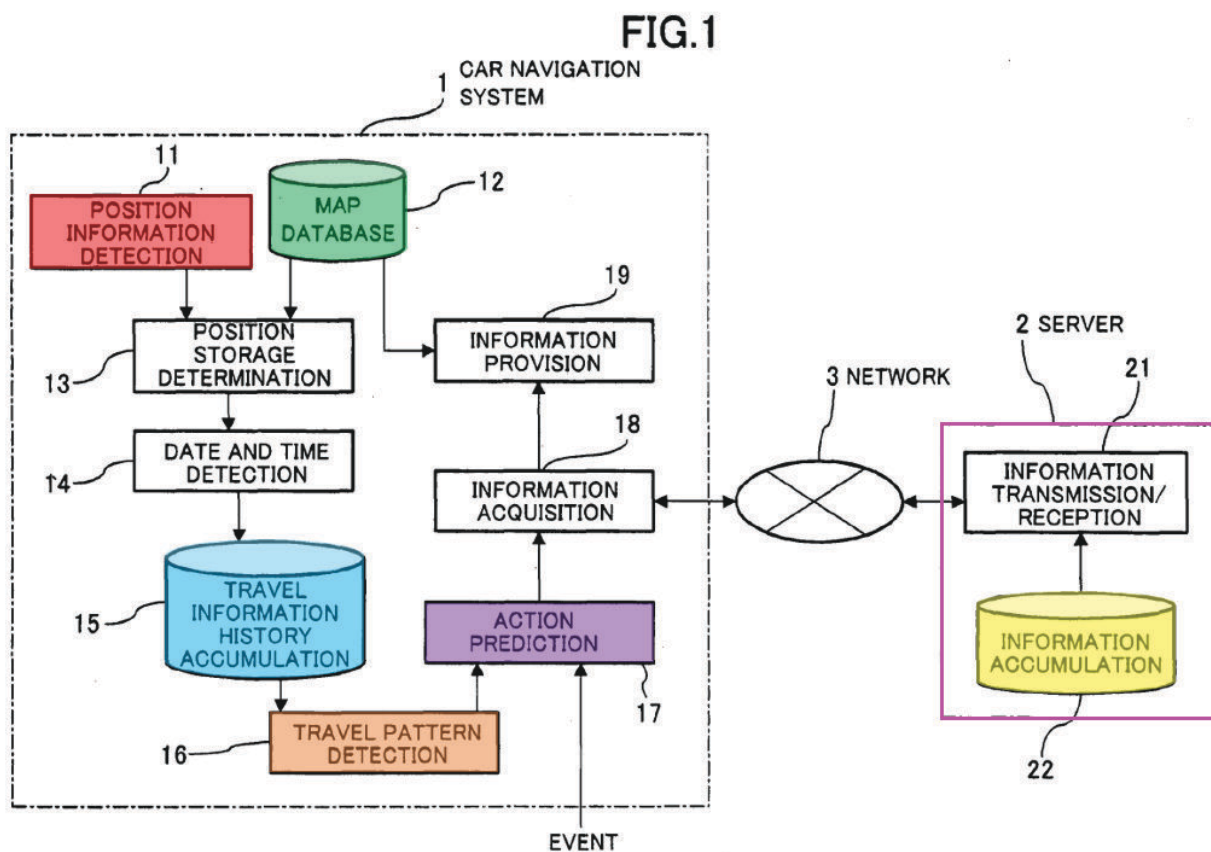
45. Kudo-325 is analogous art to the ’002 Patent. It is from the same field of endeavor (*e.g.*, vehicle navigation). *See* TESLA-1005 (Kudo-325), [0001]

(“The present invention relates to a technology for predicting a travel destination ... and acquiring information relating to the predicted travel destination”). And, it is reasonably pertinent to the problem the ’002 Patent was trying to solve (*e.g.*, assisting with vehicle operation along a route). *See id.*, [0015] (“the present invention provides [] an information presenting method for presenting information relating to a destination of a mobile body”), [0016] (“According to the present invention, prediction of a destination of a mobile body can be performed more accurately than the conventional one and appropriate information can be acquired, with a result of more appropriate information presentation to a user”).

2. Overview of Kudo-066

46. Like Kudo-325, Kudo-066 relates to “predicting a destination of a user based on a stored action pattern of the user.” TESLA-1005 (Kudo-066), [0061]. Referring to FIG. 1, which I have reproduced and annotated below, Kudo-066 describes a car navigation system that includes a “position information detection means [11, highlighted in red] for detecting information regarding the current position of the user’s vehicle by using a GPS, for example.” *Id.*, [0063]. Similar to Kudo-325’s process, each current vehicle position is stored in a travel information history accumulation means (highlighted in blue) if “the detected current position is a node,” *e.g.*, as determined based on a “map database [12, highlighted in green] for storing map information.” *Id.* A “travel pattern detection means [16,

highlighted in orange] ... detect[s] a chronological travel pattern based on information on the position and the date and time (travel information) stored in the travel information history accumulation means 15,” and an “action prediction means [17, highlighted in purple] ... predict[s] a destination of the user’s vehicle based on the travel pattern.” *Id.*.



Kudo-066, FIG. 1 (annotated)

47. Again consistent with the approach described by Kudo-325, Kudo-066’s map database stores “ID numbers allocated to the respective nodes ... to-

gether with information on the types of nodes and information on latitude and longitude.” TESLA-1005 (Kudo-066), [0065]; *see* FIG. 2, reproduced below. Kudo-066 describes that the map database can be “provided in the car navigation system 1,” or that “[a]lternatively, information on the node ID numbers ... may be stored in the server 2,” outlined in pink in FIG. 1 above. *Id.*, [0068]. In the latter case, “when receiving position information such as latitude and longitude from the car navigation system 1, the server notifies the car navigation system 1 of the associated node ID number.” *Id.*

FIG.2

12

NODE NUMBER	TYPE	EAST LONGITUDE	NORTH LATITUDE
N1	INTERSECTION	135° 20' 35"	34° 44' 35"
N2	INTERSECTION	135° 24' 35"	34° 44' 86"
N3	INTERSECTION	135° 22' 06"	34° 44' 78"
N4	INTERSECTION	135° 22' 10"	34° 45' 60"
N5	INTERSECTION	135° 22' 20"	34° 46' 79"
N6	INTERSECTION	135° 20' 42"	34° 46' 70"
N7	INTERSECTION	135° 22' 35"	34° 47' 35"
.	.	.	.
N123	LANDMARK (HOME)	135° 19' 48"	34° 42' 38"
N124	LANDMARK (OFFICE)	135° 30' 22"	34° 12' 23"
.	.	.	.
N427	AREA (UMEDA KITA)	135° 29' 51"	34° 41' 57"
N428		135° 46' 18"	34° 44' 30"

Kudo-066, FIG. 2 (annotated)

48. Kudo-066's server also stores, in an "information accumulation means 22" (yellow in FIG. 1, above), "position-related information," such as "the names and positions of information providers and information that the providers want to provide." TESLA-1005 (Kudo-066), [0092]. This information can be commercial information (*e.g.*, a notification that "all products are 20% off today" from the merchant "Sato Shop"). *Id.*, [0093]; *see* [0105]. Other information stored in Kudo-066's server-based information accumulation means includes "traffic information "traffic information indicating a traffic jam or information on traffic control by the police," which similarly is provided to the car navigation system when relevant to the vehicle's predicted destination. *Id.*, [0105]. When the predicted destination of the vehicle is determined, that predicted destination is transmitted to the server, and "the information transmission/reception means 21 in the server 2 receives the position information" and searches "information accumulated in the information accumulation means 222 ... so as to find information regarding the received position information," *e.g.*, commercial or traffic information. *Id.*, [0091]. Information pertaining to the vehicle's predicted destination "is transmitted ... to the car navigation system," *e.g.*, for display to the driver. *Id.*, [0094].

49. Kudo-325 is analogous art to the '002 Patent. It is from the same field of endeavor (*e.g.*, vehicle navigation). *See* TESLA-1006 (Kudo-066), [0001]

(“The present invention relates to a technology for providing users with information by using information equipment capable of detecting position information such as car navigation systems”). And, it is reasonably pertinent to the problem the ’002 Patent was trying to solve (*e.g.*, assisting with vehicle operation along a route). *See id.*, [0009] (“an object of the present invention is to enable accurate provision of information regarding the destination of the user without requiring the user to perform complicated operation”).

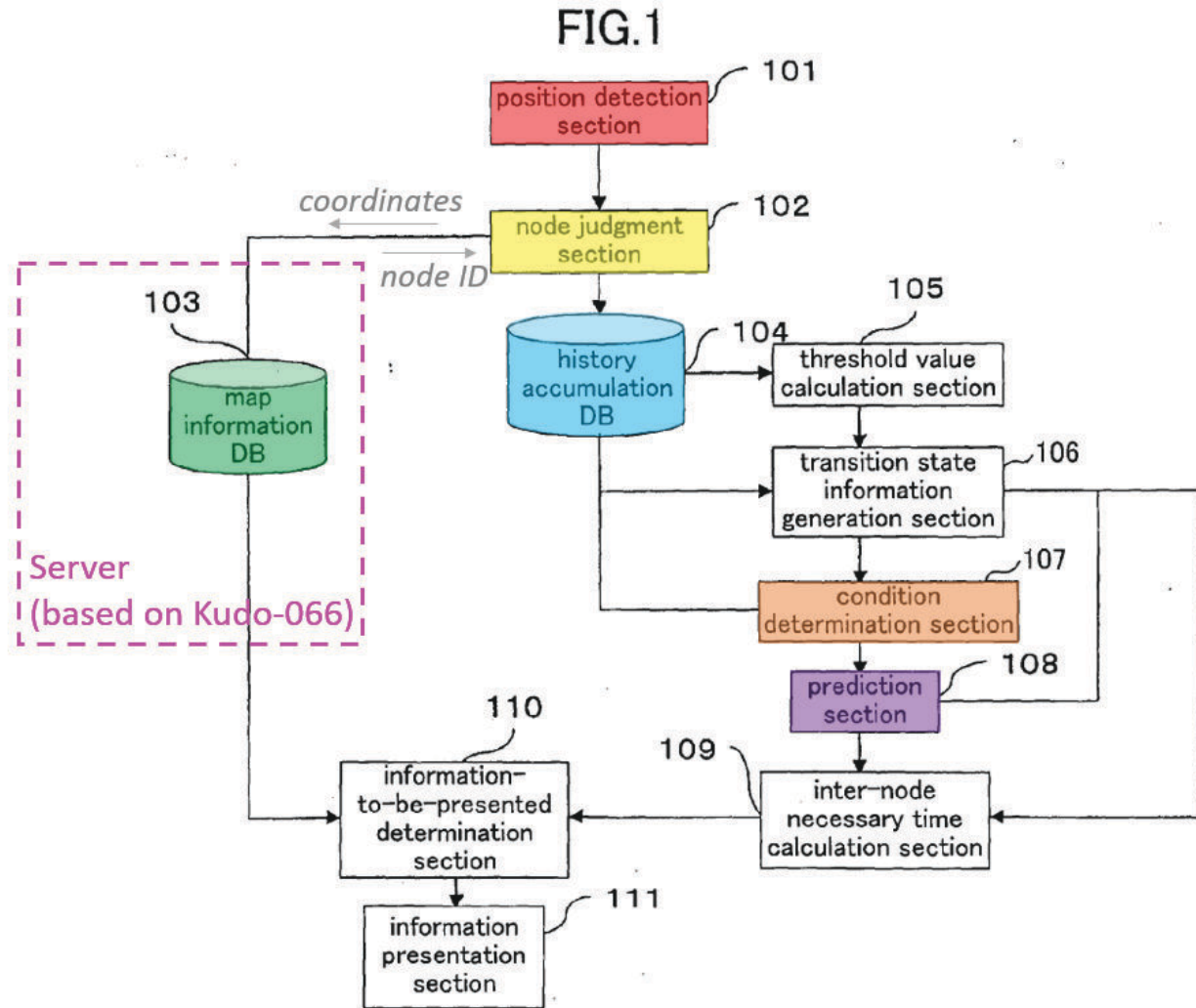
3. Combination of Kudo-325 and Kudo-066

50. As I discuss in more detail below, Kudo-325 generally describes an approach to analyzing sensor data samples stored in memory to detect a pattern characterizing a current trip of a vehicle, and using this pattern in conjunction with historical data gathered from a driver’s operation of the vehicle during multiple, past trips to predict the driver’s destination. It is my opinion that the claims are obvious in view of Kudo-325 in combination with Kudo-066, which describes a specific implementation of a destination prediction system in which the relied-upon sensor data samples constitute telemetry data, *e.g.*, location data determined by GPS.

Destination prediction in the Kudo-325/Kudo-066 combination

51. The composite figure below (based on Kudo-325’s FIG. 1, and modified based on teachings of Kudo-066) illustrates an example of a system based on

the combination of Kudo-325 and Kudo-066. In this combination system, “the current position of the car navigation system is detected” by a “position detection section 101” (highlighted in red) of a car navigation system, according to the operation of the system described by Kudo-325. TESLA-1004 (Kudo-325), [0090]. For instance, in a specific example, the position detection system can be implemented “by using ... a GPS,” as taught by Kudo-066. TESLA-1005 (Kudo-066), [0071].



Kudo-325/Kudo-066 Composite Figure based on Kudo-325, FIG. 1

52. A node judgment section (highlighted in yellow) determines “whether the current position is a node or not” by accessing a map information database, again consistent with the operation of Kudo-325’s system. TESLA-1004 (Kudo-325), [0090]. I note that Kudo-325 does not specify the location of the map information database, although it does provide the following general statement regarding the implementation of its system: “a part of the functions that a car navigation

system has may be provided in a server on a network.” TESLA-1004 (Kudo-325), [0075].

53. Kudo-066—which I previously addressed, and which describes a car navigation system that has similar architecture and function to that of Kudo-325’s car navigation system—provides some of these implementation details that are not explicitly stated in Kudo-325. For instance, Kudo-066 describes that a map database can be stored at a server. *See* TESLA-1005 (Kudo-066), [0065]. Based on this teaching of Kudo-066, it is my opinion that a POSITA would have (at least in some cases) implemented the map database in the Kudo-325/Kudo-066 combination to be housed at a server. This configuration is illustrated in the composite figure above, with the server outlined in pink and the server-based map database highlighted in green.³ The map database itself stores data as taught by Kudo-325, and importantly, as consistent with the structure of Kudo-066’s map database: for instance, it stores node ID numbers “together with information indicating the positions such as latitude/longitude information of representative points.” TESLA-

³ The implementation of the map database at the server is optional; in some implementations, the map database can alternatively be implemented locally, at the vehicle. For compact discussion, though, I have illustrated the map database at the server in the composite figures I present in this document.

1004 (Kudo-325), [0081]-[0082], FIG. 2; *see* TESLA-1005 (Kudo-066), [0065], FIG. 2.

54. In the Kudo-325/Kudo-066 combination car navigation system, “position information such as latitude and longitude” that is detected by the position detection section (*e.g.*, by GPS, as taught by Kudo-066) is provided to the server (*e.g.*, as indicated by the gray arrow labeled “coordinates” in the composite figure above). TESLA-1005 (Kudo-066), [0068]; TESLA-1004 (Kudo-325), [0090]. The server accesses the map database (housed at the server, as taught by Kudo-066) to determine “whether the current position is a node or not.” TESLA-1005 (Kudo-066), [0068]; TESLA-1004 (Kudo-325), [0090]. If the current position of the vehicle is determined to be a node, the server “notifies the car navigation system 1 of the associated node ID number” that corresponds to the current position (*e.g.*, as indicated by the gray arrow labeled “node ID” in the composite figure above). TESLA-1005 (Kudo-066), [0068].

55. Further aspects of the prediction process in the Kudo-325/Kudo-066 combination car navigation system are based on the functionality of Kudo-325’s system, which I discussed in Section V.A.1, above. Importantly, this functionality described by Kudo-325 for destination prediction is also generally consistent with the approach to destination prediction described by Kudo-066, which I discussed in

Section V.B.1, above. Specifically, in the combination system, if the current position of the vehicle is determined to a node, the ID number of the node (received from the server, as I discussed in the previous paragraph) is “accumulated in [a] history accumulation DB,” highlighted in blue in the figure above. TESLA-1004 (Kudo-325), [0090]; *see* [0087], FIG. 3; TESLA-1005 (Kudo-066), [0072]-[0073], FIG. 4. Other information such as “time, date, weather, and the like” is also accumulated in the history accumulation DB in conjunction with the stored node IDs. TESLA-1004 (Kudo-325), [0090]; *see* [0087], FIG. 3; TESLA-1005 (Kudo-066), [0072]-[0073], FIG. 4. The condition determination and prediction sections (highlighted in orange and purple, respectively) then operate to predict the destination of the vehicle, as described by Kudo-325 (and again, consistent with the operation of Kudo-066’s system)—for instance, making the prediction based on current state information characterizing the current trip of the vehicle (such as current location, time, date, weather, driver, etc.), the travel history of the current trip of the vehicle, and information about previous trips of the vehicle. *See* TESLA-1004 (Kudo-325), [0079], [0096]; TESLA-1005 (Kudo-066), [0063].

Based on Kudo-066’s teachings, a POSITA would have been led to implement the map information database of Kudo-325 at a server

56. It is my opinion that a POSITA would have been motivated to house the map information database of the Kudo-325/Kudo-066 combination system at a server, as taught by Kudo-066, for at least the following reasons.

57. The first reason why a POSITA would have been motivated to pursue this implementation is because this is just the application of known techniques (specifically, housing a map database at a server, as taught by Kudo-066) to an already-known system (specifically, Kudo-325's car navigation system). And, this combination of features produces predictable results (specifically, a car navigation system with a server-based map information database). In fact, as I have noted previously, Kudo-066 contemplates the use of a map database housed at server in the context of a system that is very similar to that of Kudo-325, thus demonstrating that housing map databases at servers was a known configuration for this type of system. (Indeed, the similarity of the two systems is not surprising given that they name overlapping sets of inventors.) This similarity, along with the predictability of the results, would have motivated a POSITA to implement the map database of the combination system at the server.

58. The second reason why a POSITA would have been motivated to house the map information database at a server is because of the accuracy advantages afforded by server-housed databases. Specifically, the accuracy of a map database that is housed at a server can be maintained more easily and efficiently than a map database housed locally on a vehicle. For instance, to update a map database housed locally on a vehicle to reflect new map information, *e.g.*, the addi-

tion of a traffic light as a new intersection node or a new shopping center construction as a new destination node, updated map information would have to be generated and then pushed out to update each vehicle's local database copy. By contrast, only a single update needs to be made to a central, server-housed map database that is accessible to multiple vehicles.

59. The ability to maintain accuracy in the server-housed map database is advantageous in the context of the destination prediction process under consideration here is because map information is provided on-demand during execution of the process. Having an accurate database (such as a server-housed database) minimizes the likelihood that a vehicle will use stale map information in its prediction process. With map databases housed locally on the vehicles themselves, if an update to the map information is delayed relative to execution of the destination prediction process, there is a risk that the destination prediction could proceed with outdated and potentially inaccurate map information. By contrast, by having a server provide map information on demand, the likelihood of the destination prediction process using stale map information is minimized. Additionally, having a server-housed map database reduces complexity, for instance, enabling the complexity of having to carefully coordinate the timing of a server pushing map up-

dates to a locally housed map database with the execution of the destination prediction process (the timing of which may depend on the proclivities of a given driver) may be avoided.

60. These advantages of a server-housed map database are compounded in circumstances where each vehicle of a fleet of vehicles implements a destination prediction process that relies on stored map information. Were each vehicle to retain its own, local copy of a map information database, the failure of any one of those vehicles to update its database could introduce version control issues arising from inconsistencies in the map database between vehicles of the fleet. These version control issues are obviated by housing the map information database at a server, such that consistent information is available to all vehicles in the fleet.

61. The third reason why a POSITA would have been motivated to implement a server-housed map database in the Kudo-325/Kudo-066 combination is that storing map information database at a server rather than locally at the vehicle can advantageously reduce per-vehicle local hardware costs. For instance, with a server-implemented map database, storage for the large amounts of data contained in the map information database does not need to be provided at each vehicle, but instead can be provided in only a single instance at the server.

62. The fourth reason why a POSITA would have been motivated to implement a server-housed map database in the Kudo-325/Kudo-066 combination is

because data storage at a server is one of a finite number of known solutions for data storage—namely, either local storage at the vehicles themselves or remote storage such as at a server. These two storage options are predictable, conventional, and well-understood, and thus a POSITA would have had a reasonable expectation of success in implementing the database at a server.

63. There are also several reasons why a POSITA would have expected success in applying Kudo-066’s teaching of a server-housed map information database to a car navigation system as disclosed by Kudo-325.

64. First, as I have noted previously, both Kudo-325 and Kudo-066 relate to, and indeed describe generally similar approaches to, predicting the destination of a vehicle based on current and historical information, and this similarity would have given the POSITA comfort that specific details described by Kudo-066 could be successfully incorporated into a system based on Kudo-325. *See* TESLA-1004 (Kudo-325), [0077], [0090]; TESLA-1005 (Kudo-066), [0063].

65. Second, implementing the map database at a server is consistent with Kudo-325’s indication that “a part of the functions that a car navigation system has may be provided in a server on a network,” and in fact, Kudo-325 even specifically states that “the node information may be stored on a network.” TESLA-1004 (Kudo-325), [0075], [0141]. Given Kudo-325’s comfort with the involvement of a

server in the destination prediction process, and specifically for storage of node-related information, a POSITA would have expected to be successful in implementing storage of the map database (which contains node-related information) on a server.

66. Third, a POSITA also would have expected success because implementation of the Kudo-325/Kudo-066 combination involves only commonly used techniques and devices: a server-based database.

67. Fourth, a POSITA would have expected success because housing a database on a server was conventional and predictable, and presents no unexpected results.

Based on Kudo-066's teachings, a POSITA would have been led to implement Kudo-325's vehicle position detection using GPS

68. It is my opinion that a POSITA would have been motivated to detect vehicle position in the Kudo-325/Kudo-066 combination using GPS, as taught by Kudo-066, for at least the following reasons.

69. The first reason why a POSITA would have been motivated to pursue this implementation is because it is just the application of known techniques (specifically, GPS detection of position in a car navigation system, as taught by Kudo-066) to an already-known system (specifically, Kudo-325's car navigation system). And, this combination of features produces predictable results (specifically, a car navigation system with GPS-based position detection). Importantly, while Kudo-

325's system detects vehicle position, Kudo-325 does not provide specific details regarding how to actually carry out this position detection. The similarity of the configurations of the car navigation systems of Kudo-325 and Kudo-066 (as I have previously discussed) would have motivated a POSITA to turn to the teachings of Kudo-066 for specific implementation details for position detection.

70. The second reason why a POSITA would have been motivated to implement vehicle position detection using GPS is because of the performance advantages offered by GPS systems. For instance, Van Buer describes that GPS position detection offers "accuracy and repeatability," and a POSITA would have recognized the advantages of accurately and repeatably detecting vehicle position, *e.g.*, in terms of providing accurate and reliable destination prediction. TESLA-1008 (Van Buer), [0016].

71. The third reason why a POSITA would have been motivated to implement GPS-based position detection in the Kudo-325/Kudo-066 combination is because GPS is one of a finite number of known solutions for position detection. Moreover, because it is a solution that is predictable, conventional, and well-understood, a POSITA would have had a reasonable expectation of success in implementing GPS for position detection.

72. There are also several reasons why a POSITA would have expected success in applying Kudo-066's teaching of GPS-based position detection to a car navigation system as disclosed by Kudo-325.

73. First, as I have noted previously, both Kudo-325 and Kudo-066 relate to, and indeed describe generally similar approaches to, predicting the destination of a vehicle based on current and historical information, and this similarity would have given the POSITA comfort that specific details described by Kudo-066 could be successfully incorporated into a system based on Kudo-325. *See* TESLA-1004 (Kudo-325), [0077], [0090]; TESLA-1005 (Kudo-066), [0063].

74. Second, a POSITA would have expected success because implementation of the Kudo-325/Kudo-066 combination involves only commonly used techniques and devices, such as integration of a GPS chip into a Kudo-325-based system.

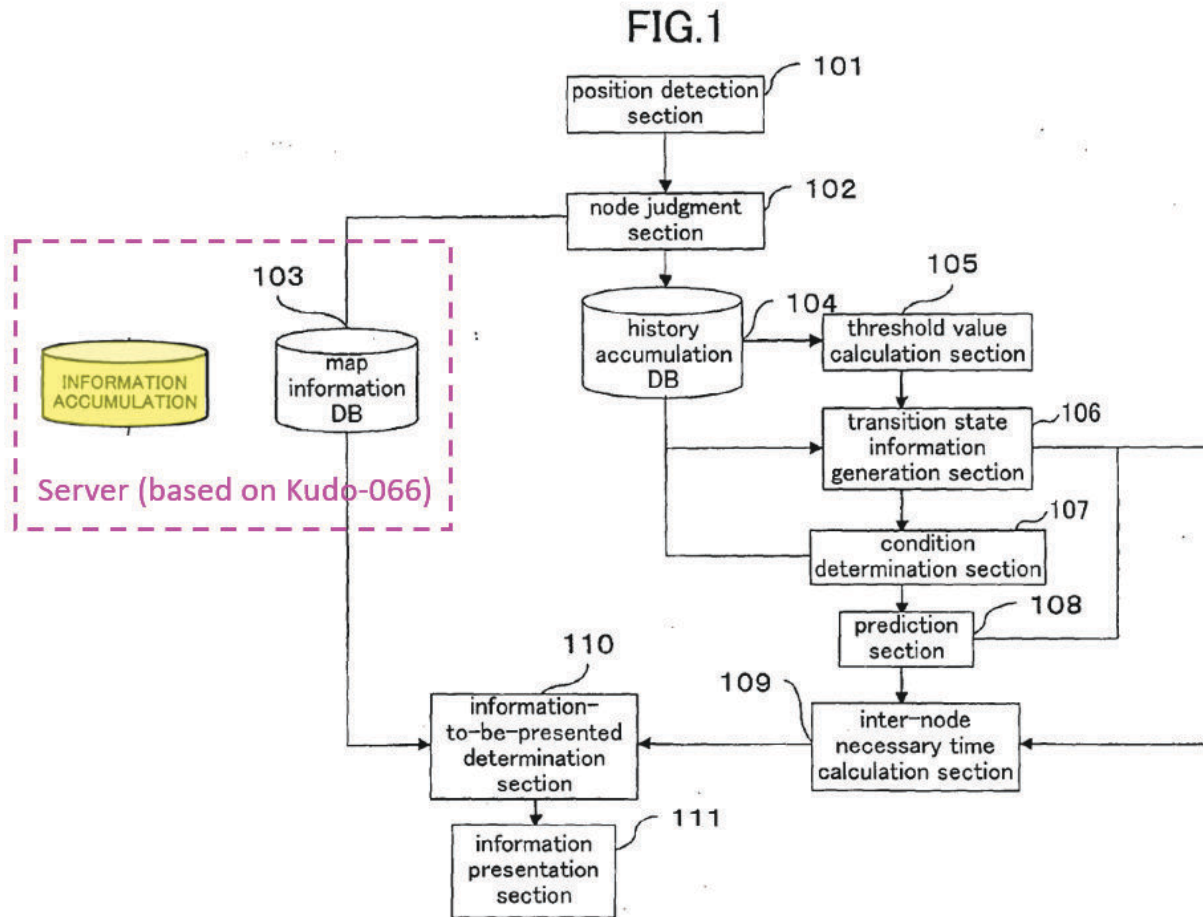
75. Third, a POSITA would have expected success because use of GPS for position detection was conventional and predictable, and presents no unexpected results.

Information relevant to predicted destinations is housed at the server in the Kudo-325/Kudo-066 combination

76. Kudo-325's car navigation system includes an "information-to-be-presented determination section" "that determines ... information to be presented to a user relating to the node predicted by the prediction section." TESLA-1004

(Kudo-325), [0080]; *see* [0067]-[0068], [0106], FIG. 1. Kudo-325 indicates that the function of this information-to-be-presented determination section can be performed, at least in part, remotely at a server: “information indicating a predicted travel destination or travel route is uploaded to a server on the network from the car navigation system, the relating information is selected by the server, and then, only information selected in the server is received by the car navigation system.” *Id.*, [0107].

77. Kudo-066 describes a similar feature: a “information accumulation means 22 for storing information to be transmitted to the car navigation system.” TESLA-1005 (Kudo-066), [0064]. And Kudo-066 is specific that this information accumulation means is housed at the server. Based on this teaching of Kudo-066, it is my opinion that a POSITA would have implemented the information accumulation means (highlighted in yellow in the composite figure below) at the server (outlined in pink) in the Kudo-325/Kudo-066 combination system.



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

78. In this combination system, as taught by Kudo-066, this server-housed information accumulation means stores information such as commercial information related to certain positions (*e.g.*, “the names and positions of information providers and information that the providers want to provide,” such as discount notifications for a shop) and/or traffic information (“information such as traffic information indicating a traffic jam or information on traffic control by the police”).

TESLA-1005 (Kudo-066), [0092]-[0093], [0150].

79. In operation, as taught by Kudo-325 (and consistent with the operation of Kudo-066's system), "information indicating a predicted travel destination or travel route is uploaded to a server on the network from the car navigation system," for instance, to obtain commercial or traffic information about the predicted destination. TESLA-1004 (Kudo-325), [0107]; *see* [0067]-[0068]. Then, "information relating to [the predicted] destination" "is selected by the server." *Id.*, [0107]. The data retrieval process that occurs at the server is implemented based on the more detailed description of Kudo-066's similar system: the server "receives the position information" and "information accumulated in the information accumulation means 22 is searched so as to find information regarding the received position information," such as commercial or traffic information. TESLA-1005 (Kudo-066), [0091]; *see* [0092]-[0093], [0095], [0150]. This "information selected in the server" is provided to the car navigation system for presentation to the user, *e.g.*, via the "information presentation section 111," as taught by Kudo-325 and still consistent with functionality of Kudo-066's similar system. TESLA-1004 (Kudo-325), [0106]-[0107]; *see* TESLA-1005 (Kudo-066), [0094].

80. It is my opinion that a POSITA would have been motivated to implement an information accumulation means at the server, as taught by Kudo-066, for at least the following reasons.

81. The first reason why a POSITA would have been motivated to pursue this implementation is because this is just the application of known techniques (specifically, storage of information relevant to destinations is at a server in the context of a car navigation system) to an already-known system (specifically, Kudo-325's car navigation system). And, this combination of features produces predictable results (specifically, a car navigation system in which information relevant to destinations is stored at a server). Importantly, while Kudo-325 describes the general concept of providing a predicted destination to a server and receiving, in response, information about that predicted destination (*see* TESLA-1004 (Kudo-325), [0107]), it does not provide specific implementation details regarding what goes on at the server to enable this functionality to be carried out. The similarity of the configurations of the car navigation systems of Kudo-325 and Kudo-066 (as I have previously discussed) would have motivated a POSITA to turn to the teachings of Kudo-066 for specific implementation details related to information storage at a server.

82. The second reason why a POSITA would have been motivated to implement an information accumulation means at the server is because a server-housed database can be updated in real time, for instance, to reflect changes in traffic conditions or to reference newly added commercial offers such as discounts. *See* TESLA-1005 (Kudo-066), [0093]-[0094], [0105]. The ability to effect real-

time updates helps to ensure that information provided to the vehicle about its predicted destination is accurate and reliable. Particularly in the context of traffic information, up-to-date information is critical for that information to be useful to the driver in making choices for an ongoing trip.

83. The third reason why a POSITA would have been motivated to implement an information accumulation means at the server in the Kudo-325/Kudo-066 combination is because data storage at a server is one of a finite number of known solutions for data storage—namely, either local storage at the vehicles themselves or remote storage such as at a server. These two storage options are predictable, conventional, and well-understood, and thus a POSITA would have had a reasonable expectation of success in implementing the database at a server.

84. There are also several reasons why a POSITA would have expected success in applying Kudo-066's teaching of a server-housed information accumulation means to a car navigation system as disclosed by Kudo-325.

85. First, as I have noted previously, both Kudo-325 and Kudo-066 relate to, and indeed describe generally similar approaches to, predicting the destination of a vehicle and providing the driver of the vehicle with information relevant to that destination. See TESLA-1004 (Kudo-325), [0107]; TESLA-1005 (Kudo-066), [0093]-[0094], [0105]. This similarity would have given the POSITA comfort that

specific details described by Kudo-066 could be successfully incorporated into a system based on Kudo-325.

86. Second, a POSITA would have expected success in implementing an information accumulation database at a server because this configuration is consistent with Kudo-325's teaching that "information indicating a predicted destination or travel route is uploaded to a server on the network from the car navigation system, the relating information is selected by the server, and then, only information selected in the server is received by the car navigation system." TESLA-1004 (Kudo-325), [0107].

87. Third, a POSITA also would have expected success because implementation of the Kudo-325/Kudo-066 combination involves only commonly used techniques and devices: a server-based database.

88. Fourth, a POSITA would have expected success because housing a database on a server was conventional and predictable, and presents no unexpected results.

4. Analysis

[1pre] *A power management device comprising:*

89. I note that none of the subsequent features of claim 1 refer to or otherwise rely on the "power management device" recited here in [1pre].

90. Nevertheless, it is my opinion that a POSITA would have found [1pre] to be obvious in view of the Kudo-325/Kudo-066 combination. For example, the “car navigation system” of the Kudo-325/Kudo-066 combination (red in the composite figure below) can be regarded as corresponding to ***a power management device***. This is the case at least because the car navigation system makes use of its predicted destination to determine whether a “necessary time” to travel to a predicted destination is “longer ... than the past average necessary time in the route predicted...” TESLA-1004 (Kudo-325), [0077], [0179]; *see* [0067]-[0068]. If the “necessary time” to reach the predicted destination is longer than the “past average necessary time,” then Kudo-325 discloses that a search is performed to identify another route having a “necessary time [that] is shorter than that of the predicted route.” *Id.* When a shorter (in time) route is identified, the information presentation section 111 of the combination car navigation system presents information relating to this different route to the user, which in turn allows the user to make decisions related to controlling operation of the vehicle. *Id.* The user’s operation of the vehicle—and in particular, their operation of the vehicle in response to the system’s automatic identification of alternate routes—can have an impact on the power consumption of the vehicle. For instance, the driver selecting and driving along an alternative route that gets the driver to their destination in a different

92. With reference to the composite figure above in element [1pre], the Kudo-325/Kudo-066 combination system is an “information acquisition system” that is configured to receive various types of sensor data samples during operation of a vehicle. TESLA-1004 (Kudo-325), [0077]; *see* FIG. 1. I discuss these sensor data samples below. I also explain below that a POSITA would have understood that a device that receives sensor data samples (namely, the “information acquisition system” of the combination, which receives sensor data samples) has *a sensor interface configured to receive sensor data samples*. TESLA-1004 (Kudo-325), [0077].

Position information corresponds to “sensor data samples”

93. In the Kudo-325/Kudo-066 combination car navigation system, position information that specifies the location of the vehicle, such as node ID numbers for the vehicle’s position, corresponds to *sensor data samples*.

94. The Kudo-325/Kudo-066 combination system includes “a position detection section that detects information on the current position of the car navigation system (the current position of an automobile as a mobile body on which the car navigation system is boarded).” TESLA-1004 (Kudo-325), [0077]; *see* [0090] (“When the current position of the car navigation system is detected in the position detection section 101”), FIG. 1 (element 101), FIG. 4 (step a1). In one example, the position information can include “latitude and longitude” that are detected “by

using, for example, a GPS,” based on the teachings of Kudo-066. TESLA-1005 (Kudo-066), [0071]; *see* [0063], Abstract. This “information on the current position” of the vehicle detected by the position detection system (*e.g.*, latitude/longitude coordinates of the vehicle’s position) uniquely corresponds to and represents a particular quantum of position information collected by a position sensor (*e.g.*, a GPS) at a particular time—for instance, at the time when the vehicle is located at the position identified by that set of GPS coordinates. TESLA-1004 (Kudo-325), [0077]; TESLA-1005 (Kudo-066), [0071].

95. This “position information such as latitude and longitude” detected by the position detection section is provided from the car navigation system to a map information database (*e.g.*, housed at a server, based on the teachings of Kudo-066 and as I explained above in Section V.A.3). *See* TESLA-1004, [0090]; TESLA-1005 (Kudo-066), [0068]. If it is determined that “the current position [is] a node,” the node ID is returned, for instance, the server “notifies the car navigation system 1 of the associated node ID number” for the current position. TESLA-1004 (Kudo-325), [0090]; TESLA-1005 (Kudo-066), [0068]; *see* TESLA-1004 (Kudo-325), [0090] (“If the node judgment system judges the current position to be a node, an ID number indicating the node is accumulated in the history accumulation DB”), [0141] (“the node information may be stored on a network”), [0078], [0138]. For instance, the server can determine that the current position is a node,

and if so, can then determine the node ID, based on the mapping between node ID and position information (such as latitude/longitude coordinates) stored in the map information database. *See* TESLA-1004 (Kudo-325), [0081]-[0082], [0090].

96. The server-based map information database, illustrated in Kudo-325's FIG. 2, which I have reproduced and annotated below, stores "information relating to nodes," where "each node number indicates an ID number assigned to a node in one-to-one correspondence," and where the node numbers are "stored together with information indicating the positions such as latitude/longitude information of representative points." *Id.*, [0082]; *see* [0084]. The node ID numbers for detected vehicle positions (when the vehicle position is at a node) correspond to ***sensor data samples***, at least because the node ID for a given node uniquely corresponds to and represents that same particular quantum of position sensor information as the latitude/longitude coordinates for that node. Indeed, the node ID is simply one convenient form for representing sensed vehicle position information in the context of the Kudo-325/Kudo-066 system: that is, the node ID is representative of the vehicle's position corresponding to a position that is identified by the map information database as a node. *See id.*, [0081]-[0084].

FIG.2

node number	kind/name	east longitude	north latitude
C1	intersection	135° 20' 35.45"	34° 44' 35.22"
C2	intersection	135° 24' 35.74"	34° 44' 86.5"
C3	intersection	135° 22' 6.22"	34° 44' 78.18"
C4	intersection	135° 22' 10.4"	34° 45' 60.75"
C5	intersection	135° 22' 20.0"	34° 46' 79.37"
C6	intersection	135° 20' 42.76"	34° 46' 70.48"
C7	intersection	135° 22' 35.39"	34° 47' 35.82"
.	.	.	.
L123	landmark (home)	135° 19' 48.42"	34° 42' 38.29"
L124	landmark (office)	135° 30' 22.33"	35° 12' 23.6"
.	.	.	.
A427	area (Umeda, North)	135° 29' 51.9"	34° 41' 57.0"
A428	area (Keihanna, Gakuentoshi)	135° 46' 18.80"	34° 44' 30.65"

node ID →

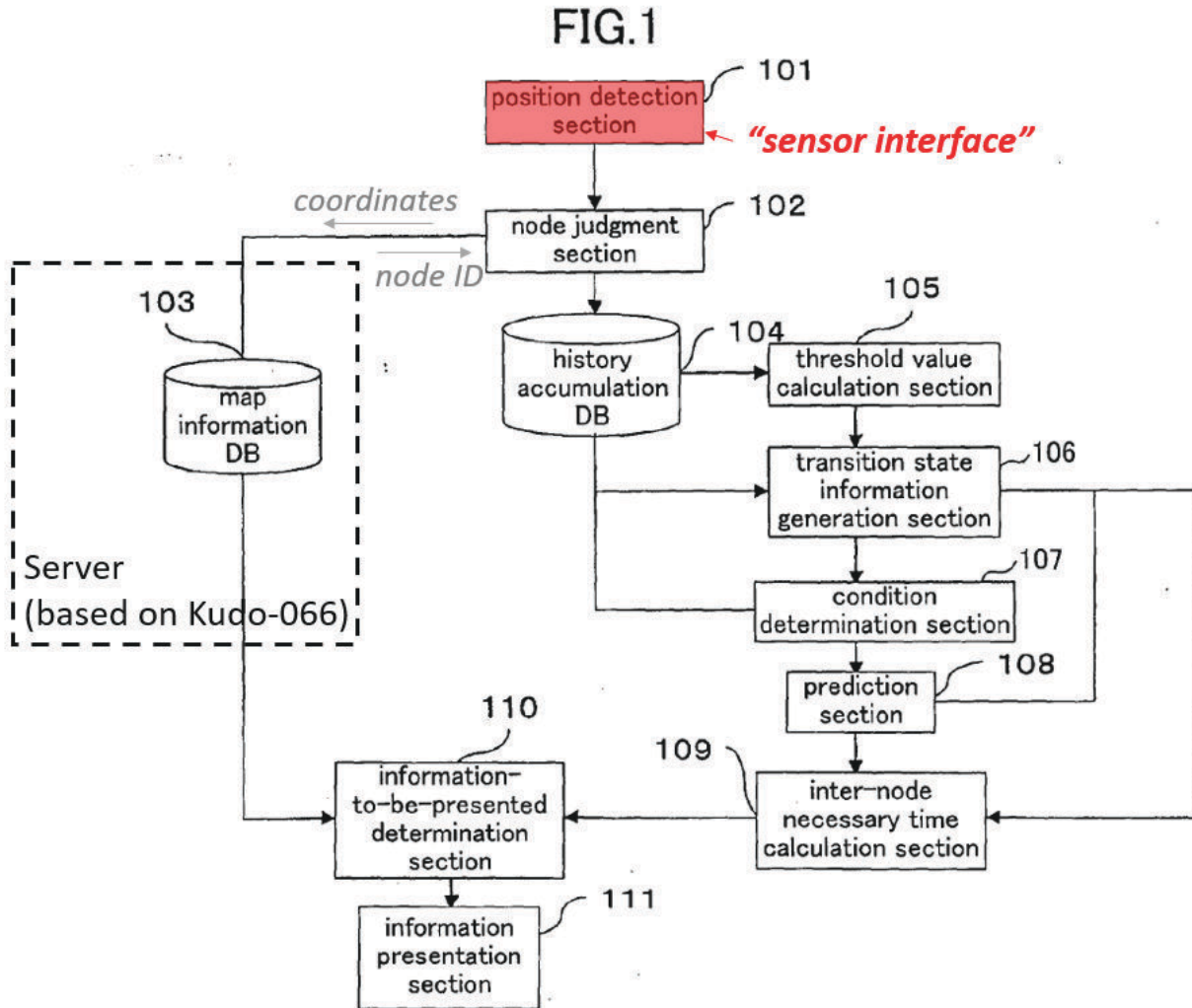
coordinates →

Excerpt from Kudo-325, FIG. 2 (annotated)

97. More generally, it is important to note that position information corresponding to the sensed vehicle position may be in any of a variety of forms while still, fundamentally, representing the sensed vehicle position data. For instance, the position information can be in a form that is readily decipherable to a human (such as latitude/longitude coordinates or node ID) or in a machine-readable form that is not readily decipherable to a human (e.g., a voltage, raw GPS data, binary code representation of the node ID). But regardless of the form of the data, that position information, when the vehicle is located at a node, corresponds to ***sensor data samples*** at least because each of these forms of information uniquely corresponds to and represents a quantum of detected position sensor information (e.g.,

the latitude/longitude coordinates and node ID for a given vehicle position each corresponds to discrete raw data detected by a position sensor) at a particular time. For instance, when the system's position detection system senses raw data indicating that the vehicle is currently located at the coordinates (135'22"35.39", 34'47"35.82") for a node, the raw data, the latitude/longitude coordinate pair, and the corresponding node ID (C7; highlighted in blue in FIG. 2, reproduced above) all uniquely correspond to and represent the same raw, sensed data sample for that node.

98. The Kudo-325/Kudo-066 combination car navigation system receives data samples representing current positions of the vehicle (*sensor data samples*, e.g., embodied as latitude/longitude coordinates) through operation of the "position detection section," red in the composite figure below, that "detects information on the current position of the car navigation system." See TESLA-1004 (Kudo-325), [0077], [0090]; TESLA-1005 (Kudo-066), [0063], [0071], Abstract. The position detection section thus corresponds to the claimed *sensor interface*.



Kudo-325/Kudo-066 Composite Figure based on Kudo-325, FIG. 1

99. These position sensor data samples sensed by the position detection section 101 of the combination system (e.g., raw data and/or latitude/longitude coordinates) are converted into the form of node IDs for more convenient processing and storage. Specifically, as I have already discussed, position sensor data samples (e.g., latitude/longitude coordinates) are provided to the server, and in response, the car navigation system receives corresponding node ID numbers (*sensor data samples*) from the server: “the server 2 notifies the car navigation system 1 of the

associated node ID number.” TESLA-1005 (Kudo-066), [0068]. As one example of the convenience facilitated by this process, the conversion of the position sensor data samples (*e.g.*, latitude/longitude coordinates) into node ID form enables multiple distinct but proximally close latitude/longitude measurements to be expressed as a single latitude/longitude value corresponding to a node ID, which thus facilitates storage of the position information and tracking/recording of the vehicle’s path. *See* TESLA-1004 (Kudo-325), [0082]-[0083].

100. The position detection section (red) of the combination car navigation system corresponds to a *sensor interface* at least because it receives data samples (latitude/longitude coordinates) conveying current positions of the vehicle. Those samples are then reformatted for ease of processing and storage as node IDs, which represent the same data samples. This is akin to a sensed analog signal being converted into a digital signal, where the digital signal’s value represents the magnitude of the sensed analog signal using finite precision based on the number of bits used to represent that magnitude. For example, an analog voltage signal might have a magnitude of 8.324569 V, which, when digitized is represented with the 3 binary digit number “100”, both the 8.324569 volts AND the “100” are different

forms of the same data sample, with the latter (reflecting a value of 8 V) being stored instead of the former to facilitate storage and further processing.⁴

101. Also in the Kudo-325/Kudo-066 combination car navigation system, position information (*sensor data samples*) are received *during operation of a vehicle*. For instance, Kudo-325 describes that “the current position of the car navigation system is detected,” *e.g.*, current position information such as latitude/longitude coordinates are received while the vehicle is located at that position. TESLA-1004 (Kudo-325), [0090]. Kudo-325 also describes that both position information of “the current position” and position information for the vehicle’s “travel history from departure” are recorded. *Id.*, [0096]; *see* FIG. 3 (showing information including “node numbers and times of passage therethrough [] stored chronologically,” *id.*, [0087]). The vehicle’s “travel history from departure” is simply the set of previous “current position[s]” of the vehicle since departure. TESLA-1004 (Kudo-325), [0096]. For instance, Kudo-325 provides the following example of travel history data, which include node IDs (*sensor data samples*): “the user departed from, passed through and stops at a node L6 at 8:05 a.m. on July 31, a node CS at

⁴ Notably, the ’002 Patent fails to provide any details as to how its sensed data samples are or are not further processed to change their form prior to storage and later processing.

8:06 a.m. on the same day, and a node C12 at 8:11 a.m. on the same day, respectively.” TESLA-1004 (Kudo-325), [0087]. A POSITA would have recognized that to record the travel history for a current trip (*e.g.*, the node IDs for multiple “current position[s]” during the trip), the position information (*sensor data samples*) would have been received as the vehicle travels its route (*received during operation of the vehicle*). TESLA-1004 (Kudo-325), [0096].

102. Alternatively or additionally, in order for the sensor interface of the vehicle’s information acquisition system to receive position information (*sensor data samples*), *e.g.*, through detection by the position detection system and/or from the server, the vehicle would have been powered on and thus in operation (*received during operation of the vehicle*).

103. Still alternatively or additionally, a POSITA would have found it obvious to use one or more software and/or hardware interfaces with the “information acquisition system” of the combination to facilitate receiving position sensor data samples during operation of a vehicle. Inclusion of such interfaces would have been routine in the art, and achieved with the use of only basic programming and/or computer architecture design skills. *See* TESLA-1018 (Pacheko), Abstract (“A notification system for reporting events occurring within a defined area being monitored thereby. The notification system includes a plurality of sensors installed at selected locations within the defined area and a sensor interface coupled to each

of the sensors. The sensor interface periodically polls the sensors and stores status information received therefrom. Coupled to the sensor interface is a computer system for receiving and analyzing the stored status data.”).

Time/date information corresponds to “sensor data samples”

104. Alternatively or additionally, each of time information and date information corresponds to ***sensor data samples***. Importantly, it is reasonable to identify time and date information as sensor data samples because this is consistent with what is described in the ’002 Patent. *See* TESLA-1001, 22:8-17 (“Sensors may be monitored (e.g., polled) in real-time, as described above. For instance, polling logic may coordinate continuous or periodic polling of Global Positioning System (GPS) information ..., speedometer information ..., date and time information (e.g., the date and time may be used to determine personal driving habits and sun angle), gyroscope information,” among other types of information.);

105. Specifically regarding time and date information in the Kudo-325/Kudo-066 combination, Kudo-325 describes that “information on time [and] date ... is accumulated” in the history accumulation database in combination” with position information. TESLA-1004 (Kudo-325), [0090]; *see* [0087] (“In the example of FIG. 3, pairs of the node numbers and times of passage therethrough are stored chronologically. For example, it indicates that the user departed from, passed through an stops at a node L6 at 8:05 a.m. on July 31, a node C8 at 8:06

a.m. on the same day, and a node C12 at 8:11 a.m. on the same day”), [0094], [0096], [0078], FIG. 3, FIG. 5.

106. Just as with position information, time and date information may be received in a form that is readily decipherable to a human or in a form that is not readily decipherable to a human (*e.g.*, raw data). Regardless of the particular form of the data, received time and date information correspond to ***sensor data samples*** at least because this information uniquely corresponds to and represents a quantum of detected sensor information (*e.g.*, time/date information).

107. Given Kudo-325’s description of storing and otherwise making use of stored time and data information, a POSITA would have understood the car navigation to have a ***sensor interface*** that is ***configured to receive*** time/date information (***sensor data samples***). *See* TESLA-1004 (Kudo-325), [0077]. An example of a sensor interface that can receive time/date information is a clock implemented in a vehicle-based computer.

108. Furthermore, time/date information (***sensor data samples***) are received ***during operation of a vehicle***. As I discussed earlier in this section for position information, both “the current position” of the vehicle as well as its “travel history from departure” are recorded. TESLA-1004 (Kudo-325), [0096]. As can be seen from FIG. 3, this position information (including current position and travel history for the current trip) is stored together with corresponding time/date

information. *See* TESLA-1004 (Kudo-325), [0087] (describing that FIG. 3 shows “node numbers and times of passage therethrough [] stored chronologically”). A POSITA would have understood, from this and related disclosure, that in order to record time/date information for both the current position and for the vehicle’s “travel history from departure,” the time/date information (*sensor data samples*) would have been received as the vehicle travels its route (*during operation of the vehicle*).

Driver identity information corresponds to “sensor data samples”

109. Driver identity information is another example of *sensor data samples* in the Kudo-325/Kudo-066 combination. The Kudo-325/Kudo-066 combination system includes “means for acquiring information for specifying a user such as a driver.” TESLA-1004 (Kudo-325), [0140]; *see* [0014], [0088]. Specifically, Kudo-325 describes that “[v]arious methods are considered as the method of acquiring information for specifying a user,” including “direct input by a user, acquisition of equipment ID, user information, or the like ..., judgment from a car key that stores information for specifying a driver, and person judgment from an on-board camera.” *Id.* This “information specifying a user” (*e.g.*, an image of a user captured by the “on-board camera”) uniquely corresponds to and represents a particular quantum of user identification sensor (*e.g.*, camera) information collected at a particular time. *Id.*

110. A POSITA would have understood that at least in some cases, this acquired “information for specifying a user” is processed to identify the driver. TESLA-1004 (Kudo-325), [0140]. For instance, a POSITA would have recognized that when “an on-board camera” is used, image processing algorithms are employed to perform “person judgment” to identify the driver from the image captured by the camera. TESLA-1004 (Kudo-325), [0140]; *see* [0088] (“information on ... a driver ... may be stored”), [0094] (“information on a driver ... may be recorded”), [0014]. An identifier of the driver, determined by processing the acquired “information for specifying a user” (*e.g.*, the image from the camera), corresponds to a *sensor data sample*, at least because a driver identifier uniquely corresponds to and represents that same particular quantum of user identification sensor information as the image from which the driver identity was determined. TESLA-1004 (Kudo-325), [0140]. Indeed, a driver identifier is simply one convenient form for representing the complex data of a captured image in the context of the Kudo-325/Kudo-066 system.

111. The “on-board camera” of the combination car navigation system corresponds to a *sensor interface* at least because it receives a data sample (an image of the driver) conveying driver identity. TESLA-1004 (Kudo-325), [0140]. That image sample is then reformatted for ease of processing and storage as a driver identifier, *e.g.*, by an algorithm capable of processing images to determine driver

identity, such that the driver identifier can be used for further processing, *e.g.*, for destination prediction, as described by Kudo-325.

112. Furthermore, a POSITA would have understood that to receive the aforementioned driver identity information (*receive sensor data samples*), *e.g.*, as the output of a processing algorithm such as an image recognition process, the vehicle would have been powered on (*during operation of a vehicle*).

113. A POSITA also would have recognized that driver identity information (*sensor data samples*) is received *during operation of a vehicle*, *e.g.*, because driver identity is used to generate destination predictions for a current vehicle trip (*during operation of the vehicle*). In the combination, Kudo-325 describes that driver identity information is relied upon to generate “appropriate prediction according to a user ... even in the case where a plurality of users use the same car navigation system,” *e.g.*, a prediction that is specific to the particular driver of the vehicle. TESLA-1004 (Kudo-325), [0140]. To generate a driver-specific prediction that is relevant to a particular trip, a POSITA would have recognized the importance of identifying the driver of that given trip at some point during that trip, *e.g.*, at the beginning of the trip or otherwise at a point during the trip in advance of generating a destination prediction (*during operation of the vehicle*). Indeed, identifying a driver was a common approach in route planning technology. *See* TESLA-1013 (Walters), 2:36-44 (describing that in the context of “a method and

device for implementing global positioning data to calculate estimated time en route and estimated time of arrival,” information including “driver identity, cartographic data, final destination, as well as several potential additional variables” are used as inputs); .

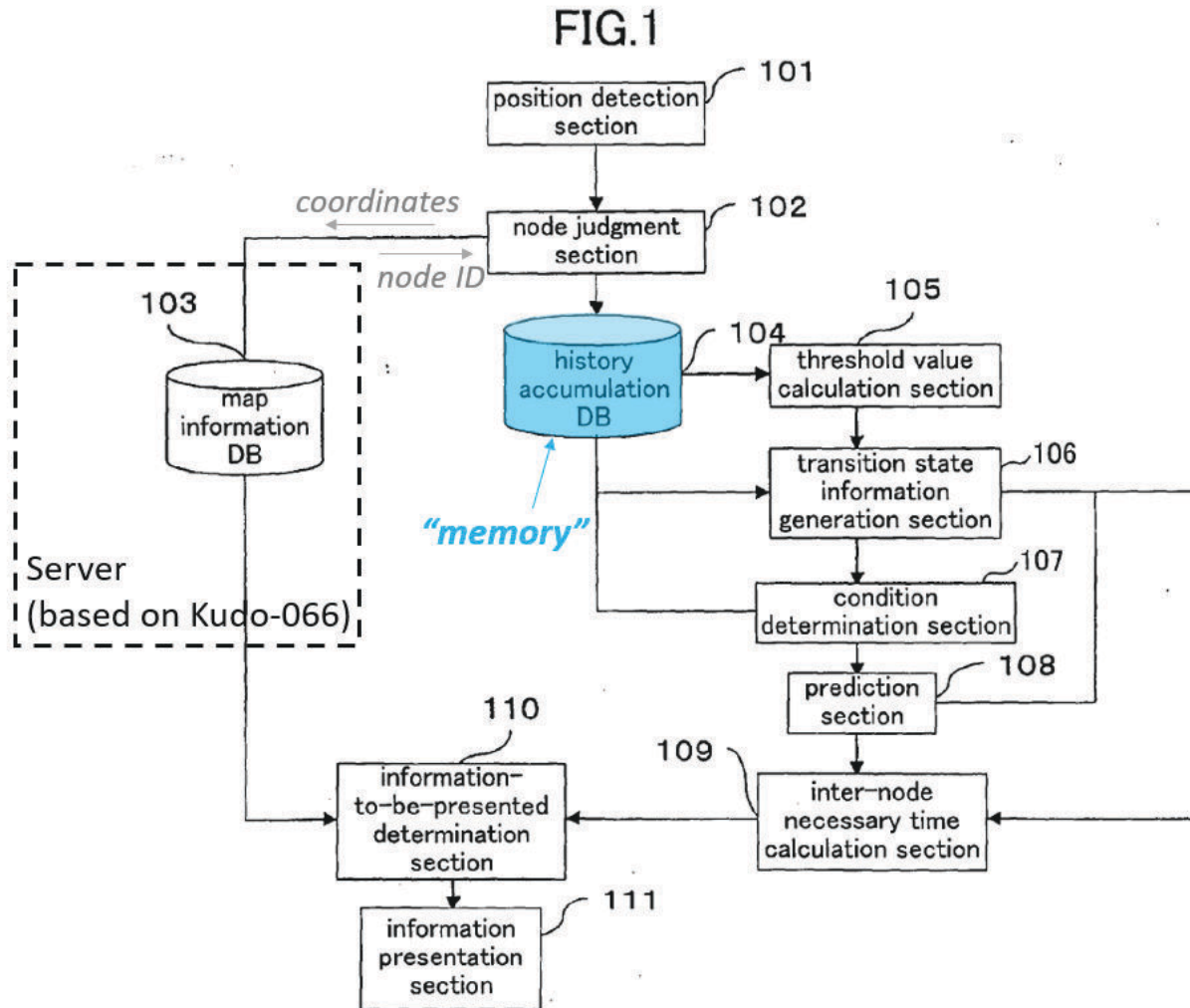
[1b] a memory configured to store said sensor data samples for different points in time along a route segment traveled by said vehicle; and

114. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1b], as I discuss in the following paragraphs.

115. For instance, the Kudo-325/Kudo-066 combination system includes “a history accumulation database (DB),” highlighted in blue in the composite figure below. TESLA-1004 (Kudo-325), [0078]. This database corresponds to *a memory*.⁵

⁵ Notably, the '002 Patent specifies that a database is an example of a memory: “the power management device may include a memory or a data structure that holds information on routes or segments or routes that the vehicle has previously traveled. The memory may comprise a database, a register, or the like.” TESLA-1001, 17:31-36;

116. Generally, in the combination, the history accumulation database (the *memory*) “accumulates a travel route obtained from a history of the position information of the automobile as a travel history,” which, as discussed below, corresponds to *storing said sensor data samples for different points in time along a route segment traveled by said vehicle*. TESLA-1004 (Kudo-325), [0078]; *see* [0013] (“accumulating, as a travel history, a travel route obtained from the history of position information of the mobile body”), [0017] (“a history accumulation section that accumulates, as a travel history, a travel route obtained from a history of position information of a mobile body”), [0057] (“the travel history is accumulated in a form of inter-node transition”), [0060] (“the travel history is accumulated in a form of segment of travel start and travel end”), [0051], [0072]-[0073].



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

The memory of the combination is configured to store position and time/date information (sensor data samples)

117. First, the history accumulation database of the combination (*memory*) stores position information such as node IDs (*configured to store sensor data samples*; see [1a]). For instance, Kudo-325 describes that if “the current position [is] a node, an ID number indicating the node is accumulated in the history accumulation

database.” TESLA-1004 (Kudo-325), [0090]; *see* [0078] (“when the current position is judged as a node ..., the node is stored”), [0087] (“pairs of the node numbers and times of passage therethrough are stored chronologically” in the history accumulation database), [0096] (“A field for storing information relating to the current travel is present in the history accumulation DB 104 ... so that a route from departure to the current node can be extracted”), [0013] (“accumulating, as a travel history, a travel route obtained from the history of position information of the mobile body”), [0017], [0051], [0057], [0060], [0072]-[0073], [0138], FIG. 4 (element a3 “accumulate history”).

118. Second, the history accumulation database (*memory*) stores time/date information (*configured to store sensor data samples*; *see* [1a]). For instance, Kudo-325 describes that “collateral information on time, date, weather, and the like is accumulated in combination” with the location information, *e.g.*, stored in the history accumulation database. TESLA-1004 (Kudo-325), [0090]; *see* [0087] (“pairs of the node numbers and times of passage therethrough are stored chronologically” in the history accumulation database), [0088] (“the time is expressed in terms of month, date, hour and minute in FIG. 3, but year, second, day of the week, and the like may be stored in addition ... the information relating to time and date ... may be stored”), [0014] (“the kind and the category of a key for retrieval from

the accumulated history are determined,” where “the kind of a key includes time, date, weather, a driver, a fellow passenger, and the like”), [0052],[0094].

119. The storing of node IDs and time/date information (*sensor data samples*) is depicted in FIG. 3, which I have reproduced and annotated below. FIG. 3 illustrates “one example of data accumulated in the history accumulation DB” in which “pairs of the node numbers and times of passage therethrough are stored chronologically.” TESLA-1004 (Kudo-325), [0087]; *see* [0096] (“A field for storing information relating to the current travel is present in the history accumulation DB”), [0057] (“the travel history is accumulated in a form of inter-node transition”).

*“sensor data samples for
different points in time”*

104

FIG.3

(a)

node number	time
L6	8:05 a.m. on July 31
C8	8:06 a.m. on July 31
C12	8:08 a.m. on July 31
C9	8:09 a.m. on July 31
C34	8:11 a.m. on July 31
.	.
L128	8:53 a.m. on July 31

node number	time
L128	12:25 p.m. on July 31
C140	12:29 p.m. on July 31
C125	12:36 p.m. on July 31
.	.
L68	1:33 p.m. on July 31

(b)

node number	time
L6	8:05 a.m. on July 31
C8	8:06 a.m. on July 31
C20	8:08 a.m. on July 31
L12	8:10 a.m. on July 31
L12	1:40 p.m. on July 31
C34	1:50 p.m. on July 31
.	.
L6	9:20 p.m. on July 31

Excerpt from Kudo-325, FIG. 3 (annotated)

120. The node IDs and time/date information (*sensor data samples*) are stored in the history accumulation database *for different points in time along a route segment traveled by the vehicle*, as discussed in the following paragraphs.

121. In the combination, Kudo-325 represents locations, such as “intersections, landmarks, area names, and the like,” as nodes, each of which is designated by “an ID number assigned to a node in a one-to-one correspondence.” TESLA-1004 (Kudo-325), [0081]-[0082]. During travel, the vehicle passes through a sequence of nodes. In a specific example provided by Kudo-325, “the user departed from, passed through ... a node L6 at 8:05 a.m. on July 31, a node C8 at 8:06 a.m. on the same day, and a node C12 at 8:11 a.m. on the same day.” TESLA-1004 (Kudo-325), [0087]; *see* [0096] (“the current position is a node ‘C9’; a travel history from departure is ‘L6 to C9’”), [0057], FIG. 3, FIG. 5. Based on Kudo-325’s disclosure, a POSITA would have understood that a path or route from one node to a next node in the vehicle’s trip corresponds to *a route segment traveled by the vehicle*.⁶ For instance, in the foregoing example, one route segment extends from node L6 to node C8 and another route segment extends from node C8 to node C12.

⁶ The ’002 Patent ascribes no specific meaning to the term “segment,” stating that “[a] segment may comprise any distance to be traveled, including the entire route, or small portions of the route.” TESLA-1001, 14:5-7;

122. In the combination, the node IDs and time/date information (*sensor data samples*) are stored in the history accumulation database *for different points in time along a route segment traveled by the vehicle*, e.g., for times at which the vehicle was located at the starting node and ending node, respectively, of each route segment traveled by the vehicle. See TESLA-1004 (Kudo-325), [0087] (“describing that in the history accumulation database, “pairs of the node numbers and times of passage therethrough are stored chronologically”), [0077] (“a history accumulation database (DB) that accumulates a travel route obtained from a history of the position information of the automobile), [0090] (“If the node judgment section 102 judges the current position to be a node, an ID number indicating the node is accumulated in the history accumulation DB ... At this time, collateral information on time, date, weather, and the like is accumulated in combination”), [0057].

123. I have highlighted in blue in FIG. 3, above, two representative entries in the history accumulation database. These two entries correspond to *sensor data samples* (e.g., node IDs and time/date information) *for different points in time* (e.g., 8:05 a.m. on July 31 for node L6 and 8:06 a.m. for node C8) *along a route segment traveled by the vehicle* (e.g., the route segment starting at node L6 and ending at node C8). See TESLA-1004 (Kudo-325), [0087].

The memory of the combination is configured to store driver identity information (sensor data samples)

124. The history accumulation database of the Kudo-325/Kudo-066 combination (***memory***) stores driver identity information (***store sensor data samples***; see my discussion above for element [1a]). For instance, Kudo-325 describes that “not only the information relating to time and date but also ... information on weather, a driver, or a fellow passenger may be stored.” TESLA-1004 (Kudo-325), [0088]; see [0094] (“Key information serving as a condition for retrieval, such as the aforementioned information on a driver and a fellow passenger may be recorded in addition”), [0014] (“the kind and the category of a key for retrieval from the accumulated history are determined,” where “the kind of a key includes time, date, weather, a driver, a fellow passenger, and the like”), [0140] (“means for acquiring information for specifying a user such as a driver ... may be provided ... for accumulating history accumulation data for each user”).

125. The driver identity information, together with position and/or time/date information (***sensor data samples***), are stored ***for different points in time along a route segment***. This is the case because at least one of the sensor data samples is stored for each of multiple points in time along a route segment. For instance, as I discussed earlier in this section, at least the position and time/date information are stored in the history accumulation database (***memory***) for the starting

and ending nodes of a segment (*for different points in time along a route segment*), while the driver identity is also stored in the history accumulation database (*memory*). TESLA-1004 (Kudo-325), [0077], [0087], [0090], [0096], FIG. 3, FIG. 5. That is, overall, there are sensor data samples stored for different points in time along a route segment, although not every type of sensor data sample is necessarily stored at every point in time—for instance, position and time/date information are stored for the start and end of each segment, while driver identity information may be stored once per trip or may be stored also for the start and end of each segment.

126. Optionally, based on Kudo-325’s description that “information on ... a driver” is stored in the history accumulation database,” a POSITA would have understood that this driver identity information is stored in conjunction with the node ID and time/date information in the history accumulation database (*for different points in time along a route segment*). TESLA-1004 (Kudo-325), [0088]. As I discussed above, Kudo-325 describes that “collateral information on time, date, weather, and the like is accumulated in combination” with a node ID when the vehicle’s current position is a node: that is, collateral information is stored together with the corresponding node ID. TESLA-1004 (Kudo-325), [0090]. This is illustrated in Kudo-325’s FIG. 3, which shows storage of node ID and time/date collateral information. *See* TESLA-1004 (Kudo-325), [0090], FIG. 3. Elsewhere,

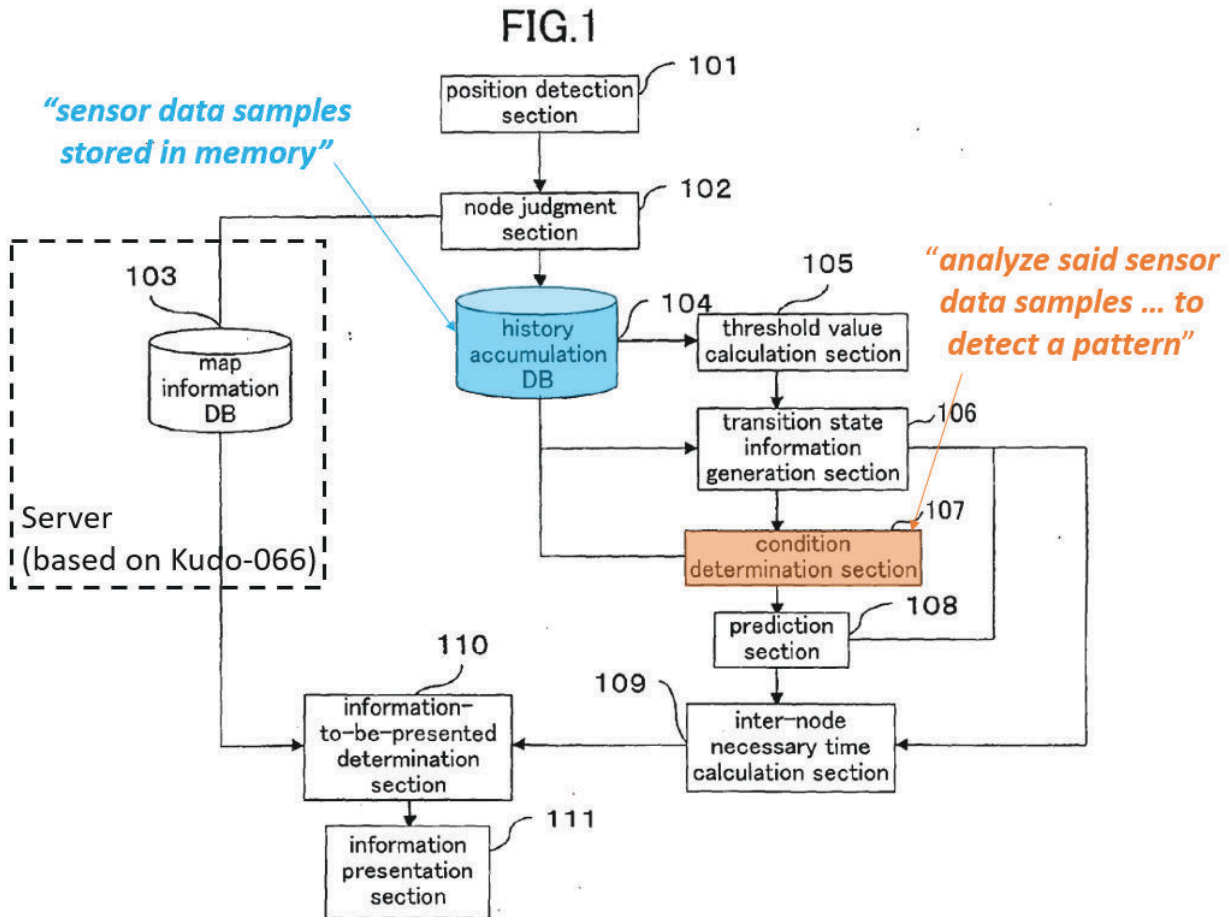
Kudo-325 indicates that driver identity is another example of such “collateral information” that is accumulated in combination with node ID, time, and date.

TESLA-1004 (Kudo-325), [0090]; *see* [0088] (“information on weather, a driver, or a fellow passenger may be stored”), [0094] (“In FIG. 5, the dates and times indicated in FIG. 3 are recorded as state information. Key information ... such as the aforementioned information on a driver and a fellow passenger may be recorded in addition. Also, the state information is recorded in some of the nodes in FIG. 5, but is recorded in all the nodes actually.”), [0014] (“the kind of a key includes time, date, weather, a driver, a fellow passenger, and the like”). Thus, a POSITA would expect driver information to be stored in a manner similar to the storage of other “collateral information” such as time/date, *e.g.*, along with the node ID for the starting node and ending node. *See* TESLA-1004 (Kudo-325), [0087], [0090], FIG. 3.

[1c-1] a processor configured to (i) analyze said sensor data samples stored in said memory to detect a pattern and

127. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1c-1], as I discuss in the following paragraphs. For instance, in the combination, at least some of the functionality of Kudo-325’s “condition determination section 107” corresponds to analyzing the sensor data samples stored in memory to detect a pattern.

128. In the combination, Kudo-325 describes that the condition determination section (orange in the composite figure below) “acquires information relating to the current state by referencing the history accumulation database” (memory; *see* my discussion above for element [1b]). TESLA-1004 (Kudo-325), [0096]; *see id.* (“A field for storing information relating to the current travel is present in the history accumulation DB 104”), [0051], [0072]. This acquired information includes information about the vehicle’s current trip, including “a route from departure to the current node,” position information (e.g., node ID), and time/date information (sensor data samples stored in memory; *see* my discussion above for elements [1a]-[1b]). *Id.*, [0096].



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

129. Also in the combination, Kudo-325 further describes that based on the “travel history from departure” and “date and time conditions” for the current trip (e.g., based on the information acquired from the history accumulation database

(*analyzing the sensor data samples stored in memory*)⁷), “any conditions (categories) such as ‘weekday,’ ‘afternoon,’ and ‘summer’ can be extracted by referencing tables as indicated in FIG. 28” (*detect a pattern*, e.g., a pattern of characteristics of vehicle travel, such as characteristics of the current trip). TESLA-1004 (Kudo-325), [0096]; *see* [0079] (“a condition determination section that determines a condition for retrieval for obtaining an appropriate prediction result from information indicating the current state accumulated in the history accumulation DB”), [0093] (“a node where the automobile travels in a period from 9 a.m. to 12 p.m. of weekday”), [0013] (“a second step of determining, as a condition for retrieval, a kind and a category of a key at retrieval from the travel history”), [0014] (identifying “morning,” “time between 6 a.m. and 10 a.m., and “time between 8 a.m. and 9:30 a.m.” as example conditions that can correspond to a current trip time of 8:30 a.m., and identifying “weekday” and “weekend” as example conditions that can correspond to a current trip date of “Friday”), [0136] (“information from start of the current travel to the current position is utilized as a condition in the present embodi-

⁷ As I discuss further from claim 5, in an alternative mapping, the act of acquiring, from the history accumulation database, the set of sensor data samples that are then used to determine the conditions can correspond to *detecting a pattern*.

ment, but other history information in a travel before the current travel (information relating to starting point, route, time and date, and the like) may be reference in addition”), [0017] (“a condition determination section that determines, as a condition for retrieval, a kind and a category of a key at retrieval from the travel history accumulated in the history accumulation section”), [0018], [0051]-[0052], [0072], [0110]-[0111], [0115]-[0120], [0127]-[0133], [0219], FIG. 28, block b1 of FIG. 5. As I discuss below for element [1c-2], the determined conditions for the current trip (*a pattern*) are used to interrogate a database of historical data to thereby predict the vehicle’s destination. *See* TESLA-1004 (Kudo-325), [0096]-[0104].

130. Determining the conditions for a current trip corresponds to *detecting a pattern*, *e.g.*, in that the determined conditions characterize aspects of the trip, such as location and time/date characteristics of the trip. *See* TESLA-1004 (Kudo-325), [0013]-[0014], [0051]-[0052], [0096]-[0097], [0102]. Moreover, these conditions are determined (*detect a pattern*) by identifying conditions that correspond to the information about the current trip that is acquired from the history accumulation database, *e.g.*, by *analyzing the sensor data samples stored in said memory*.

131. Kudo-325 provides a specific example of determining conditions (*detecting a pattern*) for a hypothetical current trip (*analyzing sensor data samples stored in memory*) for a current trip. In this example, “the current position is a

node ‘C9’; a travel history from departure is ‘L6 to C9’; and the date and time is 2 a.m. on June 3” (*sensor data samples stored in memory*). TESLA-1004 (Kudo-325), [0096]; *see* [0115]. Based on this information (*analyzing the sensor data samples*), a combination of conditions are determined that characterize the current trip (*detecting a pattern*), *e.g.*, the pattern includes the combination of the conditions “weekday,” “afternoon,” “summer,” “C9,” and “L6 to C9.” TESLA-1004 (Kudo-325), [0096]-[0097], [0102].

132. Kudo-325 also describes that “information on a driver” (*sensor data samples stored in memory*) can be “[k]ey information serving as a condition for retrieval” (*detect a pattern*), *e.g.*, in addition to position and time/date information. TESLA-1004 (Kudo-325), [0094]; *see* [0088] (“not only the information relating to time and date but also information relating to a key serving as a condition for retrieval to be determined by the condition section 107, such as information on weather, a driver, or a fellow passenger”), [0014] (“the kind of key [for retrieval of conditions] includes time, date, weather, a fellow passenger, and the like”). Based on this described role of driver information, a POSITA would have understood that one or more conditions are determined (*detect a pattern*) that correspond to driver identity information stored in the history accumulation database (*analyzing sensor data samples stored in memory*). *See* TESLA-1004 (Kudo-325), [0079], [0093],

[0096], block b1 of FIG. 5. Indeed, Kudo-325 provides specific examples of conditions that can be determined based on driver identity information: “user of Santos,” “person at age of exceeding 25,” and “father.” TESLA-1004 (Kudo-325), [0014]. As for conditions related to position and time/date, which I discussed above, the determined conditions related to driver identity are used in predicting the vehicle’s destination. *See* TESLA-1004 (Kudo-325), [0014], [0088], [0094], [0140].

133. A POSITA would have understood that the analysis of Kudo-325’s trip information to determine the conditions is performed by *a processor*. Specifically, Kudo-325 describes that its approach to destination prediction (which involves “an information acquisition system” that, among other functions, analyzes stored trip information to determine conditions; *see* TESLA-1004 (Kudo-325), [0077]) is implemented by a computer: “the present invention is a program for allowing a computer ... to execute an information acquisition method according to the present invention.” TESLA-1004 (Kudo-325), [0019]; *see* [0074]-[0075] (“a program for allowing a computer that at least one of information equipment and a server includes to execute the information acquisition method of the first aspect”), claim 24. It was well-known that computers contained processors, and moreover that analysis of data to detect patterns was a standard function of processors. *See* TESLA-1014 (Giras), [0012] (describing a vehicle navigator system including “a

pattern recognition analyzer”), TESLA-1015 (Tkachenko), [0089] (describing a “processor unit 411 [that] uses known pattern recognition algorithms to recognize and identify roads” in the context of methods for determining traffic information). Thus, in light of the conventional nature of processors, a POSITA would have recognized that Kudo-325’s computer implementing its “information acquisition method” corresponds to *a processor* implementing this information acquisition method, including analyzing stored trip information to determine conditions(*analysis of sensor data samples to detect a pattern*).

[1c-2] (ii) predict a destination of a driver in response to (a) said pattern and (b) historical data associated with operation of said vehicle,

134. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1c-2], as I discuss in the following paragraphs.

Kudo-325’s travel history corresponds to “historical data”

135. In the combination, a history accumulation database stores “a travel route obtained from a history of the position information of the automobile as a travel history.” TESLA-1004 (Kudo-325), [0078]. The travel history stored in the history accumulation database corresponds to *historical data associated with operation of the vehicle*, e.g., in that these data characterize past spatial and temporal positions of the vehicle (e.g., node IDs and time/date information for previous trips of the vehicle). For instance, the data in the history accumulation database include

“pairs of node numbers and times of passage therethrough are stored chronologically.” TESLA-1004 (Kudo-325), [0087]; *see* [0087] (“The node series may be accumulated on per segment basis according to a starting point and a destination ... or may be accumulated in a segment unit of ‘segment from departure from home to going back home’”), [0087] (“Accumulation of a travel history by segment from travel start to travel end enables prediction of a travel destination based on detailed route information”), [0096] (“A field for storing information relating to the current travel is present in the history accumulation DB 104 in addition to a field for storing the past history information”), [0013], [0017], [0051], [0072], [0091]-[0092], FIG. 3. Kudo-325 also describes that “not only the information relating to time and date but also “information on weather, a driver, or a fellow passenger may be stored” in the history accumulation database. TESLA-1004 (Kudo-325), [0088]; *see* [0014], [0052]. This weather, driver, or passenger information also corresponds to *historical data associated with operation of the vehicle*, *e.g.*, in that it characterizes the weather, driver, and/or passenger during past trips of the vehicle.

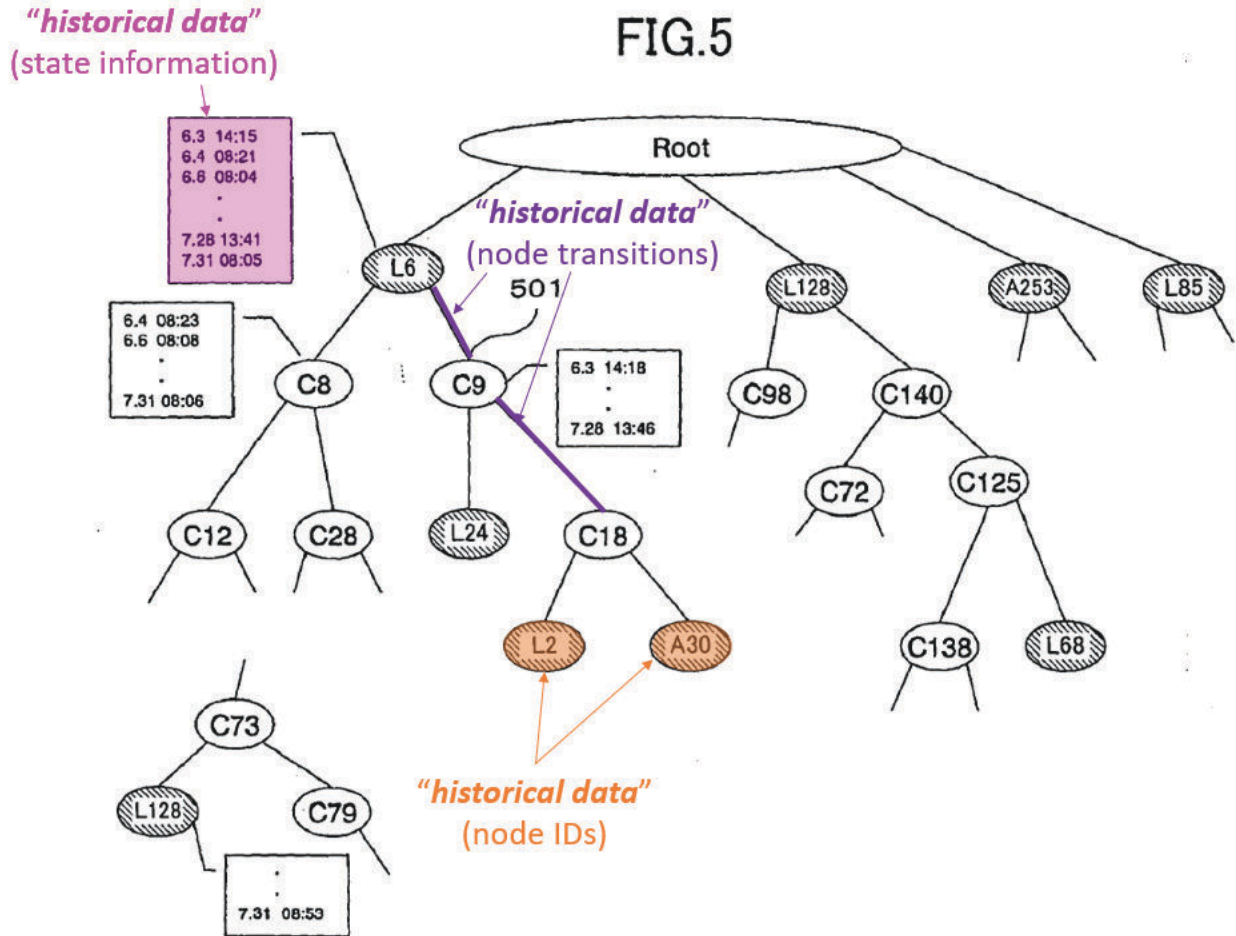
136. Also in the combination, Kudo-325 describes generating transition state information “utilizing ... the nodes accumulated in the history accumulation DB,” *e.g.*, utilizing the *historical data*. TESLA-1004 (Kudo-325), [0109]; *see* [0053] (“a step of generating transition state information indicating past position transition of the mobile body from the travel history”), [0073], [0091]-[0092],

[0223]. For instance, if a given node's frequency of appearance in the history accumulation database "exceeds [a] threshold value," transition state information is generated for that node "by utilizing the data in the history accumulation DB."

TESLA-1004 (Kudo-325), [0091]; *see* [0109], element a4-a5 of FIG. 4. That is, the transition state information is based on, and is representative of, the *historical data*. More specifically, because the transition state data was generated from and thus contains some or all of the data in the history accumulation DB (*see* TESLA-1004 (Kudo-325), [0053], [0073], [0091]-[0093], [0109]), the transition state information itself alternatively or additionally corresponds to *the historical data*.

137. An example of this "transition state information" is illustrated in FIG. 5, which I have reproduced and annotated below. As shown, the transition state information includes "nodes (starting points) ... from which a travel starts ...; histories of past node transition from the respective nodes as base points ...; and nodes (destinations) ... located at the lowermost level of the respective branches," indicating historical position information of the vehicle. TESLA-1004 (Kudo-325), [0093]. Information about these nodes (*e.g.*, node IDs and sequences of node transitions) corresponds to *historical data associated with operation of the vehicle* at least because this information reflects the position of the vehicle during past trips. *See* [0051] ("accumulating, as a travel history, a travel route obtained from a history of position information of the mobile body"), [0053] ("a step of generating

transition state information indicating past position transition of the mobile body from the travel history”), [0072]-[0073]. The transition state information also includes “state information” such as time/date at which “the automobile departs from, passes through or arrives at the node” as well as “frequencies of departure from, passing through and arrival at the node,” indicating time/date information for past trips of the vehicle. TESLA-1004 (Kudo-325), [0093]. The time, date, and frequency information for the nodes also corresponds to *historical data associated with operation of the vehicle* at least because it characterizes past operation of the vehicle, e.g., when and how often, in the past, the vehicle was located at certain nodes. In addition, the transition state information includes “information on a driver,” which also corresponds to *historical data associated with the operation of the vehicle* at least because it indicates the driver operating the vehicle during past trips of the vehicle. TESLA-1004 (Kudo-325), [0094]. Notably, this information (e.g., information on vehicle position, time/date, frequency, and driver; *historical data associated with the operation of the vehicle*) is also present in the data stored in the history accumulation database at least because the transition state data was generated from and thus contains some or all of the data in the history accumulation DB.



Excerpt from Kudo-325, FIG. 1 (annotated)

Kudo-325/Kudo-066 render obvious predicting a destination based on the pattern and the historical data

138. Generally, the combination “information acquisition system” “predict[s] one or more travel destinations or routes where the mobile body will advance” (*predict a destination.*” TESLA-1004 (Kudo-325), [0013]; *see* [0051] (“predict one or more travel destinations or travel routes where the mobile body will advance”), [0017] (“a prediction section that performs retrieval on the travel

history under the condition for retrieval and predicts one or more travel destinations for which the mobile body will advance based on the retrieval result”), [0018] (“a travel destination or a travel route where the mobile body will advance is predicted based on the result of the retrieval under the condition for retrieval”), [0056] (“each prediction probability of one or more travel destinations where the mobile body might advance is obtained, and prediction is performed based on each obtained prediction probability”), [0061], [0072]. As discussed in the following paragraphs, in the combination, Kudo-325 describes that the system predicts a destination for a driver is in response to (a) conditions for the current trip (*the pattern*); *see* [1c-1]) and (b) transition state information (which itself corresponds to *historical data*; alternatively or additionally which is based on the data stored in the history accumulation database, which corresponds to *historical data*).

139. In the combination, Kudo-325 describes that upon retrieval of the conditions for the current trip (*the pattern*), “the condition determination section 107 selects various combinations of conditions (*e.g.*, “weekday and C9,” “weekday and C9 and afternoon,” “weekday and ‘L6 to C9’ and summer”). TESLA-1004 (Kudo-325), [0097], [0102]; *see* element b1 of FIG. 6, [0013]-[0014], [0017]-[0018], [0051]-[0052], [0072]. For each combination of conditions, a starting node (*e.g.*, the node “C9”) “is retrieved from the transition state information” (*the historical*

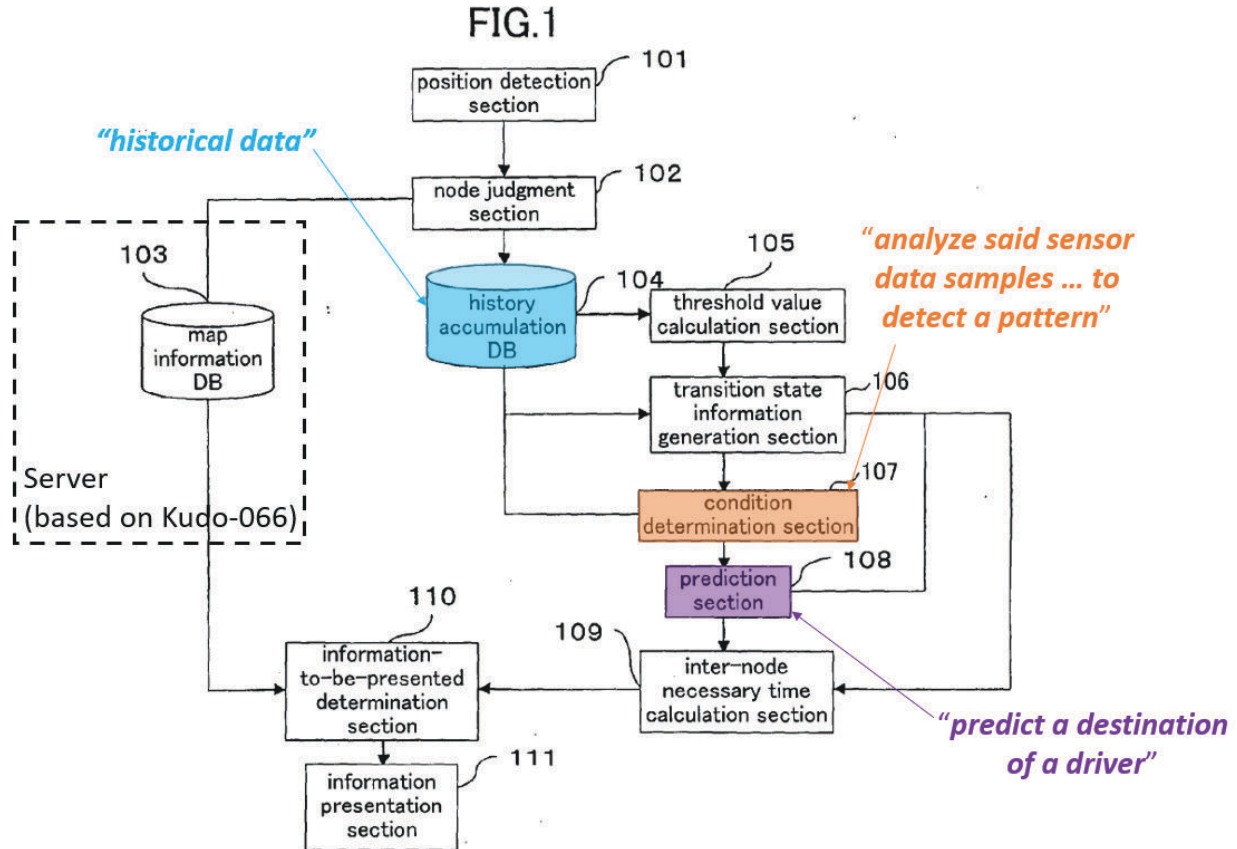
data), and “a probability of transition” from the starting node, through any intervening nodes, and to a “transition candidate node” “located at the lowermost level” of the transition state information tree structure (*e.g.*, a potential destination node) is calculated. *Id.*, [0097]; *see* [0013] (“a second step of determining, as a condition for retrieval, a kind and a category of a key at retrieval from the travel history; and a third step of performing retrieval on the travel history under the condition for retrieval”), [0014], [0053], [0073], elements b2-b6 of FIG. 6. Specifically, the probability for a given destination node is calculated using “a frequency of appearance” of the starting node in the transition state information (*historical data*) under the particular combination of conditions (*pattern*) and “a frequency that a transition candidate node” (*e.g.*, the given destination node) satisfies that combination of conditions. *Id.*, [0098]-[0099]. This process is repeated to determine probabilities for multiple possible destination nodes. *See* TESLA-1004, [0102]. That is, Kudo-325 describes that probabilities for destination nodes are calculated using (a) the conditions for the current trip (*in response to the pattern*) and (b) the transition state information (*in response to the historical data*).

140. Kudo-325 also describes that “the prediction section 108 [purple in FIG. 1, reproduced and annotated below] predicts a travel destination where the automobile will advance,” *e.g.*, ***predicts a destination***. TESLA-1004 (Kudo-325), [0104]; *see* [0013] (“predicting one or more travel destinations or routes where the

mobile body will advance”), [0017]-[0018], [0051], [0056], [0061], [0072]-[0073], block a7 of FIG. 4. Specifically, “a future transition destination node is determined by referencing the transition state information generated from the travel history.” *Id.*, [0104]. The selection of this predicted destination node “can be executed by various methods,” including, among others, “selecting the node having the highest prediction probability,” “a range is provided to each node according to the value of the prediction probability [sic] and a node having a range to which a random number value belongs is selected,” “selecting all nodes having probability values exceeding a predetermined value,” and “selecting a given number of nodes in order from the node having the highest probability value.” *Id.* This process is repeated for multiple potential destination nodes. *See* TESLA-1004 (Neiss), [0102].

141. In each of these approaches, the selection of the predicted destination node (*predicting a destination*) is based on the calculated probability values for the possible destination nodes, which, as discussed in the preceding paragraph, uses (a) the conditions for the current trip (*in response to the pattern*) and (b) the transition state information (*in response to the historical data*).⁸

⁸ As I indicated above for element [1c-1], in an alternative mapping, the set of sensor data samples used for identification of conditions corresponds to the detection



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

142. More specifically, Kudo-325 describes that the prediction of a destination for a current trip is specific to the driver for the current trip (*predict a destination of the driver*). For instance, Kudo-325 describes that “history accumulation of the pattern. Consistent with that mapping, an alternative mapping for element [1c-2] is that the identification of the conditions based on that set of sensor data samples (*the pattern*), and the resulting prediction of a destination, together correspond to the claimed prediction of a destination as recited in [1c-2]. I discuss this further for claim [5].

data for each user” (e.g., each driver) is accumulated and used to “enable[] appropriate prediction according to a user ... even in the case where a plurality of users use the same car navigation system.” TESLA-1004 (Kudo-325), [0140]; *see* [0014] (“the kind of a key includes ... a driver”), [0088], [0094].

143. A POSITA would have understood that Kudo-325’s destination prediction (*predict a destination of the driver*) is performed by *a processor*, e.g., given Kudo-325’s disclosure that its approach is implemented by computer (*see* TESLA-1004 (Kudo-325), [0019], [0074]-[0075], claim 24), given that it was well-known that computers contained processors, and given that making predictions based on data was a standard function of processors. *See* discussion in [1c-1].

[1c-3] wherein (i) at least one of said sensor data samples is driver-related and

144. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1c-3], as I discuss in the following paragraphs.

145. In the combination, vehicle position information such as node IDs (*sensor data samples*; *see* my discussion of element [1a]) is *driver-related*. For instance, vehicle position information, which specifies “the current position of an automobile as a mobile body on which the car navigation system is boarded,” is driver-related at least because it specifies a spatial position of the driver. TESLA-1004 (Kudo-325), [0077]; *see* [0090] (“If the node judgment section 102 judges the

current position to be a node, an ID number indicating the node is accumulated in the history accumulation DB”), FIG. 3 (reproduced and annotated below).

FIG.3

“driver-related”
“sensor data samples”
104

(a)

node number	time
L6	8:05 a.m. on July 31
C8	8:06 a.m. on July 31
C12	8:08 a.m. on July 31
C9	8:09 a.m. on July 31
C34	8:11 a.m. on July 31
.	.
L128	8:53 a.m. on July 31

(b)

node number	time
L6	8:05 a.m. on July 31
C8	8:06 a.m. on July 31
C20	8:08 a.m. on July 31
L12	8:10 a.m. on July 31
L12	1:40 p.m. on July 31
C34	1:50 p.m. on July 31
.	.
L6	9:20 p.m. on July 31

(a)

node number	time
L128	12:25 p.m. on July 31
C140	12:29 p.m. on July 31
C125	12:36 p.m. on July 31
.	.
L68	1:33 p.m. on July 31

146. Time/date information, such as a time and date at which the vehicle passed a node (*sensor data samples*; see my discussion of element [1a]) is another example of *driver-related* data samples at least because it specifies a temporal position of the driver. See TESLA-1004 (Kudo-325), [0087] (“pairs of the node numbers and times of passage therethrough are stored chronologically”), FIG. 3 (above).

147. Driver identity information (*sensor data samples*; see my discussion of element [1a]) is yet another example of *driver-related* data samples at least because it specifies an identity of the driver. See TESLA-1004 (Kudo-325), [0140]

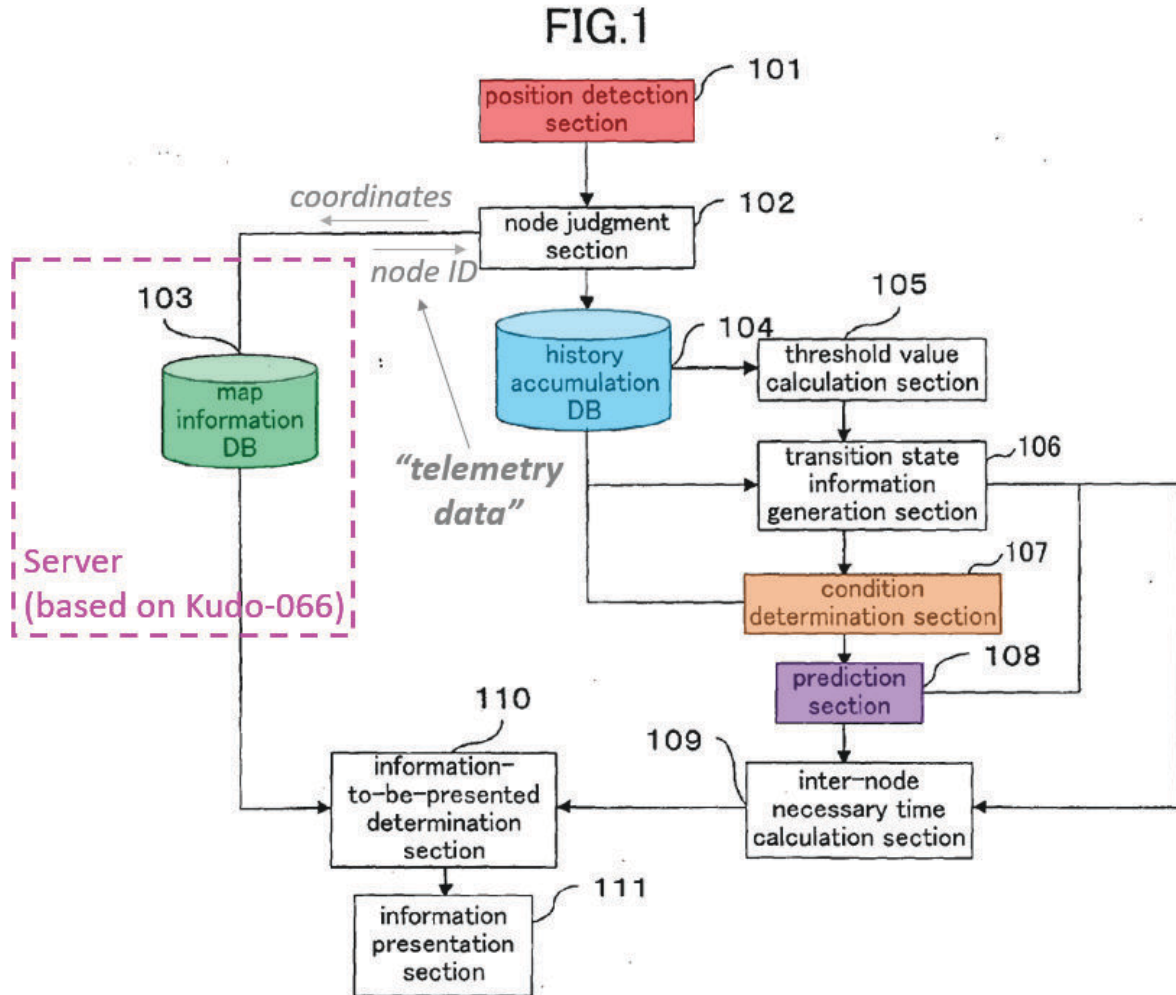
(“means for acquiring information for specifying a user such as a driver and a fellow passenger may be provided ... Various methods are considered as the method of acquiring information for specifying a user. For example, direct input by a user ..., judgment from a car key that stores information for specifying a driver, and person judgment by an on-board camera”).

[1c-4] (ii) at least one of said sensor data samples comprises telemetry data; and

148. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1c-4], as I discuss in the following paragraphs.

149. In the Kudo-325/Kudo-066 combination, vehicle position information such as node ID (*sensor data samples*; see my discussion of element [1a]) corresponds to *telemetry data*. Specifically, in the combination, “the current position of the car navigation system is detected” by a “position detection section 101” (red in the composite figure below) of a car navigation system, as described by Kudo-325. TESLA-1004 (Kudo-325), [0090]. When the map database is implemented at a server (pink) based on the teachings of Kudo-066, the detected position information (e.g., latitude/longitude coordinates) are provided to the server, which accesses the server-based map database (green) to determine whether the current position is a node. See TESLA-1005 (Kudo-066), [0068]; TESLA-1004 (Kudo-325), [0077], [0090], [0141] (“the node information may be stored on a network”). If so, the server “notifies the car navigation system 1 of the associated node ID number”

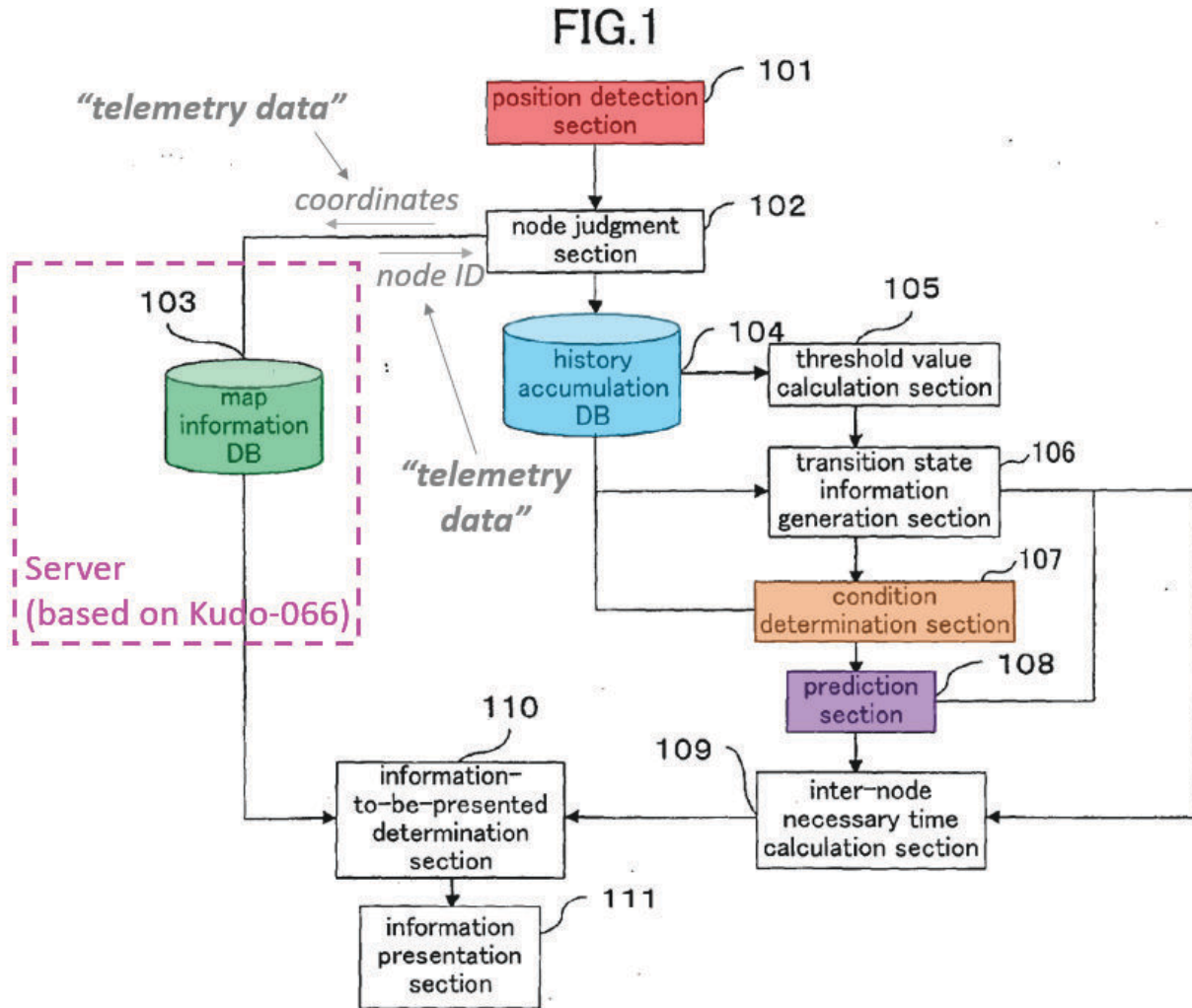
(*sensor data samples*) corresponding to the current position. TESLA-1005 (Kudo-066), [0068]. That is, the node ID number is stored in a database remote from the car navigation where the position coordinates are measured, and is wirelessly communicated from the server to the car navigation system. Thus, the node IDs (*sensor data samples*) provided from the server to the car navigation system correspond to *telemetry data* at least because they represent measurement data (*e.g.*, measured data indicative of current vehicle location) communicated over a distance (*e.g.*, between the server and the vehicle).



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

150. Alternatively or additionally, in the combination, “position information (latitude and longitude) on [sic] the user’s vehicle” is detected “by using ... a GPS,” based on Kudo-066. TESLA-1005 (Kudo-066), [0071]; *see* Abstract, [0063]. As illustrated in the composite figure below, the latitude/longitude coordinates determined by GPS correspond to **telemetry data** at least because they represent measurement data (e.g., measurement data indicative of vehicle location) com-

municated over a distance (*e.g.*, between the vehicle and the GPS satellite). Moreover, the detected position information (*e.g.*, latitude/longitude coordinates determined by GPS) are provided to the map database, which returns the node ID corresponding to those coordinates. As such, in cases where the map database is implemented at the server, the latitude/longitude coordinates also correspond to *telemetry data* because they represent measured data communicated over a distance (*e.g.*, between the vehicle and the server). *See* TESLA-1005 (Kudo-066), [0068]; TESLA-1004 (Kudo-325), [0090]; *see also* my discussion above for element [1a]. Notably, claim 2 indicates that GPS-determined coordinates can constitute telemetry data: “wherein said telemetry data comprises map coordinates determined in response to a GPS signal.” The node ID corresponding to a set of GPS-determined coordinates thus also corresponds to *telemetry data* because the node ID uniquely corresponds to and represents those GPS-determined coordinates, which themselves correspond to *telemetry data*.



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

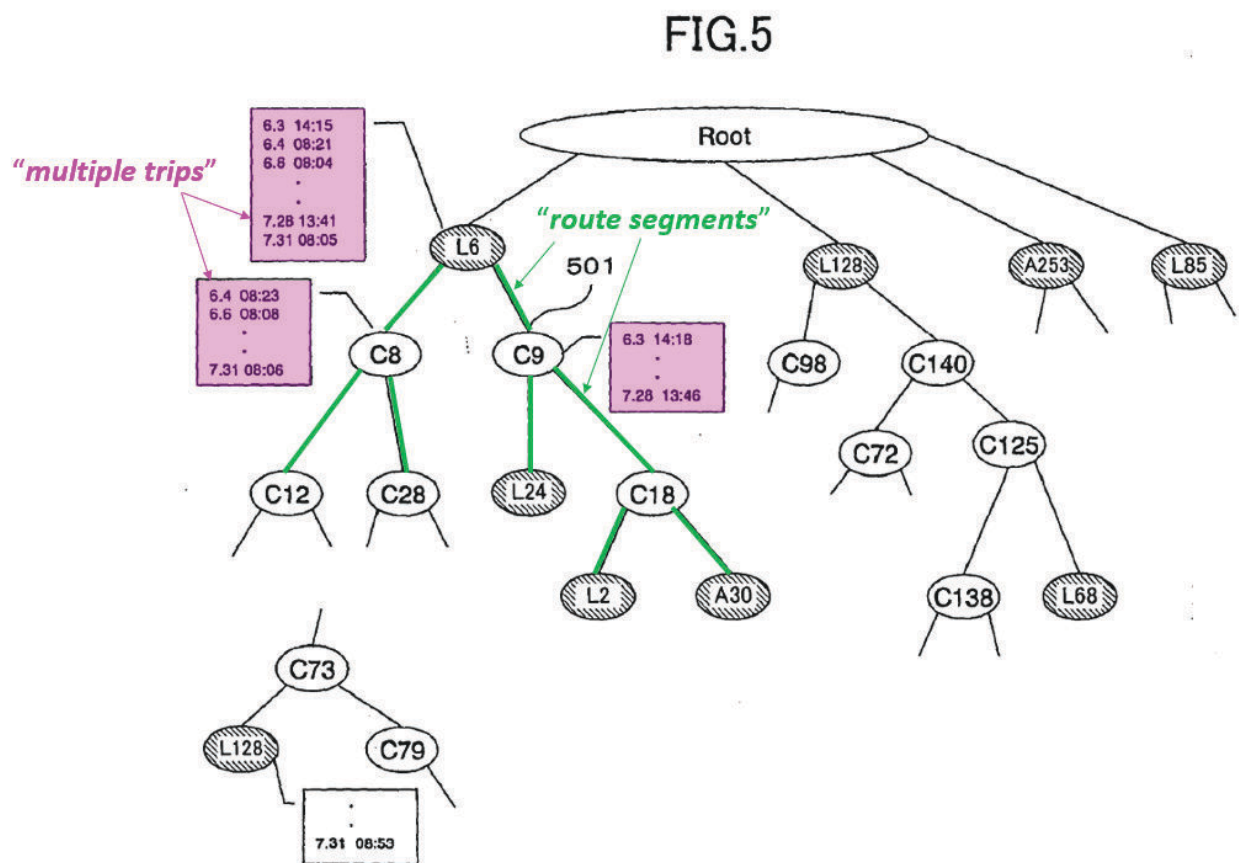
[1d-1] wherein the historical data comprises: data, regarding multiple route segments, gathered from the driver's operation of the vehicle on the multiple route segments during multiple trips;

151. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1d-1], as I discuss in the following paragraphs.

152. In the combination, Kudo-325's transition state information, *e.g.*, illustrated in FIG. 5, which I have again reproduced and annotated below, corresponds to ***historical data***, as I discussed above for element [1c-2]. Alternatively or additionally, the transition state information contains some or all of the same data that is stored in the history accumulation database, which also corresponds to ***historical data***.

153. Kudo-325's transition state information includes "nodes (starting points) of a landmark or an area from which a travel starts," "arranged at the uppermost level" of the diagram. TESLA-1004 (Kudo-325), [0093]. Node L6 is an example of a starting point node. The transition state information also includes "histories of past node transition from the respective nodes as base points, which indicate histories of travels among intersections." TESLA-1004 (Kudo-325), [0093]; *see* [0087] ("The node series may be accumulated on per segment basis according to a starting point and a destination"), [0057] ("the travel history is accumulated in a form of inter-node transition"). Nodes C9 and C18 are examples of these transition nodes. Additionally, the transition state information includes "nodes (destinations) such as a landmark, an area, and the like where the travel ends," "located at the lowermost level of the respective branches." TESLA-1004 (Kudo-325), [0093]. Nodes L24, L2, and A30 are examples of destination nodes. Each connection between a pair of nodes represents a ***route segment***, *e.g.*, in that

the connection represents a portion (*e.g.*, segment) of a route that extends from a starting node to a destination node. Thus, the connections between nodes in Kudo-325's transition state information (*e.g.*, connections (outlined in green) between nodes L6 and C9, nodes C9 and C18, nodes C18 and L2, and nodes C18 and A30, among others) correspond to *multiple route segments*.



Excerpt from Kudo-325, FIG. 5 (annotated)

154. The transition state information includes *data regarding the multiple route segments*. For instance, the node IDs for the nodes at the start and end of each route segment are an example of such data. See TESLA-1004 (Kudo-325),

[0093], FIG. 5. Moreover, Kudo-325 describes that “the dates and times” as well as “information on a driver and a fellow passenger” are “recorded in all the nodes” of the transition state information. TESLA-1004 (Kudo-325), [0094]. Date/time and driver information for the nodes at the start and end of each route segment are another example of data regarding the route segments. Additionally, “the number of pieces of the accompanying state information offers to respective frequencies of departure from, passing through and arrival at” each node. TESLA-1004 (Kudo-325), [0093]. This frequency information—*e.g.*, the frequency with which the vehicle was located at the start and end node of each route segment—is another example of data regarding the route segments.

155. The transition state information represents *multiple trips* from a starting point to a destination. Each trip is composed of one or more route segments extending between a starting node “arranged at the uppermost level” of the FIG. 5 diagram (*e.g.*, node L6) and a destination node “located at the lowermost level of the respective branches” (*e.g.*, nodes L24, L2, and A30). TESLA-1004 (Kudo-325), [0093]. For instance, one trip represented by the transition state information, from L6 to L24, involves operation of the vehicle on the route segments L6 to C9 and C9 to L24. Another trip, from L6 to L2, involves operation of the vehicle on the route segments L6 to C9, C9 to C18, and C18 to L2. Thus, the data regarding

the route segments corresponds to (e.g., *was gathered from*) *operation of the vehicle on the multiple route segments during multiple trips*.

156. Alternatively or additionally, in the combination, Kudo-325 describes that the transition state information includes data from multiple trips on at least some of the route segments (e.g., *was gathered from*) *operation of the vehicle on the multiple route segments during multiple trips*. For instance, the state information (highlighted in pink in Kudo-325's FIG. 5 above) indicates that the vehicle was located at node L6 on June 3 at 14:15 and at node C9 on June 3 at 14:18. This is one *trip* on *the route segment* between nodes L6 and C9. A second *trip* on that same *route segment* occurred on July 28 (at node L6 at 13:41 and at node C9 at 13:46). Similarly, the transition state information indicates *multiple trips* on the route segment between nodes L6 and C8 (e.g., at least trips on June 4, June 6, and July 31). Thus, the transition state information (*historical data*) illustrated in FIG. 5 includes *data gathered from operation of the vehicle on multiple route segments* (e.g., at least L6-C9 and L6-C8) *during multiple trips*.

157. Indeed, that the transition state information includes *data gathered from operation of the vehicle on multiple route segments during multiple trips* is further supported by Kudo-325's description of the generation of the transition state information. Kudo-325 describes that a node is added to the transition state information when the node's "appearance time exceeds the threshold value," e.g.,

when the number of times the node appears “in the history accumulation DB” exceeds “a threshold value of the number of times of appearance for selecting a node for composing transition state information.” TESLA-1004 (Kudo-325), [0091]-[0092]; *see* [0109] (“the transition state information may be generated utilizing all the nodes accumulated in the history accumulation DB 104”), elements a4-a5 of FIG. 4. The threshold value is determined “according to the amount of data accumulated in the history accumulation DB 104,” “by obtaining distribution of appearance times of all nodes,” or “by obtaining an average of the appearance times of all the nodes and multiplying it by a given constant.” TESLA-1004 (Kudo-325), [0091]. A POSITA would have understood that when the threshold is greater than one, a node is added to the transition state information only once the vehicle has been located at that node multiple times—*e.g.*, when the vehicle has transited that node *during multiple trips*.

158. Finally, a POSITA would have understood that the data regarding route segments in the transition state information (*the historical data*) was gathered from *the driver’s operation* of the vehicle. As I discussed above for element [1c-2], the historical data includes “information on ... a driver,” thus reflecting the driver’s operation of the vehicle. TESLA-1004 (Kudo-325), [0088]; *see* [0014], [0104].

[1d-2] data, regarding multiple sequences of route segments, gathered from the driver's operation of the vehicle on the multiple sequences of route segments during the multiple trips; and

159. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1d-2], as I discuss in the following paragraphs.

160. As illustrated in FIG. 5, reproduced and annotated below, the sequences of segments that constitute trips from starting nodes “arranged at the uppermost level” of Kudo-325’s FIG. 5 diagram to destination nodes “located at the lowermost level of the respective branches” correspond to ***sequences of route segments***. TESLA-1004 (Kudo-325), [0093]; *see* [0087] (“The node series may be accumulated on per segment basis according to a starting point and a destination”). For instance, a trip from node L6 to node L24 includes a sequence of two route segments (outlined in red): L6 to C9 and C9 to L24. Another trip, from L6 to L2, includes a sequence of three route segments (outlined in purple): L6 to C9, C9 to C18, and C18 to L2. Alternatively or additionally, sequences of route segments that do not extend from uppermost-level to lowermost-level nodes (*e.g.*, the sequence of segments L6 to C9 and C9 to C18) correspond to ***sequences of route segments***.

at the start and end of each segment of each sequence of route segments are another example of data regarding the route segments. Additionally, “the number of pieces of the accompanying state information offers to respective frequencies of departure from, passing through and arrival at” each node. TESLA-1004 (Kudo-325), [0093]. This frequency information—*e.g.*, the frequency with which the vehicle was located at the start and end node of each route segment of each sequence—is another example of data regarding the sequences of route segments.

162. The transition state information (*historical data*) represents *multiple trips* from a starting point to a destination. At least some of these trips are composed of sequences of multiple route segments. For instance, one trip represented by the transition state information, from L6 to L24, involves operation of the vehicle on a sequence of two route segments: L6 to C9 and C9 to L24. Another trip, from L6 to L2, involves operation of the vehicle on a sequence of three route segments: L6 to C9, C9 to C18, and C18 to L2. Thus, the data regarding the route segments corresponds to (*e.g., was gathered from*) *operation of the vehicle on the multiple sequences of route segments during multiple trips*.

163. Alternatively or additionally, in the combination, the transition state information includes data from (*e.g., was gathered from*) *operation of the vehicle on multiple sequences of route segments during multiple trips*. For instance, a POSITA would have understood that the transition state information represents

data from multiple trips on at least some of the sequences of route segments. As I discussed above for element [1d-1], the transition state information of FIG. 5 indicates ***multiple trips*** on the route segment between nodes L6 and C9. A POSITA would have recognized that at least some of those trips on the L6-C9 route segment continue on to the C9-L24 segment, while other of those L6-C9 trips continue on to the C9-C18 segment. With this continued transit of the vehicle, the transition state information represents (*e.g., was gathered from*) ***multiple trips*** on the L6-C9 and C9-L24 ***sequence of route segments***, and also ***multiple trips*** on the L6-C9 and C9-C18 ***sequence of route segments***.

164. Moreover, that the transition state information includes ***data gathered from operation of the vehicle on multiple sequences of route segments during multiple trips*** is further supported by Kudo-325's description of generating transition state information based on a node appearing in the history accumulation database more than a threshold number of times, as I discussed above for element [1d-1]. See TESLA-1004 (Kudo-325), [0091]-[0092], [0109].

165. Finally, a POSITA would have understood that the data regarding sequences of route segments in the transition state information (***the historical data***) was gathered from ***the driver's operation*** of the vehicle. As I discussed above for

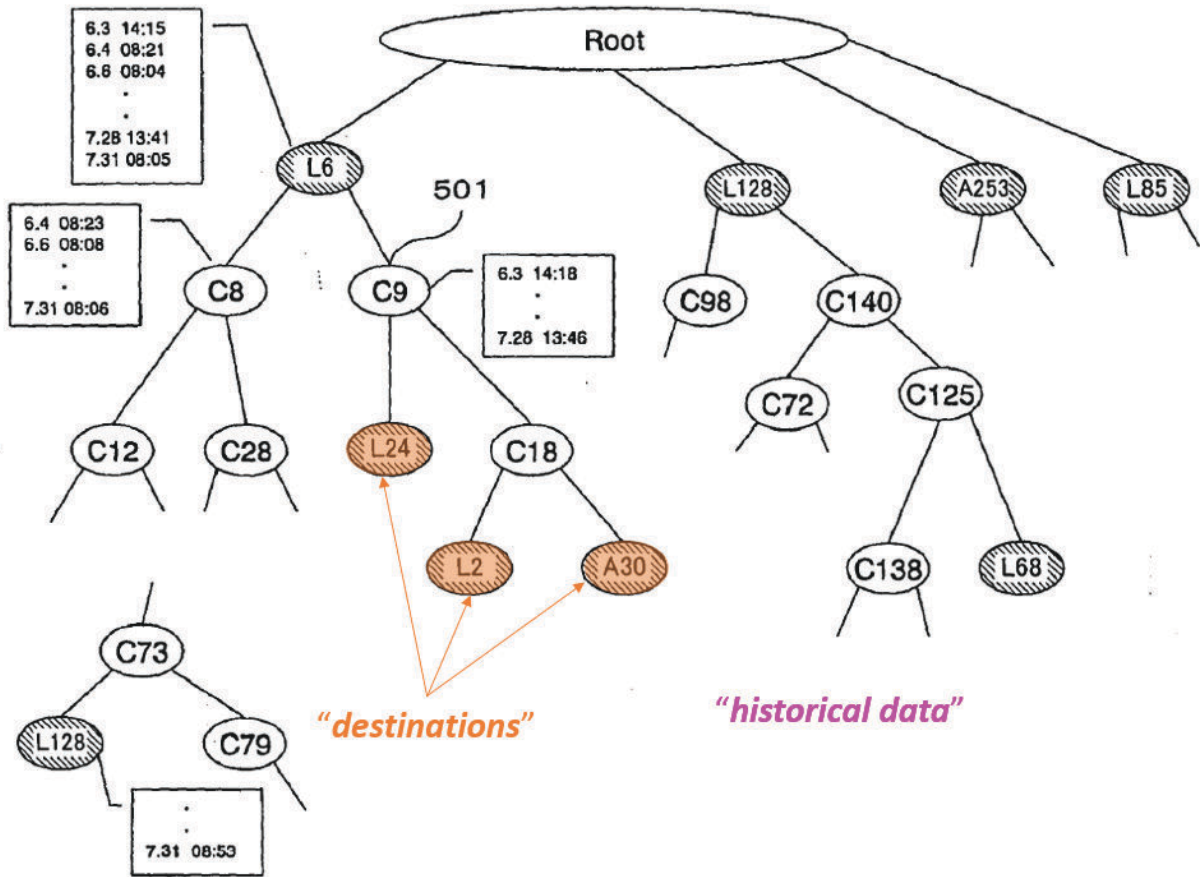
element [1c-2], the historical data includes “information on ... a driver,” thus reflecting the drivers operation of the vehicle. TESLA-1004 (Kudo-325), [0088]; *see* [0014], [0104].

[1d-3] data, regarding multiple travel destinations, gathered from the driver’s operation of the vehicle to the multiple travel destinations during the multiple trips.

166. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [1d-3], as I discuss in the following paragraphs.

167. As illustrated in FIG. 5, reproduced and annotated below, the destination nodes of Kudo-325’s transition state information, which are “located at the lowermost level of the respective branches” (*e.g.*, nodes L24, L2, and A30, highlighted in orange), correspond to ***multiple travel destinations***. TESLA-1004 (Kudo-325), [0093]; *see* [0087] (“The node series may be accumulated on per segment basis according to a starting point and a destination”).

FIG.5



Excerpt from Kudo-325, FIG. 5 (annotated)

168. The transition state information includes *data regarding the multiple travel destinations*. For instance, the node IDs for the destination nodes are an example of such data. See TESLA-1004 (Kudo-325), [0093], FIG. 5. Moreover, Kudo-325 describes that “the dates and times” as well as “information on a driver and a fellow passenger” are “recorded in all the nodes” of the transition state information. TESLA-1004 (Kudo-325), [0094]. Date/time and driver information for the destination nodes are another example of data regarding the travel destinations.

Additionally, “the number of pieces of the accompanying state information offers to respective frequencies of departure from, passing through and arrival at” each node. TESLA-1004 (Kudo-325), [0093]. This frequency information for the destination nodes is another example of data regarding the travel destinations.

169. The transition state information (*historical data*) represents *multiple trips* to the destinations. For instance, one trip represented by the transition state information is a trip from node L6 to node L24, and another trip is from node L6 to node L2. Thus, the data regarding the route segments corresponds to (*e.g., was gathered from*) *operation of the vehicle to the multiple destinations during multiple trips*.

170. Alternatively or additionally, in the combination, the transition state information includes data from (*e.g., was gathered from*) *operation of the vehicle to the multiple destinations during multiple trips*. As I discussed above for element [1d-1], the transition state information of FIG. 5 indicates *multiple trips* on the route segment between nodes L6 and C9. A POSITA would have recognized that at least some of those trips on the L6-C9 route segment continue on through the C9-L24 segment, ending at L24 as a destination, while other of those L6-C9 trips continue on to the C9-C18 segment and then end at the L2 or A30 destination. Moreover, that the transition state information includes *data gathered from opera-*

tion of the vehicle to the multiple destinations during multiple trips is further supported by Kudo-325's description of generating transition state information based on a node appearing in the history accumulation database more than a threshold number of times, as I discussed above for element [1d-1]. *See* TESLA-1004 (Kudo-325), [0091]-[0092], [0109].

171. Finally, a POSITA would have understood that the data regarding the destinations in the transition state information (*the historical data*) was gathered from *the driver's operation* of the vehicle. As I discussed above for element [1c-2], the historical data includes "information on ... a driver," thus reflecting the driver's operation of the vehicle. TESLA-1004 (Kudo-325), [0088]; *see* [0014], [0104].

172. The historical data regarding the multiple route segments, sequences of route segments, and destinations are used in conjunction with the pattern in predicting the destination (*see* my discussion above for element [1c-2]). Specifically, destination prediction is performed by using the transition state information to calculate a "probability of transition" from a current node to each of multiple possible destination nodes, *i.e.*, the *historical data regarding multiple travel destinations* are used for destination prediction. *See* TESLA-1004, [0100], [0102]. Moreover, each pathway between current node and a possible destination node involves at least one route segment, and in at least some cases involves a sequence of route

segments (*e.g.*, the one or more segments extending between current and destination nodes). *See id.*, FIG. 5. Thus, calculation of a “probability of transition” from a current node to each of multiple possible destination nodes) involves the *historical data regarding multiple route segments* and *multiple sequences of route segments*.

173. Additionally, the “travel history from departure” (which can be at least a segment, or sometimes a sequence of segments) can be one of the conditions based on which a predicted destination is identified. *See* TESLA-1004, [0096]. Each of multiple “node[s] satisfying the condition [are] retrieved”—*e.g.*, nodes sharing the same travel history, meaning nodes having the same segment or sequence of segments as the current trip—and these retrieved nodes are used for destination prediction. *Id.*, [0097]; *see* [0098]-[0104]. That is, *historical data regarding multiple route segments* and *sequences of route segments* are used to retrieve nodes for destination prediction.

[2] *The device according to claim 1, wherein said telemetry data comprises map coordinates determined in response to a GPS signal.*

174. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [2]. In the Kudo-325/Kudo-066 combination, “position information (latitude and longitude) on [sic] the user’s vehicle” is detected “by using ... a GPS,” based on Kudo-325’s general description of detecting vehicle position and

Kudo-066's specific description of using GPS to that end. TESLA-1005 (Kudo-066), [0071]; *see* Abstract, [0063]. The latitude/longitude coordinates of the vehicle's position are map coordinates, and they are determined by GPS; thus, the latitude/longitude coordinates correspond to ***map coordinates determined in response to a GPS signal***. Additionally, these GPS-determined coordinates correspond to ***telemetry data*** as I discussed above for element [1c-4], as does the node ID that uniquely corresponds to and represents the GPS-determined latitude/longitude coordinates.

[3] The device according to claim 1, wherein said telemetry data comprises map coordinates determined by a map service.

175. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [3]. In the Kudo-325/Kudo-066 combination, the node ID provided from the server to the car navigation system corresponds to ***telemetry data***, as I discussed above for element [1c-4]. *See* TESLA-1005 (Kudo-066), [0068]; TESLA-1004 (Kudo-325), [0077], [0090], [0141]. As I also discussed above for element [1a], the node ID (***telemetry data***) for the current vehicle position is determined based on a mapping between node ID and "position information (latitude and longitude)," where that mapping is stored in the map information database,. *See* TESLA-1004 (Kudo-325), [0081]-[0082], [0084], [0090], FIG. 2; TESLA-1005 (Kudo-066), [0071]; *see* Abstract, [0063].

176. The node ID (*telemetry data*) corresponds to *map coordinates* at least because it uniquely corresponds to and represents the latitude/longitude coordinates (map coordinates) of the vehicle position. *See* my discussion above for element [1c-4].

177. The map information database (which is implemented at the server based on the teachings of Kudo-066, as I also discussed above for element [1c-4] (*see* TESLA-1005 (Kudo-066), [0068])) corresponds to *a map service*. For instance, this is the case because the map information database provides a service that translates one representation of map information (latitude/longitude coordinates) into a different representation of that same map information (node ID). Thus, the node ID (which corresponds to *telemetry data*) is *determined by a map service*, *e.g.*, by the map information database.

[4] *The device according to claim 1, wherein said destination of said driver is predicted based on statistical destination logic.*

178. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [4], as I discuss in the following paragraphs.

179. I first discuss the phrase “statistical destination logic.” The ’002 Patent, which uses “statistical destination logic” to predict a destination “by generating a series of statistically weighted (*e.g.*, likely) destinations based on any, all, or

some inputs.” TESLA-1001 (’002 Patent), The ’002 Patent describes that predicting a destination based on “statistical destination logic” involves deriving a destination “by generating a series of statistically weighted (e.g., likely) destinations based on any, all, or some of these inputs,” where the inputs include information characterizing the current trip of the vehicle, including information such as “the weight of the driver, the time of the day, the current location of the vehicle, the direction that the vehicle is facing (or traveling in), the day of the week, and the speed of the vehicle.” TESLA-1001, 12:5-17. Predicted destinations are then determined based on probabilities determined according to these inputs: “The statistical destination logic may identify one or more destinations based on information held in a memory. ... These destinations may be assigned a probability weighting based on the information inputs. ... The information inputs can be used to assign a probability to a particular destination.” *Id.*, 12:18-27.

180. The Kudo-325/Kudo-066 combination system determines probabilities for respective potential destination nodes in a way that is similar to the statistical destination logic approach described by the ’002 Patent itself. Generally, and as I discuss in more detail in the next paragraph, destination prediction in the Kudo-325/Kudo-066 combination system is based on characteristics of the current trip, and predicted destination are identified based on probabilities that are deter-

mined according to those current trip characteristics. Thus, given the overlap between the approach of the Kudo-325/Kudo-066 combination system and the statistical destination logic approach described in the '002 Patent, it can be seen that like the '002 Patent, the Kudo-325/Kudo-066 combination system *predicts the destination based on statistical destination logic*.

181. Specifically, in the Kudo-325/Kudo-066 combination system, Kudo-066 describes that “a probability of transition toward” a selected destination node “is calculated” for each of multiple possible destination nodes based on “the transition state information,” *e.g.*, based on a collection of data (statistics). TESLA-1004 (Kudo-325), [0097]; *see* [0056] (“each prediction probability of one or more travel destinations where the mobile body might advance is obtained, and prediction is performed based on each obtained prediction probability”), [0054]-[0055], [0073]. Notably, these transition probabilities take into account factors that characterize the vehicle’s current trip, including factors such as the “current position” of the vehicle, the vehicle’s “travel history from departure,” “the date and time,” and the driver identity. *Id.*, [0096]; *see* [0014], [0088], [0097]-[100], [0102]. Based on these calculations, “a future transition destination node is determined ... by various methods, for example, a method of selecting the node having the highest prediction probability, a method in which a range is provided to each node according to the value of the prediction provability and a node having a range to

which a random number value belongs is selected, a method of selecting all nodes having probability values exceeding a predetermined value, and a method of selecting a given number of nodes in order from the node having the highest probability value.” TESLA-1004 (Kudo-325), [0104]. This probabilistic identification of destinations based on information characterizing the vehicle’s current trip is an approach to destination prediction that can be considered *statistical destination logic*.

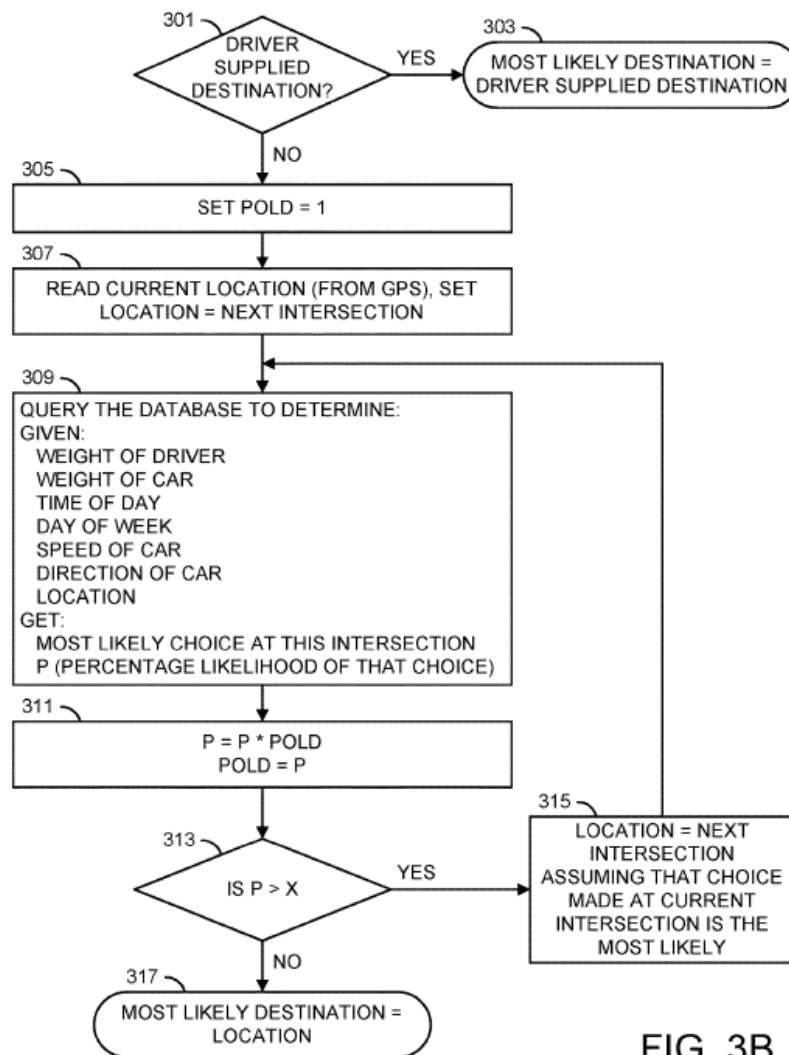
[5] *The device according to claim 1, wherein said processor is further configured to determine that a particular driver is operating said vehicle based on said pattern detected.*

182. As I discussed above for elements [1a]-1b], in the Kudo-325/Kudo-066 combination system, position, time/date, and/or driver identity information correspond to *sensor data samples*, and these sensor data sample are received and stored in memory. I also indicated above in elements [1c-1] and [1c-2] that there is an alternative mapping to the claimed *pattern* that is relevant for my analysis of claim 5. Here, before addressing claim 5, I describe, in the context of the ’002 Patent, the support for this alternative mapping.

Analysis of the ’002 Patent’s support for a “pattern”

183. The process illustrated in FIG. 3B of the ’002 Patent (which I have reproduced below_) is the main disclosure that relates to predicting a vehicle’s destination based on historical travel data. See TESLA-1001 (’002 Patent), 12:65-67

(“One variation of a procedure for determining the most likely destination is described below, and illustrated in FIG. 3B”). However, the ’002 Patent does not specifically identify what corresponds to the *pattern* recited in the claims. Thus, a POSITA would have to infer what is meant by the claimed *pattern* based on the disclosure in the ’002 Patent relating to FIG. 3B.



Excerpt from ’002 Patent, FIG. 3B

184. Two features that could be considered to be *a pattern* appear to be implicated in the process illustrated in FIG. 3B.

185. The first potential *pattern* is the set of sensed data inputs, shown in box 309. This set of sensed data inputs (*e.g.*, “weight of driver,” “weight of car,” “time of day,” etc.) is detected by analyzing stored sensor data and is used to access the historical database in order to predict the destination. *See* TESLA-1001 (’002 Patent), #cites. The second potential *pattern* is the list of predicted intersections contemplated in the loop involving step 315. *See id.* #cites.

186. Of these two potential *patterns*, the first appears more consistent with the language of the claims, which require “predict[ing] a destination of a driver in response to (a) said pattern and (b) historical data.” This is because predicting the destination, as set out in the FIG. 3B process, involves using the detected set of sensed data inputs as a key to access an historical database—*e.g.*, generally consistent with language of the claims. *See* TESLA-1001 (’002 Patent), #cites. The second potential pattern (the list of predicted intersections) is less consistent with claim language. This is because this list of predicted intersections appears to be more similar to a predicted destination than to a pattern that is first detected by analysis of stored sensor data samples, and then used to predict a destination. Moreover, this list of predicted intersections is itself already the product of historical information, and because of this, it does not appear to be well-suited to the

claim requirement that both the pattern and historical information be used to predict a destination.

187. The identification of the set of sensed data inputs as corresponding the claimed *pattern* is bolstered by the language of claim 5, which relates to driver identification. The '002 Patent describes identifying a driver based on the driver's weight (which is one of the set of sensed data inputs), but not based on the list of predicted intersections. *See* TESLA-1001 ('002 Patent), #cites. Thus, in order for claim 5, which states that a driver is determined based on the detected pattern, the driver weight would have to be part of, or otherwise derived from, the pattern. This is the case when the *pattern* is the set of sensed data inputs: the driver weight is one of these data inputs, and therefore determining the driver based on this set of sensed data inputs corresponds to the claim 5 language *determine[ing] that a particular driver is operating said vehicle based on said pattern detected*. But this would not be the case if the pattern were the list of predicted intersections: the '002 Patent does not describe determining the driver based on this list.

188. I thus conclude that the '002 Patent supports the alternative mapping of a set of sensed data samples as corresponding to a *pattern*. As I discuss in the following paragraphs, the Kudo-325/Kudo-066 combination contemplates a pro-

cess for determining driver identity that is generally similar to that of the '002 Patent: image data, which is part of a set of sensed data samples (a *pattern*) is used to determine driver identity, and is also used for predicting the destination.

Mapping of the Kudo-325/Kudo-066 combination to claim 5

189. In the Kudo-325/Kudo-066 combination, driver identity information includes “information for specifying a user such as a driver,” *e.g.*, an image of a driver captured by an “on-board camera.” TESLA-1004, [0140]; *see* [0014], [0088]. This image corresponds to a *sensor data sample*, as I discussed for element [1a]. I also note that the image corresponds to a sensor data sample because a POSITA would have understood this image to be stored in memory (*sensor data samples stored in memory*, as recited in element [1b]), *e.g.*, to enable later “person judgment” (facial recognition) to be performed. TESLA-1004, [0140].

190. As I discussed above, the set of sensor data samples used for determining conditions for the current trip corresponds to the *pattern*, and obtaining these sensor data samples for the process of analysis and destination prediction corresponds to *detecting a pattern*.⁹ In this context, driver identity information included in the *pattern* includes an image of the driver. Based on this image, Kudo-

⁹ This is consistent with the disclosure of the '002 Patent, as discussed by Dr. Morrellas. #expert.

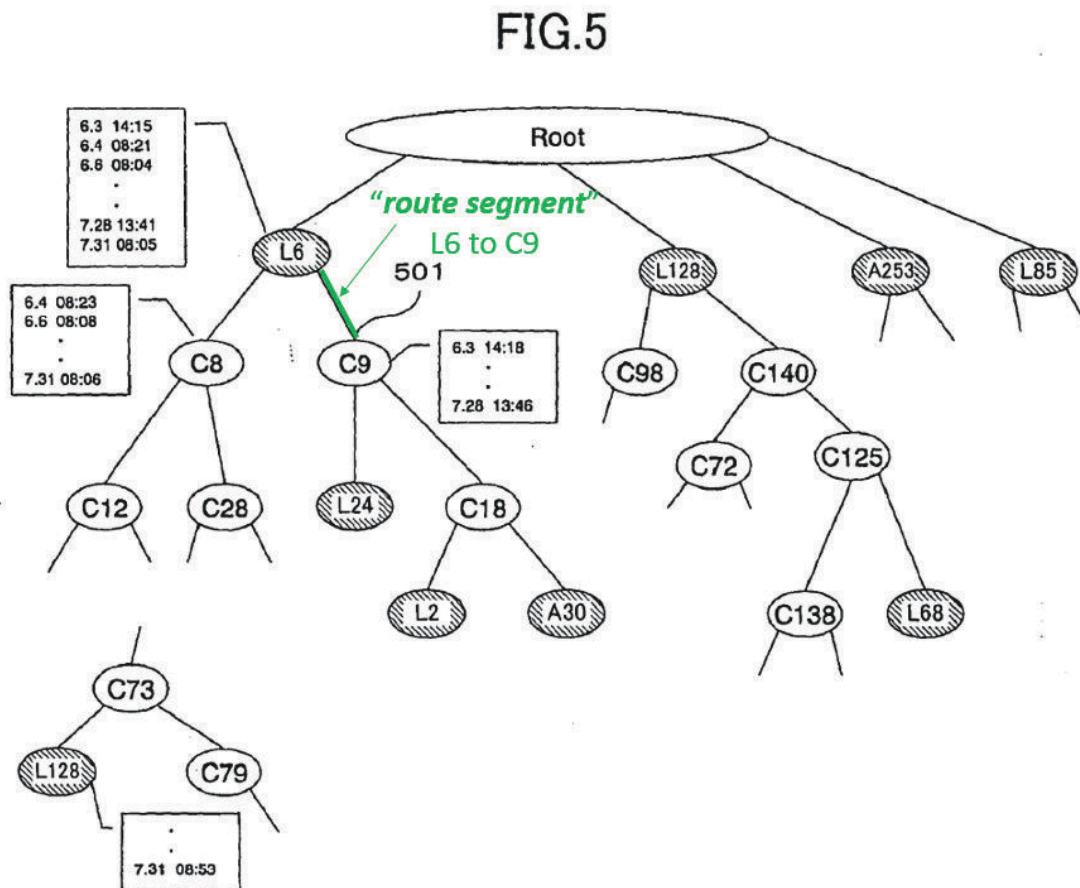
325 describes that “person judgment” is performed on the image (*pattern*) to determine the driver’s identity (*determine that a particular driver is operating said vehicle based on said pattern detected*).

[6] *The device according to claim 1, wherein said telemetry data is used to determine route segments.*

191. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [6], as I discuss in the following paragraphs.

192. In the Kudo-325/Kudo-066 combination system, Kudo-325 describes that the car navigation system “performs judgment as to whether the current position is a node or not by referencing the map information DB.” TESLA-1004 (Kudo-325), [0090]. “If the node judgement section 102 judges the current position to be a node, an ID number indicating the node is accumulated in the history accumulation DB 104.” *Id.* As I discussed above for element [1d-1], route segments extend between nodes. *See* TESLA-1004 (Kudo-325), [0093], [0094], [0087], FIG. 5, FIG. 3. Determining whether the current position is a node (which involves using node IDs (*telemetry data*), as I discuss in the next paragraph, corresponds to *determining a route segment*. For instance, determining that the current position is a node indicates that the vehicle is transiting from one segment to another segment, and thus determining that the current position is a node corresponds to determining at least the segment transited to arrive at that node. In an example, Kudo-325 describes that “the current position is a node ‘C9’; [and] a travel history

from departure is ‘L6 to C9.’” TESLA-1004 (Kudo-325), [0096]. With reference to FIG. 5, reproduced and annotated below, in this situation, the determination that the current position of the vehicle is node C9, in conjunction with the “L6 to C9” travel history, is a determination that the vehicle has just transited the route segment extending between L6 and C9 (marked in green in FIG. 5), and thus corresponds to a determination of the L6-to-C9 segment.



193. Additionally, determining whether the current position is a node (*determining a route segment*) is performed *using telemetry data*. As I discussed

above for element [1c-3], the node ID numbers provided from the server to the car navigation system correspond to *telemetry data*. That a node ID number corresponds to the current position is an indication that the vehicle's current position is a node, and thus corresponds to a determination of the immediately prior route segment, as discussed in the preceding paragraph. See TESLA-1004 (Kudo-325), [0090]. Thus, in the Kudo-325/Kudo-066 combination system, Kudo-325 describes *using telemetry data to determine route segments*.

[7] *The device according to claim 6, wherein said pattern comprises which of said route segments said vehicle has traveled.*

194. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [7]. As I discussed above for element [1c-1], the pattern in the combination corresponds to conditions that characterize aspects of vehicle travel (e.g., aspects of the current trip), such as location, node/segment history, and time/date characteristics of the trip, as determined by analyzing the stored sensor data samples. See TESLA-1004 (Kudo-325), [0013], [0017]-[0018], [0051]-[0052], [0072], [0079], [0093], [0096]-[0097], [0102], [0115]-[0120]. Among these characteristics (and thus among *the pattern*) is “a travel history from departure,” e.g., “L6 to C9.” TESLA-1004 (Kudo-325), [0096]; see [0102]. This travel history from departure, which constitutes part of the pattern, corresponds to an identification of *which route segments said vehicle has traveled*.

[8] *The device according to claim 1, wherein said device is further configured to transmit said predicted destination to a remote database.*

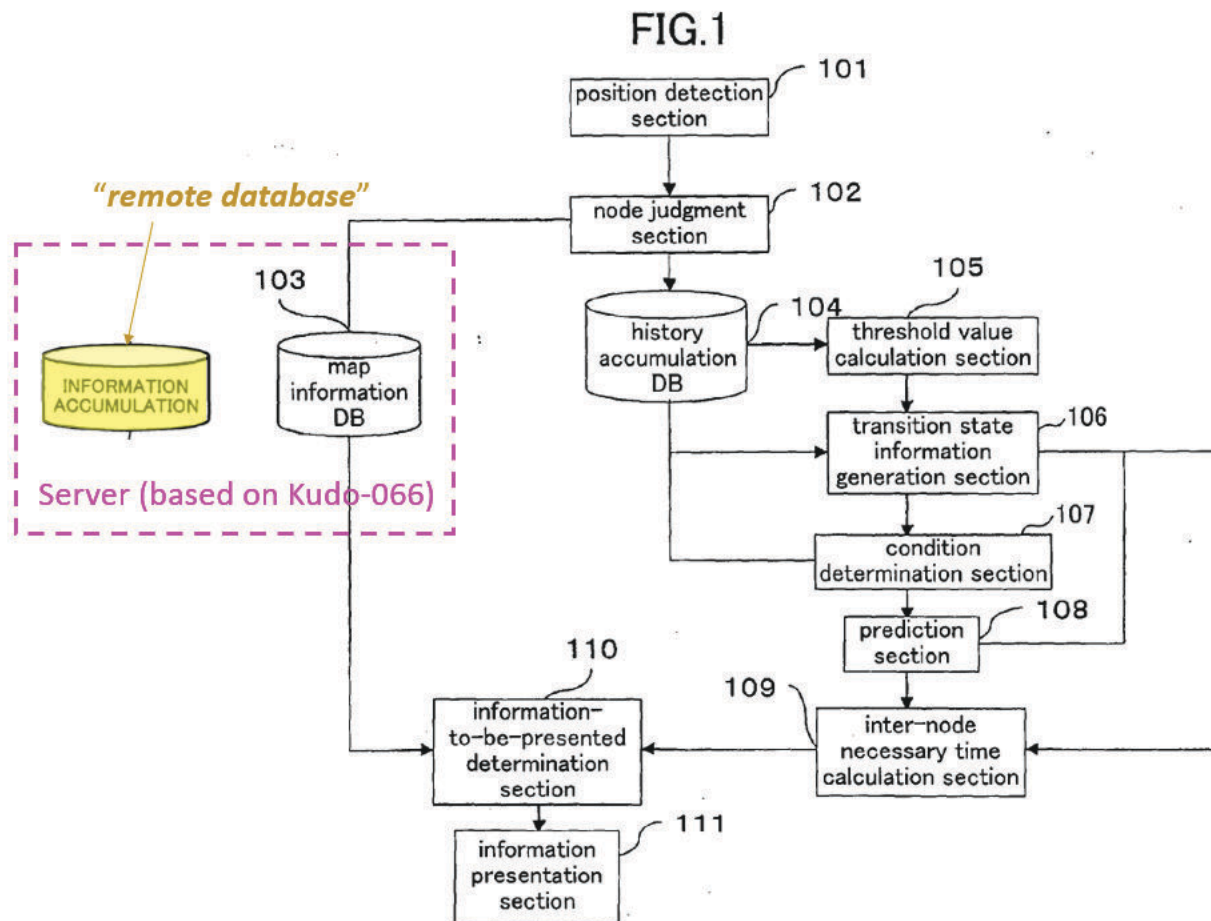
195. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [8], as I discuss in the following paragraphs.

The information accumulation means housed at the server corresponds to a remote database

196. I have included a composite figure below showing elements of the Kudo-325/Kudo-066 combination system. In the combination, the server (outlined in pink) houses an “information accumulation means [highlighted in yellow] for storing information to be transmitted to the car navigation system,” as taught by Kudo-066. TESLA-1005 (Kudo-066), [0064]. The information accumulation means stores information such as commercial information related to certain positions and/or traffic information for certain routes, and information relevant to the predicted destination can be provided to the driver of the vehicle. *See* TESLA-1005 (Kudo-066), [0092]-[0095], [0150]. Notably, this is consistent with the operation of Kudo-325’s system, which describes presenting “commercial information relating to the travel destination” to the driver. TESLA-1004 (Kudo-325), [0067]-[0069]; *see* [0107], [0139].

197. The information accumulation means (yellow) in the Kudo-325/Kudo-066 combination system corresponds to ***a remote database***. First, the information means is ***remote*** because it is housed at the server (pink), which is remote from the

vehicle. Second, the information accumulation means corresponds to a **database**, given that a database is a conventional way to store large volumes of data in an easily accessible manner.



Kudo-325/Kudo-066 composite figure based on Kudo-325, FIG. 1

198. In operation, the “information indicating a predicted travel destination or travel route is uploaded to a server on the network from the car navigation system”, as taught by Kudo-325. TESLA-1004 (Kudo-325), [0107]. That is, the predicted destination is transmitted from the vehicle’s car navigation system to the

server (*said device is further configured to transmit said predicted destination*).

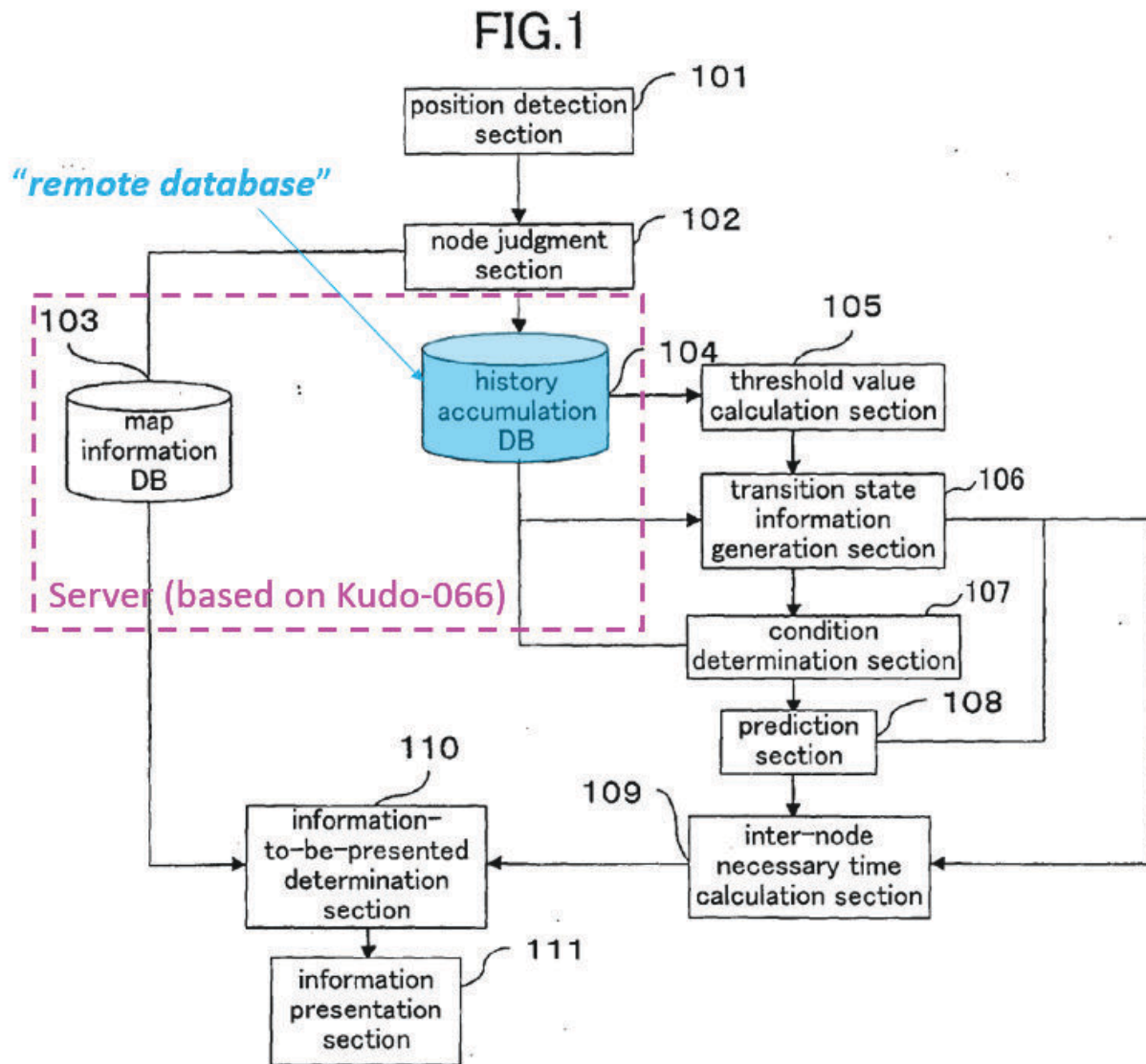
Kudo-325 provides some generic description of what occurs responsive to this transmission of the predicted destination: “information relating to [the predicted destination] “is selected by the server.” *Id.*, [0107]. And Kudo-066 provides more detail: the server “receives the position information” and “information accumulated in the information accumulation means 22 is searched so as to find information regarding the received position information.” TESLA-1005 (Kudo-066), [0091]; *see* [0092]-[0095], [0095], [0150]. This “information selected in the server” is returned to the car navigation system for presentation to the user. TESLA-1004 (Kudo-325), [0107]; *see* [0062] (“information relating to the predicted travel destination or the predicted travel route is acquired via a network”), [0013] (“information relating to the predicted travel destinations or routes is acquired”), [0015]-[0017] (“determining information to be presented relating to the travel destination”), [0106] (“The information-to-be-presented determination section 110 determines information to be presented to the user by referencing the map information DB 103, such as information on the name and other materials of the predicted node, and information relating to the estimate necessary time and the estimated arrival time (step a9). The determined information is presented to the user (a driver and a fellow passenger)”), [0051], [0063]-[0072]; TESLA-1005 (Kudo-066), [0094].

199. In summary, the server-housed information accumulation means is searched for information relevant to the predicted destination, which was determined by the car navigation system. In order for the information accumulation means to perform this search, a POSITA would have recognized that the predicted destination would be provided to the information accumulation means, *e.g.*, for use as a search query—that is, the predicted destination would be transmitted to the server-housed information accumulation means (*transmit the predicted destination to a remote database*).

The historical accumulation database housed at the server corresponds to a remote database

200. I have reproduced an alternative composite figure below showing aspects of an example of the Kudo-325/Kudo-066 combination system. In this combination system, the history accumulation database (highlighted in blue) is implemented at the server (outlined in pink). This is based on Kudo-325's teachings that "a part of the functions that a car navigation system has may be provided in a server on a network." TESLA-1004 (Kudo-325), [0075]. And in fact, I note that Kudo-325 explicitly contemplates that historical data can be stored at the server: "the history information accumulated in the history DB 104 is uploaded to the server for allowing the server to perform both prediction of a travel destination and selection of information based on the prediction result." TESLA-1004 (Kudo-

325), [0108]. In this configuration, the server-hosted history accumulation data-base corresponds to a *remote database* because it is a database that is remote from the vehicle-based car navigation system.



201. “[W]hen the current position is judged as a node” by the node judgment section of the car navigation system, “the node is stored” in the history accumulation database. TESLA-1004 (Kudo-325), [0078]; *see* [0090]. This is consistent with the functionality of Kudo-325’s history accumulation database, as I discussed above for limitation [1b]. Here specifically, the node ID is provided to the server-housed history accumulation database to be stored at the server. *See id.*, [0075]. That is, node IDs are provided to and stored in the history accumulation database as the vehicle proceeds along its route. When the current location of the vehicle matches the predicted destination of the vehicle—which occurs when the vehicle reaches the end of its trip, and when that end corresponds to the predicted destination for the trip), the node ID that is provided to and stored in the server-housed history accumulation database corresponds to the node ID for the predicted destination. That is, at the end of the vehicle’s trip, the predicted destination is transmitted to the remote history accumulation database (*transmit said predicted destination to a remote database*).

202. A POSITA would have been motivated to implement the history accumulation database of the Kudo-325/Kudo-066 combination system at the server for at least the following reasons.

203. The first reason why a POSITA would have been motivated to pursue this implementation is because storing historical data remotely at a server (*e.g.*, instead of locally on the vehicle) allows a driver's unique travel history to be accessible to multiple vehicles. For instance, this would allow driver-specific destination prediction to be deployed for a particular driver even if that driver operates multiple different vehicles.

204. The second reason why a POSITA would have been motivated to pursue this implementation is because this is just the application of known techniques (specifically, housing an historical accumulation database at a server) to an already-known system (specifically, the Kudo-325/Kudo-066 car navigation system). And, this combination of features produces predictable results (specifically, a car navigation system in which the historical data are stored remotely from the vehicle).

205. The third reason why a POSITA would have been motivated to house the historical accumulation database at the server is because data storage at a server is one of a finite number of known solutions for data storage—namely, either local storage at the vehicles themselves or remote storage such as at a server. These two storage options are predictable, conventional, and well-understood, and thus a POSITA would have had a reasonable expectation of success in implementing the database at a server.

206. There are also several reasons why a POSITA would have expected success in implementing the historical accumulation database.

207. First, a server-housed historical accumulation database is consistent with Kudo-325's statement that "a part of the functions that a car navigation system has may be provided in a server on a network." TESLA-1004 (Kudo-325), [0075]. A POSITA thus would have expected success given Kudo-325's direct indication that such an implementation is possible.

208. Second, a POSITA would have expected success in implementing the historical accumulation database at a server involves only commonly used techniques and devices: a server-based database.

209. Third, a POSITA would have expected success because housing a database on a server was conventional and predictable, and presents no unexpected results.

[9] The device according to claim 8, wherein said remote database is configured to receive a plurality of said predicted destinations and generate guidance information based on said plurality of said predicted destinations.

210. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [9], as I discuss in the following paragraphs.

211. As I discussed above for claim [8], in the Kudo-325/Kudo-066 combination system, the information accumulation means receives a predicted destination, *i.e.*, the ***remote database is configured to receive a predicted destination***. In return, the remote information accumulation means provides information relevant to the predicted destination, such as “road/traffic information up to the travel destination,” back to the vehicle for presentation to the driver. TESLA-1004 (Kudo-325), [0107]; *see* TESLA-1005 (Kudo-066), [0105] (“information such as traffic information indicating a traffic jam or information on traffic control by the police”), [0066]-[0068], [0070],[0150], Abstract.

212. Traffic information is an example of ***guidance information***. For instance, this is the case because traffic information provides guidance to the driver regarding expected traffic along a predicted route. Indeed, traffic information along a route may influence the driver’s decision-making and actions, for instance, the driver may choose to take a different route or drive to a different destination if the traffic is unexpectedly heavy.

213. Traffic information (***guidance information***) related to the predicted destination is retrieved from the database, *e.g.*, in response to a query for that information, and is processed such that it can be transmitted back to the car navigation system for presentation to the driver. These actions correspond to generating the traffic information (***generating guidance information***).

214. A POSITA would understand that the process of receiving traffic information from the server-based information accumulation means occurs multiple times according to the process I discussed above. For instance, this traffic information retrieval will occur for at least some trips taken by a vehicle. This involves providing multiple predicted destinations to the information accumulation means, *e.g.*, at least one predicted destination for each trip (*remote database receiving multiple a plurality of said predicted destinations*). This also involves generating traffic information for each of those predicted destinations (*generating guidance information based on said plurality of said predicted destinations*).

215. Alternatively or additionally, in the Kudo-325/Kudo-066 combination system, Kudo-325 describes that multiple predicted locations can sometimes be determined. *See* TESLA-1004 (Kudo-325), [0104] (“The node determination can be executed by various methods, for example, ... a method of selecting all nodes having probability values exceeding a predetermined value, and a method of selecting a given number of nodes in order from the node having the highest probability value”). Kudo-066 also describes determining multiple predicted destinations. *See* TESLA-1005 (Kudo-066), [0149] (“the destinations are ABC Co. Ltd., PQR Clinic and XYZ Supermarket at frequencies of 70%, 25% and 5%, respectively”). These multiple predicted destinations are transmitted to the server-housed information accumulation means for retrieval of traffic/route information, as taught by Kudo-066:

“the information acquisition means 18 transmits, to the server 2, information on routes to the respective predicted destinations.” *Id.*, [0149]. That is, the multiple predicted destinations for a given trip are transmitted to the server-housed database (*the remote database receiving multiple a plurality of said predicted destinations*).

216. Continuing with this scenario, based on the teachings of Kudo-066, “the server 2 searches traffic information accumulated in the information accumulation means 22 to find information concerning the route,” such as traffic information to each of the predicted destinations. TESLA-1005 (Kudo-066), [0150]; *see* [0151]-[0152]. This traffic information is provided to the car navigation system, which “calculates estimated travel time required to reach each of the possible destinations by referring to the received traffic information.” TESLA-1005 (Kudo-066), [0151]. The retrieval of traffic information for each of the multiple predicted destinations, and providing that traffic information to the car navigation system, corresponds to *generating guidance information based on said plurality of said predicted destinations*.

217. A POSITA would have been motivated to implement the car navigation system of the Kudo-325/Kudo-066 combination to provide traffic information for each of multiple predicted destinations, as taught by Kudo-066, at least in order

to provide the driver with valuable information about expected traffic. This information can help the driver to use their time productively, for instance, based on traffic information, a driver may choose a different route or a destination other than where they had originally planned to drive. The ability to provide this traffic information for multiple predicted destinations can in this way improve user experience and satisfaction with the system.

[10] *The device according to claim 8, wherein said remote database is configured to (i) receive said sensor data samples and store said sensor data samples as said historical data and (ii) present said historical data to said device.*

218. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [10], as I discuss in the following paragraphs.

219. As discussed in [8], the historical accumulation database (a ***remote database***) can be housed at the server. *See* TESLA-1004 (Kudo-325), [0075]. This remote historical accumulation database operates just as described for the local history accumulation database described by Kudo-325: “when the current position is judged as a node” by the node judgement section of the car navigation system, “the node is stored” in the history accumulation database. That is, in the server-housed configuration of the historical accumulation database, the node IDs (***sensor data samples***) are provided to the server-housed history accumulation database for storage—*i.e.*, the ***remote database is configured to receive the sensor***

data samples and store the sensor data samples. TESLA-1004 (Kudo-325), [0078]; *see* [0090]. Other examples of sensor data samples, including time/date information and/or driver identity information are also stored in the history accumulation database--*i.e.*, again, the *remote database is configured to receive the sensor data samples and store the sensor data samples.* *See* TESLA-1004 (Kudo-325), [0014], [0087]-[0088], [0090], [0094], FIG. 3.

220. The sensor data samples stored in the historical accumulation database (*e.g.*, at least for past trips taken by the vehicle) correspond to *historical data*, as I discussed above for element [1c-2]. *See* TESLA-1004 (Kudo-325), [0078], [0087]-[0088], [0091]-[0092], [0096], FIG. 3. This historical nature of the sensor data samples for past trips is not changed by the implementation of the historical accumulation database at the server.

221. Kudo-325 also describes that “the transition state information generation section” of the car navigation system “generates transition state information ... by utilizing the data in the history accumulation DB.” TESLA-1004 (Kudo-325), [0092]; *see* [0053], [0073], [0109], element 105 of FIG. 1. When the history accumulation database is housed at the server, a POSITA would have understood that the data in the history accumulation database (*historical data*) would be provided to the transition state information generation section of the car navigation system

(present said historical data to said device) to enable the car navigation system to generate that transition state information.

[11] *The device according to claim 1, wherein said memory is further configured to store said historical data.*

222. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [11]. As I discussed above for element [1c-2], the travel history data stored in the history accumulation database (*memory*; see my discussion above for element [1b]) corresponds to the *historical data*. That is, *the memory is configured to store the historical data*.

[12] *The device according to claim 1, wherein said historical data comprises information about operation of said vehicle.*

223. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [12]. As I discussed above for element [1c-2], the travel history stored in the history accumulation database (*historical data*) include “pairs of node numbers and times of passage therethrough are stored chronologically.” TESLA-1004 (Kudo-325), [0087]; see [0096], [0013], [0017], [0051], [0072], [0091]-[0092], FIG. 1. The node ID numbers and/or the date/time information correspond to *information about operation of the vehicle*. This is the case at least because they are information about the spatial and/or temporal position of the vehicle

during its trip (that is, during operation of the vehicle). Also as I discussed for element [1c-2], the travel history stored in the history accumulation database (*historical data*) include “information on weather, a driver, or a fellow passenger.”

TESLA-1004 (Kudo-325), [0088]; *see* [0014], [0052]. These types of information also correspond to *information about operation of the vehicle* at least because they are information about the weather, driver, and/or passenger during the vehicle’s trip (that is, during operation of the vehicle). Thus, these are examples of how the *historical data* includes *information about operation of the vehicle*.

[13] *The device according to claim 1, wherein at least one of said sensor data samples comprises a data sample from an optical sensor.*

224. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [13]. As I discussed above for element [1a], a driver identifier (*sensor data sample*) is determined based on “person judgment by an on-board camera.” TESLA-1004 (Kudo-325), [0140]. An “on-board camera” corresponds to an *optical sensor*, *e.g.*, because a camera captures an image based on an optical signal. The driver identifier (*sensor data sample*) determined by analysis of that captured image corresponds to *a data sample from an optical sensor* at least because the driver identifier uniquely corresponds to and represents that same particular quantum of user identification sensor information as the image from which the driver identifier was determined.

[14] *The device of claim 1, wherein the historical data comprises data gathered from multiple trips of the driver's operation of the vehicle.*

225. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim [14]. As I discussed above for elements [1d-1] through [1d-3], the transition state information (the *historical data*) includes *data gathered from multiple trips of the driver's operation of the vehicle*. For instance, with reference to FIG. 5, the transition state information includes data gathered from a trip from node L6 to L24 and another trip from node L6 to node L2 (among many other examples). *See* TESLA-1004 (Kudo-325), FIG. 5.

226. Alternatively or additionally, as I also discussed above for elements [1d-1] through [1d-3], the transition state information (the *historical data*) includes *data gathered from multiple trips of the driver's operation of the vehicle*, at least because Kudo-325 describes that a node is entered into the transition state information based on it appearing in the history accumulation database more than a threshold number of times. *See* TESLA-1004 (Kudo-325), [0091]-[0092], [0109]; *see* elements a4-a5 of FIG. 4.

[15pre] *A method performed by a processor for predicting a destination of a vehicle, comprising the steps of:*

227. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [15pre]. For example, Kudo-325 describes “a method including a first step of accumulating, as a travel history, a travel route obtained

from the history of position information of the mobile body” and then “predicting one or more travel destinations or routes where the mobile body will advance.” TESLA-1004 (Kudo-325), [0013]. Moreover, my discussion of the Kudo-325/Kudo-066 combination system in V.A.3, above, addresses in more detail how this combination provides a method for predicting the destination of a vehicle. And the method of predicting a destination is performed by a processor, as I discussed at least for claim elements [1c-1] through [1c-4], above.

[15a] (A) monitoring a plurality of sensors to generate sensor data samples during operation of a vehicle;

228. It is my opinion that the combination of Kudo-325 and Kudo-066 renders obvious claim element [15a]. In the combination, the car navigation system *monitors sensors*, e.g., position sensors (e.g., GPS), time/date sensors, and/or driver identity sensors (on-board camera) to generate *sensor data samples* (e.g., position, time/date, and/or driver identity information). See my discussion above for element [1a].

[15b] (B) storing said sensor data samples for different points in time along a route segment traveled by said vehicle;

229. See my discussion above for element [1b].

[15c] (C) analyzing said sensor data samples to detect a pattern; and (D) predicting a destination of a driver in response to (a) said pattern and (b) historical data associated with operation of said vehicle, wherein (i) at least one of said sensor data samples is driver-related and (ii)

at least one of said sensor data samples comprises telemetry data;

230. See my discussion above for elements [1c-1] through [1c-4].

[15d] wherein the historical data comprises: data, regarding multiple route segments, gathered from the driver's operation of the vehicle on the multiple route segments during multiple trips; data, regarding multiple sequences of route segments, gathered from the driver's operation of the vehicle on the multiple sequences of route segments during the multiple trips; and data, regarding multiple travel destinations, gathered from the driver's operation of the vehicle to the multiple travel destinations during the multiple trips.

231. See my discussion above for elements [1d-1] through [1d-3].

[16pre] A vehicle comprising:

232. The combination of Kudo-325 and Kudo-066 renders obvious [16pre].

For example, in the Kudo-325/Kudo-066 combination system, Kudo-325 describes *a vehicle* such as an automobile “on which the car navigation system is boarded.”

TESLA-1004 (Kudo-325), [0077]; see [0214] (“An automobile boarding a car navigation system”).

[16a] a power train;

[16b] a drive train;

233. The combination of Kudo-325 and Kudo-066 renders obvious [16a] and [16b]. In particular, as I discussed above for element [16pre], in the Kudo-325/Kudo-066 combination system, Kudo-325 discloses a vehicle such as an auto-

mobile. *See* TESLA-1004 (Kudo-325), [0077]. A POSITA would have understood that an automobile includes *a power train*, *e.g.*, an engine or motor; indeed, a power train is a standard element of an automobile. *See* TESLA-1006 (Tryon), [0024], FIG. 1; TESLA-1016 (Seksaria), [0016] (“The power train assembly may comprise an engine and transmission of the motor vehicle”); TESLA-1017 (Teraoka), 2:8-20. Similarly, a POSITA would have understood that an automobile includes *a drive train*, *e.g.*, components that deliver power produced by the engine or motor to other components of the automobile such as the wheels; indeed, a drive train is also a standard element of an automobile. *See* TESLA-1006 (Tryon), [0024], FIG. 1; TESLA-1016 (Seksaria), [0016]; TESLA-1017 (Teraoka), 2:8-20.

[16c] *a sensor interface configured to receive sensor data samples during operation of a vehicle;*

234. *See* my discussion above for element [1a].

[16d] *a storage device configured to store said sensor data samples for different points in time along a route segment traveled by said vehicle; and*

235. *See* my discussion above for element [1b].

[16e] *a processor configured to (i) analyze said sensor data samples stored in said storage device to detect a pattern and (ii) predict a destination of a driver in response to (a) said pattern and (b) historical data associated with operation of said vehicle, wherein (i) at least one of said sensor data samples is driver-related and (ii) at least one of said sensor data samples comprises telemetry data;*

236. *See* my discussion above for elements [1c-1] through [1c-4].

[16f] wherein the historical data comprises: data, regarding multiple route segments, gathered from the driver's operation of the vehicle on the multiple route segments during multiple trips; data, regarding multiple sequences of route segments, gathered from the driver's operation of the vehicle on the multiple sequences of route segments during the multiple trips; and data, regarding multiple travel destinations, gathered from the driver's operation of the vehicle to the multiple travel destinations during the multiple trips.

237. See my discussion above for elements [1d-1] through [1d-3].

B. [GROUND 1B] – Claim 3 is rendered obvious by Kudo-325, Kudo-066, and Bolger

1. Overview of Bolger

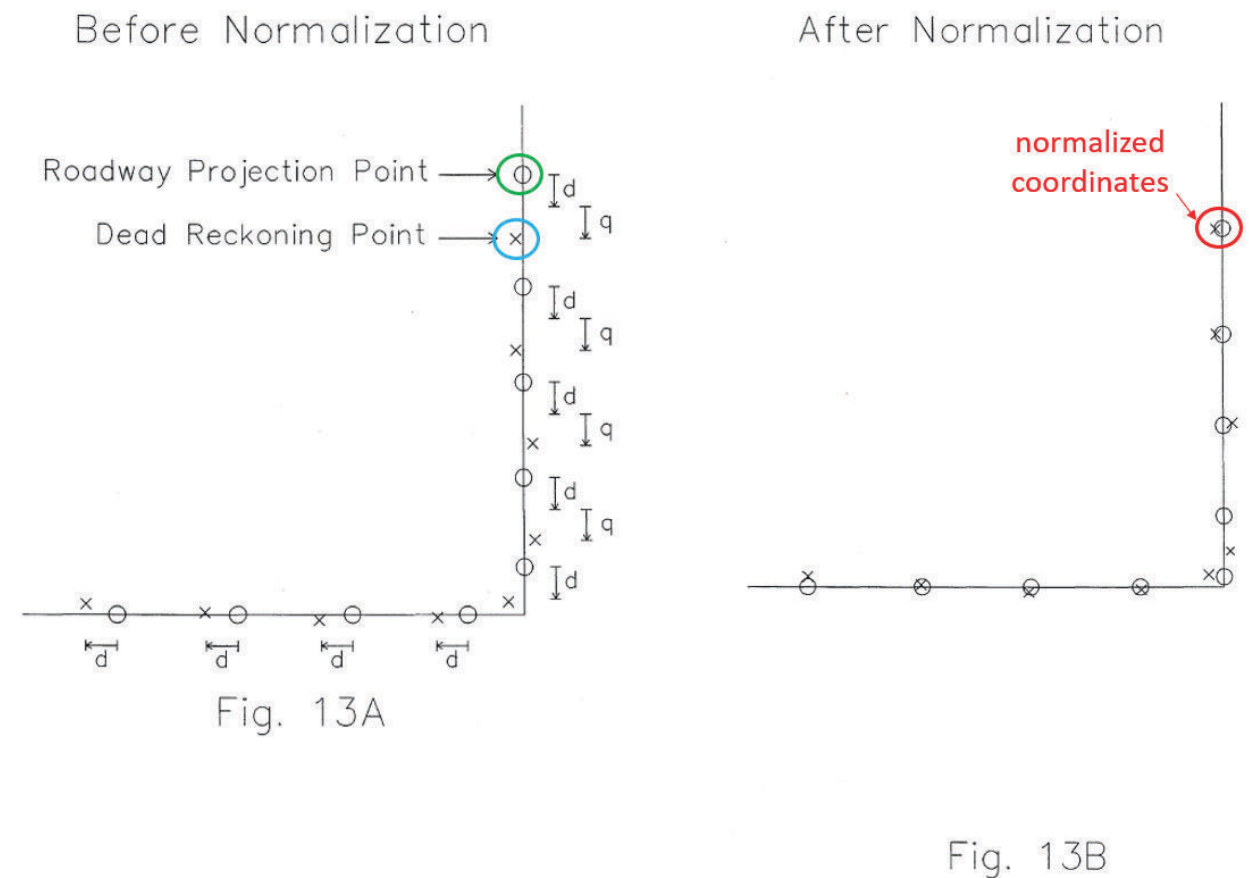
238. Bolger relates to “automobile navigation systems that use dead reckoning techniques for determining the automobile’s location.” TESLA-1007 (Bolger), 1:9-11. The vehicle’s location is used in “determin[ing] the appropriate navigation route” to a designated “destination location,” e.g., a route having “either the shortest driving distance or the fastest estimated travel time.” *Id.*, 1:51-55.

239. In Bolger’s approach, data from a “digital compass and [an] electronic distance traveled sensor” are provided “as input to a dead reckoning algorithm that in turn produces a series of vehicle coordinate locations.” *Id.*, 1:47-51. However, Bolger acknowledges that “dead reckoning data” does not “correctly represent[] the exact route driven.” *Id.*, 1:65-67. To mitigate the inaccuracies of relying solely on dead reckoning for determining the vehicle’s location, Bolger describes

“reconcil[ing] the dead-reckoned coordinates to the corresponding road way coordinates projected upon the road map database,” which “provide[s] enough information to allow reliable prediction of the navigation route through the correct street and highway intersections.” *Id.*, 1:62-2:3; *see* 2:10-14 (“The system next uses the collection of coordinates obtained from dead reckoning and roadway projected (from the road map database) to establish a χ^2 value that when minimized produces the best match between the road map database location and the dead reckoning path location”).

240. In more detail, Bolger’s approach involves “calculat[ing] the dead-reckoning location,” *e.g.*, “location coordinates x and y.” TESLA-1007 (Bolger), 6:59-61, 7:21-22. The approach also involves “determining the roadway projected location” (*e.g.*, “the roadway projected coordinates”) “from the road map database by calculating the best navigation route taken by the vehicle according to the current dead-reckoned coordinates.” *Id.*, 6:51-57, 7:31-33. The road map database is a digitized version of “the entire road system” that includes “coordinate locations that describe the roads, the connectivity between intersections, street names, block numbers, road size classification, and one-way status.” *Id.*, 4:17-23. As illustrated in FIG. 13A, reproduced and annotated below, the dead-reckoned coordinates (blue) and the roadway projected coordinates (green) do not necessarily match. *See id.*, 2:9-26. The algorithm then “normaliz[es] the dead-reckoned coordinates or

location to the roadway projected coordinates or location,” resulting in “normalized coordinates” (red in FIG. 13B, also below) that are “an optimum match” between the dead-reckoned coordinates and the roadway projected coordinates. *Id.*, 8:13-15, 9:67-10:2.



Bolger, FIGS. 13A-13B (annotated)

241. Bolger is analogous art to the '002 Patent. It is from the same field of endeavor (*e.g.*, vehicle navigation). *See* TESLA-1007 (Bolger), Abstract (“The Driver’s Associate assists a driver of a vehicle to more efficiently reach a desired destination”). And, it is reasonably pertinent to the problem the '002 Patent was

trying to solve (*e.g.*, assisting with vehicle operation along a route). *See id.*, Abstract (“The Driver’s Associate assists a driver of a vehicle to more efficiently reach a desired destination”).

2. Combination of Kudo-325, Kudo-066, and Bolger

242. An example of a system based on the Kudo-325/Kudo-066/Bolger combination is illustrated in the composite figure below. In this combination system, “the current position of the car navigation system is detected” by a “position detection section 101” of a car navigation system, consistent with the operation of Kudo-325’s car navigation system. TESLA-1004 (Kudo-325), [0090].

243. In the Kudo-325/Kudo-066/Bolger combination, the position detection system is implemented based on the approach described by Bolger, which relies on determining location coordinates using a map service. Specifically, based on Bolger, “coordinates obtained from dead reckoning and roadway projected (from the road map database)” are both used by the position detection section of the combination system to determine normalized coordinates that are a “best match between the road map database location and the dead reckoning path location.” TESLA-1007 (Bolger), 2:10-14. These normalized coordinates are provided to the server (outlined in pink), which accesses the server-based map database (highlighted in green) to determine “whether the current position is a node or not,” consistent with the operation of the Kudo-325/Kudo-066 combination system (which I

discussed above in section V.A.3). *See* TESLA-1005 (Kudo-066), [0068];
TESLA-1004 (Kudo-325), [0090].

244. It is my opinion that a POSITA would have been motivated to determine vehicle position in the Kudo-325/Kudo-066/Bolger combination system using a combination of dead reckoning and roadway projected coordinates, as taught by Bolger, for at least the following reasons.

245. The first reason why a POSITA would have been motivated to use dead reckoning (either in addition to or instead of GPS-based position detection) is because this determining vehicle location via dead reckoning can be used operational even when GPS is unavailable, such as due to obstructions. For instance, Wong describes drawbacks of GPS-based position detection systems: “receiving GPS positioning information requires that the receiver is has [sic] unobstructed line-of-sight view to a GPS satellite. Such a view may not be available when the vehicle’s view to the satellite is unobstructed by surrounding tall buildings. Accordingly, a system which can overcome this problem to report adequately accurate positioning information is valuable in a vehicle monitoring system operating in a city.” TESLA-1009 (Wong), 1:22-30. A POSITA would have recognized that having a position detection technique that is reliable in these types of situations is advantages in ensuring that the vehicle location is accurately detected, which then contributes to accurate destination prediction.

246. More specifically, a POSITA would have been motivated to use both dead reckoning and roadway projected coordinates to determine vehicle location (*e.g.*, according to specifics of the approach described by Bolger) because of the improvements in accuracy afforded by this approach. Bolger describes that an advantage of its approach “is that we can track a vehicle’s location more accurately than other similar devices that only use a simple determinate method for dead reckoning.” TESLA-1007 (Bolger), 1:40-43; *see* 2:37-38 (“To compensate for the inherent errors produced by a typical dead reckoning system”). Again, a POSITA would have recognized the value of this accuracy in facilitating downstream accuracy in destination prediction.

247. A POSITA also would have been motivated to implement position detection based on the approaches described by Bolger because this is just the application of known techniques (specifically, the use of dead reckoning and roadway maps to determine position of a vehicle) to an already-known system (specifically, the Kudo-325/Kudo-066 car navigation system). And, this combination of features produces predictable results (specifically, a car navigation system with position detection implemented via a combination of dead reckoning and roadway maps).

248. Additionally, a POSITA would have been motivated to implement position detection based on the approaches described by Bolger because determining position using dead reckoning and roadway maps is one of a finite number of

known solutions for position detection. In fact, there are many well-known ways for mapping from one coordinate system into another, such as for mapping GPS coordinates into Geospatial coordinates, and well-known software tools such as QGIS or ArcGIS can perform this conversion. Moreover, because it is a solution that is predictable, conventional, and well-understood, a POSITA would have had a reasonable expectation of success.

249. There are also several reasons why a POSITA would have expected success in implementing position detection based on the approaches described by Bolger in the car navigation system of the Kudo-325/Kudo-066 combination.

250. First, while Kudo-325 and Kudo-066 both describe the general concept of determining a vehicle's position, neither reference requires that position detection be performed in a specific way. *See* TESLA-1004 (Kudo-325), [0077], [0090]; TESLA-1005 (Kudo-066), [0063]. Kudo-325 provides no specifics at all, and while Kudo-066 identifies GPS, it is presented as an example rather than as a requirement. Thus, a POSITA would have understood the Kudo-325/Kudo-066 combination system to be flexible in terms of the precise technique used to detect vehicle position, and would have expected that a technique based on Bolger could be successfully used.

251. Second, a POSITA would have expected success because implementation of the Kudo-325/Kudo-066/Bolger combination involves only commonly

used techniques and devices, such as systems/algorithms for dead reckoning and capability for communicating with a map service.

3. Analysis

[3] The device according to claim 1, wherein said telemetry data comprises map coordinates determined by a map service.

252. It is my opinion that the combination of Kudo-325, Kudo-066, and Bolger renders obvious claim [3], as I discuss in the following paragraphs.

253. In the Kudo-325/Kudo-066/Bolger combination system, vehicle position is detected by a position detection system that determines location coordinates (*map coordinates*) based on a “best match between the road map database location and the dead reckoning path location,” as taught by Bolger. TESLA-1007 (Bolger), 2:10-14; *see* Abstract (“normalizing the vehicle’s location between the dead-reckoned coordinate and the roadway projected coordinate”), 7:31-33 (“As the vehicle moves, the present invention records the dead-reckoned coordinates and the roadway projected coordinates”), 8:13-15 “The last part of the tracking process ... is normalizing the dead-reckoned coordinates or location to the roadway projected coordinates or location”), 1:33-38, 1:62-64, claim 1. The road map database, which corresponds to *a map service*, is a digitized version of “the entire road system” that includes “coordinate locations that describe the roads, the connectivity between intersections, street names, block numbers, road size classification, and

one-way status.” *Id.*, 4:17-36; *see* Abstract (“tracking the vehicle through the road map database”), 2:32-33, 4:37-5:30. The latitude/longitude coordinates of the vehicle’s position thus correspond to *map coordinates determined by a map service* at least because they are coordinates determined by the road map database (a map service)..

254. Also in the combination, these map coordinates are provided to a server, which, assuming the current position is a node, returns “the associated node ID number” corresponding to the map coordinates for that position. TESLA-1005 (Kudo-066), [0068]. The node ID identified for the map coordinates (which correspond to *telemetry data*, as I discussed above for element [1c-4]) thus corresponds to *map coordinates determined by a map service* at least because the node ID uniquely corresponds to and represents those map coordinates.

C. [GROUND 1C] – Claim 17 is rendered obvious by Kudo-325, Kudo-066, and Tryon

1. Overview of Tryon

255. Tryon describes “an energy management system” that is “adapted to control a hybrid vehicle system 12 so as to provide for improving the efficiency of operation thereof responsive to an automatic recognition of an associated driving pattern of the vehicle.” TESLA-1006 (Tryon), [0023].

256. Referring to FIG. 1, which I have reproduced and annotated below, Tryon’s energy management system includes a “route computer system,” *red*, that

“predict[s] the ultimate destination of the vehicle 14 by comparing the present driving pattern with previous driving patterns stored in memory.” TESLA-1006 (Tryon), [0027]. With a predicted destination in hand, the route computer system “control[s] the hybrid vehicle system 12 in according with the energy and other requirements associated with the remainder of the trip,” *e.g.*, “to accomplish a particular objective ... such a[s] minimizing fuel consumption subject to reaching the destination or destinations subject to operator control of speed and braking of the vehicle.” *Id.* For instance, this control of the vehicle involves “predicting the energy or power requirements [] associated with the particular driving pattern,” *e.g.*, with a predicted destination, “and determining the associated control strategy for the power generator 16, electrical power controller 18, traction motor 20 and energy storage device 22 responsive to the particular driving pattern” TESLA-1006 (Tryon), [0041].

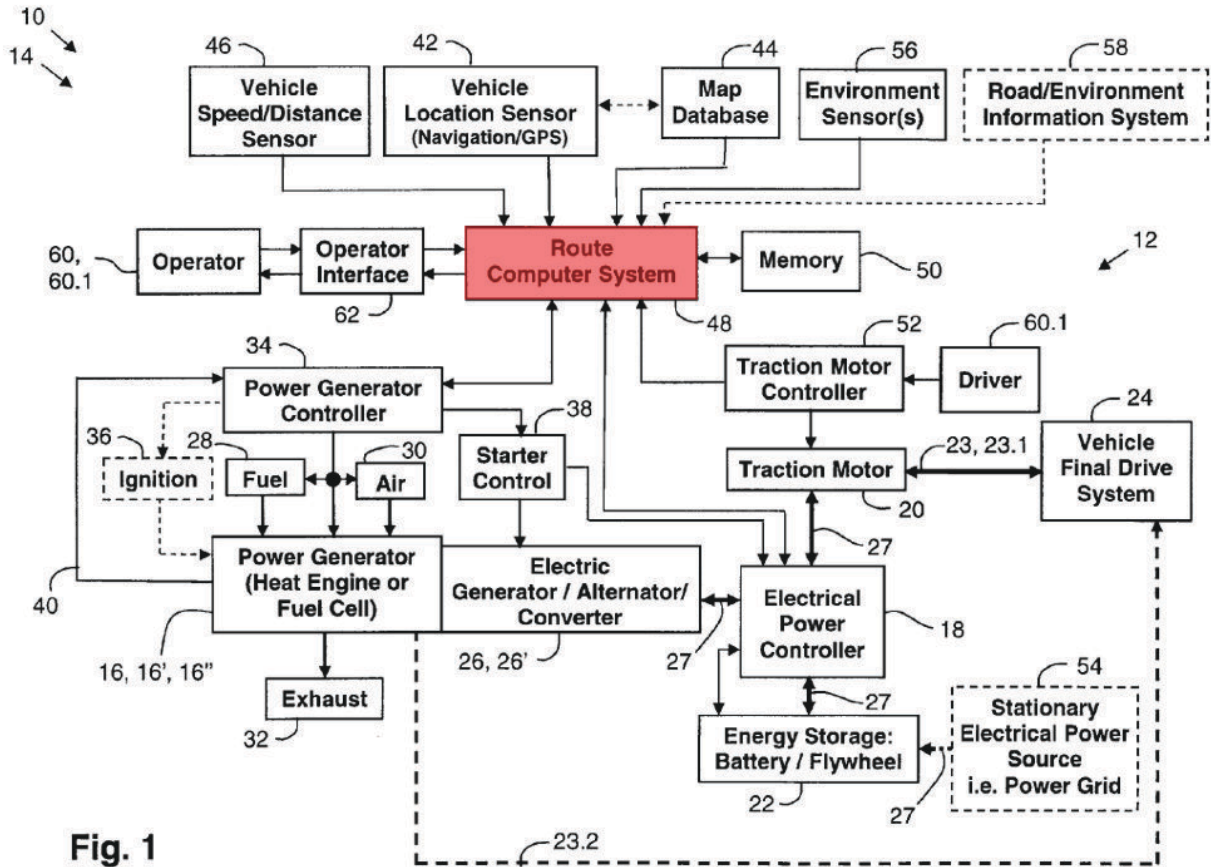
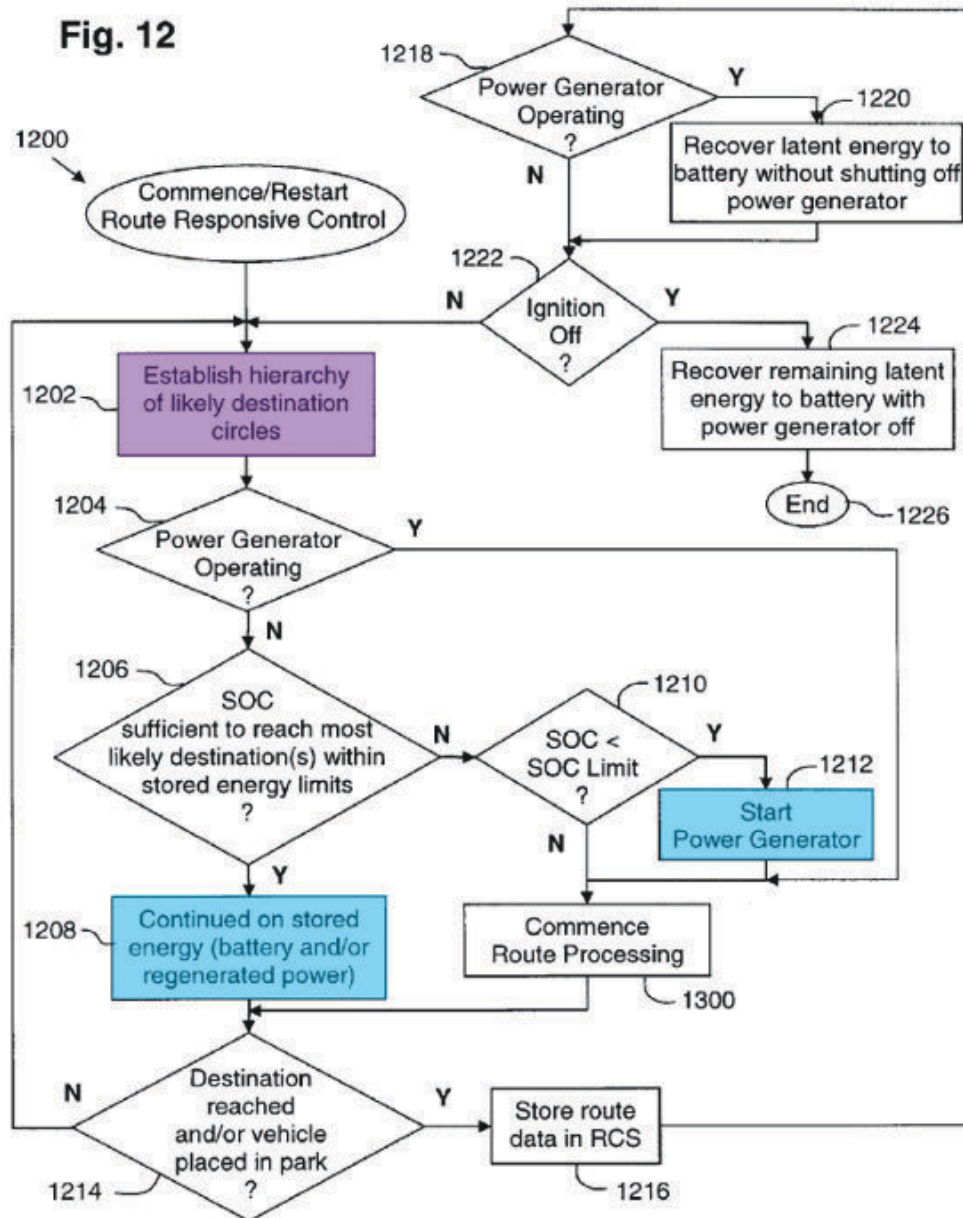


Fig. 1

Tryon, FIG. 1 (annotated)

257. In more detail, Tryon's "route computer system 48 establishes a hierarchy of likely destination circles," *e.g.*, predicted destinations for a current trip of a vehicle (step 1202, highlighted in purple in FIG. 12, reproduced and annotated below). TESLA-1006 (Tryon), [0058]; *see* [0059]. For instance, this hierarchy is established "by ranking the Likelihood values" that were calculated for each of various predicted destinations, based the date and time of the current trip and historical data "learned by the route computer system 48 from previous trips by the vehicle 14." *Id.* A "destination circle" corresponds to a group of "[d]estinations

that are sufficiently proximate to one another;” for instance, “a shopping center with different stores in relatively close proximity would be represented as a destination circle.” *Id.*, [0042].



Tryon, FIG. 12 (annotated)

258. Tryon further describes controlling the operation of the hybrid vehicle system based on the predicted destination circles, illustrated in FIG. 12, which I have reproduced and annotated above. *See* TESLA-1006 (Tryon), [0027], [0069]. In this approach, “if the power generator is not operating,” a determination is made about whether “from step (1206), the state of charge (SOC) or amount of stored energy in the energy storage device ... is sufficient to reach the most likely destination 114 or most likely destinations 114.” *Id.*, [0069]. If so, “in step (1208) [blue] the vehicle 14 continues the trip on stored energy from the energy storage device.” *Id.*, [0069]. If not, “in step (1212) [blue], the power generator 16 is started so as to generate sufficient electric power 27 to continue operating the vehicle 14.” *Id.*

259. Tryon is analogous art to the '002 Patent. It is from the same field of endeavor (*e.g.*, vehicle navigation). *See* TESLA-1006 (Tryon), Abstract (“A vehicle location sensor such as a GPS, an inertial navigation or dead reckoning system determines location data for a vehicle that travels from a known first destination to a second destination.”). And, it is reasonably pertinent to the problem the '002 Patent was trying to solve (*e.g.*, assisting with vehicle operation along a route). *See id.*, Abstract (“A power generator and an energy storage device of a hybrid electric vehicle are controlled responsive to the anticipated likely driving pattern, and possibly responsive to information from environment sensors.”).

2. Combination of Kudo-325/Kudo-066 and Tryon

260. In the Kudo-325/Kudo-066/Tryon combination, the car navigation system of the Kudo-325/Kudo-066 combination is implemented as part of a “route computer system” in the context of a hybrid vehicle system, as described by Tryon. See TESLA-1006 (Tryon), [0023]-[0024]. Referring to Tryon’s FIG. 1, reproduced again below, the route computer system (highlighted in red) implements aspects of the Kudo-325/Kudo-066 combination car navigation system.

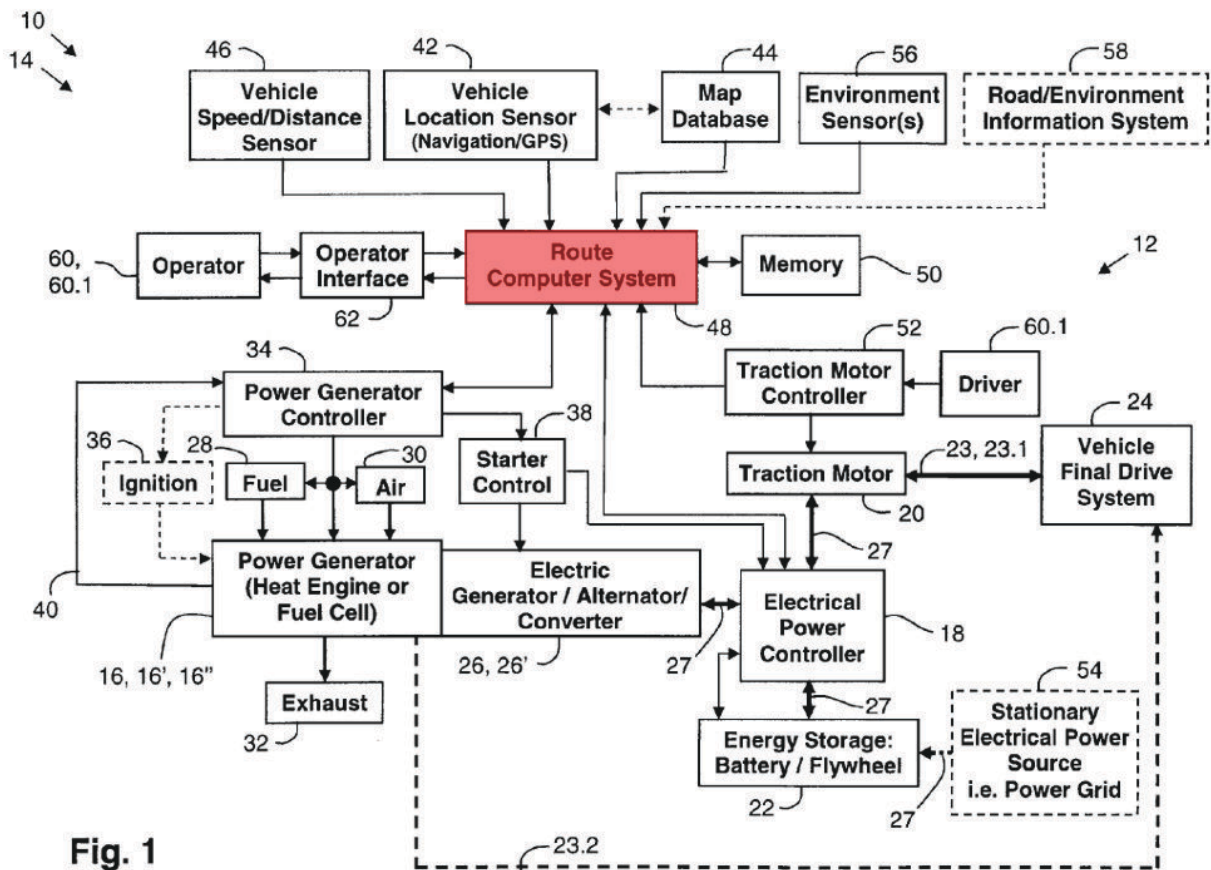
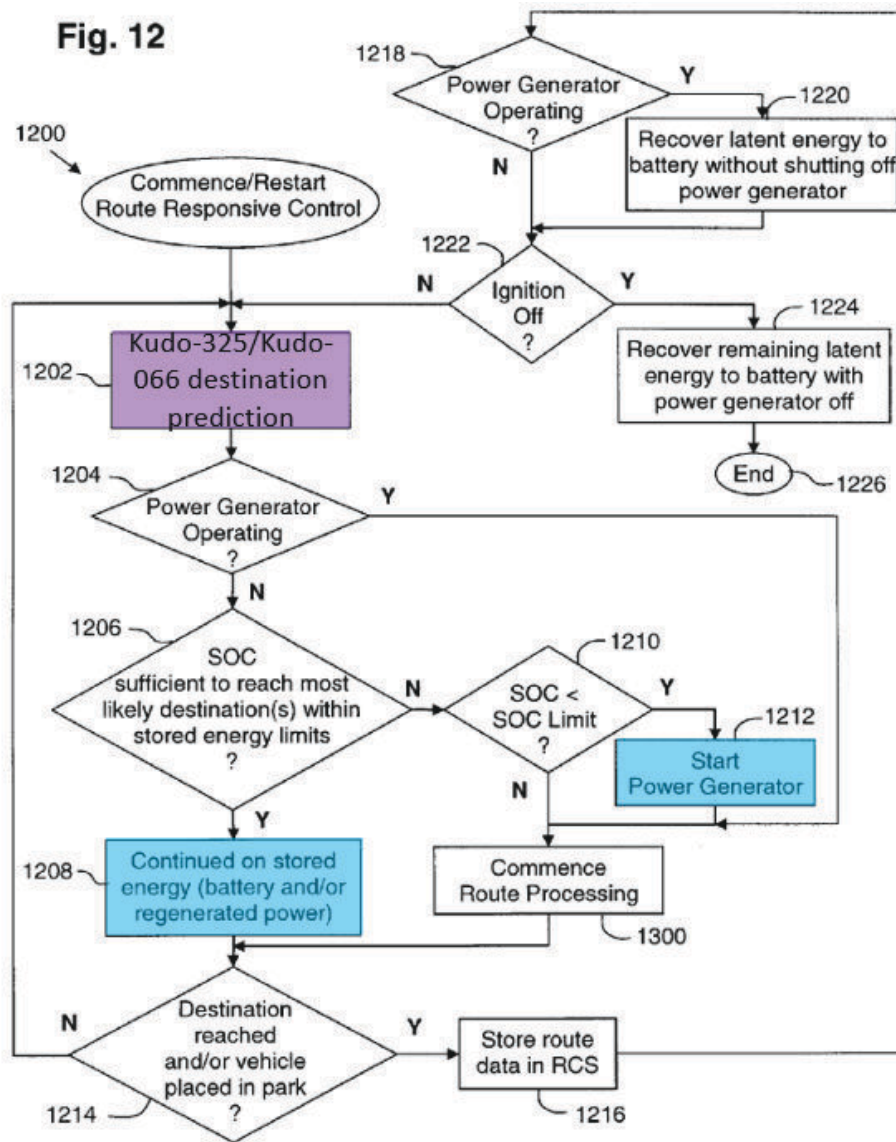


Fig. 1

Tryon, FIG. 1 (annotated)

261. An example of the operation of this combination system is illustrated in the composite figure below. This combination system, controls operation of the vehicle according to the predicted destination, as taught by Tryon, with the predicted destination being determined based on the Kudo-325/Kudo-066 combination car navigation discussed above.



Kudo-325/Kudo-066/Tryon composite figure based on Tryon, FIG. 12

262. In this Kudo-325/Kudo-066/Tryon combination system, the car navigation system predicts travel destinations for the hybrid vehicle based on information about both current and historical travel of the vehicle (*see* element 1202 of the composite flowchart, highlighted in purple), consistent with the functionality of the Kudo-325/Kudo-066 combination car navigation system discussed above in Section V.A.3. *See* TESLA-1004 (Kudo-325), [0013]-[0014], [0051], [0097]-[0102]. The operation of the hybrid vehicle system is controlled based on these predicted destinations, as taught by Tryon. *See* TESLA-1006 (Tryon), [0027], [0069]. For instance, if “the state of charge (SOC) or amount of stored energy in the energy storage device ... is sufficient to reach” the destination(s) predicted by the Kudo-325/Kudo-066 based car navigation system (depicted as decision element 1206 in the composite flowchart), “the vehicle 14 continues the trip on stored energy from the energy storage device” (element 1208 of the composite flowchart, highlighted in blue) TESLA-1006 (Tryon), [0069]. If the stored energy is not sufficient to reach the destination, “the power generator 16 is started so as to generate sufficient electric power 27 to continue operating the vehicle 14” (element 1212 of the composite flowchart, also highlighted in blue). TESLA-1006 (Tryon), [0069].

Reasons for controlling the operation of a hybrid vehicle based on its predicted destination

263. It is my opinion that a POSITA would have been motivated to use the destinations predicted by the Kudo-325/Kudo-066 combination car navigation system to control the operation of a hybrid vehicle, as taught by Tryon, for at least the following reasons.

264. The first reason a POSITA would have been motivated to pursue this implementation is to achieve the fuel efficiency benefits of such as an approach, as described by Tryon. Generally, Tryon describes that this approach to hybrid vehicle control “provides for operation with reduced fuel consumption and improved emissions.” TESLA-1006 (Tryon), [0040]. For instance, “for relatively short trips that can be accomplished strictly with stored energy from the energy storage device 22, it may be beneficial to operate entirely on stored energy, without operating the power generator 16.” *Id.* As another example, “for a hybrid vehicle system 12.1 incorporating a recuperated turbine engine 64, then under driving conditions for which the recuperated turbine engine 64 is operated, it is beneficial to be able to control the recuperated turbine engine 64 prior to reaching a destination so that the heat energy stored in the recuperator 68 can be extracted.” *Id.*

265. The second reason is that a POSITA would have recognized that reliance on a predicted destination for control of the hybrid vehicle further allows for more detailed reliance on a predicted route to that destination, and would have

been motivated to proceed with this combination to achieve further fuel efficiency advantages associated with this reliance on the predicted route. *See* TESLA-1006 (Tryon), [0079]. For instance, Tryon describes that by taking into account a predicted route to the predicted destination, “the associated control schedule governing the operation of the power generator 16 and energy storage device 22 can be optimized” to account for future conditions “rather than merely the particular operating condition at any given time.” TESLA-1006 (Tryon), [0079]. This control strategy allows for “improved overall operating efficiency.” TESLA-1006 (Tryon), [0080].

266. The third reason a POSITA would have been motivated to pursue this implementation is because this is just the application of known techniques (specifically, controlling operation of a hybrid vehicle based on a predicted destination, as in Tryon’s system) to a known system (specifically, the Kudo-325/Kudo-066 car navigation system for predicting destinations) to yield predictable results (*e.g.*, a hybrid vehicle, the operation of which is controlled based on a predicted destination for the vehicle).

267. The fourth reason a POSITA would have been motivated to pursue this implementation because the combination makes use of a known technique

(specifically, controlling operation of a hybrid vehicle based on a predicted destination) to improve a similar system (for instance, improving fuel efficiency of a vehicle having destination prediction capabilities).

268. There are also several reasons why a POSITA would have expected success in use the destinations predicted by the Kudo-325/Kudo-066 combination car navigation system to control the operation of a hybrid vehicle, as taught by Tryon.

269. First, a POSITA would have recognized that Tryon's approach to hybrid vehicle control based on determining whether there is sufficient stored energy to reach a predicted destination (*see* TESLA-1006 (Tryon), [0069]) does not depend on the particular approach used to determine that predicted destination. Thus, a POSITA would have understood Tryon's system to be flexible in terms of how predicted destinations are identified, and would have expected that the destination prediction techniques of the Kudo-325/Kudo-066 car navigation system could be successfully used in this context,

270. Second, a POSITA would have expected success because implementation of the Kudo-325/Kudo-066/Tryon combination involves common techniques and devices, such as hybrid vehicle control system.

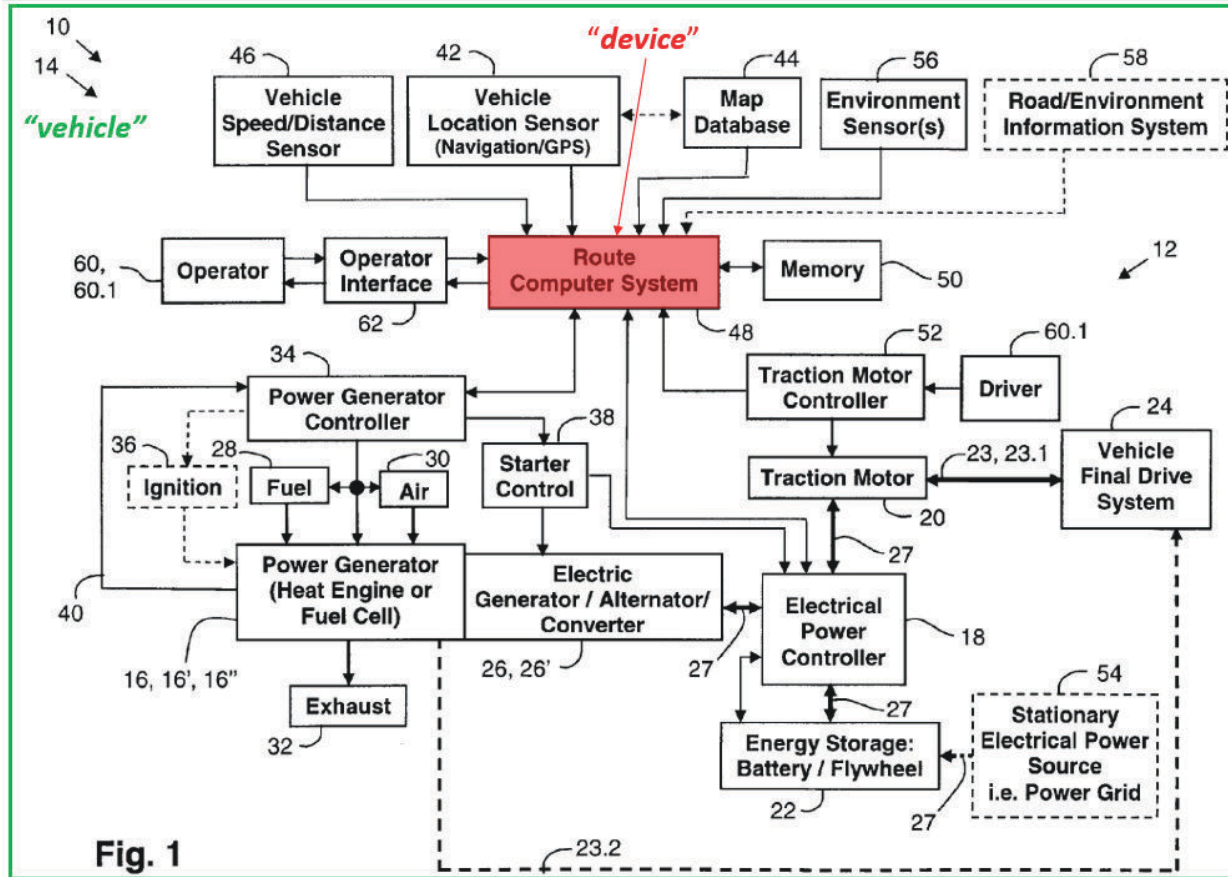
3. Analysis

[17] *The vehicle according to claim 16, further comprising: a device configured to (i) receive said predicted*

destination and (ii) adapt an operation of said vehicle based on said predicted destination.

271. It is my opinion that the combination of Kudo-325, Kudo-066, and Tryon renders obvious claim [17], as I discuss in the following paragraphs.

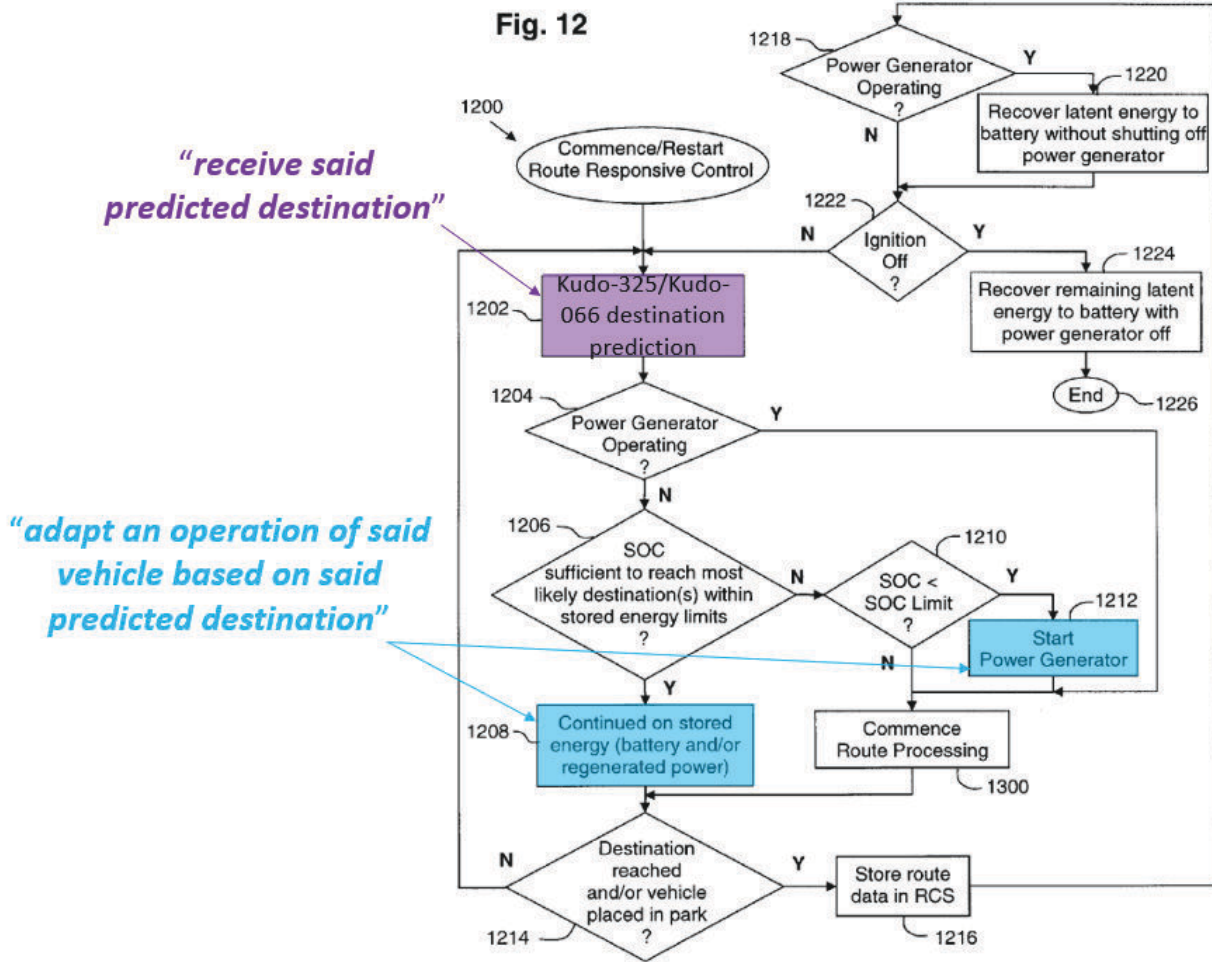
272. In the Kudo-325/Kudo-066/Tryon combination system, aspects of a car navigation system such as that of the Kudo-325/Kudo-066 combination is implemented as part of a “route computer system” based on Tryon (highlighted in red in Tryon’s FIG. 1, reproduced and annotated below) in the context of a hybrid vehicle system 12. TESLA-1006 (Tryon), [0027]; *see* Abstract. The hybrid vehicle itself (element 14, outlined in green) corresponds to ***a vehicle*** and the route computer system corresponds to ***a device***.



Tryon, FIG. 1 (annotated)

273. The operation of this combination system is illustrated in the composite figure below. In this combination system, the car navigation system (implemented as part of the route computer system) operates as I have discussed above for the Kudo-325/Kudo-066 combination: it predicts travel destinations for the hybrid vehicle based on information about both current and historical travel of the vehicle (highlighted in purple). *See* TESLA-1004 (Kudo-325), [0013]-[0014], [0051], [0097]-[0102]; *see* my discussion in Section V.A.3, above. Based on these identified predicted destinations, the route computer system “control[s] the hybrid

vehicle system 12 in accordance with the energy and other requirements associated with the remainder of the trip.” TESLA-1006 (Tryon), [0027]. That is, the route computer system (the *device*) performs control actions based on the predicted destination. A POSITA would have understood that for the route computer system (a *device*) to take an action (determining and implementing a vehicle control strategy) based on a predicted destination, the route computer system would have received that predicted destination (*a device configured to receive said predicted destination*). For instance, the predicted destination would be provided to a control module of the route computer system as an output from the process that generates the prediction.



Kudo-325/Kudo-066/Tryon composite figure based on Tryon, FIG. 12

274. Based on these predicted destinations, the route computer system (*device*) controls operation of the hybrid vehicle system (highlighted in blue), as taught by Tryon—that is, the device is *configured to adapt an operation of the vehicle based on said predicted destination*. See TESLA-1006 (Tryon), [0027] (“if a destination can be predicted, [the route computer system] provides for controlling the hybrid vehicle system 12 in accordance with the energy and other requirements

associated with the remainder of the trip”), [0041] (“if the destination can be predicted, predicting the energy or power requirements of associated with the particular driving pattern, and determining the associated control strategy for the power generator 16, electrical power controller 18, traction motor 20 and energy storage device 22 responsive to the particular driving pattern”), Abstract.

275. In a specific example, if “the state of charge (SOC) or amount of stored energy in the energy storage device ... is sufficient to reach” the destination(s) predicted by the Kudo-325/Kudo-066 based car navigation system, “the vehicle 14 continues the trip on stored energy from the energy storage device” (blue)—that is, the route computer system controls the vehicle to travel on stored energy. TESLA-1006 (Tryon), [0069]. If not, “the power generator 16 is started so as to generate sufficient electric power 27 to continue operating the vehicle 14” (blue)—that is, the route computer system controls the vehicle to operate the power generator. TESLA-1006 (Tryon), [0069]; *see* [0027], [0041], Abstract. Controlling the vehicle to operate on stored energy or to operate its power generator corresponds to ***adapting an operation of the vehicle based on the predicted destination*** at least because the operation of the vehicle (*e.g.*, which power source to use) depends on the predicted destination (*e.g.*, the distance between the vehicle’s current position and the predicted destination).

VI. LEGAL STANDARDS

A. Terminology

276. I have been informed by Counsel and understand that the best indicator of claim meaning is its usage in the context of the patent specification as understood by one of ordinary skill. I further understand that the words of the claims should be given their plain meaning unless that meaning is inconsistent with the patent specification or the patent's history of examination before the Patent Office. Counsel has also informed me, and I understand that, the words of the claims should be interpreted as they would have been interpreted by one of ordinary skill at the time of the invention was made (not today). Because I do not know at what date the invention as claimed was made, I have used the Critical Date as the point in time for claim interpretation purposes.

B. Legal Standards for Anticipation

277. I have been informed by Counsel and understand that documents and materials that qualify as prior art can render a patent claim unpatentable as anticipated. I am informed by Counsel and understand that all prior art references are to be looked at from the viewpoint of a person of ordinary skill in the art.

278. I am informed by Counsel and understand that a challenged claim is unpatentable as "anticipated" under 35 U.S.C. § 102 if it is determined that all the limitations of the claim are described in a single prior art reference. I am informed by Counsel and understand that, to anticipate a claim, a prior art reference must

disclose, either expressly or inherently, each and every limitation of that claim and enable one of ordinary skill in the art to make and use the invention.

279. I have been informed by Counsel and understand that in an *inter partes* review, “the petitioner shall have the burden of proving a proposition of unpatentability,” including a proposition of anticipation, “by a preponderance of the evidence.” 35 U.S.C. §316(e).

C. Legal Standards for Obviousness

280. I have been informed by Counsel and understand that documents and materials that qualify as prior art can render a patent claim unpatentable as obvious. I am informed by Counsel and understand that all prior art references are to be looked at from the viewpoint of a person of ordinary skill in the art at the time of the invention, and that this viewpoint prevents one from using his or her own insight or hindsight in deciding whether a claim is obvious.

281. I have been informed by Counsel and understand that a claim is unpatentable for obviousness under 35 U.S.C. § 103 “if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains.” I am informed by Counsel and understand that obviousness may be based upon a combi-

nation of references. I am informed by Counsel and understand that the combination of familiar elements according to known methods is likely to be obvious when it does no more than yield predictable results. However, I am informed by Counsel and understand that a patent claim composed of several elements is not proved obvious merely by demonstrating that each of its elements was, independently, known in the prior art.

282. I am informed by Counsel and understand that when a patented invention is a combination of known elements, a court must determine whether there was an apparent reason to combine the known elements in the fashion claimed by the patent at issue by considering the teachings of prior art references, the effects of demands known to people working in the field or present in the marketplace, and the background knowledge possessed by a person having ordinary skill in the art.

283. I am informed by Counsel and understand that a patent claim composed of several limitations is not proved obvious merely by demonstrating that each of its limitations was independently known in the prior art. I am informed by counsel for the Patent Owner and understand that identifying a reason those elements would be combined can be important because inventions in many instances rely upon building blocks long since uncovered, and claimed discoveries almost of

necessity will be combinations of what, in some sense, is already known. I am informed by Counsel and understand that it is improper to use hindsight in an obviousness analysis, and that a patent's claims should not be used as a "roadmap."

284. I am informed by Counsel and understand that an obviousness inquiry requires consideration of the following factors: (1) the scope and content of the prior art; (2) the differences between the claims and the prior art; (3) the level of ordinary skill in the pertinent art; and (4) any objective indicia of non-obviousness, such as commercial success, long-felt but unresolved need, failure of others, industry recognition, copying, and unexpected results. I understand that the foregoing factors are sometimes referred to as the "Graham factors."

285. I have been informed by Counsel and understand that an obviousness evaluation can be based on a combination of multiple prior art references. I understand that the prior art references themselves may provide a suggestion, motivation, or reason to combine, but that the nexus linking two or more prior art references is sometimes simple common sense. I have been informed by Counsel and understand that obviousness analysis recognizes that market demand, rather than scientific literature, often drives innovation, and that a motivation to combine references may be supplied by the direction of the marketplace.

286. I have been informed by Counsel and understand that if a technique has been used to improve one device, and a person of ordinary skill at the time of

invention would have recognized that it would improve similar devices in the same way, using the technique is obvious unless its actual application is beyond his or her skill.

287. I have been informed by Counsel and understand that practical and common sense considerations should guide a proper obviousness analysis, because familiar items may have obvious uses beyond their primary purposes. I have been informed by Counsel and understand that a person of ordinary skill looking to overcome a problem will often be able to fit together the teachings of multiple prior art references. I have been informed by Counsel and understand that obviousness analysis therefore takes into account the inferences and creative steps that a person of ordinary skill would have employed at the time of invention.

288. I have been informed by Counsel and understand that a proper obviousness analysis focuses on what was known or obvious to a person of ordinary skill at the time of invention, not just the patentee. Accordingly, I understand that any need or problem known in the field of endeavor at the time of invention and addressed by the patent can provide a reason for combining the elements in the manner claimed.

289. I have been informed by Counsel and understand that a claim can be obvious in light of a single reference, without the need to combine references, if

the elements of the claim that are not found explicitly or inherently in the reference can be supplied by the common sense of one of skill in the art.

290. I have been informed by Counsel and understand that secondary indicia of non-obviousness may include (1) a long felt but unmet need in the prior art that was satisfied by the invention of the patent; (2) commercial success of processes covered by the patent; (3) unexpected results achieved by the invention; (4) praise of the invention by others skilled in the art; (5) taking of licenses under the patent by others; (6) deliberate copying of the invention; (7) failure of others to find a solution to the long felt need; and (8) skepticism by experts. I understand that evidence of secondary indicia of non-obviousness, if available, should be considered as part of the obviousness analysis.

291. I have been informed by Counsel and understand that there must be a relationship between any such secondary considerations and the invention, and that contemporaneous and independent invention by others is a secondary consideration supporting an obviousness determination.

292. In sum, my understanding is that prior art teachings are properly combined where one of ordinary skill having the understanding and knowledge reflected in the prior art and motivated by the general problem facing the inventor, would have been led to make the combination of elements recited in the claims. Under this analysis, the prior art references themselves, or any need or problem

known in the field of endeavor at the time of the invention, can provide a reason for combining the elements of multiple prior art references in the claimed manner.

293. I have been informed by Counsel and understand that in an *inter partes* review, “the petitioner shall have the burden of proving a proposition of unpatentability,” including a proposition of obviousness, “by a preponderance of the evidence.” 35 U.S.C. §316(e).

VII. CONCLUSION

294. I reserve the right to supplement my opinions to address any information obtained, or positions taken, based on any new information introduced throughout this proceeding.

295. I declare under penalty of perjury that the foregoing is true and accurate to the best of my ability.

Curriculum Vitae

Education

- 1995 Ph.D. in Mech. Eng. University of Minnesota, Twin Cities.
1988 M.Sc. in Mech. Eng. Columbia University, New York, NY.
1983 Diploma Mech. Eng. National Technical University of Athens, Greece.

Current & Past Positions

- 2020- **Research Professor**, Electrical & Computer Engineering, U. of Minn., Twin Cities.
2014- **Director**, NSF center on Robots & Sensors for Human Well Being, U. of Minn., Twin Cities.
2006-2020 **Program Director**, Computer Science & Engineering, U. of Minn., Twin Cities.
2007-2014 **Co-PI**, NSF Research Center on Safety, Security and Rescue, U. of Minn., Twin Cities.
2003-2014 **Instructor**, Dept. of Mech. Eng., University of Minnesota, Twin Cities.

Industrial and Professional Experience

- 2005-2006 **Sr. Principle Research Scientist**, Adv. Tech. Labs, Honeywell Int., Inc.
1998-2005 **Principle Research Scientist**, Adv. Tech. Labs, Honeywell Int., Inc.
1995-1998 **Research Associate**, Dept. of Mech.Eng., U. of Minn., Minneapolis, MN.

Legal Experience

- **Finnegan, Henderson, Farabow, Garrett & Dunner, LLP**
August 2022: Pavemetrics vs Tetra Tech
Location: UNITED STATES DISTRICT COURT, CENTRAL DISTRICT OF CALIFORNIA
Role: Expert witness in computer vision, algorithms, and software engineering.
Provided testimony on software development practices and code analysis in a patent infringement case.

Honors and Awards

- Center for Transportation Studies: CTS Research Partnership Award, 2016.
- Best Student Paper Award, IEEE International Conference on Image Processing (ICIP), 2012.
- Technical Achievement Award, for Technical Excellence in the area of **People Tracking in Camera Networks**, *Highest Honorary Distinction* from Automation and Control Solutions (ACS) of Honeywell International Inc., April 2003.
- Technical Achievement Award, for Technical Excellence for development and installation of the **SGATE: Secure Gate Access Technology Evaluation**, *Highest Honorary Distinction* from Automation and Control Solutions (ACS) of Honeywell International Inc., April 2003.
- Technical Achievement Award, for Technical Excellence in the area of **Outdoor Visual Surveillance**, *Highest Honorary Distinction*, Honeywell International Inc., December 2001.
- Second Prize, ITS World Magazine's, GPS Applications Showcase, 1997.

- First Prize, Pan-Hellenic competition on “Heat Pumps” presented by the Rotary Club of Athens, Greece (sponsored by Toshiba), 1984.
- Fellowship from the Greek Ministry of Education for academic excellence during undergraduate studies, 1982.

Research Grants

- *Maintenance for the Truck Parking Availability System of the State of Kansas*
Role: Co-PI.
Sponsors: Kansas DOT.
Performance period: January 1, 2024 – December 31, 2029 - **Total amount:** \$725,000
- *A Real-Time Truck Parking Availability System of the State of Kansas*
Role: Co-PI.
Sponsors: Kansas DOT.
Performance period: October 1, 2016 – December 31, 2019 - **Total amount:** \$1,265,000
- *I/UCRC Phase II: Robots and Sensors for the Human Well-being*
Role: PI.
Sponsors: National Science Foundation (NSF).
Performance period: December 2019 - December 2024 - **Total amount:** \$725,000
- *MRI: Development of an Instrument that Performs Behavioral Analysis for Neurological Disorders like the Tourette Syndrome*
Role: Co-PI.
Sponsors: National Science Foundation (NSF).
Performance period: September 2019 - August 2024 - **Total amount:** \$1,823,000
- *NRI: INT: COLLAB: Robot Teams for Precision Agriculture and Plant Health Management*
Role: Senior personnel
Sponsors: National Science Foundation (NSF).
Performance period: September 2019 - August 2022 - **Total amount:** \$933,000
- *SCH: Active Learning for Medical Applications*
Role: Co-PI.
Sponsors: NIH/NCI.
Performance period: February 1, 2018 – January 31, 2022 - **Total amount:** \$1,320,000
- *CPS: TTP Option: Synergy: Collaborative Research: Dynamic Methods of Traffic Control that Impact Quality of Life in Smart Cities*
Role: Co-PI.
Sponsors: National Science Foundation (NSF).
Performance period: September 15, 2015 – February 29, 2020 - **Total amount:** \$1,248,000
- *Maintenance for the Truck Parking Availability System of the State of Kansas*
Role: Co-PI.
Sponsors: Kansas DOT.
Performance period: January 1, 2019 – December 31, 2023 - **Total amount:** \$649,000
- *A Real-Time Truck Parking Availability System for the State of Wisconsin*
Role: Co-PI.
Sponsors: MN DOT.
Performance period: June 30, 2016 – December 31, 2019 - **Total amount:** \$395,000
- *A Real-Time Truck Parking Availability System of the State of Kansas*
Role: Co-PI.
Sponsors: Kansas DOT.
Performance period: October 1, 2016 – December 31, 2019 - **Total amount:** \$1,265,000

- *I/UCRC Phase I: Robots and Sensors for the Human Well-being*
Role: PI.
Sponsors: National Science Foundation (NSF).
Performance period: September 2014–September 2019.
Total amount: \$854,600
- *MNDRIVE RSAM: Utilizing Computer Vision Technology for Cross-Cultural Developmental Screening in Early Childhood*
Role: Co-PI (with Suma Jacob, MD, PhD Department of Psychiatry, UMN).
Sponsors: University of Minnesota (MnDRIVE).
Performance period: September 2014.
Total amount: \$50,000
- *MRI: Development of an Instrument that Monitors Behaviors Associated with OCD and Schizophrenia*
Role: Co-PI (with prof. N. Papanikolopoulos, G. Bernstein, U of Minnesota).
Sponsors: National Science Foundation (NSF).
Performance period: November 2013–September 2017.
Total amount: \$560,000
- *A Comprehensive System for Assessing Truck Parking Availability*
Role: Co-PI (with N. Papanikolopoulos, U of Minnesota).
Sponsors: FHWA and MN DOT.
Performance period: January 11, 2012 – November 30, 2016.
Total amount: \$2,267,711
- *MRI: Development of a Video-Based Robotic Instrument for Behavioral Analysis and Diagnosis of at Risk Children*
Role: Co-PI (with N. Papanikolopoulos, K. Lim (U of Minnesota) and G. Sapiro (Duke University)).
Sponsors: National Science Foundation (NSF).
Performance period: October 1, 2010 – September 30, 2019.
Total amount: \$1,725,730
- *CDI-II: Computational Tools for Behavioral Analysis Diagnosis and Intervention of at Risk Children*
Role: Co-PI (with N. Papanikolopoulos, K. Lim (U of Minnesota) and G. Sapiro (Duke University)).
Sponsors: National Science Foundation (NSF).
Performance period: September 2010–September 2015.
Total amount: \$1,578,897
- *ComputerAided Cancer Diagnosis in Surgical Pathology*
Role: Co-PI, with N. Papanikolopoulos, et al.
Sponsors: Institute for Engineering in Medicine (IEM) Seed Grant
Performance period: January 2012–December 31, 2012.
Total amount: \$39,508.
- *I/UCRC: Collaborative Research: Detecting Cancer Using Advanced Computer Vision Techniques*
Role: Co-PI (with N. Papanikolopoulos, A. Banerjee, U of Minnesota).
Sponsors: NSF.
Performance period: August 2009–July 2013.
Total amount: \$99,998
- *Collaborative Research: I/UCRC for Safety, Security, and Rescue Research*
Role: Co-PI (with N. Papanikolopoulos, U of Minnesota).
Sponsors: National Science Foundation (NSF).
Performance period: August 2009–July 2013.

Total amount: \$330,000

- *Video Detection and Classification of Pedestrian Events at Roundabouts and Crosswalks*
Role: PI (with T. Morris and J. Hourdos, U of Minnesota).
Sponsors: Intelligent Transportation Systems (ITS) Institute (RITA).
Performance period: September 2011–June 2013.
Total amount: \$75,000
- *I/UCRC Basic Research Grant: A New Miniature Ground/Water Robot*
Role: Co-PI (with prof. N. Papanikolopoulos, U of Minnesota).
Sponsors: National Science Foundation (NSF).
Performance period: August 2009–July 2013.
Total amount: \$128,000
- *Sensing for HOV/HOT Lanes Enforcement*
Role: Co-PI (with prof. N. Papanikolopoulos, U of Minnesota).
Sponsors: Minnesota Dept of Transportation (MnDoT).
Performance period: July 2013–October 2013.
Total amount: \$97,200
- *Mass Transit Surveillance and Early Warning System*
Role: Principal Co-Investigator (with prof. N. Papanikolopoulos, U of Minnesota).
Sponsors: U. S. Department of Homeland Security.
Performance period: August 2004–September 2011.
Total amount: \$4.5 M
- *Appearance Models for Tracking across Multiple Cameras*
Role: Program Manager and Principal Co-Investigator (joint with prof. Larry Davis and Rama Chellappa, U of Maryland).
Sponsors: HSARPA (Homeland Security ARPA)/COTR ONR.
Performance period: May 2005–May 2007.
Total amount: \$1.3 M
- *Secure Gate Access Technology Evaluation (SGATE)*
Role: Principal Investigator.
Sponsors: Jointly sponsored by ONR and Honeywell Laboratories.
Performance Period: June 2002 – June 2003.
Total amount: \$900 K.
- *Detection of Events for Threat Evaluation and Recognition (DETER)*
Role: Principal Co-Investigator (joint with prof. I. Pavlidis of U of Houston).
Sponsors: Honeywell Laboratories.
Performance Period: June 1999–August 2002.
Total amount: \$700 K.
- *Digital Integration of Video for Airport Security (DIVAS)*
Role: Principal Investigator.
Sponsors: Honeywell Laboratories and Federal Aviation Administration (FAA).
Performance Period: June 1999–August 2004.
Total amount: \$1.2 M

Books

1. I. Pavlidis, V. Morellas and P. Roeber. *Programming cameras and pan-tilts with DirectX and Java*, Morgan Kaufmann Publishers Inc., 2003.

Book Chapters

1. I. Pavlidis and V. Morellas. *Two examples of indoor and outdoor surveillance systems*, In Video-based Surveillance Systems: Computer Vision and Distributed Processing, Kluwer Academic Publishers, Boston, pp. 39–51, 2002.

Refereed Journal Publications

1. L. Guzman, V. Morellas and N. Papanikolopoulos, *Robotic Embodiment of Human-Like Motor Skills via Reinforcement Learning*, in IEEE Robotics and Automation Letters, vol. 7, no. 2, pp. 3711–3717, April 2022, doi: 10.1109/LRA.2022.3147453.
2. A. Cherian, P. Stanitsas, J. Wang, M. Harandi, V. Morellas, and N. Papanikolopoulos. *Learning Log-Determinant Divergences for Positive Definite Matrices*, IEEE Pattern Analysis and Machine Intelligence, (PAMI), 2021.
3. P. Stanitsas, A. Cherian, V. Morellas, R. Tejpal, N. Papanikolopoulos and A. Truskinovsky. *Image Descriptors for Weakly Annotated Histopathological Breast Cancer Data*, Frontiers in Digital Health, 2020.
4. D. Zermas, V. Morellas, D. Mulla, and N. Papanikolopoulos. *3D Model processing for high-throughput phenotype extraction - The case of corn*, Journal of Computers and Electronics in Agriculture, 2020.
5. N. Walczak, J. Fasching, K. Cullen, V. Morellas, and N. Papanikolopoulos. *Toward Identifying Behavioral Risk Markers for Mental Health Disorders: An Assistive System for Monitoring Children's Movements in a Preschool Classroom*, Machine Vision and Applications, 29(3), pp 703–717, 2018.
6. G. Bernstein, T. Hadjiyanni, K. Cullen, M. Robinson, E. Harris, A. Young, J. Fasching, N. Walczak, S. Lee, V. Morellas, and N. Papanikolopoulos. *Use of Computer Vision Tools to Identify Behavioral Markers of Pediatric Obsessive-Compulsive Disorder: A Pilot Study*, J Child Adolesc Psychopharmacol.; 27(2):140-147. doi: 10.1089/cap.2016.0067. Epub 2016 Nov 10., 2017.
7. E. Harris, G. Bernstein, K. Cullen, S. Lee, T. Hadjiyanni, J. Robinson, A. Young, V. Morellas, and N. Papanikolopoulos. *1.64 Exploring Visual Design preferences in Youths with Obsessive-Compulsive Disorder*, In Journal of the American Academy of Child and Adolescent Psychiatry, 55(10) 2016.
8. A. Cherian, V. Morellas, and N. Papanikolopoulos. *Bayesian non-parametric clustering of positive definite tensors*, In IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(5), pp.862-874, 2015.
9. R. Sivalingam, D. Boley, V. Morellas, and N. Papanikolopoulos. *Tensor Dictionary Learning for Positive Definite Matrices*, In IEEE transactions on Image Processing, 24(11), pp.4592–4601 2016.
10. G. Somasundaram, A. Cherian, V. Morellas and N. Papanikolopoulos. *Action recognition using global spatio-temporal features derived from sparse representations*, Computer Vision and Image Understanding, 123: pp.1–13, 2014.
11. A. Cherian, S. Sra V. Morellas, and N. Papanikolopoulos. *Efficient nearest neighbors via robust sparse hashing*, In Transactions on Image Processing, Volume:23, Issue:8, pp.3646–3655, 2014.
12. J. Hashemi, T. V. Spina, M. Tepper, A. Esler, V. Morellas, N. Papanikolopoulos, H. Egger, G. Dawson and G. Sapiro. *Computer vision tools for low-cost and non-invasive measurement of autism-related behaviors in infants*, Autism Research and Treatment, Volume 2014, <http://dx.doi.org/10.1155/2014/935686>, 2014.
13. R. Sivalingam, D. Boley, V. Morellas and N. Papanikolopoulos. *Tensor sparse coding for positive definite matrices*, In IEEE Transactions on Pattern Analysis and Machine Intelligence, 36(3): pp.592–605, 2014.

14. G. Somasundaram, R. Sivalingam, V. Morellas and N. Papanikolopoulos. *Classification and counting of composite objects in traffic scenes using global and local image analysis*, In IEEE Transactions on Intelligent Transportation Systems (ITS), Volume:14, Issue:1, pp.69–81, 2013.
15. K. A. Patwardhan, G. Sapiro and V. Morellas. *Robust foreground detection in video using pixel layers*, In IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume 30, pp. 746–751, 2008.
16. V. Morellas, I. Pavlidis and P. Tsiamyrtzis. *Deter: detection of events for threat evaluation and recognition*, In Machine Vision and Applications, Springer-Verlag, volume 15, pp. 29–45, 2003.
17. I. Pavlidis, V. Morellas, P. Tsiamyrtzis and S. Harp. *Urban surveillance systems: from the laboratory to the commercial world*, In Proceedings of the IEEE, volume 89, pp. 1478–1497, 2001.
18. I. Pavlidis, V. Morellas and N. Papanikolopoulos. *A vehicle occupant counting system based on near-infrared phenomenology and fuzzy neural classification*, In IEEE Transactions on Intelligent Transportation Systems, Volume 1, pp. 72–85, 2000.
19. C. Nevrinceanu, V. Morellas and M. Donath. *Automated process planning: reasoning from first principles based on geometric relation constraints*, In Artificial Intelligence for Engineering, Design, Analysis and Manufacturing, Cambridge Univ Press, volume 7, pp. 159–179, 1993.
20. N. Zabaras, V. Morellas and D. Schnur. *Spatially regularized solution of inverse elasticity problems using the BEM*, In Communications in applied numerical methods, Wiley Online Library, Volume 5, pp. 547–553, 1989.

Referred Conference Publications

1. D. Zermas, V. Morellas, D. Mulla, and N. Papanikolopoulos. *Extracting Phenotypic Characteristics of Corn Crops Through the Use of Reconstructed 3D Models*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018.
2. P. Stanitsas, A. Cherian, M. Harandi, V. Morellas, and N. Papanikolopoulos. *Learning Discriminative Alpha-Beta Divergences for Positive Definite Matrices*, In IEEE International Conference of Computer Vision (ICCV), 2017.
3. P. Stanitsas, A. Cherian, V. Morellas, and N. Papanikolopoulos. *Clustering Positive Definite Matrices by Learning Information Divergences*, In Workshop on Manifold Learning: from Euclid to Riemann (ICCV), 2017.
4. P. Stanitsas, A. Cherian, A. Truskinovsky, V. Morellas, and N. Papanikolopoulos. *Active Convolutional Neural Networks for Cancerous Tissue Recognition*, In IEEE International Conference on Image Processing (ICIP), 2017.
5. N. Heller, P. Stanitsas, V. Morellas, and N. Papanikolopoulos. *A Web-Based Platform for Distributed Annotation of Computerized Tomography Scans*, 6th Joint International Workshops, CVII-STENT 2017 and 2nd International Workshop, LABELS 2017 Held in Conjunction with MICCAI 2017, Proceedings. Springer Verlag, Vol. 10552 LNCS, p. 136-145 10 p. (Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics); vol. 10552 LNCS), 2017.
6. D. Zermas, V. Morellas, D. Mulla, and N. Papanikolopoulos. *Estimating the Leaf Area Index of crops through the evaluation of 3D models*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 6155-6162, 2017.
7. P. Stanitsas, A. Cherian, X. Li, A. Truskinowski, V. Morellas, and N. Papanikolopoulos. *Evaluation of feature descriptors for cancerous tissue recognition*, In IEEE 3rd International Conference on Pattern Recognition, ICPR, pp. 1490-1495, 2016.

8. P. Stanitsas, A. Cherian, V. Morellas, and N. Papanikolopoulos. *Active Constrained Clustering via non-iterative uncertainty sampling*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp.4027-4033, 2016.
9. J. Fasching, N. Walczak, G. Bernstein, T. Hadjiyanni, K. Cullen, V. Morellas, and N. Papanikolopoulos. *Automated coding of activity videos from an OCD study*, In IEEE International Conference on Robotics and Automation (ICRA'16), pp. 5638-5643, 2016.
10. J. Fasching, N. Walczak, T. Hadjiyanni, G. Bernstein, K. Cullen, M. Mikkelsen, N. Studanski, V. Morellas, and N. Papanikolopoulos. *Exploring video descriptions for handwashing activities as part of an obsessive-compulsive disorder study*, In IEEE 24th Mediterranean Conference on Control and Automation, pp.1174-1179, 2016.
11. D. Zermas, D. Teng, P. Stanitsas, M. Bazakos, D. Kaiser, V. Morellas, D. Mulla, and N. Papanikolopoulos. *Automation solutions for the evaluation of plant health in corn fields*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp.6521-6527, 2015.
12. J. Fasching, N. Walczak, V. Morellas, and N. Papanikolopoulos. *Classification of motor stereotypes in video*, In IEEE International Conference on Robotics and Automation (ICRA'15), 2015.
13. D. Zermas, M. Bazakos, V. Morellas, D. Mulla, and N. Papanikolopoulos. *A Robotics framework for the detection of nitrogen deficiencies in corn fields*, In IEEE International Conference on Robotics and Automation (ICRA'15), 2015.
14. D. J. Cook, T. Morris, V. Morellas, and N. Papanikolopoulos. *An automated system for persistent real-time truck parking detection and information dissemination*, In IEEE International Conference on Robotics and Automation (ICRA'14), pp.3989-3994, 2014.
15. J. Duncs, R. Sivalingam, G. Somasundaram, V. Morellas, and N. Papanikolopoulos. *Recognition of ballet micro-movements for use in choreography*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp.1010-1016, 2013.
16. J. Hashemi, T. V. Spina, M. Tepper, A. Esler, V. Morellas, N. Papanikolopoulos and G. Sapiro. *A computer vision approach for the assessment of autism-related behavioral markers*, In IEEE International Conference on Development and Learning and Epigenetic Robotics (ICDL), pp. 1-7, 2012.
17. G. Somasundaram, V. Morellas and N. Papanikolopoulos. *Object classification with efficient global self-similarity descriptors based on sparse representations*, In 19th IEEE International Conference on Image Processing (ICIP), pp. 2165-2168, 2012.
18. J. Fasching, N. Walczak, R. Sivalingam, K. Cullen, B. Murphy, G. Sapiro, V. Morellas and N. Papanikolopoulos. *Detecting risk-markers in children in a preschool classroom*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp.1010-1016, 2012.
19. N. Walczak, J. Fasching, W. D. Toczyski, R. Sivalingam, N. D. Bird, K. Cullen, V. Morellas, B. Murphy, G. Sapiro and N. Papanikolopoulos. *A nonintrusive system for behavioral analysis of children using multiple RGB+depth sensors*, In IEEE Workshop on the Applications of Computer Vision (WACV), pp. 217-222, 2012.
20. R. Sivalingam, G. Somasundaram, V. Bhatawadekar, V. Morellas and N. Papanikolopoulos. *Sparse representation of point trajectories for action classification*, In IEEE International Conference on Robotics and Automation (ICRA), pp. 3601-3606, 2012.
21. R. Sivalingam, A. Cherian, J. Fasching, N. Walczak, N. Bird, V. Morellas, B. Murphy, K. Cullen, K. Lim, G. Sapiro, and N. Papanikolopoulos. *A multi-sensor visual tracking system for behavior monitoring of at-risk children*, In IEEE International Conference on Robotics and Automation (ICRA), pp. 1345-1350, 2012.

22. D. Fehr, A. Cherian, R. Sivalingam, S. Nickolay, V. Morellas and N. Papanikolopoulos. *Compact covariance descriptors in 3d point clouds for object recognition*, In IEEE International Conference on Robotics and Automation (ICRA), pp. 1793–1798, 2012.
23. J. Fasching, N. Walczak, R. Sivalingam, K. Cullen, B. Murphy, G. Sapiro, V. Morellas, N. Papanikolopoulos. *Detecting risk-markers in children in a preschool classroom*, In IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 1010–1016, 2012.
24. A. Cherian, V. Morellas and N. Papanikolopoulos. *Robust Sparse Hashing*, In 19th IEEE International Conference on Image Processing (ICIP), pp. 2417–2420, 2012. (**Best Student Paper Award**)
25. R. Sivalingam, D. Boley, V. Morellas and N. Papanikolopoulos. *Positive definite dictionary learning for region covariances*, In IEEE International Conference on Computer Vision (ICCV), pp. 1013–1019, 2011.
26. R. Sivalingam, A. D’Souza, M. Bazakos, R. Miezianko, V. Morellas and N. Papanikolopoulos. *Dictionary learning for robust background modeling*, In IEEE International Conference on Robotics and Automation (ICRA), pp. 4234–4239, 2011.
27. H. J. Min, N. Papanikolopoulos, C. E. Smith and V. Morellas. *Feature-based covariance matching for a moving target in multi-robot following*, In 19-th Mediterranean Conference on Control & Automation (MED), pp. 163–168, 2011.
28. P. K. Gali, V. Morellas and N. Papanikolopoulos. *A novel framework for annotating videos using text*, In 19th Mediterranean Conference on Control Automation (MED), pp. 1403–1408, 2011.
29. A. Cherian, V. Morellas, N. Papanikolopoulos and S. J. Bedros. *Dirichlet process mixture models on symmetric positive definite matrices for appearance clustering in video surveillance applications*, In IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 3417–3424, 2011.
30. A. Cherian, V. Morellas and N. Papanikolopoulos. *Approximate nearest neighbors via dictionary learning*, In Proc. SPIE 8058, Independent Component Analyses, Wavelets, Neural Networks, Biosystems, and Nanoengineering IX, 80581M; doi:10.1117/12.887484, 2011.
31. V. Bhatawadekar, D. Fehr, V. Morellas and N. Papanikolopoulos. *A dynamic sensor placement algorithm for dense sampling*, In Proceedings of the 14th International Conference on Information Fusion (FUSION), pp. 1–7, 2011.
32. R. Sivalingam, G. Somasundaram, V. Morellas, N. Papanikolopoulos, O. Lotfallah, Y. Park. *Dictionary learning based object detection and counting in traffic scenes*, In Proceedings of the Fourth ACM/IEEE International Conference on Distributed Smart Cameras, pp. 42–48, 2010.
33. E. Ribnick, V. Morellas and N. Papanikolopoulos. *Human motion patterns from single camera cues for medical applications*, In IEEE International Conference on Robotics and Automation (ICRA), pp. 5102–5107, 2010.
34. A. Cherian, J. Andersh, V. Morellas, B. Mettler and N. Papanikolopoulos. *Motion estimation of a miniature helicopter using a single onboard camera*, In American Control Conference (ACC), 2010, pp. 4456–4461, 2010.
35. G. Somasundaram, V. Morellas and N. Papanikolopoulos. *Counting pedestrians and bicycles in traffic scenes*, In 12th International IEEE Conference on Intelligent Transportation Systems (ITSC’09), pp. 1–6, 2009.
36. R. Sivalingam, V. Morellas, D. Boley and N. Papanikolopoulos. *Metric learning for semi-supervised clustering of region covariance descriptors*, In Third ACM/IEEE International Conference on Distributed Smart Cameras (ICDSC), pp. 1–8, 2009.

37. D. Fehr, R. Sivalingam, V. Morellas, N. Papanikolopoulos, O. Lotfallah and Y. Park. *Counting people in groups* , In Sixth IEEE International Conference on Advanced Video and Signal Based Surveillance AVSS'09, pp. 152–157, 2009.
38. A. Cherian, J. Andersh, V. Morellas, N. Papanikolopoulos and B. Mettler. *Autonomous altitude estimation of a UAV using a single onboard camera* , In IEEE/RSJ International Conference on Intelligent Robots and Systems, pp. 3900–3905, 2009.
39. A. Cherian, V. Morellas and N. Papanikolopoulos. *Accurate 3D ground plane estimation from a single image* In IEEE International Conference on Robotics and Automation, pp. 2243–2249, 2009.
40. V. Morellas, C. Johnston, A. Johnson, S. D. Roberts, G. L. Francisco. *Day, night and all-weather security surveillance automation*, In Proceedings of SPIE, volume 5778, Sensors, and Command, Control, Communications, and Intelligence (C3I) Technologies for Homeland Security and Homeland Defense IV, 757, 2005.
41. B. Schiller, V. Morellas and M. Donath. *Collision avoidance for highway vehicles using the virtual bumper controller*, In Proceedings of the IEEE International Symposium on Intelligent Vehicles, 1998.
42. V. Morellas, T. Morris, L. Alexander and M. Donath. *Preview based control of a tractor trailer using DGPS for preventing road departure accidents*, In IEEE Conference on Intelligent Transportation Systems, pp. 797–805, 1997.
43. V. Morellas, J. Minners and M. Donath. *Implementation of real time spatial mapping in robotic systems through self-organizing neural networks*, In Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems, volume 1, pp. 277–284, 1995.
44. S. Kieffer, V. Morellas and M. Donath. *Neural network learning of the inverse kinematic relationships for a robot arm*, In Proceedings of IEEE International Conference on Robotics and Automation, pp. 2418–2425, 1991.

Workshop and Other Publications

1. N. Heller, N. Papanikolopoulos, V. Morellas, and A. Truskinovsky. *Class saliency maps reveal computer vision's basis for diagnosing metastatic carcinoma in lymph nodes*, Annual Meeting of the US and Canada Academy of Pathology (USCAP), 2019.
2. N. Heller, M. Tradewell, J. Dean, V. Morellas, N. Papanikolopoulos, N. Sathianathan, and C. Weight. *A balance cascade of deep neural networks for CT renal segmentation*, Poster Annual Meeting of the Engineering Urology Society, 2018.
3. X. Li, V. Morellas, N. , A. M. Truskinovsky. *The Use of Computer Vision in the Differential Diagnosis of Ovarian Carcinomas*, Annual Meeting of the United States and Canadian Academy of Pathology (USCAP), 2016.
4. T. Morris, D. J. Cook, V. Morellas and N. Papanikolopoulos. *A comprehensive truck parking space availability system for real-time information and parking facilities performance monitoring*, Logistics, Trade and Transportation Symposium, 2014.
5. A. Kaplan, X. Li, R. Sivalingam, G. Somasundaram, A. Banerjee, V. Morellas, N. Papanikolopoulos and A. Truskinovsky. *Computer vision methods in surgical pathology: diagnosing carcinoma of the breast* , Annual Meeting of the United States and Canadian Academy of Pathology (USCAP), volume 93, pp. 380A-380A, 2013.
6. T. V. Spina, M. Tepper, A. Esler, V. Morellas, N. Papanikolopoulos, A. X. Falcao, and G. Sapiro. *Video human segmentation using fuzzy object models and its application to body pose estimation of toddlers for behavior studies*, In arXiv preprint arXiv:1305.6918, 2013.

7. N. Walczak, J. Fasching, W. Toczyski, R. Sivalingam, N. Bird, K. Cullen, V. Morellas, B. Murphy, G. Sapiro and N. Papanikolopoulos. *A nonintrusive system for behavioral analysis of children using multiple RGB+ depth sensors*, In IEEE Workshop on Applications of Computer Vision (WACV), pp. 217–222, 2012.
8. R. Sivalingam, G. Somasundaram, X. Li, J. C. Henriksen, A. Banerjee, V. Morellas, N. Papanikolopoulos, A. Truskinovsky. *Diagnosing adenocarcinoma of the prostate by computer vision methods*, Annual Meeting of the United States and Canadian Academy of Pathology (USCAP), volume 92, pp. 394A-394A, 2012.
9. R. Sivalingam, G. Somasundaram, A. Ragipindi, A. Banerjee, V. Morellas, N. Papanikolopoulos, A. Truskinovsky. *Diagnosing endometrial carcinoma via computer-assisted image analysis*, Annual Meeting of the United States and Canadian Academy of Pathology (USCAP), 2011.
10. K. A. Patwardhan, G. Sapiro and V. Morellas. *A graph-based foreground representation and its application in example based people matching in video*, Institute of Mathematics and its Applications (IMA), University of Minnesota, preprint series No. 2154, 2007.
11. K. A. Patwardhan, G. Sapiro and V. Morellas. *Pixel layering and layer propagation for video modeling and foreground detection*, In Institute of Mathematics and its Applications (IMA), University of Minnesota, preprint series No. 2080, 2005.
12. V. Morellas, T. Morris, L. Alexander and M. Donath. *Between the lines: A driver-assistive technology for staying in the lane*, In GPS World, volume 9, 1998.
13. R. Bodor, M. Donath, V. Morellas and D. Johnson. *In-Vehicle GPS-Based Lane Sensing to Prevent Road Departure*, In Abstracts of the Third World Congress on Intelligent Transport Systems, Intelligent Transportation: Realizing the Future, 1996.

Technical Reports

1. T. Morris, X. Li, V. Morellas and N. Papanikolopoulos. *Video detection and classification of pedestrian events at roundabouts and crosswalks*, Technical report, Intelligent Transportation Systems Institute, Center for Transportation Studies, 2013.
2. E. Holec, G. Somasundaram, N. Papanikolopoulos and V. Morellas. *Monitoring the use of HOV and HOT lanes*, Technical report, Intelligent Transportation Systems Institute, Center for Transportation Studies, 2013.
3. G. Somasundaram, V. Morellas and N. Papanikolopoulos. *Deployment of practical methods for counting bicycle and pedestrian use of a transportation facility*, Technical report, Intelligent Transportation Systems Institute, Center for Transportation Studies, 2012.
4. P. Modi, V. Morellas and N. Papanikolopoulos. *Counting Empty Parking Spots at Truck Stops Using Computer Vision*, Technical report, Intelligent Transportation Systems Institute, Center for Transportation Studies, 2011.
5. G. Somasundaram, V. Morellas and N. Papanikolopoulos. *Practical methods for analyzing pedestrian and bicycle use of a transportation facility*, Technical report, Intelligent Transportation Systems Institute, Center for Transportation Studies, 2010.
6. I. Pavlidis, P. Symosek, V. Morellas, B. Fritz, N. Papanikolopoulos and R. Sfarzo. *Automatic passenger counting in the HOV Lane*, Technical report No. Mn/DOT 2000-06, Intelligent Transportation Systems Institute, Center for Transportation Studies, 1999.
7. L. Alexander, S. Bajikar, H. M. Lim, V. Morellas, T. Morris and M. Donath. *Safetruck: sensing and control to enhance vehicle safety*, Technical report No. Mn/DOT 1998-29, Intelligent Transportation Systems Institute, Center for Transportation Studies, 1997.

8. L. Alexander, M. Donath, M. Hennessey, V. Morellas and C. Shankwitz. *A lateral dynamic model of a tractor-trailer experimental validation*. Technical report No. Mn/DOT 1997-18, Intelligent Transportation Systems Institute, Center for Transportation Studies, 1996.
9. R. Bodor, L. Alexander, C. Liao, S. Bajikar, V. Morellas and M. Donath. *Analysis of a differential global positioning system as a sensor for vehicle guidance*, Technical report No. Mn/DOT 1997-17, Intelligent Transportation Systems Institute, Center for Transportation Studies, 1996.

Patents

- **Crop Models and Biometrics**, (Dimitris Zermas, Vassilios Morellas, David Mulla, Nikos Papanikolopoulos, Mike Bazakos), OTC Docket No.: 20180265, University of Minnesota, 2019.
- **Automated Detection of Nitrogen Deficiency in Corn**, (Dimitris Zermas, Vassilios Morellas, David Mulla, Nikos Papanikolopoulos, Daniel Kaiser), OTC Docket No.: 20160058, University of Minnesota, 2015.
- **Computer vision approach using 3D reconstruction as a basis for parking space occupancy detection in parking facilities**, (Doug Cook, Vassilios Morellas, Ted Morris, Nikos Papanikolopoulos), OTC Docket No.: 20140124, University of Minnesota, 2014.
- **System and method for autonomous object tracking**, (Kartik B Ariyur, Saad J Bedros, Dennis W Strelow, Vassilios Morellas), 2011. (US Patent 7,907,750)
- **Object tracking system**, (Vassilios Morellas, Michael E Bazakos, Yunqian Ma, Andrew Johnson), 2010. (US Patent 7,720,257)
- **Face detection and tracking in a wide field of view**, (Michael E Bazakos, Vassilios Morellas), 2010. (US Patent 7,806,604)
- **Distributed stand-off ID verification compatible with multiple face recognition systems (FRS)**, (Michael E Bazakos, David W Meyers, Vassilios Morellas), 2010. (US Patent 7,817,013)
- **Infrared and visible fusion face recognition system**, (Michael E Bazakos, Vassilios Morellas, Yunqian Ma), 2009. (US Patent 7,602,942)
- **Unsupervised learning of events in a video sequence**, (Michael E Bazakos, Yunqian Ma, Vassilios Morellas, others), 2009. (US Patent 7,606,425)
- **Tracking a moving object from a camera on a moving platform**, (Kartik B Ariyur, Saad J Bedros, Vassilios Morellas, others), 2009. (US Patent 7,541,565)
- **Monitoring devices**, (Karen Z Haigh, Vassilios Morellas, Liana M Kiff), 2008. (EP Patent 1,782,406)
- **Infrared face detection and recognition system**, (Michael E Bazakos, Vassilios Morellas, Andrew Johnson, Yunqian Ma), 2008. (US Patent 7,469,060)
- **Tracking a moving object from a camera on a moving platform**, (Kartik B Ariyur, Saad J Bedros, Vassilios Morellas, others), 2008. (US Patent 7,411,167)
- **Face detection and tracking in a wide field of view**, (Michael Bazakos, Vassilios Morellas), 2007. (WO Patent 2,007,047,719)
- **Cooperative camera network**, (Ioannis Pavlidis, Vassilios Morellas), 2006. (US Patent 7,149,325)

- **High fidelity target identification and acquisition through image stabilization and image size regulation**, (Kartik B Ariyur, Vassilios Morellas, Saad J Bedros), 2006. (US Patent App. 11/562,563)
- **Deception detection booth**, (Ioannis Pavlidis, Vassilios Morellas, Michael Bazakos, others), 2006. (WO Patent 2,006,078,344)
- **Imaging methods and systems for concealed weapon detection**, (Donald R Singh, Vassilios Morellas), 2006. (EP Patent 1,721,192)
- **Controlled environment thermal image detection system and methods regarding same**, (Ioannis Pavlidis, Michael E Bazakos, Vassilios Morellas), 2006. (US Patent 7,138,905)
- **Method for monitoring a moving object and system regarding same**, (Ioannis Pavlidis, Vassilios Morellas), 2004. (EP Patent 1,399,889)
- **Method and apparatus for tracking with identification**, (Anthony E Faltesek, Vassilios Morellas), 2004. (EP Patent 1,388,140)

Invited Talks

- **Key Note Talk:** *Video analytics for security and transportation applications*, 4th Joint IEEE International Workshop on Object Tracking and Classification Beyond the Visible Spectrum (OTCBVS'07), June 22, 2007.
- *A pragmatic view on modern video surveillance systems*, Advanced Transportation Technologies Seminar Series, Institute for Transportation Studies (ITS), University of Minnesota, October 9, 2007.
- *Imaging methods for surveillance*, IMA/MCIM Industrial Problems Seminar, Institute for Mathematics and Its Applications (IMA), University of Minnesota, March 3, 2006.
- *Advanced technology for homeland security applications*, Institute for Transportation Studies (ITS), University of Minnesota, June 2, 2003.

Student Advising and Mentoring

Master Thesis

- Haoyuan Du, Haoyi Shi, MS 2023
Thesis: *Advancing the Functionalities of a Socially-Assistive Robot as a Companion for Aging Adults.*
- Doug J. Cook, MS 2012
Thesis: *Parking space occupancy detection utilizing 3D reconstruction techniques.*
- Luis Guzman, MS 2021
Thesis: *Robotic Embodiment of Human-Like Motor Skills via Sim-to-Real Reinforcement Learning.*
- Matthew Tlachac, MS 2021
Thesis: *Tumbling Robot Optimization Using a Learned Control Policy.*

Doctoral Dissertations

- Anoop Cherian, PhD 2013
Thesis: *Similarity search in visual data.*
Current Appointment: Mitsubishi Electric Research Laboratories, Boston, MA.
- Ravishankar Sivalingam, PhD 2013
Thesis: *Tensor sparse coding for positive definite matrices.*
Current Appointment: 3M, St. Paul, Minnesota.

- Guruprasad Somasundaram, PhD 2012
Thesis: *Salient image regions for enhancing segmentation object detection and intra-class diversity.*
Current Appointment: 3M, St. Paul, Minnesota.
- Panagiotis Stanitsas, PhD 2018
Thesis: *Machine Learning Methods with Emphasis on Cancerous Tissue Recognition.*
Current Appointment: 3M, St. Paul, Minnesota.
- Dimitrios Zermas, PhD 2018
Thesis: *Combining Machine Learning with Computer Vision for Precision Agriculture Applications.*
Current Appointment: Accepted a job offer from Sentra LLC, Bloomington MN.

PhD Thesis Committees

- Kedar Patwardhan, Jon Andersh.

Synergistic Activities

- Associate Editor, IEEE/RSJ International Conference on Intelligent Robots and Systems, 2019.
- Technical Committee, 22nd International Conference on Pattern Recognition (ICPR 2014).
- Program Committee, IEEE International Symposium on Safety, Security, and Rescue Robotics, (Years 2012, 2013).
- Program Area Chair, 5th IEEE International Conference on Advanced Video and Signal Based Surveillance, 2008.
- Program Committee, IEEE Workshop on Computer Vision Beyond the Visible Spectrum: Methods and Applications, in conjunction with CVPR (Years 2000, 2001).