US011189049B1

(12) **United States Patent**
Chakravarty et al.

(10) **Patent No.: US 11,189,049 B1**
(45) **Date of Patent: Nov. 30, 2021**

(54) **VEHICLE NEURAL NETWORK PERCEPTION AND LOCALIZATION**

(71) Applicant: **Ford Global Technologies, LLC**, Dearborn, MI (US)

(72) Inventors: **Punarjay Chakravarty**, Campbell, CA (US); **Shubham Shrivastava**, Sunnyvale, CA (US)

(73) Assignee: **Ford Global Technologies, LLC**, Dearborn, MI (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **17/072,334**

(22) Filed: **Oct. 16, 2020**

(51) **Int. Cl.**
G06K 9/00 (2006.01)
G06T 7/73 (2017.01)

(52) **U.S. Cl.**
CPC ***G06T 7/73*** (2017.01); ***G06K 9/00201*** (2013.01); ***G06K 9/00791*** (2013.01);
(Continued)

(58) **Field of Classification Search**
CPC G06T 7/73; G06T 2207/10028; G06T 2207/20084; G06T 2207/20081;
(Continued)

(56) **References Cited**

U.S. PATENT DOCUMENTS

10,529,089 B2 1/2020 Ahmad et al.
10,671,860 B2 6/2020 Liu et al.
(Continued)

FOREIGN PATENT DOCUMENTS

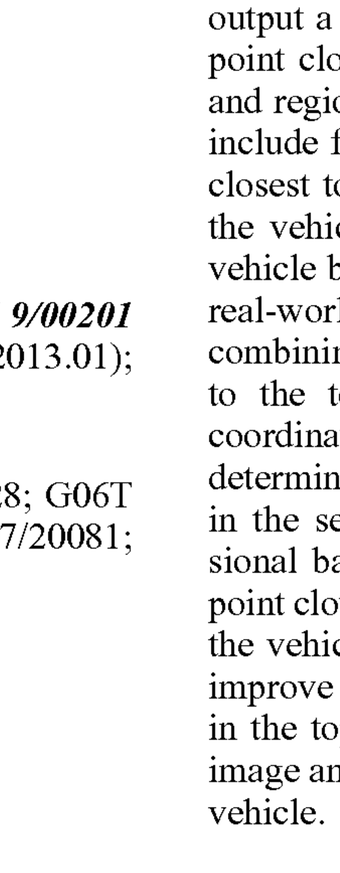
WO 2020132233 A1 6/2020

Primary Examiner — Carol Wang
(74) *Attorney, Agent, or Firm* — Bejin Bieneman PLC; Frank A. MacKenzie

(57) **ABSTRACT**

A computer, including a processor and a memory, the memory including instructions to be executed by the processor to determine a plurality of topological nodes wherein each topological node includes a location in real-world coordinates and a three-dimensional point cloud image of the environment at the location of the topological node and process an image acquired by a sensor included in a vehicle using a variational auto-encoder neural network trained to output a semantic point cloud image, wherein the semantic point cloud image includes regions labeled by region type and region distance relative to the vehicle. The instructions include further instructions to determine a topological node closest to the vehicle and a six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle based on the semantic point cloud data, determine a real-world six degree-of-freedom pose for the vehicle by combining the six degree-of-freedom for the vehicle relative to the topological node and the location in real-world coordinates of the topological node closest to the vehicle and determine a location and size of a three-dimensional object in the semantic point cloud image based on three-dimensional background subtraction using the three-dimensional point cloud image included in the topological node closest to the vehicle. The instructions include further instructions to improve the three-dimensional point cloud image included in the topological node based on the semantic point cloud image and the real-world six degree-of-freedom pose for the vehicle.

20 Claims, 10 Drawing Sheets



(52) **U.S. Cl.**
CPC *G06T 2207/10012* (2013.01); *G06T 2207/10028* (2013.01); *G06T 2207/20081* (2013.01); *G06T 2207/20084* (2013.01); *G06T 2207/30252* (2013.01)

(58) **Field of Classification Search**
CPC G06T 2207/30252; G06T 2207/10012; G06K 9/00791; G06K 9/00201
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

2019/0096086	A1*	3/2019	Xu	G06T 7/60
2019/0217476	A1*	7/2019	Jiang	B25J 13/08
2020/0029490	A1	1/2020	Bertucci et al.	
2020/0098135	A1	3/2020	Ganjineh et al.	
2021/0048312	A1*	2/2021	Choi	G01S 19/14
2021/0286068	A1*	9/2021	Kumar	G01S 13/867

* cited by examiner

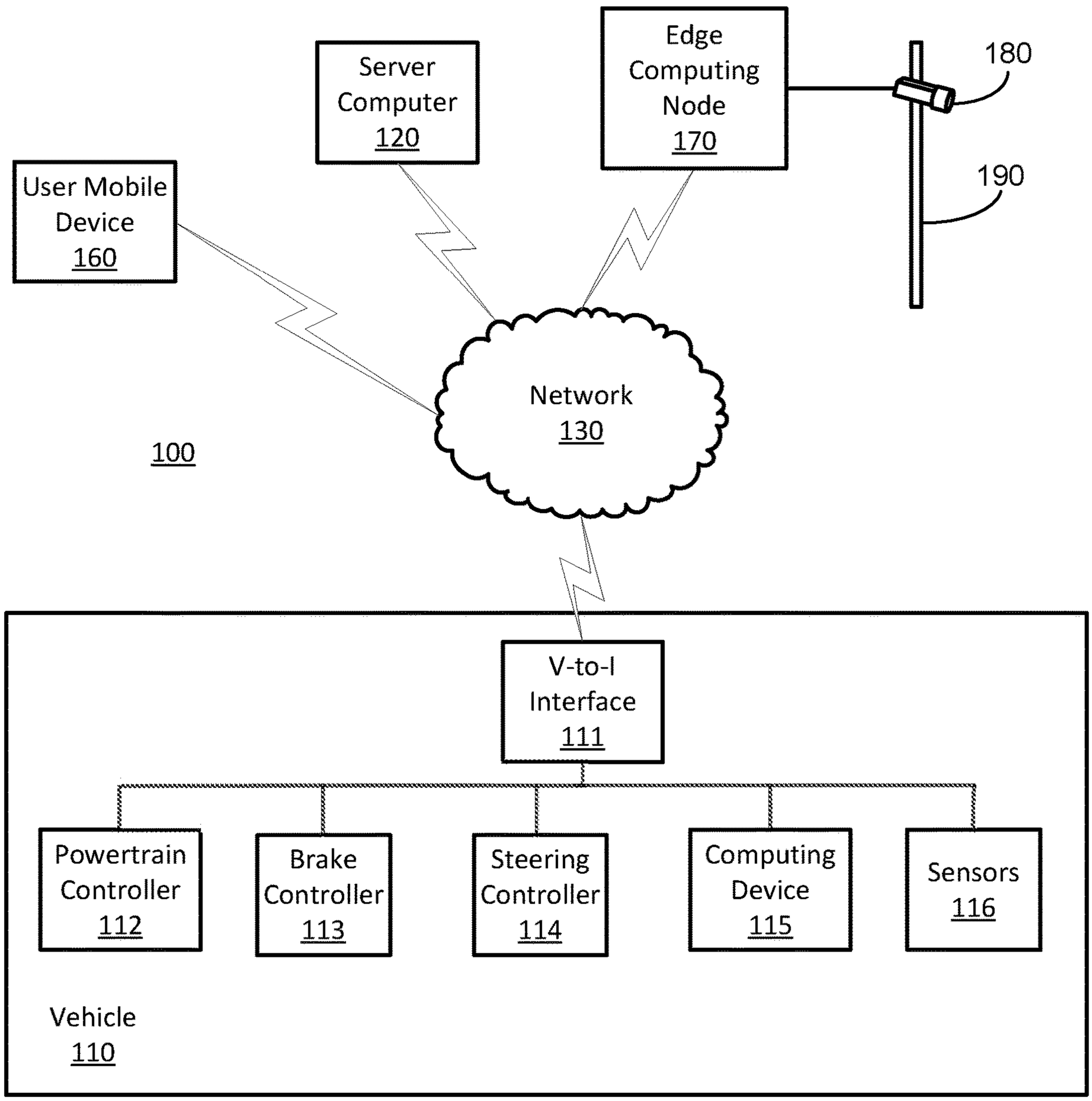

Server Computer 120
Edge Computing Node 170
180
190
User Mobile Device 160
Network 130
100
V-to-I Interface 111
Powertrain Controller 112
Brake Controller 113
Steering Controller 114
Computing Device 115
Sensors 116
Vehicle 110

Fig. 1

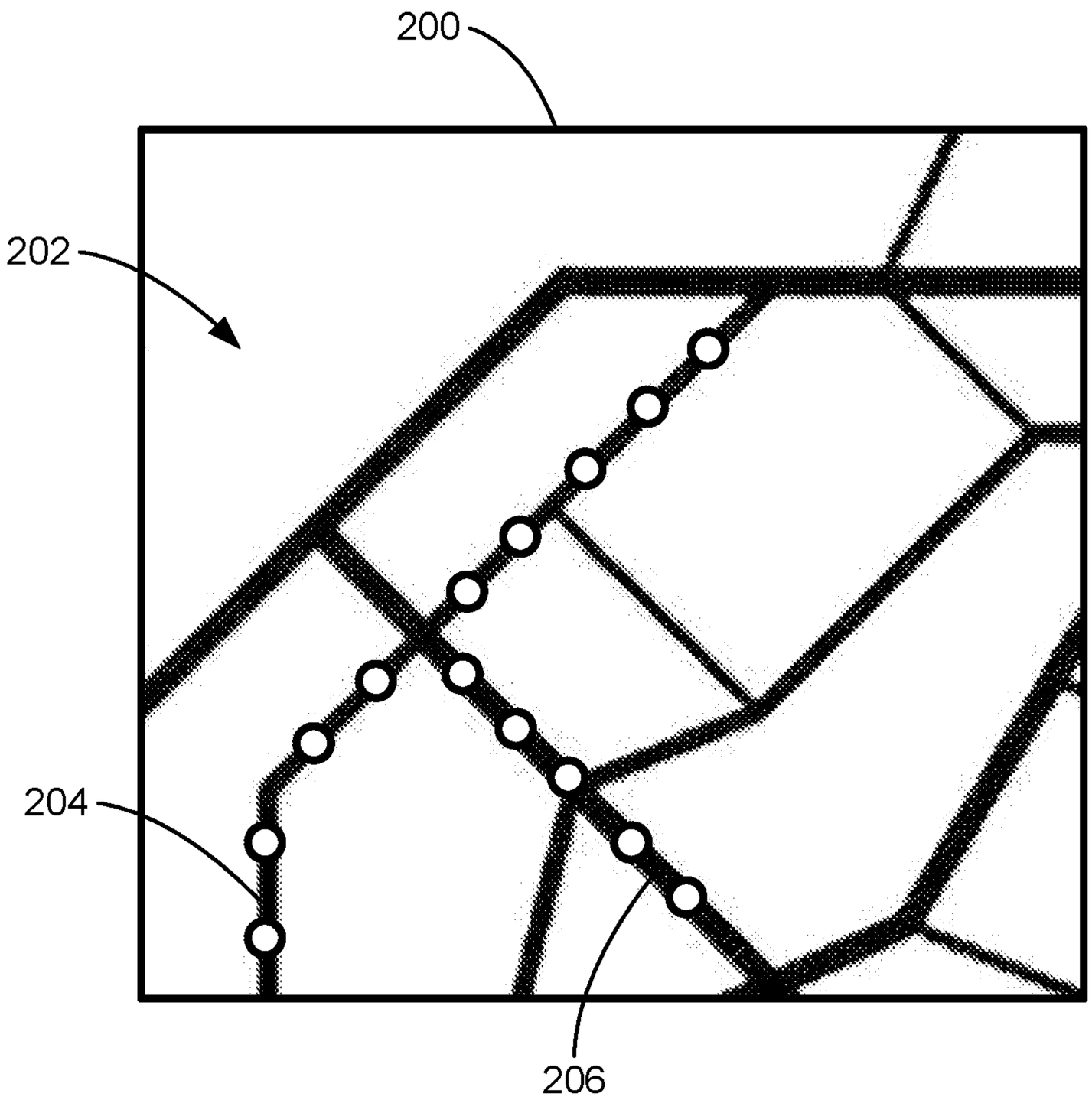


Fig. 2

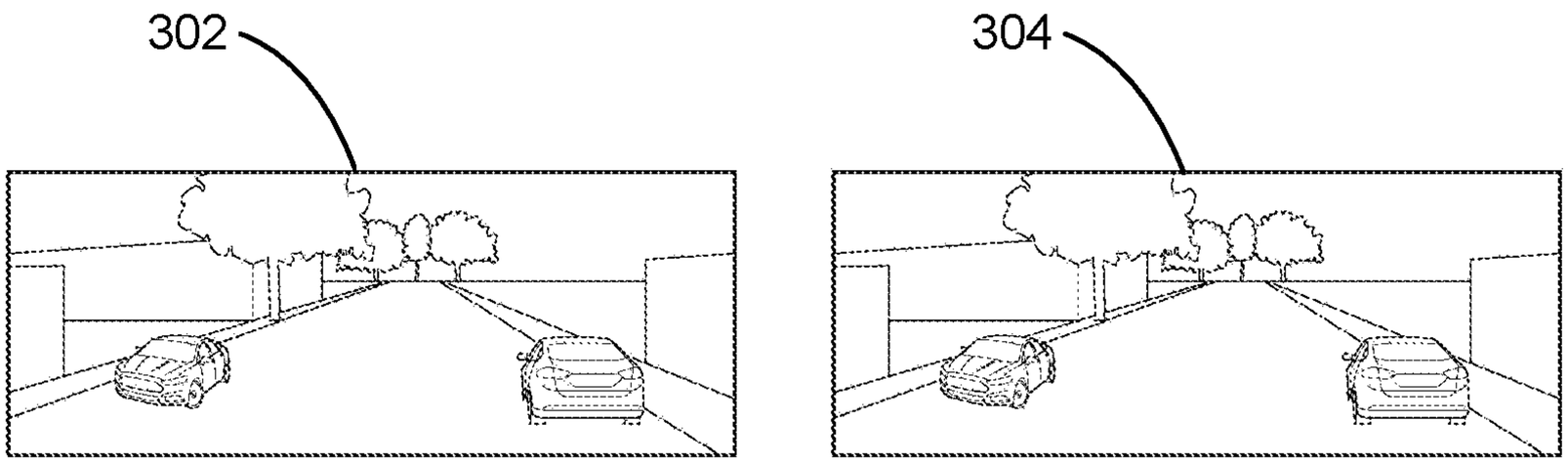


Fig. 3

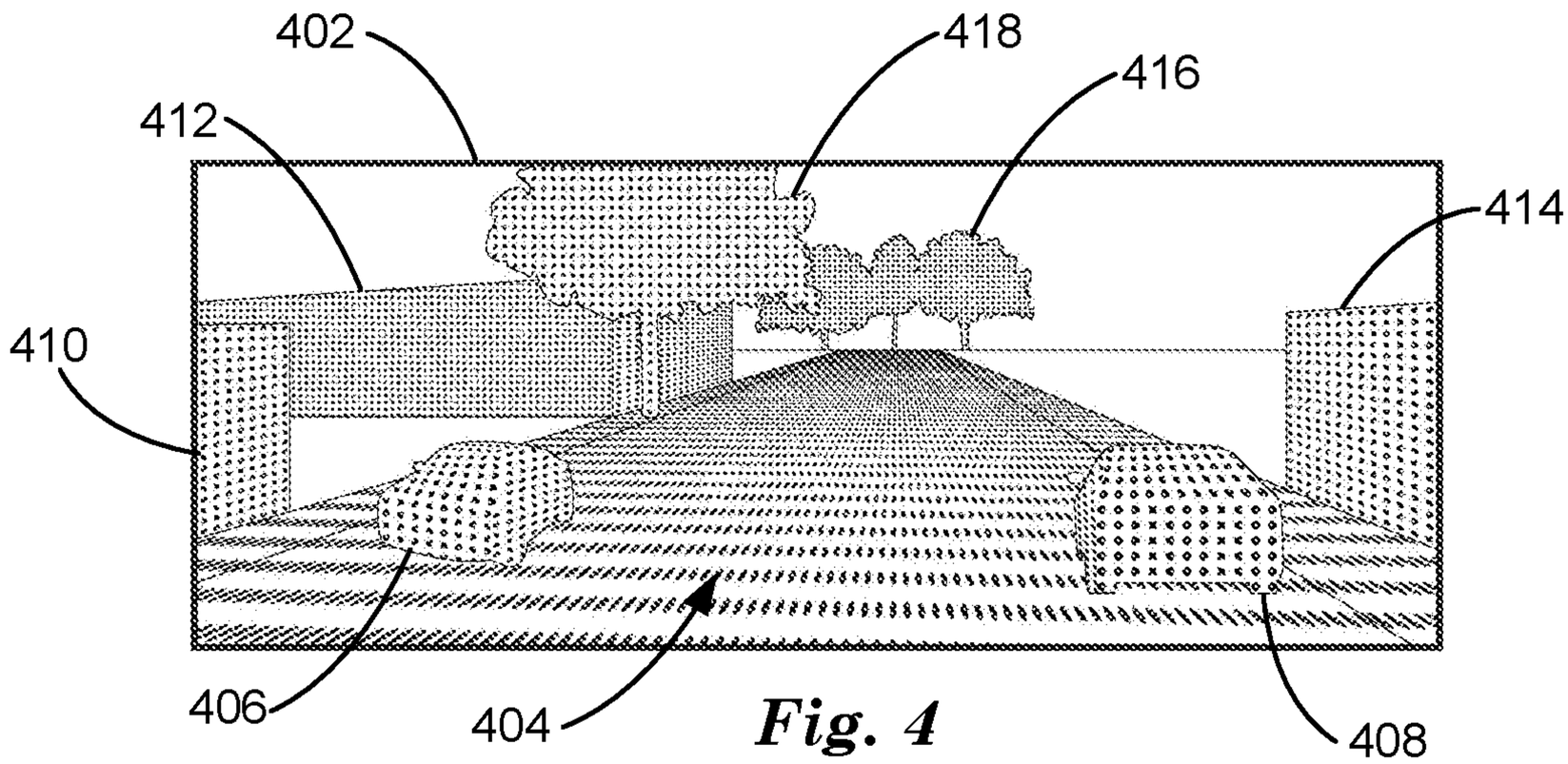


Fig. 4

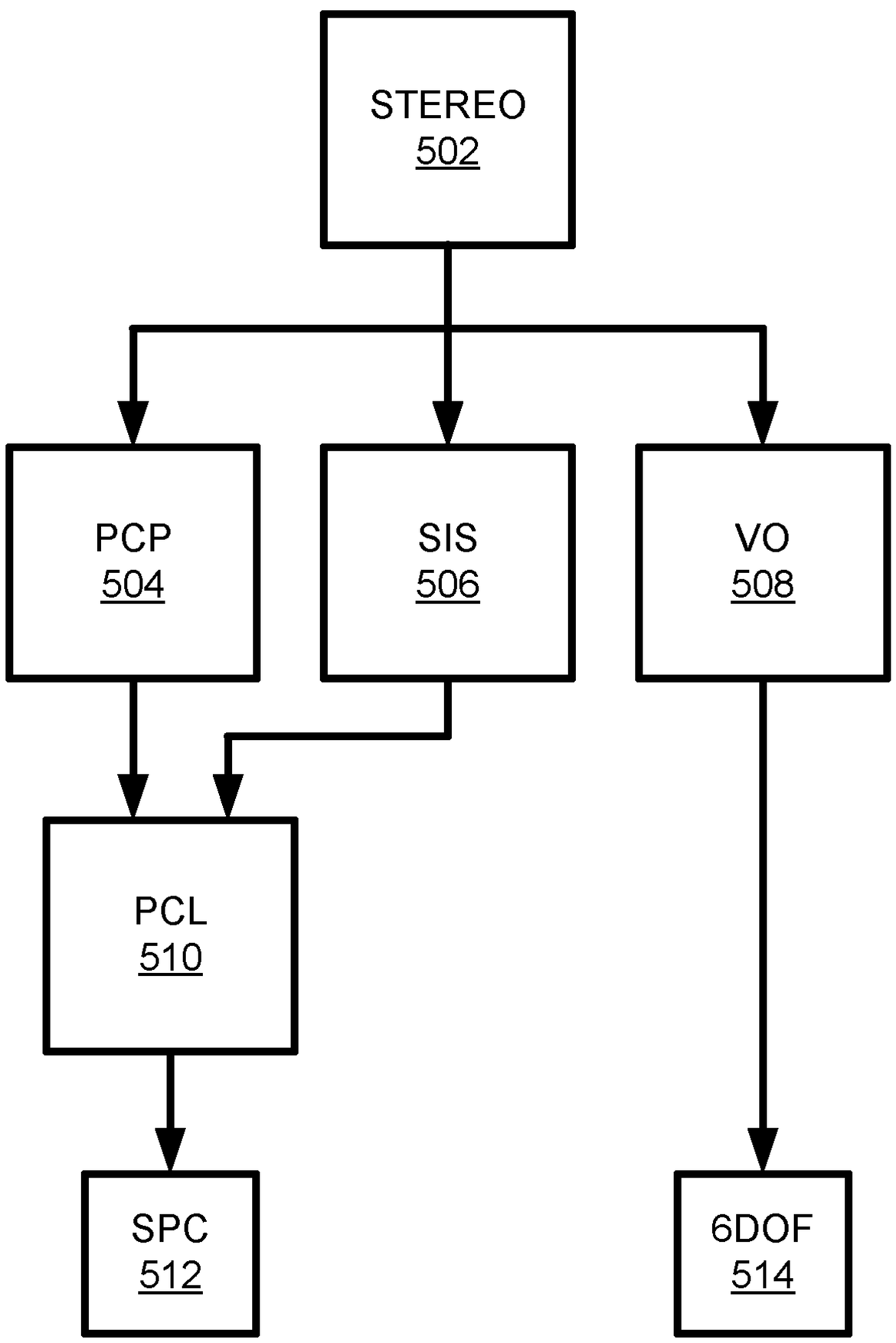


Fig. 5

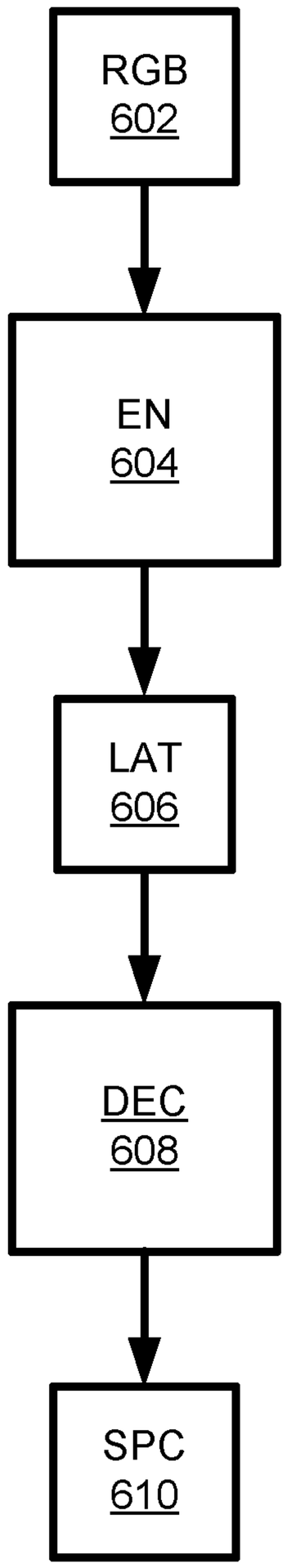


Fig. 6

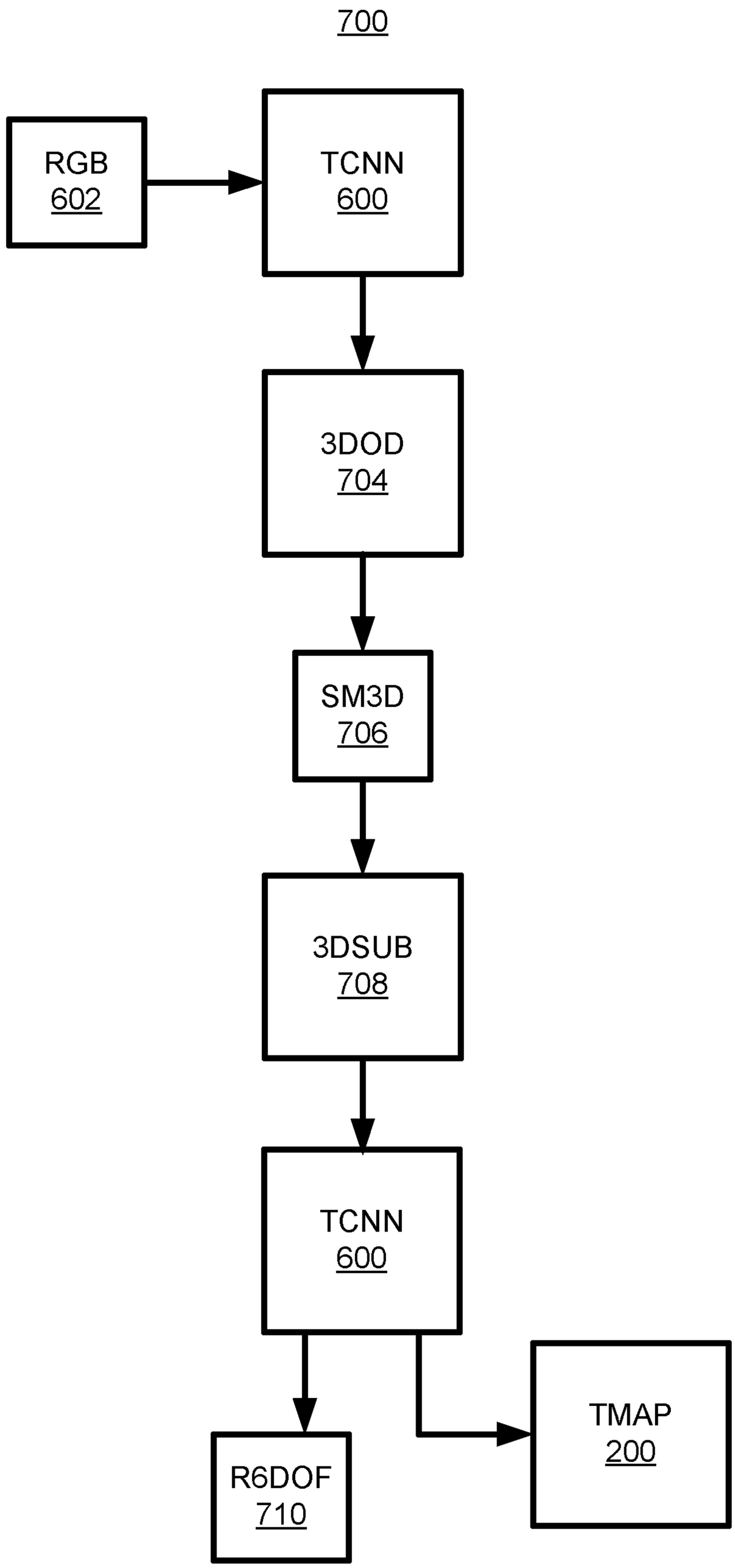

700
RGB
602
TCNN
600
3DOD
704
SM3D
706
3DSUB
708
TCNN
600
R6DOF
710
TMAP
200

Fig. 7

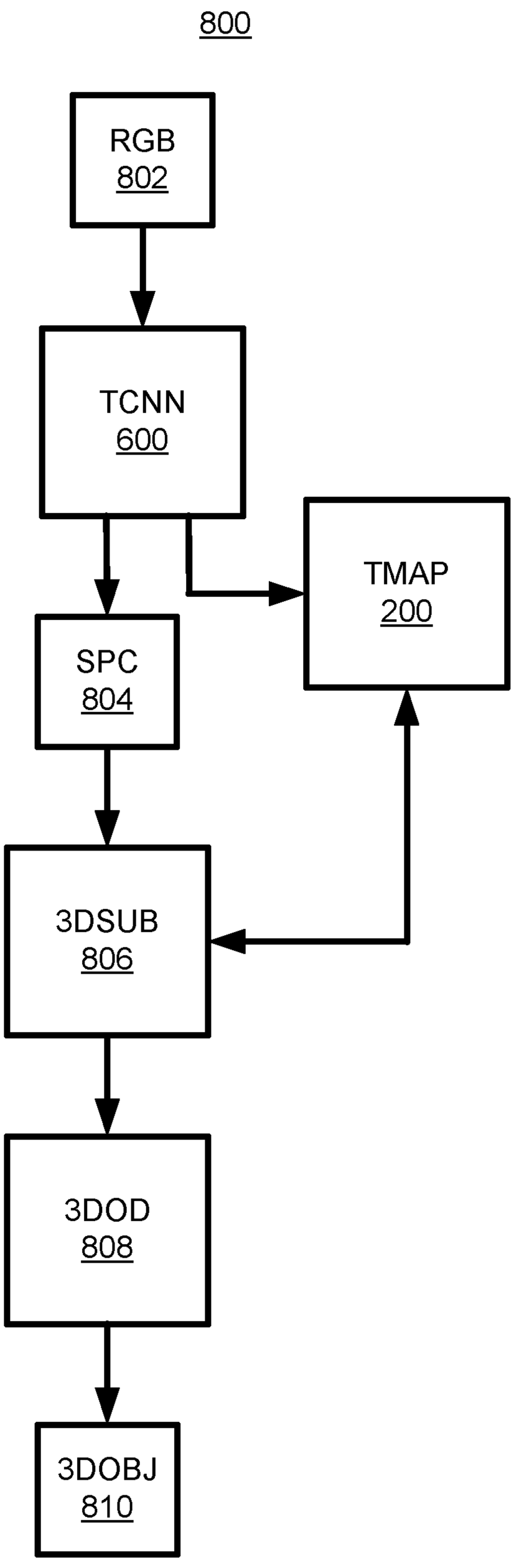

800
RGB
802
TCNN
600
TMAP
200
SPC
804
3DSUB
806
3DOD
808
3DOBJ
810

Fig. 8

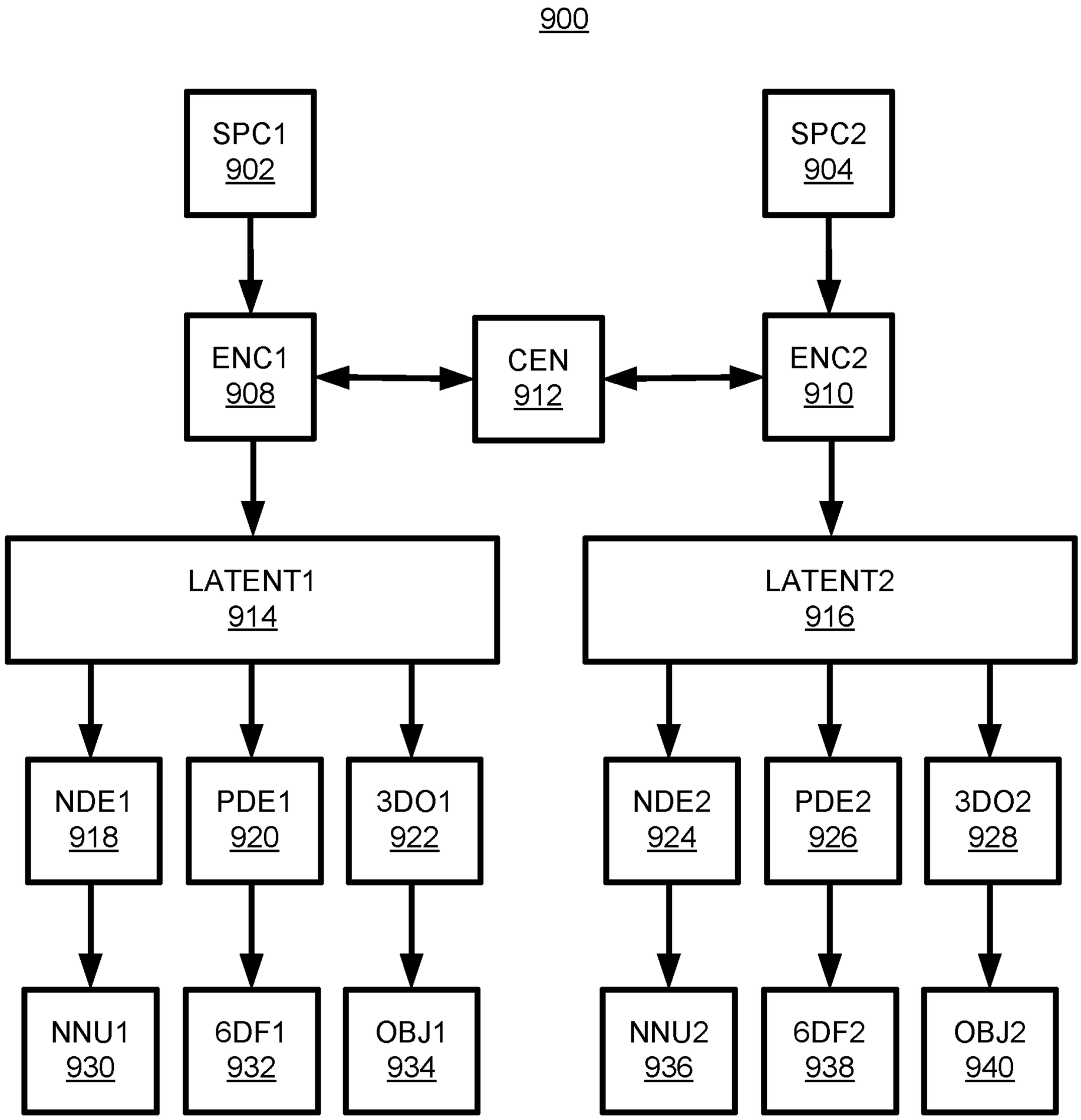

900
SPC1
902
SPC2
904
ENC1
908
CEN
912
ENC2
910
LATENT1
914
LATENT2
916
NDE1
918
PDE1
920
3DO1
922
NDE2
924
PDE2
926
3DO2
928
NNU1
930
6DF1
932
OBJ1
934
NNU2
936
6DF2
938
OBJ2
940

Fig. 9

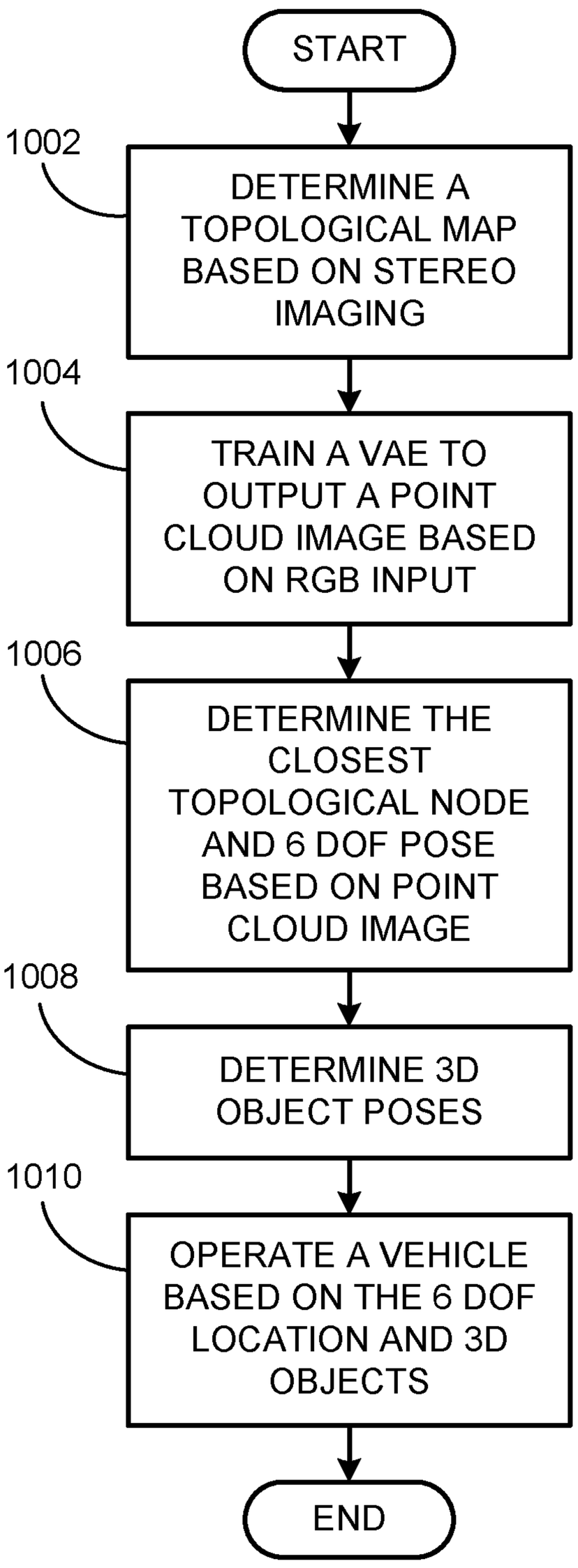

1000
START
1002
DETERMINE A TOPOLOGICAL MAP BASED ON STEREO IMAGING
1004
TRAIN A VAE TO OUTPUT A POINT CLOUD IMAGE BASED ON RGB INPUT
1006
DETERMINE THE CLOSEST TOPOLOGICAL NODE AND 6 DOF POSE BASED ON POINT CLOUD IMAGE
1008
DETERMINE 3D OBJECT POSES
1010
OPERATE A VEHICLE BASED ON THE 6 DOF LOCATION AND 3D OBJECTS
END

Fig. 10

VEHICLE NEURAL NETWORK PERCEPTION AND LOCALIZATION

BACKGROUND

Vehicles can be equipped with computing devices, networks, sensors, and controllers to acquire data regarding the vehicle's environment and to operate the vehicle based on the data. Vehicle sensors can provide data concerning routes to be traveled and objects to be avoided in the vehicle's environment. Operation of the vehicle can rely upon acquiring accurate and timely data regarding objects in a vehicle's environment while the vehicle is being operated on a roadway.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a diagram of an example traffic infrastructure system.

FIG. **2** is a diagram of an example illustration of a topoplogical map.

FIG. **3** is a diagram of example stereo images.

FIG. **4** is a diagram of an example point cloud image.

FIG. **5** is an example node system that generates topological nodes.

FIG. **6** is an example of a topological convolutional neural network.

FIG. **7** is an example of a six degree of freedom localization system.

FIG. **8** is an example of a three dimensional object detection system.

FIG. **9** is an example of a Siamese network.

FIG. **10** is a flowchart diagram of an example process to operate a vehicle based on six degree of freedom localization and three dimensional object detection.

DETAILED DESCRIPTION

A computing device in a traffic infrastructure system can be programmed to acquire data regarding the external environment of a vehicle and to use the data to determine a vehicle path upon which to operate a vehicle in an autonomous or semi-autonomous mode. A vehicle can operate on a roadway based on a vehicle path by determining commands to direct the vehicle's powertrain, braking, and steering components to operate the vehicle to travel along the path. The data regarding the external environment can include the location of one or more objects such as vehicles and pedestrians, etc., in an environment around a vehicle and can be used by a computing device in the vehicle to operate the vehicle.

Determining a vehicle path can include solving two problems: perception and localization. Perception includes determining locations of objects in an environment around a vehicle. Objects can include other vehicles, pedestrians, traffic barriers, etc. Localization includes determining a six degree-of-freedom (DoF) pose for the vehicle with respect to a map of the environment around the vehicle. A six DoF pose includes a location in three orthogonal coordinates (x, y, and z, for example) and orientation in three rotations about the axes of each of the three orthogonal coordinates (roll, pitch, and yaw, for example). Localizing a vehicle with respect to a map and perceiving objects in an environment around a vehicle can permit a computing device in a vehicle to determine a vehicle path upon which the vehicle can travel to reach a destination on the map while avoiding contact with objects in the environment around the vehicle.

A vehicle path can be a polynomial function determined to maintain lateral and longitudinal accelerations of the vehicle within upper and lower limits as it travels on the vehicle path.

Solving localization and perception problems for vehicle routing can begin by recognizing that vehicles typically travel repeatedly along the same routes. Techniques disclosed herein can take advantage of predictable travel patterns by creating a topological map of repeatedly traveled routes that can be used by a vehicle to solve localization and perception problems using less expensive equipment and fewer computer resources that would otherwise be required to determine a vehicle route. Techniques described herein perform perception and localization of an environment around a vehicle by first determining a topological map of a route to be traveled by the vehicle. A route is defined as a path that describes successive locations of a vehicle as it travels from one point to a second point on a map, typically on roadways. The topological map is a map that includes location and image data that can be used by a computing device in a vehicle to determine data including vehicle location and locations of objects in an environment around the vehicle. A topological map is generated by processing a plurality of stereo images of the route to form a plurality of nodes as illustrated in FIG. **2**. Each node includes six DoF data for a location along a route and 3D image data that includes three-dimensional (3D) features based on an RGB image from a stereo image pair. The features are extracted from the RGB images using machine vision techniques and 3D data extracted from stereo image data as will be discussed below in relation to FIGS. **3-5**. The six DoF data and the 3D image data is used to train a neural network to input a color or reg, green, blue (RGB) image acquired by a sensor included in a vehicle and output data identifying the closest node of the topological map and a labeled point cloud image as will be discussed in relation to FIGS. **6-8**. A point cloud image is point cloud data that includes distances or range to points in the image. A semantic point cloud is a point cloud image includes labels that identify regions within the image corresponding to objects. Regions so labeled can include roadways, sidewalks, vehicles, pedestrians, buildings and foliage, etc. Techniques disclosed herein improve localization and perception by determining a six DoF location of a vehicle and identifying objects in an environment around a vehicle based on a single monocular image, thereby eliminating the expense and computational resources required by stereo cameras or lidar sensors. Techniques described herein also discuss updating the topological map with new data acquired by vehicles traversing the route, thereby improving the data included at each node of the topological map to reflect any changes to the route.

Disclosed herein is a method, including inputting an image acquired by a sensor in a vehicle to a variational auto-encoder neural network that outputs a semantic point cloud image that includes regions labeled by region type and region distance relative to the vehicle and, from a plurality of topological nodes, determining a topological node closest to the vehicle and a six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle based on the semantic point cloud image, wherein each topological node includes a location in real-world coordinates and a three-dimensional point cloud image of an environment including the location of the topological node. A real-world six degree-of-freedom pose for the vehicle can be determined by combining the six degree-of-freedom pose for the vehicle relative to the topological node and the location in real-world coordinates of the topological node

closest to the vehicle and a location and size of a three-dimensional object in the semantic point cloud image can be determined based on three-dimensional background subtraction using the three-dimensional point cloud image included in the topological node closest to the vehicle. The real-world six degree-of-freedom pose for the vehicle can be determined based on a single monocular image acquired by the sensor in the vehicle without including an inertial measurement unit in the vehicle.

The semantic point cloud image can be determined based on a single monocular image acquired by the sensor in the vehicle without including a stereo camera or lidar sensor in the vehicle. The topological nodes can be determined by acquiring point cloud images with a stereo camera and determining locations of the point cloud images in real-world coordinates with visual odometry. The real-world six degree-of-freedom pose for the vehicle can be determined in coordinates based on orthogonal x, y, and z axes and roll, pitch, and yaw rotations about the x, y, and z axes, respectively. The location and size of an object in semantic point cloud data can be determined with a convolutional neural network trained to determine a three-dimensional bounding box that includes the three-dimensional object and a real-world location relative to the vehicle for the object. Three-dimensional background subtraction using the point cloud image can be used to determine the three-dimensional bounding box by reducing background clutter caused by labeled regions that occur in both a current semantic point cloud and a semantic point cloud image included in a topological node. The convolutional neural network can include convolutional layers that output first latent variables to first fully connected neural network layers. The variational auto-encoder neural network can determine the semantic point cloud image by outputting second latent variables to second fully connected neural network layers. The variational auto-encoder neural network can be trained to output the semantic point cloud image in a Siamese network configuration wherein the variational auto-encoder neural network is trained in parallel with a second variational auto-encoder network trained using a plurality of three-dimensional point cloud images acquired while traveling along a route that includes the plurality of topological nodes. The semantic point cloud image region types can include roadway, sidewalk, vehicle, building, and foliage based on the plurality of three-dimensional point cloud images. The variational autoencoder neural network can include an encoder, a decoder and a loss function. The variational autoencoder neural network encoder processes input image data to form latent variables. The variational autoencoder neural network decoder can be trained to determine six degree of freedom data from the latent variables.

Further disclosed is a computer readable medium, storing program instructions for executing some or all of the above method steps. Further disclosed is a computer programmed for executing some or all of the above method steps, including a computer apparatus, programmed to input an image acquired by a sensor in a vehicle to a variational auto-encoder neural network that outputs a semantic point cloud image that includes regions labeled by region type and region distance relative to the vehicle and, from a plurality of topological nodes, determine a topological node closest to the vehicle and a six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle based on the semantic point cloud image, wherein each topological node includes a location in real-world coordinates and a three-dimensional point cloud image of an environment including the location of the topological node. A real-world six degree-of-freedom pose for the vehicle can be determined by combining the six degree-of-freedom pose for the vehicle relative to the topological node and the location in real-world coordinates of the topological node closest to the vehicle and a location and size of a three-dimensional object in the semantic point cloud image can be determined based on three-dimensional background subtraction using the three-dimensional point cloud image included in the topological node closest to the vehicle. The real-world six degree-of-freedom pose for the vehicle can be determined based on a single monocular image acquired by the sensor in the vehicle without including an inertial measurement unit in the vehicle.

The computer can be further programmed to determined the semantic point cloud image based on a single monocular image acquired by the sensor in the vehicle without including a stereo camera or lidar sensor in the vehicle. The topological nodes can be determined by acquiring point cloud images with a stereo camera and determining locations of the point cloud images in real-world coordinates with visual odometry. The real-world six degree-of-freedom pose for the vehicle can be determined in coordinates based on orthogonal x, y, and z axes and roll, pitch, and yaw rotations about the x, y, and z axes, respectively. The location and size of an object in semantic point cloud data can be determined with a convolutional neural network trained to determine a three-dimensional bounding box that includes the three-dimensional object and a real-world location relative to the vehicle for the object. Three-dimensional background subtraction using the point cloud image can be used to determine the three-dimensional bounding box by reducing background clutter caused by labeled regions that occur in both a current semantic point cloud and a semantic point cloud image included in a topological node. The convolutional neural network can include convolutional layers that output first latent variables to first fully connected neural network layers. The variational auto-encoder neural network can determine the semantic point cloud image by outputting second latent variables to second fully connected neural network layers. The variational auto-encoder neural network can be trained to output the semantic point cloud image in a Siamese network configuration wherein the variational auto-encoder neural network is trained in parallel with a second variational auto-encoder network trained using a plurality of three-dimensional point cloud images acquired while traveling along a route that includes the plurality of topological nodes. The semantic point cloud image region types can include roadway, sidewalk, vehicle, building, and foliage based on the plurality of three-dimensional point cloud images. The variational autoencoder neural network can include an encoder, a decoder and a loss function. The variational autoencoder neural network encoder processes input image data to form latent variables. The variational autoencoder neural network decoder can be trained to determine six degree of freedom data from the latent variables.

FIG. **1** is a diagram of a traffic infrastructure system **100** that includes a vehicle **110** operable in autonomous ("autonomous" by itself in this disclosure means "fully autonomous"), semi-autonomous, and occupant piloted (also referred to as non-autonomous) mode. One or more vehicle **110** computing devices **115** can receive data regarding the operation of the vehicle **110** from sensors **116**. The computing device **115** may operate the vehicle **110** in an autonomous mode, a semi-autonomous mode, or a non-autonomous mode.

The computing device **115** includes a processor and a memory such as are known. Further, the memory includes one or more forms of computer-readable media, and stores instructions executable by the processor for performing various operations, including as disclosed herein. For example, the computing device **115** may include programming to operate one or more of vehicle brakes, propulsion (e.g., control of acceleration in the vehicle **110** by controlling one or more of an internal combustion engine, electric motor, hybrid engine, etc.), steering, climate control, interior and/or exterior lights, etc., as well as to determine whether and when the computing device **115**, as opposed to a human operator, is to control such operations.

The computing device **115** may include or be communicatively coupled to, e.g., via a vehicle communications bus as described further below, more than one computing devices, e.g., controllers or the like included in the vehicle **110** for monitoring and/or controlling various vehicle components, e.g., a powertrain controller **112**, a brake controller **113**, a steering controller **114**, etc. The computing device **115** is generally arranged for communications on a vehicle communication network, e.g., including a bus in the vehicle **110** such as a controller area network (CAN) or the like; the vehicle **110** network can additionally or alternatively include wired or wireless communication mechanisms such as are known, e.g., Ethernet or other communication protocols.

Via the vehicle network, the computing device **115** may transmit messages to various devices in the vehicle and/or receive messages from the various devices, e.g., controllers, actuators, sensors, etc., including sensors **116**. Alternatively, or additionally, in cases where the computing device **115** actually comprises multiple devices, the vehicle communication network may be used for communications between devices represented as the computing device **115** in this disclosure. Further, as mentioned below, various controllers or sensing elements such as sensors **116** may provide data to the computing device **115** via the vehicle communication network.

In addition, the computing device **115** may be configured for communicating through a vehicle-to-infrastructure (V-to-I) interface **111** with a remote server computer **120**, e.g., a cloud server, via a network **130**, which, as described below, includes hardware, firmware, and software that permits computing device **115** to communicate with a remote server computer **120** via a network **130** such as wireless Internet (WI-FI®) or cellular networks. V-to-I interface **111** may accordingly include processors, memory, transceivers, etc., configured to utilize various wired and/or wireless networking technologies, e.g., cellular, BLUETOOTH® and wired and/or wireless packet networks. Computing device **115** may be configured for communicating with other vehicles **110** through V-to-I interface **111** using vehicle-to-vehicle (V-to-V) networks, e.g., according to Dedicated Short Range Communications (DSRC) and/or the like, e.g., formed on an ad hoc basis among nearby vehicles **110** or formed through infrastructure-based networks. The computing device **115** also includes nonvolatile memory such as is known. Computing device **115** can log data by storing the data in nonvolatile memory for later retrieval and transmittal via the vehicle communication network and a vehicle to infrastructure (V-to-I) interface **111** to a server computer **120** or user mobile device **160**.

As already mentioned, generally included in instructions stored in the memory and executable by the processor of the computing device **115** is programming for operating one or more vehicle **110** components, e.g., braking, steering, propulsion, etc., without intervention of a human operator. Using data received in the computing device **115**, e.g., the sensor data from the sensors **116**, the server computer **120**, etc., the computing device **115** may make various determinations and/or control various vehicle **110** components and/or operations without a driver to operate the vehicle **110**. For example, the computing device **115** may include programming to regulate vehicle **110** operational behaviors (i.e., physical manifestations of vehicle **110** operation) such as speed, acceleration, deceleration, steering, etc., as well as tactical behaviors (i.e., control of operational behaviors typically in a manner intended to achieve safe and efficient traversal of a route) such as a distance between vehicles and/or amount of time between vehicles, lane-change, minimum gap between vehicles, left-turn-across-path minimum, time-to-arrival at a particular location and intersection (without signal) minimum time-to-arrival to cross the intersection.

Controllers, as that term is used herein, include computing devices that typically are programmed to monitor and/or control a specific vehicle subsystem. Examples include a powertrain controller **112**, a brake controller **113**, and a steering controller **114**. A controller may be an electronic control unit (ECU) such as is known, possibly including additional programming as described herein. The controllers may communicatively be connected to and receive instructions from the computing device **115** to actuate the subsystem according to the instructions. For example, the brake controller **113** may receive instructions from the computing device **115** to operate the brakes of the vehicle **110**.

The one or more controllers **112**, **113**, **114** for the vehicle **110** may include conventional electronic control units (ECUs) or the like including, as non-limiting examples, one or more powertrain controllers **112**, one or more brake controllers **113**, and one or more steering controllers **114**. Each of the controllers **112**, **113**, **114** may include respective processors and memories and one or more actuators. The controllers **112**, **113**, **114** may be programmed and connected to a vehicle **110** communications bus, such as a controller area network (CAN) bus or local interconnect network (LIN) bus, to receive instructions from the computing device **115** and control actuators based on the instructions.

Sensors **116** may include a variety of devices known to provide data via the vehicle communications bus. For example, a radar fixed to a front bumper (not shown) of the vehicle **110** may provide a distance from the vehicle **110** to a next vehicle in front of the vehicle **110**, or a global positioning system (GPS) sensor disposed in the vehicle **110** may provide geographical coordinates of the vehicle **110**. The distance(s) provided by the radar and/or other sensors **116** and/or the geographical coordinates provided by the GPS sensor may be used by the computing device **115** to operate the vehicle **110** autonomously or semi-autonomously, for example.

The vehicle **110** is generally a land-based vehicle **110** capable of autonomous and/or semi-autonomous operation and having three or more wheels, e.g., a passenger car, light truck, etc. The vehicle **110** includes one or more sensors **116**, the V-to-I interface **111**, the computing device **115**, and one or more controllers **112**, **113**, **114**. The sensors **116** may collect data related to the vehicle **110** and the environment in which the vehicle **110** is operating. By way of example, and not limitation, sensors **116** may include, e.g., altimeters, cameras, LIDAR, radar, ultrasonic sensors, infrared sensors, pressure sensors, accelerometers, gyroscopes, temperature sensors, pressure sensors, hall sensors, optical sensors, voltage sensors, current sensors, mechanical sensors such as switches, etc. The sensors **116** may be used to sense the

environment in which the vehicle **110** is operating, e.g., sensors **116** can detect phenomena such as weather conditions (precipitation, external ambient temperature, etc.), the grade of a road, the location of a road (e.g., using road edges, lane markings, etc.), or locations of target objects such as neighboring vehicles **110**. The sensors **116** may further be used to collect data including dynamic vehicle **110** data related to operations of the vehicle **110** such as velocity, yaw rate, steering angle, engine speed, brake pressure, oil pressure, the power level applied to controllers **112**, **113**, **114** in the vehicle **110**, connectivity between components, and accurate and timely performance of components of the vehicle **110**.

Traffic infrastructure system **100** can include one or more edge computing nodes **170**. Edge computing nodes **170** are computing devices as described above that can be located near roadways, and can be in communication with stationary or moveable sensors. For example, a stationary video camera **180** can be attached to a pole **190**, building, or other structure to give the video camera **180** a view of traffic. Mobile sensors can be mounted on drones or other mobile platforms to provide views of traffic from positions not available to stationary sensors. Edge computing nodes **170** further can be in communication with computing devices **115** in vehicle **110**, server computers **120**, and user mobile devices **160** such as smart phones. Server computers **120** can be cloud-based computer resources that can be called upon by edge computing nodes **170** to provide additional computing resources when needed.

Vehicles can be equipped to operate in both autonomous and occupant piloted mode. By a semi- or fully-autonomous mode, we mean a mode of operation wherein a vehicle can be piloted partly or entirely by a computing device as part of a system having sensors and controllers. The vehicle can be occupied or unoccupied, but in either case the vehicle can be partly or completely piloted without assistance of an occupant. For purposes of this disclosure, an autonomous mode is defined as one in which each of vehicle propulsion (e.g., via a powertrain including an internal combustion engine and/or electric motor), braking, and steering are controlled by one or more vehicle computers; in a semi-autonomous mode the vehicle computer(s) control(s) one or more of vehicle propulsion, braking, and steering. In a non-autonomous mode, none of these are controlled by a computer.

FIG. **2** is a diagram of a topological map **200**. Topological map **200** can be constructed by acquiring and processing stereo video data using video odometry to determine topological nodes **202** along a route or roadway **204**, **206**. A topological map **200** is a set of nodes **202**, each of which includes real world coordinate data regarding the location of the node and three dimensional (3D) image data derived from the stereo video data as discussed in relation to FIGS. **3-6**, below. A topological map **200** can be illustrated as in FIG. **2** by modifying a street map by adding nodes **202**, illustrated as circles on roadways or routes **204**, **206**. The terms roadways and routes will be used interchangeably herein. Each node **202** is located on a roadway **204**, **206** that can be traveled along by a vehicle **110**. Nodes are located with one to 10 meters distance between adjacent nodes. Spacing out nodes in this fashion permits location of a vehicle **110** within a few centimeters, for example one to 25 centimeters, in x, y, and z directions while maintaining a limit on the amount of data required to represent the route. The roadway **204**, **206** is mapped using a vehicle equipped with a stereo camera to generate stereo point cloud data and RGB images corresponding to the stereo point cloud data. Each node **202** in the topological map includes a representative RGB image with corresponding features derived from latent variables from a neural network to be described in relation to FIGS. **7** and **8**. Each node also includes 2D image points extracted from the RGB image using machine vision techniques described in relation to FIGS. **3-6** and corresponding 3D locations derived from stereo point cloud data.

FIG. **3** is a diagram of a pair of stereo images **302**, **304**. Stereo images can be acquired by a stereo camera, where two cameras are arranged to view the same scene with a lateral separation. The lateral separation, also referred to as the baseline, causes the cameras to generate images where corresponding points in each image will be displaced with respect to the image by an amount that is a function of the lateral separation of the cameras and the distance of the point in space from the camera. Because the lateral separation of the cameras can be precisely determined, a simple geometric transformation can yield distances to points in the images, e.g., as described further below.

FIG. **4**. is a diagram of a stereo point cloud image **402** generated from a pair of stereo images **302**, **304**. While the pixels values in a pair of stereo images **302**, **304** correspond to the amount of light received by the sensors, in a stereo point cloud image **402** the value of the pixels correspond to distances from the point corresponding to the pixel to the sensor. A stereo point cloud image **402** can be constructed from a pair of stereo images **302**, **304** based on stereo disparity. Stereo disparity is defined as the difference in corresponding feature point locations in a pair of stereo images **302**, **304**. Corresponding feature points are defined as locations in the pair of stereo images **302**, **304** that share similar pixel values including regions around the locations. For example, corners, edges and textures in the pair of stereo images **302**, **304** can be corresponding feature points. The feature points can be determined by known machine vision techniques which determine feature points by processing regions in images to find pixel locations that can be defined by patterns of abrupt changes in pixel values, for example edges and corners and textures. Patterns of pixel values around feature points can be compared between pairs of stereo images to identify corresponding feature points that occur in both images. The difference in location with respect to the array of image points can be used to measure stereo disparity. An example of feature point detection can be found in SURF (US Patent Application 2009238460, Ryuji Funayama, Et. Al., ROBUST INTEREST POINT DETECTOR AND DESCRIPTOR, published 2009 Sep. 24).

Once corresponding feature points in a pair of stereo images **302**, **304** by determining similar arrangements of pixel values. Because the distance between the stereo cameras determined by the fixed mount to which the cameras are attached, a baseline is established that permits the distance from the sensors to corresponding feature points to be determined by triangulation. An equation for determining the distance from an image sensor to a point $P=x_p, y_p, z_p$ in overlapping fields of view of a pair of stereo image sensors corresponding to image feature locations $P(u_1, v_1)$, $P(u_2, v_2)$ in first and second stereo image based on stereo disparity is given by the equations:

$$d=u_1-u_2 \tag{1}$$

$$x_p = \frac{bu_1}{d}, y_p = \frac{bv_1}{d}, z_p = \frac{bf}{d} \tag{2}$$

Where d is the disparity determined by a difference in feature coordinates locations u_1-u_2 in the x-direction, b is

the baseline between the centers of first and second image sensors and f is the common focal distance of the image sensors. Distances to a plurality of corresponding feature points determined in this fashion can be assembled into a point cloud image.

A stereo point cloud image can also be determined by training a convolutional neural network (CNN) to determine a point cloud image **402** from a pair of stereo images **302**, **304**. A convolutional neural network includes a plurality of convolutional layers followed by a plurality of fully connected layers. The convolutional layers can determine the feature points, which are passed as latent variables to the fully connected layers, which calculate the equivalent of equations (1) and (2). A CNN can be trained to determine a point cloud image **402** from a pair of stereo images **302**, **304** using a training dataset that includes pairs of stereo images **302**, **304** along with ground truth point cloud images **402** that have been determined using feature points and geometric processing based on equations (1) and (2). Ground truth is data corresponding to a correct result output from a CNN, i.e., data correctly representing a real-world state, where the ground truth data is acquired from a source independent from the CNN. Ground truth is used to compare to the result output from a CNN when training the CNN to determine when the CNN is outputting a correct result. For example, ground truth for point cloud data can be determined by manually selecting corresponding features in a pair of stereo images and manually calculating distances based on measured baseline and camera focal length to form ground truth point cloud data.

In addition to distances, the pixels of the stereo point cloud image **402** can be labeled according to the objects they correspond to. One or more of the RGB images included in the stereo image pairs **302**, **304** can be input to a convolutional neural network (CNN) that has been trained to segment images. Image segmentation is a machine vision technique that labels objects in image data. The CNN can label objects in an input image and then the labels can be transferred to point cloud data. In stereo point cloud image **402**, objects corresponding to a roadway, vehicles, trees and buildings adjacent to the roadway have been labeled to identify the regions of pixels in the stereo point cloud image **402** corresponding to the labeled objects. The CNN can be trained by labeling a plurality of RGB images manually to create ground truth images. The RGB images can be labeled by humans using image processing software to label regions of the images that correspond to objects as defined above.

Point cloud image **402** has been processed using the node system **500** described in relation to FIG. **5** to form a semantic point cloud **512** where objects and regions are labeled. For example, point cloud image includes labeled regions corresponding to a roadways, sidewalks, vehicles, pedestrians, buildings, foliage, etc.

FIG. **5** is a diagram of a node system **500** that generates node **202** data from pairs of stereo images (STEREO) **502** acquired as a mapping vehicle equipped with stereo video sensors travels along a roadway **204**, **206** to be mapped. Node system **500** can be implemented as software operating on a computing device **115**, for example. Pairs of stereo images **502** are acquired by a vehicle as the vehicle travels along a route **204**, **206** and input to node system **500**. The pairs of stereo images **502** are processed by point cloud processor (PCP) **504** to form a point cloud image by determining three dimensional locations of corresponding feature points by determining stereo disparity between the pairs of stereo images **502**. Point cloud processor can be a CNN as discussed above in relation to FIG. **4**, above.

The pairs of stereo images **502** are also passed to an image segmentation processor (SIS) **506**. Image segmentation processor **506** segments one or both RGB images in the pair of stereo images **502** to generate a one or more segmented RGB images using a CNN as discussed above in relation to FIG. **4**. The pairs of stereo images **502** are processed one at a time as RGB images (RGB) **504** by segmentation processor (SIS) **506**. Segmentation processor is a CNN trained to label regions in RGB image **504** data. A CNN can be trained to label regions in RGB image **504** data by first constructing a training dataset, where images are labeled manually by humans using image processing software to draw boundaries around objects and filling in the boundaries with pixel values corresponding to the objects. The manually labeled images are ground truth to be compared with the output of the CNN. The dataset can include more than 1000 RGB images **504** with corresponding ground truth. The CNN is executed a plurality of times with the same RGB image **504** as input while changing sets of parameters that govern the operation of the convolutional layers and fully connected layer included in the CNN. The sets of parameters are graded depending upon how similar the output is to the corresponding ground truth. The highest scoring sets of parameters over the training dataset are retained as the set of parameters to use when operating the trained CNN.

The one or more segmented RGB images are passed to point cloud labeling (PCL) **510** where a point cloud image from point cloud processor **504** is combined with segmented RGB images formed from the same stereo pair that generated the point cloud image to form a semantic point cloud **512**. A semantic point cloud **504** is a point cloud image where the point cloud data corresponding to distances is also labeled to identify the type of object or region. For example, in point cloud image **402** a roadway **404**, vehicles **406**, **408**, buildings **410**, **412**, **414** and foliage **416**, **418** have been labeled, making point cloud image **402** a semantic point cloud **514**.

A plurality of pairs of stereo images **502** are input to a visual odometry processor (VO) **508**. Stereo visual odometry is a technique for determining a six DoF (6DOF) pose **514** for a vehicle **110** based on determining changes in the locations of features extracted from the images as the vehicle **110** moves through a scene. Visual odometry can be performed by a trained variational autoencoder (VAE). A VAE is a neural network that includes an encoder, a decoder and a loss function. A VAE can be trained to input image data, encode the image data to form latent variables that correspond to an ecoded representation of the input image data and decode the latent variables to output an image that includes portions of the input image data modified in a deterministic fashion. The VAE can be trained by determining a loss function which measures how accurately the VAE has encoded and decoded the image data. Once a VAE is trained, the encoder portion, or "head" can be removed from the VAE and used to form latent variables that correspond to the input images. The latent variables formed by the encoder can be processed by decoding sections that derive additional types of data, for example six DoF data that describes the pose of the camera that acquired the input image as discussed below.

Visual odometry is a known technique for determining six DoF data from a sequential series of images. Visual odometery can be determined by training a VAE to input stereo pairs of images and outputting six DoF data. The VAE determines corresponding feature points in sequential images and calculates the change in location of the sensor between images. A six DoF pose for the camera can be

determined by triangulating two or more sets of feature points to determine translation and rotation to determine a frame of reference for the sensor in global coordinates. The VAE can be trained by determining ground truth using an inertial measurement unit (IMU) and real time kinematic-enhanced global positioning systems (GPS-RTK).

A VAE includes an encoder, a decoder and a loss function. The encoder inputs image data and encodes the input image data into latent variables. The latent variables are then decoded to form a six DoF pose for the vehicle based on the input image data. The loss function is used to train the encoder and decoder by determining whether the six DoF poses **514** are valid poses for a vehicle on a roadway based on training the encoder and decoder using ground truth data regarding six DoF poses **514** corresponding to the input images determined based on real-world measurements of a vehicle six DoF poses **514**. Visual odometry processor **508** determines six DoF poses **514** based on a plurality of pairs of stereo images **502** acquired as the mapping vehicle travels along the path to be topologically mapped. The six DoF pose **514** locates the vehicle with respect to global coordinates.

When the mapping vehicle has progressed along the roadway **204**, **206** a specified distance from the previous node **202**, which can be two to 10 meters, for example, the computing device **115** can create a new node **202** place in into the topological map. Each node **202** in the topological map includes a semantic point cloud **512**, one or more RGB images from the pair of stereo images **502** and a six DoF pose corresponding to the location of the node **202** on the topological map.

FIG. **6** is a diagram of a topological CNN **600**. A topological CNN **600** is a type of VAE. A topological CNN **600** is a neural network that can be trained to input an RGB image (RGB) **602** and output a semantic point cloud (SPC) **610**. The topological CNN **600** can be trained using the RGB images from the pairs of stereo images **502** and input and semantic point clouds **512**. The VAE includes an encoder (EN) **604** which includes convolutional layers that encode the input RGB image **602** into latent variables (LAT) **606** and a decoder (DEC) **608**, that uses full-connected layers to decode the latent variables **606** into a semantic point cloud **626**. The encoder **604** or "head" can be detached from the rest of the VAE and used as the input processing portion of two additional neural networks, six DoF localization system **700** neural networks and 3D object detection system **800** neural networks, as discussed further below.

FIG. **7** is a diagram of a six DoF localization system **700**. Six DoF localization system **700** determines a six DoF pose for a vehicle **110**. Six DoF localization system **700** includes two topological CNNs **600** and a 3D object detection system **704**. Six DoF localization system **700** takes as input the output of a topological CNN **600**. Topological CNN **600** inputs an RGB image **602** and outputs a semantic point cloud corresponding to the RGB image **602**. The topological CNN **600** can also be trained to output a six DoF pose corresponding to the location of the vehicle **110** that acquired the RGB image **602**. Six DoF localization system **700** can improve the estimate of the six DoF pose of the vehicle **110** by combining 3D object detection and six DoF localization. A 3D object detector **704** can be used to remove 3D objects from semantic point cloud data where the 3D objects correspond to dynamic obstacles such as other vehicles, pedestrians and traffic barriers, for example. This can improve determining six DoF data for localization of a vehicle **110** because the presence of these dynamic obstacles which were not present during topological mapping of the scene can obscure the signature of the scene and thereby cause errors in determining the six DoF pose of the vehicle based on processing by topological CNN **600**.

Six DoF localization system **700** determines an estimate of a six DoF pose for a vehicle by first inputting an RGB image **602** acquired by a vehicle **110** traveling on a roadway **204**, **206** included in a topological map **200** to the encoder topological CNN **600** of FIG. **6**. In response to the RGB image **602**, the topological CNN **600** outputs a semantic point cloud **610** to 3D object detector (3DOD) **704**. The 3D object detector **704** is a VAE trained to detect objects in a semantic point cloud **610** by first determining bounding boxes for each object in a semantic point cloud **610** and then filtering the bounding boxes to determine objects that occur on or adjacent to a roadway. The VAE can be trained using semantic point cloud data as ground truth. Point cloud data from stereo cameras or lidar sensors can be manually labeled by human operators. The human operators can also determine bounding boxes for the labeled objects. The ground truth including labeled bounding boxes can be compared to the output from the VAE to train the VAE to correctly label point cloud data.

The 3D object detector **704** outputs a semantic point cloud (SM3D) **706** with 3D objects corresponding to vehicles, pedestrians, traffic barriers, etc. marked in the semantic point cloud data by bounding boxes, where a bounding box is a rectangular 3D wire frame shape parallel to the detected roadway in the point cloud data. The semantic point cloud **706** including bounding boxes for detected 3D objects is passed to 3D subtraction (3DSUB) **708** where the detected 3D objects are subtracted from the point cloud data by subtracting all of the pixels within the bounding boxes from the semantic point cloud **708**. The semantic point cloud **708** with the 3D objects subtracted is passed to the topological CNN **600** for processing. The topological CNN **600** again processes the semantic point cloud **708** with 3D objects removed to obtain a refined six DoF pose (R6DOF) **710** for the vehicle **110** along with the node number of the closest topological node **202**. The topological CNN **600** can also output a refined semantic point cloud and a topological node number to be returned to the topological map to refine the semantic point cloud data included at the node number indicated by the output by the topological CNN **600**.

Six DoF localization system **700** improves vehicle localization by processing a semantic point cloud with 3D objects removed to improve the estimate of the six DoF pose for the vehicle **110**. Six DoF localization system **700** also improves the topological map **200** by updating the semantic point cloud data included in the topological map **200** at a particular node to include changes that may have occurred in the scene since the first semantic point cloud was acquired and input to the topological map. Six DoF localization system **700** outputs node number corresponding to the closest topological node **202** included in the topological map **200**. Six DoF localization system **700** also outputs a refined six DoF pose **710** determined relative to the closest node **202**. The vehicle can determine a six DoF pose in real-world coordinates for the vehicle using the equation:

$$P_o^v = P_o^n \cdot P_n^v \tag{3}$$

Where P_o^v is the six DoF pose of the vehicle in real-world coordinates measured with respect to the origin of the topological map, obtained from the, P_o^n is the six DoF pose of the closest node **202** measured with respect to the topological map origin, and P_n^v is the six DoF pose **710** of the vehicle **110** measured with respect to the closest topological node **202**.

FIG. **8** is a diagram of 3D object detection system **800**. Six DoF localization of a vehicle as determined by six DoF system **700** and 3D object detection are complementary tasks. 3D object detection system **800** can improve six DoF localization as discussed above in relation to FIG. **6**, and six DoF localization can improve 3D object detection system **800**. Six DoF localization system **700** determines the location of a vehicle with respect to the topological map **200** allows the subtraction of the current semantic point cloud based on an RGB image acquired by the vehicle from the semantic point cloud in the topological map **200**. This can be done with 3D background subtraction. Subtraction of the semantic point clouds can be used as a guide to the location of the dynamic objects in the scene which were not present during mapping. The 3D bounding box detection network can then be focused on these regions of the scene, which can speed up the algorithm up considerably by reducing background clutter caused by labeled 3D regions in the semantic point cloud not related to 3D objects of interest such as buildings and foliage.

In 3D object detection, an RGB image acquired by a vehicle **110** is input to topological CNN **600** to produce a semantic point cloud **804**. Topological CNN **600** also identifies a topological node number that gets passed to the topological map **200**. In response to the input topological node number, topological map (TMAP) **200** outputs the stored semantic point cloud to 3D subtraction (3DSUB) where it is subtracted from the semantic point cloud **804** produced in response to the input RGB image **802** from vehicle **110** sensors. Subtracting the stored semantic point cloud from the topological map **200** from the current semantic point cloud **804** yields a point cloud image with the approximate position of the 3D objects indicated by non-zero data points, i.e., regions where the current point cloud **804** differs from the stored semantic point cloud. These regions are passed to a 3D object detector (3DOD) **808** where the regions output by 3D subtraction are used to guide the 3D object detector **808**, thereby speeding up the 3D object detector **808** and reducing the required computing resources required for 3D object detection. The 3D object detector is described in relation to FIG. **8**, above. The 3D object detector **808** outputs locations and labels that identify the 3D objects (3DOBJ) **810** in the semantic point cloud **804** to permit a computing device **115** in the vehicle **110** to determine a vehicle path that avoids the 3D objects **810**.

FIG. **9** is a diagram of a Siamese network **900** that can be used to train localization networks and 3D object detection networks simultaneously. The duality of object detection and localization can be used to improve both processes in addition to the techniques discussed in relation to FIGS. **7** and **8**. Multiple traversals of the route can be used to train a Siamese network **900**. A Siamese network **900** is a neural network configured to share some encoder layers between two neural networks. One branch of the Siamese network **900** inputs the semantic point cloud (SPC**1**) **902** from the topological node when the route is traversed without dynamic obstacles. The other branch of the Siamese network **900** inputs the semantic point cloud (SPC**1**) **904** when there are dynamic obstacles. These pairs of semantic point clouds **902**, **904** from each topological node **202**, with and without dynamic objects are used to train the Siamese network **900**, both to determine vehicle six DoF localization as discussed in relation to FIGS. **7** and 3D object pose detection as discussed in relation to FIG. **8**. As discussed in relation to FIG. **6**, a VAE with encoder-decoder architecture to recreate semantic point clouds can be pre-trained and its encoder (ENCODE) **908** can be detached and used as the heads of the Siamese network **900**.

Siamese network **900** includes two encoders (ENC**1**, ENC**2**) **908**, **910** that input semantic point cloud data **902**, **904**, respectively. The encoders **908**, **910** share convolutional layers (CEN) **912** included in each encoder **908**, **910**. Having shared convolutional layers **912** means that the parameters determined for the shared convolutional layers **912** during training will be the same for each encoder **908**, **910**. Shared convolutional layers **912** permit encoders **908**, **910** to share ground truth data when training the neural networks, thereby improving the training of each encoder **908**, **910** by effectively increasing the number of training images and corresponding ground truth data to the total number of sematic point clouds **902**, **904**. Encoders **908**, **910** output latent variables (LATENT**1**, LATENT**2**) **914**, **916**. The latent variables **914**, **916** are input to node number decoding layers (NDE**1**, NDE**2**) **918**, **924**, pose decoding layers (PDE**1**, PDE**2**) **920**, **926**, and 3D object decoding layers (3DO**1**, 3DO**2**) **922**, **928**, respectively. Node number decoding layers **918**, **924** input latent variables **914**, **916** and output the node number (NNU**1**, NNU**2**) **930**, **936** of the node **202** closest to the input semantic point cloud **902**, **904**, respectively as discussed in relation to FIG. **6**, above. Pose decoding layers **920**, **926** input latent variables **914**, **916** and output six DoF poses (6DF**1**, 6DF**2**) **932**, **938** for the vehicle that acquired the semantic point cloud **902**, **904** with respect to the node **202** identified by the node number **930**, **936** as discussed in relation to FIG. **6**, above. 3D object decoding layers **922**, **928** input latent variables **914**, **916** and output 3D bounding boxes and labels for objects in the semantic point clouds **902**, **904** as discussed above in relation to FIG. **7**.

Techniques described herein improve determining vehicle six DoF locations and 3D object detection by permitting vehicle six DoF vehicle locations and 3D object detection to be performed using a monocular RGB camera on routes that have been previously mapped to form a topological map **200**. Using a monocular RGB camera to perform 3D object detection is far less expensive and requires fewer computing resources than using stereo cameras or lidar sensors. Techniques described herein can determine six DoF vehicle locations much less expensively and using fewer computing resources than using an inertial measurement unit (IMU) or real time kinematic-enhanced global positioning systems (GPS-RTK). Techniques described herein can also improve the topological map **200** corresponding to a route by updating the node data corresponding to the nodes **202** of the topological map **200** based on the node numbers **622**, six DoF pose **624**, and semantic point clouds **626** determined based on input RGB images **602** acquired as the vehicle **110** traverses a give route.**10**

FIG. **10** is a diagram of a flowchart, described in relation to FIGS. **1-9**, of a process **1000** for determining vehicle six DoF pose and 3D object detection from RGB images. Process **1000** can be implemented by a processor of computing device, taking as input information from sensors, and executing commands, and outputting object information, for example. Process **1000** includes multiple blocks that can be executed in the illustrated order. Process **1000** could alternatively or additionally include fewer blocks or can include the blocks executed in different orders.

Process **1000** begins at block **1002**, where a topological map **202** is determined for a roadway by traversing the roadway with a mobile platform equipped with a stereo camera as discussed in relation to FIG. **2**. The stereo images are processed by a computing device **115** to produce a

semantic point cloud, where distance to points in the image are grouped and labeled as discussed in relation to FIG. **5**. For example, a semantic point cloud can include labels for roadways, vehicles, pedestrians, buildings and foliage. The topological map **200** includes a plurality of nodes **202**, where each node includes a six DoF location and a semantic point cloud. The technique is described herein using ground vehicles operating on roads, however, the techniques can be used to determine a route for any mobile platform, including mobile robots, drones or boats, for example.

At block **1004** a computing device **115** trains a topological CNN **600** to input a monocular RGB image and output a semantic point cloud as discussed in relation to FIG. **6**. The topological CNN **600** can also be trained to output a six DoF pose for the vehicle **110** that acquired the RGB image and a topological node number corresponding to the closest topological node **202** from the topological map **200**. The closest topological node is defined as the topological node with a six DoF location that has the least Euclidian distance in three dimensions from the six DoF location of the vehicle as determined by six DoF localization system **700**.

At block **1006** the computing device **115** uses the trained topological CNN to determine a six DoF pose for the vehicle and the node number of the closest topological node **202** in the topological map **200**. As discussed above in relation to FIG. **7**, the computing device **115** can detect and label 3D objects in a semantic point cloud output by the topological CNN to remove them from the semantic point cloud and thereby determine a refined six DoF pose for the vehicle **110**. The data determined by the computing device **115** at block **1006** can be passed back to the topological map **200** to update the topological map **200**.

At block **1008** the computing device **115** can determine 3D object locations in the point cloud data determined by the topological CNN **600**. A semantic point cloud from the topological map **200** can be used to determine an approximate location for the 3D objects in the semantic point cloud output by the topological CNN **600** which can be used to increase the efficiency of 3D object detection system **800**. The locations of 3D objects determined at block **1008** can be passed back to the topological map **200** to update the semantic point cloud included in the closest topological node **202**.

At block **1010** the computing device **115** can use the six DoF pose of the vehicle **110** with respect to the topological map **200** output by six DoF localization system **700** and the locations of 3D objects detected by 3D object detection system **800** to operate the vehicle. Computing device **115** can determine a vehicle path upon which to operate the vehicle **110** by sending commands to vehicle brake, steering and powertrain controllers. The vehicle path can be a polynomial function determined to stay within the roadway and avoid 3D objects. The vehicle path can be determined based on maintaining lower and upper limits on lateral and longitudinal accelerations. Following block **1010** process **1000** ends.

Computing devices such as those discussed herein generally each includes commands executable by one or more computing devices such as those identified above, and for carrying out blocks or steps of processes described above. For example, process blocks discussed above may be embodied as computer-executable commands.

Computer-executable commands may be compiled or interpreted from computer programs created using a variety of programming languages and/or technologies, including, without limitation, and either alone or in combination, Java™, C, C++, Python, *Julia*, SCALA, Visual Basic, Java Script, Perl, HTML, etc. In general, a processor (e.g., a microprocessor) receives commands, e.g., from a memory, a computer-readable medium, etc., and executes these commands, thereby performing one or more processes, including one or more of the processes described herein. Such commands and other data may be stored in files and transmitted using a variety of computer-readable media. A file in a computing device is generally a collection of data stored on a computer readable medium, such as a storage medium, a random access memory, etc.

A computer-readable medium includes any medium that participates in providing data (e.g., commands), which may be read by a computer. Such a medium may take many forms, including, but not limited to, non-volatile media, volatile media, etc. Non-volatile media include, for example, optical or magnetic disks and other persistent memory. Volatile media include dynamic random access memory (DRAM), which typically constitutes a main memory. Common forms of computer-readable media include, for example, a floppy disk, a flexible disk, hard disk, magnetic tape, any other magnetic medium, a CD-ROM, DVD, any other optical medium, punch cards, paper tape, any other physical medium with patterns of holes, a RAM, a PROM, an EPROM, a FLASH-EEPROM, any other memory chip or cartridge, or any other medium from which a computer can read.

All terms used in the claims are intended to be given their plain and ordinary meanings as understood by those skilled in the art unless an explicit indication to the contrary in made herein. In particular, use of the singular articles such as "a," "the," "said," etc. should be read to recite one or more of the indicated elements unless a claim recites an explicit limitation to the contrary.

The term "exemplary" is used herein in the sense of signifying an example, e.g., a reference to an "exemplary widget" should be read as simply referring to an example of a widget.

The adverb "approximately" modifying a value or result means that a shape, structure, measurement, value, determination, calculation, etc. may deviate from an exactly described geometry, distance, measurement, value, determination, calculation, etc., because of imperfections in materials, machining, manufacturing, sensor measurements, computations, processing time, communications time, etc.

In the drawings, the same reference numbers indicate the same elements. Further, some or all of these elements could be changed. With regard to the media, processes, systems, methods, etc. described herein, it should be understood that, although the steps or blocks of such processes, etc. have been described as occurring according to a certain ordered sequence, such processes could be practiced with the described steps performed in an order other than the order described herein. It further should be understood that certain steps could be performed simultaneously, that other steps could be added, or that certain steps described herein could be omitted. In other words, the descriptions of processes herein are provided for the purpose of illustrating certain embodiments, and should in no way be construed so as to limit the claimed invention.

The invention claimed is:

1. A computer, comprising:

a processor; and

a memory, the memory including instructions executable by the processor to:

input an image acquired by a sensor in a vehicle to a variational auto-encoder neural network that outputs

a semantic point cloud image that includes regions labeled by region type and region distance relative to the vehicle;

from a plurality of topological nodes, determine a topological node closest to the vehicle, and a six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle, based on the semantic point cloud image, wherein each topological node includes a location in real-world coordinates and a three-dimensional point cloud image of an environment including the location of the topological node;

determine a real-world six degree-of-freedom pose for the vehicle by combining the six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle and the location in real-world coordinates of the topological node closest to the vehicle; and

determine a location and size of a three-dimensional object in the semantic point cloud image based on three-dimensional background subtraction using the three-dimensional point cloud image included in the topological node closest to the vehicle.

2. The computer of claim **1**, the instructions including further instructions to determine the real-world six degree-of-freedom pose for the vehicle based on a single monocular image acquired by the sensor in the vehicle without including an inertial measurement unit in the vehicle.

3. The computer of claim **1**, the instructions including further instructions to determine the semantic point cloud image based on a single monocular image acquired by the sensor in the vehicle without including a stereo camera or lidar sensor in the vehicle.

4. The computer of claim **1**, the instructions including further instructions to determine the plurality of topological nodes by acquiring point cloud images with a stereo camera and determining locations of the point cloud images in real-world coordinates with visual odometry.

5. The computer of claim **1**, wherein the real-world six degree-of-freedom pose for the vehicle is determined in coordinates based on orthogonal x, y, and z axes and roll, pitch, and yaw rotations about the x, y, and z axes, respectively.

6. The computer of claim **1**, the instructions including further instructions to determine the location and size of the three-dimensional object in the semantic point cloud image with a convolutional neural network trained to determine a three-dimensional bounding box that includes the three-dimensional object and a real-world location relative to the vehicle for the three-dimensional object.

7. The computer of claim **6**, wherein three-dimensional background subtraction using the point cloud image is used to determine the three-dimensional bounding box by reducing background clutter caused by labeled regions that occur in both a current semantic point cloud and a semantic point cloud image included in a topological node.

8. The computer of claim **7**, wherein the convolutional neural network includes convolutional layers that output first latent variables to first fully connected neural network layers.

9. The computer of claim **1**, wherein the variational auto-encoder neural network determines the semantic point cloud image by outputting second latent variables to second fully connected neural network layers.

10. The computer of claim **1**, the instructions including further instructions to train the variational auto-encoder neural network to output the semantic point cloud image in a Siamese network configuration wherein the variational auto-encoder neural network is trained in parallel with a second variational auto-encoder network trained using a plurality of three-dimensional point cloud images acquired while traveling along a route that includes the plurality of topological nodes.

11. The computer of claim **10**, wherein region types included in the semantic point cloud image include roadway, sidewalk, vehicle, building, and foliage based on the plurality of three-dimensional point cloud images.

12. A method, comprising:

inputting an image acquired by a sensor in a vehicle to a variational auto-encoder neural network that outputs a semantic point cloud image that includes regions labeled by region type and region distance relative to the vehicle;

from a plurality of topological nodes, determining a topological node closest to the vehicle, and a six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle, based on the semantic point cloud image, wherein each topological node includes a location in real-world coordinates and a three-dimensional point cloud image of an environment including the location of the topological node;

determining a real-world six degree-of-freedom pose for the vehicle by combining the six degree-of-freedom pose for the vehicle relative to the topological node closest to the vehicle and the location in real-world coordinates of the topological node closest to the vehicle; and

determine a location and size of a three-dimensional object in the semantic point cloud image based on three-dimensional background subtraction using the three-dimensional point cloud image included in the topological node closest to the vehicle.

13. The method of claim **12**, further comprising determining the real-world six degree-of-freedom pose for the vehicle based on a single monocular image acquired by the sensor in the vehicle without including an inertial measurement unit in the vehicle.

14. The method of claim **12**, further comprising determining the semantic point cloud image based on a single monocular image acquired by the sensor in the vehicle without including a stereo camera or lidar sensor in the vehicle.

15. The method of claim **12**, further comprising determining the plurality of topological nodes by acquiring point cloud images with a stereo camera and determining locations of the point cloud images in real-world coordinates with visual odometry.

16. The method of claim **12**, wherein the real-world six degree-of-freedom pose for the vehicle is determined in coordinates based on orthogonal x, y, and z axes and roll, pitch, and yaw rotations about the x, y, and z axes, respectively.

17. The method of claim **12**, the instructions including further instructions to determine the location and size of the three-dimensional object in the semantic point cloud image with a convolutional neural network trained to determine a three-dimensional bounding box that includes the three-dimensional object and a real-world location relative to the vehicle for the three-dimensional object.

18. The method of claim **17**, wherein three-dimensional background subtraction using the point cloud image is used to determine the three-dimensional bounding box by reducing background clutter caused by labeled regions that occur

in both a current semantic point cloud and a semantic point cloud image included in a topological node.

19. The method of claim **18**, wherein the convolutional neural network includes convolutional layers that output first latent variables to first fully connected neural network layers.

20. The method of claim **12**, wherein the variational auto-encoder neural network determines the semantic point cloud image by outputting second latent variables to second fully connected neural network layers.

* * * * *