US 20230136871A1

(19) **United States**
(12) **Patent Application Publication**
Chakravarty et al.
(10) **Pub. No.: US 2023/0136871 A1**
(43) **Pub. Date: May 4, 2023**

(54) **CAMERA CALIBRATION**

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

(72) Inventors: **Punarjay Chakravarty**, Campbell, CA (US); **Shubham Shrivastava**, Sunnyvale, CA (US); **Bhushan Ghadge**, Sunnyvale, CA (US); **Mostafa Parchami**, Ann Arbor, MI (US); **Gaurav Pandey**, College Station, TX (US)

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

(21) Appl. No.: **17/515,855**

(22) Filed: **Nov. 1, 2021**

Publication Classification

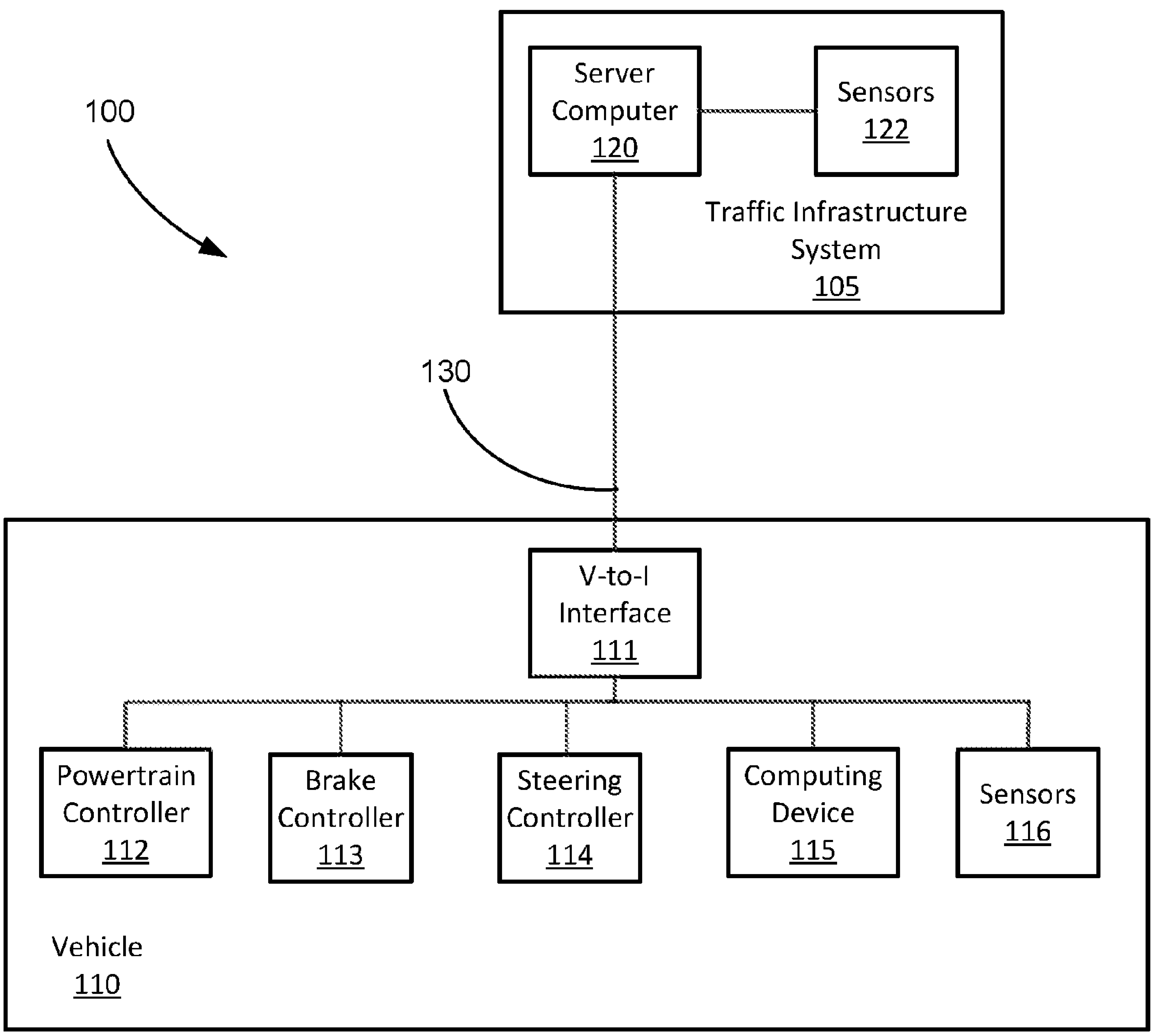
(51) **Int. Cl.**

G05D 1/00	(2006.01)
G06T 7/80	(2006.01)
G06T 7/70	(2006.01)

(52) **U.S. Cl.**
CPC ***G05D 1/0033*** (2013.01); ***G06T 7/80*** (2017.01); ***G06T 7/70*** (2017.01); *G06T 2207/30244* (2013.01); *G06T 2207/20084* (2013.01); *G06T 2210/12* (2013.01); *G05D 2201/0213* (2013.01)

(57) **ABSTRACT**

A first plurality of center points of first two-dimensional bounding boxes corresponding to a vehicle occurring in a first plurality of images acquired by a first camera can be determined. A second plurality of center points of second two-dimensional bounding boxes corresponding to the vehicle occurring in a second plurality of images acquired by a second camera can also be determined. A plurality of non-linear equations based on the locations of the first and second pluralities of center points and first and second camera parameters corresponding to the first and second cameras can be determined. The plurality of non-linear equations can be solved simultaneously for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera. Real-world coordinates of the six degree of freedom pose of the second camera can be determined based on real-world coordinates of a six degree of freedom pose of the first camera.



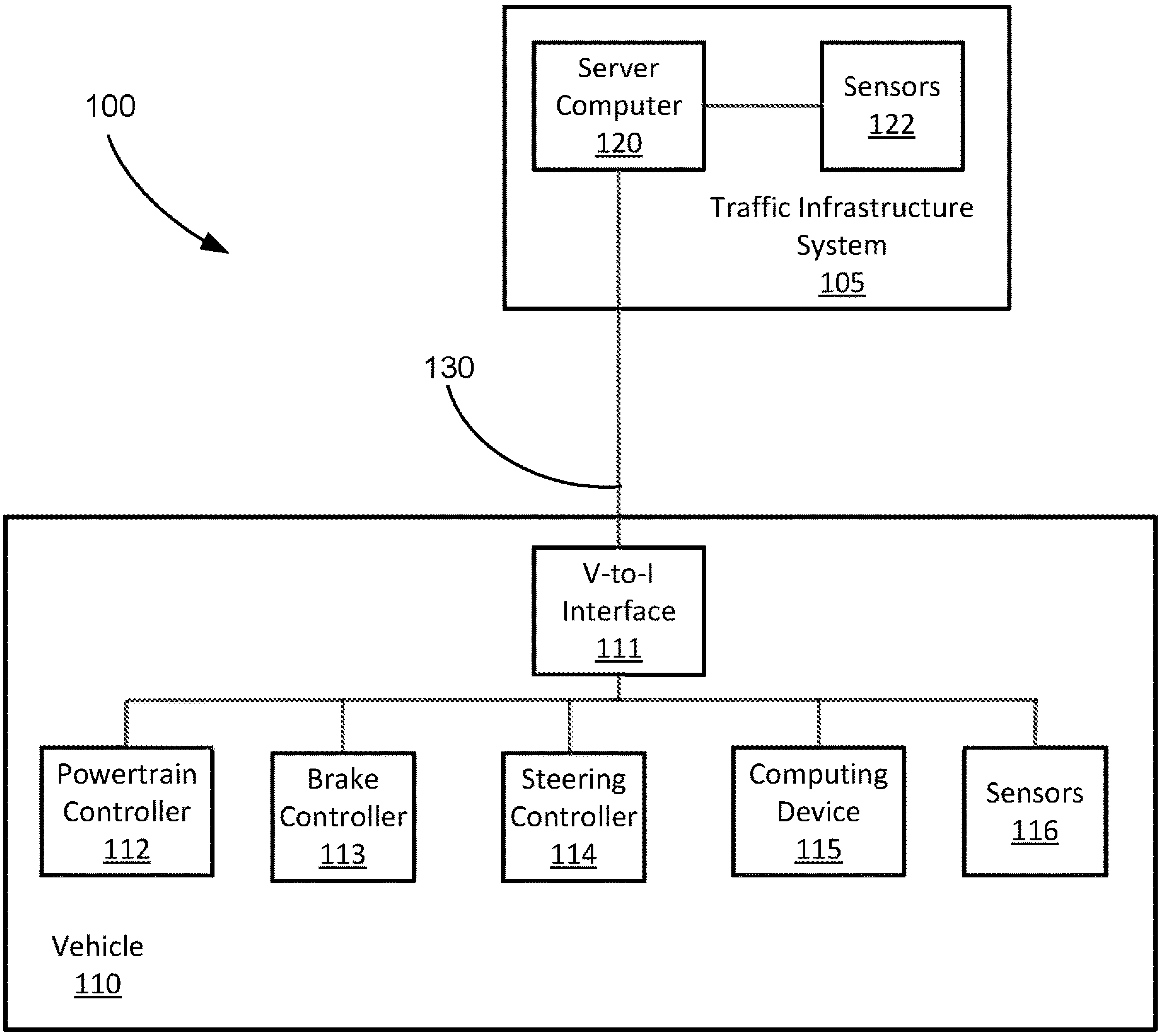

100
Server Computer 120
Sensors 122
Traffic Infrastructure System 105
130
V-to-I Interface 111
Powertrain Controller 112
Brake Controller 113
Steering Controller 114
Computing Device 115
Sensors 116
Vehicle 110

Fig. 1

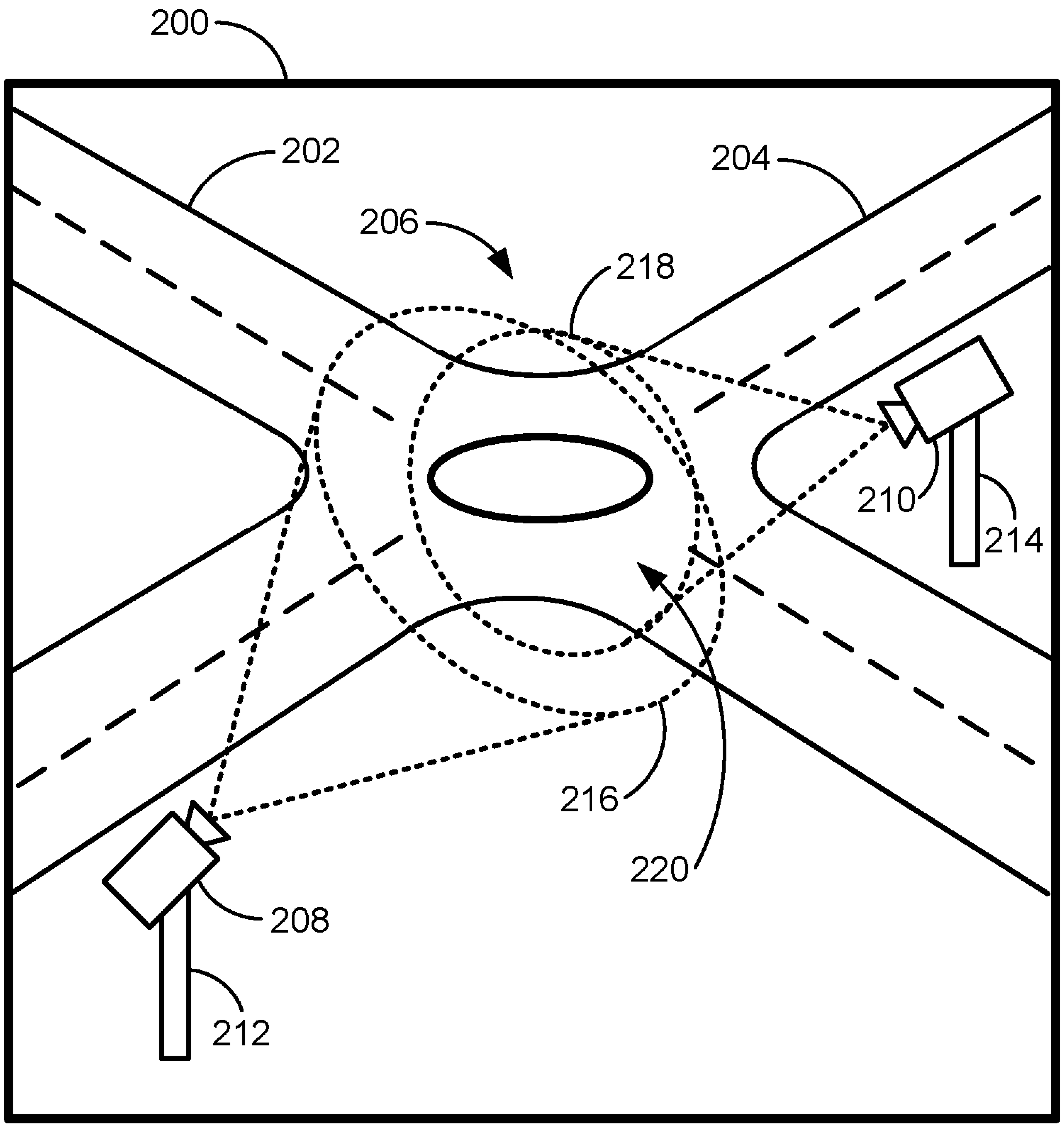


Fig. 2

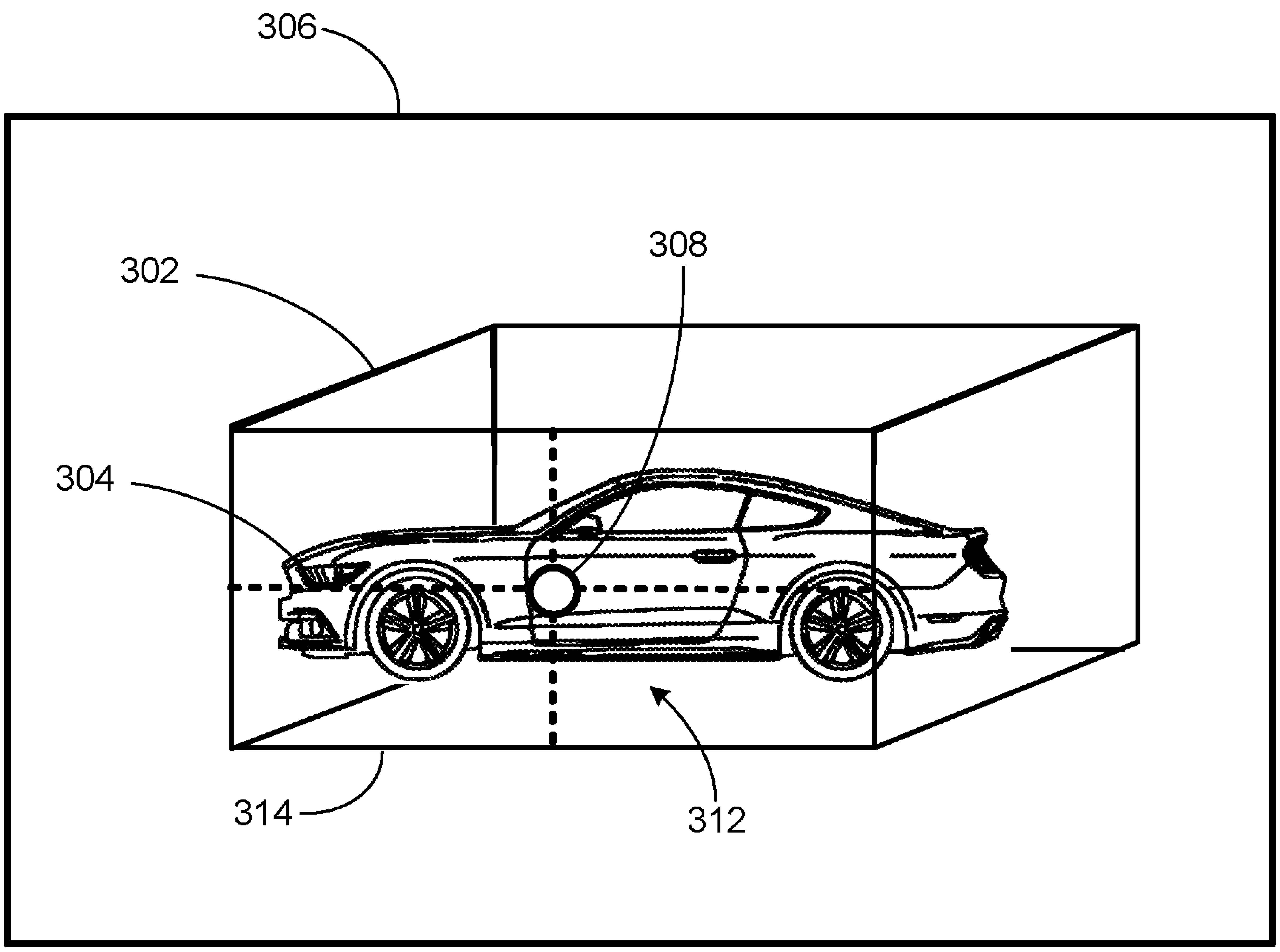


Fig. 3

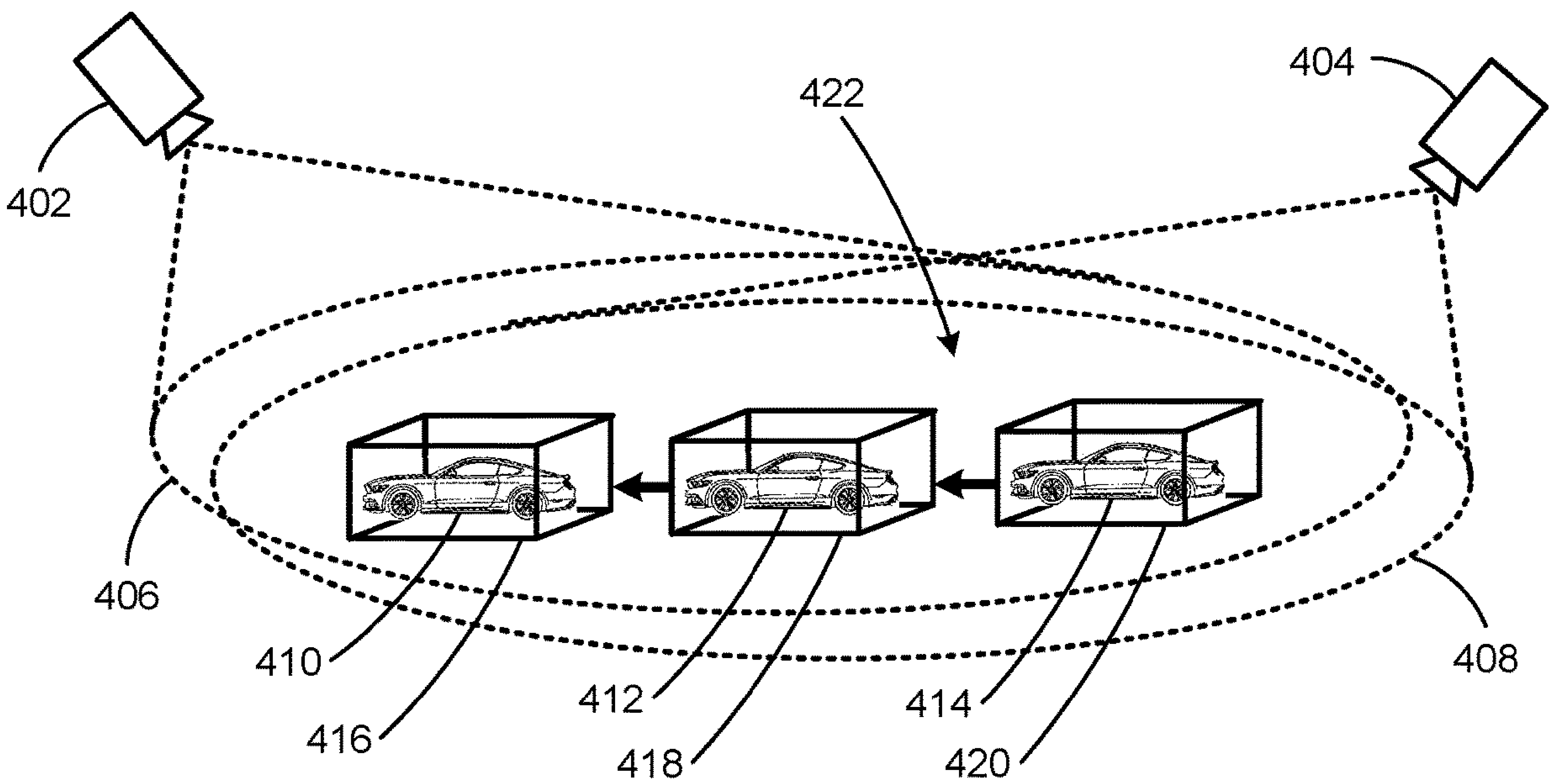


Fig. 4

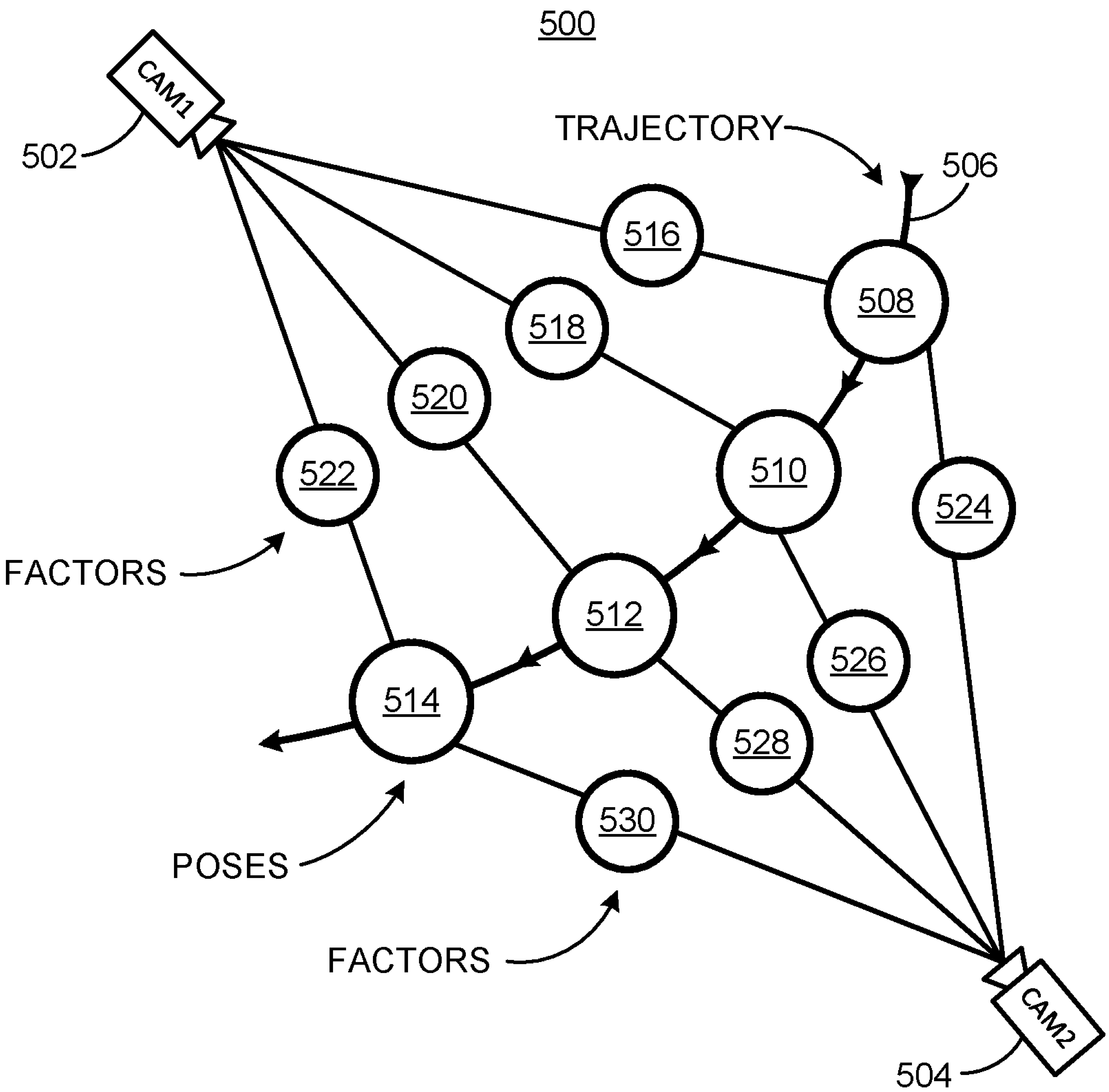

500
CAM1
502
TRAJECTORY
506
516
508
518
520
510
522
524
FACTORS
512
526
514
528
530
POSES
FACTORS
CAM2
504

Fig. 5

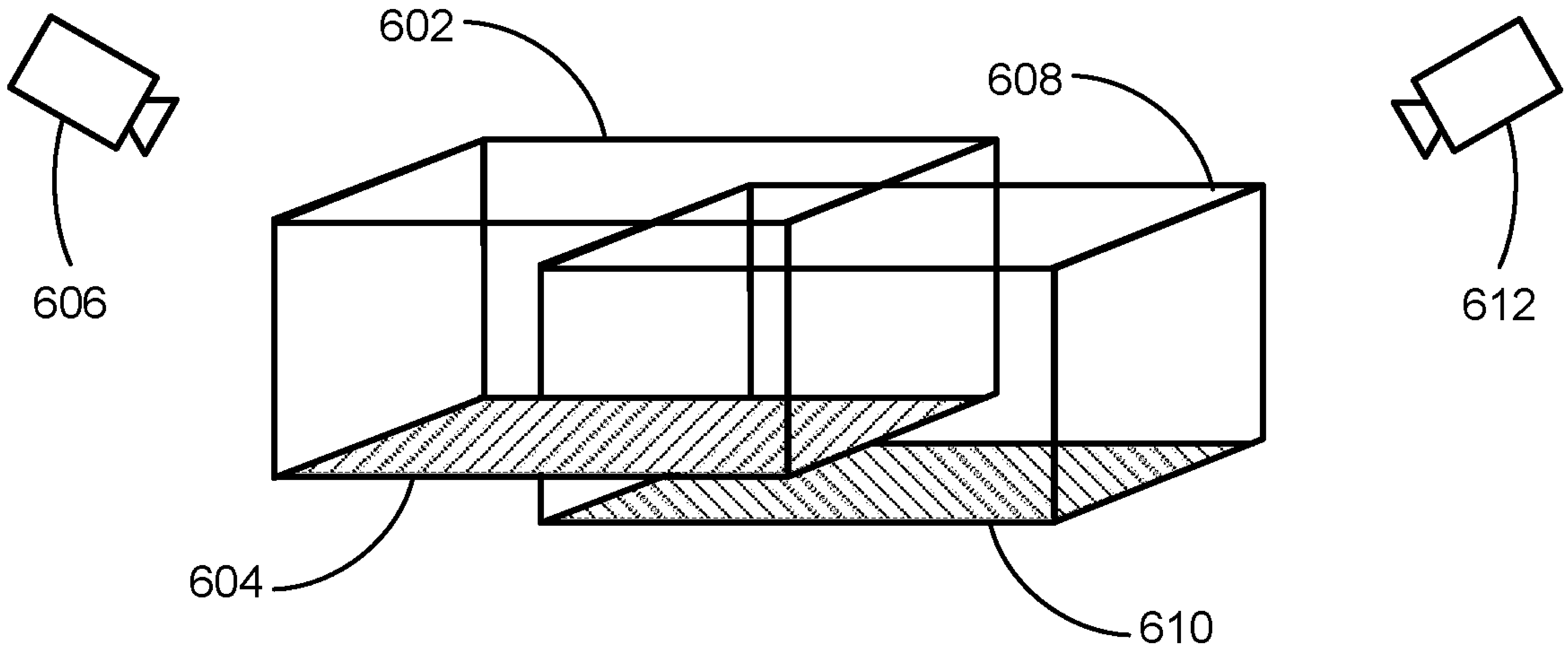


Fig. 6

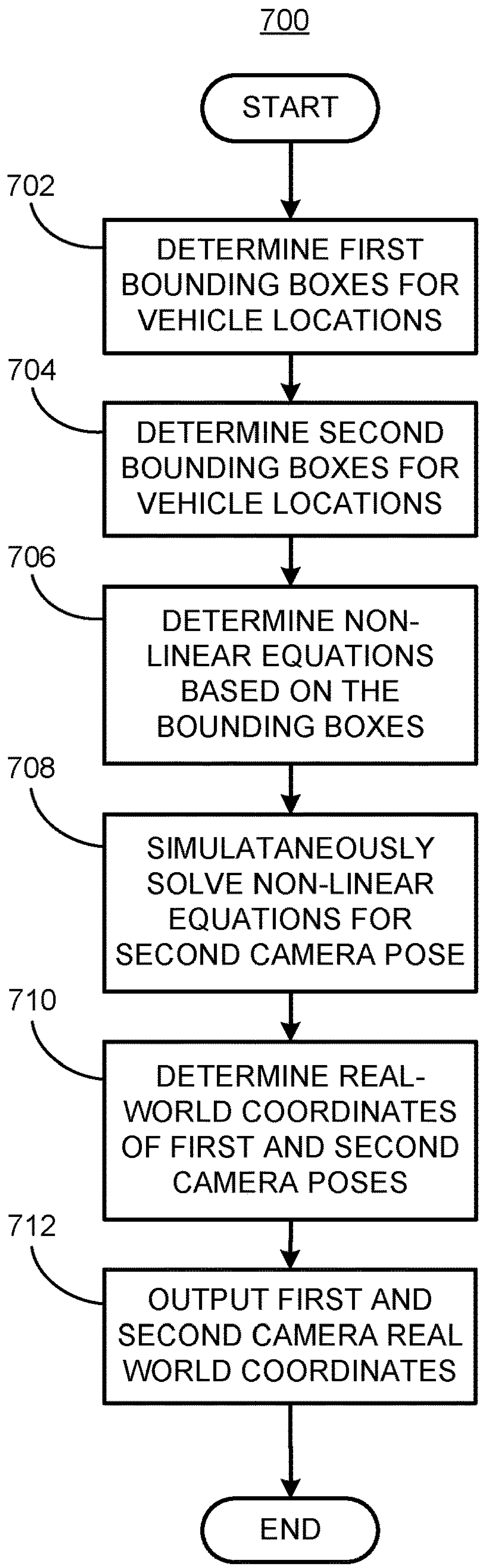

700
START
702
DETERMINE FIRST BOUNDING BOXES FOR VEHICLE LOCATIONS
704
DETERMINE SECOND BOUNDING BOXES FOR VEHICLE LOCATIONS
706
DETERMINE NON-LINEAR EQUATIONS BASED ON THE BOUNDING BOXES
708
SIMULATANEOUSLY SOLVE NON-LINEAR EQUATIONS FOR SECOND CAMERA POSE
710
DETERMINE REAL-WORLD COORDINATES OF FIRST AND SECOND CAMERA POSES
712
OUTPUT FIRST AND SECOND CAMERA REAL WORLD COORDINATES
END

Fig. 7

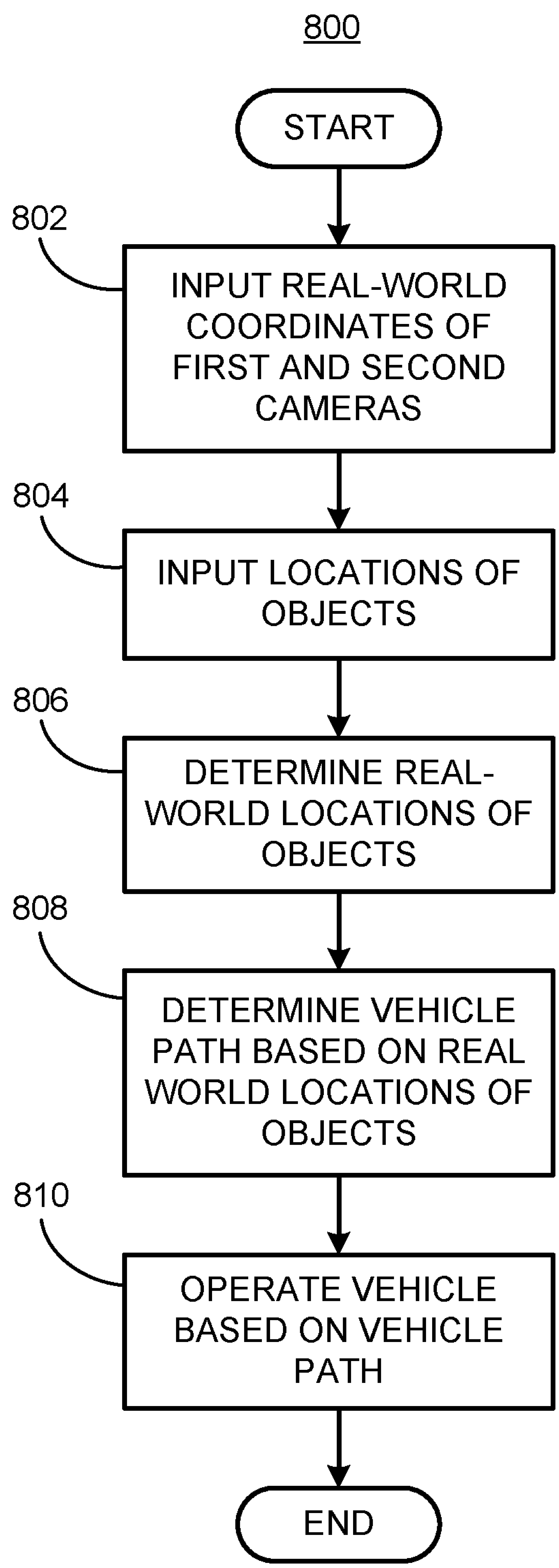

800
START
802
INPUT REAL-WORLD COORDINATES OF FIRST AND SECOND CAMERAS
804
INPUT LOCATIONS OF OBJECTS
806
DETERMINE REAL-WORLD LOCATIONS OF OBJECTS
808
DETERMINE VEHICLE PATH BASED ON REAL WORLD LOCATIONS OF OBJECTS
810
OPERATE VEHICLE BASED ON VEHICLE PATH
END

Fig. 8

CAMERA CALIBRATION

BACKGROUND

[0001] Images can be acquired by sensors and processed using a computer to determine data regarding objects in an environment around a system. Operation of a sensing system can include acquiring accurate and timely data regarding objects in the system's environment. A computer can acquire images from one or more images sensors that can be processed to determine locations of objects. Object location data extracted from images can be used by a computer to operate systems including vehicles, robots, security, and object tracking systems.

BRIEF DESCRIPTION OF THE DRAWINGS

[0002] FIG. **1** is a block diagram of an example traffic infrastructure system.

[0003] FIG. **2** is a diagram of an example image of a traffic scene.

[0004] FIG. **3** is a diagram of an example bounding box.

[0005] FIG. **4** is a diagram of example bounding boxes.

[0006] FIG. **5** is a diagram of an example factor graph.

[0007] FIG. **6** is a diagram of example bounding boxes including ground planes.

[0008] FIG. **7** is a flowchart diagram of an example process to locate a camera.

[0009] FIG. **8** is a flowchart diagram of an example process to operate a vehicle using a located camera.

DETAILED DESCRIPTION

[0010] A sensing system can acquire data, for example image data, regarding an environment around the system and process the data to determine identities and/or locations of objects. For example, a deep neural network (DNN) can be trained and then used to determine objects in image data acquired by sensors in systems including vehicle guidance, robot operation, security, manufacturing, and product tracking. Vehicle guidance can include operation of vehicles in autonomous or semi-autonomous modes in environments that include a plurality of objects. Robot guidance can include guiding a robot end effector, for example a gripper, to pick up a part and orient the part for assembly in an environment that includes a plurality of parts. Security systems include features where a computer acquires video data from a camera observing a secure area to provide access to authorized users and detect unauthorized entry in an environment that includes a plurality of users. In a manufacturing system, a DNN can determine the location and orientation of one or more parts in an environment that includes a plurality of parts. In a product tracking system, a deep neural network can determine a location and orientation of one or more packages in an environment that includes a plurality of packages.

[0011] Vehicle guidance will be described herein as a non-limiting example of using a computer to detect objects, for example vehicles and pedestrians, in a traffic scene and determine a vehicle path for operating a vehicle based on the detected objects. A traffic scene is an environment around a traffic infrastructure system or a vehicle that can include a portion of a roadway and objects including vehicles and pedestrians, etc. For example, a computing device in a traffic infrastructure system can be programmed to acquire one or more images from one or more sensors included in the traffic infrastructure system, detect objects in the images and communicate labels that identify the objects along with locations of the objects. The sensors can include video or still image cameras that acquire images corresponding to visible or infrared wavelengths of light. The sensors can be stationary and can be mounted on poles, buildings, or other structures to give the sensors a view of the traffic scene including objects in the traffic scene. Sensors can also include lidar sensors, which typically emit infrared wavelengths of light, radar sensors which emit radio waves, and ultrasound sensors which emit sound waves. Lidar, radar, and ultrasound sensors all measure distances to points in the environment.

[0012] In some examples a computing device can acquire one or more images of a traffic scene and communicate the image data along with data describing a location and orientation of the sensor along with data regarding camera parameters that permit a computing device in a vehicle to determine labels and real-world coordinates of objects included in the image data. The location and orientation of a sensor can be described in six degree of freedom coordinates. Six degree of freedom coordinates include x, y, and z location coordinates determined with respect to orthogonal axes of a global coordinate frame such as latitude, longitude, and altitude, and roll, pitch, and yaw orientation coordinates determined with respect to the x, y, and z axes, respectively. Sensor parameters determine how the portion of the traffic scene within the field of view of a sensor are projected onto an image plane by a lens included in the sensor to generate an image. Sensor parameters can be expressed mathematically as matrices that transforms point locations in an image to real world coordinates of locations in the real world. Sensor parameters will be discussed in relation to FIG. **2**, below.

[0013] Data from sensors in a traffic infrastructure system including locations and direction of movement of objects in a traffic scene can be used to direct the motion of vehicles. For example, the location and direction of motion of pedestrians can be used to determine where and when vehicles can be permitted to operate in a traffic scene. Accuracy and reliability of data from sensors in a traffic infrastructure system can depend upon locating the sensor to determine the location and orientation of the sensors with respect to a global coordinate frame that is shared by the traffic infrastructure system and a vehicle with which it communicates. Data regarding the location of an object in sensor data acquired by a sensor in a traffic infrastructure system can be combined with data regarding the location and orientation of the sensor and sensor parameters to determine a real-world location of the object expressed in a global coordinate frame. The real-world location of the object can be communicated to a vehicle to permit the vehicle to determine a vehicle path that avoids the object in the shared global coordinate frame.

[0014] Accuracy and reliability of data from sensors in a traffic infrastructure system can be improved by acquiring two or more images from two or more sensors having overlapping fields of view. Overlapping fields of view will be discussed in relation to FIG. **2**, below. Combining data from two or more sensors can be improved by determining extrinsic localization of the two or more sensors to determine six degree of freedom location and orientation for each of the sensors relative to a common global coordinate frame. Techniques discussed herein improve localization of image sensors such as video cameras by selecting a first sensor and localizing one or more other image sensors to the first sensor by acquiring a plurality of images of a moving object and solving a set of non-linear equations for the locations of the sensors and the object simultaneously. Localization of two or more image sensors in a traffic infrastructure system permits the traffic infrastructure system to combine two or more views of the same object to improve the accuracy and reliability of an estimate of a real-world location of an object in a global coordinate frame.

[0015] Disclosed herein is a method, including determining a first plurality of center points of first two-dimensional bounding boxes corresponding to locations of a vehicle occurring in a first plurality of images acquired by a first camera, determining a second plurality of center points of second two-dimensional bounding boxes corresponding to the locations of the vehicle occurring in a second plurality of images acquired by a second camera and determining a plurality of non-linear equations based on respective locations of the first and second pluralities of center points and first and second camera locations including camera parameters corresponding to the first and second cameras. The plurality of non-linear equations can be simultaneously solved for the locations of the vehicle with respect to the first and second cameras and a six degree of freedom pose of the second camera with respect to the first camera and real-world coordinates of the six degree of freedom pose of the second camera can be determined based on real-world coordinates of a six degree of freedom pose of the first camera. The motion of a second vehicle can be controlled based on the real-world coordinates of the first camera and the real-world coordinates of the second camera. First and second camera parameters can include the six degree of freedom poses of the first and second cameras. The real-world coordinates of the first camera can be determined by locating the first camera using lidar data. The first and second plurality of center points can be determined based on first and second bounding boxes by inputting the first and second pluralities of images to a convolutional neural network.

[0016] The plurality of non-linear equations can be solved using Gauss-Newton iteration. Solving the plurality of non-linear equations using Gauss-Newton iteration can include determining a Jacobian matrix of partial derivatives. The non-linear equations can be solved using a Levenberg-Marquardt algorithm. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the first and second two-dimensional bounding boxes to a plane. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on lidar data. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on one or more of global positioning system data, inertial measurement unit data and visual odometry data. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on map data. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on center points determined based on three-dimensional bounding boxes. Controlling motion of a second vehicle can include controlling vehicle powertrain, vehicle steering, and vehicle brakes.

[0017] 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 determine a first plurality of center points of first two-dimensional bounding boxes corresponding to locations of a vehicle occurring in a first plurality of images acquired by a first camera, determine a second plurality of center points of second two-dimensional bounding boxes corresponding to the locations of the vehicle occurring in a second plurality of images acquired by a second camera and determine a plurality of non-linear equations based on respective locations of the first and second pluralities of center points and first and second camera locations including camera parameters corresponding to the first and second cameras. The plurality of non-linear equations can be simultaneously solved for the locations of the vehicle with respect to the first and second cameras and a six degree of freedom pose of the second camera with respect to the first camera and real-world coordinates of the six degree of freedom pose of the second camera can be determined based on real-world coordinates of a six degree of freedom pose of the first camera. The motion of a second vehicle can be controlled based on the real-world coordinates of the first camera and the real-world coordinates of the second camera. First and second camera parameters can include the six degree of freedom poses of the first and second cameras. The real-world coordinates of the first camera can be determined by locating the first camera using lidar data. The first and second plurality of center points can be determined based on first and second bounding boxes by inputting the first and second pluralities of images to a convolutional neural network.

[0018] The instructions can include further instructions to solve the plurality of non-linear equations using Gauss-Newton iteration. Solving the plurality of non-linear equations using Gauss-Newton iteration can include determining a Jacobian matrix of partial derivatives. The non-linear equations can be solved using a Levenberg-Marquardt algorithm. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the first and second two-dimensional bounding boxes to a plane. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on lidar data. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on one or more of global positioning system data, inertial measurement unit data and visual odometry data. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on map data. Simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera can include constraining the locations of the vehicle based on center points determined based on three-dimensional bounding boxes. Controlling motion of a second vehicle can include controlling vehicle powertrain, vehicle steering, and vehicle brakes.

[0019] FIG. **1** is a diagram of a sensing system **100** that can include a traffic infrastructure system **105** that includes a server computer **120** and sensors **122**. Sensing system **100** 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.

[0020] 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.

[0021] 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.

[0022] 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.

[0023] 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**.

[0024] 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 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.

[0025] 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**.

[0026] The one or more controllers **112**, **113**, **114** for the vehicle **110** may include known 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.

[0027] 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.

[0028] 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**.

[0029] 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.

[0030] FIG. **2** is a diagram of a traffic scene **200**. Traffic scene **200** includes roadways **202**, **204** that meet at a traffic circle intersection **206**. Traffic circle intersection **206** is viewed by two cameras **208**, **210** mounted on two poles **212**, **214**, respectively. Cameras **208**, **210** can be sensors **122** included in a traffic infrastructure system **105**, In this example, cameras **208**, **210** can be video cameras that can each acquire a plurality of frames of video data, where a frame of video data is a rectangular array of red, green, and blue (RGB) pixels that correspond to a color image. Each camera **208**, **210** includes a field of view **216**, **218**, where a field of view is the portion of the traffic scene **200** that will be included in an image acquired by the cameras **208**, **210**. The fields of view **216**, **218** overlap, meaning that objects in the traffic scene **200** that occur in the intersection **220** of fields of view **216**, **218** will be represented in respective images acquired by the cameras **208**, **210** at substantially a same time, i.e., where both images are acquired within a short time period, for example one second.

[0031] Determining locations for an object in two or more images of the same portion of a traffic scene **200** acquired at substantially the same time by two or more cameras **208**, **210** can improve the accuracy and reliability with which a location for an object is determined. Determining the location of an object based on two or more images acquired by two or more cameras **208**, **210** depends upon camera localization. Camera localization herein means determining respective locations of the two or more fields of view **216**, **218** of the two or more cameras **208**, **210** with respect to the traffic scene **200** in real world coordinates. Once the locations of the fields of view **216**, **218** for the cameras **208**, **210** are located, objects located in images acquired by cameras **208**, **210** can be determined in real world coordinates. The real world coordinates of the objects can be compared to determine the accuracy and reliability of the object's location data.

[0032] Camera localization data, i.e., locations or respective cameras' fields of view, can be determined by acquiring range data of a traffic scene **200** using a lidar. As discussed above in relation to FIG. **1**, a lidar sensor can include a laser, typically operating in the infrared wavelengths, that emits pulses or modulated beams of light energy. The emitted light energy is reflected back to the lidar sensor from surfaces in the traffic scene **200**, where the reflected energy is received to measure a time-of-flight of the pulses or a phase shift of the modulated beam to determine the distance or range to a location in the traffic scene **200**. The light energy can be scanned to produce a point cloud corresponding to a range image of a field of view corresponding to a portion of a traffic scene **200**. By measuring the location and orientation of the lidar sensor, location of points in the traffic scene **200** can be determined in real world coordinates.

[0033] Techniques discussed herein improve camera localization by determining camera localization parameters and the location of one or more second cameras **210** with respect to a first camera **208** by acquiring a plurality of images of an object in overlapping portions of the first and second sensor's fields of view **216**, **218** as the object moves through the traffic scene **200**. Based on the sensor parameters, a series of non-linear equations are set up and solved for unknown sensor locations and unknown object locations simultaneously. Based on this technique, a plurality of cameras **208**, **210** having at least partially overlapping fields of view **216**, **218** can be located with respect to a first camera **208**. Because techniques described herein are based on observing an object moving in a traffic scene **200**, the localization can be repeated without requiring any further intervention by a user. Locating cameras **208**, **210** in this fashion is much less expensive and time consuming than locating cameras **208**, **210** using a lidar or fiducial markers. Locating cameras **208**, **210** in this fashion does not require an additional equipment or user intervention and can be repeated whenever a moving object travels in the overlapping fields of view **216**, **218** of the cameras **208**, **210**. Techniques described herein can be used to locate lidar, radar, or ultrasound sensors in addition to cameras **208**, **210**.

[0034] Techniques described herein are based on a plurality of simultaneous observations of a moving vehicle through the common field of view of two or more cameras to constrain the six degree of freedom pose (x, y, z, roll, pitch, yaw) between the two or more cameras. Each camera has its own 2D object detector, and the 3D object is viewed as a 2D bounding box in the image plane of that object as discussed above in relation to FIG. **3**, below. Because the cameras are time-synchronized to acquire corresponding images of the moving vehicle at substantially the same time, the projective geometry-based equations for the projection of the center point of the 3D bounding box of the vehicle into the image plane of each camera can be set up as a system of equations that constrains the trajectory of the vehicle in a global coordinate frame. The system of equations can also constrain the relative pose of the two or more cameras in the same global coordinate frame. The system of equations can assume that the global coordinate frame belongs to the first camera, and every successive camera can be extrinsically located relative to the first camera.

[0035] FIG. **3** is a diagram of an example three-dimensional (3D) bounding box **302**. 3D bounding box **302** is determined based on an image of an object, in this example a vehicle **304** included in an image **306**, that can be acquired by a sensor **122** included in a traffic infrastructure system **105**. 3D bounding box **302** can be determined by a server computer **120** included in a traffic infrastructure system **105** in communication with the sensor **122** that acquired the image **306**. 3D bounding box **302** can be determined by inputting the image **306** to a deep neural network executing on server computer **120**. An example of a deep neural network that can determine a 3D bounding box **302** for an object such as a vehicle **304** in an image **306** is CenterNet. CenterNet is a convolutional neural network available at the website https://github.com/xingyizhou/CenterNet, as of Sep. 2, 2021.

[0036] CenterNet inputs an image **306** and outputs a 3D bounding box **302** including a center point **308**. Center point **308** is determined as the center **312** (dashed lines) of a two-dimensional (2D) bounding box **314** that is a face of the 3D bounding box **302**. CenterNet software can also be trained to output a projection of the center of the 3D bounding box **302** onto the 2D bounding box **314** to improve correspondence of the projection of the center of the 3D bounding box **302** to the 3D center of vehicle **304** in images **306** acquired from differing points of view with respect to the vehicle **304**. Determining a center point **308** in this fashion permits the location of the object, such as vehicle **304**, to be represented by x, y pixel coordinates of a single point rather than the more cumbersome plurality of coordinates required to determine 3D bounding box **302**. Camera parameters as above described in relation to FIG. **2** can be used to determine equations that describe the locations in global coordinates that correspond to a particular location in x, y pixel coordinates based on projective geometry. Projective geometry provides a mathematical basis for determining transformations that project points in a field of view **216**, **218** of a camera **208**, **210** onto a sensor plane that forms an image **306**. Equations (1)-(x), below, illustrate the projective geometry-based system of equations for the projection of the center point **308** corresponding to the 3D bounding box **302** circumscribing the vehicle **304** into the image plane of each camera **208**, **210**. The system of equations can constrain a trajectory of a vehicle **304** in a global coordinate frame and constrain the relative pose of the cameras **208**, **210** in the same global coordinate frame.

[0037] FIG. **4** is a diagram of a plurality of images which include vehicles **410**, **412**, **414** including 3D bounding boxes **416**, **418**, **420**, respectively. Images of vehicles **410**, **412**, **414** are acquired by cameras **402**, **404** included in a traffic infrastructure system **105** as the vehicle **410**, **412**, **414** travels through the overlap **422** between field of view **406**, **408** of cameras **402**, **404**. At each position of vehicle **410**, **412**, **414** cameras **402**, **404** each acquire an image of vehicle **410**, **412**, **414** at substantially the same time, i.e., within a few milliseconds, so that the vehicle **410**, **412**, **414** will be at the substantially same location within the fields of view **406**, **408** of cameras **402**, **404** i.e., within a few millimeters in global coordinates in corresponding pairs of images. The pairs of images of vehicles **410**, **412**, **414** can be input to a deep neural network included in a server computer **120** in a traffic infrastructure system **105** to determine pairs of 3D bounding boxes **416**, **418**, **420** and corresponding pairs of center points for each vehicle **410**, **412**, **414** position. This technique can be expanded to include a plurality of cameras **402**, **404**, all included in a traffic infrastructure system **105** and all having an overlap **422** between their respective fields of view **406**, **408**. Techniques disclosed herein can determine a series of non-linear equations that include a series of constraints between the 3D pose (Xi) of a detected and tracked vehicle **410**, **412**, **414** and the projections (zi) of the vehicle **410**, **412**, **414** onto the camera **402**, **404** sensors.

[0038] FIG. **5** is a diagram of a factor graph **500** that includes a first camera (CAM1) **502**, a second camera (CAM2) **504**, and a plurality of 3D poses (x_1) of a vehicle, pose x_1 **508**, pose x_2 **510**, pose x_3 **512**, and pose x_4 **514**, as the vehicle travels along a trajectory **506**. The factor graph **500** illustrates a plurality of non-linear equations based on center points of bounding boxes corresponding to locations of vehicles and locations of cameras including camera parameters corresponding to first and second cameras. A 3D pose is the six degree of freedom location and orientation of the vehicle at the times the cameras **502**, **504** acquire each pair of images of the vehicle. Each observation of the 3D pose can be expressed as factor $\phi(c_1, x_1)$ **516**, factor $\phi(c_1, x_2)$ **518**, factor $\phi(c_1, x_3)$ **520**, factor $\phi(c_1, x_4)$ **522**, factor $\phi(c_2, x_1)$ **524**, factor $\phi(c_2, x_2)$ **526**, factor $\phi(c_2, x_3)$ **528**, and factor $\phi(c_2, x_4)$ **530**. Where each factor $\phi(c_1, x_1)$ **516**, **518**, **520**, **522**, **524**, **526**, **528**, **530** is a function of a camera pose c_1 and a vehicle pose x_1. A joint posterior probability density of the system of equations that describes the camera poses c_1 and vehicle poses x_1 is given by:

$$\phi(x_1,x_2,x_3,x_4,c_1,c_2)=\phi(c_1,x_1)*\phi(c_1,x_2)*\phi(c_1,x_3)*\phi(c_1,x_4)*\phi(c_2,x_1)*\phi(c_2,x_2)*\phi(c_2,x_3)*\phi(c_2,x_4) \quad (1)$$

Each factor $\phi(c_j, x_i)$ **516**, **518**, **520**, **522**, **524**, **526**, **528**, **530** is a residual based on an error between an observation of the vehicle's pose and a prediction of the vehicle pose estimated by the system of equations.

[0039] Each vehicle observation by a camera can be set up as an error constraint. A vehicle pose x_i viewed from the first camera **502** gives an error term e1:

$$e1=\|K_1x_i-z_i^1\| \quad (2)$$

Where K_1 are the camera parameters for the first camera **502** and z_i^1 is the vehicle pose based on the ith image acquired by the first camera. Camera parameters correspond to the pose, which includes translation and rotation, of a camera with respect to the global coordinate system. The error term for the same vehicle pose x_1 viewed by the second camera **504** is given by:

$$e2=\|K_2(T_1^2x_i)-z_i^2\| \quad (3)$$

Where T_1^2 is an estimated transform between the second camera **504** pose and the first camera **502** pose, K_2 are the camera parameters for the first camera **502** and z_i^2 is the vehicle pose based on the ith image acquired by the second camera. Each residual for additional cameras is determined by an equation of the form:

$$\|e_i^j=\|K_j(T_1^jx_i)-z_i^j\| \quad (4)$$

Where j is the camera number, K_j are the camera parameters for camera j, and T_1^j is a transform between the camera j pose and the first camera **502** pose.

[0040] The solution of the factor graph is based on determining a maximum a posteriori (MAP) estimate X_{MAP}* of the parameters of the system of equations:

$$X_{MAP}^*=\text{argmax}_x\Pi_i\phi_i(X_i) \quad (5)$$

Where each factor ϕ_i (X_i) is of the form:

$$\phi_i(X_i)=-\exp[-\tfrac{1}{2}\|K_j(T_1^jx_i)-z_i^j\|^2] \quad (6)$$

Because each factor determined by equation (6) corresponds to a Gaussian form, or negative exponential of an L2 norm, the negative log of equation (6) converts equation (5) to argmin form, yielding an equation to determine X_{MAP}*, a vector that includes the poses and transformation parameters of a first camera **502** with respect to a second camera **504**:

$$X_{MAP}^*=\text{argmin}_x\Sigma_i\|K_j(T_1^jx_i)-z_i^j\| \quad (7)$$

[0041] Converting equation (7) to argmin form puts it in condition to be solved using least squares techniques. Least squares techniques describe mathematical techniques for solving systems of equations by changing input parameters in directions that minimize the squared differences between successive steps. The system of equations defined by equation (7) corresponds to a non-linear least squares problem because the observations of the vehicle poses are non-linear. Non-linear least squares equations can be solved by iterative techniques including the Levenberg-Marquardt algorithm and Gauss-Newton iteration. Techniques described herein use Gauss-Newton iteration to solve the system of non-linear equations.

[0042] Gauss-Newton iteration begins by selecting an initial solution X^0. Any value for X^0 can be used to start, however, choosing a starting point that is somewhat close to the final solution can speed up the algorithm. A starting point can be chosen based on previous results, for example. Gauss-Newton iteration begins by iterating the solution over time. At each step, a next step X^{t+1} is determined based the result from the last step X^t plus a gradient Δ_{gn}:

$$X^{t+1}=X^t+\Delta_{gn} \quad (8)$$

Where the gradient Δ_{gn} is a directional derivative of the factor equations in (7) determined based on a direction that minimizes the next step. The direction can be determined by updating the gradient Δ_{gn} using a Jacobian matrix J of partial derivatives of the residuals relative to the variables being solved for:

$$\Delta_{gn}=-(J^TJ)^{-1}J^Te \quad (9)$$

Where e is the error term being solved for from equation (4), above. The Jacobian matrix J of partial derivatives is defined as:

$$J_i^j=\begin{bmatrix} \delta e_i^j/\delta x\ \delta e_i^j/\delta y\ \delta e_i^j/\delta z\ \delta e_i^j/\delta T_{1,x}^j\ \delta e_i^j/\delta T_{1,y}^j\ \delta e_i^j/\delta T_{1,z}^j \\ \delta e_i^j/\delta T_{1,roll}^j\ \delta e_i^j/\delta T_{1,pitch}^j\ \delta e_i^j/\delta T_{1,yaw}^j \end{bmatrix} \quad (10)$$

[0043] Each observation and corresponding error term from each point in the trajectory **506** is used to assemble one Jacobian sub-matrix. The Jacobian sub-matrices are stacked to yield the final Jacobian matrix J to be solved for the gradient Δ_{gn}. Error residuals from all points are used to solve for the vehicle trajectory $X_i=(x_1, x_2, x_3, x_4)$, where x_1, x_2, x_3, x_4 correspond to the 3D location of the objects and the six degree of freedom pose of the second camera **504** relative to the first camera **502**, $T_i^j=[T_x\ T_y\ T_{roll}\ T_{pitch}\ T_{yaw}]$. This technique can be extended to more than two cameras **502**, **504** by determining a Jacobian matrix J and gradient Δ_{gn} for each additional camera with respect to the first camera **502**.

[0044] Once the six degree of freedom poses of each additional camera **504** is determined with respect to the first camera **502** in global coordinates, locations of objects determined by each of the cameras **502**, **504** can be determined with respect to the same global coordinates and communicated to a vehicle **110** to permit a computing device **115** in the vehicle **110** to operate based on the object data. Sensors **116** included in vehicle **110**, such as GPS or an accelerometer-based inertial measurement unit (IMU) can be used by computing device **115** to determine a location and direction of travel of the vehicle **110** in global coordinates. Data regarding the location of objects and the direction of travel of the objects can be used by computing device to determine a vehicle path upon which to operate which avoids the objects, for example. A vehicle path can be a polynomial function determined based on upper and lower limits on permitted latitudinal and longitudinal accelerations. Computing device **115** can transmit commands to controllers **112**, **113**, **114** to control vehicle powertrain, steering and brakes to permit vehicle **110** to travel on the determined vehicle path.

[0045] Techniques described herein can locate a plurality of cameras included in a traffic infrastructure system **105** having overlapping fields of view **216**, **218** with a first camera **502**. The entire group of located cameras can be located with respect to a global coordinate system by operating a vehicle **110** having GPS and IMU sensors **116** along a trajectory **506** and determining the vehicle **110** six degree of freedom pose at the times the cameras acquire the image data used to determine equation (7). A comparison of the locations determined by the sensors **116** included in the vehicle **110** with the locations determined by minimizing equation (7) can be used to locate the first camera **502** with respect to the global coordinate system and thereby locate the plurality of additional cameras. Techniques discussed herein can be used to located sensors included in a traffic infrastructure system on a continuous or ongoing basis without requiring inefficient, cumbersome, and/or time-consuming processes involving lidar sensors or fiducial markers, thereby improving the accuracy and reliability of data generated based on image data acquired by the sensors included in the traffic infrastructure system.

[0046] FIG. **6** is a diagram of bounding boxes **602**, **608** determined based on image data acquire by a first camera **606** and a second camera **612**. Bounding boxes **602**, **608** include ground planes **604**, **610**, respectively. Because bounding boxes **602**, **608** are determined based on a vehicle traveling on a roadway within a relatively short distance, it can be assumed that the ground planes **604**, **610** lie in the same plane. This can be used as an additional constraint for the solution of the system of equations in (7), above. Assuming that the ground plane **604** corresponding to the first camera **606** is defined by the equation:

$$ax+by+cz+d=0 \tag{11}$$

If the ground plane **610** corresponding to the second camera **612** is defined as a vector $S^i=[s_x^i\ s_y^i\ s_z^i]$ and assuming the ground plane **610** is parallel to the first ground plane **604**, then:

$$[a\,b\,c\,d]\begin{bmatrix} s_x^i \\ s_y^i \\ s_z^i \\ 1 \end{bmatrix} = 0 \tag{12}$$

[0047] A residual can be calculated based on the rotation R_1^2 and a translation in $z=t_1^2$:

$$e = \sum_{s^i} [a\,b\,c\,d]\begin{bmatrix} R_1^2 s^i + t_1^2 \\ 1 \end{bmatrix} \tag{13}$$

A Jacobian sub-matrix for the planar constraint can be determined for the x, y, z, roll, pitch, and yaw vehicle pose parameters and solved for six degree of freedom camera pose transform parameters.

$$J = \Sigma\begin{bmatrix} \delta e^{s^i}/\delta a\ \delta e^{s^i}/\delta b\ \delta e^{s^i}/\delta c\ \delta e^{s^i}/\delta d\ \delta e^{s^i}/\delta T_{1,x}^2\ \delta e^{s^i}/\delta T_{1,y}^2\ \delta e^{s^i}/\delta T_{1,z}^{j2} \\ \delta e_i^j/\delta T_{1,roll}^j\ \delta e_i^j/\delta T_{1,pitch}^j\ \delta e_i^j/\delta T_{1,yaw}^j \end{bmatrix} \tag{14}$$

The Jacobian sub-matrices can be stacked for the sets of plane parameters and point coordinates from a set of bounding box observations from pairs of cameras as discussed above and solved to determine a gradient Δ_{gn} to determine the next step to minimize the error.

[0048] Additional constraints can be used to increase the accuracy of the global coordinate estimate for the camera pose and speed up convergence of the Gauss-Newton iteration. For example, if the vehicle being imaged by the cameras as it travels on the trajectory **506** in equipped with a global positioning system (GPS) and/or inertial measurement unit (IMU), data regarding the six degree of freedom pose of the vehicle based on GPS data and/or IMU data can be input to the system of equations in the same manner as the ground plane constraints discussed above. In addition, if lidar based depth estimation of the location of the vehicle traveling on trajectory **506** is available, that data can also be input to the system of equations in the same manner as ground plane constraints discussed above. Another source of data that can be included in the system of equations is visual odometry data. Visual odometry is location and pose data determined by inputting image data acquired by sensors included in a vehicle to a deep neural network that includes high resolution map data corresponding to the environment around the vehicle. Based on high resolution map data and images of the environment, a deep neural network can be trained to determine where on the map the vehicle was located at the time the images were acquired. Another source of location data is high resolution mapping. Assuming the vehicle traveling on the trajectory **506** is maintaining a location in the center of a traffic lane, mapping data that describes the location of the traffic lane can be used to constrain the location of the vehicle and vehicle trajectory. These additional sources of location data can be input to the system of non-linear equations to improve the accuracy of the estimates of the location of the cameras included in the traffic infrastructure system.

[0049] FIG. **7** is a diagram of a flowchart, described in relation to FIGS. **1-6**, of a process determining real world coordinates of cameras **402**, **404** included in a traffic infrastructure system **105**. Process **700** can be implemented by a processor of a server computer **120**, taking as input data from sensors **122**, and executing commands, and outputting locations of objects. Process **700** includes multiple blocks that can be executed in the illustrated order. Process **700** could alternatively or additionally include fewer blocks or can include the blocks executed in different orders.

[0050] Process **700** begins at block **702**, where images acquired by sensors **122** included in a traffic infrastructure system **105** are input to a server computer **120** as described in relation to FIGS. **3** and **4** to determine bounding boxes **416**, **418**, **420** for images of a vehicle **410**, **412**, **414** acquired at a plurality of first time steps by a first camera **402**, where the first time step at which each image is acquired is recorded by server computer **120**. First camera includes a field of view **406** that includes the images of the vehicle **410**, **412**, **414**. The bounding boxes **416**, **418**, **420** can each include a center point **308** that identifies the center of each bounding box **416**, **418**, **420** as discussed in relation to FIG. **3**, above.

[0051] At block **704** server computer **120** inputs images of a vehicle **410**, **412**, **414** acquired at a second plurality of time steps by a second camera **404** and determines bounding boxes **416**, **418**, **420** and center points for each bounding box **416**, **418**, **420**. Second camera includes a field of view **408** that includes the images of the vehicle **410**, **412**, **414**. The second time steps are determined by computer server computer **120** to occur at substantially the same as the first time steps, so that the center points of images of vehicles **410**, **412**, **414** based on images acquired by the first camera **402** will occur at the same locations in global coordinates as corresponding center points of images of vehicle **410**, **412**, **414** acquired by the second camera **404**.

[0052] At block **706** server computer **120** determines a set of non-linear equations describing the six degree of freedom pose of the first and second cameras in global coordinates and the locations of center points of images of vehicles **410**, **412**, **414** in global coordinates as described above in relation to factor graph **500** in FIG. **5** and equations (10)-(7), above.

[0053] At block **708** server computer **120** solves the set of non-linear equations by Gauss-Newton iteration as described above in relation to FIG. **5** and equations (8)-(9), above to determine six degree of freedom poses for the second camera **404** with respect to the first camera **402** and locations of vehicles **410**, **412**, **414** in global coordinates.

[0054] At block **710** server computer **120** can determine global coordinates for the six degree of freedom poses for the first and second cameras **402**, **404** by comparing the determined locations of the vehicles **410**, **412**, **414** to global coordinates of the vehicle locations determined by sensors included in the vehicle, for example GPS and IMU sensors and/or vehicle locations determined by visual odometry as discussed above in relation to FIG. **5**.

[0055] At block **712** server computer **120** can output the real world coordinates of the six degree of freedom poses of the first and second cameras **402**, **404** to a computing device **115** included in a vehicle **110**. Server computer **120** can also output locations of objects detected in images acquired by first and second cameras **402**, **404**. As discussed above in relation to FIG. **4**, process **700** can be extended to a plurality of cameras, a plurality of images of vehicles, and to sensors other than cameras such as lidar, radar, or ultrasound. Process **700** can also be extended to use constraints such as ground planes, location data uploaded from vehicles, and location data determined by sensors included in traffic infrastructure system **105** such lidar, radar, or ultrasound. After block **712** process **700** ends.

[0056] FIG. **8** is a diagram of a flowchart, described in relation to FIGS. **1-7**, of a process for operating a vehicle **110** based on camera and object location data downloaded from a traffic infrastructure system **105**. Process **800** can be implemented by a processor of a computing device **115**, taking as input data from server computer **120**, and executing commands, and operating vehicle **110**. Process **800** includes multiple blocks that can be executed in the illustrated order. Process **800** could alternatively or additionally include fewer blocks or can include the blocks executed in different orders.

[0057] Process **800** begins at block **802**, where a computing device **115** in a vehicle **110** downloads data regarding real world locations of first and second cameras **402**, **404** included in a traffic infrastructure system **105**. The real world locations of first and second cameras **402**, **404** can be determined by process **700** as discussed in relation to FIG. **7**, above.

[0058] At block **804** computing device **115** downloads data regarding locations of one or more objects in the fields of view **406**, **408** of cameras **402**, **404**. The objects can include vehicles and pedestrians, for example.

[0059] At block **806** computing device **115** can determine the real world coordinates of locations of the one or more objects downloaded at block **804**. Computing device **115** can determine the six degree of freedom real world coordinates of the pose of vehicle **110** using sensors such as GPS, IMU, and/or visual odometry.

[0060] At block **808** computing device **115** can determine a vehicle path as described above in relation to FIG. **5**, above based on the determined real world locations of objects in the fields of view **406**, **408** of cameras **402**, **404**. The vehicle path can permit the vehicle **110** to operate while avoiding the objects, for example.

[0061] At block **810** computing device **115** can operate vehicle **110** on the determined vehicle path by controlling motion of the vehicle by controlling vehicle powertrain, steering, and brakes by outputting commands to controllers **112**, **113**, **114**. Following block **810** process **800** ends.

[0062] 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.

[0063] 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.

[0064] A computer-readable medium (also referred to as a processor-readable medium) includes any non-transitory (e.g., tangible) medium that participates in providing data (e.g., instructions) that may be read by a computer (e.g., by a processor of a computer). Such a medium may take many forms, including, but not limited to, non-volatile media and volatile media. Instructions may be transmitted by one or more transmission media, including fiber optics, wires, wireless communication, including the internals that comprise a system bus coupled to a processor of a computer. Common forms of computer-readable media include, for example, RAM, a PROM, an EPROM, a FLASH-EEPROM, any other memory chip or cartridge, or any other medium from which a computer can read.

[0065] 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.

[0066] 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.

[0067] 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.

[0068] 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.

1. A computer, comprising:

a processor; and

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

determine a first plurality of center points of first two-dimensional bounding boxes corresponding to locations of a vehicle occurring in a first plurality of images acquired by a first camera;

determine a second plurality of center points of second two-dimensional bounding boxes corresponding to the locations of the vehicle occurring in a second plurality of images acquired by a second camera;

determine a plurality of non-linear equations based on respective locations of the first and second pluralities of center points and first and second camera locations including camera parameters corresponding to the first and second cameras;

simultaneously solve the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and a six degree of freedom pose of the second camera with respect to the first camera; and

determine real-world coordinates of the six degree of freedom pose of the second camera based on real-world coordinates of a six degree of freedom pose of the first camera.

2. The computer of claim **1**, the instructions including further instructions to control motion of a second vehicle based on the real-world coordinates of the first camera and the real-world coordinates of the second camera.

3. The computer of claim **1**, wherein first and second camera parameters include the six degree of freedom poses of the first and second cameras.

4. The computer of claim **1**, wherein the real-world coordinates of the first camera are determined by locating the first camera using lidar data.

5. The computer of claim **1**, the instructions including further instructions to determine the first and second plurality of center points based on first and second bounding boxes by inputting the first and second pluralities of images to a convolutional neural network.

6. The computer of claim **1**, the instructions including further instructions to solve the plurality of non-linear equations using Gauss-Newton iteration.

7. The computer of claim **6**, wherein solving the plurality of non-linear equations using Gauss-Newton iteration includes determining a Jacobian matrix of partial derivatives.

8. The computer of claim **1**, the instructions including further instructions to solve the non-linear equations using a Levenberg-Marquardt algorithm.

9. The computer of claim **1**, wherein simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera includes constraining the first and second two-dimensional bounding boxes to a plane.

10. The computer of claim **1**, wherein simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera includes constraining the locations of the vehicle based on lidar data.

11. The computer of claim **1**, wherein simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera includes constraining the locations of the vehicle based on one or more of global positioning system data, inertial measurement unit data and visual odometry data.

12. The computer of claim **1**, wherein simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera includes constraining the locations of the vehicle based on map data.

13. The computer of claim **1**, wherein simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and the six degree of freedom pose of the second camera with respect to the first camera includes constraining the locations of the vehicle based on center points determined based on three-dimensional bounding boxes.

14. A method, comprising:

determining a first plurality of center points of first two-dimensional bounding boxes corresponding to a vehicle occurring in a first plurality of images acquired by a first camera;

determining a second plurality of center points of second two-dimensional bounding boxes corresponding to the vehicle occurring in a second plurality of images acquired by a second camera;

determining a plurality of non-linear equations based on respective locations of the first and second pluralities of center points and first and second camera locations including camera parameters corresponding to the first and second cameras;

simultaneously solving the plurality of non-linear equations for the locations of the vehicle with respect to the first and second cameras and a six degree of freedom pose of the second camera with respect to the first camera; and

determining real-world coordinates of the six degree of freedom pose of the second camera based on real-world coordinates of a six degree of freedom pose of the first camera.

15. The method of claim **14**, further comprising controlling motion of a second vehicle based on the real-world coordinates of the first camera and the real-world coordinates of the second camera.

16. The method of claim **14**, wherein first and second camera parameters include the six degree of freedom poses of the first and second cameras.

17. The method of claim **14**, wherein the real-world coordinates of the first camera are determined by locating the first camera using lidar data.

18. The method of claim **14**, further comprising determining the first and second plurality of center points based on first and second bounding boxes by inputting the first and second pluralities of images to a convolutional neural network.

19. The method of claim **14**, further comprising solving the plurality of non-linear equations using Gauss-Newton iteration.

20. The method of claim **19**, wherein solving the plurality of non-linear equations using Gauss-Newton iteration includes determining a Jacobian matrix of partial derivatives.

* * * * *