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(54) EFFICIENT NEURAL NETWORKS

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(51) **Int. Cl.**

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G06V 10/82	(2022.01)
G06V 20/56	(2022.01)

(52) **U.S. Cl.**
CPC ***B60W 60/0025*** (2020.02); ***G06V 10/82*** (2022.01); ***G06V 20/56*** (2022.01); *B60W 2556/55* (2020.02); *B60W 2756/10* (2020.02)

(58) **Field of Classification Search**
CPC B60W 60/0025; B60W 2556/55; B60W 2756/10; G06V 10/82; G06V 20/56; G06V 10/454; G06V 10/764; G06N 3/08; G06N 3/126
See application file for complete search history.

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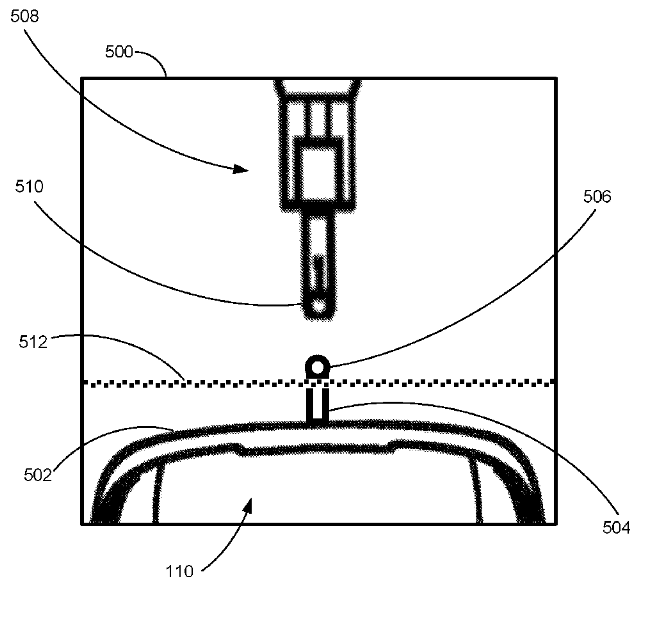
(57) **ABSTRACT**

A location of a first object can be determined in an image. A line can be drawn on the first image based on the location of the first object. A deep neural network can be trained to determine a relative location between the first object in the image and a second object in the image based on the line. The deep neural network can be optimized by determining a fitness score that divides a number of deep neural network parameters by a performance score. The deep neural network can be output.

20 Claims, 9 Drawing Sheets



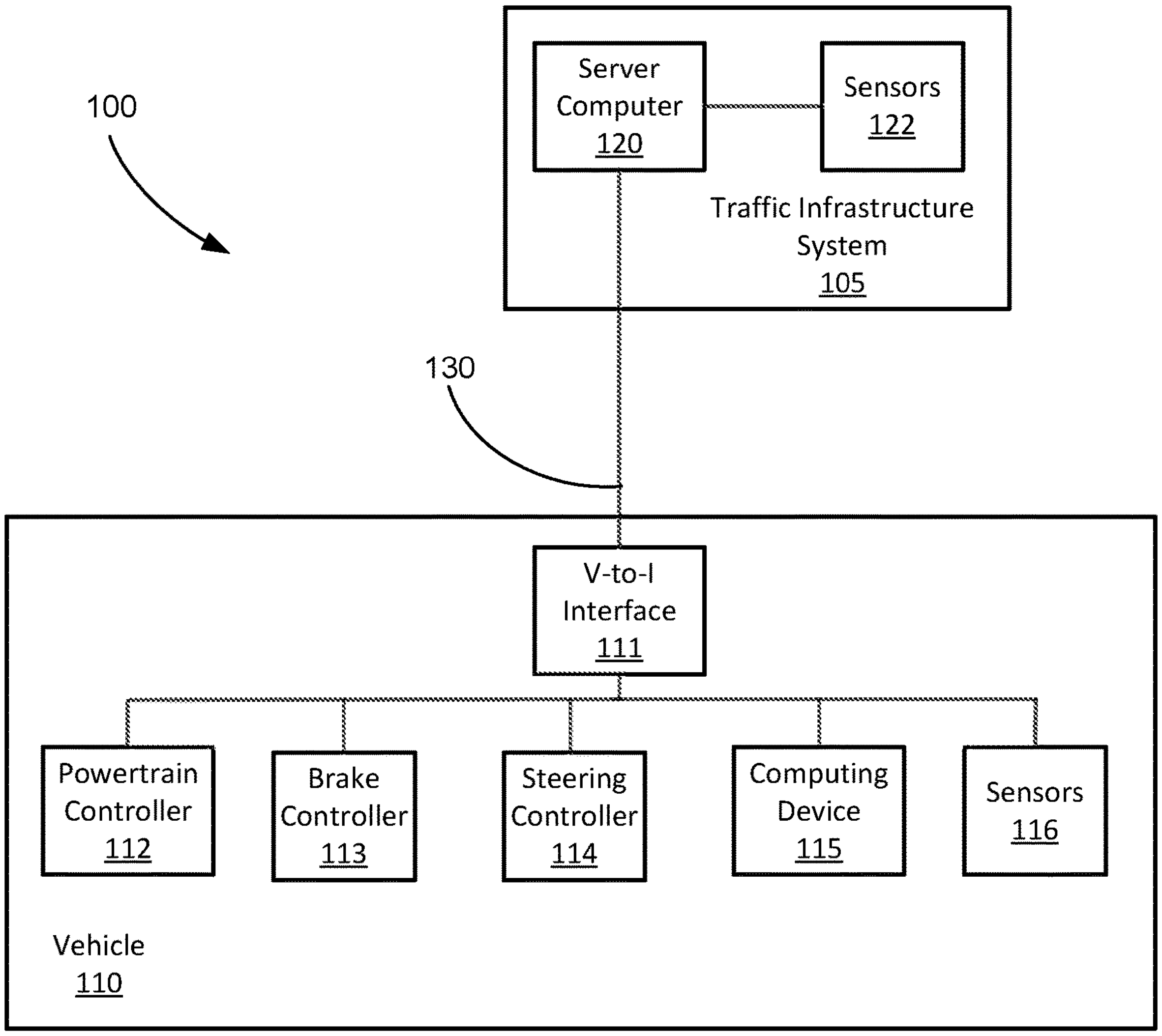

100
Server Computer 120
Sensors 122
Traffic Infrastructure System 105
130
V-to-I Interface 111
Powertrain Controller 112
Brake Controller 113
Steering Controller 114
Computing Device 115
Sensors 116
Vehicle 110

Fig. 1

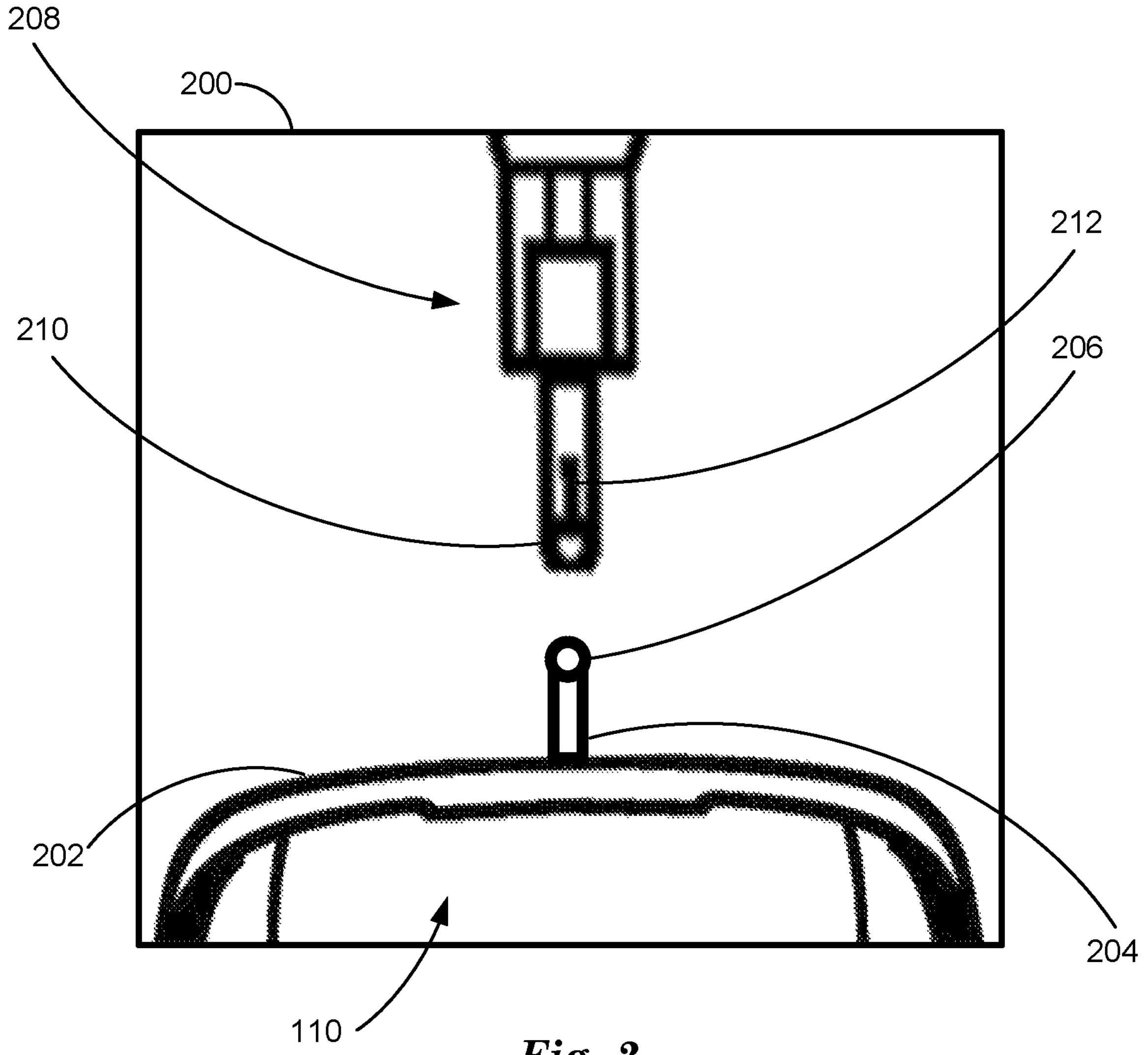


Fig. 2

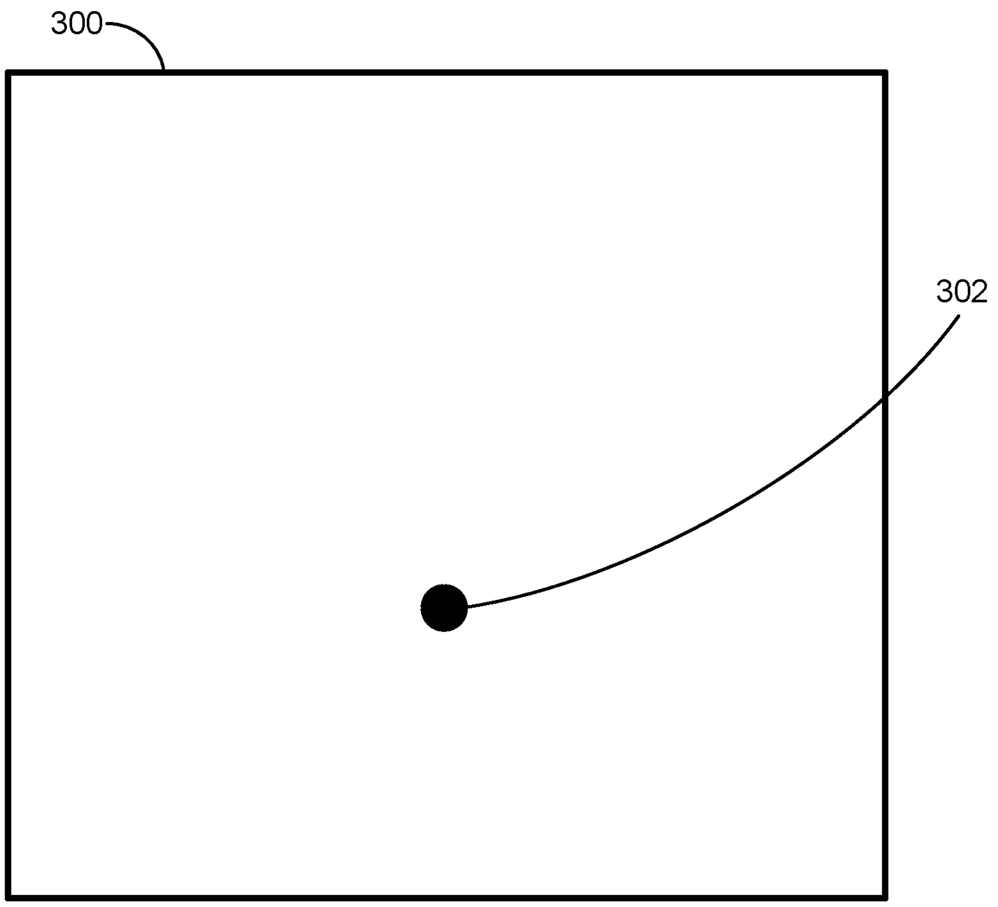


Fig. 3

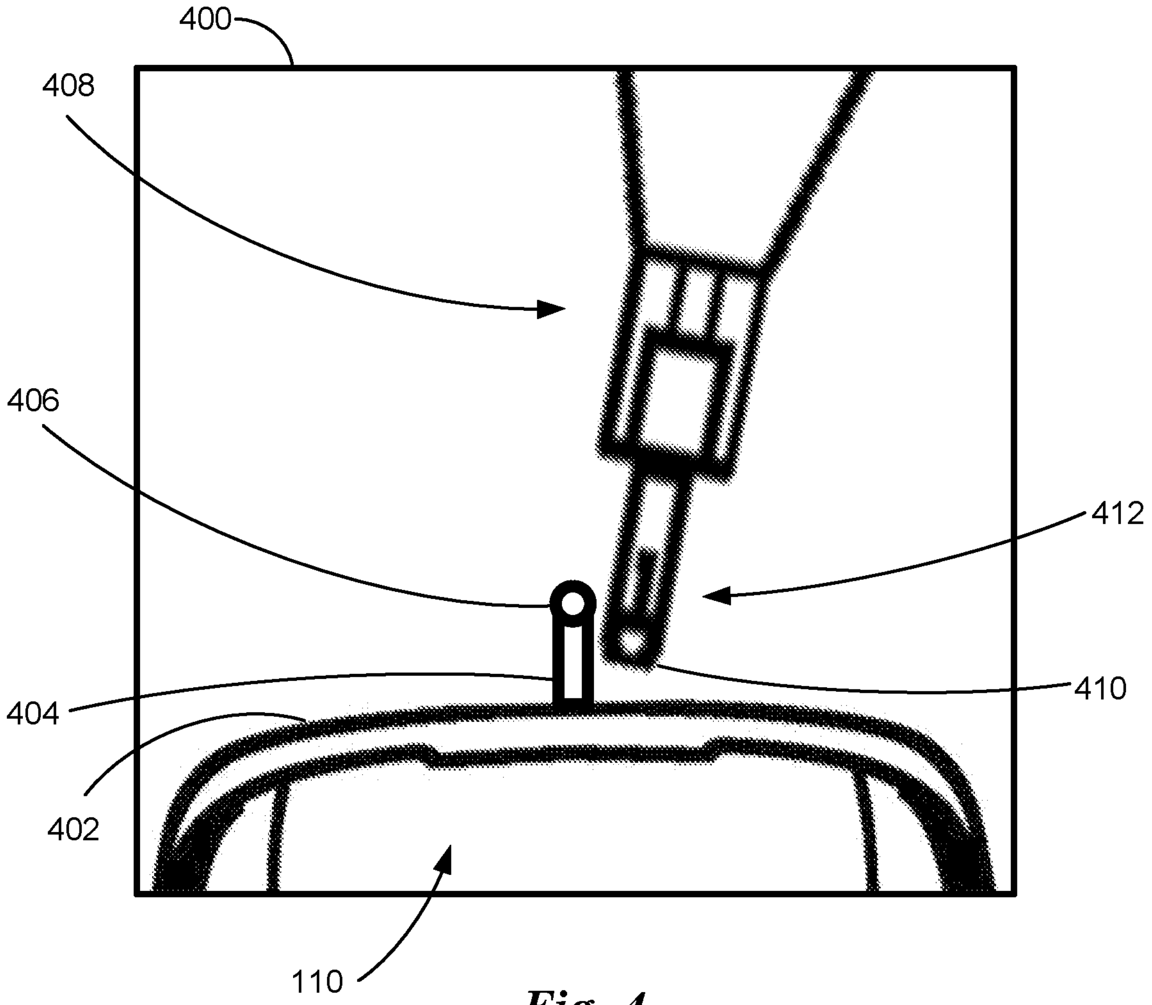


Fig. 4

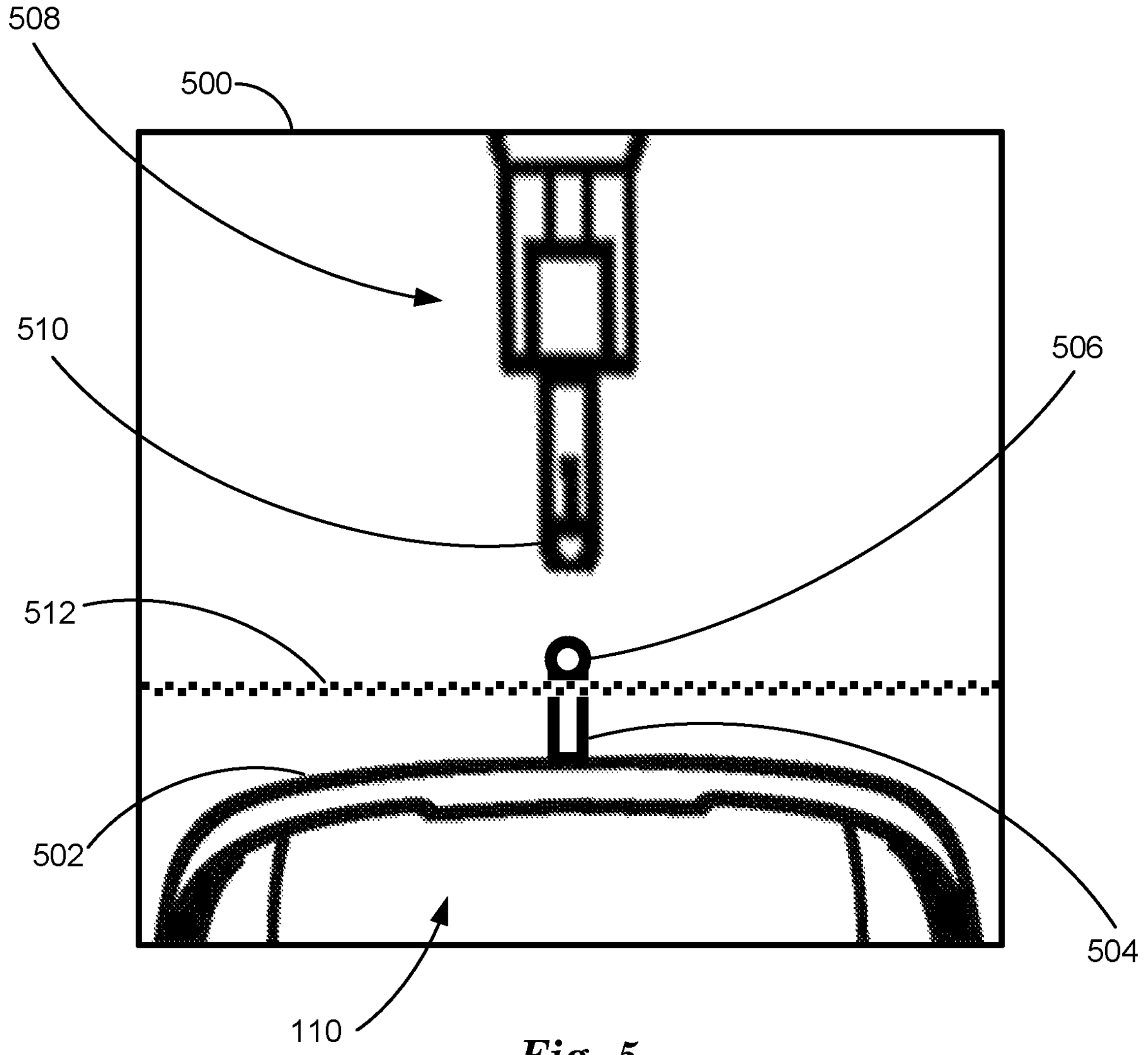


Fig. 5

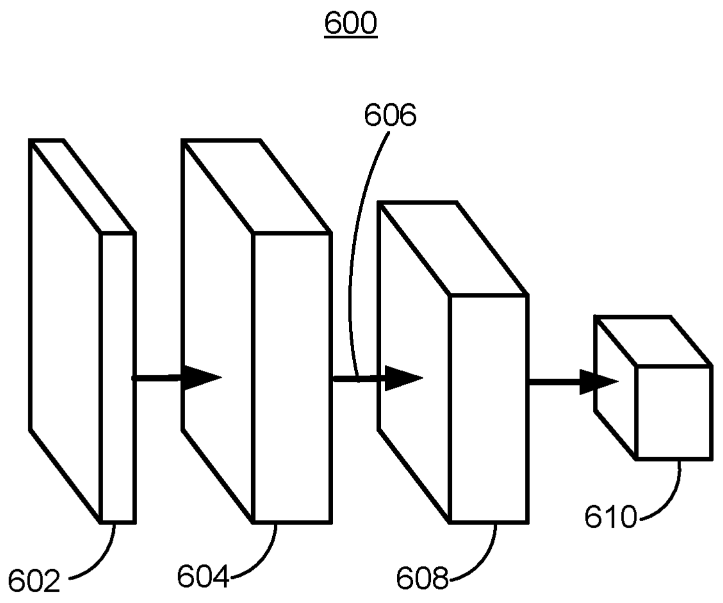


Fig. 6

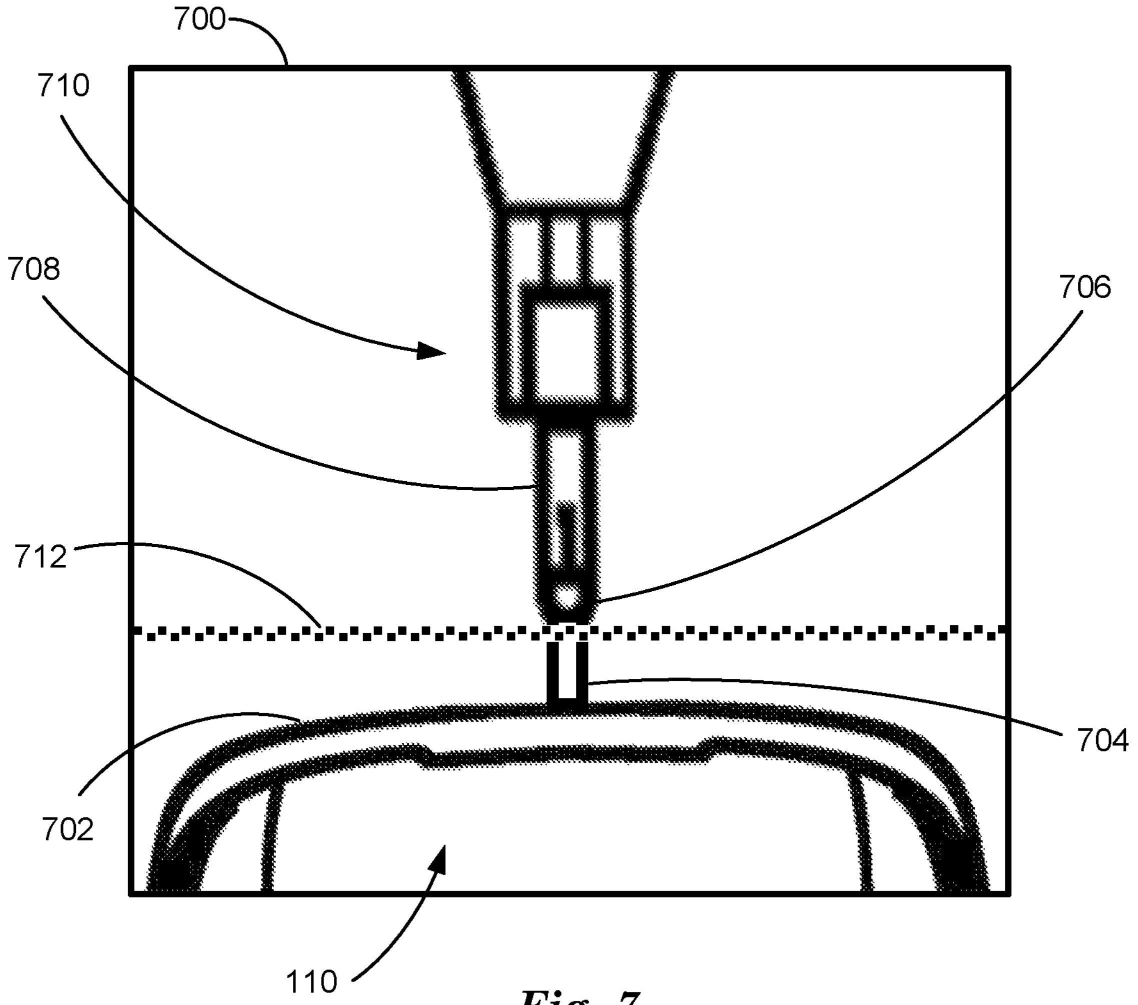


Fig. 7

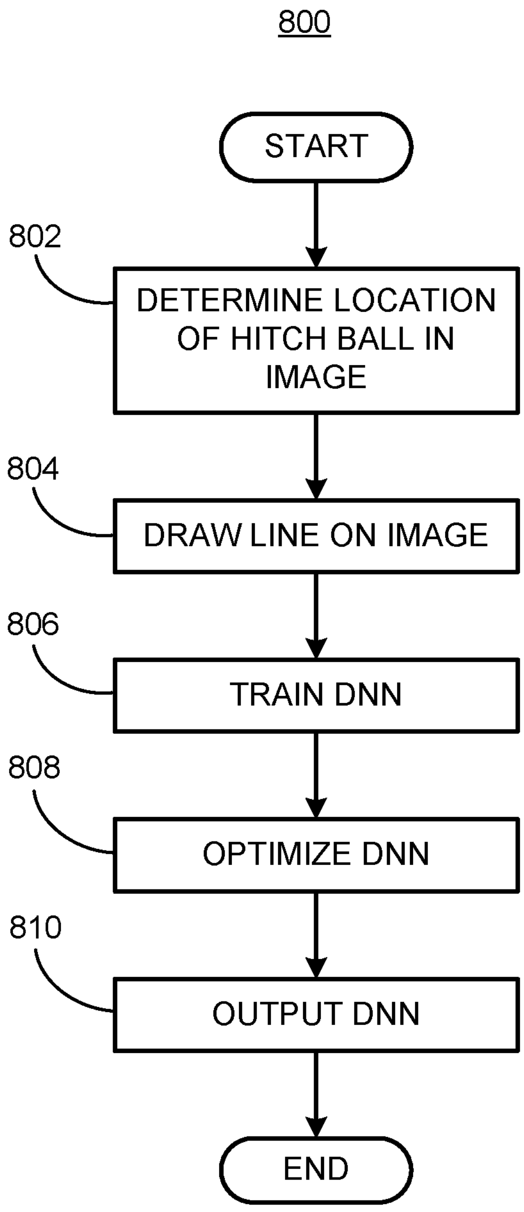

800
START
802
DETERMINE LOCATION OF HITCH BALL IN IMAGE
804
DRAW LINE ON IMAGE
806
TRAIN DNN
808
OPTIMIZE DNN
810
OUTPUT DNN
END

Fig. 8

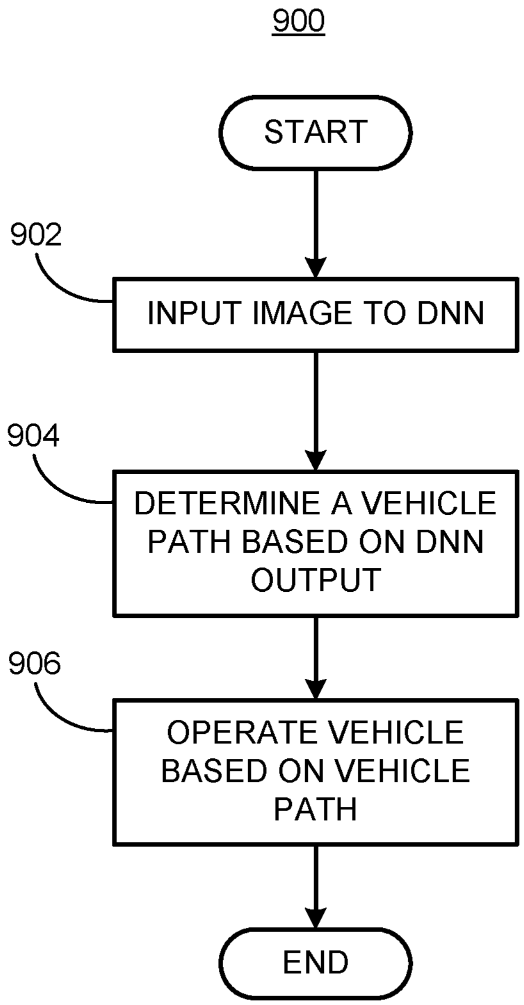

900
START
902
INPUT IMAGE TO DNN
904
DETERMINE A VEHICLE PATH BASED ON DNN OUTPUT
906
OPERATE VEHICLE BASED ON VEHICLE PATH
END

Fig. 9

EFFICIENT NEURAL NETWORKS

BACKGROUND

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

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

FIG. **2** is a diagram of an example image including features in an environment around a vehicle, including a trailer hitch.

FIG. **3** is a diagram of an example segmented image of a trailer hitch.

FIG. **4** is a diagram of another example image of a trailer hitch.

FIG. **5** is a diagram of another example image of a trailer hitch.

FIG. **6** is a diagram of an example deep neural network.

FIG. **7** is a diagram of another example image of a trailer hitch.

FIG. **8** is a flowchart diagram of an example process to train and optimize a DNN.

FIG. **9** is a flowchart diagram of an example process to operate a vehicle based on an optimized DNN.

DETAILED DESCRIPTION

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.

Vehicle guidance will be described herein as a non-limiting example of using a computer to detect objects in an image and determine a vehicle path for operating a vehicle based on the detected object. The image can be of an environment around a vehicle and can include a portion of a vehicle and objects including a trailer coupler and a hitch

ball. A trailer coupler is the portion of a vehicle trailer that detachably connects a vehicle trailer to a vehicle by positioning the trailer coupler on a hitch ball connected to the vehicle via a trailer hitch. For example, a computing device in a vehicle can be programmed to acquire one or more images from one or more sensors included in the vehicle and locate objects in the one or more images including a trailer coupler and a hitch ball. The sensors can include video or still image cameras that acquire images corresponding to visible or infrared wavelengths of light. The sensor can be mounted on the vehicle and located to provide a view of the hitch ball and an area around the hitch ball. In some examples the sensor can be included in a traffic infrastructure system and mounted on a structure such as a pole or building and the image and/or object data can be communicated to the vehicle. 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.

Advantageously, techniques discussed herein improve the ability of a computing device to identify and locate objects by decreasing the time and computing resources required to determine objects in image data by adding fiducial lines to images. In addition, time and computing resources required to determined objects can be reduced by optimizing a DNN used to locate an object using a genetic algorithm as will be described below in relation to FIGS. **2-5**.

Disclosed herein is a method, including determining a location of a first object in an image, drawing a line on the image based on the location of the first object, training a deep neural network to determine a relative location between the first object in the image and a second object in the image based on the line and optimizing the deep neural network by determining a fitness score that divides a plurality of deep neural network parameters by a performance score. The method further includes a second computer in a vehicle, wherein the deep neural network is output to the second computer in the vehicle. The second computer can include a second processor and a second memory, the second memory including second instructions executable by the second processor to operate the vehicle based on acquiring a second image and inputting the second image to the deep neural network included in the second computer to determine a vehicle path. The second computer can control one or more of vehicle powertrain, vehicle steering, and vehicle brakes to operate the vehicle on the vehicle path determined based on the deep neural network. The relative location between the first object in the image and the second object in the image can be determined based on the line includes the second object being located on the line.

The location of the first object can be determined by inputting the image to a second deep neural network. The line can include a pattern of light pixels and dark pixels. The first object can be a hitch ball attached to a vehicle and the second object is a trailer coupler. The line can be drawn between the hitch ball and the vehicle. The line can be drawn based on the location of the first object. The deep neural network can be a convolutional neural network that includes convolutional layers and fully connected layers. The deep neural network parameters can include convolutional parameters including one or more of a plurality of convolutional filters, an activation type, a pooling type, and a number of neurons. The deep neural network parameters can include fully connected parameters including an activation type and a number of neurons. Training the deep neural network can include determining a loss function based on comparing output results from the deep neural network with ground truth corresponding to images included in a training dataset.

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 determine a location of a first object in an image, draw a line on the image based on the location of the first object, train a deep neural network to determine a relative location between the first object in the image and a second object in the image based on the line and optimize the deep neural network by determining a fitness score that divides a plurality of deep neural network parameters by a performance score. The method further includes a second computer in a vehicle, wherein the deep neural network is output to the second computer in the vehicle. The second computer can include a second processor and a second memory, the second memory including second instructions executable by the second processor to operate the vehicle based on acquiring a second image and inputting the second image to the deep neural network included in the second computer to determine a vehicle path. The second computer can control one or more of vehicle powertrain, vehicle steering, and vehicle brakes to operate the vehicle on the vehicle path determined based on the deep neural network. The relative location between the first object in the image and the second object in the image can be determined based on the line includes the second object being located on the line.

The instructions can include further instructions to determine the location of the first object by inputting the image to a second deep neural network. The line can include a pattern of light pixels and dark pixels. The first object can be a hitch ball attached to a vehicle and the second object is a trailer coupler. The line can be drawn between the hitch ball and the vehicle. The line can be drawn based on the location of the first object. The deep neural network can be a convolutional neural network that includes convolutional layers and fully connected layers. The deep neural network parameters can include convolutional parameters including one or more of a plurality of convolutional filters, an activation type, a pooling type, and a number of neurons. The deep neural network parameters can include fully connected parameters including an activation type and a number of neurons. Training the deep neural network can include determining a loss function based on comparing output results from the deep neural network with ground truth corresponding to images included in a training dataset.

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 stationary 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.

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 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 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.

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**.

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 an image **200** including features of an environment around a vehicle **110**. Image **200** includes the rear bumper **202** portion of a vehicle **110**, a trailer hitch **204** attached to vehicle **110** and a hitch ball **206** attached to the trailer hitch **204**. Image **200** also includes a portion of a trailer **208** including a trailer coupler **210**. Trailer **208** can be removably attached to vehicle **110** by operating vehicle **110** using vehicle powertrain, vehicle steering, and/or vehicle brakes to position the hitch ball **206** underneath trailer coupler **210**. When hitch ball **206** is positioned underneath trailer coupler **210**, trailer **208** can be lowered to engage trailer coupler **210** with hitch ball **206**. When trailer coupler **210** is lowered to engage with hitch ball **206**, coupler lock **212** can be engaged to lock the trailer coupler **210** to the hitch ball **206**. Software executing on computing device **115** or server computer **120** can acquire sensor data including images **200** and radar data and determine locations of a hitch ball **206**, a trailer coupler **210** and a relative location of the hitch ball **206** to trailer coupler **210**. The locations of the hitch ball **206**, the trailer coupler **210** and the relative location of the hitch ball **206** to trailer coupler **210** can be measured in global coordinates. Global coordinates can be determined with respect to a coordinate system such as latitude, longitude, and altitude, for example. The locations of the hitch ball **206**, the trailer coupler **210** and the relative location of the hitch ball **206** to trailer coupler **210** can be measured as x, y coordinates in a plane parallel to the roadway or surface that supports the vehicle **110** and the trailer **208**. These three locations can be used by computing device **115** or server computer **120** to determine a vehicle path that positions the hitch ball **206** underneath trailer coupler **210**.

A vehicle path can be described by a polynomial function, sometimes called a path polynomial, determined based on the locations of the hitch ball **206**, the trailer coupler **210** and the relative location of the hitch ball **206** and trailer coupler **210**. The path polynomial can be determined by an equation with the form:

$$y=a_i x^i+ \dots +a_2 x^2+a_1 x+a_0 \tag{1}$$

where x and y are distances measured in a plane parallel to the drivable surface of a roadway and are typically measured in global coordinates determined based on degrees of latitude and longitude, for example. The value of i can be predetermined to limit the number of coefficients to be calculated based on a distance to be traveled by vehicle **110** and predetermined limits on rates of change in vehicle **110** direction and speed. For example, the polynomial function can be determined based on upper and lower limits for lateral and longitudinal accelerations. The polynomial coefficients a_1, a_2, a_1, a_0 can be obtained by curve fitting, for example using least-squares techniques, wherein the polynomial equations are fit to at least i+1 cardinal points associated with the locations of the hitch ball **206**, the trailer coupler **210** and the relative location of the hitch ball **206** to the trailer coupler **210**. The cardinal points can be associated with starting and ending points of the vehicle path, changes in direction in a vehicle path, or at predetermined intervals along a vehicle path, for example. Vehicle **110** can be operated along the vehicle path by computing device **115** issuing commands to one or more of vehicle powertrain, vehicle steering and vehicle brakes via controllers **112**, **113**, **114** to position hitch ball **206** underneath trailer coupler **210**.

The locations of the hitch ball **206**, the trailer coupler **210** and the relative location of the hitch ball **206** and trailer coupler **210** can be determined in a plurality of images **200** by inputting the plurality of images **200** into a recurrent neural network (RNN) type of DNN. Because of variability in the appearance of the hitch ball **206** and trailer coupler **210** in images **200** and movement of the vehicle **110** while the images **200** are being acquired an RNN, which uses both spatial and temporal data to determine object locations in image data, can be used to determine the locations of the hitch ball **206**, the trailer coupler **210** the relative location of the hitch ball **206** and trailer coupler **210**. An RNN includes memory and data paths that connect a plurality of DNNs, where a DNN is instanced for each of a plurality of images **200** input to the RNN. An RNN can thus generate results based on processing images **200** acquired before and after a given image **200**. Examples of RNN processing include natural language understanding where the meaning of a given word can depend upon other words occurring in a sentence either before or after the given word.

An RNN trained to determine the locations of the hitch ball **206**, the trailer coupler **210** and the relative location of the hitch ball **206** and trailer coupler **210** can require tens of millions of parameters. An RNN with tens of millions of parameters is too large to permit the RNN to be stored in memory and executed on the types of computing devices **115** such as ECUs typically included in vehicles **110**. In addition, the time required to process a plurality of input images **300** on an RNN with tens of millions of parameters means that an RNN cannot achieve real time performance in a vehicle **110**. Real-time performance is when a result is available from the RNN within a fixed number of milliseconds (ms) from the time the plurality of images **300** are acquired, for example 100 ms.

A technique for overcoming the limitations of RNN-based solutions to the problem of locating a hitch ball **206**, a trailer coupler **210** and a relative location of the hitch ball **206** and trailer coupler **210** includes, as explained herein, an Enet DNN architecture. An Enet DNN architecture is a lightweight neural network architecture specifically designed to determine low-latency or real time solutions. Enet DNNs have a plurality of parallel data paths, where a single main computational branch is accompanied by parallel extensions that include convolutional kernels separate from the main computational branch. An Enet DNN can be trained to locate one of a hitch ball **206**, a trailer coupler **210** or a relative location of the hitch ball **206** and trailer coupler **210** using about 0.39 million parameters. Post-processing heuristics based on image processing techniques can then be applied to the output of the Enet DNN to determine the values of the other two locations relative to the location determined by the Enet DNN.

FIG. **3** is a diagram of an image **300** with a segment **302** corresponding to the location of the hitch ball **206** from image **200** in FIG. **2**. Image segmentation is when a contiguous region of pixels is labeled as corresponding to the location of an object in an image **200**. To determine a location corresponding to either a hitch ball **206**, a trailer coupler **210** or a relative location of the hitch ball **206** and trailer coupler **210**, the Enet DNN first performs image segmentation on an input image **200** to determine a segment **302** corresponding to the hitch ball **206** from image **200**. The segmented image **300** can be output by the Enet DNN as a portion of the data output in response to an input image **200**.

FIG. **4** is a diagram of an image **400** that includes overshoot **412**. Overshoot **412** is when a trailer coupler **410** of a trailer **408** travels past a hitch ball **406** attached to a hitch **404**. When a trailer coupler **410** overshoots **412** a hitch ball **406**, the trailer coupler **410** will be closer to bumper **402** than the hitch ball **406**. During overshoot **412**, the interaction between the trailer coupler **410** and the hitch ball **406** within the Enet DNN results in disruption in the hitch ball **406** segmentation output from the network. Disruption caused by overshoot **412** can result in a segment **302** corresponding to hitch ball **406** having an irregular shape and can result in an erroneous estimate of the location of the hitch ball **406**. As a post-processing step, this disruption can be quantified and utilized to infer the trailer coupler **410** location and its location relative to the hitch ball **406** using heuristics. For example, image processing techniques can be used to compare the shape of a segment **302** with a segment **302** produced from an image **200** without overshoot and determine a corrected location of hitch ball **406**. The corrected location of hitch ball **406** can be combined with a determined location of the trailer coupler **410** to determine a relative location for the hitch ball **406** and the trailer coupler **410**.

While post-processing using image processing software can perform well on certain cases and on devices with good computational power, limited memory and limited computational power available on typical computing devices **115** included in a vehicle **110** can prevent post-processing image processing software from being able to determine the location of a trailer coupler **410** and the location of the trailer coupler **410** relative to the hitch ball **406** in in some examples. To process the image **400** in real time using post-processing image processing software it can be necessary to perform quantization to have it run on a typical vehicle computing device **115** at a good frame rate, based on the size of the Enet DNN. Quantization is a process for reducing the size of input data by representing a contiguous group of data values by a single data value. For example, a series of 8-bit numbers corresponding to 256 different data values can be represented by a series of 4-bit numbers corresponding to 16 different data values thus saving memory and computation time. Quantization can be applied to images **400** in one or more of the x, y, or z axes. Quantizing an image **400** processed by the Enet DNN can result in a considerable reduction (about 20%) in accuracy of the determined locations as compared to a full resolution image **400**.

FIG. **5** is a diagram of an image **500** including a vehicle **110** including a bumper **502**, a hitch **504** and a hitch ball **506** attached to the hitch **504**. Image **500** also includes a trailer **508** and a trailer coupler **510** attached to the trailer **508**. As discussed above in relation to FIG. **4**, there can be examples of trailer coupler **510** overshoot **412** that cause disruptions and reductions in accuracy. Detection of overshoot **412** and location accuracy determination can be improved by adding a fiducial line **512** to an image **500** and using the fiducial line **512** to detect overshoot **412**. Overshoot **412** can be detected by processing an image **500** that includes a fiducial line **512** with a second DNN trained to determine overshoot **412** of a trailer coupler **510** with respect to the fiducial line **512**. Inclusion of the fiducial line **512** simplifies the problem space by permitting the use of a binary classification approach. Rather than segmenting images and estimating x, y coordinates of segmented regions, the second DNN can be trained to output a simple TRUE or FALSE condition, i.e., does an image **500** include overshoot **412**. Reducing the problem space to a binary classification permits the second DNN to use a much smaller network. Because the problem space is reduced, the second DNN can be optimized to determine the best performance per DNN parameter. Optimization is discussed below in relation to FIG. **7**.

The location of hitch ball **506** with respect to the bumper **502** can be determined by Enet DNN or image processing software prior to the introduction of a trailer **508** and a trailer coupler **510** into the field of view of a camera included in vehicle **110** acquiring the image **500**, for example. Because the camera acquiring the image **500** is in a fixed position with respect to vehicle **110**, the locations of hitch ball **506** and bumper **502** will not change in subsequent images **500** acquired by the camera. Fiducial line **512** can be drawn on image **500** using image processing software such as Photoshop, available from Adobe, Inc. San Jose, CA 95110.

A fiducial line **512** can be drawn as illustrated in image **500** with a space cushion from the hitch ball **506** location and the bumper **502**. The fiducial line **512** can be drawn with a checkerboard pattern including dark pixels and light pixels in order to make it visible to the second DNN during shadow and bright light conditions. Moreover, the checkerboard pattern helps the second DNN determine the location of this line. The second DNN determines the location of the trailer coupler **510** with respect to the fiducial line **512** and outputs a binary value equal to TRUE if the trailer coupler **510** has crossed the line and FALSE if it has not. The width of the line is a trade-off between visibility and performance. Too wide a line will mask underlying image information while too thin a line will make it hard for the network to localize the line. A width of 2 pixels was determined to be optimal.

Correctly locating the fiducial line **512** in an image **500** can depend upon correct determination of the location of the hitch ball **506** in image **500**. Incorrectly locating the fiducial line **512** too close to the bumper **502** can be avoided by incorporating a limit to prevent the fiducial line **512** from being drawn on the bumper **502**. Because the camera location is constant with respect to the bumper **502** for a particular vehicle **110**, the number of rows of pixels at the bottom of the image **500** that contain the bumper **502** are constant. For example, the bottom 50 rows of pixels in an image **500** can be determined to include the bumper **502**. A limit equal to the bottom 50 rows of pixels can be set and the image processing software can be instructed to never draw the fiducial line **512** in the bottom 50 rows of pixels. Preventing the fiducial line from being drawn in the bottom 50 rows of pixels may prevent a collision between the trailer coupler **510** the bumper **502** thus satisfying the overshoot **412** requirement even when the hitch ball **506** location input is erroneous.

Determining overshoot **412** using a fiducial line **512** simplifies the problem space by permitting the use of a binary classification approach. Binary classification is a much simpler task than segmentation as discussed above in relation to FIG. **2**. Using binary classification to determine overshoot permits a much smaller, faster second DNN to be used rather than an RNN. Because the second DNN can operate on full-resolution image **500** data in real time, more accurate data is available more quickly for operating a vehicle **110** using fewer computing resources than an approach that employs an RNN.

FIG. **6** is a diagram of the second DNN **600**. Second DNN **600** inputs an image **602**. Image **602** is input to convolutional layers **604** which convolve the input image **602** using a plurality of convolutional kernels and output latent variables **606** to fully connected layers **608**. Fully connected layers **608** process the latent variables **606** with a plurality of linear and/or non-linear algebraic functions to determine a binary output results **610** (TRUE/FALSE) corresponding to the overshoot **412** condition present in the input image **602**.

Second DNN **600** is trained using a training dataset that includes a plurality of input images **602** and user determined ground truth corresponding to the input images **602**. Ground truth includes the correct answer regarding overshoot **412** included in a particular image **602**. During training, parameters corresponding to the convolution kernels and algebraic functions can be randomly selected and an input image **602** is processed to determine a binary output results **610**. The binary output results **610** can be compared to the ground truth corresponding to the input image **602** and a loss function can be determined. The loss function is input to the convolutional layers **604** and fully connected layers **608** to select parameters for the convolution kernels and algebraic functions that result in the best correspondence between the binary output results **610** and ground truth, thus training the second DNN **600**. Training the second DNN **600** can include both training and testing. Training and testing the second DNN **600** can include dividing a dataset of images **500** and corresponding ground truth into two portions, a training dataset and a testing dataset. The second DNN **600** can be trained using the training dataset as discussed above and then tested using the testing dataset. Testing includes comparing the binary output results **610** with the corresponding ground truth to determine whether the second DNN **600** has output the correct result. The second DNN **600** is scored based on the percentage of correct results. If the percentage of correct results is less than a user selected level, for example 99%, a second dataset of images **500** and ground truth can be used to re-train and re-test the second DNN **600**. The re-training and re-testing process can repeat until the second DNN achieves the user selected level of correct results.

Once the second DNN **600** is trained to produce correct results, a genetic algorithm can be applied to the second DNN **600** to optimize the second DNN **600**. Optimization determines a minimal configuration of convolutional layers **604** and fully connected layers **608** that achieve results similar to the fully trained second DNN **600**. A genetic algorithm is a heuristics-based search technique that minimizes a function, in this example the second DNN, against a set of constraints mimicking the processes of natural selection and evolution. In this context, the inclusion of the fiducial line **512** greatly simplified the problem and a smaller network can be sufficient to achieve the same level of performance. Because the second DNN network architecture begins as a general-purpose architecture, it is not guaranteed to be the smallest possible architecture that performs well for a given task. A genetic algorithm can be used to determine a network architecture with the least number of parameters that can perform well on a test dataset.

A genome in a genetic algorithm encodes the architecture that it represents. Because the second DNN is a convolutional neural network, the architecture includes convolutional layers **604** followed by fully connected layers **608**. The second DNN was limited to a maximum of five convolutional layers **604** and two fully connected layers **608**. Each position in the genome corresponds to factors such as the number of filters, stride, the activation, and the type of pooling for a convolutional layer while the genes for the fully connected layers decided the number of neurons in that layer. The genome structure for this example has a genome length of 24 and is illustrated in Table 1.

TABLE 1

Genome structure.

Gene [0]-Gene [4] Conv 0-4 Number of Filters	Gene [5]-Gene [9] Conv 0-4 Stride	Gene [10]-Gene[14] Conv 0-4 Activation Type	Gene [15]-Gene[19] Conv 0-4 Pooling Type	Gene [20] FC 0 Number of Neurons	Gene [21] FC 0 Activation	Gene [22] FC 1 Number of Neurons	Gene [23] FC 1 Activation

Genes [0-4], Number of Filters, correspond to the number of convolution kernels for each of the five convolutional layers. The number of filters can take a value of 0 to 128 for convolutional layers one to five and a value of 1 to 128 for the first convolutional layer **604**. A filter value of 0 indicates that the convolutional layer **604** should be skipped, so requiring a value of 1 for the first convolutional layer **604** (layer 0) means that at least one convolution will be performed. Genes [5-9], Stride, correspond to the size in pixels of the movement of the convolutional kernels over the input data for the five convolutional layers **602**. Stride for the convolutional layers **602** can be set from one to four, meaning that between each pixel and each fourth pixel in an image will have a convolutional kernel applied to it. Genes [10-14], Activation, correspond to a function applied to the output from a layer that conditions the output before inputting to the next convolutional layer **604**. Activation can be one of ReLU, Leaky ReLU, or ELU. ReLU is a function that sets negative values to 0. Leaky ReLU sets negative values to a fraction of their values. ELU sets negative values to $\alpha(e^x-1)$, where a is a constant. Genes [15-19], Pooling, correspond to a function that reduces the resolution of output from a convolutional layer **604** before inputting to the next layer. Pooling can be either max pooling, which outputs one value equal to the maximum of a neighborhood of pixels or average pooling, which outputs one value equal to the average of a neighborhood of pixels.

Gene [20], Number of Neurons, corresponds to the number of neurons in the first fully connected layer **608**. A neuron corresponds to a single algebraic function and can take any value between 0 and 128. Gene [21], Activation, corresponds to the type of activation for the outputs from the first fully connected layer **608**. Activation can be ReLU, Leaky ReLU, or ELU as discussed above. Gene [22], Number of Neurons, corresponds to the number of neurons in the second fully connected layer **608**. A neuron corresponds to a single algebraic function and can take any value between 0 and 128. Gene [23], Activation, corresponds to the type of activation for the outputs from the second fully connected layer **608**. Activation can be ReLU, Leaky ReLU, or ELU as discussed above.

A genetic algorithm can be evaluated by determining values for the genomes based on the number of parameters and the performance of the network, according to the following fitness function:

$$\text{Fitness} = \frac{N}{F1\ \text{Score}_{test} + \Delta} \tag{2}$$

Where N is the number of parameters of the network, F1 Score$_{test}$ is the result of testing the second DNN based on a test dataset with a value between 0 and 1, and A is a constant to avoid a divide by zero error equal to e^8. To minimize the fitness function (2), the genetic algorithm trains and evaluates multiple architectures and iteratively converges to the best performing network with the least number of parameters. The genetic algorithm can be run for a set number of generations with a specific population size. For example, the second DNN converged on a **1200** parameter network with an F1 Score$_{test}$ of 0.98 on the test dataset. This corresponded to about a 300× improvement over the ENet architecture. The converged network did not require any quantization or pruning and was able to run it at 25 frames per second on a typical computing device **115** included in a vehicle **110**.

FIG. **7** is a diagram of an image **700** of the results of directing the operation of a vehicle **110** to hitch a trailer coupler **708** on a trailer **710** to a hitch ball **706** on a hitch **704** using a fiducial line **712** between the hitch ball **706** and the bumper **702**. The location of the trailer coupler **708** with respect to the fiducial line **712** is determined by processing the image **700** with a second DNN trained and optimized as discussed above in relation to FIG. **6**. Because the location of the trailer coupler **708** with respect to the fiducial line **712** can be determined at 25 frames per second using limited computing resources available to a typical computing device **115** included in a vehicle **110**, a vehicle path that directs the vehicle to position the hitch ball **706** underneath the trailer coupler **708** can be determined in real time. Determining the vehicle path in real time permits the computing device **115** to be able to operate the vehicle **110** by commanding one or more of vehicle powertrain, vehicle steering and vehicle brakes in a smooth and efficient fashion to correctly position the vehicle **110** with respect to the trailer **710** using minimal computing resources.

FIG. **8** is a diagram of a flowchart, described in relation to FIGS. **1-7**, of a process for training and optimizing a second DNN **600** to locate an object with respect to a fiducial line. Process **800** can be implemented by a processor of a computing device **115**, taking as input image data from sensors **116**, and executing commands, and outputting a trained and optimized second DNN **600**. 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.

Process **800** begins at block **802**, where a computing device **115** in a vehicle **110** can determine a location of a first object in an image **500**. The first object can be a hitch ball **506** in and image **500** that includes a trailer **508**, a trailer coupler **510**, a portion of a vehicle **110**, a bumper **502** included in the vehicle and a hitch **504**. The hitch ball **506** can be determined using image processing software that can include an Enet neural network, for example, as discussed above in relation to FIG. **3**.

At block **804** can draw a fiducial line **512** on an image **500** based on the location of a hitch ball **506** determined at block **802**. The fiducial line **512** can be drawn on the image to determine when a second object, which can be a trailer coupler **510**, overshoots **412** a location of the first object, which can be a hitch ball **506** as discussed above in relation to FIGS. **4** and **5**, above.

At block **806** a second DNN **600** can be trained based on a training dataset and a test dataset and corresponding ground truth as discussed above in relation to FIG. **6**, above.

At block **808** the second DNN **600** can be optimized based on a genetic algorithm as discussed above in relation to FIG. **6**.

At block **810** the second DNN **600** can be output to a computing device **115** included in a vehicle **110**. After block **810** process **800** ends.

FIG. **9** is a diagram of a flowchart, described in relation to FIGS. **1-8**, of a process for operating a vehicle **110** based on determining a vehicle path based on output from a second DNN trained and optimized as discussed in relation to FIG. **8**, above. Process **900** can be implemented by a processor of a computing device **115**, taking as input data sensors **116**, and executing commands, and operating vehicle **110**. Process **900** includes multiple blocks that can be executed in the illustrated order. Process **900** could alternatively or additionally include fewer blocks or can include the blocks executed in different orders.

Process **900** begins at block **902**, where a computing device **115** in a vehicle **110** inputs an image **500**, draws a fiducial line **512** on the image **500** and inputs the image **500** to a second DNN **600** trained and optimized as discussed in relation to FIG. **8**, above to determine overshoot **412**.

At block **904** computing device **115** determines a vehicle path based on the output from second DNN **600**. A vehicle path is a polynomial function that includes maximum and minimum lateral and longitudinal accelerations to be applied to vehicle motion as it travels along the vehicle path. Because second DNN **600** can determine trailer coupler **508** overshoot in real time using limited computer resources, the vehicle path can be determined in real time using computing resources available in typical computing device **115** included in vehicles **110**.

At block **906** computing device **115** outputs commands to controllers **112**, **113**, **114** to control vehicle powertrain, vehicle steering, and vehicle brakes to control vehicle motion to operate vehicle **110** along the vehicle path determined at block **904**. Following block **906** process **900** 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 (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.

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 system, comprising a first computer that includes

a first processor; and

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

determine a location of a first object in an image;

draw a line on the image based on the location of the first object;

train a deep neural network to determine a relative location between the first object in the image and a second object in the image based on determining overshoot between the second object and the first object based on the line; and

optimize the deep neural network by determining a fitness score that divides a plurality of deep neural network parameters by a performance score.

2. The system of claim **1**, further comprising a second computer in a vehicle, the first instructions including instructions to output the deep neural network to the second computer in the vehicle.

3. The system of claim **2**, the second computer including a second processor and a second memory, the second memory including second instructions executable by the second processor to operate the vehicle based on acquiring a second image and inputting the second image to the deep neural network included in the second computer to determine a vehicle path.

4. The system of claim **3**, the second instructions further including instructions to control one or more of vehicle powertrain, vehicle steering, and vehicle brakes to operate the vehicle on the vehicle path determined based on the deep neural network.

5. The system of claim **1**, wherein determining the relative location between the first object in the image and the second object in the image based on the line includes the second object being located on the line.

6. The system of claim **1**, the instructions including further instructions to determine the location of the first object by inputting the image to a second deep neural network.

7. The system of claim **1**, wherein the line includes a pattern of light pixels and dark pixels.

8. The system of claim **1**, wherein the first object is a hitch ball attached to a vehicle and the second object is a trailer coupler.

9. The system of claim **8**, wherein the line is drawn between the hitch ball and the vehicle.

10. The system of claim **1**, wherein the line is drawn based on the location of the first object.

11. The system of claim **1**, wherein the deep neural network is a convolutional neural network that includes convolutional layers and fully connected layers.

12. The system of claim **1**, wherein the deep neural network parameters include convolutional parameters including one or more of a plurality of convolutional filters, an activation type, a pooling type, and a number of neurons.

13. The system of claim **1**, wherein the deep neural network parameters include fully connected parameters including an activation type and a number of neurons.

14. The system of claim **1**, wherein training the deep neural network includes determining a loss function based on comparing output results from the deep neural network with ground truth corresponding to images included in a training dataset.

15. The system of claim **1**, wherein the performance score is based on comparing output results from the deep neural network with ground truth corresponding to images included in a training dataset.

16. A method comprising:

determining a location of a first object in an image;

drawing a line on the image based on the location of the first object;

training a deep neural network to determine a relative location between the first object in the image and a second object in the image based on determining overshoot between the second object and the first object based on the line; and

optimizing the deep neural network by determining a fitness score that divides a plurality of deep neural network parameters by a performance score.

17. The method of claim **16**, further comprising a second computer in a vehicle, wherein the deep neural network is output to the second computer in the vehicle.

18. The method of claim **17**, the second computer including a second processor and a second memory, the second memory including second instructions executable by the second processor to operate the vehicle based on acquiring a second image and inputting the second image to the deep neural network included in the second computer to determine a vehicle path.

19. The method of claim **18**, wherein the second computer controls one or more of vehicle powertrain, vehicle steering, and vehicle brakes to operate the vehicle on the vehicle path determined based on the deep neural network.

20. The method of claim **16**, wherein determining the relative location between the first object in the image and the second object in the image based on the line includes the second object being located on the line.

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