US 20210397198A1

(19) United States

(12) Patent Application Publication

(10) Pub. No.: US 2021/0397198 A1

(43) Pub. Date: Dec. 23, 2021

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(54) ENHANCED VEHICLE OPERATION

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(21) Appl. No.: **16/904,653**

(22) Filed: **Jun. 18, 2020**

Publication Classification

(51) **Int. Cl.**

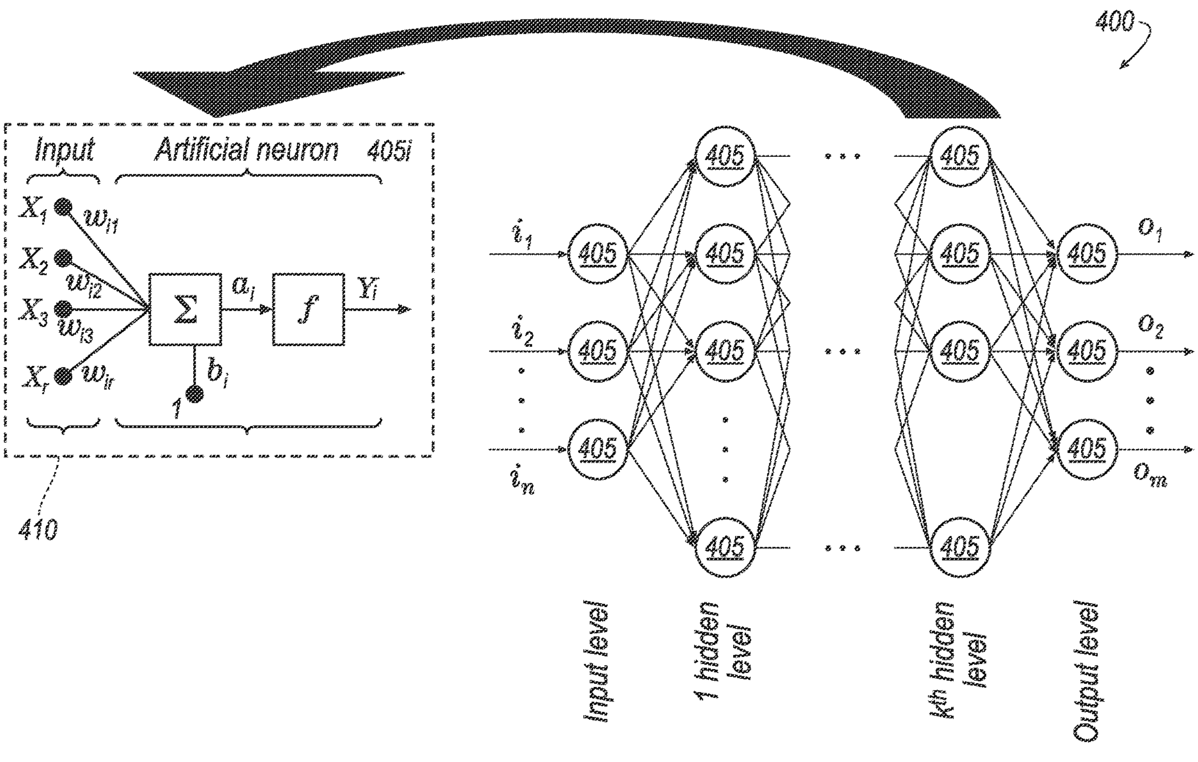
G05D 1/02	(2006.01)
G06K 9/00	(2006.01)
G06K 9/62	(2006.01)
G01C 21/36	(2006.01)
G01C 21/34	(2006.01)
G06N 20/00	(2006.01)
G06F 17/18	(2006.01)

(52) **U.S. Cl.**

CPC ***G05D 1/0246*** (2013.01); ***G06K 9/00791*** (2013.01); ***G06K 9/6215*** (2013.01); ***G06K 9/6256*** (2013.01); ***G01C 21/3679*** (2013.01); *G05D 1/0287* (2013.01); ***G05D 1/0212*** (2013.01); ***G01C 21/3644*** (2013.01); ***G06N 20/00*** (2019.01); ***G06F 17/18*** (2013.01); ***G01C 21/3407*** (2013.01)

(57) **ABSTRACT**

A computer includes a processor and a memory storing instructions executable by the processor to receive an image including a physical landmark, output a plurality of synthetic images, wherein each synthetic image is generated by simulating at least one ambient feature in the received image, generate respective feature vectors for each of the plurality of synthetic images, and actuate one or more vehicle components upon identifying the physical landmark in a second received image based on a similarity measure between the feature vectors of the synthetic images and a feature vector of the second received image, the similarity measure being one of a probability distribution difference or a statistical distance.



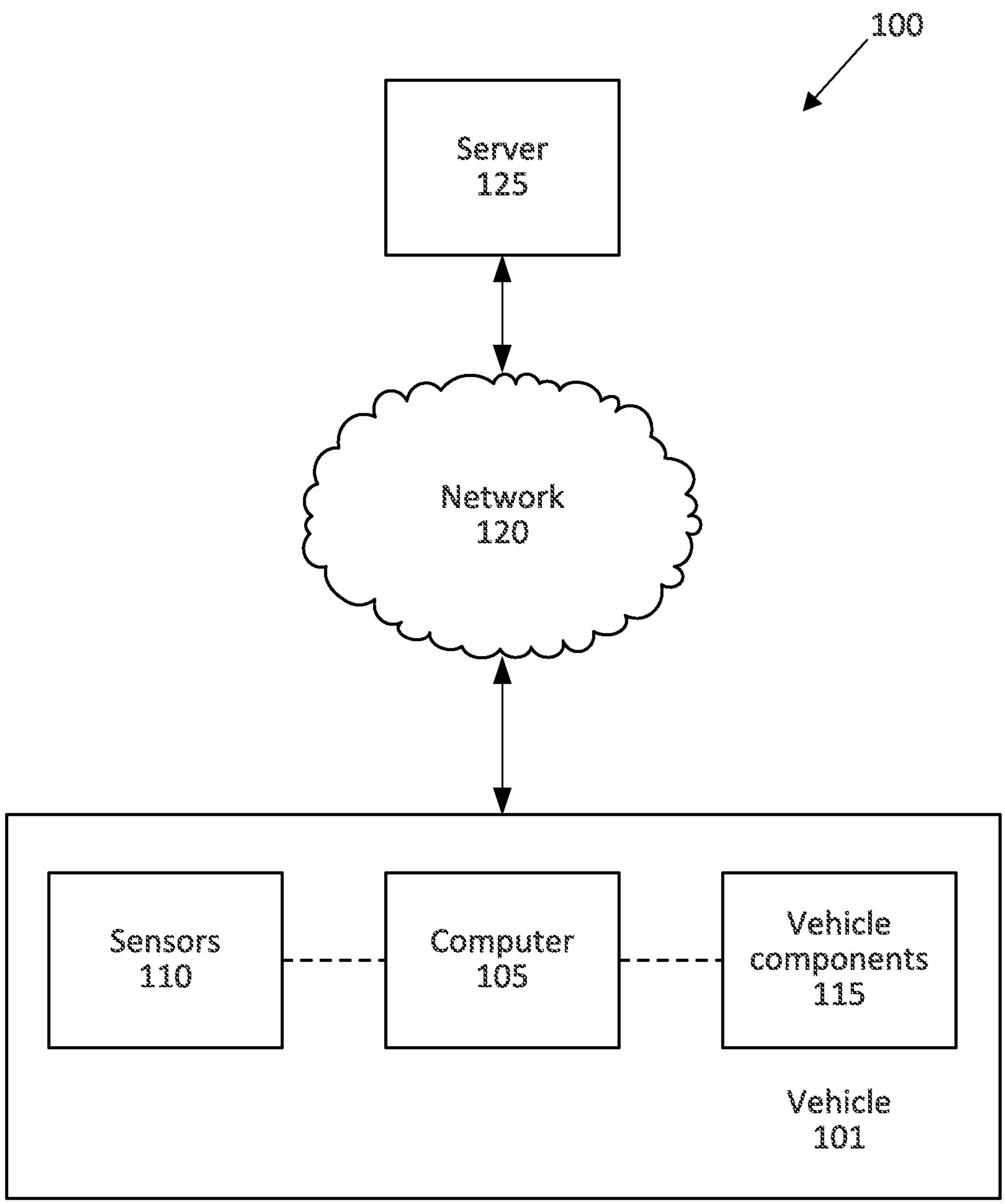

100
Server
125
Network
120
Sensors
110
Computer
105
Vehicle
components
115
Vehicle
101

FIG. 1

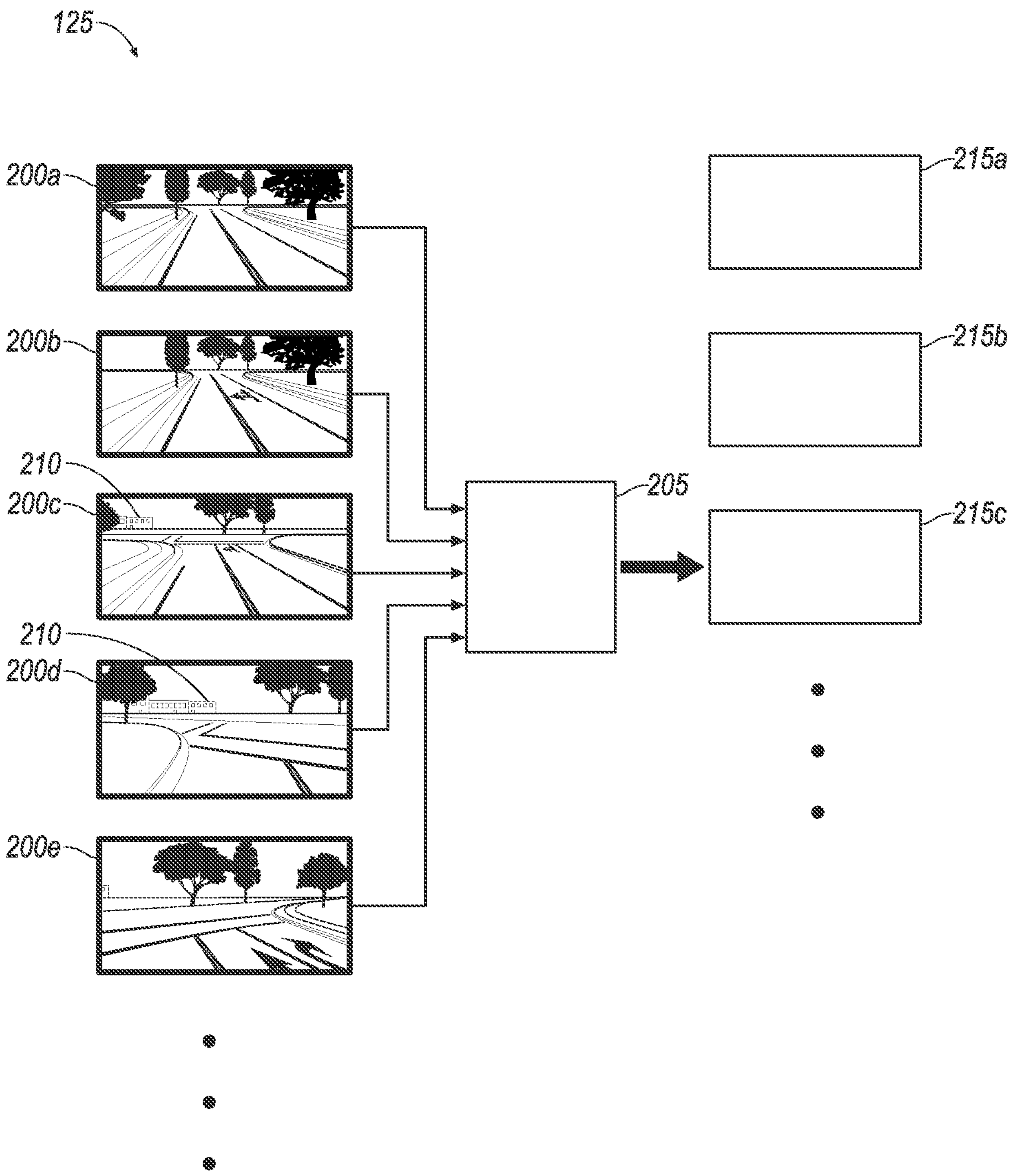


FIG. 2

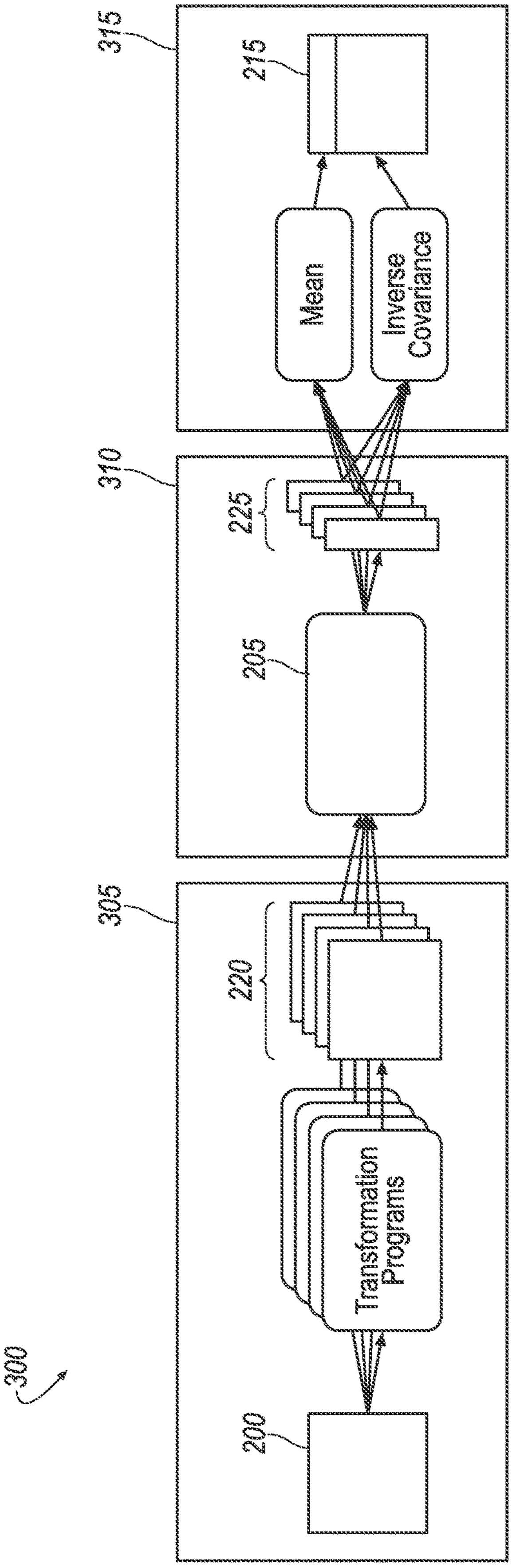

300
305
200
Transformation Programs
220
310
205
225
315
Mean
Inverse Covariance
215

FIG. 3

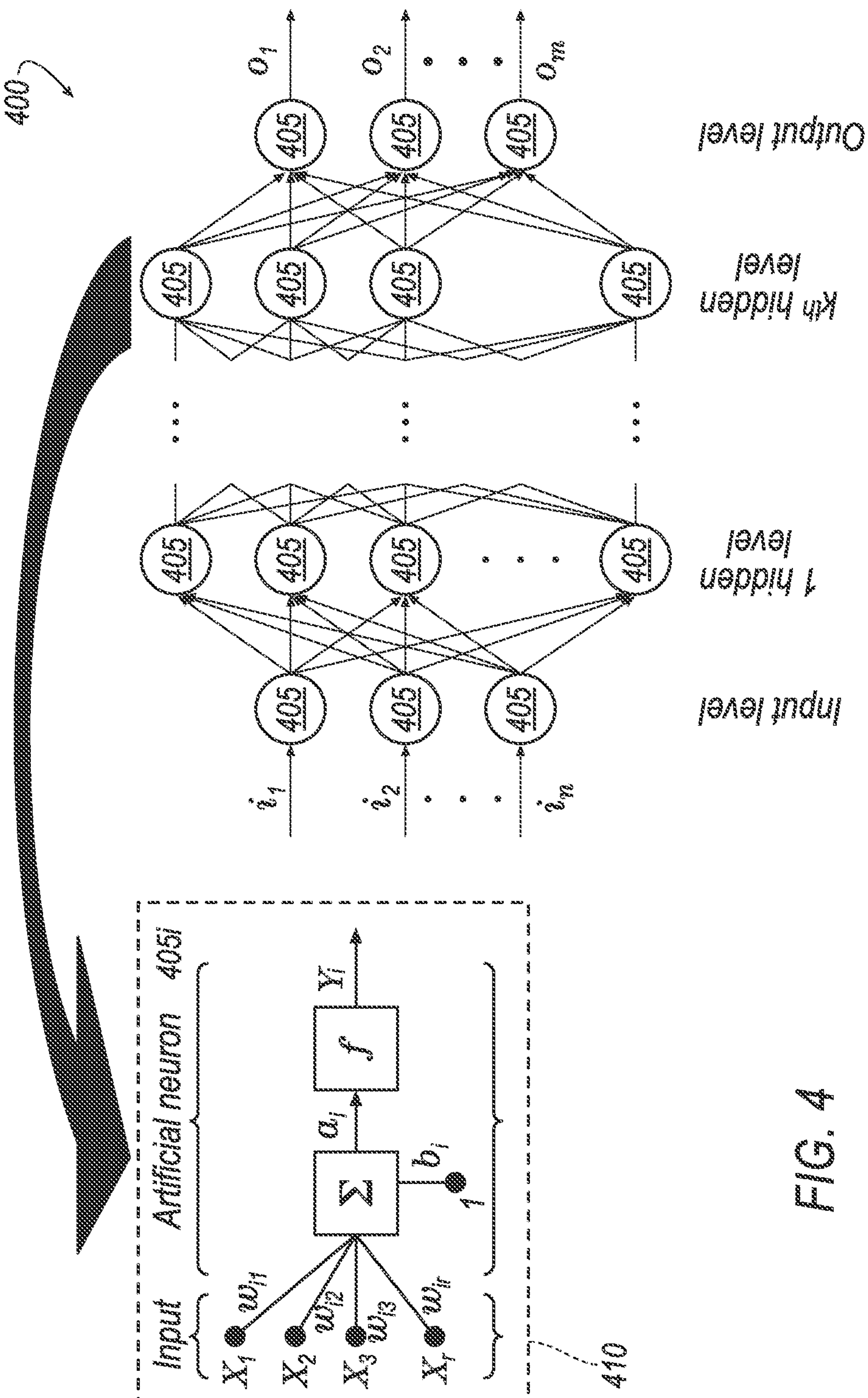

400
O_1
O_2
O_m
405
Output level
Kth hidden level
1 hidden level
Input level
i_1
i_2
i_n
Input
Artificial neuron
405i
X_1
X_2
X_3
X_r
w_{i1}
w_{i2}
w_{i3}
w_{ir}
Σ
a_i
b_i
1
f
Y_i
410

FIG. 4

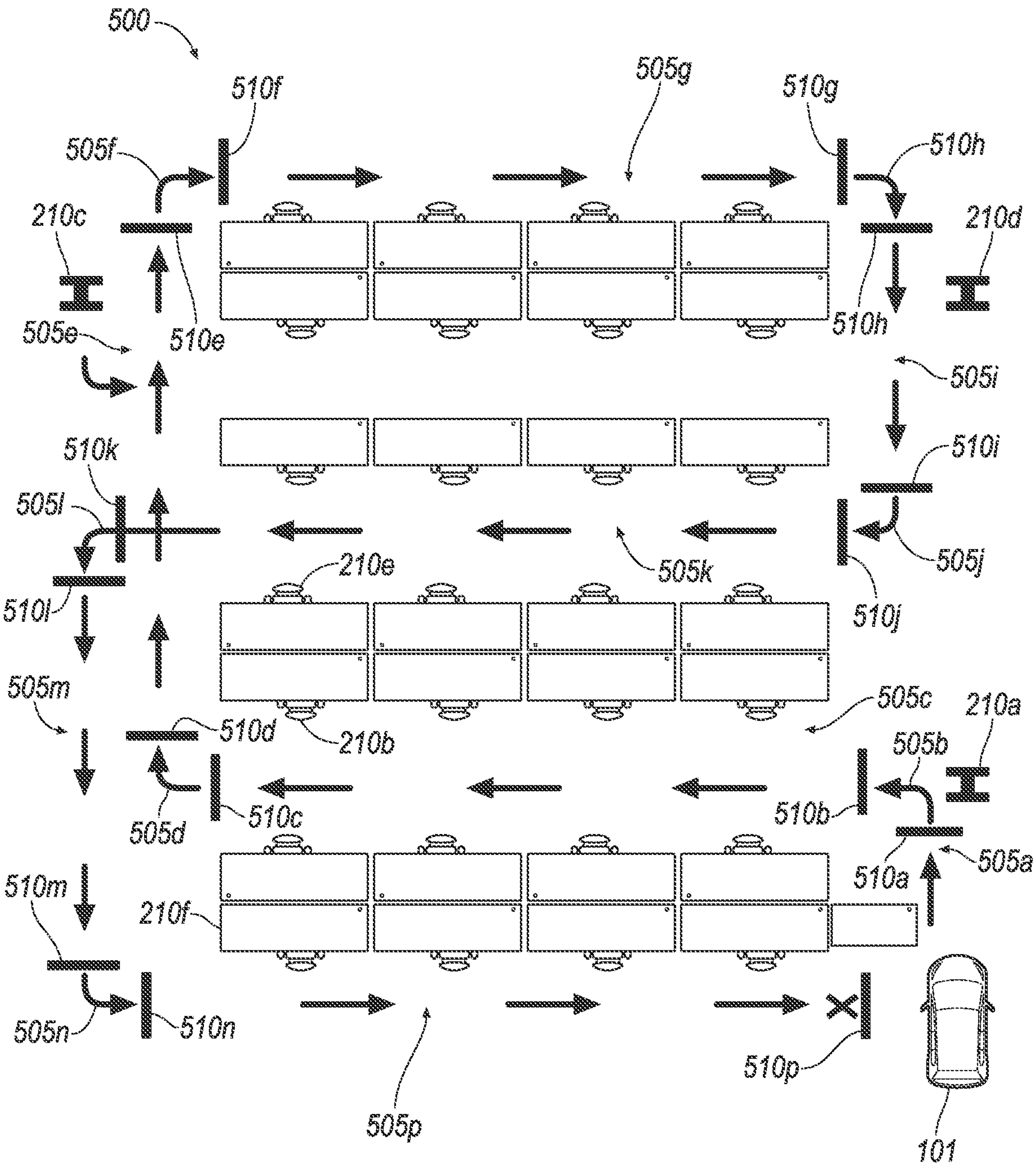

500
505g
510f
510g
505f
510h
210c
210d
510e
510h
505e
505i
510k
510i
505l
505j
505k
210e
510l
510j
505m
505c
210a
510d
505b
210b
510b
510c
505d
505a
510a
510m
210f
505n
510n
510p
505p
101

FIG. 5

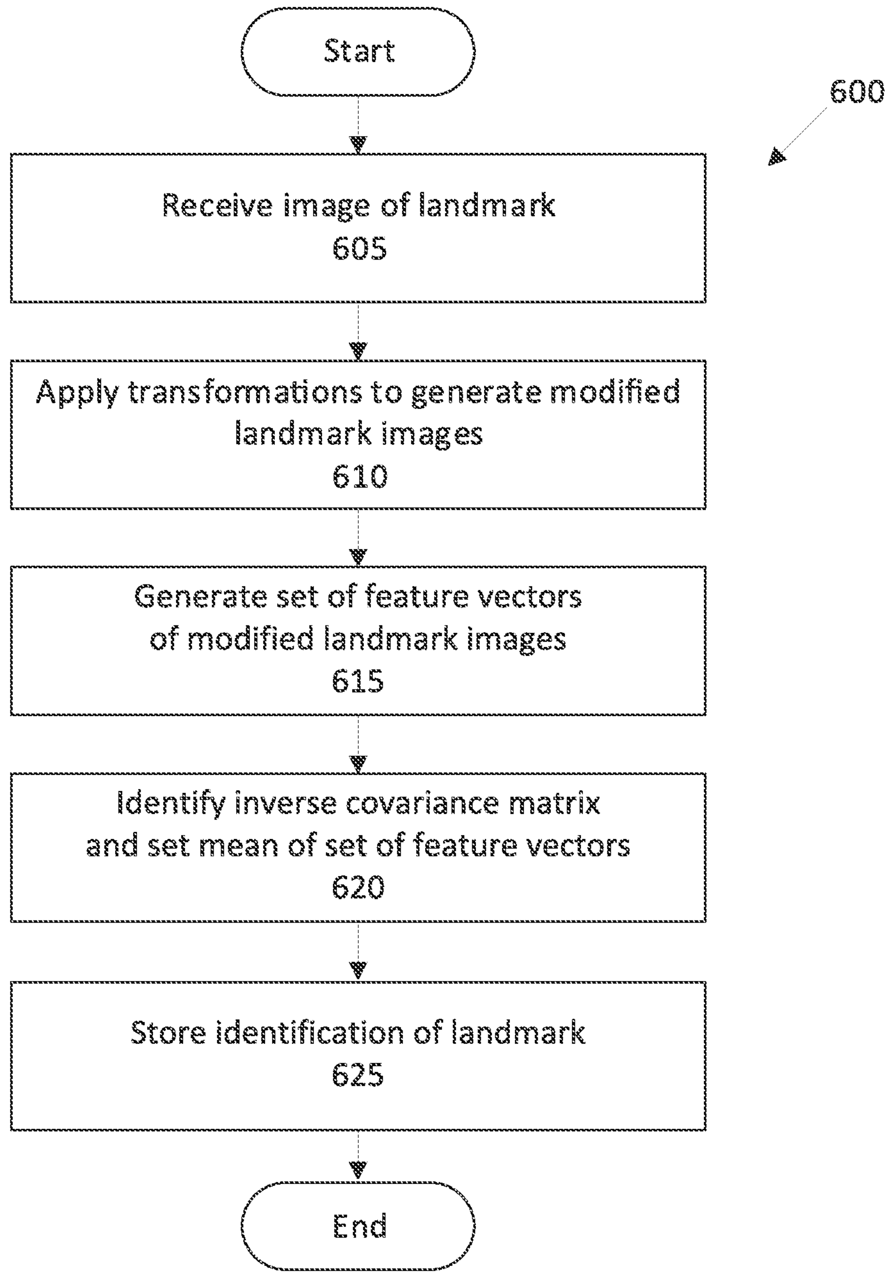
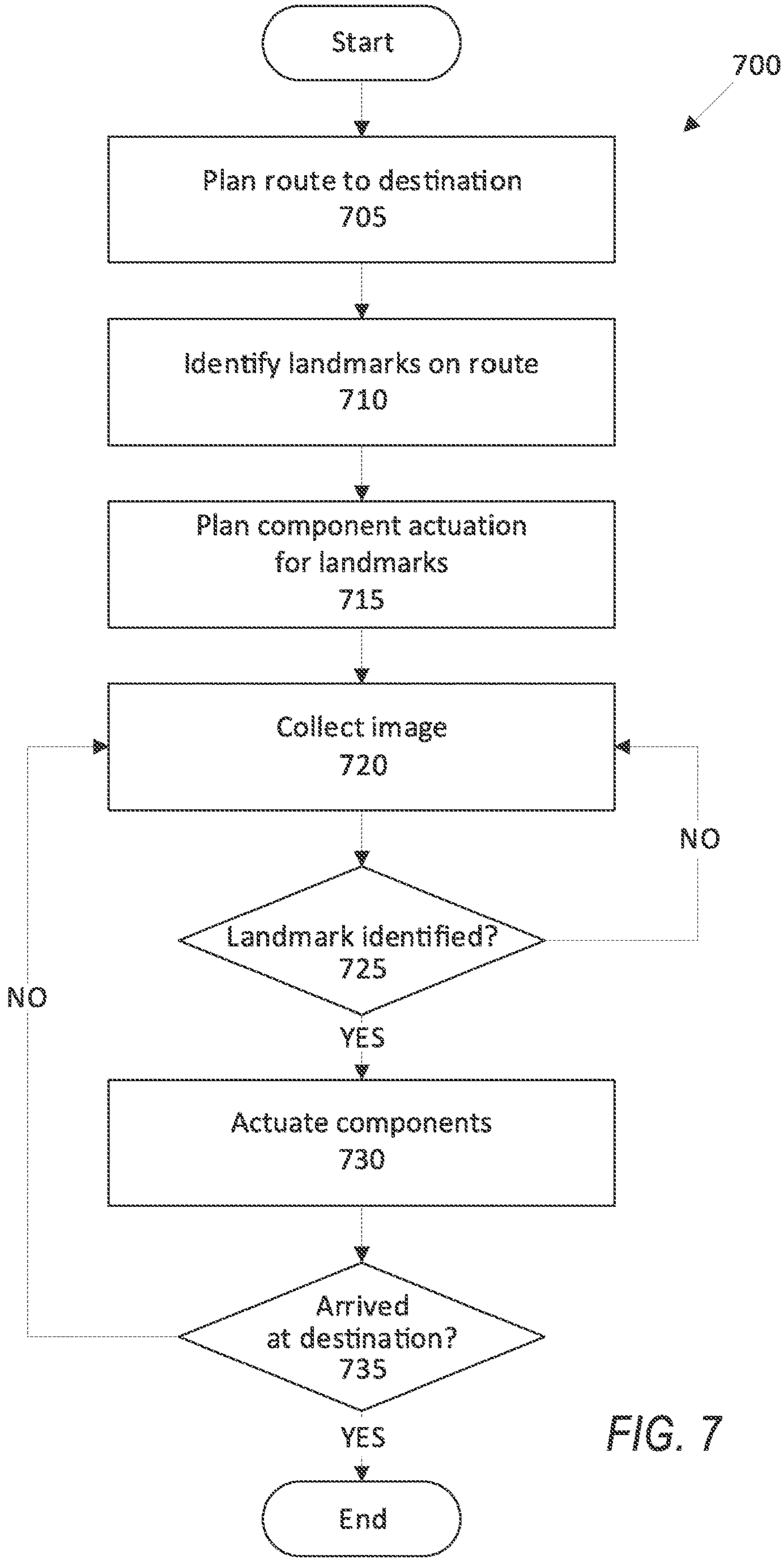

Start
600
Receive image of landmark
605
Apply transformations to generate modified landmark images
610
Generate set of feature vectors of modified landmark images
615
Identify inverse covariance matrix and set mean of set of feature vectors
620
Store identification of landmark
625
End

FIG. 6



Start
700
Plan route to destination
705
Identify landmarks on route
710
Plan component actuation for landmarks
715
Collect image
720
NO
Landmark identified?
725
YES
NO
Actuate components
730
Arrived at destination?
735
YES
End

FIG. 7

ENHANCED VEHICLE OPERATION

BACKGROUND

[0001] Vehicles can be equipped with computing devices, networks, sensors and controllers to acquire data regarding the vehicle's environment and to operate the vehicle based on the data. Vehicle sensors can provide data concerning routes to be traveled and objects to be avoided in the vehicle's environment. Operation of the vehicle can rely upon acquiring accurate and timely data regarding objects in a vehicle's environment while the vehicle is being operated on a roadway. Vehicles may use neural networks to identify objects from image data collected by the vehicle sensors.

BRIEF DESCRIPTION OF THE DRAWINGS

[0002] FIG. **1** is a diagram of an example system for operating a vehicle.

[0003] FIG. **2** is a diagram of an example server storing identified landmarks.

[0004] FIG. **3** is a diagram of an example process for identifying and storing the landmarks in the example server.

[0005] FIG. **4** is a diagram an example machine learning program.

[0006] FIG. **5** is a top-down view of the vehicle traveling along a route.

[0007] FIG. **6** is a diagram of an example process for identifying and storing the landmarks.

[0008] FIG. **7** is a diagram of an example process for identifying a landmark in a collected image.

DETAILED DESCRIPTION

[0009] A system includes a computer including a processor and a memory, the memory storing instructions executable by the processor to receive an image including a physical landmark, output a plurality of synthetic images, wherein each synthetic image is generated by simulating at least one ambient feature in the received image, generate respective feature vectors for each of the plurality of synthetic images, and actuate one or more vehicle components upon identifying the physical landmark in a second received image based on a similarity measure between the feature vectors of the synthetic images and a feature vector of the second received image, the similarity measure being one of a probability distribution difference or a statistical distance.

[0010] The instructions can further include instructions to generate a route for a vehicle, to identify one or more physical landmarks along the route, and to plan actuation of the one or more vehicle components based on the identified one or more physical landmarks.

[0011] The instructions can further include instructions to, while the vehicle is traveling along the route, collect the second received image with a camera, to identify the physical landmark in the second received image, and to actuate the one or more vehicle components based on the planned actuation based on the identified one or more physical landmarks.

[0012] The instructions can further include instructions to assign a maneuver to each identified physical landmark on the route, the maneuver being one of a left turn, a right turn, or a straight path.

[0013] The instructions can further include instructions to identify a plurality of feature vectors associated with the physical landmark, and to identify the similarity measure of the feature vectors.

[0014] The instructions can further include instructions to identify the physical landmark when the similarity measure of a first plurality of the feature vectors is above a threshold and to identify a second physical landmark based when the similarity measure of a second plurality of the feature vectors is above the threshold.

[0015] The instructions can further include instructions to identify a similarity measure between a mean feature vector of the synthetic images and feature vectors of a plurality of received images and to identify the physical landmark when the similarity measure is above a threshold.

[0016] The statistical distance can be a Mahalanobis distance.

[0017] The probability distribution difference can be a KL divergence.

[0018] The ambient feature can be one of an insolation, precipitation, cloudiness, an amount of traffic, or a change in viewing angle.

[0019] The instructions can further include instructions to generate a covariance matrix of the feature vectors of the plurality of synthetic images, to generate an inverse covariance matrix that is a matrix inverse of the covariance matrix, and to determine the similarity measure based on at least one of the covariance matrix or the inverse covariance matrix.

[0020] The instructions can instructions further include instructions to generate the feature vectors of the plurality of synthetic images with a machine learning program.

[0021] A method includes receiving an image including a physical landmark, outputting a plurality of synthetic images, wherein each synthetic image is generated by simulating at least one ambient feature in the received image, generating respective feature vectors for each of the plurality of synthetic images, and actuating one or more vehicle components upon identifying the physical landmark in a second received image based on a similarity measure between the feature vectors of the synthetic images and a feature vector of the second received image, the similarity measure being one of a probability distribution difference or a statistical distance

[0022] The method can further include generating a route for a vehicle, identifying one or more physical landmarks along the route, and planning actuation of the one or more vehicle components based on the identified one or more physical landmarks.

[0023] The method can further include, while the vehicle is traveling along the route, collecting the second received image with a camera, identifying the physical landmark in the second received image, and actuating the one or more vehicle components based on the planned actuation based on the identified one or more physical landmarks.

[0024] The method can further include assigning a maneuver to each identified physical landmark on the route, the maneuver being one of a left turn, a right turn, or a straight path.

[0025] The method can further include identifying a plurality of feature vectors associated with the physical landmark and identifying the similarity measure of the feature vectors.

[0026] The method can further include identifying the physical landmark when the similarity measure of a first plurality of the feature vectors is above a threshold and identifying a second physical landmark based when the similarity measure of a second plurality of the feature vectors is above the threshold.

[0027] The method can further include identifying a similarity measure between a mean feature vector of the synthetic images and feature vectors of a plurality of received images and identifying the physical landmark when the similarity measure is above a threshold.

[0028] The method can further include generating a covariance matrix of the feature vectors of the plurality of synthetic images, generating an inverse covariance matrix that is a matrix inverse of the covariance matrix, and determining the similarity measure based on at least one of the covariance matrix or the inverse covariance matrix.

[0029] The method can further include generating the feature vectors of the plurality of synthetic images with a machine learning program.

[0030] Further disclosed is a computing device programmed to execute any of the above method steps. Yet further disclosed is a vehicle comprising the computing device. Yet further disclosed is a computer program product, comprising a computer readable medium storing instructions executable by a computer processor, to execute any of the above method steps.

[0031] A vehicle can actuate a sensor to collect images while vehicle is traveling along a route. Physical landmarks can be identified along the route prior to embarking on the route. By identifying a physical landmark in the images along the route, a vehicle computer can determine a location of the vehicle along the route without geo-coordinate data from an external server. That is, the vehicle computer can assign actuation of specific vehicle components to the portion of the route at which the landmark is located, and upon identifying the landmark, the vehicle computer can perform the assigned actuation. Thus, the vehicle computer can navigate the vehicle along the route without additional geo-coordinate data by actuating components according to identified landmarks along the route.

[0032] A machine learning program, e.g., a neural network, can be trained to identify the landmark. The machine learning program can be trained to generate data identifying the landmark for a memory allocation of an external server. The machine learning program can generate a reference feature vector from reference images that identify the landmark. Upon collecting an image along the route, the vehicle computer can input the image to the machine learning program and compare the output feature vector to the reference feature vector collected in advance in a memory. Based on a similarity measure, such as a statistical distance or a probability distribution difference, between the output feature vector and the reference feature vector, the vehicle computer can identify the landmark.

[0033] FIG. **1** illustrates an example system **100** for operating a vehicle **101**. A computer **105** in the vehicle **101** is programmed to receive collected data from one or more sensors **110**. For example, vehicle **101** data may include a location of the vehicle **101**, data about an environment around a vehicle, data about an object outside the vehicle such as another vehicle, etc. A vehicle **101** location is typically provided in a conventional form, e.g., geo-coordinates such as latitude and longitude coordinates obtained via a navigation system that uses the Global Positioning System (GPS). Further examples of data can include measurements of vehicle **101** systems and components, e.g., a vehicle **101** velocity, a vehicle **101** trajectory, etc.

[0034] The computer **105** is generally programmed for communications on a vehicle **101** network, e.g., including a conventional vehicle **101** communications bus such as a CAN bus, LIN bus, etc., and or other wired and/or wireless technologies, e.g., Ethernet, WIFI, etc. Via the network, bus, and/or other wired or wireless mechanisms (e.g., a wired or wireless local area network in the vehicle **101**), the computer **105** may transmit messages to various devices in a vehicle **101** and/or receive messages from the various devices, e.g., controllers, actuators, sensors, etc., including sensors **110**. Alternatively or additionally, in cases where the computer **105** actually comprises multiple devices, the vehicle network may be used for communications between devices represented as the computer **105** in this disclosure. For example, the computer **105** can be a generic computer with a processor and memory as described above and/or may include a dedicated electronic circuit including an ASIC that is manufactured for a particular operation, e.g., an ASIC for processing sensor data and/or communicating the sensor data. In another example, computer **105** may include an FPGA (Field-Programmable Gate Array) which is an integrated circuit manufactured to be configurable by a user. Typically, a hardware description language such as VHDL (Very High Speed Integrated Circuit Hardware Description Language) is used in electronic design automation to describe digital and mixed-signal systems such as FPGA and ASIC. For example, an ASIC is manufactured based on VHDL programming provided pre-manufacturing, whereas logical components inside an FPGA may be configured based on VHDL programming, e.g. stored in a memory electrically connected to the FPGA circuit. In some examples, a combination of processor(s), ASIC(s), and/or FPGA circuits may be included in computer **105**.

[0035] In addition, the computer **105** may be programmed for communicating with the network **120**, which, as described below, may include various wired and/or wireless networking technologies, e.g., cellular, Bluetooth®, Bluetooth® Low Energy (BLE), wired and/or wireless packet networks, etc.

[0036] The memory can be of any type, e.g., hard disk drives, solid state drives, servers, or any volatile or non-volatile media. The memory can store the collected data sent from the sensors **110**. The memory can be a separate device from the computer **105**, and the computer **105** can retrieve information stored by the memory via a network in the vehicle **101**, e.g., over a CAN bus, a wireless network, etc. Alternatively or additionally, the memory can be part of the computer **105**, e.g., as a memory of the computer **105**.

[0037] Sensors **110** can include a variety of devices. For example, various controllers in a vehicle **101** may operate as sensors **110** to provide data via the vehicle **101** network or bus, e.g., data relating to vehicle speed, acceleration, location, subsystem and/or component status, etc. Further, other sensors **110** could include cameras, motion detectors, etc., i.e., sensors **110** to provide data for evaluating a position of a component, evaluating a slope of a roadway, etc. The sensors **110** could, without limitation, also include short range radar, long range radar, LIDAR, and/or ultrasonic transducers.

[0038] Collected data can include a variety of data collected in a vehicle **101**. Examples of collected data are provided above, and moreover, data are generally collected using one or more sensors **110**, and may additionally include data calculated therefrom in the computer **105**, and/or at the server **125**. In general, collected data may include any data that may be gathered by the sensors **110** and/or computed from such data.

[0039] The vehicle **101** can include a plurality of vehicle components **115**. In this context, each vehicle component **115** includes one or more hardware components adapted to perform a mechanical function or operation—such as moving the vehicle **101**, slowing or stopping the vehicle **101**, steering the vehicle **101**, etc. Non-limiting examples of components **115** include a propulsion component (that includes, e.g., an internal combustion engine and/or an electric motor, etc.), a transmission component, a steering component (e.g., that may include one or more of a steering wheel, a steering rack, etc.), a brake component, a park assist component, an adaptive cruise control component, an adaptive steering component, a movable seat, and the like. Components **115** can include computing devices, e.g., electronic control units (ECUs) or the like and/or computing devices such as described above with respect to the computer **105**, and that likewise communicate via a vehicle **101** network.

[0040] For purposes of this disclosure, the term "autonomous vehicle" refers to a vehicle **101** operating in a fully autonomous mode. A fully autonomous mode is defined as one in which each of vehicle **101** propulsion (typically via a powertrain including an electric motor and/or internal combustion engine), braking, and steering are controlled by the computer **105**. A semi-autonomous mode is one in which at least one of vehicle **101** propulsion (typically via a powertrain including an electric motor and/or internal combustion engine), braking, and steering are controlled at least partly by the computer **105** as opposed to a human operator. In a non-autonomous mode, i.e., a manual mode, the vehicle **101** propulsion, braking, and steering are controlled by the human operator.

[0041] The system **100** can further include a network **120** connected to a server **125**. The computer **105** can further be programmed to communicate with one or more remote sites such as the server **125**, via the network **120**, such remote site possibly including a processor and a memory. The network **120** represents one or more mechanisms by which a vehicle computer **105** may communicate with a remote server **125**. Accordingly, the network **120** can be one or more of various wired or wireless communication mechanisms, including any desired combination of wired (e.g., cable and fiber) and/or wireless (e.g., cellular, wireless, satellite, microwave, and radio frequency) communication mechanisms and any desired network topology (or topologies when multiple communication mechanisms are utilized). Exemplary communication networks include wireless communication networks (e.g., using Bluetooth®, Bluetooth® Low Energy (BLE), IEEE 802.11, vehicle-to-vehicle (V2V) such as Dedicated Short Range Communications (DSRC), etc.), local area networks (LAN) and/or wide area networks (WAN), including the Internet, providing data communication services.

[0042] FIG. **2** is a diagram of images **200** input to a machine learning program **205** to generate stored landmarks **210** for a plurality of roadways. FIG. **2** shows five images, **200***a*, **200***b*, **200***c*, **200***d*, and **200***e*, collectively, "images **200**." The images **200** include one or more landmarks **210**. In this context, a "landmark" is a physical object on or near a roadway. The landmark can be, e.g., an infrastructure element such as a bridge or a utility pole, a building, a work of public art, etc. FIG. **2** shows one landmark **210** in the images **200***c*, **200***d*. By identifying the landmarks **210**, the computer **105** can actuate one or more components **115** of the vehicle **101** to follow a route, as described below.

[0043] The server **125** can input the images to the machine learning program **205**. The machine learning program **205** can be a deep neural network (DNN), described below and best shown in FIG. **4**. Alternatively, the machine learning program **205** can be, e.g., a convolutional neural network (CNN), a gradient boosted tree algorithm, etc. Using a machine learning program **205** allows the computer **105** of the vehicle **101** to identify the landmarks **210** without conventional image processing techniques (such as Canny edge detection) and/or without collecting geo-location data while the vehicle **101** is moving along a route. That is, the computer **105** can use the machine learning program **205** to identify the landmarks **210** with less computing resources than conventional image processing techniques and can identify the landmarks **210** when geo-location data is not available.

[0044] The server **125** can store landmarks **210** to be identified by a computer **105** of a vehicle **101**. Inputting the images **200** for a specified location, e.g., an intersection, to the machine learning program **205** to identify the landmarks **210** at the location. The server **125** can assign each location to a specific memory allocation **215**. A "memory allocation" in the present context is an amount of hard drive space of the server **125** assigned to store data describing a specific landmark **210** and a location (e.g., a memory address) from which the server **125** can locate the data describing the specific landmark **210**. FIG. **2** shows three memory allocations **215***a*, **215***b*, **215***c*, collectively, memory allocations **215**. The server **125** can include a specified memory allocation **215** for each identified landmark **210**. The server **125** can transmit data from the memory allocation **215** over the network **120** to the computer **105** of the vehicle **101**. Alternatively or additionally, the computer **105** can identify the landmarks **210** and store the data in a memory allocation **215** of a memory of the computer **105**.

[0045] FIG. **3** is a diagram of an example process **300** for generating a memory allocation **215** storing an identification of a landmark **210**. The process **300** begins in a block **305**, in which a reference image **200** is input into a plurality of transformation programs, each transformation program generating a synthetic image **220** that is the reference image **200** with an ambient feature incorporated. An "ambient feature" is a modification to an image **200** to include a specific environmental attribute (e.g., increased lighting, decreased lighting, increased contrast, decreased contrast, precipitation, cloudiness, insolation, plant color, season, etc.) and/or to change a view of objects in the image **200** (e.g., decreasing a size of an object, changing an angle of view of the object, increasing the size of the object, etc.) and/or other objects in the image **200** (e.g., an amount of traffic). That is, the ambient features can provide environmental and scenario variations to the reference image **200** that may not have been collected by camera collecting the reference image **200**. Incorporating ambient features to the reference image **200** allows synthetic images **220** to show scenarios and environmental effects that can be difficult to collect because of occlusion by precipitation or because the desired environmental feature does not occur during collection of the reference image **200**. For example, the reference image **200** may have been collected during daylight in spring, when collecting images **200** is easier than collecting images at night in winter, which may occlude objects from the camera collecting the reference image **200**. A "transformation program" is an algorithm, e.g., implemented in the server **125** and/or the computer **105**, that generates a synthetic image **200** by inserting the ambient feature into a copy of the reference image **200**. The transformation programs can be, e.g., unsupervised image-to-image translation algorithms, image processing algorithms that adjust color values of pixels in the reference image **200**, variational autoencoder algorithms, generative adversarial networks, etc.

[0046] The transformation program include a generative adversarial network (GAN). Image data output from a photorealistic rendering software program can be input to a GAN to generate images in the data set of training images corresponding to underrepresented noise characteristics. A GAN is a neural network that includes a generative network that modifies input images and a discriminator network that is trained to determine whether a modified image is similar to a real image. Image similarity can be determined by comparing images using image subtraction, where a first image is subtracted from a second image and the absolute or squared differences between the two images are summed. Small absolute or squared differences (<1% of total summed pixel values) indicate similar images. Image similarity can also be determined based on correlation techniques that correlate regions of a first image with regions of a second image. High correlation (>90%) between the two images indicate similar images. The GAN is trained to modify input synthetic images realistically enough to be determined as "real" by the discriminator network. A generative adversarial network can be trained to modify an input image to simulate the effects of different noise characteristics. For example, a GAN can be trained to modify a synthetic image of a trailer rendered in full sunlight to appear as if it was raining when the photorealistic image was generated. The GAN can be trained to produce output images with a specified level of noise. For example, a GAN can produce an output image with an ambient feature such as low, medium, or high amounts of rainfall.

[0047] The transformation program can include a variable autoencoder (VAE). A VAE includes a policy optimization network to generate a reconstructed policy from a vehicle state by combining a latent reward function based on a prior experience expert policy, and an adversarial discriminator network to discriminate the reconstructed policy and expert policy. VAEs solve the problem of underdetermined equations by generating a plurality of reconstructed policies distributed over the solution space of reconstructed policies and determining which reconstructed policies of the plurality of reconstructed policies match expert policies. Techniques described herein use an adversarial process including a discriminator network to determine if a policy generated by an encoder neural network is an expert policy. Using an adversarial process, a transformation program can be trained to generate reconstructed policies that are generally indistinguishable from expert policies.

[0048] A VAE/GAN transformation program can generate synthetic images **220** from the reference image **200** by encoding the reference image **200** with the VAE to incorporate an ambient feature and using a discriminator from the GAN to output the synthetic image **220** with the ambient feature incorporated. Using a VAE/GAN hybrid program to generate the synthetic image **220** can reduce blurriness in the synthetic images **220** compared to synthetic images **220** generated from a VAE or a GAN alone. That is, VAEs can be easy to train, but output from the VAE can be blurry compared to a reference image. A GAN can output synthetic images **220** much closer to the reference image **200** than VAEs, but GANs can be difficult to train. Using a VAE to generate an intermediate image and a GAN to reduce the blurriness of the intermediate image can output a synthetic image **220** that is less blurry than output from either the VAE or the GAN alone.

[0049] Next, in a block **310**, the server **125** and/or the computer **105** inputs the synthetic images **220** to a machine learning program **205** to train the machine learning program **205**. As described further below, the synthetic images **220** can include annotations of landmarks **210**, and the machine learning program **205** can learn the identification of the landmarks **210** from the annotations. The machine learning program **205** can output a plurality of feature vectors **225** of the synthetic images **220**. A "feature vector" is a 1-dimensional array of values that encode information from the 2-dimensional synthetic image **220**. Each value of the feature vector **225** identifies a characteristic of a pixel or a group of neighboring pixels of the synthetic image **220**, e.g., an intensity, an RGB value, a gradient magnitude, an indicator that the pixel is or is not at an edge of an object, etc. Each value may quantify a characteristic of the synthetic image **220**, e.g., the existence and intensity of objects with circular shape, objects with sharp edges, etc.

[0050] Next, in a block **315**, the server **125** and/or the computer **105** identifies a mean feature vector **225** and an inverse covariance matrix of the feature vectors **225**. The server **125** and/or the computer **105** can store the set mean and the inverse covariance matrix of the identified landmark **210** in the memory allocation **215**.

[0051] Upon generating the memory allocations **215** for the landmarks **210**, the computer **105** can identify a landmark **210** in an input image **200** by determining a similarity measure between the input image **200** and the landmark **210**. In this context, a "similarity measure" is a measure of a difference between two feature vectors **225** in a set of a plurality of feature vectors **225**. One example of a similarity measure is a statistical distance, e.g., a Mahalanobis distance. A "statistical distance" is a distance between two points relative to an overall mean of a plurality of data points. In this context, the statistical distance is a value that represents how values of a given feature vector **225** differ from a mean feature vector **225**, i.e., an arithmetic mean of the plurality of feature vectors **225**. The server **125** and/or the computer **105** can identify the statistical distance between feature vectors **225** of the synthetic images **220** and/or the images **200**.

[0052] For example, the statistical distance can be a Mahalanobis distance d:

$$d(\vec{x})=\sqrt{(\vec{x}-\vec{y})^T S^{-1}(\vec{x}-\vec{y})} \quad (1)$$

where a first vector $\vec{x}=[x_1, x_2 \ldots x_n]^T$, each x_i, $i\in[1, n]$ being one of a first set of n feature vectors **225** in a first set of images **200**, **220**, e.g., the images **200**, **220** used to generate the memory allocation **215** described above. A second vector $\vec{y}=[y_1, y_2 \ldots y_n]^T$, each y_i, $i \in [1, n]$ being one of a second set of n feature vectors **225** in a second set of images **200**, **220**, e.g., collected by a sensor **110** of the vehicle **101**. S^{-1} is an inverse covariance matrix, as described below, and T is a matrix transposition function. S is a covariance matrix, i.e., a matrix in which each element S(i,j) ($i,j \in [1, n]$) is the covariance of values x_i and y_j. That is, the covariance of two variables a, b having average values $\bar{a}$, $\bar{b}$ is $\text{cov}(a, b)=E[(a-\bar{a})(b-\bar{b})]=\sigma_{ab}^2$, where E is the conventional expected value function that outputs an expected value, i.e., probability-weighted sums of a variable a provided states b, and σ_{ab} is the standard deviation of a, b. The inverse covariance matrix S^{-1} is the mathematical inverse of the covariance matrix S. Thus, the server **125** can determine the Mahalanobis distance d between each feature vector **225** in the first set of images **200**, **220** and each feature vector **225** in the second set of images **200**, **220**.

[0053] Using the Mahalanobis distance d, the computer **105** can determine whether a feature vector **225** of an input image **200** includes a landmark **210**. The computer **105** can collect a plurality of images **200** with a camera **110** while the vehicle **101** is traveling on a roadway. The computer **105** can generate a plurality of synthetic images **220** by applying the transformation programs described above to the collected images **220** and can determine a mean feature vector **225** of the images **200**, **220**. The computer **105** can determine the Mahalanobis distance d between the mean feature vector **225** of the images **200**, **220** and the inverse covariance matrix S^{-1} of the landmark **210** stored in the memory allocation **215**. That is, in Equation 1 above, the feature vectors **225** of the images **200**, **220** can be the first vector $\vec{x}$, the mean feature vector **225** from the memory allocation **215** can be the second vector $\vec{y}$, and the computer **105** can determine the Mahalanobis distance with the inverse covariance matrix S^{-1} in the memory allocation **215**. Determining the Mahalanobis distance of the mean feature vector **225** of images **200**, **220** with the inverse covariance matrix S^{-1} in the memory allocation is a "forward" Mahalanobis distance d_f. The computer **105** can determine a "reverse" Mahalanobis distance d_r between the mean feature vector **225** of the landmark **210** stored in the memory allocation **215** and an inverse covariance matrix S_0^{-1}, the covariance matrix S_0 being the matrix in which each element is the covariance of the images **200**, **220** generated from the collected images **200**. With the forward and reverse Mahalanobis distances d_f, d_r, the computer **105** can identify the landmark **210** in the collected images **200**, as described below.

[0054] Using the Mahalanobis distance to identify the landmark **210** can provide a more accurate identification of the landmark **210** than a Euclidian distance (i.e., a straight line distance) because the Mahalanobis distance accounts for the covariance and/or correlation between the feature vector **225** of the input image **200** and the feature vectors **225** used to generate the mean feature vector **225** and the inverse covariance matrix S^{-1}. That is, A Euclidian distance between two feature vectors **225** may provide a false positive identification of the landmark **210** because the feature vectors **225** can be close in Euclidian distance but are not part of the same landmark **210**. The Mahalanobis distance is greater than the Euclidian distance for two feature vectors **225** of different landmarks **210** because those feature vectors **225** would be farther from their respective mean feature vectors **225** than each other, further normalized by the expected variances of the features. Thus, the Mahalanobis distance between feature vectors **225** of an input image **200** and the feature vectors **225** used to generate the mean feature vector **225** and inverse covariance matrix S^{-1} of the memory allocation can better identify landmarks **210** than the Euclidian distance between those feature vectors **225**.

[0055] Another example of a similarity measure is a probability distribution difference. A "probability distribution difference" is a measure of how a first probability distribution differs from a second probability distribution. The probability distribution difference can be a Kullback-Leibler (KL) divergence D_{KL} of a first set P of n feature vectors **225** and a second set Q of n feature vectors **225**, assuming Gaussian distributions:

$$D_{KL}(P\|Q) = \frac{1}{2}tr(S_1^{-1}S_0) + n + \ln\left(\frac{\det(S_1)}{\det(S_0)}\right) \quad (2)$$

where tr( ) is the trace function that sums the diagonal elements of a square matrix, det( ) is the determinant of a matrix, S_0 is the covariance matrix of one or more images **200** collected by a sensor **110** of the vehicle **101**, S_1 is the covariance matrix of the memory **215** of the landmark **210**, and n is the length of the feature vectors **225** used to determine the covariance matrix S_1.

[0056] In calculation of the KL divergence the probability distributions of the sets P, Q are assumed to be Gaussian and zero-mean. That is, the values of the feature vectors in the sets P, Q are assumed to be distributed in a conventional Gaussian distribution and are shifted to have a mean value of zero. Two Gaussian, zero-mean distributions differ based only on their covariance matrix S, so the KL divergence simplifies to the Equation listed above. This simplified equation can be applied more quickly by the computer **105** than a conventional KL divergence algorithm that can require additional calculations for specific probability density functions in a specified probability space. The distances rooted in the mean shift are captured via the Mahalanobis distances.

[0057] The first set P can be feature vectors **225** of a set of synthetic and real images **200**, **220** without annotations of a landmark **210**, and the set Q can be feature vectors **225** of a set of synthetic and real images **220** with annotations of a landmark **210**. Thus, the KL divergence between P and Q characterizes the difference between the probability distribution of the feature vectors **225** of the images **220** that may include the landmark **210** and the feature vectors **225** of the images **200**, **220** annotated with the landmark **210** associated with the memory allocation **215**. When the KL divergence is below a difference threshold, the computer **105** can identify the landmark **210** in the feature vectors **225** of the synthetic images **220** without the annotations. The difference threshold can be a predetermined value based on inputting a plurality of test images **200** with landmarks **210** and identifying a maximum KL divergence at which the machine learning program **205** correctly identifies the landmark **210**.

[0058] The computer **105** can input the KL divergence D_{KL} and the Mahalanobis distances d_f, d_r into a fully connected neural network to identify a landmark **210** in an input image **200**. In a "fully connected" neural network, each neuron of a given layer is connected to each of the neurons in a subsequent layer. That is, the machine learning program

205 can include one or more fully connected layers to determine a probability that the collected images **200** include the landmark **210**. That is, the output of the fully connected layers is a number between 0 and 1, where 0 indicates that images **200** do not include the landmark **210** and 1 indicates that the images **200** include the landmark **210**, and values between 0 and 1 indicate a mathematical probability that the images **200** include the landmark **210**. When the output of the fully connected layers is above a probability threshold, the computer **105** identifies the landmark **210** in the images **200**, **220**. The probability threshold is a value determined based on empirical testing of vehicles **101** collecting images **200** of predetermined landmarks **210** and comparing the output probability values to a visual inspection of the images **200**. The probability threshold can be a minimum output of the machine learning program above which the computer **105** correctly identifies the landmarks **210** in the images **200** and correctly identifies no landmarks **210** in images **200** without landmarks **210**. The probability threshold can be, e.g., 0.8. The fully connected layers can be trained with annotated images **200**, **220** and landmarks **210** in memory allocations **215**, as described below.

[0059] The computer **105** can collect a plurality of images **200** with a camera **110** while the vehicle **101** is traveling on a roadway. The computer **105** can generate a plurality of synthetic images **220** by applying one or more transformation programs to the collected images **200**. The computer **105** can identify a covariance matrix S_0 and a mean feature vector **225** of the images **200**, **220**. The computer **105** can identify a forward Mahalanobis distance d_f between the mean feature vector **225** of the images **200**, **220** and the feature vectors of each landmark **210** stored in the memory allocation **215** using an inverse covariance matrix S_1^{-1} of the feature vectors of each landmark **210**. The computer **105** can identify a reverse Mahalanobis distance d_r between the mean feature vector **225** of the feature vectors of each landmark **210** stored in the memory allocation **215** and the feature vectors of the collected images **200**, **220** using the inverse covariance matrix S_0^{-1} of the images **200**, **220**. The computer **105** can determine the KL divergence D_{KL} between the feature vector **225** of the image **200** for the respective inverse covariance matrix S_1^{-1} of each memory allocation **215**. The computer **105** can input the Mahalanobis distances d_f, d_r and the KL divergence for each landmark **210** to fully connected layers of a machine learning program that outputs a value between 0 and 1 indicating a probability that the images **200**, **220** include the respective landmark **210**. If the output from the fully connected layers is above a predetermined threshold, the computer **105** identifies the respective landmark **210** in the images **200**, **220**.

[0060] FIG. **4** is a diagram of an example machine learning program **400**. The machine learning program **400** can be a deep neural network (DNN) **400** that could be trained to identify a physical landmark **210** from an input image **200**. The DNN **400** can be a software program that can be loaded in memory and executed by a processor included in the infrastructure server **135**, for example. The DNN **400** can include n input nodes **405**, each accepting a set of inputs i (i.e., each set of inputs i can include one or more inputs X). The DNN **400** can include m output nodes (where m and n may be, but typically are not, a same natural number) provide sets of outputs $o_1 \ldots o_m$. The DNN **400** includes a plurality of layers, including a number k of hidden layers, each layer including one or more nodes **405**. The nodes **405** are sometimes referred to as artificial neurons **405**, because they are designed to emulate biological, e.g., human, neurons. The neuron block **410** illustrates inputs to and processing in an example artificial neuron **405*i***. A set of inputs $X_1 \ldots X_r$ to each neuron **405** are each multiplied by respective weights $w_{i1} \ldots w_{ir}$, the weighted inputs then being summed in input function Σ to provide, possibly adjusted by a bias b_i, net input a_i, which is then provided to activation function f, which in turn provides neuron **405*i*** output Y_i. The activation function f can be a variety of suitable functions, typically selected based on empirical analysis. As illustrated by the arrows in FIG. **4**, neuron **405** outputs can then be provided for inclusion in a set of inputs to one or more neurons **405** in a next layer.

[0061] The DNN **400** can be trained to accept as input data, e.g., synthetic images **220** from a plurality of transformation programs that input ambient features to a reference image **200**, and to output one or more parameters for identifying a landmark **210**. For example, the DNN **400** could be trained to output an identification of a building, an infrastructure element, etc.

[0062] That is, the DNN **400** can be trained with ground truth data, i.e., data about a real-world condition or state. Weights w can be initialized by using a Gaussian distribution, for example, and a bias b for each node **405** can be set to zero. Training the DNN **400** can including updating weights and biases via conventional techniques such as back-propagation with optimizations.

[0063] A set of weights w for a node **405** together are a weight vector for the node **405**. Weight vectors for respective nodes **405** in a same layer of the DNN **400** can be combined to form a weight matrix for the layer. Bias values b for respective nodes **405** in a same layer of the DNN **400** can be combined to form a bias vector for the layer. The weight matrix for each layer and bias vector for each layer can then be used in the trained DNN **400**.

[0064] In the present context, the ground truth data used to train the DNN **400** could include annotations identifying the landmarks **210** in the synthetic images **220**. For example, a sensor can collect a plurality of images **200** that can be annotated and then be labeled for training the DNN **400**, i.e., tags can be specified identifying the landmarks **210**, such as just described, in the images **200**. As described above, the images **200** can be input to a plurality of transformation programs to generate the synthetic images **220** while retaining the annotations of the landmarks **210**. The DNN **400** can then be trained to output data values that correlate to the landmarks **210**, and the output data values can be compared to the annotations to identify a difference, i.e., a cost function of the output data values and the input annotated images. The weights w and biases b can be adjusted to reduce the output of the cost function, i.e., to minimize the difference between the output data values and the input annotated images. When the cost function is minimized, the server **125** can determine that the DNN **400** is trained.

[0065] FIG. **5** is a view of an example vehicle **101** moving along a route **500**. A "route" **500** is a path from an origin to a destination that the vehicle **101** follows to reach the destination. The route **500** can be a path generated from a path planning algorithm, e.g., a path polynomial. The path planning algorithm is programming of the computer **105** that generates a path for the vehicle **101** as the vehicle **101** moves from an origin to a destination. The path planning algorithm can be stored in a memory of the computer **105**. The path planning algorithm can be, e.g., a navigational algorithm that generates location coordinates for the vehicle **101** over time. As an example, the path planning algorithm can determine the path with a path polynomial. The path polynomial p(x) is a model that predicts the path as a line traced by a polynomial equation. The path polynomial p(x) predicts the path for a predetermined upcoming distance x, by determining a lateral coordinate p, e.g., measured in meters:

$$p(x)=a_0+a_1x+a_2x^2+a_3x^3 \tag{3}$$

where a_0 an offset, i.e., a lateral distance between the path and a center line of the vehicle **101** at the upcoming distance x, a_1 is a heading angle of the path, a_2 is the curvature of the path, and a_3 is the curvature rate of the path. In the present context, the "upcoming distance" x is a predetermined longitudinal distance in front of the vehicle **101** from a front bumper of the vehicle **101** at which the sensors **110** collect data and the computer **105** predicts the path. The upcoming distance x can be determined based on, e.g., a current speed of the vehicle **101**, a predetermined time threshold, determined based on empirical simulation data, a detection range of the sensors **110**, etc. The time threshold can be, e.g., 1 second. The path polynomial can include one or more Bezier curves, i.e., polynomial functions that each represent a disjoint subset of points representing the path, and that taken together, represent the entire set of points representing the path. Bezier curves can be constrained to be continuously differentiable and have constraints or limits on the permitted derivatives, e.g. limits on the rates of change, with no discontinuities. Bezier curves can also be constrained to match derivatives with other Bezier curves at boundaries, providing smooth transitions between subsets. Constraints on Bezier curves can make a vehicle path polynomial a steerable path polynomial by limiting the rates of longitudinal and lateral accelerations required to pilot a vehicle along the vehicle path polynomial, where braking torque and powertrain torque are applied as positive and negative longitudinal accelerations and clockwise and counter clockwise steering torque are applied as left and right lateral accelerations. By determining lateral and longitudinal accelerations to achieve predetermined target values within predetermined constraints within predetermined numbers of time periods, the vehicle path polynomial can be constrained to provide a vehicle path polynomial can be operated upon by the computer **105** without exceeding limits on lateral and longitudinal accelerations.

[0066] The computer **105** can plan actuation of one or more components **115** based on the route **500**. That is, the computer **105** can actuate at least one of a propulsion, a steering, and/or a brake to move the vehicle **101** along the route **500**. The computer **105** can actuate the components **115** to, e.g., turn the vehicle **101** to the left, turn the vehicle **101** to the right, maintain forward motion, etc. The route **500** includes a plurality of portions **505***a*-**505***p* (collectively, portions **505**). The portions **505** are indicated by arrows between respective boundaries **510***a*-**510***p* (collectively, boundaries **510**), the arrows indicating the direction of the route **500** that the vehicle **101** follows. Each portion **505** can be assigned a single "maneuver," i.e., a trajectory defined by a path and respective velocities and/or accelerations at points on the path, that the vehicle **101** follows. The maneuver can start at one of the boundaries **510** and end at a successive boundary **510**. The maneuver can be, e.g., a left turn, a right turn, a straight path, etc. The computer **105** can actuate components **115** to perform the maneuver to follow the route **500**. For example, the maneuver assigned to the portion **505***a* can be a straight path to the boundary **510***a*.

[0067] The route **500** can pass by one or more landmarks **210***a*-**210***f* (collectively, landmarks **210**) as shown in FIG. **5**. As described above, the landmarks **210** can be physical structures, e.g., infrastructure elements, buildings, road signs, etc. In FIG. **5**, the landmarks **210** can be, e.g., portions of buildings, road signs, public works of art, portions of infrastructure elements, etc. For example, the landmark **210***a* can be an infrastructure element (e.g., a utility pole), the landmark **210***b* can be a front portion of a building, the landmark **210***c* can be another infrastructure element, the landmark **210***d* can be another infrastructure element, the landmark **210***e* can be a front portion of another building, and the landmark **210***f* can be a side portion of another building. The computer **105** can identify landmarks **210** that are the closest landmarks **210** to the route **500** (i.e., having a smallest Euclidian (i.e., straight-line) distance from the route **500**) than other landmarks **210** in a geographic area. Prior to embarking on the route **500**, the computer **105** can identify the landmarks **210** along the route **500**, e.g., from geographic data from the server **125**. While the vehicle **101** is traveling along the route **500**, the computer **105** can actuate a camera **110** to collect images **200** of an environment around the vehicle **101**. Upon collecting the images **200**, the computer **105** can input the images **200** to the machine learning program **205** described above to identify landmarks **210** in the images **200**. Upon identifying one of the landmarks **210** in one of the images **200**, the computer **105** can actuate one or more components **115**, as described below, to perform the maneuver assigned to the landmark **210** to follow the route **500**.

[0068] The computer **105** can assign specific maneuvers, i.e., one or more specific actuations of the components **115**, based on the portion **505** of the route **500** closest to the identified landmarks **210**. For example, as shown in FIG. **5**, at a first landmark **210***a*, the portion **505***a* of the route **500** turns to the left relative to forward motion of the vehicle **101**. Prior to embarking on the route **500**, the computer **105** can plan to turn the vehicle **101** to the left upon collecting an image **200** including the first landmark **210***a*, as described above. The computer **105** can identify a second landmark **210***b* at which the portion **505***c* the route **500** is a straight path and an upcoming portion **505***d* is a right turn. That is, upon identifying the landmark **210***b*, the computer **105** can actuate the components **115** to leave the straight path of the portion **505***c*, pass the boundary **510***c*, and begin the right turn of the portion **505***d*.

[0069] The computer **105** can generate a table of maneuvers for each identified landmark **210**, an example of which is shown in Table 1:

TABLE 1

List of Maneuvers

Landmark	Maneuver
210a	Left Turn
210b	Right Turn
210c	Right Turn
210d	Straight Path

TABLE 1-continued

List of Maneuvers	
Landmark	Maneuver
210e	Left Turn
210f	Right Turn

[0070] The computer **105** can determine whether the vehicle **101** has arrived at the destination. For example, the computer **105** can compare a current location of the vehicle **101** to the path polynomial defining the route **500**. When the predicted upcoming distance x of the path polynomial is below a threshold (such as an average length of the vehicle **101**, e.g., 2 meters), the computer **105** can determine that the vehicle **101** has arrived at the destination. Additionally or alternatively, the computer **105** can compare geo-coordinate data of a location of the vehicle **101** to geo-coordinate data of the destination. If a distance between the location of the vehicle **101** and the geo-coordinates of the destination is below the threshold (e.g., 2 meters as described above), the computer **105** can determine that the vehicle has arrived at the destination. Yet additionally or alternatively, the computer **105** can identify a landmark **210** at the destination and determine that the vehicle **101** has arrived at the destination upon identifying the landmark **210**.

[0071] FIG. **6** is a diagram of an example process **600** for generating a plurality of memories **215** of landmarks **210**. The process **600** begins in a block **605**, in which a server **125** receives a reference image **200** including a landmark **210**. The reference image **200** can be, e.g., an image **200** collected by a sensor **110** of a vehicle **101**, as described above. The reference image **200** can include an annotation of a landmark **210**.

[0072] Next, in a block **610**, the server **125** applies one or more transformation programs to generate synthetic images **220**, each synthetic image **220** including at least one ambient feature. As described above, the transformation programs are programming of the server **125** that incorporates an ambient feature (such as a change in lighting or a change in viewing angle, a time of day, seasonal variations, weather condition such a rain or clouds, etc.) into a copy of the reference image **200** to generate the synthetic image **220**. A plurality of transformation programs can each insert a respective ambient feature to a copy of the reference image **200** to generate a set of synthetic images **220** with different ambient features. The synthetic images **220** thus can provide different scenarios for the machine learning program **205** than the reference image **200** alone can. The synthetic images **220** can preserve to annotation of the landmark **210** of the reference image **200**.

[0073] Next, in a block **615**, the server **125** generates a feature vector **225** for each synthetic image **220**. As described above, the server **125** can input the synthetic image **220** to a machine learning program **205** to generate the feature vector **225**. The feature vector **225** is a 1-dimensional array of values that encode information from the 2-dimensional synthetic image **220**, as described above.

[0074] Next, in a block **620**, the server **125** identifies a mean feature vector **225** and an inverse covariance matrix of the population of feature vectors **225** of the synthetic images **220** as described above. The server **125** can identify a mean and/or an inverse covariance of the feature vectors **225** to determine a statistical distance and/or a probability distribution difference, as described below.

[0075] Next, in a block **625**, the server **125** stores the mean feature vector **225** and the inverse covariance matrix S in a memory allocation **215**. The memory allocation **215** can be an allocation of memory in the server **125** assigned to the landmark **210**. The memory allocation **215** can include the mean and/or the inverse covariance matrix of the feature vectors **225** of the synthetic images **220** including the landmark **210**. Following the block **625**, the process **600** ends.

[0076] FIG. **7** is a block diagram of an example process **700** for operating a vehicle **101**. The process **700** begins in a block **705** in which a computer **105** in the vehicle **101** plans a route **500** from an origin to a destination. As described above, the route **500** is a path from an origin to a destination that the vehicle **101** follows to reach the destination. The computer **105** can identify the path with a path polynomial, as described above.

[0077] Next, in a block **710**, the computer **105** identifies one or more landmarks **210** along the route **500**. The computer **105** can request a high-resolution map from the server **125** that includes identifications of landmarks **210** in a geographic area including the route **500**. The computer **105** can identify landmarks **210** from the map that are on or near the route **500**.

[0078] Next, in a block **715**, the computer **105** plans actuation of one or more components **115** of the vehicle **101** based on the landmarks **210**. As described above, the landmarks **210** may be located at portions **505** of the route **500** where a change in a trajectory of the vehicle **101**, e.g., a left turn, a right turn, etc., may be performed to remain on the route **500**. The computer **105** can plan actuation of the components **115** upon collecting an image **200** that includes the landmark **210** while traveling along the route **500**.

[0079] Next, in a block **720**, the computer **105** actuates one or more sensors **110** to collect images **200** of an environment around the vehicle **101** as the vehicle **101** moves along the route **500**. For example, the computer **105** can actuate a camera **110** to collect the images **200**.

[0080] Next, in a block **725**, the computer **105** determines whether one of the images **200** includes an identified landmark **210**. As described above, the computer **105** can input the images **200** into a machine learning program **205** that identifies the landmark **210**. That is, the machine learning program **205** can identify a similarity measure between a feature vector **235** of the input image **200** and a reference feature vector **225** of the landmark **210** transmitted by the server **125** over the network **120** from a memory allocation **215** of the server **125**. Alternatively, a memory of the computer **105** can store the memory allocations **215** of the landmarks **210**. The similarity measure can be a probability distribution difference or a statistical distance, such as a Mahalanobis distance or a KL divergence. The machine learning program **205** can output a probability that the images **200** include the landmark **210**. When the probability is above a predetermined threshold, the machine learning program **205** can output an identification of the landmark **210**. If the computer **105** identifies a landmark **210**, the process **700** continues in a block **730**. Otherwise, the process **700** returns to the block **720** to collect more images **200**.

[0081] In the block **730**, the computer **105** actuates the components **115** according to the planned actuation assigned to the identified landmark **210**. As described above, the computer **105** can actuate the components **115** to follow the route **500** upon identifying the landmark **210**. For example, upon identifying one of the landmarks **210**, the computer **105** can determine that the planned actuation is a left turn, and the computer **105** can actuate a propulsion, a brake, and a steering to perform the left turn.

[0082] Next, in a block **735**, the computer **105** determines whether the vehicle **101** has arrived at the destination at the end of the route **500**. The computer **105** can collect geo-coordinate data of a location of the vehicle **101** and compare the location of the vehicle **101** to the geo-coordinates of the destination. Alternatively or additionally, the computer **105** can identify a landmark **210** at the destination to determine that the vehicle **101** has arrived at the destination. If the computer **105** determines that the vehicle **101** has not arrived at the destination at the end of the route **500**, the process **700** returns to the block **720** to collect more images **200**. Otherwise, the process **700** ends.

[0083] Computing devices discussed herein, including the computer **105**, include processors and memories, the memories generally each including instructions executable by one or more computing devices such as those identified above, and for carrying out blocks or steps of processes described above. Computer executable instructions 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++, Visual Basic, Java Script, Python, Perl, HTML, etc. In general, a processor (e.g., a microprocessor) receives instructions, e.g., from a memory, a computer readable medium, etc., and executes these instructions, thereby performing one or more processes, including one or more of the processes described herein. Such instructions and other data may be stored and transmitted using a variety of computer readable media. A file in the computer **105** is generally a collection of data stored on a computer readable medium, such as a storage medium, a random access memory, etc.

[0084] A computer readable medium includes any medium that participates in providing data (e.g., instructions), which may be read by a computer. Such a medium may take many forms, including, but not limited to, non volatile media, volatile media, etc. Non volatile media include, for example, optical or magnetic disks and other persistent memory. Volatile media include dynamic random access memory (DRAM), which typically constitutes a main memory. Common forms of computer readable media include, for example, a floppy disk, a flexible disk, hard disk, magnetic tape, any other magnetic medium, a CD ROM, DVD, any other optical medium, punch cards, paper tape, any other physical medium with patterns of holes, a RAM, a PROM, an EPROM, a FLASH EEPROM, any other memory chip or cartridge, or any other medium from which a computer can read.

[0085] With regard to the media, processes, systems, methods, etc. described herein, it should be understood that, although the steps 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. For example, in the process **600**, one or more of the steps could be omitted, or the steps could be executed in a different order than shown in FIG. **6**. In other words, the descriptions of systems and/or processes herein are provided for the purpose of illustrating certain embodiments and should in no way be construed so as to limit the disclosed subject matter.

[0086] Accordingly, it is to be understood that the present disclosure, including the above description and the accompanying figures and below claims, is intended to be illustrative and not restrictive. Many embodiments and applications other than the examples provided would be apparent to those of skill in the art upon reading the above description. The scope of the invention should be determined, not with reference to the above description, but should instead be determined with reference to claims appended hereto and/or included in a non-provisional patent application based hereon, along with the full scope of equivalents to which such claims are entitled. It is anticipated and intended that future developments will occur in the arts discussed herein, and that the disclosed systems and methods will be incorporated into such future embodiments. In sum, it should be understood that the disclosed subject matter is capable of modification and variation.

[0087] The article "a" modifying a noun should be understood as meaning one or more unless stated otherwise, or context requires otherwise. The phrase "based on" encompasses being partly or entirely based on.

[0088] The adjectives "first" and "second" are used throughout this document as identifiers and are not intended to signify importance or order.

What is claimed is:

1. A system, comprising a computer including a processor and a memory, the memory storing instructions executable by the processor to:

receive an image including a physical landmark;

output a plurality of synthetic images, wherein each synthetic image is generated by simulating at least one ambient feature in the received image;

generate respective feature vectors for each of the plurality of synthetic images; and

actuate one or more vehicle components upon identifying the physical landmark in a second received image based on a similarity measure between the feature vectors of the synthetic images and a feature vector of the second received image, the similarity measure being one of a probability distribution difference or a statistical distance.

2. The system of claim **1**, wherein the instructions further include instructions to generate a route for a vehicle, to identify one or more physical landmarks along the route, and to plan actuation of the one or more vehicle components based on the identified one or more physical landmarks.

3. The system of claim **2**, wherein the instructions further include instructions to, while the vehicle is traveling along the route, collect the second received image with a camera, to identify the physical landmark in the second received image, and to actuate the one or more vehicle components based on the planned actuation based on the identified one or more physical landmarks.

4. The system of claim **2**, wherein the instructions further include instructions to assign a maneuver to each identified physical landmark on the route, the maneuver being one of a left turn, a right turn, or a straight path.

5. The system of claim **1**, wherein the instructions further include instructions to identify a plurality of feature vectors associated with the physical landmark, and to identify the similarity measure of the feature vectors.

6. The system of claim **5**, wherein the instructions further include instructions to identify the physical landmark when the similarity measure of a first plurality of the feature vectors is above a threshold and to identify a second physical landmark based when the similarity measure of a second plurality of the feature vectors is above the threshold.

7. The system of claim **1**, wherein the instructions further include instructions to identify a similarity measure between a mean feature vector of the synthetic images and feature vectors of a plurality of received images and to identify the physical landmark when the similarity measure is above a threshold.

8. The system of claim **1**, wherein the statistical distance is a Mahalanobis distance.

9. The system of claim **1**, wherein the probability distribution difference is a KL divergence.

10. The system of claim **1**, wherein the ambient feature is one of an insolation, precipitation, cloudiness, an amount of traffic, or a change in viewing angle.

11. The system of claim **1**, wherein the instructions further include instructions to generate a covariance matrix of the feature vectors of the plurality of synthetic images, to generate an inverse covariance matrix that is a matrix inverse of the covariance matrix, and to determine the similarity measure based on at least one of the covariance matrix or the inverse covariance matrix.

12. The system of claim **1**, wherein the instructions further include instructions to generate the feature vectors of the plurality of synthetic images with a machine learning program.

13. A method, comprising:

receiving an image including a physical landmark;

outputting a plurality of synthetic images, wherein each synthetic image is generated by simulating at least one ambient feature in the received image;

generating respective feature vectors for each of the plurality of synthetic images; and

actuating one or more vehicle components upon identifying the physical landmark in a second received image based on a similarity measure between the feature vectors of the synthetic images and a feature vector of the second received image, the similarity measure being one of a probability distribution difference or a statistical distance.

14. The method of claim **13**, further comprising generating a route for a vehicle, to identify one or more physical landmarks along the route and planning actuation of the one or more vehicle components based on the identified physical landmarks.

15. The method of claim **14**, further comprising, while the vehicle is traveling along the route, collecting the second received image with a camera, identifying the physical landmark in the second received image, and actuating the one or more vehicle components based on the planned actuation associated with the physical landmark.

16. The method of claim **14**, further comprising assigning a maneuver with each identified physical landmark on the route, the maneuver being one of a left turn, a right turn, or a straight path.

17. The method of claim **13**, further comprising identifying a similarity measure between a mean feature vector of the synthetic images and feature vectors of a plurality of received images and identifying the physical landmark when the similarity measure is above a threshold.

18. The method of claim **13**, wherein the ambient feature is one of an insolation, precipitation, cloudiness, an amount of traffic, or a change in viewing angle.

19. The method of claim **13**, further comprising generating a covariance matrix of the feature vectors of the plurality of synthetic images, generating an inverse covariance matrix that is a matrix inverse of the covariance matrix, and to determine the similarity measure based on at least one of the covariance matrix or the inverse covariance matrix.

20. The method of claim **13**, further comprising generating the feature vectors of the plurality of synthetic images with a machine learning program.

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