United States Patent	12392619
Kind Code	B2
Date of Patent	August 19, 2025
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Vehicle localization system and method

Abstract

A vehicle localization system and method includes acquiring, from a first sensor, first data indicative of a first navigation state of a vehicle; acquiring, from a second sensor, second data indicative of an environment in the vicinity of the vehicle; generating, using a processor communicatively coupled to the first sensor and the second sensor, a second navigation state based on matching the second data to a known map of the environment; and, generating, using the processor, a current navigation state based on the first navigation state and the second navigation state.

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Appl. No.:	**17/926875**
Filed (or PCT Filed):	**May 20, 2021**
PCT No.:	**PCT/CA2021/050687**
PCT Pub. No.:	**WO2021/232160**
PCT Pub. Date:	November 25, 2021

Prior Publication Data

Document Identifier	Publication Date
US 20230194269 A1	Jun. 22, 2023

Related U.S. Application Data

us-provisional-application US 63029021 20200522

Publication Classification

Int. Cl.: **G01C21/30** (20060101); **G01C21/00** (20060101); **G01S13/86** (20060101); **G01S13/89** (20060101); **G01S17/86** (20200101); **G01S17/89** (20200101)

U.S. Cl.:

CPC **G01C21/30** (20130101); **G01C21/3848** (20200801); **G01S13/865** (20130101); **G01S13/867** (20130101); **G01S13/89** (20130101); **G01S17/86** (20200101); **G01S17/89** (20130101);

Field of Classification Search

CPC: G01C (21/30); G01C (21/3848); G01C (21/3867); G01S (13/865); G01S (13/867); G01S (13/89); G01S (17/86); G01S (17/89); G01S (13/86)

References Cited

U.S. PATENT DOCUMENTS

Patent No.	Issued Date	Patentee Name	U.S. Cl.	CPC
9194949	12/2014	Becker et al.	N/A	N/A
9701305	12/2016	Paul et al.	N/A	N/A
9947223	12/2017	Mielenz	N/A	N/A
10286903	12/2018	Irion et al.	N/A	N/A
10473780	12/2018	Brown	N/A	N/A
11422253	12/2021	Mahmoud et al.	N/A	N/A
11440537	12/2021	Kim	N/A	N/A
11442464	12/2021	Chen	N/A	G06N 3/045
2017/0351267	12/2016	Mielenz	N/A	N/A
2018/0113209	12/2017	Campbell	N/A	N/A
2019/0052842	12/2018	Du	N/A	G08G 1/167
2019/0094877	12/2018	Smith et al.	N/A	N/A
2019/0094878	12/2018	Campbell et al.	N/A	N/A
2019/0101649	12/2018	Jensen	N/A	N/A
2019/0113927	12/2018	Englard	N/A	G06F 16/285
2019/0138024	12/2018	Liang et al.	N/A	N/A
2019/0154452	12/2018	Kim et al.	N/A	N/A
2019/0180618	12/2018	Nordbruch	N/A	N/A
2019/0184982	12/2018	Latotzki	N/A	N/A
2019/0184983	12/2018	Tada	N/A	N/A
2019/0202444	12/2018	Golgiri et al.	N/A	N/A
2019/0226853	12/2018	Kubiak et al.	N/A	N/A
2019/0228240	12/2018	Stamatopoulos et al.	N/A	N/A

2019/0232952	12/2018	Kim et al.	N/A	N/A
2019/0236954	12/2018	Komura et al.	N/A	N/A
2019/0279511	12/2018	Wu	N/A	N/A
2019/0294869	12/2018	Naphade	N/A	G06T 7/73
2019/0323844	12/2018	Yendluri et al.	N/A	N/A
2019/0329761	12/2018	Kim et al.	N/A	N/A
2019/0339383	12/2018	Campbell	N/A	N/A
2019/0362164	12/2018	Yamamoto et al.	N/A	N/A
2019/0368882	12/2018	Wheeler	N/A	N/A
2019/0383945	12/2018	Wang et al.	N/A	N/A
2020/0003567	12/2019	Minamiguchi et al.	N/A	N/A
2020/0025575	12/2019	Weissman et al.	N/A	N/A
2020/0082185	12/2019	Yamamoto	N/A	B60R 1/27
2020/0109954	12/2019	Li et al.	N/A	N/A
2020/0207375	12/2019	Mehta	N/A	G05D 1/0088
2020/0218910	12/2019	Herman	N/A	B60R 1/27
2020/0264301	12/2019	Birkedahl et al.	N/A	N/A
2022/0244351	12/2021	Bybee et al.	N/A	N/A

FOREIGN PATENT DOCUMENTS

Patent No.	**Application Date**	**Country**	**CPC**
107167155	12/2016	CN	N/A
107270915	12/2016	CN	N/A
109050522	12/2017	CN	N/A
109318803	12/2018	CN	N/A
109522870	12/2018	CN	N/A
109733383	12/2018	CN	N/A
109905194	12/2018	CN	N/A
110136049	12/2018	CN	N/A
110136199	12/2018	CN	N/A
110146097	12/2018	CN	N/A
110147094	12/2018	CN	N/A
110147705	12/2018	CN	N/A
110148170	12/2018	CN	N/A
110906939	12/2019	CN	N/A
113853508	12/2020	CN	N/A
106546977	12/2021	CN	N/A
111273274	12/2021	CN	N/A
102016207865	12/2016	DE	N/A
102018008755	12/2018	DE	N/A
102018008763	12/2018	DE	N/A
3517996	12/2018	EP	N/A
3955030	12/2021	EP	N/A
4027115	12/2021	EP	N/A
2019084866	12/2018	JP	N/A
2013071921	12/2012	WO	N/A
2016118672	12/2015	WO	N/A
2019058578	12/2018	WO	N/A
2019060524	12/2018	WO	N/A

2019096508	12/2018	WO	N/A
2019135032	12/2018	WO	N/A
2020012852	12/2019	WO	N/A

OTHER PUBLICATIONS

Automated Valet Parking retrived from https://www.bosch.com/stories/automated-valet-parking/. cited by applicant
European Patent Application No. 21808737.7, European Office action dated May 10, 2024. cited by applicant
European Patent Application No. 21808737.7, Extended European Search Report dated Apr. 22, 2024. cited by applicant
Ibisch, et al., “Towards Autonomous Driving in a Parking Garage: Vehicle Localization and Tracking Using Environment-embedded LIDAR Sensors,” IEEE Symposium on Intelligent Vehicle, 2013, pp. 1-6. cited by applicant
Intenational Patent Application No. PCT/CA2021/050687, International Preliminary Report on Patentability, dated Nov. 17, 2022. cited by applicant
International Patent Application No. PCT/CA2021/050687, International Search Report and Written Opinion dated Sep. 20, 2021. cited by applicant
Klemm, et al., “Autonomous Multi-story Navigation for Valet Parking,” IEEE 19th International Conference on Intelligent Transportation Systems, 2016, pp. 1126-1133. cited by applicant
Sakr, et al., “Radar-based Multi-floor Localization for Automated Valet Parking,” 33rd International Technical Meeting of the Satellite Division of the Institute of Navigation, 2020, pp. 1-6. cited by applicant
Skar, et al., “Reliable Localization Using Multi-sensor Fusion for Automated Valet Parking Applications,” China Satellite Navigation Conference, 2020, pp. 740-747. cited by applicant

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Background/Summary

FIELD

(1) The present disclosure relates generally to vehicle localization systems and methods, and more particularly to using ranging sensors in combination with navigation sensors for vehicle localization.

BACKGROUND

(2) GNSS receivers are the most common solution for determining vehicle location outdoors. GNSS receivers provide accuracy, which may vary based on different modes and operating conditions, from a few centimeters to several meters. For example, GNSS receivers operating on either differential mode (which requires a local reference station within a specific distance from the rover GNSS receiver or virtual reference station networks) or precise point positioning (PPP) mode can provide centimeter, decimeter or sub-meter level accuracy. However, GNSS receivers cannot maintain their accuracy without a clear view of the sky and direct line-of-sight to multiple satellites simultaneously. As a result, GNSS performance is greatly degraded in urban areas with high rise buildings, when passing through underground tunnels, when traveling under overpasses, or when driving under tree canopies or other obstructions.

(3) Autonomous and connected vehicles may employ a multi-sensor fusion approach for vehicle

localization, to overcome limitations inherent in GNSS only approaches. Such multi-sensor fusion approaches may combine data from GNSS, with other sensor systems, such as inertial sensors, cameras, and LiDAR devices. This approach similarly suffers from varying performance based on operating conditions, such as low visibility (by night or foggy environments), rain (which can scatter LiDAR signals and cover the cameras lens), and snow (which can block the cameras lens and the LiDAR transmitter).

(4) A further approach to vehicle localization relies on external sensor infrastructure embedded in the environment for monitoring and tracking vehicles. This approach is prevalent in closed or controlled indoor or outdoor environments. However, the need to install and maintain specialized infrastructure in the region of interest, greatly increases the cost and complexity of vehicle localization systems and limits their application to specific areas having the required external sensor infrastructure.

(5) It remains desirable to develop further improvements and advancements in vehicle localization, to overcome shortcomings of known techniques, and to provide additional advantages.

(6) This section is intended to introduce various aspects of the art, which may be associated with the present disclosure. This discussion is believed to assist in providing a framework to facilitate a better understanding of particular aspects of the present disclosure. Accordingly, it should be understood that this section should be read in this light, and not necessarily as admissions of prior art.

Description

BRIEF DESCRIPTION OF THE DRAWINGS

(1) Embodiments will now be described, by way of example only, with reference to the attached Figures.

(2) FIG. **1** is a diagram of a vehicle operating with a RADAR based vehicle localization system as disclosed herein and a corresponding point map based on the RADAR data generated by the RADAR sensors equipped on the vehicle.

(3) FIG. **2** is a block diagram of an embodiment of the RADAR based vehicle localization system equipped on the vehicle depicted in FIG. **1**.

(4) FIG. **3** is a diagram of the vehicle depicted in FIG. **1** including an overlay of an x-y coordinate system for each RADAR sensors' frame of reference, the vehicle frame of reference, and the navigation frame of reference.

(5) FIG. **4**A to **4**D are embodiments of providing one or more RADAR sensors on a vehicle in accordance with vehicle localization system and method as disclosed herein.

(6) FIG. **5** is a diagram of a FIFO structure embodiment, used for storing RADAR sensor data, relative vehicle pose transformations, and time epochs.

(7) FIG. **6**A is an embodiment of a known map comprising a plurality of objects.

(8) FIG. **6**B is the known map illustrated in FIG. **6**A, further divided into four map regions.

(9) FIG. **6**C is an illustration of the south-west corner map region depicted in FIG. **6**B

(10) FIG. **6**D is an illustration of the map region depicted in FIG. **6**C, comprising visible and non-visible map elements, as seen from a vehicle.

(11) FIG. **6**E illustrates the map region depicted in FIG. **6**D, further subdivided into cells, for generating a probability distribution function for each cell.

(12) FIG. **7** is an embodiment of a state transition graph for the known map illustrated in FIGS. **6**A and **6**B, for use in determining a transition to different maps and different map regions.

(13) FIG. **8** is a block diagram of a RADAR based vehicle localization method, based on the vehicle localization system illustrated in FIG. **2**.

(14) FIG. **9** is a system and block diagram illustrating further steps of the RADAR based vehicle

localization method depicted in FIG. **8**.
(15) FIG. **10** is a known map for an underground parkade expressed as a dense point cloud, used for a vehicle traversing the test trajectory illustrated in FIG. **11**, wherein the vehicle is equipped with an embodiment of a RADAR based vehicle localization system in accordance with the disclosure herein.
(16) FIG. **11** is an overlay of a vehicle test trajectory on the dense point cloud illustrated in FIG. **10**. The vehicle traversed the test trajectory equipped with an embodiment of a RADAR based vehicle localization system as disclosed herein.
(17) FIG. **12**A illustrates an un-processed RADAR point cloud generated over the course of the vehicle test trajectory illustrated in FIG. **11**
(18) FIG. **12**B illustrates the RADAR point cloud depicted in FIG. **12**A having been processed to remove noise.
(19) FIG. **13**A is a point cloud based on the RADAR data generated at a discrete point in time (25 seconds) into the test trajectory, as marked in FIG. **12**B.
(20) FIG. **13**B is a point cloud based on the RADAR data generated at a discrete point in time (60 seconds) into the test trajectory, as marked in FIG. **12**B.
(21) FIG. **14** illustrates an environment used for a second vehicle test. The environment is illustrated as four maps, including a map of an indoor area, a map of an outdoor area, and two maps of ramps interconnecting the indoor area and the outdoor area. A vehicle equipped with a vehicle localization system and method as disclosed herein traversed the four areas, as further illustrated in FIG. **15**
(22) FIG. **15** illustrates a vehicle trajectory superimposed on the four maps illustrated in FIG. **14**. The vehicle trajectory reflects the navigation states resulting from the vehicle localization system and method provided on the vehicle.
(23) Throughout the drawings, sometimes only one or fewer than all of the instances of an element visible in the view are designated by a lead line and reference character, for the sake only of simplicity and to avoid clutter. It will be understood, however, that in such cases, in accordance with the corresponding description, that all other instances are likewise designated and encompassed by the corresponding description.
DETAILED DESCRIPTION
(24) The following are examples of a vehicle localization system and method, as disclosed herein.
(25) In an aspect, a vehicle localization system disclosed herein includes a first sensor configured to generate first data indicative of a first navigation state of the vehicle; a second sensor configured to generate second data indicative of an environment in the vicinity of the vehicle; and, a processor communicatively coupled to the first sensor and the second sensor, the processor configured to: generate a second navigation state based on matching the second data to a known map of the environment, and generate a current navigation state based on the first navigation state and the second navigation state.
(26) In an embodiment, the processor is configured to generate a point cloud based on the second data, wherein the second navigation state is based on matching the point cloud and the known map. In an embodiment, the point cloud comprises a plurality of reflection points indicative of objects in the vicinity of the vehicle. In an embodiment, the processor is configured to remove reflection points indicative of dynamic objects. In an embodiment, the processor is configured to generate the point cloud based on accumulating the second data into a common frame of reference using a relative vehicle pose transformation derived from the first data. In an embodiment, the common frame of reference is the navigation frame of reference.
(27) In an embodiment, the first navigation state includes a first vehicle pose comprising a first vehicle position and a first vehicle heading. In an embodiment, the relative vehicle pose transformation is a change in vehicle pose from a previous vehicle pose to the first vehicle pose.
(28) In an embodiment, the processor is configured to generate a map transformation function

based on transforming the point cloud to match the known map. In an embodiment, the second navigation state is based on the map transformation function. In an embodiment, the transformation is an iterative transformation comprising transformation parameters. In an embodiment, the transformation parameters include a maximum number of iterations and a smallest iteration step. In an embodiment, the transformation parameters include a map resolution.
(29) In an embodiment, the processor is configured to generate a match likelihood score based on a match between the point cloud and the known map. In an embodiment, the match likelihood score is generated based on a Bayesian matching approach or a point cloud registration method. In an embodiment, the point cloud registration method is an iterative closest point method, or a normal-distribution transform method.
(30) In an embodiment, the known map comprises a plurality of map elements representing objects in the environment. In an embodiment, the plurality of map elements comprise at least one of a line segment or a point. In an embodiment, the processor is configured to remove non-visible map elements from the known map based on the first vehicle navigation state. In an embodiment, the processor is configured to obtain a new map based on detecting the first navigation state in a boundary area adjacent the new map.
(31) In an embodiment, the first sensor is configured to generate the first data in a first frame of reference and the second sensor is configured to generate the second data in a second frame of reference. In an embodiment, the processor is configured to transform the first data and the second data into a vehicle frame of reference.
(32) In an embodiment, the second sensor is a ranging sensor and the second data is ranging data generated by the ranging sensor.
(33) In an embodiment, the ranging sensor is a Radio Detection and Ranging (RADAR) sensor and the ranging data is RADAR data generated by the RADAR sensor. In an embodiment, the RADAR sensor is a plurality of RADAR sensors. In an embodiment, the RADAR data includes range information and bearing information. In an embodiment, the RADAR data includes relative velocity information.
(34) In an embodiment, the ranging sensor is a Light Detection and Ranging (LiDAR) sensor and the ranging data is LIDAR data generated by the LIDAR sensor.
(35) In an embodiment, the first sensor is a navigation sensor configured to generate navigation data. In an embodiment, the navigation sensor comprises a wheel tick encoder, inertial sensors, and a steering wheel sensor. In an embodiment, the navigation sensors further include a camera. In an embodiment, the camera is a plurality of cameras. In an embodiment, the navigation sensor further includes a GNSS device.
(36) In an embodiment, the vehicle localization system further comprises a memory communicatively coupled to the processor, wherein the known map is stored in the memory. In an embodiment, the memory is a database, remote server, or cloud server. In an embodiment, the memory is local to the system, remote to the system, or a combination thereof.
(37) In an aspect, a computer-implemented method for vehicle localization includes acquiring, from a first sensor, first data indicative of a first navigation state of a vehicle; acquiring, from a second sensor, second data indicative of an environment in the vicinity of the vehicle; generating, using a processor communicatively coupled to the first sensor and the second sensor, a second navigation state based on matching the second data to a known map of the environment; and, generating, using the processor, a current navigation state based on the first navigation state and the second navigation state.
(38) In an embodiment, the computer-implemented vehicle localization method further includes generating, using the processor, a point cloud based on accumulating the second data wherein generating the second navigation state is based on matching the point cloud to the known map.
(39) In an embodiment, the computer-implemented vehicle localization method further includes generating, using the processor, a relative vehicle pose transformation based on a change in

navigation state between the first navigation state and a previous first navigation state; and, wherein the processor generates the point cloud based on using the relative vehicle pose transformation to accumulate the second data relative to the first navigation state.

(40) In an embodiment the known map comprises a plurality of objects, wherein the computer-implemented vehicle localization method further includes using the processor to subdivide the known map into a plurality of cells and evaluating each cell to generate a corresponding probability distribution function indicative of a corresponding subset of the plurality of objects occupying the corresponding cell.

(41) In an embodiment, matching the point cloud and the known map is based on evaluating the point cloud against the corresponding probability distribution function for each of the plurality of cells. In an embodiment, matching the point cloud to the know map further comprises iteratively transforming the point cloud and evaluating a likelihood of each iterative point cloud matching the known map, wherein the second navigation state is based on the iterative point cloud having a highest likelihood of matching the known map. In an embodiment, evaluating the likelihood of matching comprises a normal distributions transform approach.

(42) In an embodiment, the current navigation state is based on fusing the first navigation state and the second navigation state using a Bayesian filter.

(43) In an embodiment, the first sensor is a navigation sensor, and the second sensor is a Radio Detection and Ranging (RADAR) sensor. In an embodiment, the RADAR sensor is a plurality of RADAR sensors.

(44) In an aspect is a computer readable medium storing computer executable instructions thereon that when executed by a computer perform a computer-implemented method for vehicle localization in accordance with the disclosure herein.

(45) For simplicity of ease of explanation, the description and illustrations provided herein are with respect to a two-dimensional x-y Cartesian coordinate system, generally expressed with respect to a local sensor frame of reference, a vehicle frame of reference, and/or a navigation frame of reference. Those skilled in the art will appreciate however, that the invention is not so-limited and a vehicle localization system and method as disclosed herein may be implemented with different degrees of freedom, different coordinate systems, and different frames of references without departing from the teachings of the disclosure.

(46) A vehicle localization system and method as disclosed herein includes a multi-sensor approach to seamless indoor-outdoor vehicle localization. The system and method include providing a first sensor on a vehicle for generating data indicative of a navigation state of the vehicle; and, providing a second sensor on the vehicle for generating data indicative of an environment in the vicinity of the vehicle. A processor communicatively coupled with the first sensor and the second sensor is configured to generate a first and second vehicle navigation state. The first vehicle navigation state is based on the first sensor data, and is derived independent of the second sensors. The second vehicle navigation state is based on accumulating the second sensor data into a frame of reference in common with a known map, using the first navigation state and a transformation function derived from the first sensor data. The accumulated second sensor data is evaluated against the known map of the environment for use in generating the second navigation state estimate. The processor subsequently generates a current vehicle state based on evaluating the first and second vehicle navigation states. The vehicle localization systems and methods disclosed herein do not require GNSS, nor do they require a pre-existing sensor infrastructure embedded in the surrounding environment. However, if such positioning systems and sensors are available, the systems and methods disclosed herein may nevertheless make use of such systems and sensors. First sensors may include, but are not limited to, navigation sensors including a wheel tick encoder, inertial measurement unit, accelerometers, gyroscopes, one or more cameras, a steering wheel sensor, a GNSS receiver, and combinations thereof. Second sensors may include, but are not limited to, ranging sensors including a time-of-flight sensor, including a Radio Detection and

Ranging (RADAR) sensor, a Light Detection and Ranging (LiDAR) sensor, and combinations thereof.

(47) The system and methods disclosed herein generate first and second sensor data in real-time. The processor may accumulate the sensor data for a window of time representing a plurality of time epochs. The window of time may be a sliding window of fixed width, including embodiments wherein the sliding window is a non-overlapping sliding window and embodiments wherein the sliding window is an overlapping sliding window. The processor may obtain a first vehicle navigation state directly from the first sensor data, or indirectly, for example by inputting the first sensor data into a vehicle motion model to generate the first navigation state. The processor may further derive a vehicle pose transformation function based on a change in the vehicle navigation state between two time epochs. The processor uses the vehicle pose transformation function to conform and accumulate the second sensor data. The processor uses the first navigation state to transform the accumulated second sensor data into a frame of reference in common with a known map. In an embodiment, the known map is expressed in the navigation frame of reference.

(48) As an example, the processor may receive first sensor data for a current time epoch, for use in generating a first navigation state. The processor further generates a vehicle pose transformation function, based on a change in vehicle navigation state between the first navigation state and a previous navigation state. The processor uses the vehicle pose transformation function to transform the second sensor data, accumulated to the previous navigation state, into the first navigation state. In this manner, the systems and methods disclosed herein accumulate second sensor data into a common frame of reference by iteratively transforming second sensor data using a corresponding change in vehicle pose.

(49) Accumulating second sensor data may illustratively resemble clouds. For example, RADAR data may include a plurality of reflection points for a given object. Accumulating such reflection points over time may result in a cloud of reflection points, whereby the RADAR data resembles a fuzzy or cloud-like version of the object. Such points clouds are but one way to describe and/or illustrate reflection points. For example, raw RADAR data may undergo a step of processing to transform reflection points into line segments, polygons, or other constructs. Accordingly, point clouds are not limited to expressing data as a cloud of points; rather, point clouds encompass data accumulation over time, whether the data is represented as points, line segments, polygons, or otherwise.

(50) The systems and methods disclosed herein compare a point cloud with a known map of the environment. The comparison is based on transforming the point cloud to match the known map. In an embodiment, the comparison is based on transforming the point cloud using different vehicle poses to maximize a likelihood of matching with the known map. In an embodiment, the matching is based on a point cloud registration method, including iterative closes point (ICP) or normal distributions transform (NDT) approaches. The resulting vehicle pose transformation characterises a second vehicle navigation state estimate. The first and second navigation states are evaluated, to generate a current vehicle navigation state. In an embodiment, the first and second navigation states are fused together based on a Bayesian approach. Embodiments as further disclosed herein include generating a likelihood score based on a likelihood that the point cloud matches the known map, for use in estimating a certainty of the second navigation state.

(51) FIGS. **1** and **2** illustrate a RADAR based vehicle localization system and method as disclosed herein. FIG. **1** illustrates a vehicle **110** operating in an environment **140** comprising a plurality of objects **142**. Objects may be static or dynamic in nature. Static objects may include but are not limited to pillars, walls, fences, barriers, trees, and parked vehicles. Dynamic objects may include, but are not limited to, people, animals, and moving vehicles. The vehicle **110** is equipped with a vehicle localization system **100**, including a first sensor **120** communicatively coupled to a processor **150**. The first sensor **120** generates data indicative of a navigation state of the vehicle. As depicted in FIG. **2**, the first sensor **120** includes a plurality of navigations sensors **122** including

inertial sensors **122***a*, a wheel tick encoder **122***b*, a steering wheel sensor **122***c*, a GNSS device **122***d*, and one or more cameras **122***e*. Other embodiments include a stand-alone navigation sensor **122**, such as an inertial measurement unit comprising accelerometers and gyroscopes. The navigation sensors **122** generate vehicle navigation data with respect to a frame of reference such as a local sensor frame of reference, a vehicle frame of reference, or a navigation frame of reference. Vehicle navigation data may include, but is not limited to, absolute vehicle position (e.g. longitude, latitude, and altitude), relative vehicle position, vehicle orientation (e.g. pitch, roll, and yaw), vehicle velocity, and vehicle pose. For example, the GNSS device **122***d* may generate navigation data indicative of an absolute vehicle position in a geographic frame of reference; the inertial sensors **122***a* may generate navigation data indicative of changes in vehicle position and orientation; the steering wheel sensor **122***c* may generate navigation data indicative of changes in the vehicle heading; and so forth. The processor **150** receives the navigation data from the navigation sensors **122**, for storage in a memory **152**, such as a local memory **152***a* or a remote memory **152***b*. Remote memory **152***b* includes but is not limited to, storage on a mobile device, a database, a remote server, or a cloud server. The processor may generate a first navigation state of the vehicle directly, or indirectly, from the navigation data. A vehicle navigation state includes but is not limited to, a vehicle pose (position and heading).

(52) As an example of generating a first navigation state, the wheel tick encoder **122***b* may be configured to generate navigation data indicative of a vehicle navigation state, including a vehicle displacement and heading. The processor **122***b* may generate the first navigation state directly from the navigation data or, based on a vehicle motion model for mapping the navigation data to a position or a relative position. A vehicle motion model may include generating the first navigation state based on a relative change from a previous navigation state, as may be the case in dead-reckoning navigation systems. The wheel tick encoder **122***b* captures wheel rotation data, which the processor **150** can combine with known parameters of the vehicle wheels, to generate a relative change in a vehicle navigation state. For example, the processor **150** can derive a relative change in vehicle displacement and heading from a previous navigation state in accordance with equations (1) to (4) below. The relative change in vehicle displacement and heading is based on a change in a rear left wheel displacement Δd.sub.L and a change in a rear right wheel displacement Δd.sub.R, as may be derived from the wheel tick encoder data and known wheel parameters:

Δ*d*.sub.L=*N*.sub.L*S*.sub.L (1)

Δ*d*.sub.R=*N*.sub.R*S*.sub.R (2)

(53) N.sub.L and N.sub.R are a change in wheel pulse count since the previous navigation state, for the left and right wheels, respectively. S.sub.L and S.sub.R are a wheel scale defined in units of (m/pulse) for the left and right wheels, respectively. Using the change in wheel displacements Δd.sub.L and Δd.sub.R, the processor **150** can determine a change in a vehicle distance Δd and heading Δθ relative to the previous navigation state, based on equations (3) and (4):

(54) $d = \frac{(d_L + d_R)}{2}$ (3) $\Delta\theta = \frac{(d_L - d_R)}{b}$ (4)

(55) Where b is the distance between wheels or the wheel track, which is a constant for a given vehicle. The processor **150** can thus use the navigation data generated by the wheel tick encoder **122***b* to generate a first navigation state based on the change in vehicle distance Δd and the change in vehicle heading Δθ relative to a previous navigation state.

(56) As illustrated in FIG. **3**, data may be expressed in different frames of reference such as the local RADAR sensor frames of reference O.sub.r1, O.sub.r2, O.sub.r3, and O.sub.r4; the vehicle frame of reference O.sub.v, and the navigation frame of reference O.sub.n. Consequently, further steps may be required to transform first and second sensor data into a different frame of reference, such as into the navigation frame of reference O.sub.n. The vehicle heading θ for example, may be expressed as an angle between a y-axis of the vehicle frame of reference O.sub.v, and a y-axis of the navigation frame of reference O.sub.n. Conventionally, when the vehicle frame of reference

O.sub.v coincides with the navigation frame of reference O.sub.n, the vehicle heading θ is zero degrees. A positive change in heading Δθ conventionally indicates a clockwise vehicle rotation. Other conventions are possible. Using the stated conventions, the first navigation state may be expressed in the navigation frame O.sub.n in accordance with equations (5) to (7):

$$\theta_k = \theta_{k-1} + \Delta\theta_{k-1} \quad (5)$$

$$x_k = x_{k-1} + \Delta d_{k-1} \sin(\theta_{k-1}) \quad (6)$$

$$y_k = y_{k-1} + \Delta d_{k-1} \cos(\theta_{k-1}) \quad (7)$$

(57) Where x.sub.k and y.sub.k are a horizontal vehicle position in the navigation frame O.sub.n and θ.sub.k is the corresponding vehicle heading. The vehicle position (x, y) and heading θ collectively represent a vehicle pose for a corresponding vehicle navigation state. Equations (5) to (7) thus generate a current vehicle pose, based on a previous vehicle pose from a previous time epoch k−1.

(58) The vehicle **110** is further equipped with a second sensor **130** communicatively coupled to the processor **150**. The second sensor **130** generates data indicative of an environment in the vicinity of the vehicle. As particularly illustrated in FIGS. **2** and **3**, the vehicle **110** is equipped with a second sensor **130** comprising respective first, second, third, and fourth RADAR sensors **131**, **132**, **133**, and **134**, provided at four respective locations **111**, **112**, **113**, and **114** on the vehicle **110**. Further embodiments for providing RADAR sensors on the vehicle **110** are illustrated in FIGS. **4**A to **4**D which respectively depict a single RADAR sensor embodiment, a two RADAR sensor embodiment, a different two RADAR sensor embodiment, and a three RADAR sensor embodiment. Those skilled in the art will appreciate that the manner in which sensors are equipped to a vehicle for scanning an environment in the vicinity of the vehicle are not so limited to the embodiments disclosed herein. For example, the second sensor **130** may comprise more than four RADAR sensors, or may place the RADAR sensors at different locations on the vehicle.

(59) Each RADAR sensor **131**, **132**, **133**, and **134** transmits and receives RADAR signals for use in generating RADAR data relative to a respective local sensor frame of reference O.sub.r1, O.sub.r2, O.sub.r3, and O.sub.r4. The systems and methods disclosed herein further include transforming the RADAR data from a corresponding local sensor frame of reference O.sub.r1, O.sub.r2, O.sub.r3, and O.sub.r4, into the vehicle frame of reference O.sub.v and subsequently to the navigation frame of reference O.sub.n for comparison with a known map. The transformation may incorporate calibration data derived from the setup of the local sensor frames of reference O.sub.r1, O.sub.r2, O.sub.r3, and O.sub.r4 for use in transforming the RADAR data into a different frame of reference. Calibration data may be obtained for example, prior to operating the vehicle **110** and/or during operation of the vehicle **110**.

(60) The RADAR sensors **131**, **132**, **133**, and **134** transmit signals and receives reflections of the transmitted signals that have reflected off objects **142**. The reflected signals are processed to generate RADAR data. RADAR data may include ranging data such as, but not limited to, a range, a bearing, an angle, and/or a relative velocity of an object. As such, the RADAR sensors **131**, **132**, **133**, and **134** can detect and characterize objects in the vicinity of the vehicle **110** for generating corresponding RADAR data indicative of the environment **140** in the vicinity of the vehicle **110**. The processor **150** receives the RADAR data for storage in the memory **152** and for use in other vehicle localization steps. For example, the processor **150** uses the navigation data to transform the RADAR data to generate a point cloud **160**, for use in generating a second vehicle navigation state. The first and second vehicle navigation states are used to generate a current vehicle navigation state. In an embodiment, the processor **150** first transforms the RADAR data, from the corresponding local sensor frames O.sub.r1, O.sub.r2, O.sub.r3, and O.sub.r4, to a frame of reference in common with the navigation sensors **122**.

(61) Prior to generating the point cloud **160**, the processor **150** may refine, filter, or otherwise pre-process the RADAR data. For example, the processor **150** may evaluate the RADAR data to remove noise, remove outlier data, down-sample, and/or identify valid targets. Valid targets may

include static objects only. Accordingly, embodiments disclosed herein include configuring the processor **150** to pre-process the RADAR data prior to generating the point cloud **160**. Advantages of pre-processing include but are not limited to, reducing a size of memory required to store the RADAR data and improving a quality of the RADAR data, which may provide corresponding improvements in vehicle localization estimates.

(62) In an embodiment, the processor **150** is configured to generate the point cloud **160** in the navigation frame of reference O.sub.n, for comparison with a known map, such as the know map **180** illustrated in FIG. **6**A. The point cloud **160** includes a plurality of object reflection points **162** accumulated over time, indicative of the environment **140** in the vicinity of the vehicle **110**. The object reflection points **162** are based on the RADAR data, which includes data on the objects **142** detected by the RADAR sensors **131**, **132**, **133**, and **134**. The processor **150** generates the point cloud **160** based on using the navigation data to accumulate and transform the RADAR data into the navigation frame of reference O.sub.n, to commonly express the plurality of object reflection points **162** in the same frame of reference as the known map **180**. In this manner, RADAR data acquired over a plurality of time epochs is transformed and accumulated in conformity with a corresponding change in the vehicle navigation state.

(63) In an embodiment, the processor **150** is configured to partition data into the memory **152** using a first in first out (FIFO) data structure **170**, such as a queue, as depicted in the example embodiment of FIG. **5**. The data structure **170** may function as a real-time sliding window of data. The data structure **170** may have a fixed window size or length N, for holding N frames or units of data. The data structure **170** may be indexed sequentially from a first frame i=0 to a last frame i=N−1, where each frame corresponds to an epoch of time t. As an illustrative example, a difference between consecutive time epochs Δt may be inversely proportional to a sensor scanning rate. Thus, a sensor scanning at a 20 Hz rate may correspond to a 0.05 second long time epoch. Accordingly, a data structure of size N=40 would provide a 2 second window. A data structure of size N=20 would provide a 1 second window. And so forth. Consequently, the point cloud **160** expresses object reflection points **162** obtained over a particular length or window of time. Selecting a window size N is thus an integrated exercise. RADAR sensors **131**, **132**, **133**, and **134**, may require several scans to generate RADAR data having a sufficient density of object reflection points **162**, while real-time processing and hardware constraints may limit the size of the data structure **170**.

(64) In an embodiment, the RADAR data **174** is expressed in a vehicle frame of reference O.sub.v for use in further steps with the vehicle navigation data **175**. The processor **150** partitions the RADAR data **174** into a first FIFO data structure **171** comprising a plurality of RADAR data frames F.sub.k to F.sub.k−N+1 for storage in the memory **152**. Each RADAR data frame F.sub.k to F.sub.k−N+1 represents the RADAR data **174** generated for a corresponding time epoch t.sub.k to t.sub.k−N+1. Each RADAR data frame F.sub.k to F.sub.k−N+1 includes a variable plurality m of object reflection points p, such as object reflection points **162**. For example, the RADAR data frame F.sub.k includes a plurality m(k) of object reflection points p, i.e. F.sub.k={p.sub.0, p.sub.m-1}, acquired during a current time epoch t.sub.k. Similarly, the RADAR data frame F.sub.k−1 includes a plurality m(k−1) of object reflection points p, i.e. F.sub.k+1={p.sub.0, . . . , p.sub.m-1}, acquired during the time epoch t.sub.k−1 preceding the current time epoch t.sub.k. The number m of object reflection points p for each time epoch t is variably dependent on the RADAR data **174** generated by the RADAR sensors **131**, **132**, **133**, and **134** during the corresponding time epoch.

(65) The navigation data **175** includes data indicative of a vehicle navigation state, for use in transforming the RADAR data into the navigation frame of reference O.sub.n. A relative vehicle pose transformation may be derived by evaluating a change between navigation states. For example, navigation data **175** for a first time epoch includes a first vehicle pose; and navigation data **175** for a second time epoch includes a second vehicle pose. A relative vehicle pose transformation is based on the change in vehicle pose from the first vehicle pose to the second

vehicle pose. Accordingly, the processor evaluates the navigation data **175**, to generate a relative vehicle pose transformation T between epochs of time t, for use in transforming RADAR data **174** collected at a first time epoch and a first vehicle pose, for accumulation with the data collected at a second time epoch and a second vehicle pose. The processor **150** may recursively derive vehicle pose transformations to continuously accumulate RADAR data in subsequent time epochs. In this manner, the processor **150** partitions the navigation data **175** into a second FIFO data structure **172** comprising a plurality of relative vehicle pose transformations T.sub.k.sup.k-1 to T.sub.k−N+1.sup.k-N for storage in the memory **152**. Each vehicle pose transformation T.sub.k.sup.k-1 to T.sub.k−N+1.sup.k-N represents the relative pose transformation between two consecutive time epochs t. For example, the vehicle pose transformation T.sub.k.sup.k-1 represents the relative vehicle pose transformation between time epoch t.sub.k and t.sub.k−1. The processor **150** may recursively transform each RADAR data frame F.sub.k to F.sub.k−N+1 using the corresponding vehicle pose transformation T.sub.k.sup.k-1 to T.sub.k−N+1.sup.k-N to accumulate the RADAR data **174** into the navigation frame of reference O.sub.n relative to a current vehicle pose P.sub.k, thereby generating a point cloud **160** in accordance with the following pseudo code:
(66) TABLE-US-00001 Input: Vehicle pose P.sub.k   Set of N radar point cloud frames {F.sub.k, ..., F.sub.k−N+1}   Set of N relative transformations inverse {T.sub.k.sup.k−1, ..., T.sub.k−N+1.sup.k−N} Output: Radar point cloud at the current vehicle pose PC.sub.k 1 PC.sub.k ← Ø; T.sub.k.sup.k = I.sub.4×4 2 for i ← 0 to N − 1 do 3   Evaluate the pose at epoch k − i: P.sub.k−t ← T.sub.k.sup.k−i × P.sub.k 4   for all p ϵ F.sub.k−i do 5   Transform point p to its corresponding pose P.sub.k−i: p.sup.k−i ← P.sub.k−i × p 6   Add point p.sup.k−i to the point cloud PC.sub.k: PC.sub.k ← PC.sub.k ∪ p.sup.k−i 7   end for 8   Evaluate transformation from epoch k to epoch k − i − 1:   T.sub.k.sup.k−i−1 ← T.sub.k−1.sup.k−i−1 × T.sub.k.sup.k−i 9 end for
(67) The processor **150** iteratively generates a new relative vehicle pose transformation, for use in accumulating a corresponding new RADAR data frame and for expressing the point cloud relative to the new vehicle pose P.sub.k.
(68) The processor **150** compares the point cloud **160** with a known map **180** of the surrounding environment **140**, for use in further vehicle localization steps. The systems and methods disclosed herein may previously acquire and store the known map **180** in a memory **152**, such a local memory **152***a* or remote memory **152***b*. In an embodiment, the known map **180** is acquired in real-time. In an embodiment, a communication device **154** communicatively coupled to the memory **152** obtains the known map **180** from a remote memory **152***b*, such as a mobile device, a database, a remote server, or a cloud server. The processor **150** may need to format the known map **180** to express the known map **180** in a format readily comparable with the point cloud. Comparable formats may include, but are not limited to, a geospatial vector map including in a shape-file format, or a point cloud.
(69) As depicted in the illustrative embodiment of FIGS. **6**A and **6**B, the known map **180** is expressed in a two-dimensional x-y coordinate system, provided in the navigation frame of reference, and further includes a vehicle **110** superimposed thereon. The known map **180** comprises a plurality of objects **142** and is divided into four respective map regions **180***a*, **180***b*, **180***c*, and **180***d*, each representing a different region within the known map **180**. As particularly illustrated in FIG. **6**C, the map region **180***a* includes a plurality of objects **142**, depicting square pillars **142***a*, **142***b*, **142***c*, and **142***d*, a two-sided barrier **142***e*, and a fence **142***f*, each object expressed as a plurality of map elements **144**, namely line segments **146**. Map elements may include, but are not limited to, line segments, points, polygons, point clouds, and other constructs that represent or otherwise make up part or all of an object expressed in a map.
(70) The vehicle **110** is equipped with a vehicle localization system as disclosed herein, including the processor **150**, further configured to evaluate the known map **180**. For example, the processor **150** may evaluate the vehicle navigation state to assess which map region the vehicle **110** occupies.

As illustrated in FIGS. **6**A and **6**B, the vehicle **110** occupies map region **180***a* of the known map **180**. The processor may also evaluate the vehicle navigation state to generate a subset of map elements **144***a* which are visible to the vehicle **110**. FIG. **6**C illustrates the map region **180***a* and FIG. **6**D illustrates a set of visible map elements **144***a* and non-visible map elements **144***b* based on the vehicle navigation state. Such pre-processing steps advantageously reduces computational complexity in subsequent vehicle localization steps, and may further improve vehicle navigation state estimates. Further, matching the point cloud **160** to the set of visible map elements **144***a* may improve ease of transforming the point cloud **160** to match the known map **180**. For example, RADAR sensors **131**, **132**, **133**, **134** may be limited in their ability to generate RADAR data for objects or parts of objects not within their field-of-view. Consequently, a point cloud **160** may inherently exclude objects and/or parts of objects not visible to the RADAR sensors at a given navigation state. The point cloud **160** may thus more readily match with a set of visible map elements **144***a* that similarly excludes objects and/or parts of objects not visible to the vehicle from the same navigation state.

(71) As the vehicle **110** moves, the processor **150** may re-generate or update the set of visible elements **144***a* based on the new vehicle navigation state. The processor may also evaluate the vehicle navigation state to determine whether a new map is required for evaluation, or whether a different map region is required for evaluation. For example, the processor can evaluate the vehicle navigation state to determine if the vehicle **110** is at an edge or boundary area of the known map **180**, in anticipation of the vehicle moving to a new map. Similarly, the processor can evaluate the vehicle navigation state to determine if the vehicle **110** is at an edge or boundary area of a map region, in anticipation of the vehicle moving to a new map region or new map. As the vehicle transitions between maps or different map regions, the processor **150** updates the set of map elements used for comparison with the point cloud **160**. In an embodiment, the processor **150** evaluates the point cloud **160** against the new map elements and the current map elements while the vehicle remains in a transition region overlapping a current map and a new map. In an embodiment, the processor **150** evaluates the point cloud **160** against the new map elements and the current map elements while the vehicle remains in a transition region overlapping a current map region and a new map region. As the new map and current map may be provided in different frames of reference, embodiments as disclosed herein include transforming the vehicle navigation state and the point cloud into a frame of reference in common with the new map.

(72) The new map may similarly be pre-loaded or stored in the local memory **152***a* communicatively coupled to the processor **150**, or may be retrieved from a remote memory **152***b*, such as a mobile device, a database, a remote server, or a cloud server. In an embodiment, the relationship between maps, and map regions, may be encoded in a graph structure, such as a state transition graph. FIG. **7** is an illustrative embodiment of a state transition graph **185** for the known map **180** illustrated in FIGS. **6**A and **6**B. Each vertex **180***a*, **180***b*, **180***c*, and **180***d* represents the corresponding map region for known map **180**. Each directional edge **181**, **182**, and **183** represents a possible transition between map regions. Vertex **190** represents a different known map **190** and directional edge **184** represents a possible transition between the map **190** and the map region **180***d* of the known map **180**. Accordingly, when the vehicle operates in the map region **180***a*, the processor **150** can evaluate a vehicle navigation state to determine whether the vehicle **110** remains in the map region **180***a*; whether the vehicle is in a transition region between the map region **180***a* and the map region **180***b*; or, whether the vehicle is in a transition region between the map region **180***a* and the map region **180***c*. Similarly, when the vehicle **110** operates in the map region **180***c*, the processor **150** can evaluate the vehicle navigation state to determine whether the vehicle **110** remains in the map region **180***c*; or, whether the vehicle is in a transition region between the map region **180***c* and the map region **180***a*. And so forth.

(73) The systems and methods disclosed herein compare the point cloud **160** against the known map **180** to generate a second vehicle navigation state. The comparison is based on transforming

the point cloud **160** to match the known map **180**. In an embodiment, the comparison is based on iteratively transforming the point cloud **160** to maximize a likelihood of matching the point cloud **160** with the known map **180** wherein the transformation parameters include a maximum number of iterations and the minimum transformation iteration. The resulting point cloud transformation characterizes a second navigation state. As the point cloud is initially expressed based on the first navigation state, transforming the point cloud inherently reflects a transformation of the first navigation state. In an embodiment, the processor is configured to generate the second navigation state based on transforming the first navigation state with the transformation resulting from matching the point cloud **160** with the known map **180**. In an embodiment, the processor **150** generates a likelihood score for each iterative point cloud transformation wherein the likelihood score reflects a likelihood that the iterative point cloud **160** matches the known map **180**. In an embodiment as further disclosed herein, the likelihood score is based on a point cloud registration approach including the iterative closest point (ICP) approach or the normal distributions transform (NDT). In an embodiment, the known map **180** is a map region.
(74) In an embodiment, the processor **150** is configured to evaluate the likelihood score using a Bayesian approach. In an embodiment, the processor is configured to evaluate the likelihood score using a point cloud registration method. In an embodiment, the point cloud registration method is the iterative closest point approach (ICP) or the normal distributions transform (NDT) approach. For example, the normal distributions transform includes dividing the known map into a plurality of cells **148**, as further illustrated in FIG. **6**E. A probability distribution function **149** for each cell **148** characterizes the probability of finding corresponding objects **142** in each cell **148**. In this manner, the processor evaluates points in a point cloud corresponding to a particular cell, with the probability distribution function for that cell, to evaluate the likelihood of a match. In an embodiment, the plurality of cells are equally sized squares.
(75) In an embodiment, a probability distribution function may be expressed as a multivariate normal distribution wherein the likelihood p(x.sub.i) of an individual point p in a point cloud belonging to the distribution, and by extension matching to a corresponding obstacle point in the cell, may be determined in accordance with equation (8):

(76) $$p(x_i) = \frac{1}{(2\ )^{D/2}\sqrt{.\mathrm{Math}.\quad .\mathrm{Math}.}}\exp\left(-\frac{(x_i -\ )^T\ ^{-1}(x_i -\ )}{2}\right) \quad (8)$$

(77) Where μ and Σ are the mean and the variance, respectively, of the obstacle points probability density function inside a cell. And, x.sub.i is the coordinates of the point p, for example x.sub.i= (x.sub.i, y.sub.i); and, wherein the mean μ and variance Σ of the cell may be evaluated in accordance with equations 9 and 10:

(78) $$= \frac{1}{m}\ .\mathrm{Math}._{j=1}^{m}\ y_j \quad (9) \qquad = \frac{1}{m-1}\ .\mathrm{Math}._{j=1}^{m}\ (y_j -\ )(y_j -\ )^T \quad (10)$$

(79) Where y.sub.j is the position of an obstacle point j in the cell, and m is the number of obstacle points inside the cell. The objective of the NDT algorithm is to find a pose of the vehicle P.sub.v to transform the points in the point cloud in a manner that maximizes the likelihood function of each point, Φ.

(80) $$= .\mathrm{Math}._{i=1}^{n}\ p(T(P_v, x_i)) \quad (11)$$

(81) Where n is the number of points in the point cloud, and T(P.sub.v,x.sub.i) is a function for transforming a point x.sub.i using a pose P.sub.v.
(82) FIGS. **8** and **9** illustrate a RADAR based vehicle localization method **200** in a accordance with a vehicle localization system as disclosed herein, such as the vehicle localization system **100** illustrated in FIG. **2** The method includes steps of: **210** acquiring navigation data; **220** generating a first vehicle navigation state based on the navigation data; **230** acquiring RADAR data; **240** generating a point cloud based on accumulating the RADAR data using the first navigation state; **250** pre-processing a known map; **260** generating a second vehicle navigation state based on

comparing the point cloud and the known map; and, **270** generating a current vehicle navigation state based on fusing the first and second vehicle navigation states.

(83) Embodiments of the method step **210** include acquiring navigation data indicative of a vehicle navigation state from one or more navigation sensors, such as navigation sensors **122**. The method step **220** includes generating a first vehicle navigation state in the navigation frame of reference, based on the navigation data obtained in step **210**. The first vehicle navigation state may be obtained directly from the navigation data, or may require additional processing steps, such as a method step **222** of dead-reckoning to determine a change relative to a previous navigation state. The method step **224** includes deriving a relative vehicle pose transformation based on a relative change in the vehicle pose between the first navigation state and the previous vehicle navigation state. Applying the relative vehicle pose transformation to corresponding RADAR data conforms and accumulates RADAR data for generating a point cloud. In an embodiment, a method step **226** includes storing the relative vehicle pose transformation, generated in the method step **224**, in a FIFO structure

(84) Embodiments for the method step **230** of acquiring RADAR data indicative of an environment in the vicinity of a vehicle including acquiring RADAR data from one or more RADAR sensors **131**, **132**, **135**, etc., that are provided on the vehicle. Embodiments include processing the acquired RADAR data through the method steps **232**, **234**, and/or **236**. Method step **232** includes transforming the RADAR data into a vehicle frame of reference. Method step **234** includes evaluating the RADAR data to identify static objects and discard, delete, or remove RADAR data pertaining to dynamic objects. Method step **236** includes storing the RADAR data in a FIFO data structure.

(85) The method step **240** generates a point cloud based on accumulating the RADAR data using the relative vehicle pose transformation derived in the method step **224**, and further transforming the accumulated RADAR data into the navigation frame using the first navigation state derived in method step **220**.

(86) The method step **250** generally relates to pre-processing the known map and includes the method step **252** of retrieving a known map from a memory **152**, such as a local memory **152***a* or a remote memory **152***b*. Embodiments may further include processing the known map through the method step **254** to remove non-visible map elements from the known map based on the first navigation state derived in the method step **220**. The method step **256** includes subdividing the known map into a plurality of cells and generating a corresponding probability density function (PDF) of the obstacle points in each cell. In an embodiment, each cell is a square of equal width.

(87) The method step **260** includes comparing the point cloud generated by the method step **240** with the known map output by the method step **250**. The comparison is based on transforming the point cloud to match the known map. The resulting point cloud transformation characterizes a second navigation state. As the point cloud is initially expressed at the first navigation state, the second navigation state inherently reflects a transformation of the first navigation state. In an embodiment, the method step **260** includes iteratively transforming the point cloud to match the known map, wherein a likelihood score is generated for each iteration, to evaluate a likelihood that the iterative point cloud matches the known map. In an embodiment, the method step **260** includes maximizing a likelihood of matching the point cloud and the known map, wherein the transformation parameters include a maximum number of iterations and a minimum transformation iteration.

(88) The method step **270** includes generating a current vehicle navigation state based on the first navigation state output by the method step **220** and the second vehicle navigation state output by the method step **260**. Further embodiments include using a Bayesian Filter to fuse the first and second vehicle navigation states.

(89) FIGS. **10** to **13** relate to a first working example of a vehicle operating in an underground parkade, equipped with a vehicle localization system in accordance with the disclosure herein. FIG.

10 illustrates a known map of the underground parkade in the form of a two-dimensional point cloud map and FIG. **11** includes a vehicle test trajectory superimposed on the known map illustrated in FIG. **10**. The vehicle test trajectory spanned approximately 300 meters, over a period of approximately 3 minutes. The vehicle test trajectory begins at starting point A, then heads generally west towards the North-East corner of the map. The vehicle completes a multi-point turn in the North-East corner, then moving south before heading generally West, towards the finishing point B.
(90) The vehicle was equipped with four RADAR sensors and a dead reckoning system for use in localizing a vehicle position in accordance with the systems and methods disclosed herein. In particular, the four RADAR sensors were mounted on four different corners of the vehicle, as similarly illustrated in FIG. **3**. The dead-reckoning system comprised wheel encoders. FIG. **12**A illustrates the un-processed RADAR point cloud generated over the totality of the vehicle test trajectory. FIG. **12**B illustrates the RADAR point cloud depicted in FIG. **12**A having been processed to remove noise. FIGS. **13**A and **13**B illustrate the RADAR point clouds for two discrete time epochs, at 25 seconds and 60 seconds into the vehicle trajectory, respectively marked as **13**A and **13**B in FIG. **12**B.
(91) FIGS. **14** and **15** relate to a second working example of a vehicle operating in a multi-level indoor-outdoor environment, equipped with a vehicle localization system and method as disclosed herein. In particular, FIG. **14**. illustrates four interconnected maps for an indoor area, an outdoor area, and two ramps for interconnecting the indoor and outdoor areas. FIG. **15** illustrates the resulting vehicle trajectory derived from the localization system and method implemented with vehicle travelling through the maps. The trajectory includes completing a loop, beginning at point X on the indoor map. The loop continues with the vehicle proceeding generally east towards the exit ramp for transitioning to the outdoor area. The loop continues in the outdoor area, with the vehicle travelling generally west towards the entry ramp, returning back to the indoor area to complete a first loop. The vehicle continues driving and completes the loop a second time, culminating in the vehicle parking adjacent the spot marked with a Y. The vehicle trajectory particularly illustrates the ability of the vehicle localization system and method to resolve a vehicle navigation state seamlessly between different maps and elevations, including transitioning seamlessly between indoor and outdoor environments.
(92) In the preceding description, for purposes of explanation, numerous details are set forth in order to provide a thorough understanding of the embodiments. However, it will be apparent to one skilled in the art that these specific details are not required. In other instances, well-known electrical structures and circuits are shown in block diagram form in order not to obscure the understanding. For example, specific details are not provided as to whether the embodiments described herein are implemented as a software routine, hardware circuit, firmware, or a combination thereof. The scope of the claims should not be limited by the particular embodiments set forth herein, but should be construed in a manner consistent with the specification as a whole.
(93) Embodiments of the disclosure can be represented as a computer program product stored in a machine-readable medium (also referred to as a computer-readable medium, a processor-readable medium, or a computer usable medium having a computer-readable program code embodied therein). The machine-readable medium can be any suitable tangible, non-transitory medium, including magnetic, optical, or electrical storage medium including a diskette, compact disk read only memory (CD-ROM), memory device (volatile or non-volatile), or similar storage mechanism. The machine-readable medium can contain various sets of instructions, code sequences, configuration information, or other data, which, when executed, cause a processor to perform steps in a method according to an embodiment of the disclosure. Those of ordinary skill in the art will appreciate that other instructions and operations necessary to implement the described implementations can also be stored on the machine-readable medium. The instructions stored on the machine-readable medium can be executed by a processor or other suitable processing device,

and can interface with circuitry to perform the described tasks.
(94) The above-described embodiments are intended to be examples only. Alterations, modifications and variations can be effected to the particular embodiments by those of skill in the art without departing from the scope, which is defined solely by the claims appended hereto.

Claims

1. A localization system for a vehicle, comprising a first sensor configured to generate first data indicative of a first navigation state of the vehicle; a second sensor configured to generate second data indicative of an environment in the vicinity of the vehicle; a processor communicatively coupled to the first sensor and the second sensor, the processor configured to: generate a second navigation state based on matching the second data to a known map of the environment, the known map including a plurality of objects; subdivide the known map into a plurality of cells and evaluate each of the plurality of cells to generate a corresponding probability distribution function indicative of a corresponding subset of the plurality of objects occupying the corresponding cell; generate a point cloud based on the second data wherein the second navigation state is based on matching the point cloud and the known map, and generate a current navigation state based on the first navigation state and the second navigation state.
2. The system of claim 1, wherein the point cloud comprises a plurality of reflection points indicative of objects in the vicinity of the vehicle; and wherein the processor is configured to remove reflection points indicative of dynamic objects.
3. The system of claim 1, wherein the processor is configured to generate the point cloud based on accumulating the second data into a common frame of reference using a relative vehicle pose transformation derived from the first data.
4. The system of claim 3, wherein the common frame of reference comprises a navigation frame of reference; wherein the first navigation state includes a first vehicle pose comprising a first vehicle position and a first vehicle heading; and wherein the relative vehicle pose transformation comprises a change in vehicle pose from a previous vehicle pose to the first vehicle pose.
5. The system of claim 1, wherein the processor is configured to generate a map transformation function based on transforming the point cloud to match the known map.
6. The system of claim 5, wherein the second navigation state is based on the map transformation function; wherein the transforming comprises an iterative transformation comprising transformation parameters; wherein the transformation parameters include a maximum number of iterations, a smallest iteration step, and a map resolution; wherein the processor is configured to generate a match likelihood score based on a match between the point cloud and the known map; and wherein the match likelihood score is generated based on a Bayesian matching approach, an iterative closest point method, or a normal-distribution transform method.
7. The system of claim 1, wherein the known map comprises a plurality of map elements representing the plurality of objects in the environment; wherein the plurality of map elements comprise at least one of a line segment, a point, or a polygon; wherein the processor is configured to remove non-visible map elements from the known map based on the first vehicle navigation state; and wherein the processor is configured to obtain a new map based on detecting the first navigation state in a boundary area adjacent to the new map.
8. The system of claim 1, wherein the first sensor is configured to generate the first data in a first frame of reference and the second sensor is configured to generate the second data in a second frame of reference; wherein the processor is configured to transform the first data and the second data into a vehicle frame of reference; wherein the second sensor comprises a ranging sensor and the second data comprises ranging data generated by the ranging sensor; wherein the ranging sensor comprises a Radio Detection and Ranging (RADAR) sensor and the ranging data comprises RADAR data generated by the RADAR sensor; and wherein the RADAR data includes range

information, bearing information, and relative velocity information.

9. The system of claim 1, wherein the first sensor comprises a navigation sensor configured to generate navigation data; wherein the navigation sensor comprises a wheel tick encoder, inertial sensors, a steering wheel sensor, a camera, and a GNSS device; the system further comprising a memory communicatively coupled to the processor, wherein the known map is stored in the memory; and wherein the memory is local to the system, remote to the system, or a combination thereof.

10. A computer-implemented method for vehicle localization, comprising: acquiring, from a first sensor, first data indicative of a first navigation state of a vehicle; acquiring, from a second sensor, second data indicative of an environment in the vicinity of the vehicle; generating, using a processor communicatively coupled to the first sensor and the second sensor, a second navigation state based on matching the second data to a known map of the environment, the known map including a plurality of objects; subdividing, using the processor, the known map into a plurality of cells and evaluating each cell to generate a corresponding probability distribution function indicative of a corresponding subset of the plurality of objects occupying the corresponding cell; generating, using the processor, a point cloud based on accumulating the second data wherein generating the second navigation state is based on matching the point cloud to the known map, and generating, using the processor, a current navigation state based on the first navigation state and the second navigation state.

11. The computer-implemented method of claim 10, further comprising: generating, using the processor, a relative vehicle pose transformation based on a change in navigation state between the first navigation state and a previous first navigation state, and wherein the processor generates the point cloud based on using the relative vehicle pose transformation to accumulate the second data relative to the first navigation state.

12. The computer-implemented method of claim 10, wherein matching the point cloud and the known map is based on evaluating the point cloud against the corresponding probability distribution function for each of the plurality of cells.

13. The computer-implemented method of claim 10, wherein matching the point cloud to the known map further comprises: iteratively transforming the point cloud and evaluating a likelihood of each iterative point cloud matching the known map, wherein the second navigation state is based on the iterative point cloud having a highest likelihood of matching the known map; and wherein evaluating the likelihood of matching comprises a normal distributions transform approach.

14. The computer-implemented method of claim 10, wherein the current navigation state is based on fusing the first navigation state and the second navigation state using a Bayesian filter.

15. The computer-implemented method of claim 10, wherein the first sensor is a navigation sensor, and the second sensor is a Radio Detection and Ranging (RADAR) sensor.

16. The computer-implemented method of claim 15, wherein the RADAR sensor comprises a plurality of RADAR sensors.

17. A non-transitory computer readable medium storing computer executable instructions thereon that when executed by a computer perform the method according to claim 10.