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(54) **RADAR REFERENCE MAP GENERATION**

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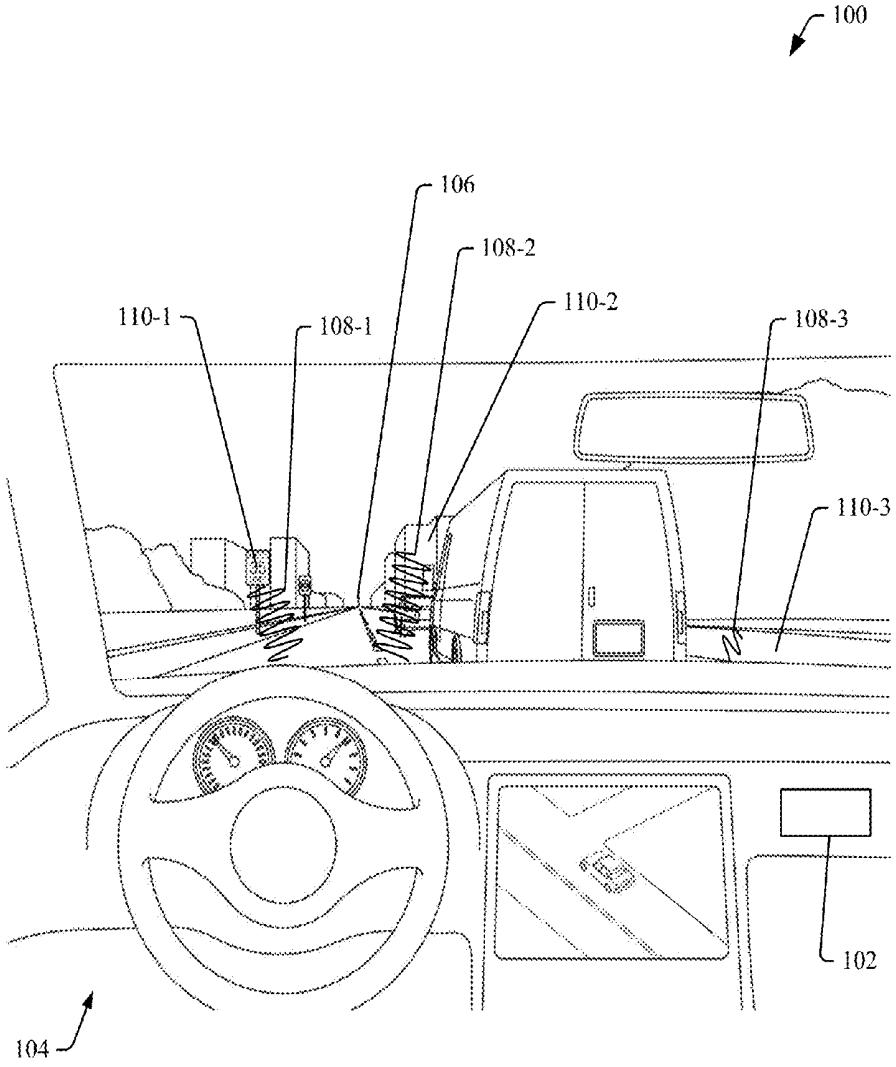
(52) **U.S. Cl.**

CPC ***G01S 13/89*** (2013.01); ***H04L 67/10*** (2013.01); ***G06N 7/005*** (2013.01)

(57) **ABSTRACT**

Methods and systems are described that enable radar reference map generation. A high-definition (HD) map is received and one or more HD map objects within the HD map are determined. Attributes of the respective HD map objects are determined, and, for each HD map object, one or more occupancy cells of a radar occupancy grid are indicated as occupied space based on the attributes of the respective HD map object. By doing so, a radar reference map may be generated without a vehicle traversing through an area corresponding to the radar reference map.



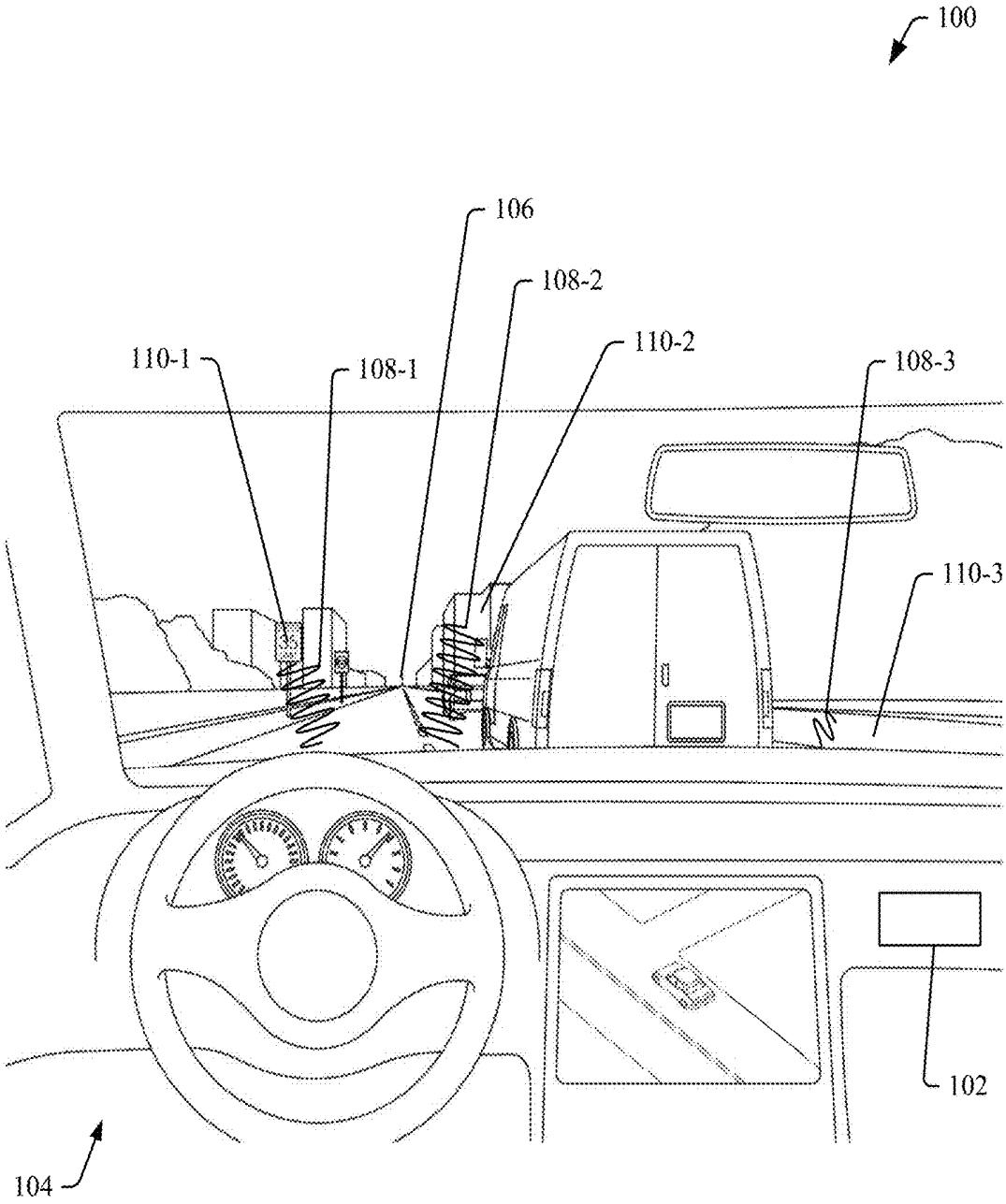


Fig. 1

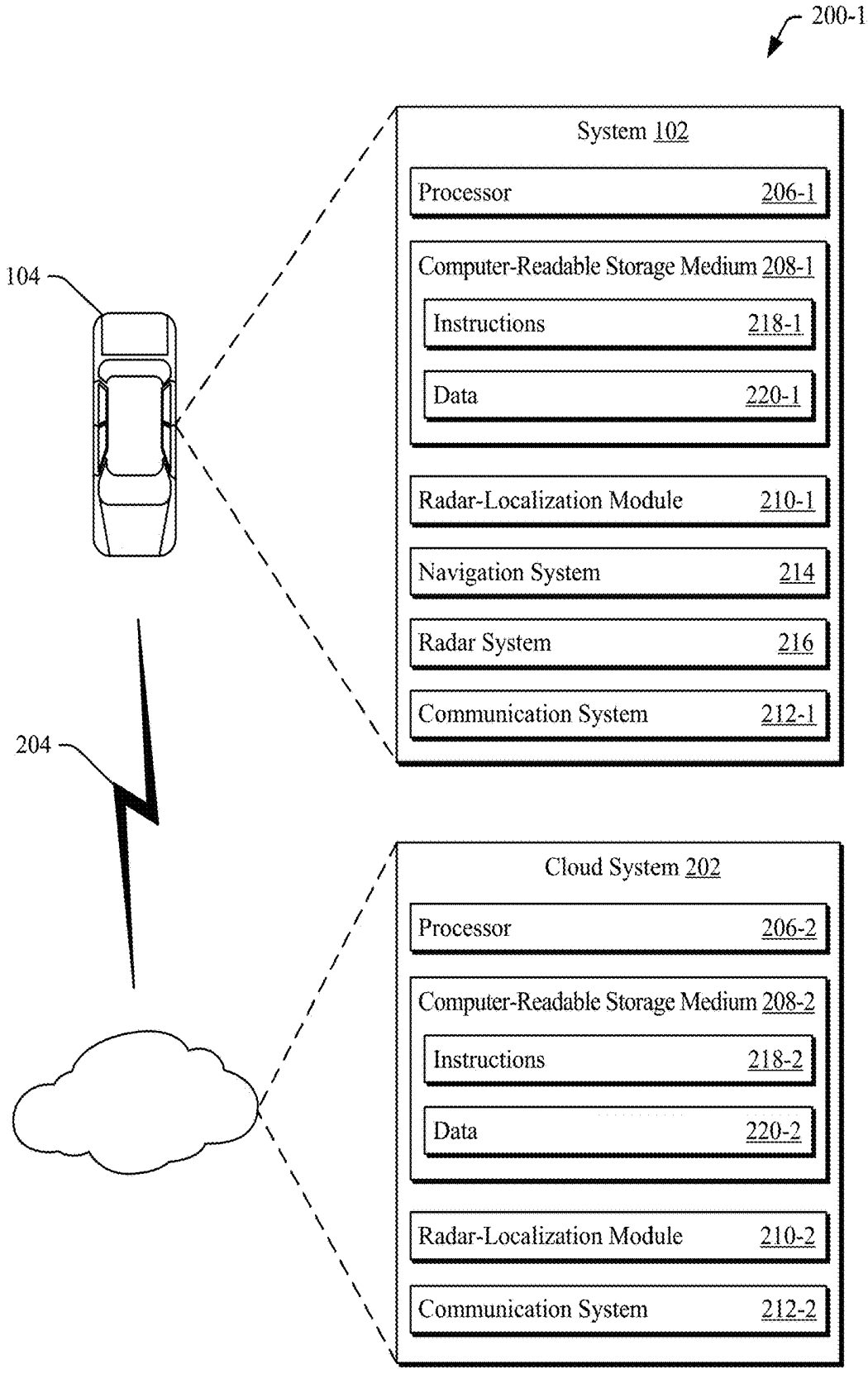

200-1
System 102
Processor 206-1
Computer-Readable Storage Medium 208-1
Instructions 218-1
Data 220-1
Radar-Localization Module 210-1
Navigation System 214
Radar System 216
Communication System 212-1
104
204
Cloud System 202
Processor 206-2
Computer-Readable Storage Medium 208-2
Instructions 218-2
Data 220-2
Radar-Localization Module 210-2
Communication System 212-2

Fig. 2-1

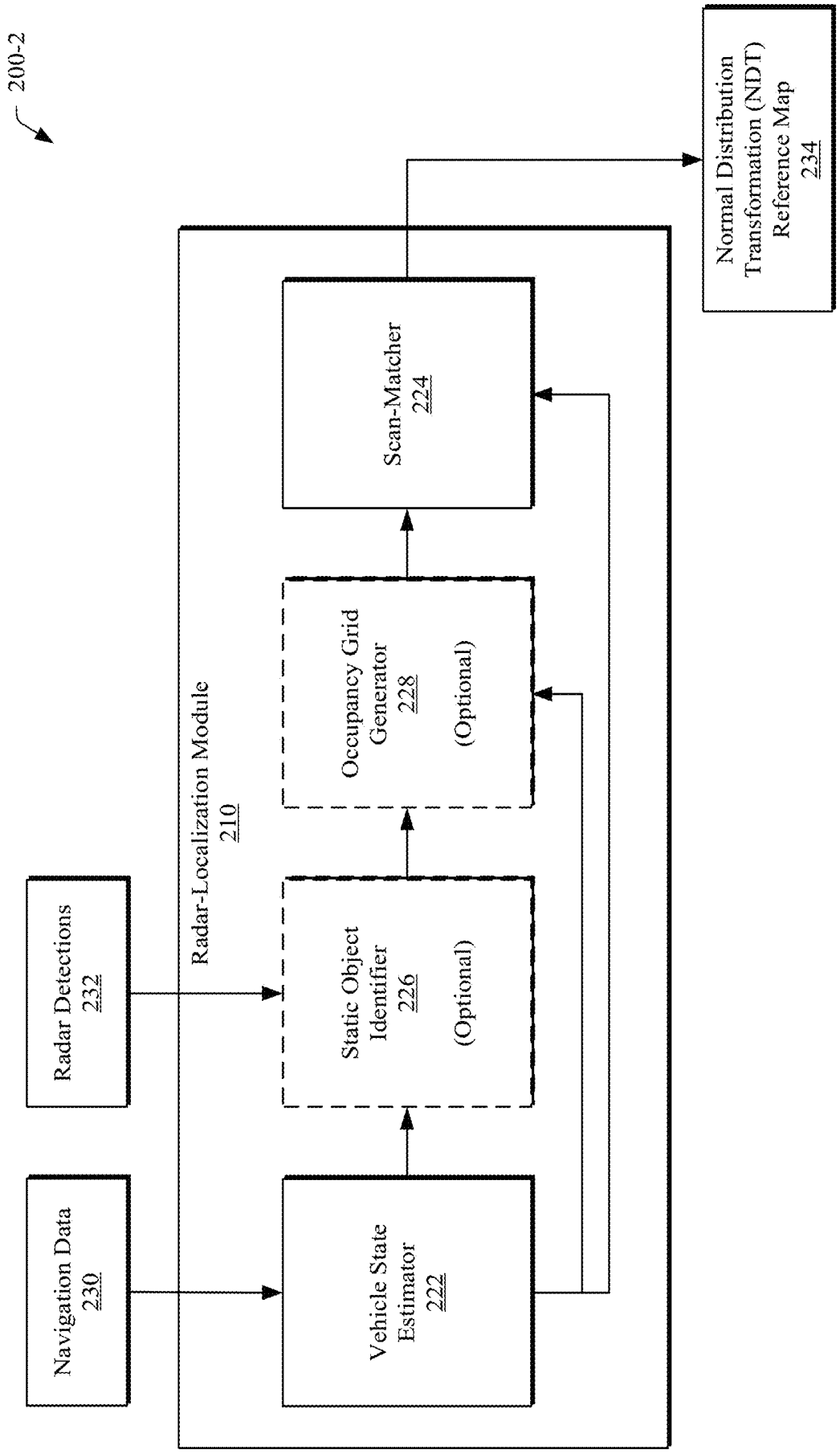

200-2
Normal Distribution Transformation (NDT) Reference Map 234
Scan-Matcher 224
Occupancy Grid Generator 228 (Optional)
Static Object Identifier 226 (Optional)
Vehicle State Estimator 222
Radar-Localization Module 210
Radar Detections 232
Navigation Data 230

Fig. 2-2

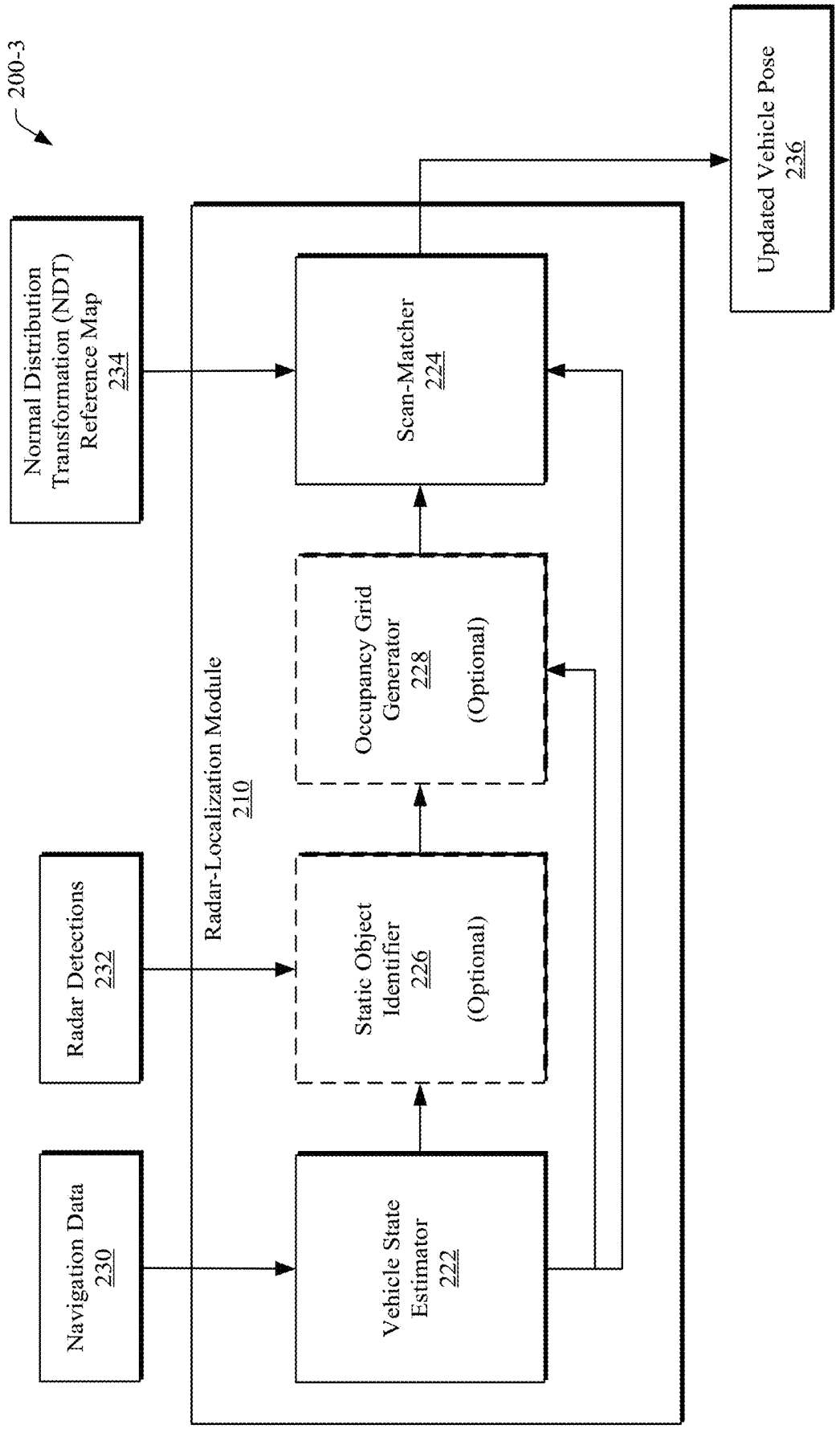

200-3
Normal Distribution Transformation (NDT) Reference Map 234
Radar Detections 232
Navigation Data 230
Radar-Localization Module 210
Vehicle State Estimator 222
Static Object Identifier 226 (Optional)
Occupancy Grid Generator 228 (Optional)
Scan-Matcher 224
Updated Vehicle Pose 236

Fig. 2-3

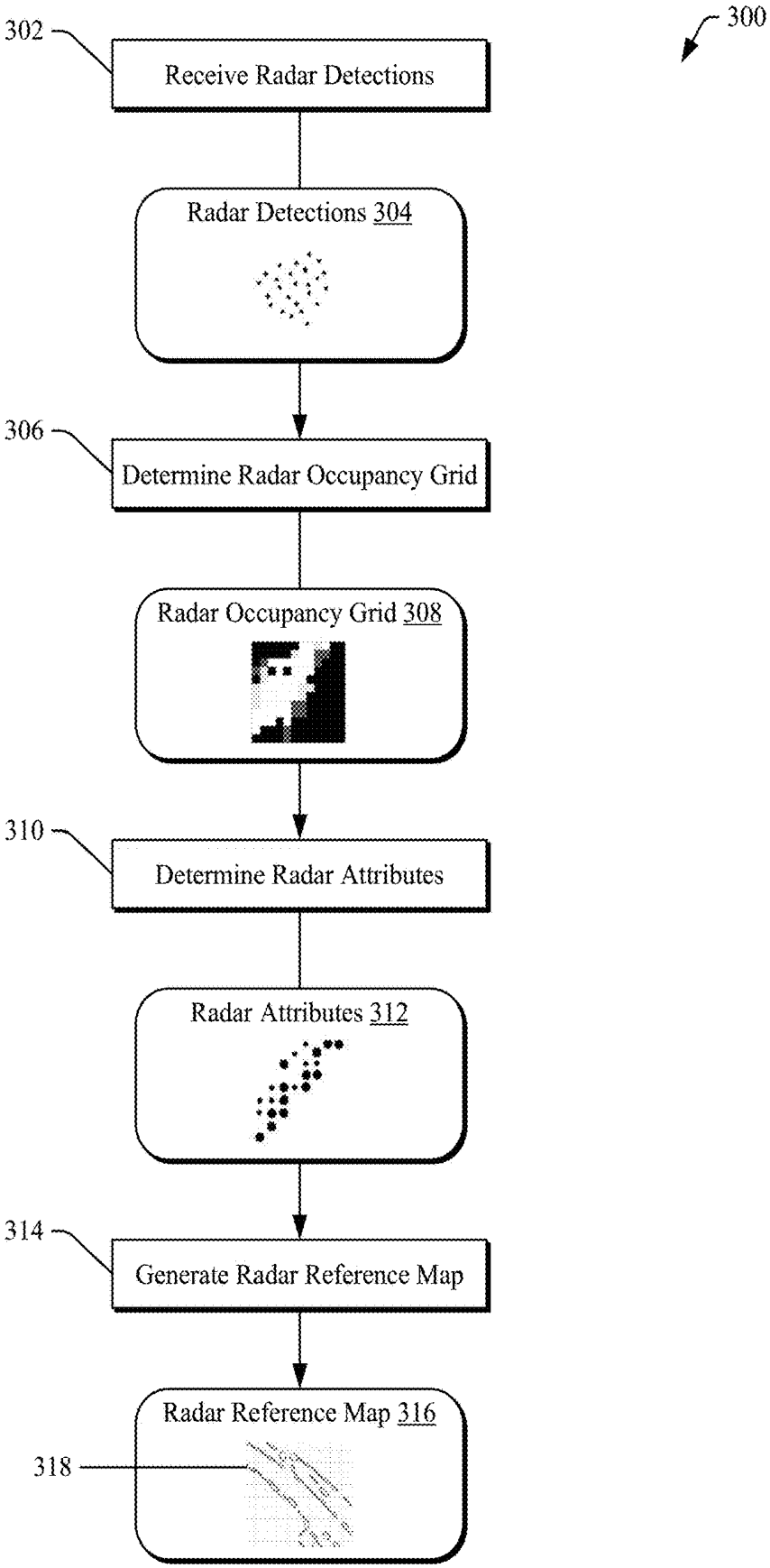

300
302
Receive Radar Detections
Radar Detections 304
306
Determine Radar Occupancy Grid
Radar Occupancy Grid 308
310
Determine Radar Attributes
Radar Attributes 312
314
Generate Radar Reference Map
Radar Reference Map 316
318

Fig. 3

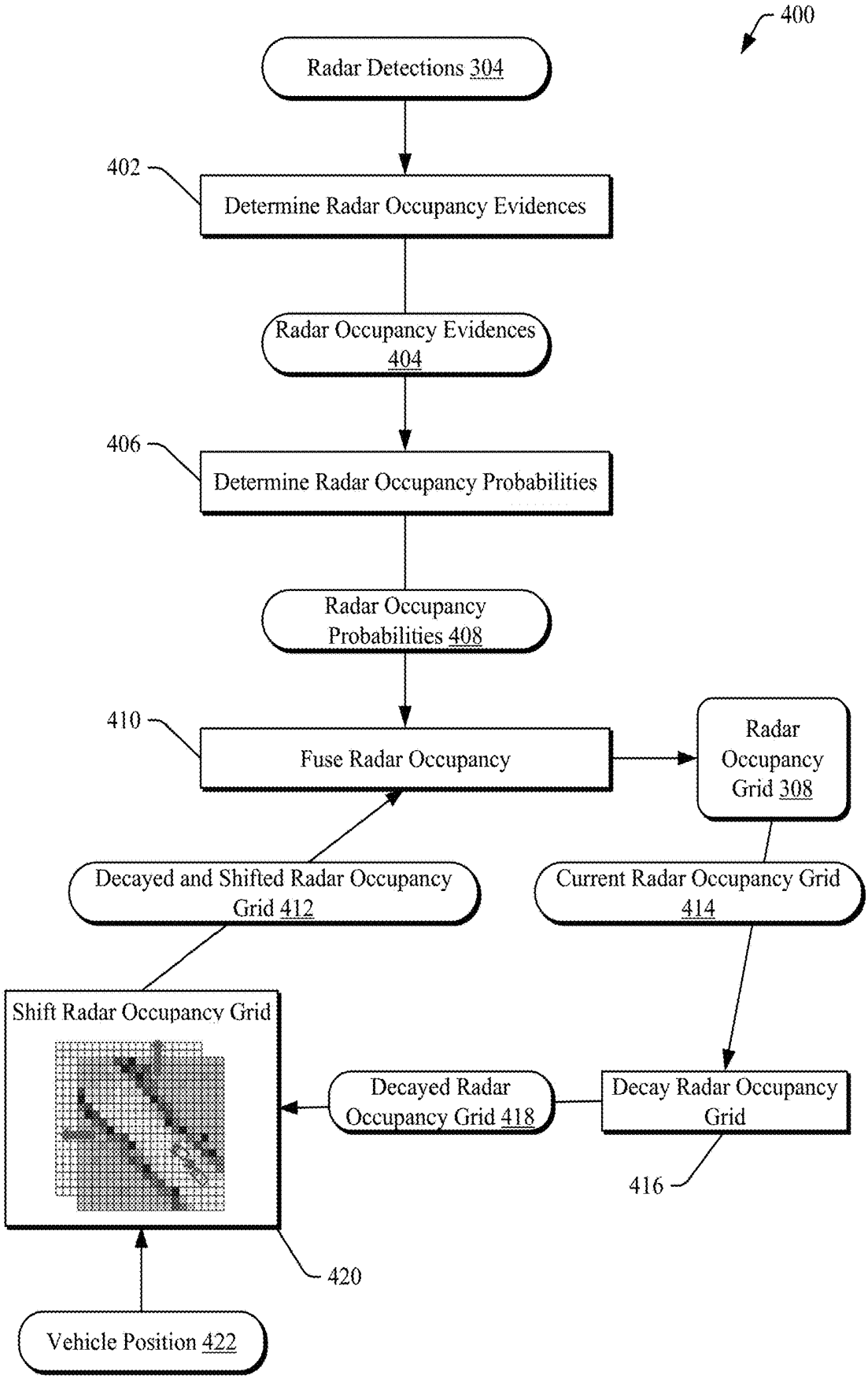

400
Radar Detections 304
402
Determine Radar Occupancy Evidences
Radar Occupancy Evidences 404
406
Determine Radar Occupancy Probabilities
Radar Occupancy Probabilities 408
410
Fuse Radar Occupancy
Radar Occupancy Grid 308
Decayed and Shifted Radar Occupancy Grid 412
Current Radar Occupancy Grid 414
Shift Radar Occupancy Grid
Decayed Radar Occupancy Grid 418
Decay Radar Occupancy Grid
416
420
Vehicle Position 422

Fig. 4

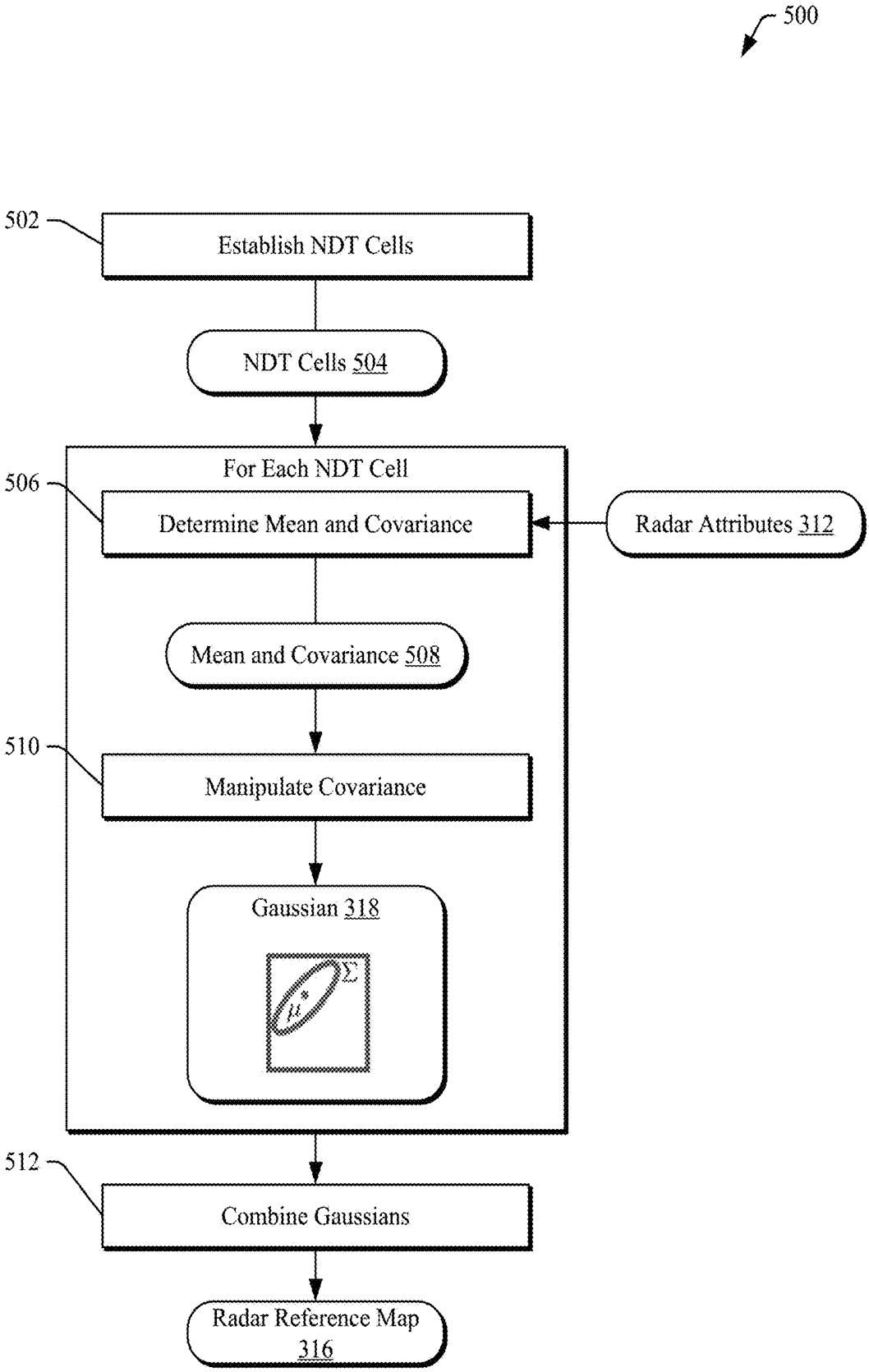

500
502
Establish NDT Cells
NDT Cells 504
For Each NDT Cell
506
Determine Mean and Covariance
Radar Attributes 312
Mean and Covariance 508
510
Manipulate Covariance
Gaussian 318
Σ
μ
512
Combine Gaussians
Radar Reference Map 316

Fig. 5

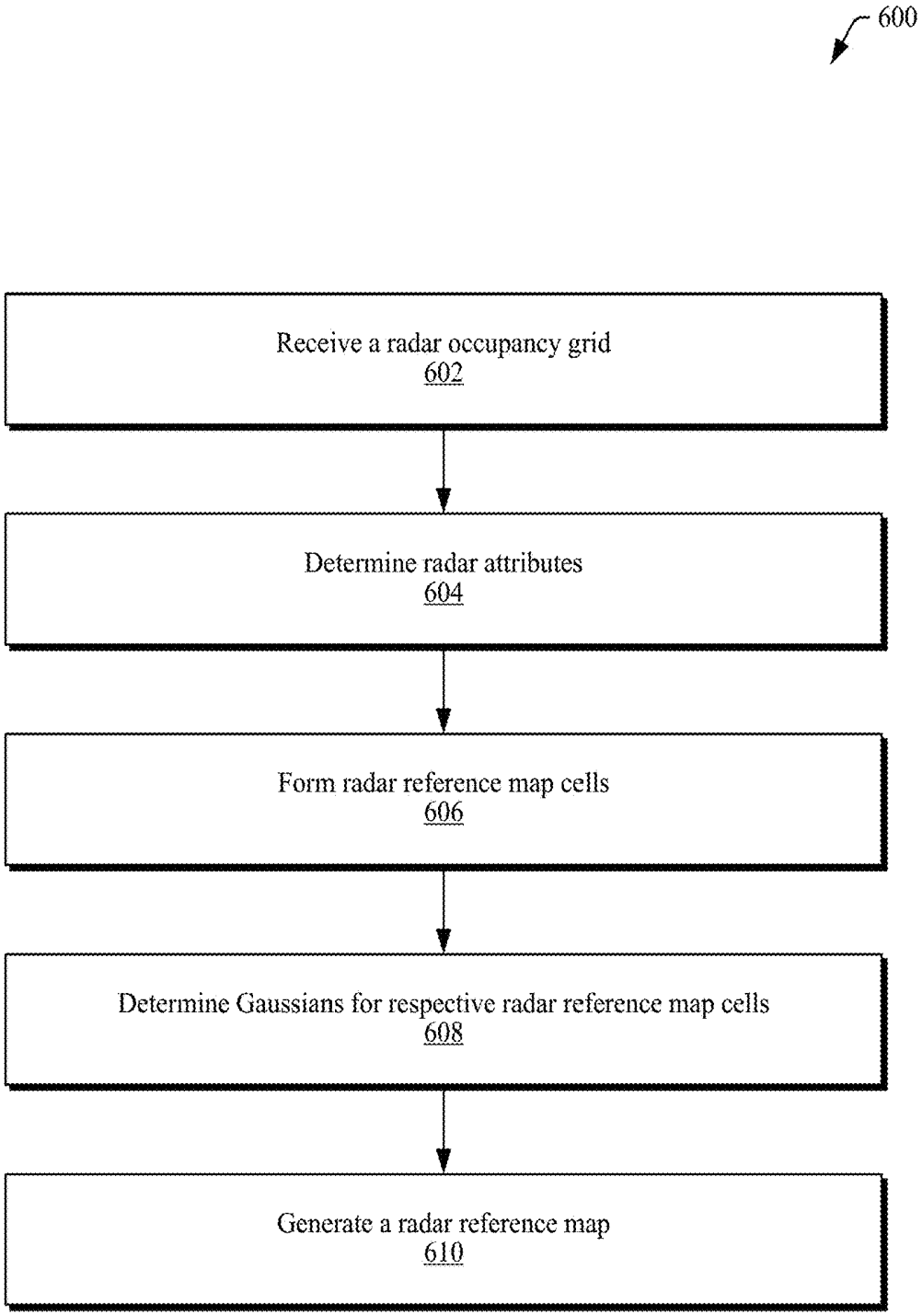

600
Receive a radar occupancy grid
602
Determine radar attributes
604
Form radar reference map cells
606
Determine Gaussians for respective radar reference map cells
608
Generate a radar reference map
610

Fig. 6

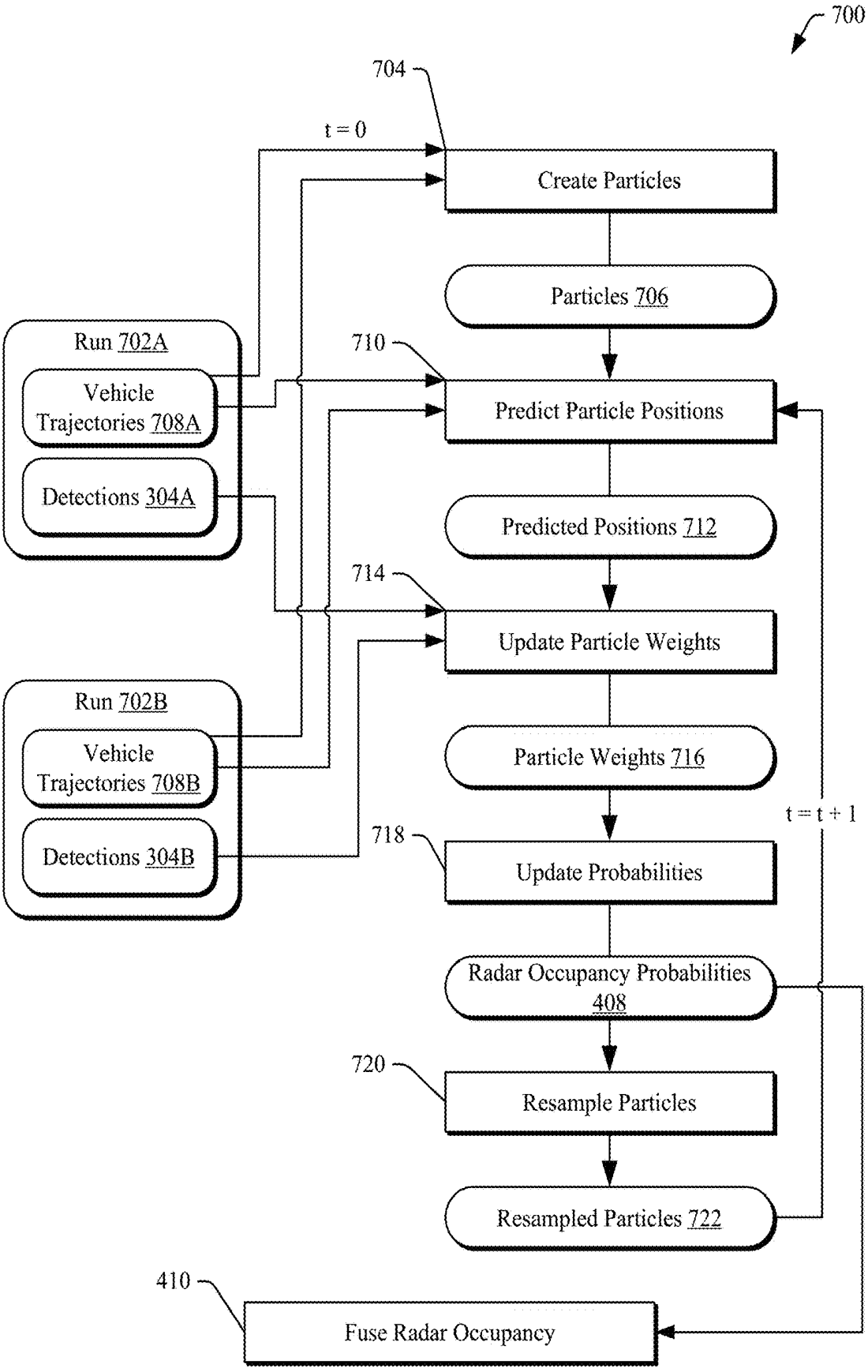

700
704
t = 0
Create Particles
Particles 706
Run 702A
Vehicle Trajectories 708A
Detections 304A
710
Predict Particle Positions
Predicted Positions 712
714
Update Particle Weights
Run 702B
Vehicle Trajectories 708B
Detections 304B
Particle Weights 716
t = t + 1
718
Update Probabilities
Radar Occupancy Probabilities 408
720
Resample Particles
Resampled Particles 722
410
Fuse Radar Occupancy

Fig. 7

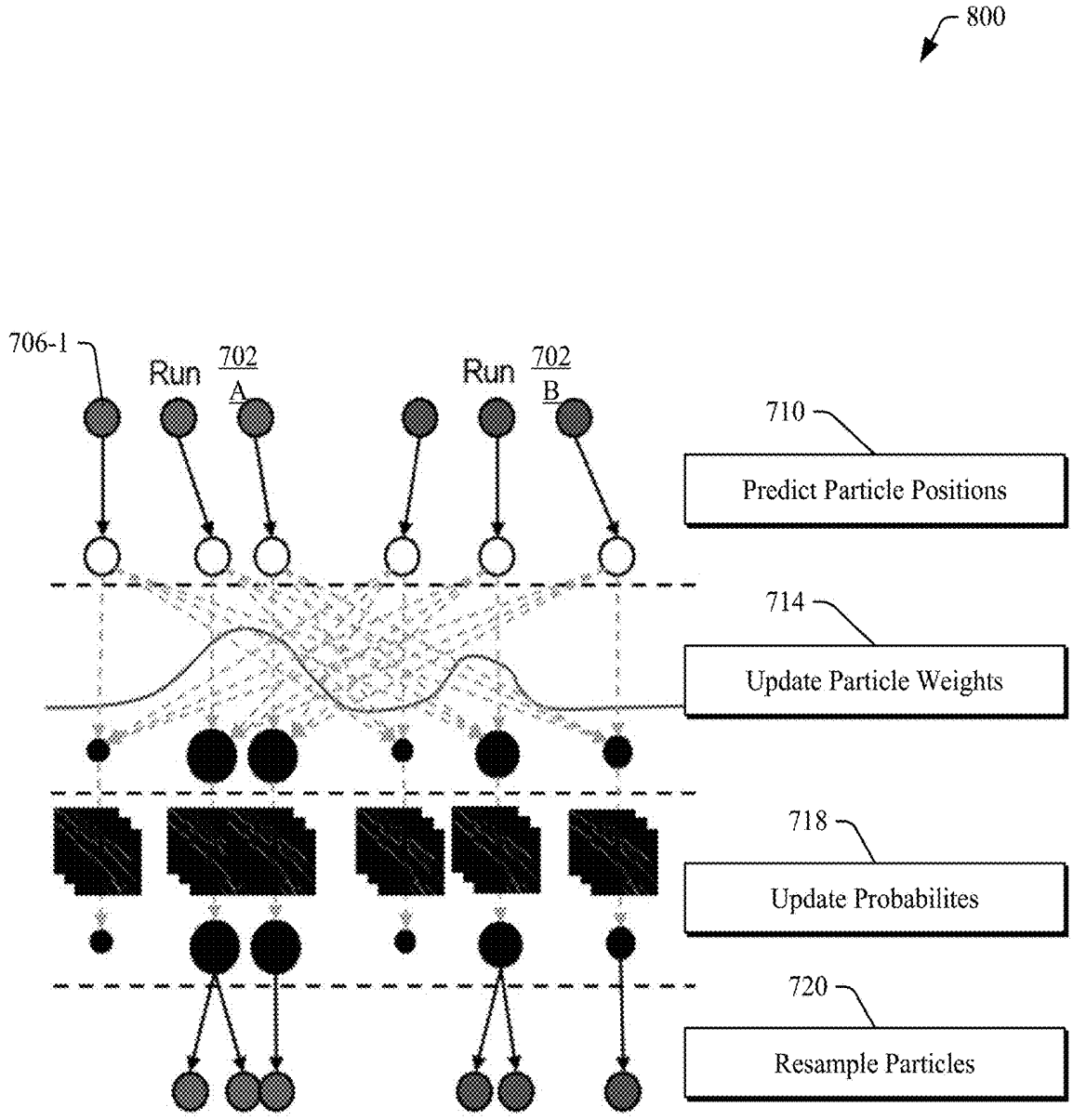

800
706-1
Run
702
A
Run
702
B
710
Predict Particle Positions
714
Update Particle Weights
718
Update Probabilites
720
Resample Particles

Fig. 8

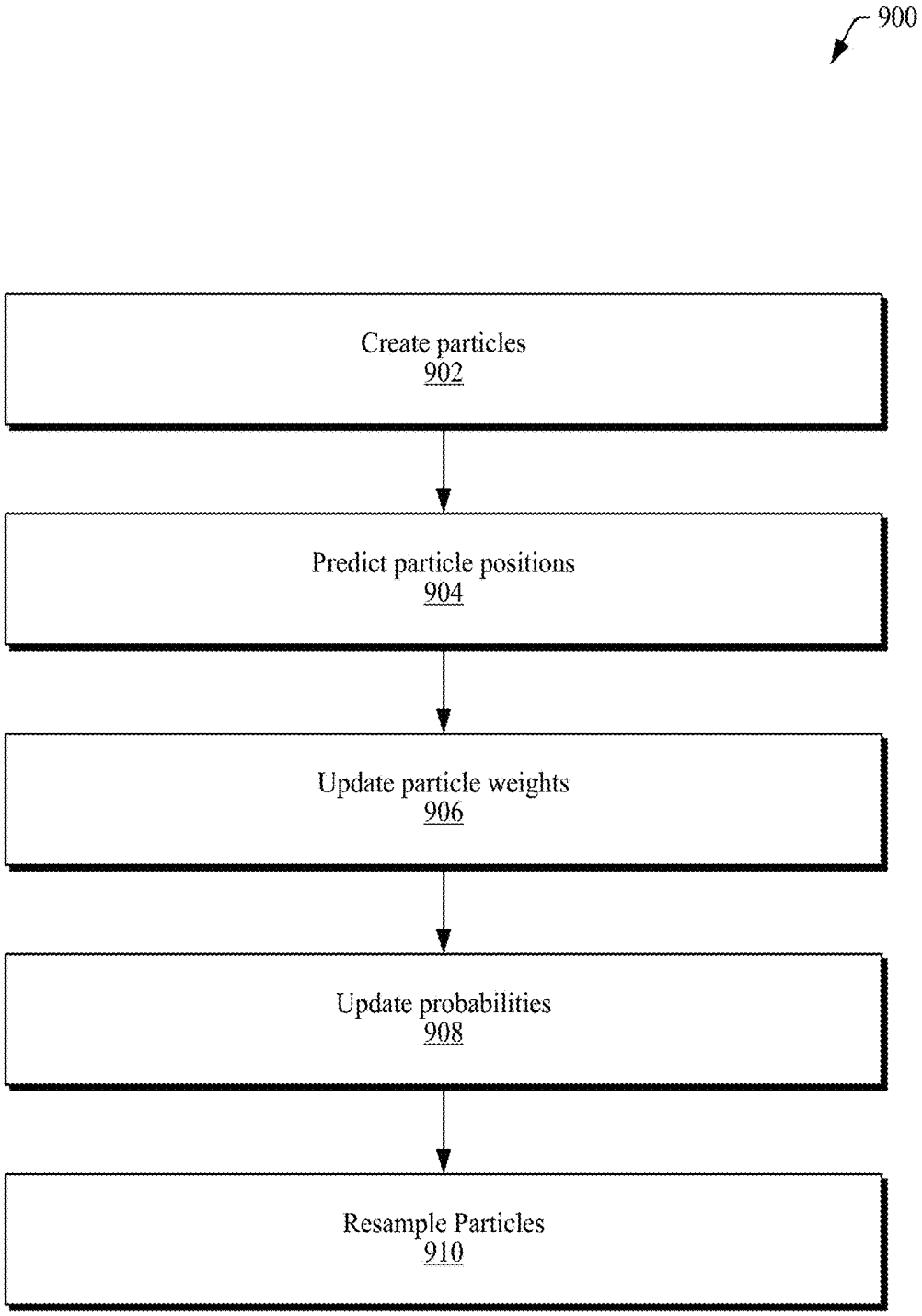

900
Create particles
902
Predict particle positions
904
Update particle weights
906
Update probabilities
908
Resample Particles
910

Fig. 9

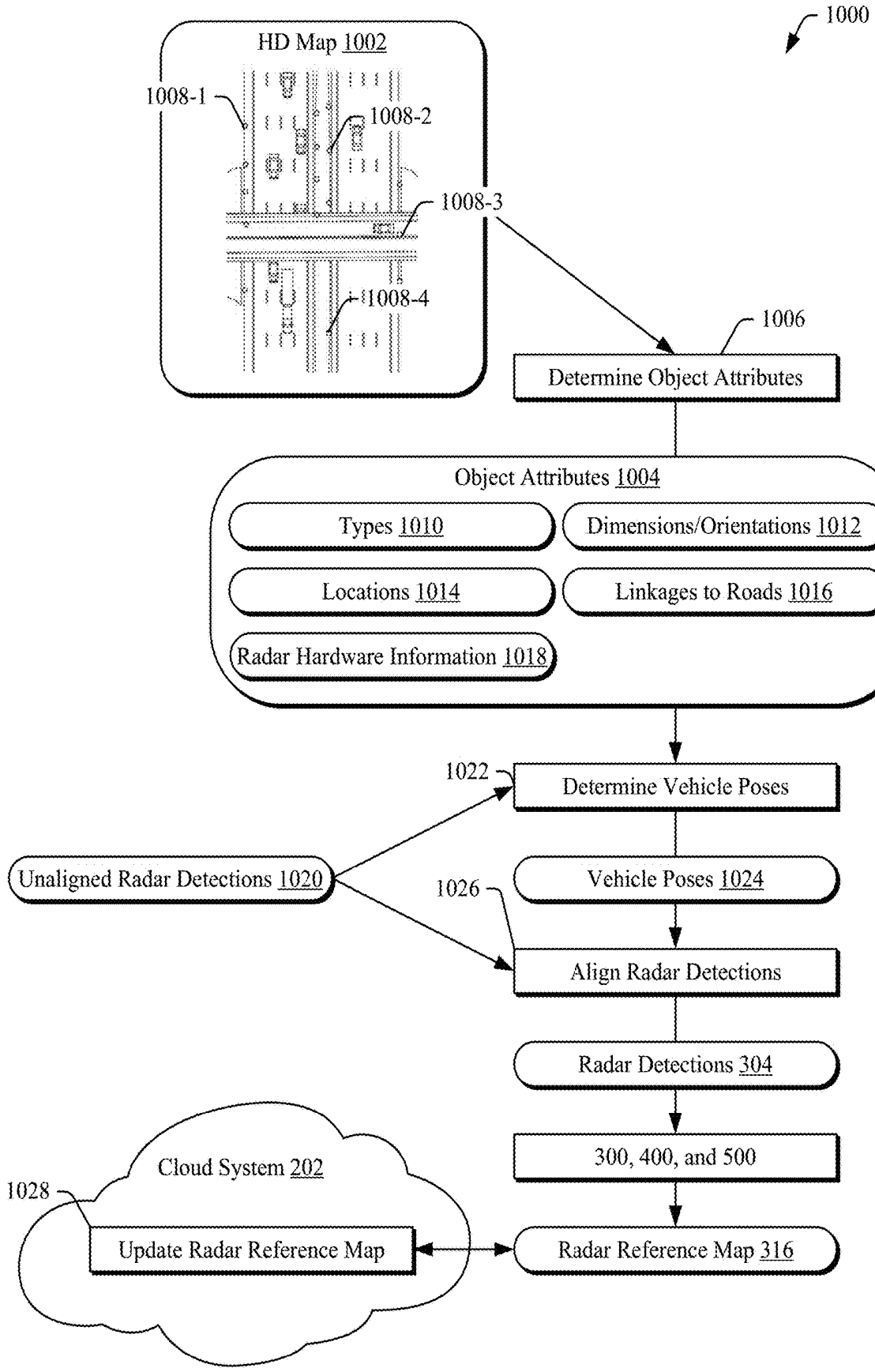

1000
HD Map 1002
1008-1
1008-2
1008-3
1008-4
1006
Determine Object Attributes
Object Attributes 1004
Types 1010
Dimensions/Orientations 1012
Locations 1014
Linkages to Roads 1016
Radar Hardware Information 1018
1022
Determine Vehicle Poses
Unaligned Radar Detections 1020
Vehicle Poses 1024
1026
Align Radar Detections
Radar Detections 304
300, 400, and 500
Cloud System 202
1028
Update Radar Reference Map
Radar Reference Map 316

Fig. 10

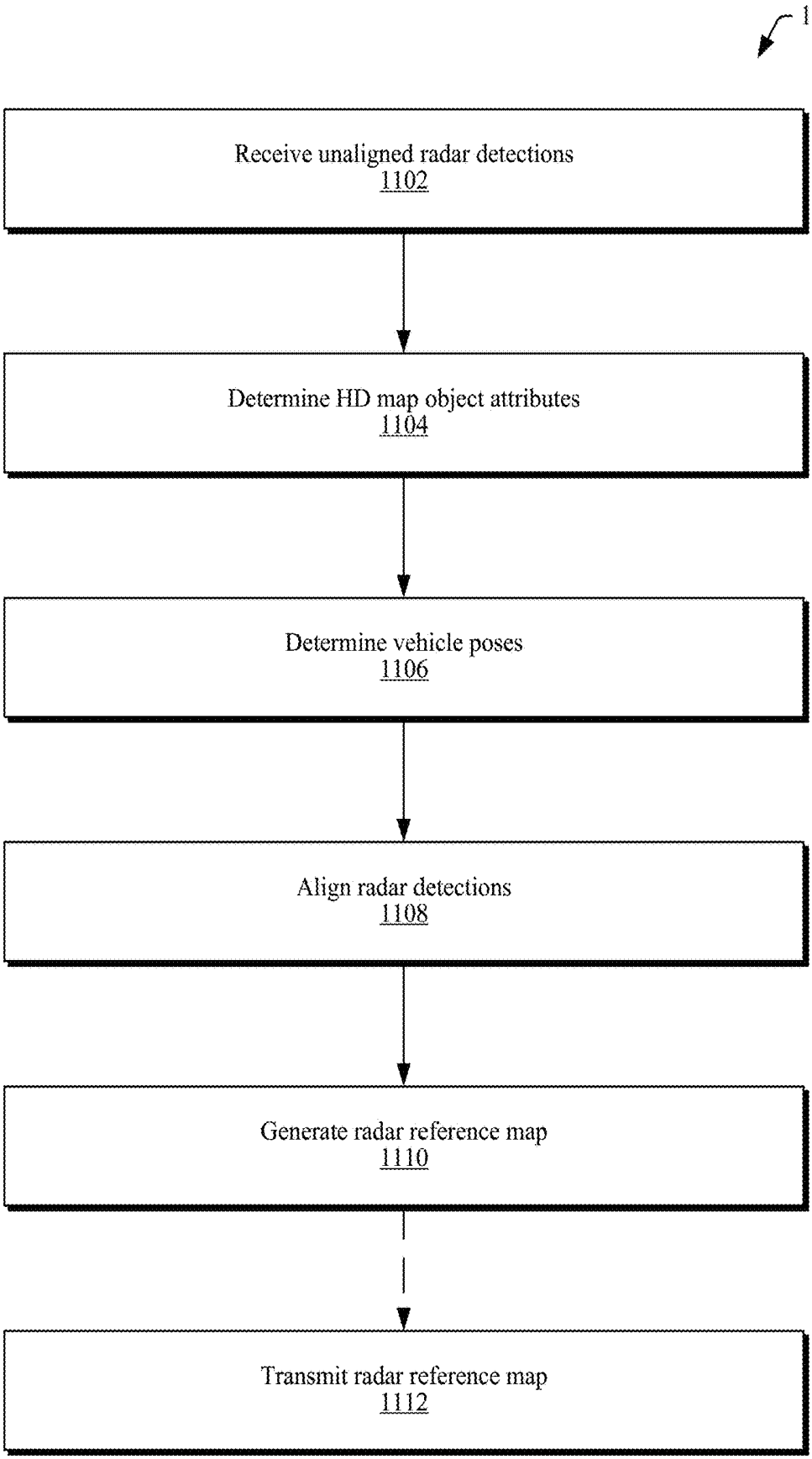

1100
Receive unaligned radar detections
1102
Determine HD map object attributes
1104
Determine vehicle poses
1106
Align radar detections
1108
Generate radar reference map
1110
Transmit radar reference map
1112

Fig. 11

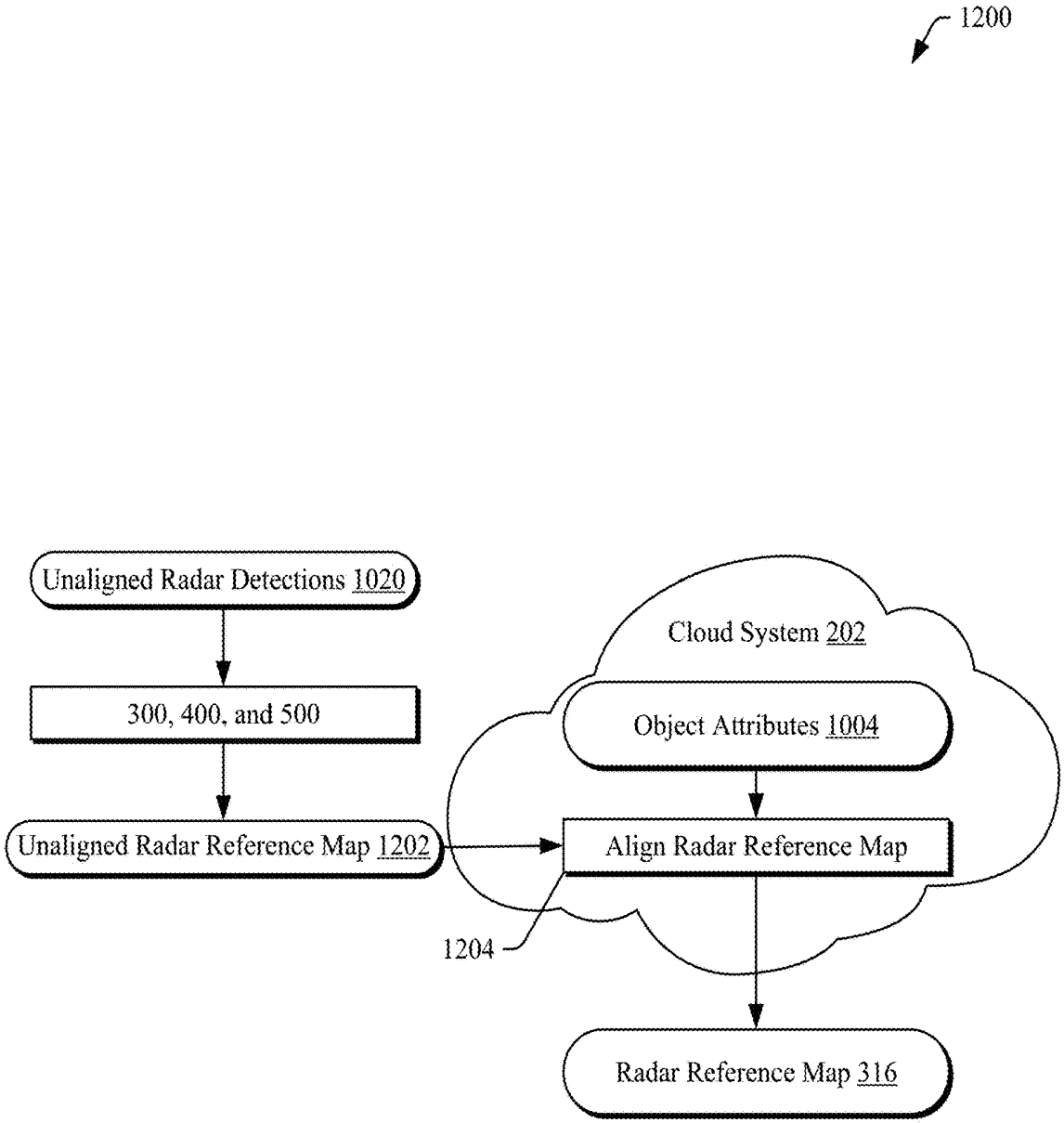

1200
Unaligned Radar Detections 1020
300, 400, and 500
Unaligned Radar Reference Map 1202
Cloud System 202
Object Attributes 1004
Align Radar Reference Map
1204
Radar Reference Map 316

Fig. 12

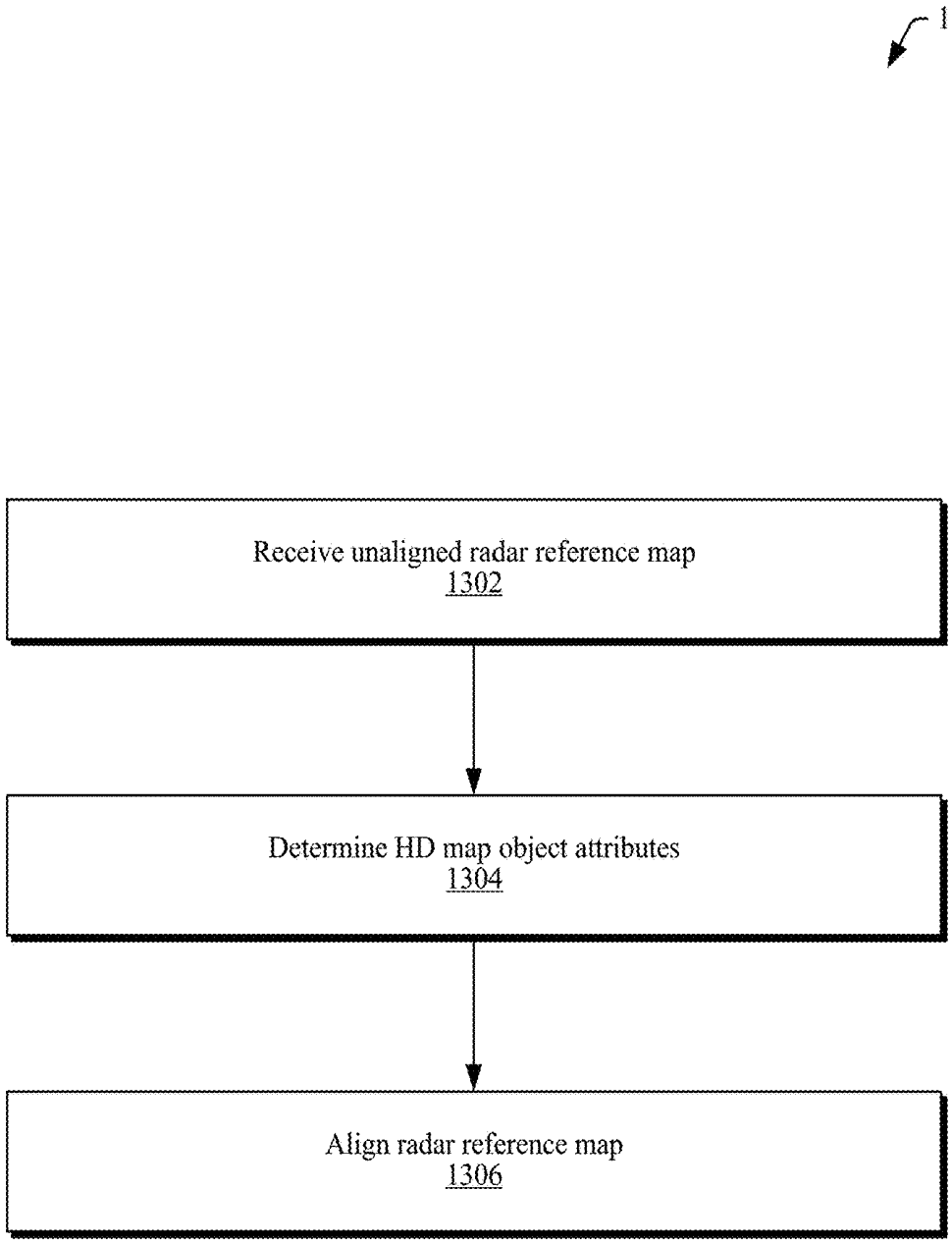

1300
Receive unaligned radar reference map
1302
Determine HD map object attributes
1304
Align radar reference map
1306

Fig. 13

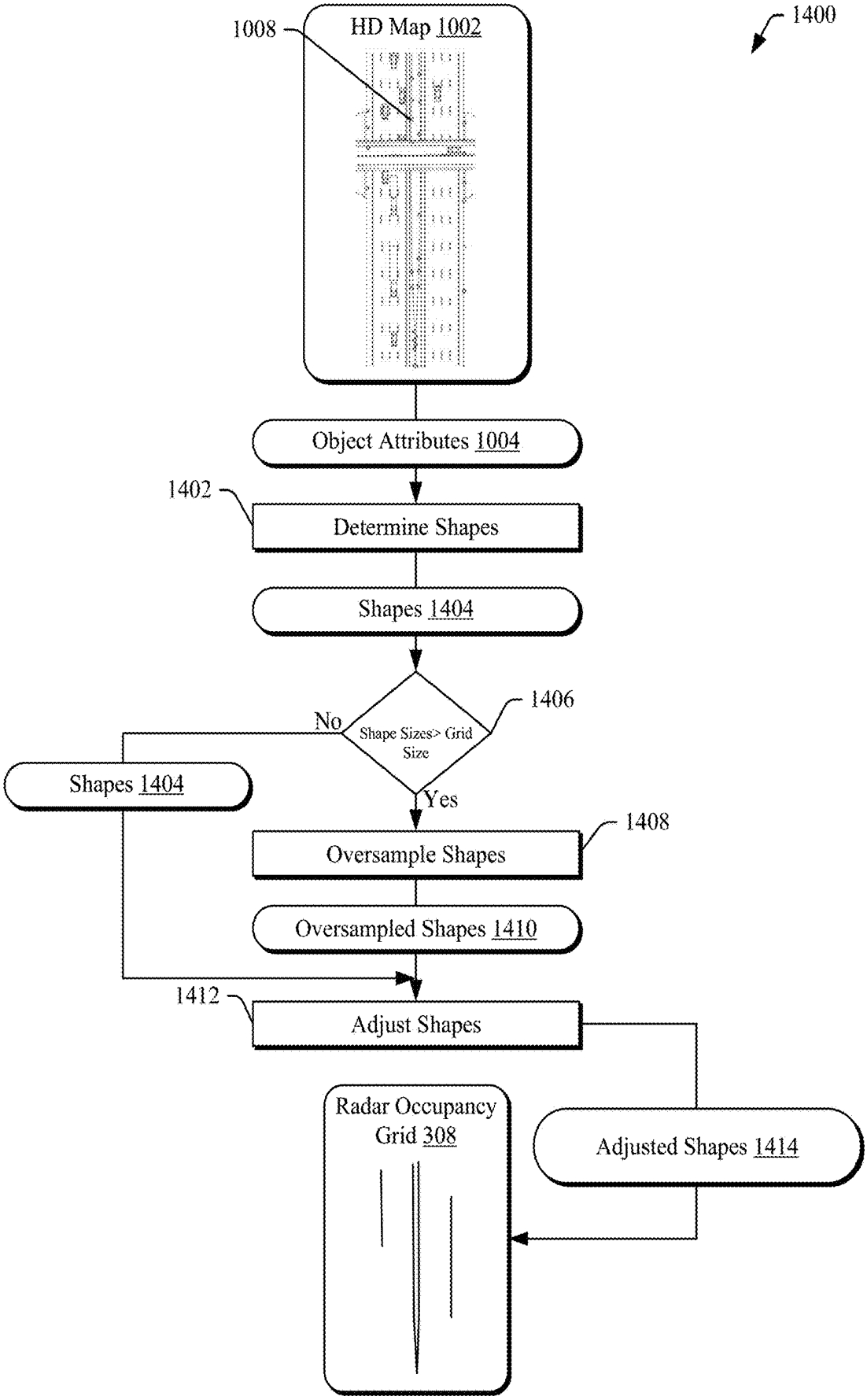

1400
1008
HD Map 1002
Object Attributes 1004
1402
Determine Shapes
Shapes 1404
1406
No
Shape Sizes> Grid Size
Shapes 1404
Yes
1408
Oversample Shapes
Oversampled Shapes 1410
1412
Adjust Shapes
Radar Occupancy Grid 308
Adjusted Shapes 1414

Fig. 14

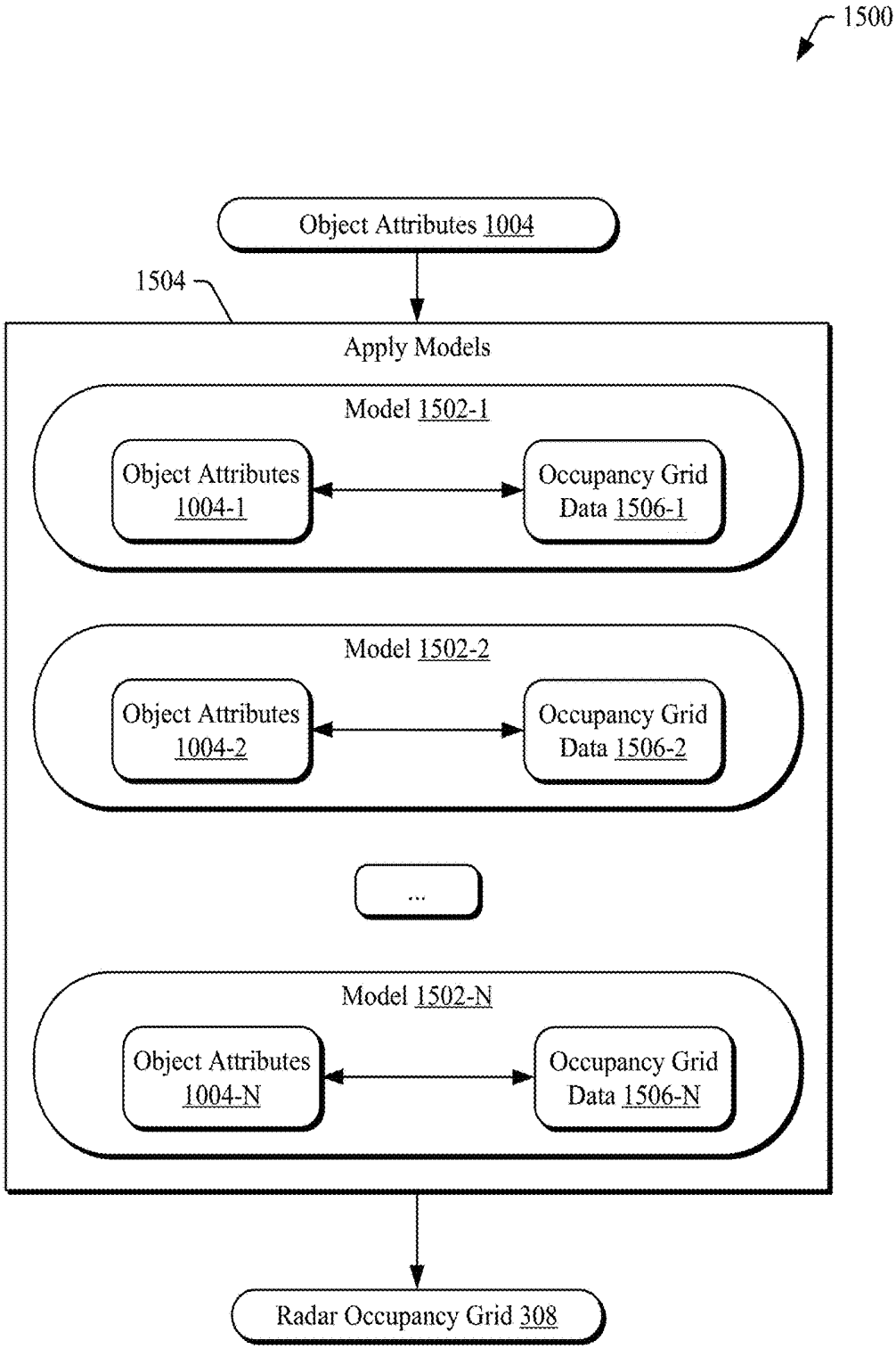

1500
Object Attributes 1004
1504
Apply Models
Model 1502-1
Object Attributes 1004-1
Occupancy Grid Data 1506-1
Model 1502-2
Object Attributes 1004-2
Occupancy Grid Data 1506-2
...
Model 1502-N
Object Attributes 1004-N
Occupancy Grid Data 1506-N
Radar Occupancy Grid 308

Fig. 15

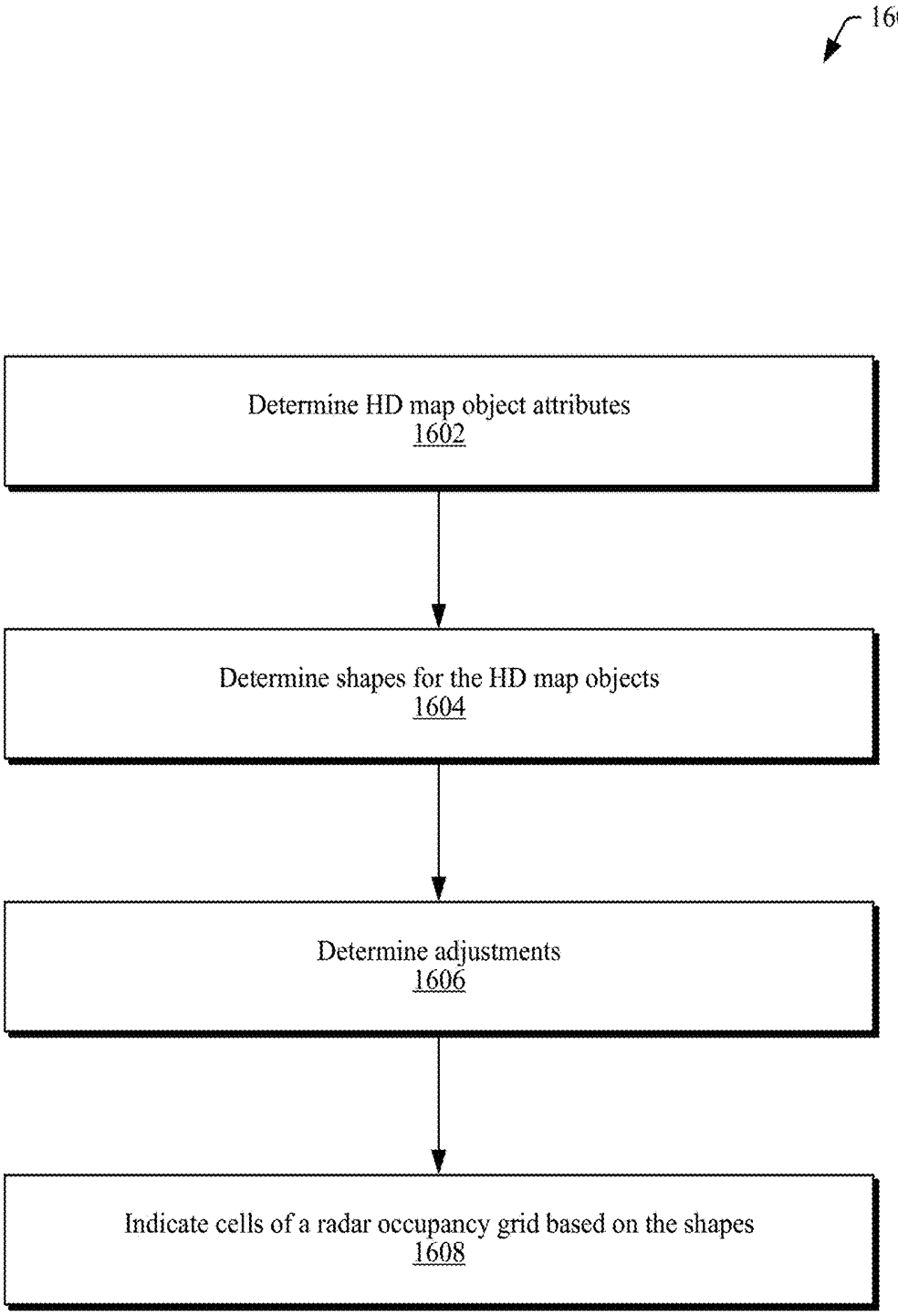

1600
Determine HD map object attributes
1602
Determine shapes for the HD map objects
1604
Determine adjustments
1606
Indicate cells of a radar occupancy grid based on the shapes
1608

Fig. 16

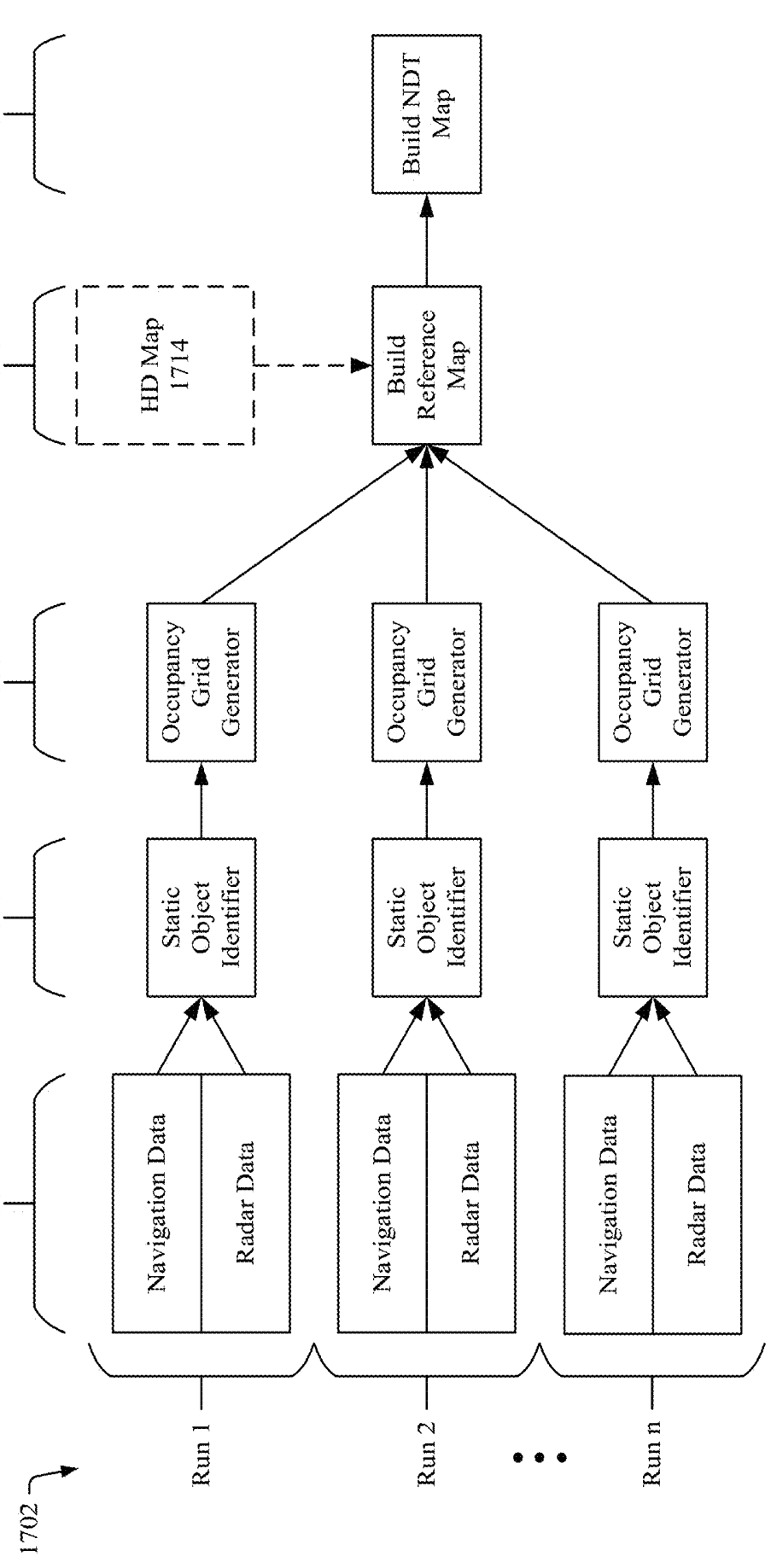

1700
1712
Build NDT Map
1710
HD Map 1714
Build Reference Map
1708
Occupancy Grid Generator
Occupancy Grid Generator
Occupancy Grid Generator
1706
Static Object Identifier
Static Object Identifier
Static Object Identifier
1704
Navigation Data
Radar Data
Navigation Data
Radar Data
Navigation Data
Radar Data
Run 1
Run 2
Run n
1702

Fig. 17

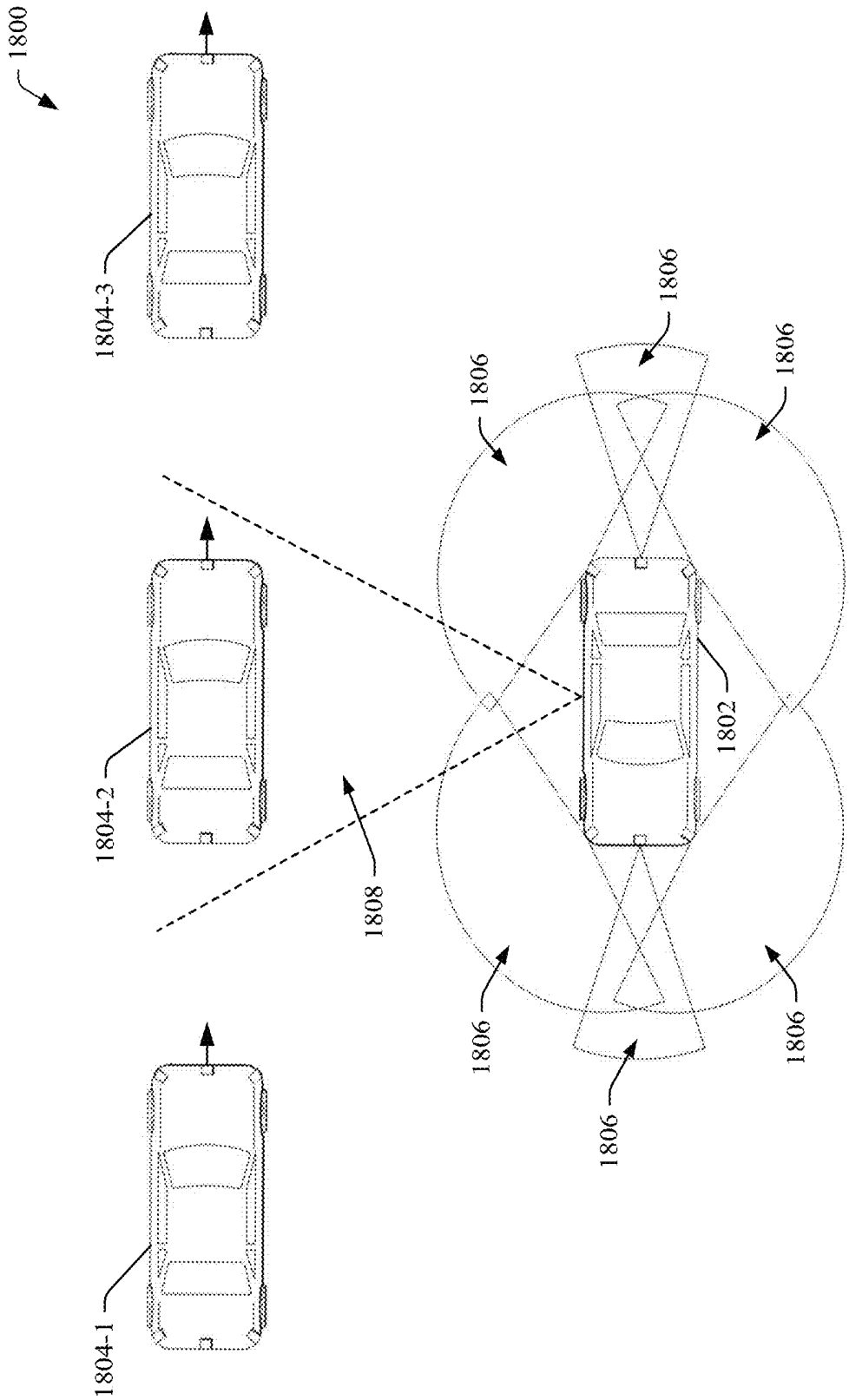

1800
1804-3
1804-2
1804-1
1808
1806
1806
1806
1806
1806
1806
1802

Fig. 18

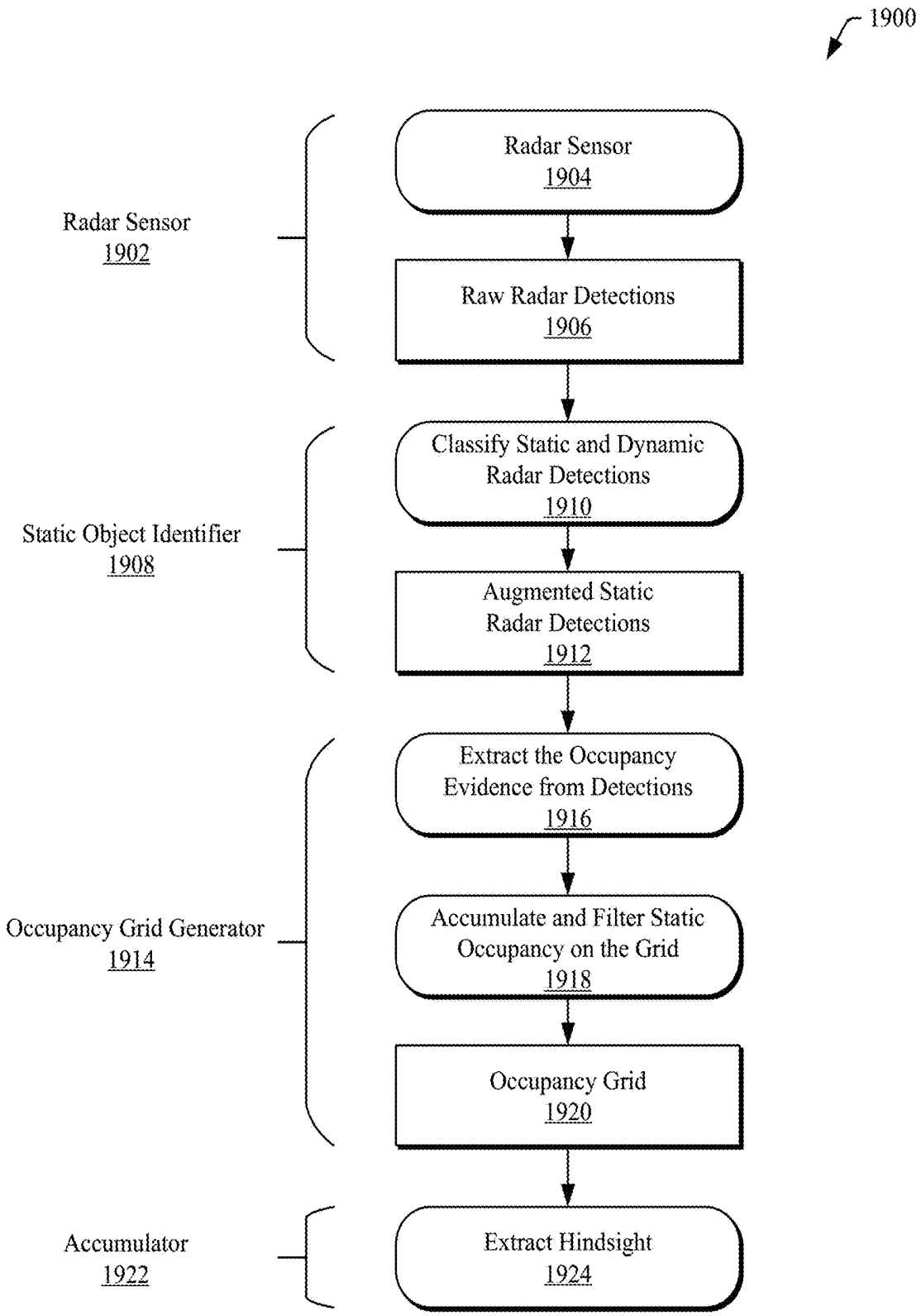

1900
Radar Sensor
1902
Radar Sensor
1904
Raw Radar Detections
1906
Static Object Identifier
1908
Classify Static and Dynamic Radar Detections
1910
Augmented Static Radar Detections
1912
Occupancy Grid Generator
1914
Extract the Occupancy Evidence from Detections
1916
Accumulate and Filter Static Occupancy on the Grid
1918
Occupancy Grid
1920
Accumulator
1922
Extract Hindsight
1924

Fig. 19

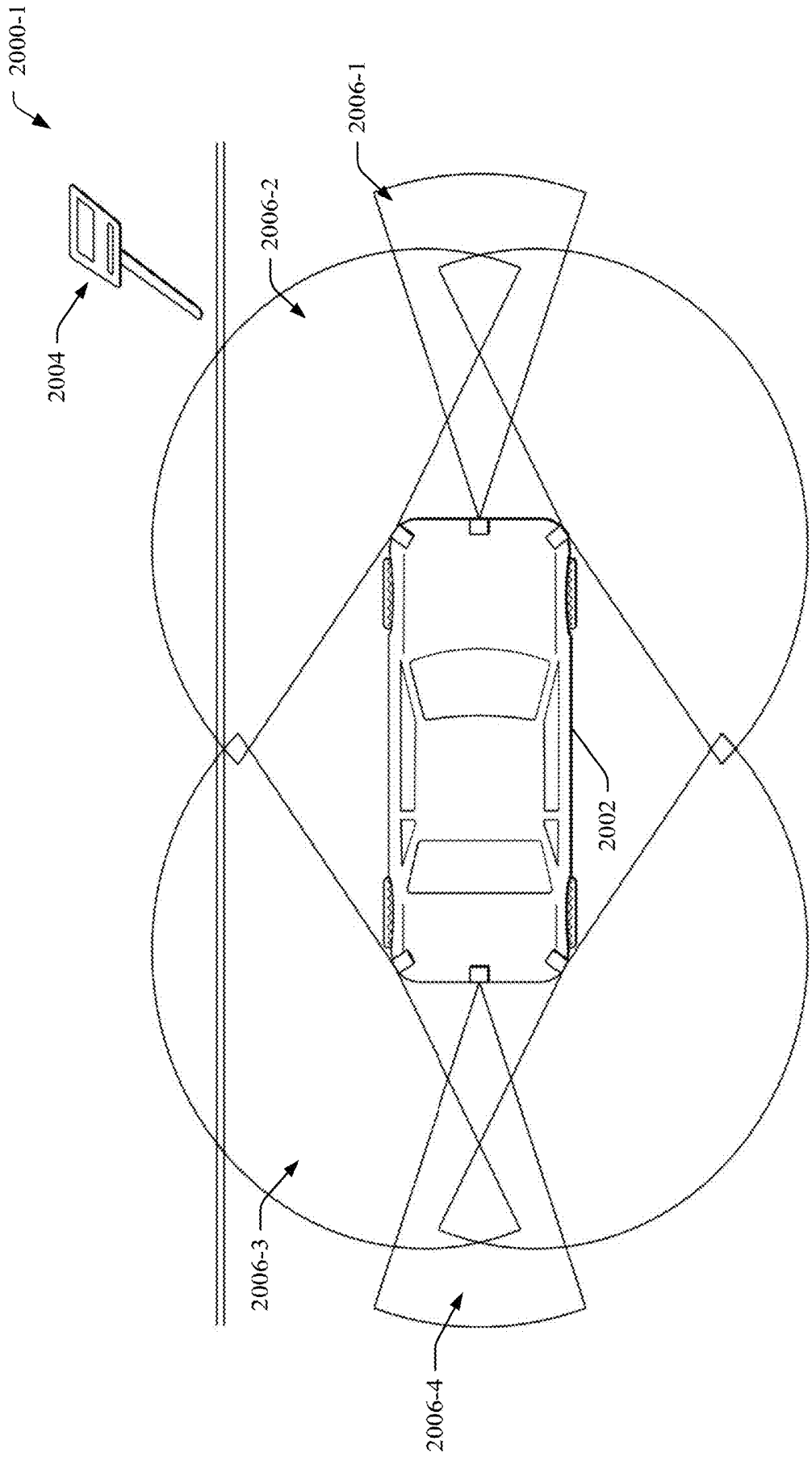


Fig. 20-1

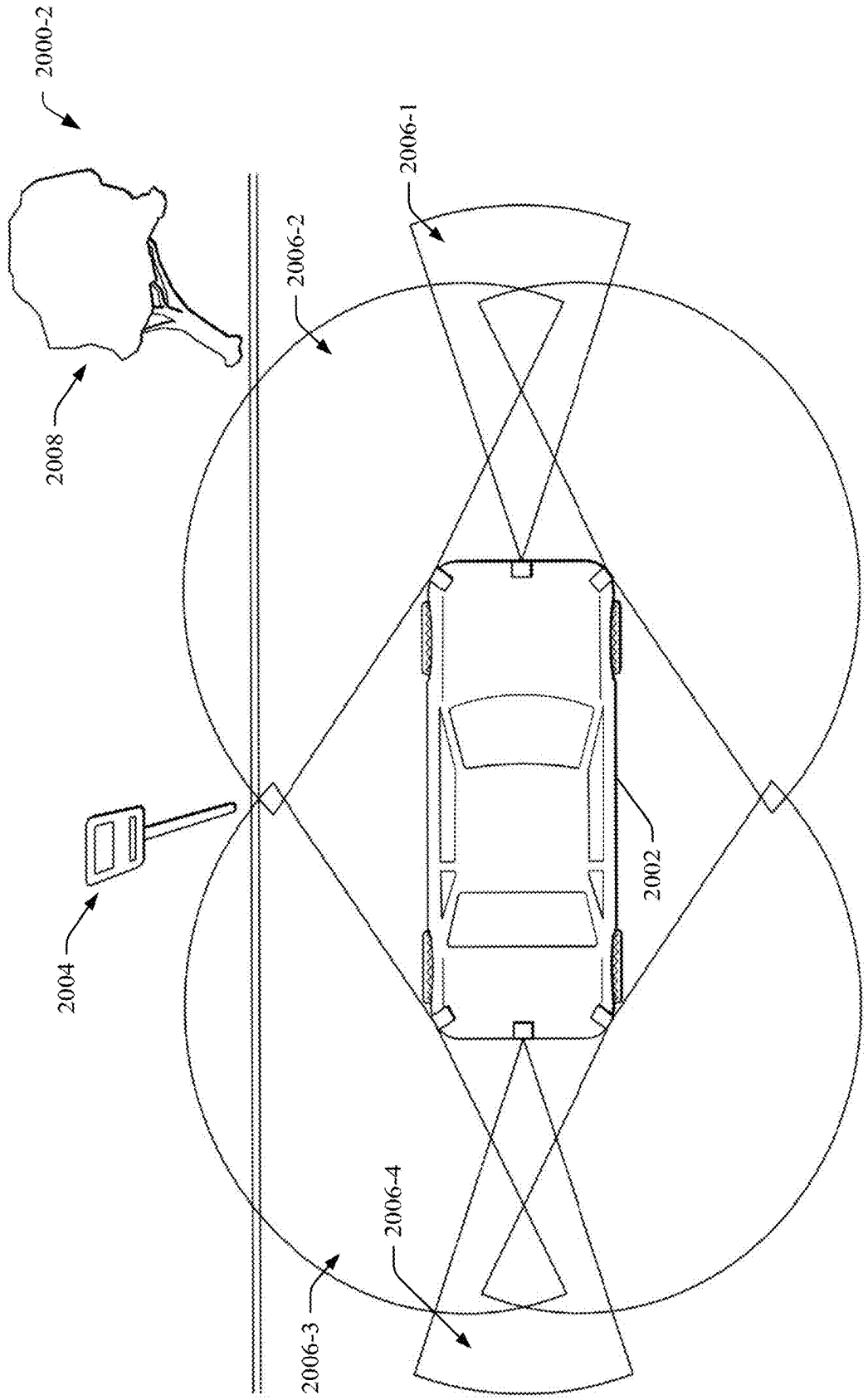


Fig. 20-2

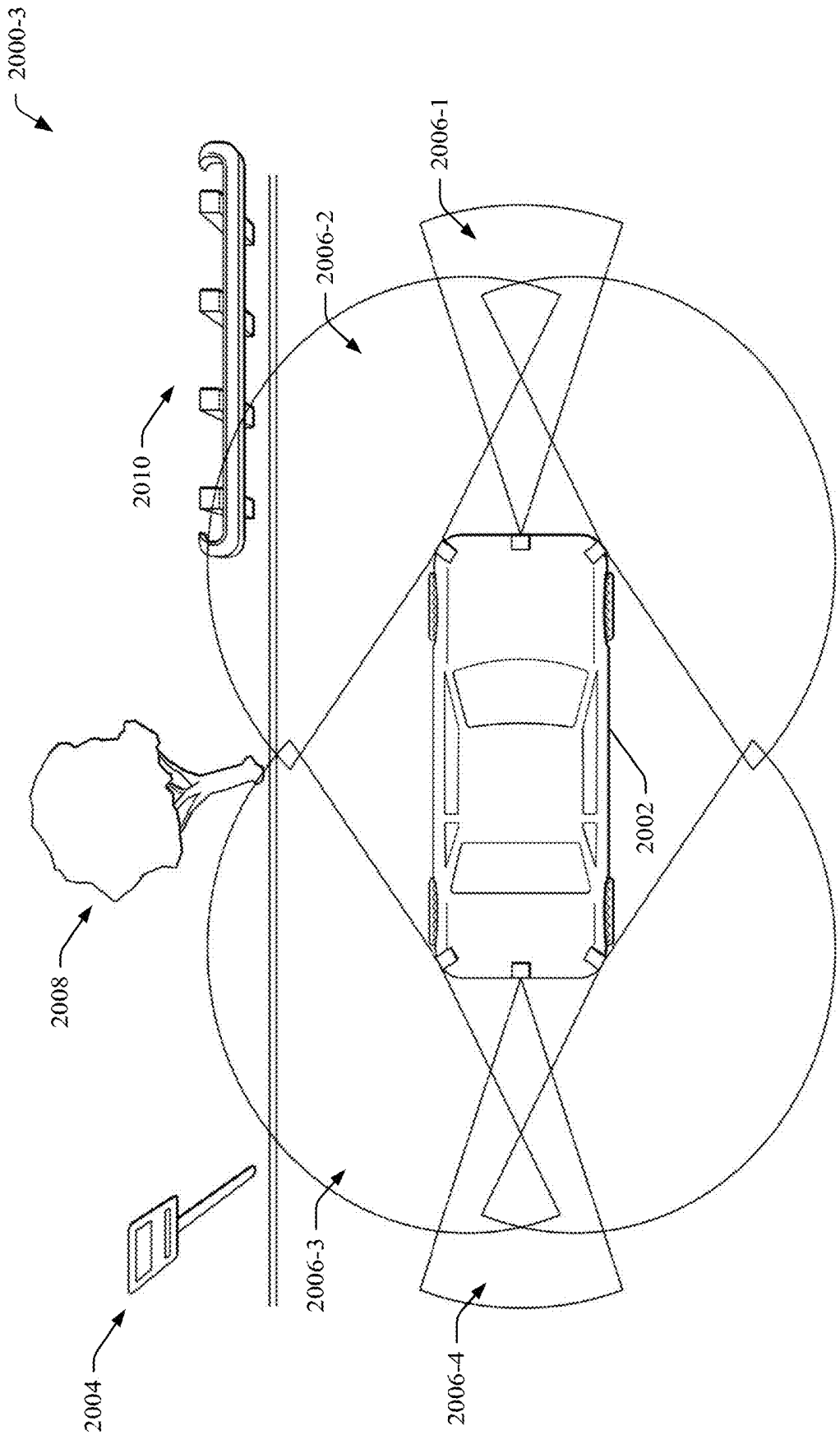


Fig. 20-3

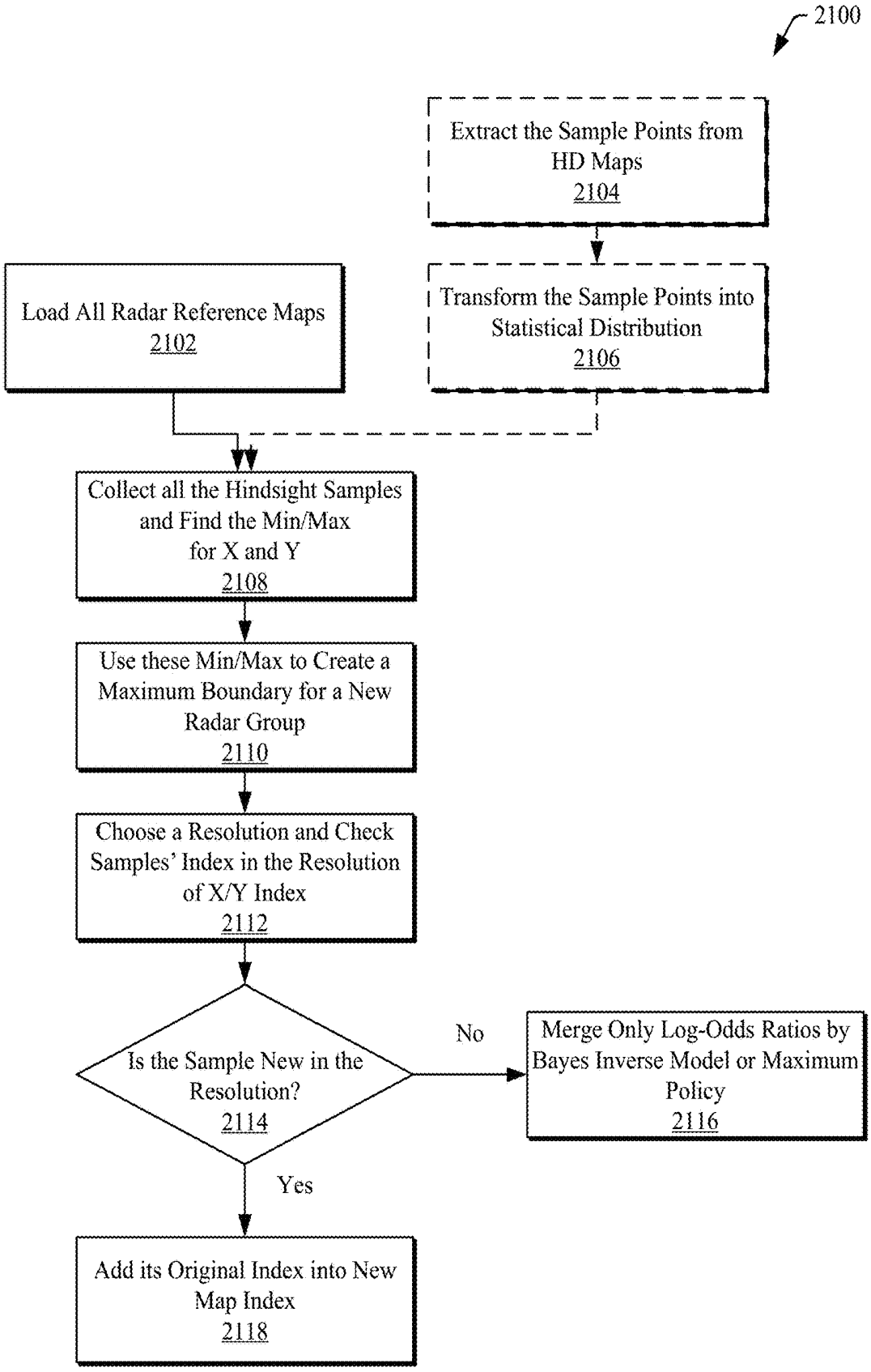

2100
Extract the Sample Points from HD Maps
2104
Load All Radar Reference Maps
2102
Transform the Sample Points into Statistical Distribution
2106
Collect all the Hindsight Samples and Find the Min/Max for X and Y
2108
Use these Min/Max to Create a Maximum Boundary for a New Radar Group
2110
Choose a Resolution and Check Samples' Index in the Resolution of X/Y Index
2112
Is the Sample New in the Resolution?
2114
No
Merge Only Log-Odds Ratios by Bayes Inverse Model or Maximum Policy
2116
Yes
Add its Original Index into New Map Index
2118

Fig. 21

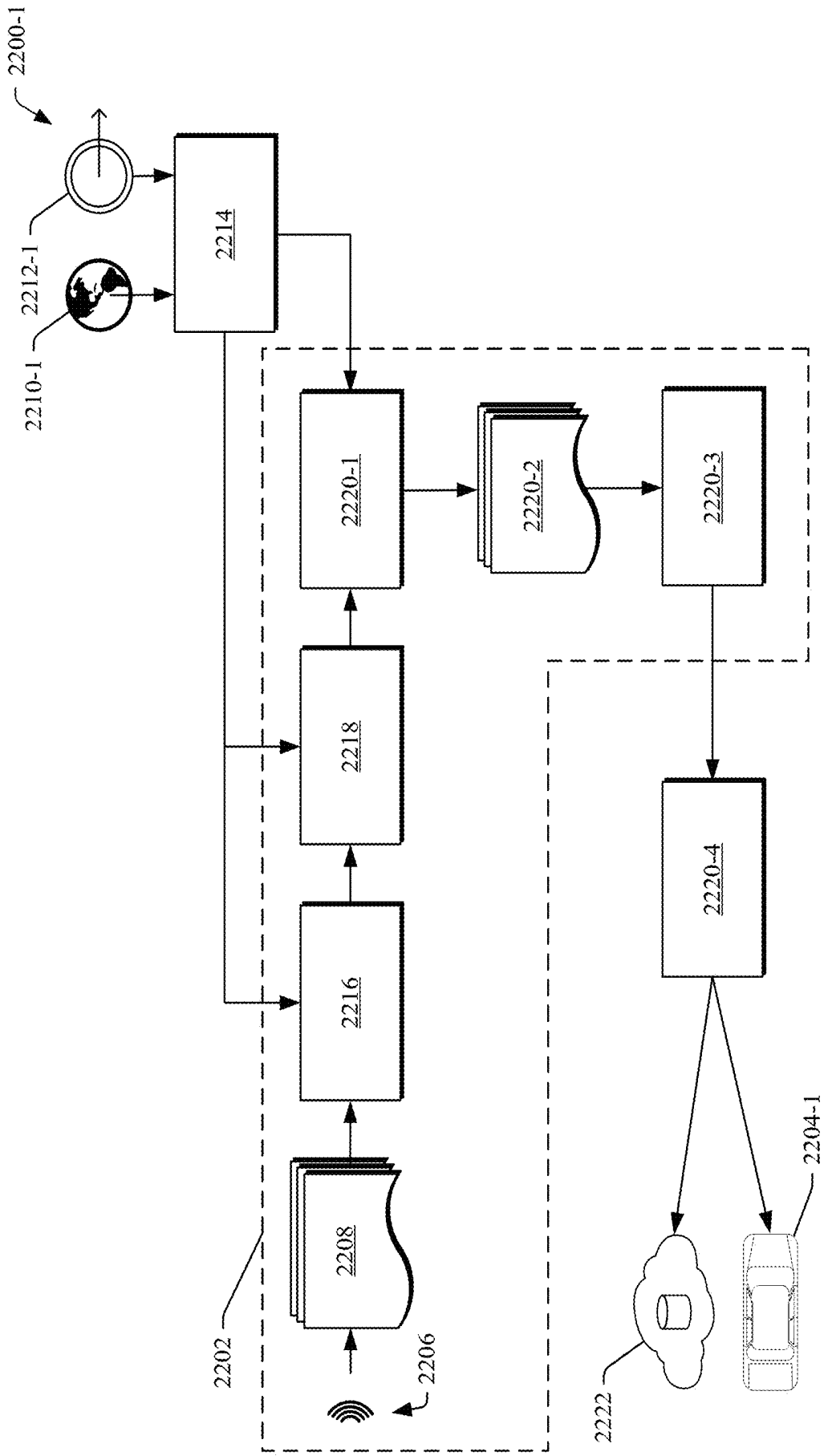

2200-1
2212-1
2210-1
2214
2220-1
2220-2
2220-3
2218
2216
2208
2202
2206
2220-4
2204-1
2222

Fig. 22-1

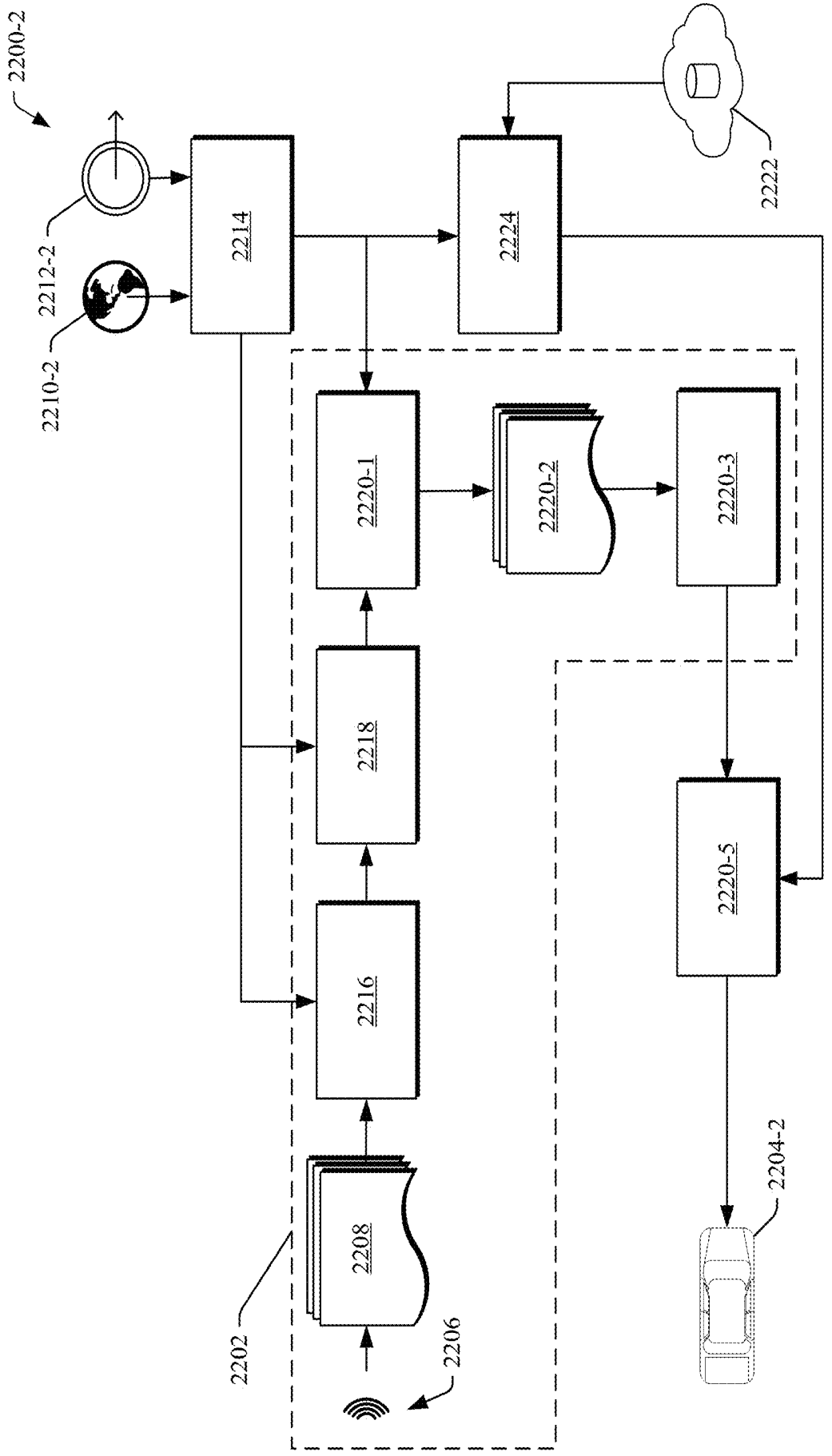

2200-2
2212-2
2210-2
2214
2224
2222
2220-1
2220-2
2220-3
2218
2216
2220-5
2208
2202
2206
2204-2

Fig. 22-2

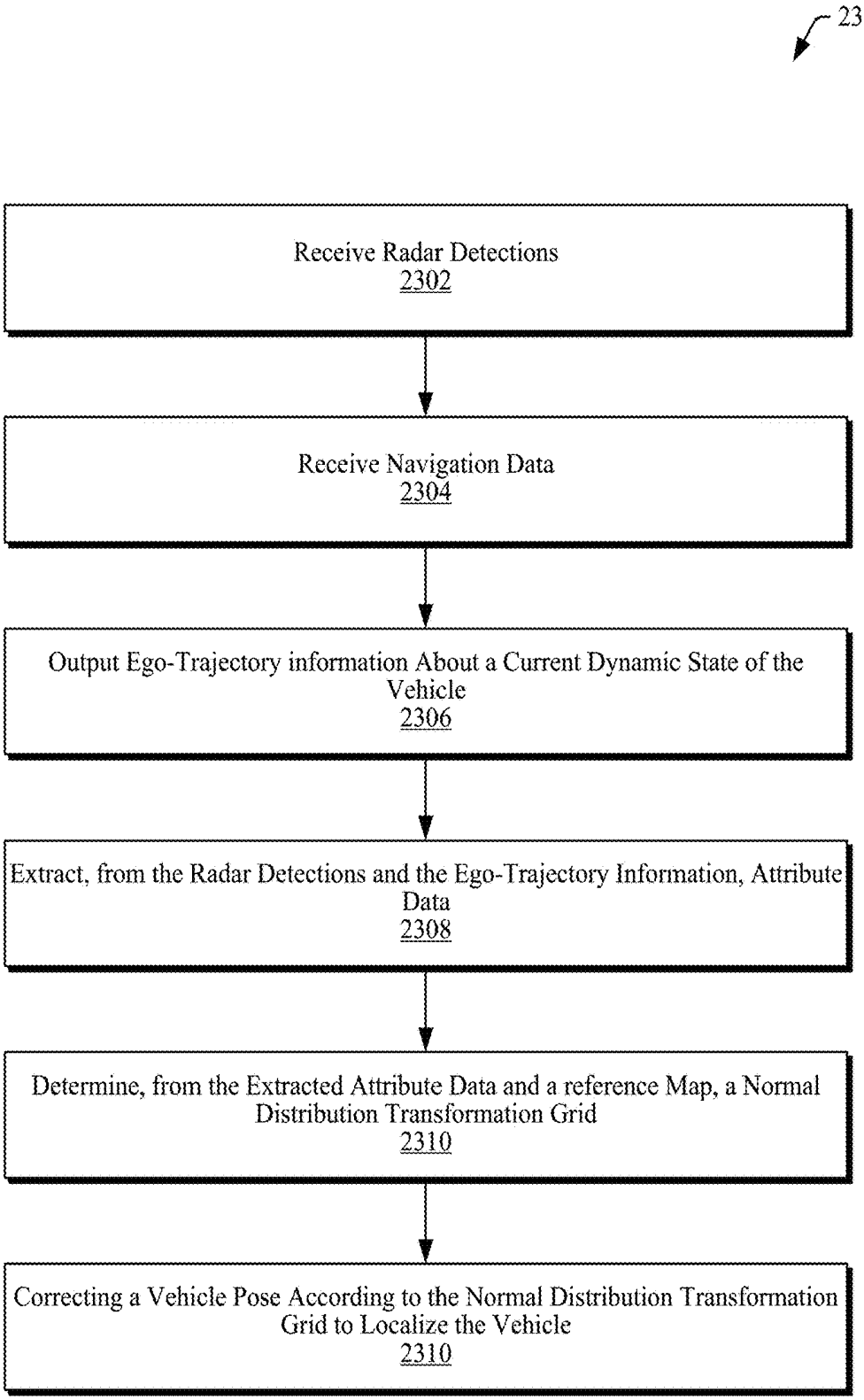

2300
Receive Radar Detections
2302
Receive Navigation Data
2304
Output Ego-Trajectory information About a Current Dynamic State of the Vehicle
2306
Extract, from the Radar Detections and the Ego-Trajectory Information, Attribute Data
2308
Determine, from the Extracted Attribute Data and a reference Map, a Normal Distribution Transformation Grid
2310
Correcting a Vehicle Pose According to the Normal Distribution Transformation Grid to Localize the Vehicle
2310

Fig. 23

RADAR REFERENCE MAP GENERATION

CROSS-REFERENCE TO RELATED APPLICATIONS

[0001] This application claims the benefit under 35 U.S.C. 119(e) of U.S. Provisional Application No. 63/146,483, filed Feb. 5, 2021, and U.S. Provisional Application No. 63/127,049, filed Dec. 17, 2020, the disclosures of which are incorporated by reference in their entireties herein.

BACKGROUND

[0002] Radar localization is a technique of using radar reflections to localize a vehicle to a reference map (e.g., determining a location of the vehicle on the map). Radar localization may be used to support autonomous vehicle operations (e.g., navigation, path planning, lane determination and centering, and curve execution without lane markers). In order to accurately position the vehicle relative to its environment, radar localization includes obtaining reflections from stationary localization objects (e.g., road-adjacent objects or spatial statistical patterns) with known locations on the map (e.g., locations in a Universal Transverse Mercator or UTM frame). When an availability of such localization objects is not sufficient (e.g., a poor quality or incomplete radar reference map is used), a driver takeover is often initiated, which may override semi-autonomous or fully autonomous controls. Increased driver takeovers may be less safe, and their frequency can decrease driver satisfaction compared to when a vehicle operates under autonomous control. As such, complete and accurate maps that are easy to generate, update, and use can greatly benefit driver assist or autonomous driving capabilities.

SUMMARY

[0003] Aspects described below include methods for radar reference map generation. The methods include receiving a high-definition (HD) map and determining one or more HD map objects within the HD map. The methods also include determining attributes of the respective HD map objects and, for each HD map object, indicating one or more occupancy cells of a radar occupancy grid as occupied space based on the attributes of the respective HD map object.

[0004] Aspects described below also include systems for radar reference map generation. The systems include at least one processor and at least one computer-readable storage medium comprising instructions that, when executed by the processor, cause the systems to receive a high-definition (HD) map and determine one or more HD map objects within the HD map. The instructions also cause the systems to determine attributes of the respective HD map objects and, for each HD map object, indicate occupancy cells of a radar occupancy grid as occupied space based on the attributes of the respective HD map object.

BRIEF DESCRIPTION OF THE DRAWINGS

[0005] Systems and techniques enabling radar reference map generation are described with reference to the following drawings. The same numbers are used throughout the drawings to reference like features and components:

[0006] FIG. **1** is an example illustration of an environment in which radar reference map generation may be implemented, in accordance with techniques of this disclosure;

[0007] FIG. **2-1** is an example illustration of systems that may be used to implement radar reference map generation and vehicle localization based on radar detections, in accordance with techniques of this disclosure;

[0008] FIG. **2-2** is an example illustration of a radar-localization module that may be used to implement vehicle localization based on radar detections;

[0009] FIG. **2-3** is another example illustration of a radar-localization module that may be used to implement vehicle localization based on radar detections;

[0010] FIG. **3** is an example illustration of generating a radar reference map, in accordance with techniques of this disclosure;

[0011] FIG. **4** is an example illustration of determining a radar occupancy grid, in accordance with techniques of this disclosure;

[0012] FIG. **5** is an example illustration of generating a radar reference map from radar attributes, in accordance with techniques of this disclosure;

[0013] FIG. **6** is an example illustration of a process of generating a radar reference map, in accordance with techniques of this disclosure;

[0014] FIG. **7** is an example illustration of generating a radar occupancy grid based on multiple vehicle-runs with low-accuracy location data, in accordance with techniques of this disclosure;

[0015] FIG. **8** is another example illustration of generating a radar occupancy grid based on multiple vehicle-runs with low-accuracy location data, in accordance with techniques of this disclosure;

[0016] FIG. **9** is an example illustration of a process of generating a radar occupancy grid based on multiple vehicle-runs with low-accuracy location data, in accordance with techniques of this disclosure;

[0017] FIG. **10** is an example illustration of generating a radar reference map using low-accuracy location data and a high-definition (HD) map, in accordance with techniques of this disclosure;

[0018] FIG. **11** is an example illustration of a process of generating a radar reference map using low-accuracy location data and an HD map, in accordance with techniques of this disclosure;

[0019] FIG. **12** is another example illustration of generating a radar reference map using low-accuracy location data and an HD map, in accordance with techniques of this disclosure;

[0020] FIG. **13** is another example illustration of a process of generating a radar reference map using low-accuracy location data and an HD map, in accordance with techniques of this disclosure;

[0021] FIG. **14** is an example illustration of determining a radar occupancy grid using an HD map, in accordance with techniques of this disclosure;

[0022] FIG. **15** is another example illustration of determining a radar occupancy grid using an HD map, in accordance with techniques of this disclosure;

[0023] FIG. **16** is an example illustration of a process of determining a radar occupancy grid using an HD map, in accordance with techniques of this disclosure;

[0024] FIG. **17** illustrates a flow chart as an example process for updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections, in accordance with techniques of this disclosure;

[0025] FIG. **18** illustrates an example implementation **1800** of a system configured to update, through multiple iterations, a radar reference map used for vehicle localization based on radar detections, in accordance with techniques of this disclosure;

[0026] FIG. **19** illustrates a pipeline for updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections, in accordance with techniques of this disclosure;

[0027] FIGS. **20-1** to **20-3** illustrate an example implementation of hindsight used to update, through multiple iterations, a radar reference map used for vehicle localization based on radar detections, in accordance with techniques of this disclosure;

[0028] FIG. **21** illustrates an example process for determining a hindsight maximum boundary for radar coordinates when updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections, in accordance with techniques of this disclosure;

[0029] FIGS. **22-1** to **22-2** illustrate a flow chart of an example of a process for vehicle localization based on radar detections, in accordance with techniques of this disclosure; and

[0030] FIG. **23** illustrates a flow chart of an example process for vehicle localization based on radar detections.

DETAILED DESCRIPTION

[0031] Overview

[0032] Radar localization is a technique of using radar reflections to localize a vehicle relative to stationary objects (e.g., radar-localization objects). One application of radar localization is localizing a vehicle to a map, similar to geospatial positioning systems (e.g., GPS, GNSS, GLONASS). Just as those positioning systems require adequate signal reception, radar localization requires radar reflections from radar-localization objects with known locations (e.g., guardrails, signs, or statistical patterns). The locations of those objects are generally comprised by a radar-reference map.

[0033] Methods and systems are described that enable radar reference map generation. By utilizing the techniques described herein, robust and wide-spanning radar reference maps may be generated, often times without dedicated or expensive sensor modules. For example, a radar occupancy grid is received, and radar attributes are determined from occupancy probabilities within the radar occupancy grid. Radar reference map cells are formed, and the radar attributes are used to determine Gaussians for the radar reference map cells that contain a plurality of the radar attributes. A radar reference map is then generated that includes the Gaussians determined for the radar referenced map cells that contain the plurality of radar attributes. By doing so, the generated radar reference map is accurate while being spatially efficient. This improved localization capability may improve driving when used by a controller to operate the vehicle with greater safety and comfort. With improved localization, the vehicle does not hesitate and can maneuver in an environment with greater degrees of accuracy, which may put passengers at ease when the vehicle drives under automated or semi-automated control.

[0034] Example Environment

[0035] FIG. **1** is an example illustration **100** of an environment in which radar reference maps may be generated, updated, or used. In the example illustration **100**, a system **102** is disposed in a vehicle **104** (e.g., a host vehicle or "ego-vehicle") that is traveling along a roadway **106**.

[0036] The system **102** utilizes a radar system (not shown) to transmit radar signals (not shown). The radar system receives radar reflections **108** of the radar signals from objects **110**. In example illustration **100**, the radar reflection **108-1** corresponds to object **110-1** (e.g., a sign), the radar reflection **108-2** corresponds to object **110-2** (e.g., a building), and the radar reflection **108-3** corresponds to object **110-3** (e.g., a guardrail).

[0037] The radar reflections **108** may be used to generate a radar reference map, as discussed in reference to FIGS. **3-13**. The radar reflections **108** may also be used to update an existing radar reference map, as discussed in reference to FIGS. **17-21**. The radar reflections **108** may further be used in conjunction with an existing radar reference map to radar-localize the vehicle **104**, as discussed in reference to FIGS. **22** and **23**.

[0038] Example Systems

[0039] FIG. **2-1** is an example illustration **200-1** of systems that may be used to generate, update, or use radar reference maps. The example illustration **200-1** comprises the system **102** of the vehicle **104** and a cloud system **202**. Although the vehicle **104** is illustrated as a car, the vehicle **104** may comprise any vehicle (e.g., a truck, a bus, a boat, a plane, etc.) without departing from the scope of this disclosure. The system **102** and the cloud system **202** may be connected via communication link **204**. One or both of the system **102** and the cloud system **202** may be used to perform the techniques described herein.

[0040] As shown underneath the respective systems, the systems include at least one processor **206** each (e.g., processor **206-1** and processor **206-2**), at least one computer-readable storage medium **208** each (e.g., computer-readable storage medium **208-1** and **208-2**), radar-localization modules **210** (e.g., radar-localization module **210-1** and **210-2**), and communication systems **212** (e.g., communication system **212-1** and **212-2**). The communication systems **212** facilitate the communication link **204**.

[0041] The system **102** additionally contains a navigation system **214** and a radar system **216**. The navigation system **214** may include a geospatial positioning system (e.g., a GPS, GNSS, or GLONASS sensor), an inertial measurement system (e.g., a gyroscope or accelerometer), or other sensors (e.g., a magnetometer, software positioning engine, wheel tick sensor, lidar odometer, vision odometer, radar odometer, or other sensor odometer). The navigation system **214** may provide high-accuracy location data (e.g., to within a meter) or low-accuracy location data (e.g., to within a couple of meters). The radar system **216** is indicative of a radar hardware used to transmit and receive radar signals (e.g., radar reflections **108**). In some implementations, the radar system **216** provides static detections to the radar-localization modules **210** (e.g., filtering may be performed within the radar system **216**).

[0042] The processors **206** (e.g., application processors, microprocessors, digital-signal processors (DSP), or controllers) execute instructions **218** (e.g., instructions **218-1** and **218-2**) stored within the computer-readable storage media **208** (e.g., non-transitory storage devices such as hard drives, SSD, flash memories, read-only memories (ROM), EPROM, or EEPROM) to cause the system **102** and cloud system **202** to perform the techniques described herein. The

instructions **218** may be part of operating systems and/or one or more applications of the system **102** and cloud system **202**.

[0043] The instructions **218** cause the system **102** and the cloud system **202** to act upon (e.g., create, receive, modify, delete, transmit, or display) data **220** (e.g., **220-1** and **220-2**). The data **220** may comprise application data, module data, sensor data, or I/O data. Although shown as being within the computer-readable storage media **208**, portions of the data **220** may be within random-access memories (RAM) or caches of the system **102** and the cloud system **202** (not shown). Furthermore, the instructions **218** and/or the data **220** may be remote to the system **102** and the cloud system **202**.

[0044] The radar-localization modules **210** (or portions thereof) may be comprised by the computer-readable storage media **208** or be stand-alone components (e.g., executed in dedicated hardware in communication with the processors **206** and computer-readable storage media **208**). For example, the instructions **218** may cause the processors **206** to implement or otherwise cause the system **102** or the cloud system **202** to implement the techniques described herein.

[0045] FIG. **2-2** is an example illustration **200-2** of the radar-localization module **210** that may be used to implement vehicle localization based on radar detections. In the example illustration **200-2**, the radar-localization module **210** is configured to be in a reference mode. The reference mode is used when the radar-localization module **210** is being used to build a radar reference map. The radar-localization module **210** includes two sub-modules, a vehicle state estimator **222**, a scan-matcher **224**, and two optional sub-modules, a static object identifier **226**, and an occupancy grid generator **228**. One or both of the static object identifier **226** and the occupancy grid generator **228** may or may not be present.

[0046] The vehicle state estimator **222** receives navigation data **230** from navigation systems (e.g., the navigation system **214** from FIG. **2-1**). Generally, in the reference mode, the navigation data **230** may be sourced from a high-quality navigation system that provides a higher degree of accuracy than commercial or consumer-grade navigation systems (e.g., navigation systems used for mass production). From the navigation data **230**, the vehicle state estimator **222** determines ego-trajectory information about the current dynamic state (e.g., speed, yaw rate) of the vehicle **104** and may provide the state estimates and other navigation data **230** (e.g., latitude and longitude of the vehicle **104**) to any of the other sub-modules that are present in the radar-localization module **210**. Ego-trajectory information includes information, originating from systems of a vehicle, that may be used to project the direction and velocity of the vehicle.

[0047] The static object identifier **226** receives radar detections **232** from one or more radar sensors positions around the vehicle **104**. If the static object identifier **226** is not being utilized, then the radar detections **232** may be received by the occupancy grid generator **228**, the scan-matcher **224**, or another sub-module designed to accept the radar detections **232** and distribute the radar data to other modules and sub-modules of the vehicle system. The static object identifier **226** determines whether a radar detection **232** is a static detection based on the ego-trajectory information from the vehicle state estimator **222** and outputs any identified static detections to either the occupancy grid generator **228**, if it is being utilized, or the scan-matcher **224**.

[0048] The occupancy grid generator **228** may receive, as inputs, either the radar detections **232**, if the static object identifier **226** is not being utilized by the radar-localization module **210**, or the static radar detections output by the static object identifier **226**, as well as, the ego-trajectory information and the navigation data **230** output from the vehicle state estimator **222**. The occupancy grid generator **228** uses the inputs to determine a statistical probability (e.g., occupancy grid) of the occupancy at any given location in the environment of the vehicle **104**, as discussed in other sections of this document.

[0049] The scan-matcher **224** may receive, as input, the ego-trajectory information and attribute data. Attribute data may be either the radar detections **232**, the static radar detections from the static object identifier **226**, or the occupancy grid that is output by the occupancy grid generator **228**, depending on which optional sub-modules are being utilized. As described in other sections of this document, the scan-matcher **224** finds an optimal normal distribution transformation (NDT) between the attribute data and the high-quality navigation data **230** and outputs an NDT radar reference map **234**.

[0050] FIG. **2-3** is another example illustration **200-3** of a radar-localization module that may be used to implement vehicle localization based on radar detections. In the example illustration **200-3**, the radar-localization module **210** is configured to be in a real-time localization mode. The primary differences between the real-time localization mode and the reference mode of the radar-localization module **210** include the navigation data **230** originating from a lower-quality navigation system and an extra input to the scan-matcher module **224**. The output of the radar-localization module **210** in real-time localization mode is an updated vehicle pose **236** of the vehicle **104**.

[0051] In real-time localization mode, the scan-matcher **224** receives the NDT radar reference map **234** as input, in addition to the attribute data and the ego-trajectory information. The inputs are used by the scan-matcher to determine an NDT grid. The NDT grid is compared to the NDT radar reference map to determine the updated vehicle pose **236**.

[0052] In one non-limiting example, the radar-localization module **210** may be used in the reference mode in the vehicle **104**, equipped with a high-quality GNSS system, that is specially configured to create or assist in the creation of NDT radar reference maps. The real-time localization mode may be considered a normal operating mode of the radar-localization module **210**; that is, vehicles not specially configured to create the NDT radar reference maps may normally operate with the radar-localization module **210** in the real-time localization mode.

[0053] Building a Radar Reference Map

[0054] FIG. **3** is an example illustration **300** of generating a radar reference map from radar detections. Example illustration **300** may be performed by the system **102** and/or the cloud system **202**. At **302**, radar detections **304** are received. The radar detections **304** comprise stationary radar detections (e.g., detections of stationary objects from radar system **216**) with corresponding global coordinates for respective times/locations (e.g., from navigation system **214**). The detections may be of objects such as signs, poles, barriers, landmarks, buildings, overpasses, curbs, or road-adjacent

objects such as fences, trees, flora, or foliage, or of spatial statistical patterns. The global coordinates may comprise high-accuracy location data (e.g., when the navigation system **214** is a high-accuracy navigation system). The radar detections **304** may comprise point clouds, have corresponding uncertainties, and/or include various radar data or sensor measurements.

[0055] At **306**, a radar occupancy grid **308** is determined from the radar detections **302**. The radar occupancy grid **308** is a grid-based representation of an environment. For example, the radar occupancy grid **308** may be a Bayesian, Dempster-Shafer, or other type of occupancy grid. Each cell of the radar occupancy grid **308** represents an independent portion of space, and each cell value of the radar occupancy grid **308** represents a probability (e.g., 0-100%) that the corresponding portion of space is occupied. A probability of around 0% for a cell may indicate that the corresponding portion of space is free, while a probability closer to 100% may indicate that the corresponding portion of space is occupied, and therefore, not free space. Techniques of determining the radar occupancy grid **308** are discussed further in regard to FIGS. **4**, **7-9**, and **14-17**.

[0056] At **310**, radar attributes **312** (e.g., attributes or attribute data) are determined from the radar occupancy grid **308**. The radar attributes **312** may be center coordinates of respective groups of cells of the radar occupancy grid **308** with probabilities greater than a threshold. In some implementations, the radar attributes **312** may be based on other aspects such as radar cross sections (RCS), amplitudes of the radar detections **304**, information from other sensors, or machine learning, separately or in combination with the probabilities. Regardless of how they are determined, the radar attributes **312** comprise clusters, contours, or bounding boxes of the cells of the radar occupancy grid **308**. The radar attributes **312** may have weights based on one or more of probabilities, classifications, or cross-section values of the respective radar attributes **312**. The radar attributes **312** may be determined using binarization, a clustering algorithm, or machine learning on the radar occupancy grid **308**. The determination of the radar attributes **312** generally groups cells of the radar occupancy grid **308** while removing noise.

[0057] At **314**, a radar reference map **316** is generated from the radar attributes **312**. The radar reference map **316** may be a statistical reference map (e.g., a Gaussian representation). The radar reference map **316** is a collection of Gaussians **318** corresponding to occupied areas. The Gaussians **318** (or the cells of the radar reference map **316**) have associated location information (e.g., low or high-quality location information depending on how the radar reference map **316** is generated). Each cell of the radar reference map **316** can have a single Gaussian **318** or be blank. Although not required, the radar reference map **316** has cells that are larger than the cells of the radar occupancy grid **308**. The radar reference map **316** can be a stand-alone map or a layer in another map (e.g., a layer in a high-definition (HD) map).

[0058] The radar reference map **316** may contain metadata associated with the respective Gaussians **318**. For example, the metadata may contain information about shapes or dimensions of clusters of Gaussians **318**. The metadata may also include object associations, e.g., certain Gaussians **318** belong to a sign or guardrail. The location data may also be contained within the metadata. Techniques of generating the radar reference map **316** are discussed further in regard to FIGS. **5**, **6**, and **10-13**.

[0059] FIG. **4** is an example illustration **400** of determining the radar occupancy grid **308** from the radar detections **304**. Example illustration **400** is generally performed by the system **102**, although portions or all of example illustration **400** may be performed by the cloud system **202**. Example illustration **400** assumes that the location data associated with the radar detections **304** is high-accuracy location data (e.g., the navigation system **214** contains a high-accuracy GNSS).

[0060] At **402**, one set (e.g., time) of the radar detections **304** is received (e.g., a radar detection **304** corresponding to a zero-point), and radar occupancy evidences **404** are determined from the one set of radar detections **304**. The radar occupancy evidences **404** correspond to respective cells of the radar occupancy grid **308** and are indicative of occupied spaces within the radar occupancy grid **308**. The radar occupancy evidences **404** are based on radar reflections **108** corresponding to the one set of radar detections **304** and associated range and azimuth uncertainties.

[0061] At **406**, radar occupancy probabilities **408** are determined from the radar occupancy evidences **404**. For example, the radar occupancy probabilities **408** may be given by Equation 1:

$$p=0.5+0.5\cdot e \quad [1]$$

[0062] where p is a radar occupancy probability **408** and e is an occupancy evidence **404**.

[0063] Steps **402** and **406** may be repeated for other sets of radar detections **304** corresponding to later times/locations. For each of the later times/locations, the radar occupancy probabilities **408** are fused, at **410**, with a decayed and shifted radar occupancy grid **412**. The decayed and shifted radar occupancy grid **412** represents a current radar occupancy grid **414** (e.g., the radar occupancy grid **308** at the current time/location) with decayed probabilities and cells that have been shifted due to a movement of the vehicle between the previous time/location and current ones. The fusing is used to update the radar occupancy grid **308** based on subsequent radar detections **304** corresponding to the later times/locations.

[0064] In order to generate the decayed and shifted radar occupancy grid **412**, at **416**, the current radar occupancy grid **414** (e.g., at the respective location) is decayed to form a decayed radar occupancy grid **418**. The decay comprises forgetting, minimizing, or otherwise removing old evidence from the current radar occupancy grid **414**. This ensures that only recently generated cells are used for the fusing. It should be noted that the radar occupancy grid **308** is not decayed; rather, the current radar occupancy grid **414**, which is a snapshot of the radar occupancy grid **308**, is decayed.

[0065] The decayed radar occupancy grid **418** is then shifted, at **420**, to form the decayed and shifted radar occupancy grid **412**. Each cell of the radar occupancy grid **308** (and the current radar occupancy grid **414**) represents an area. As such, as the vehicle **104** moves, the grid must be shifted. To shift the grid, a vehicle position **422** at the time of the shift/decay is received. The decayed radar occupancy grid **418** is shifted by integer numbers of cells that correspond to the vehicle position **422**. For example, the integer numbers may be based on a change between a vehicle position **422** that corresponds to the unshifted occupancy grid (e.g., the decayed radar occupancy grid **418** and the current radar occupancy grid **414**) and the vehicle position **422**.

[0066] As stated above, the decayed and shifted radar occupancy grid **412** is fused, at **410**, with the radar occupancy probabilities **408** of the current set of radar detections **304**. The fusion effectively accumulates radar occupancy probabilities **408** over time to enable the radar occupancy grid **308** to be more robust. Any fusion method may be used. For example, a Bayesian fusion method may be used according to Equation 2:

$$p_{new} = \frac{p_{old} \cdot p_{measured}}{(p_{old} \cdot p_{measured}) + (1 - p_{old}) \cdot (1 - p_{measured})} \quad [2]$$

[0067] where p_{new} is an occupancy probability for a respective cell (e.g., in the radar occupancy grid **308**), p_{old} is an existing radar occupancy probability for the respective cell (e.g., in the decayed and shifted radar occupancy grid **412**), and $p_{measured}$ is a radar occupancy probability **408** for the respective cell.

[0068] By using the example illustration **400**, radar occupancy probabilities **408** from multiple times/locations may be fused. In so doing, the radar occupancy grid **308** becomes accurate and robust for use in the example illustration **300**.

[0069] FIG. **5** is an example illustration **500** of determining the radar reference map **316** from the radar attributes **312**. At **502**, normal distribution transform (NDT) cells **504** are established. The NDT cells **504** are the cells of the radar reference map **316**. The NDT cells **504** are generally much larger (e.g., 15 times larger) than the cells of the radar occupancy grid **308**.

[0070] For each NDT cell **504** that has a plurality of radar attributes **312**, a Gaussian **318** (e.g., a multivariate distribution with a mean and covariance) is determined. In order to do so, at **506**, a mean and covariance **508** are determined for the respective NDT cell **504**. The mean and covariance **508** are based on radar attributes **312** identified within the respective NDT cell **504**. The mean for the respective NDT cell **504** may be determined based on Equation 3:

$$\mu_i = \Sigma_{j=1}^{n} p_j x_j \quad [3]$$

[0071] where p_j is the occupancy probability of the radar occupancy grid **308** at a given cell of the radar occupancy grid **308**, x_j is the given cell position, and n is a number of cells within the radar attributes **312** of the respective NDT cell **504**.

[0072] The covariance (e.g., 2×2 matrix) for the respective NDT cell **504** may be determined based on Equation 4:

$$\Sigma_i = \Sigma_{j=1}^{n} p_j (x_j - \mu_i)(x_j - \mu_i)^T \quad [4]$$

[0073] Advantageously, the mean and covariance **508** are based on occupancy probability. At **510**, the covariance for the respective NDT cell **504** may be manipulated such that the smallest eigenvalue of the covariance matrix is at least some multiple of the largest eigenvalue of the covariance matrix. The mean and covariance **508** (or a manipulated covariance if step **510** is performed) make up the Gaussian **318** for the respective NDT cell **504**. If there are one or fewer radar attributes **312** within the respective NDT cell **504**, the respective NDT cell **504** is indicated as unoccupied.

[0074] Steps **506** and **510** can then be performed for others of the NDT cells **504**. At **512**, the Gaussians **318** for the respective NDT cells **504** are combined to form the radar reference map **316**. Once combined, the NDT cells **504** of the radar reference map **316** may a single Gaussian **318** or nothing (e.g., indicated as unoccupied).

[0075] Although steps **506** and **510** are discussed as being performed on a respective NDT cell **504** and then other NDT cells **504**, in some implementations, step **506** may be performed on the NDT cell **504** as a group prior to performing step **510** on the group. For example, the mean and covariance **508** may be determined for each NDT cell **504** of a group. Then, the covariances may be manipulated, as needed, for each NDT cell **504** of the group.

[0076] By using the techniques of example illustrations **300**, **400**, and **500**, an accurate and space efficient radar reference map may be generated. Using a space efficient map lowers computational requirements and enables faster localization to support driver assist and autonomous driving functionalities.

[0077] FIG. **6** is an example illustration **600** of a method of building the radar reference map **316**. The example illustration **600** may be implemented utilizing the previously described examples, such as the example illustrations **100**, **300**, **400**, and **500**. Operations **602** through **610** may be performed by one or more entities of the system **102** and/or the cloud system **202** (e.g., the radar-localization module **210**). The order in which the operations are shown and/or described is not intended to be construed as a limitation, and any number or combination of the operations can be combined in any order to implement the illustrated method or an alternate method.

[0078] At **602**, a radar occupancy grid is received. For example, the radar-localization module **210** may receive the radar occupancy grid **308**.

[0079] At **604**, radar attributes are determined from the radar occupancy grid. For example, the radar-localization module **210** may use thresholding on occupancy probabilities within the radar occupancy grid **308** to determine the radar attributes **312**. The radar attributes **312** may comprise center coordinates of respective groups of cells of the radar occupancy grid that have occupancy probabilities above a threshold, or within a threshold range.

[0080] At **606**, radar reference map cells are formed. For example, the radar-localization module **210** may create the NDT cells **504** of the radar reference map **316**.

[0081] At **608**, Gaussians are determined for radar reference map cells that contain a plurality of radar attributes. For example, the radar-localization module **210** may determine the mean and covariance **508** for each of the NDT cells **504** that contain a plurality of radar attributes **312**.

[0082] At **610**, a radar reference map is generated. The radar reference map comprises the radar reference map cells that include the Gaussians and radar reference map cells indicated as unoccupied. The radar reference map cells that are indicated as unoccupied correspond to radar reference map cells that do not contain a plurality of radar attributes. For example, the radar-localization module **210** may combine the NDT cells **504** with Gaussians **318** and NDT cells **504** that are indicated as unoccupied to form the radar reference map **316**.

[0083] FIG. **7** is an example illustration **700** of determining the radar occupancy probabilities **408** using multiple vehicle runs with low-accuracy location data. FIG. **8** is an example illustration **800** of a similar process. As such, the following description describes example illustrations **700** and **800** simultaneously. Example illustrations **700** and **800** are generally performed by the cloud system **202** based on

radar detections **304** received from the multiple vehicle runs, although one or more of the steps may be performed by the system **102** (e.g., the gathering of the radar detections **304** and transmitting the radar detections **304** to the cloud system **202** using the communication system **212**). The radar occupancy probabilities **408** may then be fused at **410** to create the radar occupancy grid **308**. The radar reference map **316** may then be generated from the radar occupancy grid **308**, similar to example illustrations **100** and **300**.

[0084] Gathering high-accuracy location data is often impractical or expensive for large areas. Example illustrations **700** and **800** determine the radar occupancy probabilities **408** using multiple runs with low-accuracy location data, such as that generated by most navigation systems (e.g., navigation system **214**) implemented within consumer and commercial vehicles. Because of the low-accuracy location data, multiple runs are needed to get occupancy probabilities **408** that are accurate. Conventional techniques, such as multiple run averaging, often lead to smeared and useless probability data.

[0085] Example illustrations **700** and **800** use a statistical map fusion of multiple runs **702** (e.g., run **702**A and run **702**B) to correct for the errors in the low-accuracy location data. Any number of runs **702** may be used (albeit more than one), and the runs **702** may be created using the same vehicle or multiple vehicles and at different times. The statistical map fusion may be an extended particle filter simultaneous localization and mapping (SLAM) algorithm.

[0086] At **704**, particles **706** are created at a given location (e.g., at time t=0). The particles **706** correspond to respective possible future locations of the vehicle **104**, although the specific further locations have not been determined yet. The particles **706** are based on vehicle trajectories **708** that correspond to the given location (e.g., from navigation system **214**).

[0087] At **710**, future positions of the particles are predicted to form predicted positions **712** (e.g., of the vehicle **104**). The predictions are based on the vehicle trajectories **708**. For example, the vehicle trajectories **708** may comprise speed and yaw rate information. The speed and yaw rates may be used to predict new poses for the respective runs **702** and thus, the predicted positions **712** of the particles **706**.

[0088] At **714**, particle weights **716** are updated. In order to do so, the particles **706** are projected onto the radar occupancy grid **308**, where each particle **706** has corresponding grid cells. The sum of all of the probability values (e.g., from the multiple runs **702**) in the corresponding grid cell is the weight of the particle **706**. In other words, the weight of a particle **706** corresponds to how well a next radar detection **304** fits the predicted position **712**.

[0089] At **718**, existing probabilities are updated using the particle weights **716** to create the radar occupancy probabilities **408**.

[0090] At **720**, the particles are resampled to create resampled particles **722**. Particles with high weights may be split, while particles with low weights may disappear. The resampled particles **722** become the particles at time t+1 for use in the position prediction (step **710**). The resampled particles **722** may also be used to correct the vehicle trajectories **708**.

[0091] As the time t is incremented, the radar occupancy probabilities **408** are updated, and the radar occupancy probabilities **408** are fused with previous radar occupancy probabilities per **410**.

[0092] One advantage of example illustrations **700** and **800** is that they build the radar occupancy probabilities **408** using data from the runs **702** simultaneously. As such, each set of particles **706** contains the same data for all the runs **702**. This means that the radar occupancy probability **408** for one particle **706** contains data from all of the runs **702**. Furthermore, the radar occupancy probabilities **408** are updated (e.g., at **718**) using more than one particle **706**. The statistical map fusion also allows for newer runs to be weighted more than older runs such that change detection (seasonal vegetation change, constructions, etc.) may be compensated on a cell level of the radar occupancy grid **308**.

[0093] By using the techniques of example illustrations **700** and **800**, accurate radar reference maps may be generated without using high-accuracy location data (e.g., by using consumer vehicles). As such, the radar reference maps are easier/more feasible to generate in a wider variety of locations.

[0094] FIG. **9** is an example illustration **900** of a method of determining the radar occupancy probabilities **408**. The example illustration **900** may be implemented utilizing the previously described examples, such as the example illustrations **700** and **800**. Operations **902** through **910** may be performed by one or more entities of the system **102** and/or the cloud system **202** (e.g., the radar-localization module **210**). The order in which the operations are shown and/or described is not intended to be construed as a limitation, and any number or combination of the operations can be combined in any order to implement the illustrated method or an alternate method.

[0095] At **902**, particles are created. For example, the radar-localization module **210** may receive radar detections **304** and create particles **706** that correspond to possible future locations of the vehicle **104** (or vehicles if the runs **702** correspond to multiple vehicles).

[0096] At **904**, particle positions are predicted for the particles. For example, the radar-localization module **210** may receive the vehicle trajectories **708** and determine the predicted positions **712**.

[0097] At **906**, particle weights of the particles are updated. For example, the radar-localization module **210** may determine the particle weights **716** based on radar detections **304** that correspond to a later time.

[0098] At **908**, probabilities are updated based on the particle weights. For example, the radar-localization module **210** may use the particle weights **716** to determine the radar occupancy probabilities **408** for fusing at **410**.

[0099] At **910**, the particles are resampled. For example, the radar-localization module **210** may create resampled particles **722** for predicting future positions at **710**.

[0100] FIG. **10** is an example illustration **1000** of generating the radar reference map **316** using low-accuracy location data and an HD map **1002**. The example illustration **1000** is generally implemented by the system **102**.

[0101] The HD map **1002** contains object attributes **1004** that are determined at **1006** for HD map objects **1008** within the HD map **1002**. The HD map objects **1008** may comprise street signs, overpasses, guard rails, traffic control devices, posts, buildings, k-rails, or other semi-permanent objects. The HD map **1002** contains information about each of the HD map objects **1008**.

[0102] Object attributes **1004** that may be determined at **1006** include aspects such as types **1010**, dimensions/orientations **1012**, locations **1014**, linkages to roads **1016** for the

respective HD map objects **1008**, and radar hardware information **1018**. The types **1010** may define the respective HD map objects **1008**, such as being street signs, overpasses, guard rails, traffic control devices, posts, buildings, k-rails, or other semi-permanent objects. The dimensions/orientations **1012** may comprise physical dimensions and/or orientations (e.g., portrait vs. landscape, rotation relative to the ground, height relative to the ground) of the respective HD map objects **1008**.

[0103] The locations **1014** may comprise UTM coordinates of the respective objects, and the linkages to roads **1016** may comprise specific locations of the respective objects relative to the corresponding roads. For example, a guardrail may have a certain offset relative to its cited location. In other words, the guard rail itself may not exist exactly at its location **1014**. The linkage to road **1016** may account for that. In some implementations, the linkage to road **106** may have a height or elevation aspect. For example, two objects may have similar coordinates but correspond to different roads. The height or elevation may be used to differentiate the two objects. The radar hardware information **1018** may comprise any information that affects a radar reflection **108** from the respective HD map object **1008**.

[0104] Unaligned radar detections **1020** are received, at **1022**, along with the object attributes **1004**. The unaligned radar detections **1020** are similar to the radar detections **304** with low-accuracy location data. The object attributes **1004** are used to determine vehicle poses **1024** for the vehicle **104** at the respective times of the unaligned radar detections **1020**.

[0105] In order to do so, the vehicle may localize itself relative to one or more of the HD map objects **1008** for each set of unaligned radar detections **1020**. For example, the respective set of unaligned radar detections **1020** may contain detections of the one or more HD map objects **1008**. Since the locations **1014** (and other object attributes **1004**) of the one or more HD map objects **1008** are known, the radar-localization module **210** can determine the vehicle pose **1024** at the respective set of unaligned radar detections **1020**.

[0106] Once the vehicle poses **1024** are known for the respective unaligned radar detections **1020**, the unaligned radar detections **1020** may be aligned at **1026**. The alignment may comprise shifting or rotating the unaligned radar detections **1020** based on the respective vehicle poses **1024**.

[0107] The aligned radar detections become the radar detections **304**. The radar detections **304** may then be used in example illustrations **300**, **400**, and **500** to generate the radar reference map **316**.

[0108] The radar reference map **316** may optionally be sent to the cloud system **202**. There, at **1028**, the radar reference map **316** may be updated based on, or compiled with, other radar reference maps based on other similar runs by the vehicle or other vehicles.

[0109] By using the techniques of example illustration **1000**, accurate radar reference maps may be generated without using high-accuracy location data (e.g., by using consumer vehicles). As such, the radar reference maps are easier/more feasible to generate in a wider variety of locations.

[0110] FIG. **11** is an example illustration **1100** of a method of generating the radar reference map **316** using low-accuracy location data and an HD map **1002**. The example illustration **1100** may be implemented utilizing the previously described examples, such as the example illustration **1000**. Operations **1102** through **1110** are generally performed by the system **102**. The order in which the operations are shown and/or described is not intended to be construed as a limitation, and any number or combination of the operations can be combined in any order to implement the illustrated method or an alternate method.

[0111] At **1102**, unaligned radar detections are received. For example, the radar-localization module **210** may receive the unaligned radar detections **1020**.

[0112] At **1104**, HD map object attributes are determined. For example, the radar-localization module **210** may determine the object attributes **1004** for the HD map objects **1008** of the HD map **1002**.

[0113] At **1106**, vehicle poses are determined for each set of unaligned radar detections. For example, the radar-localization module **210** may determine the vehicle poses **1024** based on the unaligned radar detections **1020** and the object attributes **1004**.

[0114] At **1108**, the unaligned radar detections are aligned. For example, the radar-localization module **210** may use the vehicle poses **1024** to shift the unaligned radar detections **1020**. The aligned radar detections essentially become the radar detections **304**.

[0115] At **1110**, a radar reference map is generated. For example, the radar-localization module **210** may perform the example illustrations **300**, **400**, and **500** to generate the radar reference map **316** from the aligned radar detections (radar detections **304**).

[0116] Optionally, at **1112**, the radar reference map may be transmitted to a cloud system for updating. The updating may be based on similar reference maps generated by the vehicle or another vehicle. For example, the radar-localization module **210** of the cloud system **202** may modify or update the radar reference map **316** based on other similar radar reference maps received from the vehicle or other vehicles.

[0117] FIG. **12** is an example illustration **1200** of generating the radar reference map **316** using low-accuracy location data and the HD map **1002** (not shown). The example illustration **1200** is generally performed by the cloud system **202** based on information received from the system **102**.

[0118] At the system **102**, the unaligned radar detections **1020** are run through the example illustrations **300**, **400**, and **500** to generate an unaligned radar reference map **1202**. The unaligned radar reference map **1202** may be similar to the radar reference map **316**, except that the Gaussians **318** may not be in correct places (due to low-accuracy location data).

[0119] In some implementations, only a portion of example illustration **400** may be performed. For example, the steps up to step **410** may be performed to form individual occupancy grids for respective sets of unaligned radar detections **1020**, as the low-accuracy location data may not lend itself to fusing with other data to form a single radar occupancy grid (e.g., radar occupancy grid **308**). Each unaligned radar occupancy grid may then be used to form the unaligned radar reference map **1202**.

[0120] The unaligned radar reference map **1202** (e.g., with unaligned Gaussians that are similar to Gaussians **318**) is then sent to the cloud system **202**. At **1204**, the object attributes **1004** of the HD map **1002** are used by the cloud system **202** to align the unaligned radar reference map **1202** to generate the radar reference map **316**.

[0121] In order to do so, similarly to example illustration **1000**, the object attributes **1004** are usable to align or change the Gaussians **318** within the unaligned radar reference map **1202**. For example, the object attributes **1004** may be used to determine Gaussians **318** within the unaligned radar reference map **1202** that correspond to the corresponding HD map objects **1008**. Since the locations of those objects are known, the Gaussians **318** can be shifted to correct locations.

[0122] If the unaligned radar detections **1020** are contiguous in space (e.g., they incrementally follow a path), then the unaligned radar reference map **1202** may have accurate locations of the Gaussians **318** relative to one another. In such a case, the unaligned radar reference map **1202** may only need to be shifted or rotated globally (instead of having to align each Gaussian **318**).

[0123] The unaligned radar detections **1020** may also be sent to the cloud system **202** to process in a manner similar to example illustration **1000**. The unaligned radar reference map **1202**, however, is much smaller and therefore easier to transmit.

[0124] By using the techniques of example illustration **1200**, accurate radar reference maps may be generated without using high-accuracy location data (e.g., by using consumer vehicles). As such, the radar reference maps are easier/more feasible to generate in a wider variety of locations.

[0125] FIG. **13** is an example illustration **1300** of a method of generating the radar reference map **316** using low-accuracy location data and an HD map **1002**. The example illustration **1300** may be implemented utilizing the previously described examples, such as the example illustration **1200**. Operations **1302** through **1306** are generally performed by the cloud system **202**. The order in which the operations are shown and/or described is not intended to be construed as a limitation, and any number or combination of the operations can be combined in any order to implement the illustrated method or an alternate method.

[0126] At **1302**, an unaligned radar reference map is received. For example, the radar-localization module **210** may receive the unaligned radar reference map **1202** from the system **102**.

[0127] At **1304**, HD map object attributes are determined. For example, the radar-localization module **210** may determine the object attributes **1004** for the HD map objects **1008** of the HD map **1002**.

[0128] At **1306**, the unaligned radar reference map is aligned based on the HD map object attributes. For example, the radar-localization module **210** may use the object attributes **1004** to determine Gaussians within the unaligned radar reference map **1202** that correspond to the associated HD map objects **1008**. Differences between locations of the corresponding Gaussians and the HD map objects **1008** may then be used to correct, adjust, shift, or otherwise correct the unaligned radar reference map **1202** to form the radar reference map **316**.

[0129] FIG. **14** is an example illustration **1400** of generating the radar occupancy grid **308** using the HD map **1002**. The example illustration **1400** may be integrated with example illustrations **300** and **500** to generate the radar reference map **316**. The example illustration **1400** does not need radar (e.g., radar reflections **108**, radar detections **304**) to create the radar occupancy grid **308**. As will be apparent, however, example illustration **1400** does rely on an availability of the HD map objects **1008** in the HD map **1002**.

[0130] Similar to example illustrations **1000** and **1200**, the object attributes **1004** of the HD map objects **1008** are determined. The object attributes **1004** are used to determine, at **1402**, shapes **1404**. The shapes **1404** are geometric representations of the HD map objects **1008** relative to the radar occupancy grid **308**. The shapes **1404** may be lines, polylines, polygons, geometric shapes, curves, complex curves, or statistical representations. For example, a location, orientation, and specifics (e.g., offset) of a guardrail may be used to generate a shape **1404** of occupied spaces in the radar occupancy grid **308** that correspond to the guardrail.

[0131] At **1406**, sizes of the respective shapes **1404** are compared to a grid size of the radar occupancy grid **308**. If a shape **1406** is not longer than a grid cell of the radar occupancy grid **308**, the corresponding grid cell is marked as being occupied.

[0132] If, however, a shape **1406** is longer than a grid cell, the shape **1406** is oversampled, at **1408**, to create an oversampled shape **1410**. The oversampling comprises adding more points along the respective shape **1404** to simulate a radar occupancy grid output from radar detections (e.g., from radar detections **304**).

[0133] The shapes **1404** or the oversampled shapes **1410** are then adjusted (e.g., transformed) based on the object attributes **1004** or some other information, at **1412**, to form adjusted shapes **1414**. Continuing with the guardrail example above, the system may know that guardrails of a certain type are always some distance further away from an edge of the road than the location contained within the object attributes **1004**. The adjusted shapes **1414** are used to mark corresponding grid cells of the radar occupancy grid **308** as occupied.

[0134] In some implementations, the shapes **1404** or the oversampled shapes **1410** may be used to determine the radar reference map **316** instead of the radar occupancy grid **308**. In other words, the Gaussians **318** may be generated based on the shapes **1404** or the oversampled shapes **1400** without first generating the radar occupancy grid **308**.

[0135] As shown in the example radar occupancy grid **308**, the HD map objects **1008** (e.g., the guardrails) are represented as occupied spaces. In this way, the radar occupancy grid **308** may be generated without necessitating a vehicle driving through the corresponding area.

[0136] FIG. **15** is an example illustration **1500** of generating the radar occupancy grid **308** using the HD map **1002** and machine-learned models. The example illustration **1500** may be integrated with example illustration **1400** (e.g., to determine transformations for the adjusting at **1412**). In some implementations, however, the machine-learned models may be used to indicate cells of the radar occupancy grid **308** directly (e.g., without example illustration **1400**).

[0137] In example illustration **1500**, the object attributes **1004** are used to select and apply models **1502** that are used to adjust the shapes at **1412**. The models **1502** are based on respective object attributes **1004**.

[0138] At **1504**, a model **1502** is selected and applied to each HD map object **1008**. The models **1502** are categorized by respective object attributes **1004**. For example, a model **1502** may exist for each type of HD map object **1008** (e.g., model **1502-1** for a guardrail, model **1502-2** for a sign, model **1502-3** for a building, etc.). Multiple models **1502**

may also exist for a single type of object. For example, different types of guardrails may have different respective models **1502**.

[0139] The models **1502** are previously generated and may be taught using machine learning on real-world occupancy grid data. For example, occupancy data (e.g., portions of that determined by example illustrations **300** and **400**) may be fed into a model training program along with object attributes **1004** and HD map locations of the corresponding HD map objects **1008**. In so doing, the system is able to form rules and dependencies that "learn" how to represent corresponding HD map objects **1008** in the radar occupancy grid **308** (e.g., through shape adjustments).

[0140] The output of the respective models **1502** is occupancy grid data **1506** that corresponds to shape adjustment data. The shape adjustment data may then be used to adjust the shapes **1404** of example illustration **1400**.

[0141] In some implementations, the occupancy grid data **1506** may comprise direct occupancy grid data. In such cases, shapes are not used, and the occupancy grid data **1506** is used as direct inputs to the radar occupancy grid **308** (e.g., the occupancy grid data **1506** is usable to indicate cells of the radar occupancy grid **308** as occupied).

[0142] As discussed above, the radar occupancy grid **308** can then be used to generate the radar reference map **316**. In this way, real-world radar occupancy data can be used to estimate adjustments or occupancy of HD map objects **608** for representation in the radar occupancy grid **308**.

[0143] By using the techniques of example illustrations **1400** and **1500**, accurate radar reference maps may be generated without using radar detections of the corresponding areas (although, in some implementations, they may be used to update the maps and/or provide additional map data). As such, the radar reference maps are easier/more feasible to generate for a wider variety of locations. Furthermore, the maps may be generated completely offline as long as the HD map has sufficient objects.

[0144] FIG. **16** is an example illustration **1600** of a method of generating the radar occupancy grid **308** using the HD map **1002**. The example illustration **1600** may be implemented utilizing the previously described examples, such as the example illustrations **1400** and **1500**. Operations **1602** through **1608** are generally performed by the cloud system **202** as there is no need for the vehicle **104**. The operations **1602** through **1608** (or portions thereof) may be performed by the system **102**, however. The order in which the operations are shown and/or described is not intended to be construed as a limitation, and any number or combination of the operations can be combined in any order to implement the illustrated method or an alternate method.

[0145] At **1602**, HD map object attributes are determined for HD map objects within an HD map. For example, the radar-localization module **210** may determine the object attributes **1004** for the HD map objects **1008** of the HD map **1002**.

[0146] At **1604**, shapes for the HD map objects are determined. In some implementations, the shapes may be oversampled based on sizes of the respective shapes and a grid size of a desired radar occupancy grid. For example, the radar-localization module **210** may determine the shapes **1404** for the HD map objects **1008** and oversample the shapes **1404** if they are longer than a grid size of the radar occupancy grid **308**.

[0147] At **1606**, adjustments are applied to the shapes as needed. The adjustments may be based on the HD map object attributes or machine-learned models for the respective HD map objects. For example, the radar-localization module **210** may adjust the shapes **1404** based on the object attributes **1004** or the models **1502**.

[0148] At **1608**, cells of a radar occupancy grid are indicated as occupied based on the shapes. For example, the radar-localization module **210** may indicate cells of the radar occupancy grid **308** based on the shapes **1404** (after oversampling and adjustment per **1406** and **1412**).

[0149] By performing one or more of the techniques described above, accurate and space efficient radar reference maps may be generated. In this way, accurate localization may be achieved to support driver assist or autonomous driving capabilities with limited driver takeover. Less driver takeover leads to increased safety and driver satisfaction.

[0150] Updating a Radar Reference Map

[0151] The following section describes techniques for updating a radar reference map. Constant improvement of the radar reference map is required because any particular environment through which a vehicle travels tends to change over time. The radar reference map may include temporary obstacles that may not be considered attributes, which may be added or removed. Additionally, a radar reference map may include false attribute data or missing attributes (e.g., occlusions in the radar reference map). Current techniques for updating the radar reference map often use different sensors gathering attribute data in a single traversal of an environment. The techniques described below use radar-centric data gathered from multiple iterations of traversing the environment to update the quality of the radar reference map. The techniques use a process to ensure accurate and stable data, referred to as hindsight; two non-limiting examples of which are illustrated. One example uses radar detections of objects and compares them with an HD map. The second example uses only radar detections in using hindsight as a way to ensure the data is accurate and stable.

[0152] FIG. **17** illustrates a flow chart **1700** for updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections. The flow chart includes multiple runs **1702** (e.g., run **1** to run n where n can be any integer greater than 1), with each run being an iteration through an environment represented by a radar reference map. A first step **1704** of a radar-localization module (e.g., radar-localization module **210** from FIG. **2-1**) is to receive radar detections and navigation data. In a step **1706**, the radar detections and navigation data may be used by a static object identifier to identify static objects from the raw radar detections and navigation data collected in step **1704**. A step **1708** generates an occupancy grid based on the static objects identified in step **1706**. In a step **1710**, a radar reference map is built from each occupancy grid generated in each run **1702**. A final step **1712** builds (in the initial run **1**) and updates (in each successive run n) a relative NDT radar reference map (e.g., a map relative to the vehicle and using a relative coordinate system) based on the radar reference map generated in step **1710**. The final step **1710** is conditioned on an HD map **1714** not being utilized in step **1710** in combination with the occupancy grids generated in step **1708**. Otherwise if the HD map **1714** is utilized in step **1710**, the final step **1712** updates an absolute map (e.g., a universal map using a global coordinate system such as the UTM coordinate system) during each run **1702**.

[0153] FIG. **18** illustrates an example implementation **1800** of updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections. In the example implementation **1800**, a vehicle **1802** equipped with a radar-localization module (e.g., onboard, accessed through a cloud) uses hindsight to accumulate accurate and stable radar data about a dynamic object **1804**. Radar sensors on the vehicle **1802** have radar sweeps **1806** that transmit electromagnetic energy and receive the reflections of the electromagnetic energy off of objects. The radar sweeps **1806** may not be illustrated to scale in FIG. **18** or in any of the other figures in which they are depicted. The dynamic object **1804** is moving from in front (dynamic object **1804-1**) of the vehicle **1802** to beside (dynamic object **1804-2**) the vehicle **1802** to behind (dynamic object **1804-3**) the vehicle **1802**. A blind spot **1808** represents a range-rate blind spot of one or more radar sensors on the vehicle **1802**. Although in the example implementation **1800**, the blind spot **1808** is related to the range rate state of the dynamic object, any dynamic state of the dynamic object **1804** may be used as an example.

[0154] Corner radar sensors mounted on the vehicle **1802** are configured such that the bore angles of the radar sensors are 45° in relation to the longitudinal axis of the vehicle **1802**. This enables the corner radar sensors to have the same radar performance as the front and rear radar sensors of the vehicle **1802**. The accumulated data from all the radar sensors present the most stable results of object detection at the rear of the vehicle **1802** with the dynamic object **1804** reflecting several radar detections from the different radar sensors. As an occupancy grid presents accumulated data, all available sensor detections contribute to a radar reference map even if the rear detection is the only one taken into consideration. The detections from all the radar sensors contribute to the occupancy probability, and none of the radar data are omitted. This process may be interpreted as an application of binary weights for each cell of the occupancy grid, and the dynamic object **1804** may be excluded from the updated radar reference map.

[0155] FIG. **19** illustrates a pipeline **1900** for updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections. At a radar sensor stage **1902** of the pipeline **1900**, a radar sensor **1904** receives raw radar detections **1906**. At a static object identifier **1908** stage, the raw radar detections **1904** are classified at **1910** as static or dynamic radar detections, and augmented static radar detections **1912** are passed to an occupancy grid generator **1914** stage. In the occupancy grid generator **1914** stage, occupancy evidence from the augmented static radar detections **1912** is extracted at **1916**. At **1918**, the extracted occupancy evidence from **1916** is used to accumulate and filter static occupancy on an occupancy grid **1920**. An accumulator **1922** stage then extracts hindsight information at **1924**.

[0156] FIGS. **20-1** to **20-3** illustrate an example implementation of hindsight used to update, through multiple iterations, a radar reference map used for vehicle localization based on radar detections. In FIG. **20-1**, a vehicle **2002**, equipped with a radar-localization module (e.g., onboard, accessed through a cloud) uses hindsight to accumulate accurate and stable radar data about a static object **2004** (a street sign **2004**). In a first time frame **2000-1** in FIG. **20**, the street sign **2004** may be detected first by radar sweeps **2006-1** and **2006-2**. Radar sweeps **2006-3** and **2006-4** have not yet detected the street sign **2004**.

[0157] In a second time frame **2000-2** in FIG. **20-2**, the vehicle **2002** has moved down the road, and the street sign **2004** is lateral to the vehicle **2002**. At least radar sweeps **2006-1**, **2006-2**, and possibly radar sweep **2006-3** have detected the street sign **2004**. Additionally, radar sweeps **2006-1** and **2006-2** may have detected a second static object **2008** (a tree **2008**).

[0158] In a third time frame **2000-3** in FIG. **20-3**, the vehicle **2002** has moved forward such that the street sign **2004** has been detected by radar sweeps **2006-1**, **2006-2**, **2006-3**, and **2006-4**, accumulatively. At this point, the street sign is in hindsight of the radar sweeps, and the radar data relative to the street sign may be considered stable and accurate with a high confidence level. At least radar sweeps **2006-1**, **2006-2**, and possibly radar sweep **2006-3** have detected the tree in time frame **2000-3** and have a moderate confidence level, but higher than a third static object **2010** (a guard rail **2010**). Only sweeps **2006-1** and **2006-2** may have detected the guard rail **2010**.

[0159] Driving on the road in the depictions **2000-1** to **2000-3** over multiple iterations may increase the confidence level that the static objects **2004**, **2008**, and **2010** are permanent and can be considered attributes. If any of the static objects **2004**, **2008**, and **2010** disappear during any of the multiple iterations of runs down the road, the confidence level for that object may fall, and the object may be removed from the updated radar reference map. Furthermore, consider a moving vehicle traveling in another direction (e.g., in a lane adjacent to the vehicle **2002**). Conventional techniques may consider the moving vehicle when it is immediately adjacent to the vehicle **2002**. By using hindsight, the moving vehicle will not be considered. In this manner, the radar reference map may be updated after each iteration to add or remove attributes as they are detected or disappear, and to remove any spurious noise that may be present in the radar reference map.

[0160] FIG. **21** illustrates an example process **2100** to determine and use a hindsight maximum boundary for radar coordinates when updating, through multiple iterations, a radar reference map used for vehicle localization based on radar detections. There are two options for radar coordinates, radar relative coordinates, and radar absolute coordinates. At **2102**, all radar reference maps are loaded. Additionally, if using radar absolute coordinates, at **2104**, sample points from one or more HD maps are extracted, and at **2106**, the extracted sample points are transformed into a statistical distribution. At **2108**, all of the hindsight samples are collected, and a minimum and maximum for the coordinates (X and Y) are found. At **2110**, the minimum and maximum for the coordinates are used to create a maximum boundary for a new radar group. At **2112**, a resolution is chosen, and an index of the samples in the resolution of the coordinates index is checked. At **2114**, based on the outcomes of the check procedure at **2112**, if the sample is not new in the chosen resolution, then at **2116**, only the log-odds ratios, by either Bayes Inverse Model or by maximum policy, are merged into the radar reference maps. If, at **2114**, the sample is new in the chosen resolution, then at **2118**, the original index of the new sample is added into a new map index.

[0161] Example Architecture

[0162] Applying the techniques discussed in this document to localize a vehicle based on radar detections may have many advantages. By using radar-centric systems (e.g., a radar system including four short-range radar sensors, one radar sensor located at each of the four corners of a vehicle), adverse weather and lighting conditions that may degrade the effectiveness of other systems (e.g., cameras, LiDAR) are overcome by only using radar systems. Additionally, the radar systems used may be less expensive than some other sensor systems.

[0163] The techniques and systems described in this document enable a vehicle to determine its vehicle pose, or location, at a sub-meter accuracy level. To localize a vehicle based on radar detections, according to the techniques described herein, two steps may be performed, including steps to: construct an accurate radar reference map, and compare the radar reference map against radar detections generated in real time to accurately locate the vehicle. FIGS. **22-1** and **22-2** describe one detailed example of how to achieve these two steps with a radar-localization module, such as the radar-localization module illustrated in FIGS. **2-2** and **2-3**. Other examples may preclude some of the details in FIGS. **22-1** and **22-2** (e.g., some submodules of the radar-localization module are optional, as illustrated in FIGS. **2-2** and **2-3**).

[0164] FIGS. **22-1** to **22-2** illustrate an example flow diagram **2200** of a process for vehicle localization based on radar detections. FIG. **22-1** covers the first step as flow diagram **2200-1**, and FIG. **22-2** covers the second step as flow diagram **2200-2**. The sub-steps within a dashed box **2202** of FIG. **22-1** and FIG. **22-2** are identical in each step.

[0165] The first step of vehicle localization **2204** is to construct an accurate radar reference map containing attribute information. Details of several different processes of constructing the radar reference map have been described above. The example flow diagram illustrated in FIG. **22-1** details the architecture of constructing the radar reference map in the vehicle **2204-1** specially equipped with a high-quality navigation system. The radar-localization module is in a reference mode for this step.

[0166] In the example flow diagram illustrated in FIG. **22-1**, one or more radar sensors **2206** receive raw radar detections **2208**. Simultaneously, high-quality GNSS **2210-1** and inertial measurement unit (IMU) **2212-1** data are collected by a vehicle state estimator **2214** to determine the vehicle state and vehicle pose. The raw radar detections **2208** are collected at a certain rate, for example, every 50 milliseconds (ms). The raw radar detections **2208** are identified as static detections or dynamic detections by a static object identifier **2216**. The static object identifier **2216** uses vehicle state information (e.g., range rate) provided by the vehicle state estimator **2214** to determine (e.g., determine through range rate de-aliasing) the identification of the raw radar detections **2208**.

[0167] The static detections are output to an occupancy grid generator **2218**. The occupancy grid generator **2218** estimates an occupancy probability for each cell (e.g., 20 centimeters (cm) by 20 cm cell) in the occupancy grid. The cell size may impact the processing time for this sub-step. Different processes, including Bayesian inference, Dempster Shafer theory, or other processes, can be used to estimate the occupancy probability for each cell. The occupancy grid generated by the occupancy grid generator **2218** may be in relative coordinates (e.g., local frame of reference) to the vehicle **2204-1** as the occupancy grid generator **2218** receives vehicle state data from the vehicle state estimator **2214** that assists in the creation of the occupancy grid.

[0168] A scan-matcher **2220** performs a series of sub-steps **2220-1** to **2220-4**. Sub-step **2220-1** transforms the occupancy grid from a relative coordinate system to a UTM coordinate system. Vehicle state information from the vehicle state estimator **2214** is used in the transformation process. Sub-step **2220-2** accumulates occupancy grid outputs from sub-step **2220-1** at a certain rate (e.g., 10 Hz). The rate may be tuned based on a driving scenario (e.g., quantity of attributes in the environment of the vehicle **2204-1**) and outputs the accumulated occupancy grid to sub-step **2220-3**. Sub-step **2220-3** chooses occupancy grid cells based on a high-occupancy probability (e.g., a probability equal to or greater than 0.7). The chosen occupancy grid cells may be represented as a point cloud. Sub-step **2220-4** transforms the chosen occupancy grid cells in a Gaussian representation to create a Gaussian, or NDT, radar reference map. The NDT radar reference map can be stored locally on the vehicle **2204-1** or uploaded to a cloud **2222**.

[0169] The second step of vehicle localization **2204** is to determine an adjusted vehicle pose based on a comparison of radar detections of attributes with a radar reference map. The example flow diagram in FIG. **22-2** details the architecture used to determine this adjusted vehicle pose for the vehicle **2204-2**. It can be assumed in this example that the vehicle **2204-2** is configured as a non-luxury vehicle manufactured in mass quantities and at cost margins that make using high-quality GNSS and sensor packages not practical. That is, the GNSS system **2210-2** and the IMU **2212-2** used in the vehicle **2204-2** may be considered average (lower quality) commercial navigation systems. The radar-localization module is in a real-time localization mode for the second step. All of the sub-steps inside the dashed box **2202** are identical to those of the first step illustrated in FIG. **22-1** and, for simplicity, will not be covered again.

[0170] At step **2224**, a radar reference map, based on the vehicle state as determined by the vehicle state estimator **2214**, is downloaded from the cloud **2222**. The radar reference map is compared to the chosen occupancy grid cells at sub-step **2220-5**, and based on that comparison, the vehicle pose is corrected for the vehicle **2204-2**. A confidence level of an accuracy of the corrected pose may be used in determining the accuracy of the corrected pose. Additionally, the corrected vehicle pose may be used to remove errors (e.g., drift) in the GNSS system **2210-2** and the IMU **2212-2**.

[0171] The comparison process matches the radar reference map, the radar reference map being a set of Gaussian representations that minimize memory size of the data and contain statistical information, with a real-time "map" that is derived from real-time radar detections. The real-time map is a sub-section of the area represented by the radar reference map and contains the same Gaussian-type statistical information as the radar reference map. In another implementation, the filtered outputs from the occupancy grid may be directly compared to the Gaussians in the radar reference map.

[0172] The NDT process matches statistical probability distributions between reference data (e.g., discretized cells with a built-in statistical model). For any given transformation (e.g., x, y, and rotation) for real-time points (e.g., occupancy grid outputs), the real-time points can be

assigned to discretized NDT cells that contain the statistical distribution in a model from the radar reference map. The real-time points are occupancy grid cells that are considered occupied but are treated as points with a probability value attached to the points. Probability distributions of the real-time points can therefore be calculated. The NDT process finds an optimal transformation that maximizes the probability distributions.

[0173] FIG. **23** illustrates an example process **2300** for vehicle localization based on radar detections. At **2302**, radar detections are received by at least one or more processors of a vehicle. At **2304**, navigation data is received by at least one or more processors of a vehicle. At **2306**, Ego-trajectory information about a current dynamic state of the vehicle is output by at least one or more processors of the vehicle. This ego-trajectory information may include at least one of direction of travel, velocity, range rate, and yaw rate, as determined from the radar detections and navigation data. At **2308**, attribute data is extracted from the radar detections and the ego-trajectory information. At **2310**, a normal distribution transformation grid is determined from the extracted attribute data and a radar reference map. At **2312**, a vehicle pose is corrected according to the normal distribution transformation grid to localize the vehicle.

[0174] In this manner, the techniques and systems described herein use cost-effective systems, disregard dynamic objects, maximize a statistical distribution pattern, and handle static noise efficiently to accurately adjust the pose of a vehicle.

EXAMPLES

[0175] Example 1: A method comprising: receiving a high-definition (HD) map; determining one or more HD map objects within the HD map; determining attributes of the respective HD map objects; and for each HD map object: indicating one or more occupancy cells of a radar occupancy grid as occupied space based on the attributes of the respective HD map object.

[0176] Example 2: The method of example 1, further comprising generating a radar reference map based on the radar occupancy grid, wherein the radar reference map comprises statistical representations of the occupancy cells of the radar occupancy grid that are indicated as occupied space.

[0177] Example 3: The method of example 1 or 2, wherein the attributes comprise one or more of a type, location, dimensions, orientation, linkage to a corresponding road, or radar hardware information for the respective HD map object.

[0178] Example 4: The method of any preceding example, wherein the method is performed by a cloud system that is external to a vehicle.

[0179] Example 5: The method of any preceding example, further comprising forming a shape for the respective HD map object, wherein the indicating is based on the shape.

[0180] Example 6: The method of any preceding example, further comprising applying an adjustment to the shape based on the attributes of the respective HD map object to form an adjusted shape, wherein the indicating is based on the adjusted shape.

[0181] Example 7: The method of any preceding example, further comprising determining if the shape is longer than one of the occupancy cells, wherein the indicating is based on the shape responsive to determining that the shape is not longer than one of the occupancy cells.

[0182] Example 8: The method of any preceding example, further comprising, responsive to determining that the shape is longer than one of the occupancy cells, oversampling the shape to form an oversampled shape, wherein the indicating is based on the oversampled shape.

[0183] Example 9: The method of any preceding example, further comprising selecting a model for the respective HD map object from a plurality of models corresponding to respective types or attributes of HD map objects, wherein the adjustment is based on the model.

[0184] Example 10: The method of any preceding example, further comprising: inputting the attributes of the respective HD map object into the model; and receiving an output from the model, wherein the adjustment is based on the output from the model.

[0185] Example 11: A method comprising: receiving a high-definition (HD) map; determining one or more HD map objects within the HD map; determining attributes of the respective HD map objects; and for each HD map object: forming a Gaussian for each of one or more radar reference map cells based on the attributes of the respective HD map object.

[0186] Example 12: A system comprising: at least one processor; and at least one computer-readable storage medium comprising instructions that, when executed by the processor, cause the system to: receive a high-definition (HD) map; determine one or more HD map objects within the HD map; determine attributes of the respective HD map objects; and for each HD map object: indicate occupancy cells of a radar occupancy grid as occupied space based on the attributes of the respective HD map object.

[0187] Example 13: The system of example 12, wherein: the instructions further cause the system to generate a radar reference map based on the radar occupancy grid; and the radar reference map comprises statistical representations of the occupancy cells of the radar occupancy grid that are indicated as occupied space.

[0188] Example 14: The system of example 12 or 13, wherein the attributes comprise one or more of a type, location, dimensions, orientation, or linkage to a corresponding road for the respective HD map object.

[0189] Example 15: The system of any of examples 12 to 14, wherein: the instructions further cause the system to form a shape for the respective HD map object; and the indication is based on the shape.

[0190] Example 16: The system of any of examples 12 to 15, wherein: the instructions further cause the system to apply an adjustment to the shape based on the attributes of the respective HD map object to form an adjusted shape; and the indication is based on the adjusted shape.

[0191] Example 17: The system of any of examples 12 to 16, wherein: the instructions further cause the system to determine if the shape is longer than one of the occupancy cells; and the indication is based on the shape responsive to determining that the shape is not longer than one of the occupancy cells.

[0192] Example 18: The system of any of examples 12 to 17, wherein: the instructions further cause the system to, responsive to determining that the shape is longer than one of the occupancy cells, oversample the shape to form an oversampled shape; and the indication is based on the oversampled shape.

[0193] Example 19: The system of any of examples 12 to 18, wherein: the instructions further cause the system to select a model for the respective HD map object; and the adjustment is based on the model.

[0194] Example 20: The system of any of examples 12 to 19, wherein: the instructions further cause the system to: input the attributes of the respective HD map object into the model; and receive an output from the model; and the adjustment is based on the output from the model.

CONCLUSION

[0195] Although implementations for radar reference map generation have been described in language specific to certain features and/or methods, the subject of the appended claims is not necessarily limited to the specific features or methods described. Rather, the specific features and methods are disclosed as example implementations for radar reference map generation. Further, although various examples have been described above, with each example having certain features, it should be understood that it is not necessary for a particular feature of one example to be used exclusively with that example. Instead, any of the features described above and/or depicted in the drawings can be combined with any of the examples, in addition to or in substitution for any of the other features of those examples.

What is claimed is:

1. A method comprising:
receiving a high-definition (HD) map;
determining one or more HD map objects within the HD map;
determining attributes of the respective HD map objects; and
for each HD map object:
indicating one or more occupancy cells of a radar occupancy grid as occupied space based on the attributes of the respective HD map object.

2. The method of claim **1**, further comprising generating a radar reference map based on the radar occupancy grid,
wherein the radar reference map comprises statistical representations of the occupancy cells of the radar occupancy grid that are indicated as occupied space.

3. The method of claim **1**, wherein the attributes comprise one or more of a type, location, dimensions, orientation, linkage to a corresponding road, or radar hardware information for the respective HD map object.

4. The method of claim **1**, wherein the method is performed by a cloud system that is external to a vehicle.

5. The method of claim **1**, further comprising forming a shape for the respective HD map object,
wherein the indicating is based on the shape.

6. The method of claim **5**, further comprising applying an adjustment to the shape based on the attributes of the respective HD map object to form an adjusted shape,
wherein the indicating is based on the adjusted shape.

7. The method of claim **5**, further comprising determining if the shape is longer than one of the occupancy cells,
wherein the indicating is based on the shape responsive to determining that the shape is not longer than one of the occupancy cells.

8. The method of claim **7**, further comprising, responsive to determining that the shape is longer than one of the occupancy cells, oversampling the shape to form an oversampled shape,
wherein the indicating is based on the oversampled shape.

9. The method of claim **6**, further comprising selecting a model for the respective HD map object from a plurality of models corresponding to respective types or attributes of HD map objects,
wherein the adjustment is based on the model.

10. The method of claim **9**, further comprising:
inputting the attributes of the respective HD map object into the model; and
receiving an output from the model,
wherein the adjustment is based on the output from the model.

11. A method comprising:
receiving a high-definition (HD) map;
determining one or more HD map objects within the HD map;
determining attributes of the respective HD map objects; and
for each HD map object:
forming a Gaussian for each of one or more radar reference map cells based on the attributes of the respective HD map object.

12. A system comprising:
at least one processor; and
at least one computer-readable storage medium comprising instructions that, when executed by the processor, cause the system to:
receive a high-definition (HD) map;
determine one or more HD map objects within the HD map;
determine attributes of the respective HD map objects; and
for each HD map object:
indicate occupancy cells of a radar occupancy grid as occupied space based on the attributes of the respective HD map object.

13. The system of claim **12**, wherein:
the instructions further cause the system to generate a radar reference map based on the radar occupancy grid; and
the radar reference map comprises statistical representations of the occupancy cells of the radar occupancy grid that are indicated as occupied space.

14. The system of claim **12**, wherein the attributes comprise one or more of a type, location, dimensions, orientation, or linkage to a corresponding road for the respective HD map object.

15. The system of claim **12**, wherein:
the instructions further cause the system to form a shape for the respective HD map object; and
the indication is based on the shape.

16. The system of claim **15**, wherein:
the instructions further cause the system to apply an adjustment to the shape based on the attributes of the respective HD map object to form an adjusted shape; and
the indication is based on the adjusted shape.

17. The system of claim **15**, wherein:
the instructions further cause the system to determine if the shape is longer than one of the occupancy cells; and
the indication is based on the shape responsive to determining that the shape is not longer than one of the occupancy cells.

18. The system of claim **15**, wherein:
the instructions further cause the system to, responsive to determining that the shape is longer than one of the occupancy cells, oversample the shape to form an oversampled shape; and
the indication is based on the oversampled shape.
19. The system of claim **16**, wherein:
the instructions further cause the system to select a model for the respective HD map object; and
the adjustment is based on the model.
20. The system of claim **19**, wherein:
the instructions further cause the system to:
input the attributes of the respective HD map object into the model; and
receive an output from the model; and
the adjustment is based on the output from the model.

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