(19) **United States**

(12) **Patent Application Publication** (10) Pub. No.: **US 2025/0264334 A1**
Fox-Rabinovitz et al. (43) **Pub. Date:** **Aug. 21, 2025**

(54) **METHODS AND APPARATUS FOR KALMAN FILTER ERROR RECOVERY THROUGH Q-BOOSTING ALONG OBSERVATION SUB-SPACES**

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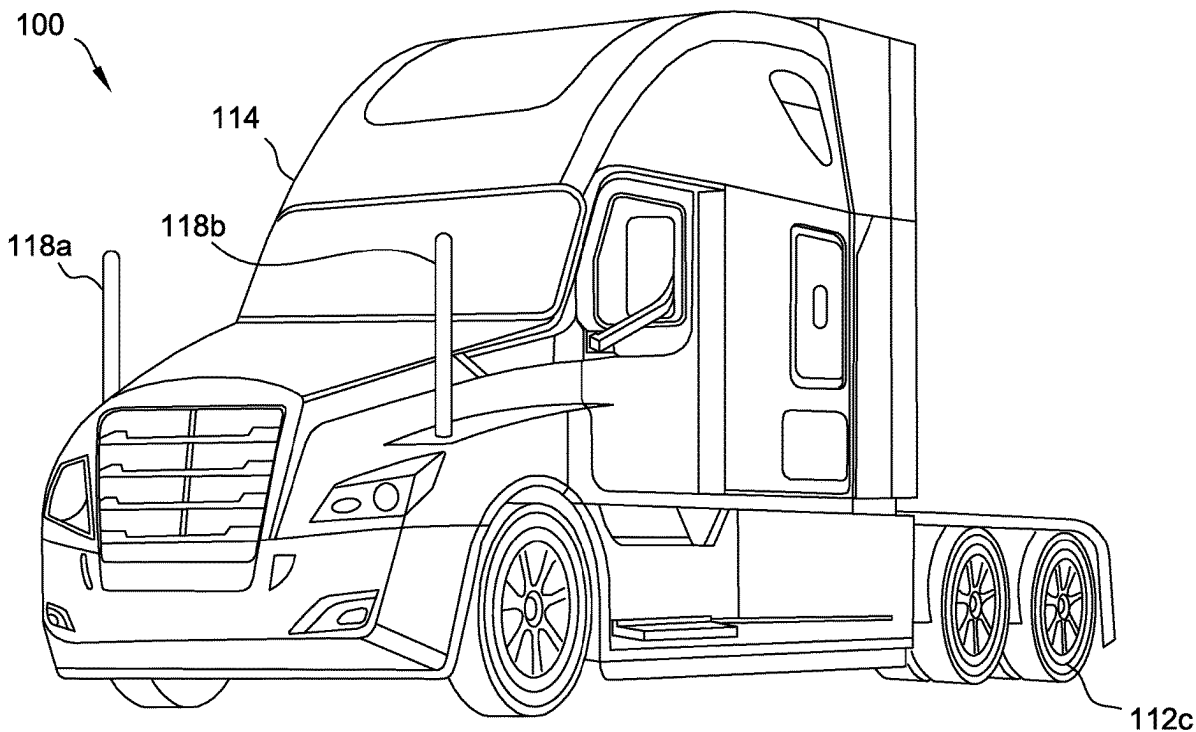(72) Inventors: **Joseph R. Fox-Rabinovitz**, Blacksburg, VA (US); **Vicent Rodrigo Marco**, Blacksburg, VA (US)

(52) **U.S. Cl.**
CPC *G01C 21/165* (2013.01); *G01C 25/005* (2013.01)

(57) **ABSTRACT**

An autonomous vehicle including a Kalman filter error recovery system is disclosed. The Kalman filter error recovery system includes at least one processor and at least one memory storing instructions, which, when executed by the at least one processor, cause the Kalman filter error recovery system to perform operations including increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or more position sensors, and boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.
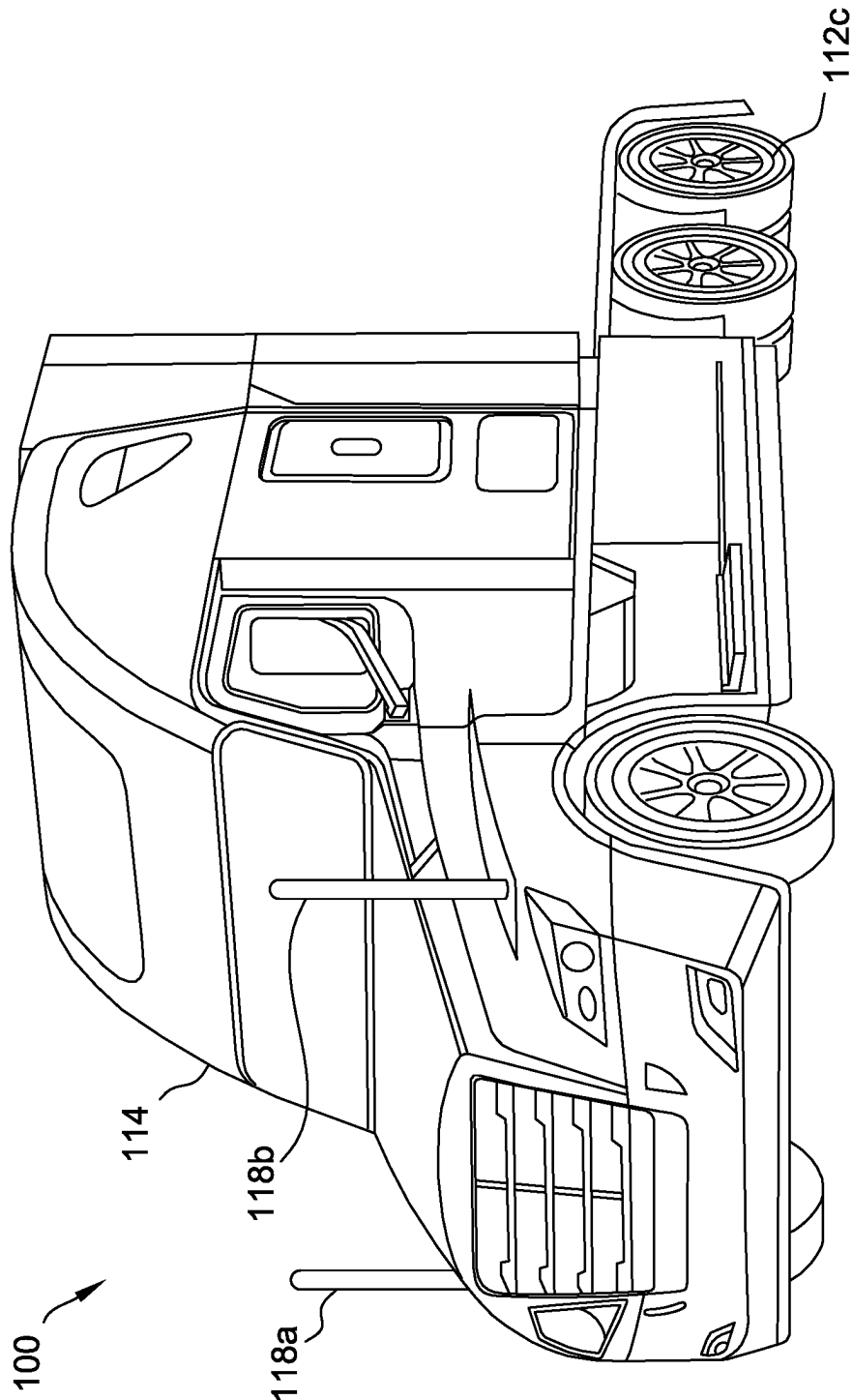
FIG. 1

FIG. 2

FIG. 3

400

Att (3)

Vel(3)

402

Pos (3)

404

A Bias (3)

402

G Bias (3)

404

WSS (4)

402

404

FIG. 4

FIG. 5

600

602

Boost Y

604

Shrink X

606

Boost random axis

608

Boost minor axis

FIG. 6

700

705

Kalman Filter Error Recovery Engine

Filter Initiation Circuitry
710

Outlier Detection Circuitry
715

Filter Resetting Circuitry
720

Subspace Projection Circuitry
725

Covariance Resetting Circuitry
730

735

Network

740

Network

FIG. 7

800

802

INCREASE EIGENVALUES OF A COVARIANCE
MATRIX TO ADJUST PROBABILITY
DISTRIBUTION OF A STATE VECTOR ERROR

804

BOOST A PLURALITY OF COVARIANCES BY
INCREASING DIAGONAL ELEMENTS OF AN
ENTIRE BLOCK CORRESPONDING TO
VECTOR MEASUREMENTS

FIG. 8

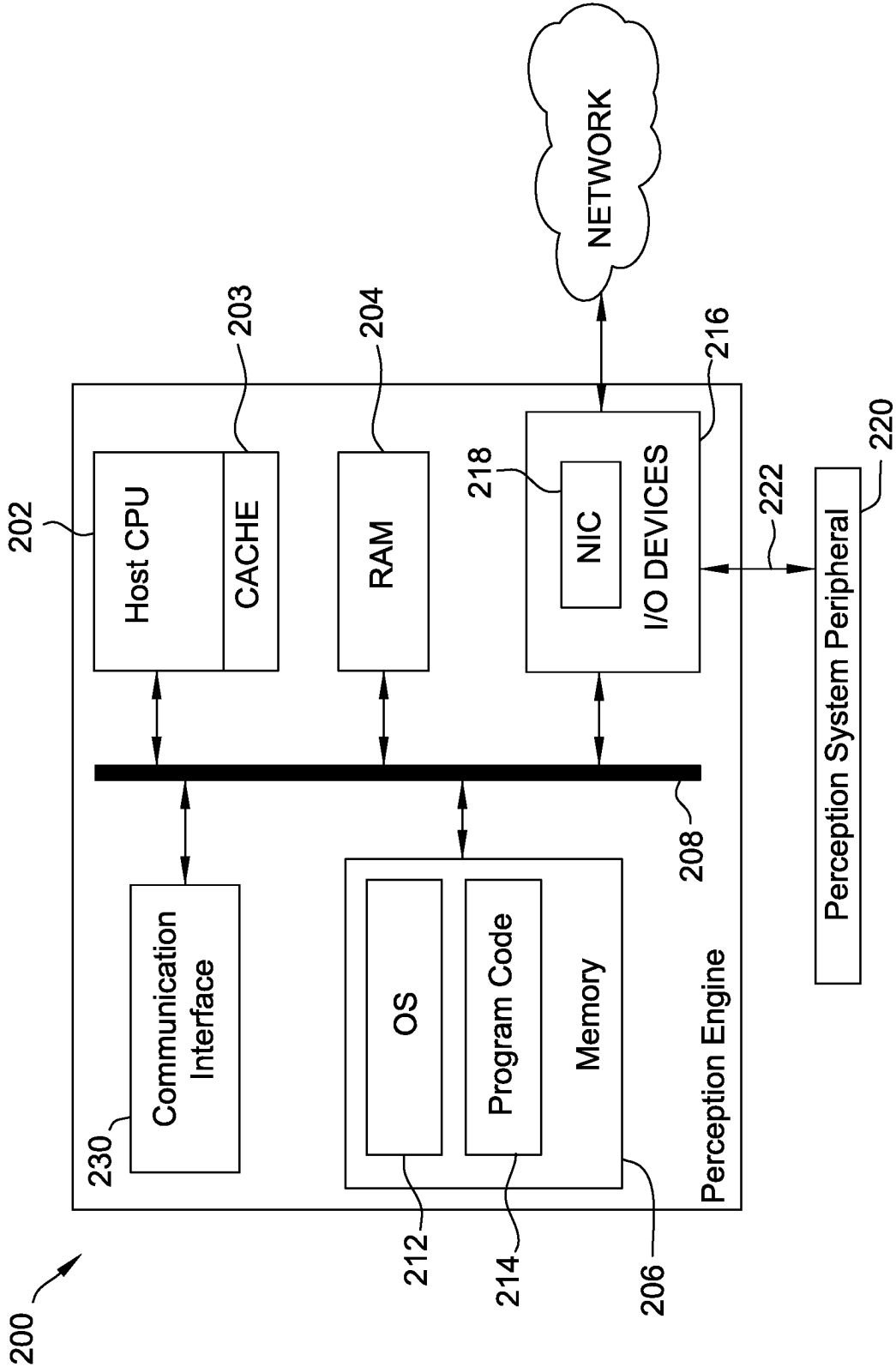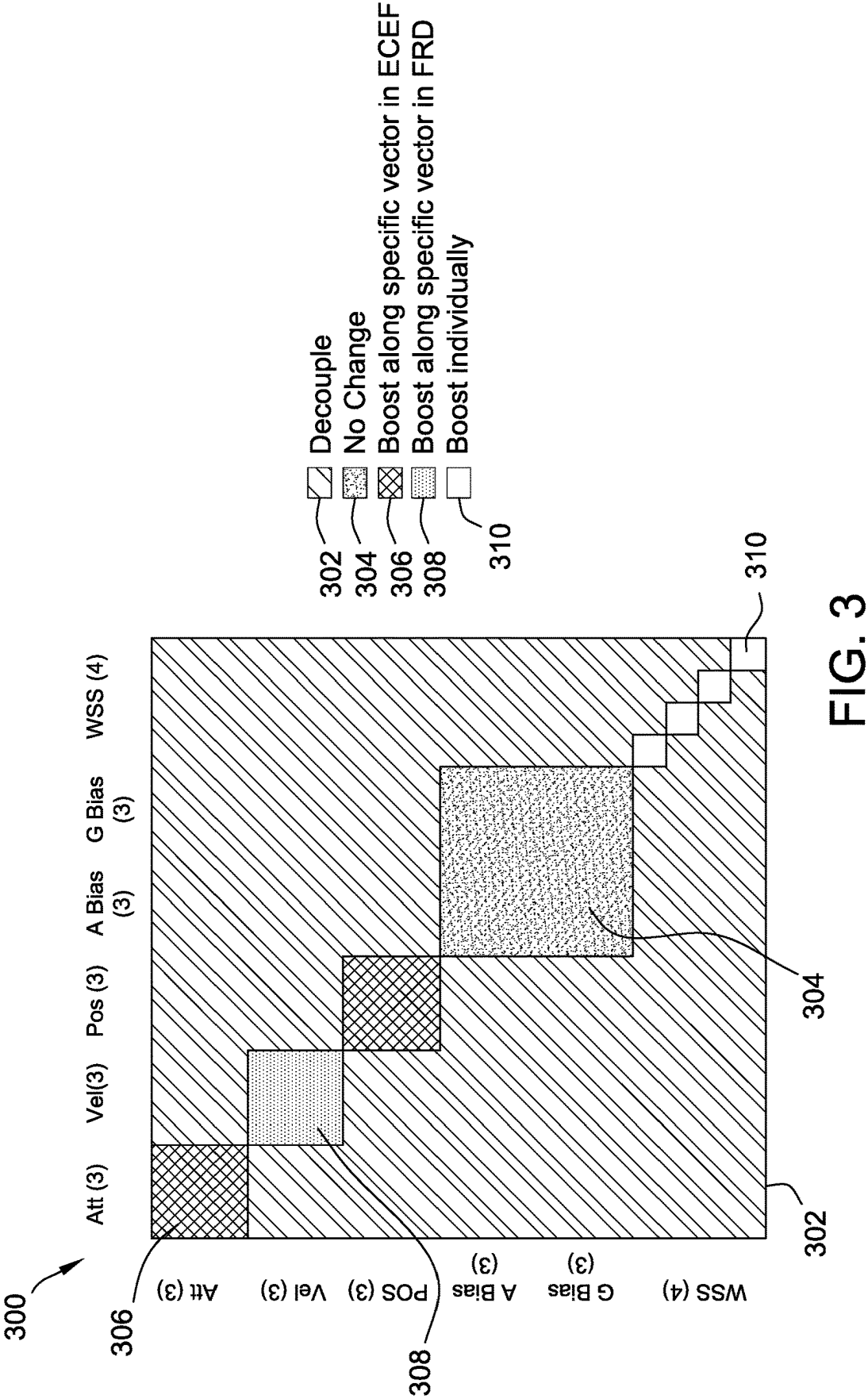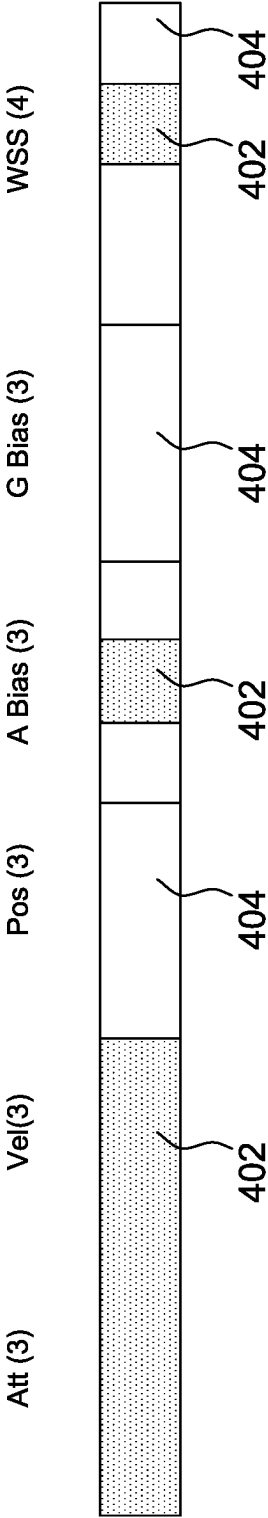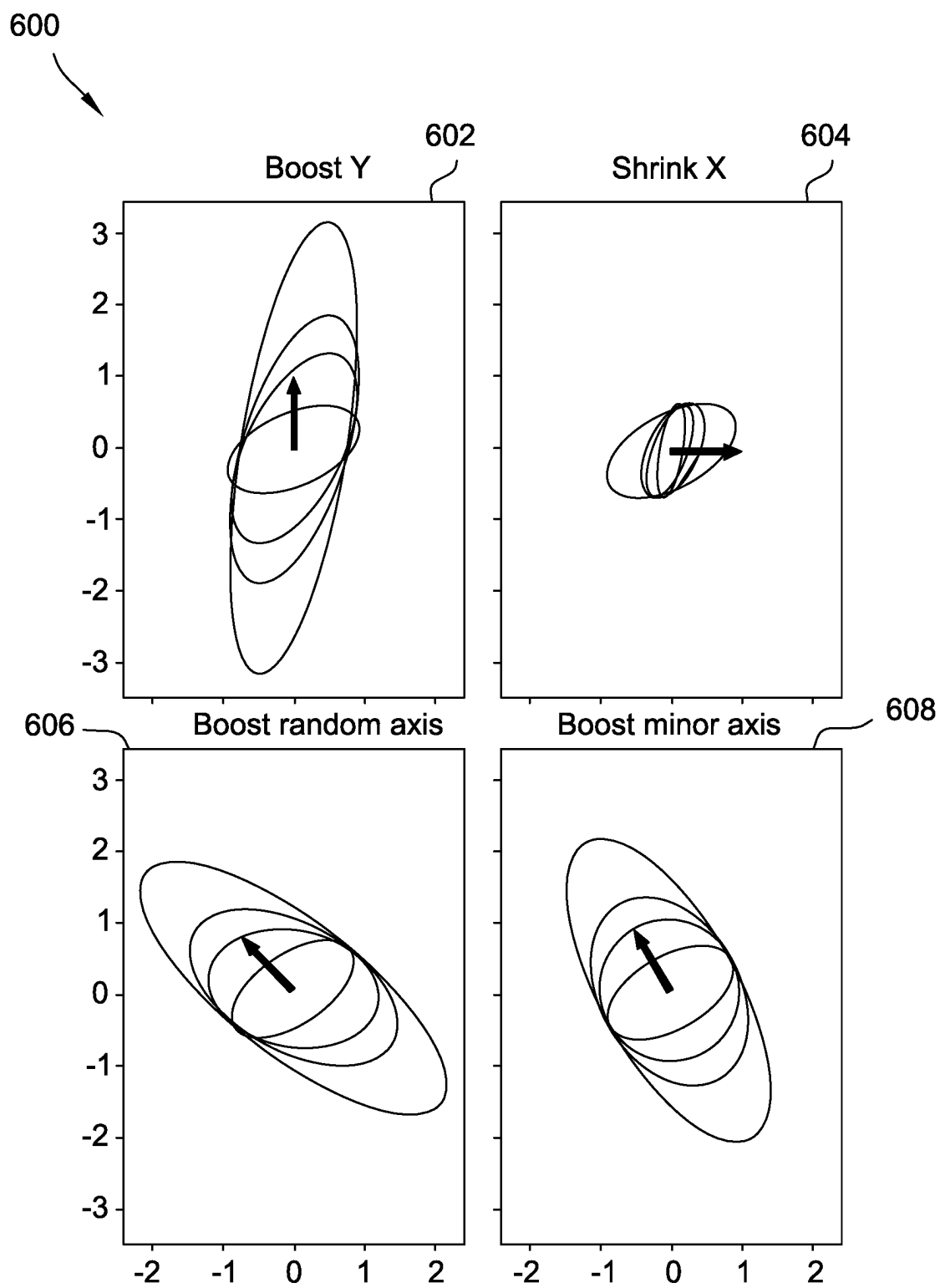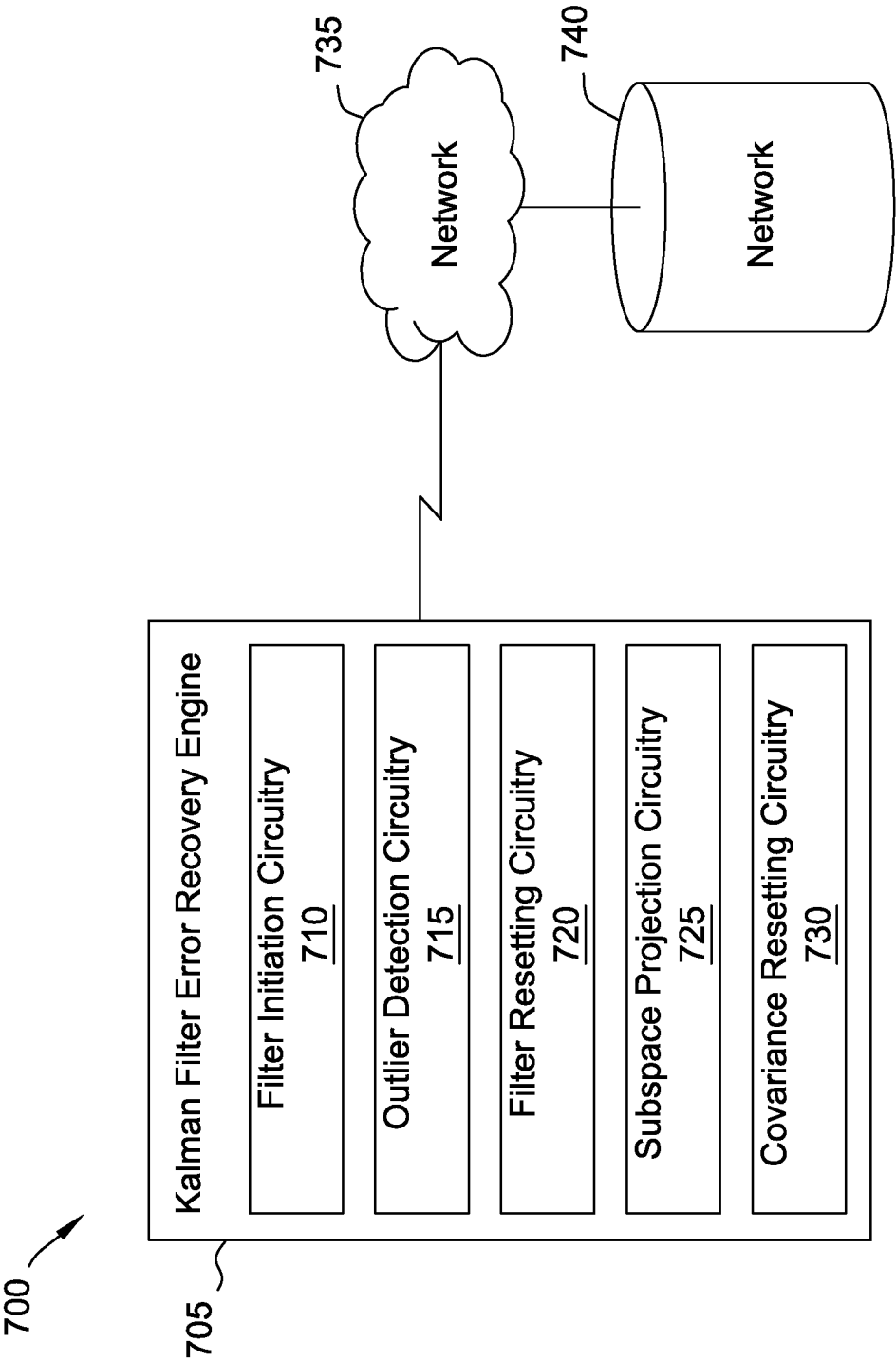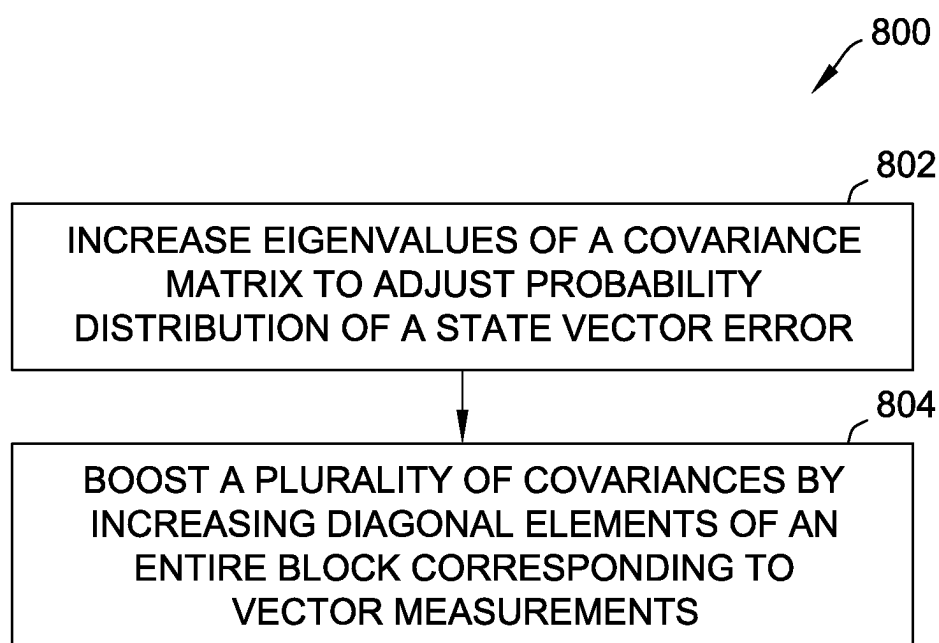# METHODS AND APPARATUS FOR KALMAN FILTER ERROR RECOVERY THROUGH Q-BOOSTING ALONG OBSERVATION SUB-SPACES

TECHNICAL FIELD

[0001] The field of the disclosure relates to methods and apparatus for recovery of Kalman Filters equipped with outlier rejection mechanisms through Q-boosting restricted to the sub-spaces of individual observations with and without covariance reset.

BACKGROUND

[0002] Autonomous vehicles employ fundamental technologies such as, perception, localization, behaviors and planning, and control. Perception technologies enable an autonomous vehicle to sense and process its environment. Perception technologies process a sensed environment to identify and classify objects, or groups of objects, in the environment, for example, pedestrians, vehicles, or debris. Localization technologies determine, based on the sensed environment, for example, where in the world, or on a map, the autonomous vehicle is. Localization technologies process features in the sensed environment to correlate, or register, those features to known features on a map. Localization technologies may rely on inertial navigation system (INS) data. Behaviors and planning technologies determine how to move through the sensed environment to reach a planned destination. Behaviors and planning technologies process data representing the sensed environment and localization or mapping data to plan maneuvers and routes to reach the planned destination for execution by a controller or a control module. Controller technologies use control theory to determine how to translate desired behaviors and trajectories into actions undertaken by the vehicle through its dynamic mechanical components. This includes steering, braking and acceleration.

[0003] Various versions of the Kalman filter (e.g., extended, unscented) have seen widespread usage throughout the field of state estimation since its inception in localization technologies, and especially in the area of a global navigation satellite system (GNSS) based navigation. The original goal of the filter was to simplify the computation and tuning of the estimation algorithm. The filter's popularity is a testament to how successfully that goal was met. Alternative state estimation methods such as factor graph approaches can yield more accurate results but come with the cost of significant additional computation load and more complex setup. Another reason for the ubiquity of Kalman Filters is the body of work done on their analysis and characterization.

[0004] In the GNSS-based navigation, Kalman filtering is generally used to avoid long-term error accumulations from error sources like noise, bias, scale factor errors, misalignments, temperature dependencies, and gyro g-sensitivity, etc. Without error rejection, a Kalman filter may temporarily enter a bad state, but which will be recoverable. While outlier rejection mechanisms are commonly used to prevent unmodeled measurement errors from corrupting the estimates of Kalman filters, however, the combination of an outlier rejection mechanism with, biased state estimates and overoptimistic Kalman filter state uncertainty, may result in an unrecoverable situation. Accordingly, in some applica-

tions, it is a broad practice to combine outlier rejection techniques with recovery strategies to increase the uncertainty of the state estimates. Currently known recovery techniques for outlier rejection, for example, outlier rejection of a position signal being fused into extended Kalman filtering is Q-boosting and returning the state covariance to its initial form usually by diagonalizing the matrix and referred herein as a naïve covariance reset. Q-boosting is an expansion of the state covariance matrix, which compensates for unaccounted process noise that is conventionally denoted by Q. The GNSS-based navigation may also be referred as an inertial navigation system based (INS-based) navigation, which uses an inertial measurement unit (IMU) and a global navigation satellite system (GNSS) receiver.

[0005] Both of the Q-boosting and naïve covariance reset techniques for outlier rejection have certain drawbacks or deficiencies in some typical scenarios. For example, when the state covariance is not diagonal in its own reference frame, for example, when the position covariance ellipsoid is approximately aligned to north, east, down (NED) from repeated GNSS measurements while the state is in earth-centered, earth-fixed (ECEF) coordinates, the naïve covariance reset technique (or algorithm) initially decreases the largest eigenvalue of the state covariance and extends the recovery procedure. In other words, in the naïve covariance reset algorithm, the return of the covariance matrix to a diagonal form and ostensible boosting of eigenvalues may cause problems with Q-boosting because of the improper handling of the rotation of the covariance eigenspace.

[0006] Additionally, some sensors (or pseudo-sensors) may measure an incomplete subset of the available dimensions, such as a map localizer pseudo-sensor measures in north east directions of NED, a barometer sensor measuring in down direction of NED, wheel speed sensors measuring in forward direction of forward, right, down (FRD) coordinate system or reference frame while enabling side-slip measurement in forward, right (FR) directions in FRD coordinate system or reference frame. Most sensors generally measure in three dimensions, and so are fully resolvable in their measurement space. Methods for boosting along the subspace according to Q-boosting algorithm and defined by the measurement matrix of the sensor may require extensive computational power. Accordingly, there is a need of improvement in error recovery mechanisms of Kalman filters equipped with outlier rejection mechanisms.

[0007] This section is intended to introduce the reader to various aspects of art that may be related to various aspects of the present disclosure described or claimed below. This description is believed to be helpful in providing the reader with background information to facilitate a better understanding of the various aspects of the present disclosure. Accordingly, it should be understood that these statements are to be read in this light and not as admissions of prior art.

SUMMARY

[0008] In one aspect, an autonomous vehicle including a Kalman filter error recovery system is disclosed. The Kalman filter error recovery system includes at least one processor and at least one memory storing instructions, which, when executed by the at least one processor, cause the Kalman filter error recovery system to perform operations including increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or

more position sensors, and boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.

[0009] In another aspect, a method performed by a Kalman filter error recovery system of an autonomous vehicle is disclosed. The method includes increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or more position sensors and boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.

[0010] In yet another aspect, a non-transitory computer-readable medium (CRM) is disclosed. The CRM embodies programmed instructions which, when executed by at least one processor of a Kalman filter error recovery system of an autonomous vehicle, cause the at least one processor to perform operations including increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or more position sensors and boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.

[0011] Various refinements exist of the features noted in relation to the above-mentioned aspects. Further features may also be incorporated in the above-mentioned aspects as well. These refinements and additional features may exist individually or in any combination. For instance, various features discussed below in relation to any of the illustrated examples may be incorporated into any of the above-described aspects, alone or in any combination.

BRIEF DESCRIPTION OF DRAWINGS

[0012] The following drawings form part of the present specification and are included to further demonstrate certain aspects of the present disclosure. The disclosure may be better understood by reference to one or more of these drawings in combination with the detailed description of specific embodiments presented herein.

[0013] FIG. 1 is a schematic view of an autonomous truck.

[0014] FIG. 2 is a block diagram of a perception system.

[0015] FIG. 3 depicts regions of coupled covariances to boosted in response to outlier measurements.

[0016] FIG. 4 depicts a multi-element mask to be applied to the regions of coupled covariances shown in FIG. 3.

[0017] FIG. 5 depicts regions of coupled covariances with the mask shown in FIG. 4 applied to the regions to boost in response to outlier measurements.

[0018] FIG. 6 depicts boosting, shrinking, and decoupling of regions of coupled covariances applied to a two-dimensional shape.

[0019] FIG. 7 is a block diagram of an example Kalman filter error recovery system, implemented in accordance with the teachings of this disclosure.

[0020] FIG. 8 is an example flow-chart of method operations performed by the Kalman filter recovery system shown in FIG. 7.

[0021] Corresponding reference characters indicate corresponding parts throughout the several views of the drawings. Although specific features of various examples may be shown in some drawings and not in others, this is for convenience only. Any feature of any drawing may be reference or claimed in combination with any feature of any other drawing.

DETAILED DESCRIPTION

[0022] The following detailed description and examples set forth preferred materials, components, and procedures used in accordance with the present disclosure. This description and these examples, however, are provided by way of illustration only, and nothing therein shall be deemed to be a limitation upon the overall scope of the present disclosure. The following terms are used in the present disclosure as defined below.

[0023] An autonomous vehicle: An autonomous vehicle is a vehicle that is able to operate itself to perform various operations such as controlling or regulating acceleration, braking, steering wheel positioning, and so on, without any human intervention. An autonomous vehicle has an autonomy level of level-4 or level-5 recognized by National Highway Traffic Safety Administration (NHTSA).

[0024] A semi-autonomous vehicle: A semi-autonomous vehicle is a vehicle that is able to perform some of the driving related operations such as keeping the vehicle in lane and/or parking the vehicle without human intervention. A semi-autonomous vehicle has an autonomy level of level-1, level-2, or level-3 recognized by NHTSA.

[0025] A non-autonomous vehicle: A non-autonomous vehicle is a vehicle that is neither an autonomous vehicle nor a semi-autonomous vehicle. A non-autonomous vehicle has an autonomy level of level-0 recognized by NHTSA.

[0026] The tuning of Kalman filters depends on being able to accurately model the process and observation and/or measurement noise. Process noise is a measure of state uncertainty that grows over time when no observations are available, for example, when the GNSS receiver does not receive signals from one or more satellites for a significant time duration. Observation noise can be thought of as the error distribution sampled by an individual sensor. Both process noise and/or observation noise may be modeled as zero-mean Gaussian distributions in a Kalman filter. It is typical to underestimate the true values of the covariances of the noise distributions. For one, estimating the true uncertainty is difficult, and error budgets may not account for all sources of error. Secondly, not all noise distributions are well modeled by a Gaussian model, and not all processes are linear, even if they work reasonably well with a Kalman Filter of the appropriate type. A good example of both cases that commonly appears in navigation is Global Navigation Satellite System (GNSS) sensors, which can have a non-Gaussian distribution, and typically report a lower signal covariance than its statistical protection level warrants.

[0027] Kalman filters are often equipped with an innovation-based outlier rejection mechanism. A typical mechanism is to reject innovations, or pre-fit residuals that have a Mahalanobis distance greater than some threshold amount (e.g., between 2.5 and 5). Rejection helps maintain that Gaussian assumption regarding observation error distributions at the cost of rejecting a very small number of valid observations. However, depending on the sources of error, outlier rejection can result in a state and covariance that force the rejection of valid observations. This is especially true when covariance estimates are overoptimistic.

[0028] Navigation filters that rely on a mixture of GNSS and odometry for positioning provide excellent illustrations of how the state estimation might enter a mode with unbounded error when error rejection is implemented. During periods of low or no GNSS availability, the global position estimate tends to drift from ground truth beyond the

value reported by the state covariance due to accumulated errors in odometry and attitude estimation (i.e., dead reckoning). When reliable GNSS becomes available, good observations may be rejected after sufficiently long outages.

[0029] In some examples where outliers are known to lie on one side of the mean, as with GNSS multipath, one sided outlier rejection or gating may be sufficient. However, when outliers are not consistently distributed relative to the mean, multi-modal filters, such as multi-hypothesis tracking (i.e., filter bank), can be used to track multiple solutions with different initial conditions initialized at distinct times. Tracking allows for the evaluation of observations in the context of different solutions, which works well for situations like GNSS multipath, for example, but may come with significant additional computational cost. A simpler approach, as disclosed in embodiments herein, would be to reset or reinitialize the entire filter when a significant number of outliers has been detected or when a statistically implausible sequence of rejected observations has been detected.

[0030] In some examples, as described herein, covariance boosting may increase state uncertainty extended Kalman filtering (EKF) when a bad measurement is encountered in one of the IMU sensors. Covariance boosting may allow quick recovery from situations like GNSS outages, where the estimated altitude wanders due to velocity being integrated along an imperfectly aligned pitch, and yaw wanders due to integrated angular rate errors. By way of a non-limiting example, the diagonal elements of the covariance may be boosted exponentially in proportion to the number of outlying measurements that are encountered in succession, and states may be decoupled from each-other by decreasing the off-diagonal elements.

[0031] In some examples, all available states may be boosted when a bad measurement is encountered, which may cause issues when the eigenspaces of measurements are aligned with a different coordinate system from the state. For example, a position may be measured in ECEF coordinates, but the covariance ellipsoid of the position may be closely aligned with local altitude in one axis. Accordingly, blindly, or randomly increasing the diagonal and shrinking the off-diagonal may decrease the eigenvalues of the position block of the covariance matrix for positions that are not along ECEF axes because the off-diagonal elements may carry a major portion of the covariance information.

[0032] Accordingly, in some examples, some of the shape information may be preserved when boosting covariances by increasing entire 3×3 blocks on the diagonal corresponding to vector measurements. A bad position measurement may decrease certainty of the entire position and decouple it from the other states. A constant block wise boosting factor may be appropriate to use for sensors that measure with three degrees of freedom (or 6). As described herein, a sensor may increase covariance in the directions that it is able to measure. When running with map localizer feedback during a GNSS outage, a series of bad map localizer measurements may boost the entire position covariance block without collapsing it back because the map localizer does not have an eigenvector in that direction. As a result, the altitude covariance may blow up until the GNSS outage ends. In some examples, the altitude covariant may blow up greater than floating point capacity.

[0033] In some embodiments, to respect the eigenspace of a given measurement, and to cap the maximum diagonal values of the covariance matrix at some predetermined threshold values (or some meaningful values), a boosting may require three inputs for each given outlier measurement: a rotation from the eigenspace of the measurement to ECEF, a selected eigenvector (or vectors) to boost, and a mask indicating which states are affected by the measurement. In this case, it is assumed that all non-ECEF states have a known rotation to ECEF.

[0034] In some examples, when boosting is applied to EKF, a first subset of states of coupled covariances may be decreased, a second subset of states of the coupled covariances may be not altered and remain untouched. A third subset, a fourth subset, and a fifth subsets of states of the coupled covariances may be boosted in response to outlier measurements. The third subset of states of the coupled covariances may be boosted along a specific vector in ECEF and the fourth subset of states of the coupled covariances may be boosted along a specific vector in FRD. The fifth subset of states of the coupled covariances may be boosted individually. The states of the third, fourth, and fifth subsets to boost may be determined using a mask to decouple the states that are affected by outlier measurements from the filter while leaving the remaining states unmodified.

[0035] In some examples, the mask may correspond to the first part of a wheel speed sensor (WSS) update for the front left wheel, and the mask may be a 19-element mask. The mask may be applied, for example, to boost attitude and velocity covariances in the forward direction since the forward direction has components generally in all ECEF axes, and, therefore, the entire block may be updated. Additionally, the couplings of attitude and velocity to other states may be decreased, and the right bias of the accelerometer may be decoupled from everything but the other IMU states. While working with mask corresponding to the WSS update for the front left wheel, the state corresponding to the WSS update corresponding to the front left wheel may be boosted and decoupled from all the other states.

[0036] In some examples, the velocity 3×3 covariance block in the forward direction may be boosted by predetermined percentage. By way of a non-limiting example, boosting of the velocity 3×3 covariance block may be boosted since the velocity covariance block is in FRD direction, and, thereby, rotations may be generalized later. As described herein, scaling the first column of the covariance matrix may result in an asymmetrical matrix, as shown in below:

$$P'_{vel} \neq S_{Fwd} \cdot P_{vel} \quad S_{Fwd} = \begin{bmatrix} 1.01 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

[0037] As described herein, any transformation T when applied to random vectors with covariance P may alter the covariance as TPT^{T1}, which may scale random vectors by

$$S^{\frac{1}{2}},$$

where the square root reflects scaling of the 1–σ ellipsoid. Since S happens to be its transpose, P'_{vel} may become

$$P'_{vel} = S_{Fwd}^{\frac{1}{2}} \cdot P_{vel} \cdot S_{Fwd}^{\frac{1}{2}}.$$

[0038] Accordingly, in some examples, 3×3 covariance block rotation in the forward direction may be boosted. The rotation covariance may represent the variance and cross couplings of the components of a rotation vector in ECEF, for example, the rotation of the vehicle FRD frame relative to ECEF. In some examples, it may be apparent from the construction of Jacobians, where to increase its action along the forward axis, state vectors are rotated first in the FRD reference frame. The boosting action and the action of covariance may be then applied before rotating back into ECEF. In other words,

$$P'_{att} = A_{att} \cdot P_{att} \cdot A_{att}^T, \text{ where } A_{att} = R_{FRD}^{ECEF} \cdot S_{Fwd}^{\frac{1}{2}} \cdot R_{ECEF}^{FRD}$$

[0039] In the above equations, $A=A^T$, and a similar approach may be sufficient to scale the position block except that the eigenspace of the measurement may not be FRD (NED for GNSS and the NE plane for the Map Localizer). For example, the rotation on the right may be from the state coordinate system to the measurement, apply scaling and rotate back. The left rotation may be similar to the rotation on the right. This approach, as described herein, may scale well when full 3×3 updates are used for measurements instead of performing them row-by-row on the Jacobian because the selection matrix may include as many boosting coefficients as the measurement has degrees of freedom. For GNSS, measured in NED, the position boost may look like as shown below:

$$P'_{pos} = A_{pos} \cdot P_{pos} \cdot A_{pos}; A_{att} = R_{NED}^{ECEF} \cdot S_{GNSS}^{\frac{1}{2}} \cdot R_{ECEF}^{NED};$$

$$S_{GNSS} = \begin{bmatrix} 1.01 & 0 & 0 \\ 0 & 1.01 & 0 \\ 0 & 0 & 1.01 \end{bmatrix}$$

[0040] Since the measurement covers all available degrees of freedom,

$$S_{GNSS}^{\frac{1}{2}}$$

may be equivalent to a scalar multiplier, and, accordingly, the entire operation may be reduced to $P'_{pos}=1.01 \cdot P_{pos}$. For the Map Localizer, which does not an altitude component, measurements may be taken in the NE plane regardless of their exact eigenspace, and the value of S may be replaced for example as:

$$S_{MapLoc} = \begin{bmatrix} 1.01 & 0 & 0 \\ 0 & 1.01 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

[0041] In some examples, in an alternative geometric interpretation of the above equation, a rotation of the boosting action may be interpreted as a rotation of the covariance matrix from its coordinates to the eigenspace of the measurement before scaling of the appropriate axes and rotating back. For example, the GNSS position may be dissected as:

$$P' = R_{FRD}^{ECEF} \cdot \left(S^{\frac{1}{2}} \cdot \left(R_{FRD}^{ECEF} \cdot P \cdot R_{ECEF}^{FRD} \right) \cdot S^{\frac{1}{2}} \right) \cdot R_{ECEF}^{FRD}$$

[0042] In some examples, a series of scales may be applied to each covariance in a factor of 4 or ¼. The various examples, as described herein, may be used to move the ellipses' affected eigenvectors in the desired direction without disturbing or affecting other dimensions.

[0043] In the following table, suggested example clipping thresholds for boosted elements of the covariance matrix are provided for clipping elements of the covariance matrix that grow too large as a result of boosting. With sufficient magnitudes, a slight change in the shape may not be a concern. Accordingly, example pick values that are sufficiently large but do not exceed floating point numerical precision are provided in the table below.

TABLE 1

Block	1-σ Threshold		σ^2 Threshold		Reasoning
Attitude		$\pi/2$	2.5		If our attitude estimate has a 1-sigma of 90°, we are not going to have a good day. One decimal point should be sufficient.
Velocity	50	m/s	2500	m²/s²	100 mph is ~44.7 m/s. If our velocity estimation is not at least that good, we are having a very bad day.
Position	1e6	m	1e12	m²	40 Mm is the circumference of the Earth. We should be able to tell where we are to at least ¹⁄₁₀th of the right quadrant, even after hours of dead reckoning.
WSS Scale	1.0		1.0		The scale factors should always be in the neighborhood of 1. If they can drift to 0 or 2, we are having a bad day.

[0044] In comparison to mitigating covariance shrinking using the naive approach, this approach may be more robust, fairly naive, which relies on a fixed factor to boost the covariances and a masking technique to determine the elements to increase and decrease. Given that the mask is derived from the Jacobian, an approach that combines the Jacobian and the eigenspace of the measurement may be used to optimize the operation and reduce unintended side

effects of the cross-coupling reduction. Additionally, or alternatively, for the Jacobian, H, computed in the eigenspace of the measurement, the eigenvectors V of $H^T H$ may encode both a normalization (mask) and directional information to replace the eigenvalues with a selection matrix S such that the entire covariance may be transformed at once, without requiring the masked to be determined separately, using the following transform.

$$P' = A \cdot P \cdot A, \text{ where } A = V^T \cdot S \cdot V$$

[0045] One embodiment of the disclosed systems includes an autonomous vehicle including a variety of sensors, including at least one acoustic sensor, for perceiving the environment around the autonomous vehicle. The autonomous vehicle includes a perception system, including one or more processors and the variety of sensors, for detecting objects and obstacles in the environment and, in some cases, for determining their relative locations, velocities, and to make judgments about their future states or actions. Environmental perception includes object detection and understanding and may be based at least in part on data collected by acoustic sensors, image data collected, for example, by LiDAR sensors, radar, sonar, ultrasonic, or visual or RGB cameras, among other suitable active or passive sensors.

[0046] One embodiment of the disclosed systems includes an autonomous vehicle including one or more processors or processing systems that execute localization, i.e., a localization system. Localization is the process of determining the precise location of the autonomous vehicle using data from the perception system and data from other systems, such as a global navigation satellite system (GNSS) (e.g., a global positioning system (GPS) or an inertial measurement unit (IMU). The autonomous vehicle's position, both absolute and relative to other objects in the environment, is used for global and local mission planning, as well as for other auxiliary functions, such as determining expected weather conditions or other environmental considerations based on externally generated data.

[0047] One embodiment of the disclosed systems includes an autonomous vehicle including one or more processors or processing systems that execute behavior planning and control, i.e., a behavior planning and control system. Behavior planning and control includes planning and implementing one or more behavioral-based trajectories to operate an autonomous vehicle similar to a human driver-based operation. The behavior planning and control system uses inputs from the perception system or localization system to generate trajectories or other actions that may be selected to follow or enact as the autonomous vehicle travels. Trajectories may be generated based on known appropriate interaction with other static and dynamic objects in the environment, e.g., those indicated by law, custom, or safety. The behavior planning and control system may also generate local objectives including, for example, lane changes, obeying traffic signs, etc.

[0048] FIG. 1 illustrates a vehicle 100 which may include a truck that may further be conventionally connected to a single or tandem trailer to transport the trailers (not shown) to a desired location. The vehicle 100 includes a cabin 114 that can be supported by, and steered in, the required direction by front wheels 112a, 112b, and rear wheels 112c

that are partially shown in FIG. 1. Wheels 112a, 112b are positioned by a steering system that includes a steering wheel and a steering column (not shown in FIG. 1). The steering wheel and the steering column may be located in the interior of cabin 114.

[0049] The vehicle 100 may be an autonomous vehicle, then the vehicle 100 may not have a steering wheel and a steering column to steer the vehicle 100. Rather, the vehicle 100 may be driven by a MCU (not shown) of the vehicle 100 based on data collected by a sensor network (not shown in FIG. 1) including one or more sensors.

[0050] FIG. 2 is a block diagram of an example perception system 200 for sensing an environment in which an autonomous vehicle is positioned. Perception system 200 includes a CPU 202 coupled to a cache memory 203, and further coupled to RAM 204 and memory 206 via a memory bus 208. Cache memory 203 and RAM 204 are configured to operate in combination with CPU 202. Memory 206 is a computer-readable memory (e.g., volatile, or non-volatile) that includes at least a memory section storing an OS 212 and a section storing program code 214. In alternative embodiments, one or more section of memory 206 may be omitted and the data stored remotely. For example, in certain embodiments, program code 214 may be stored remotely on a server or mass-storage device and made available over a network 232 to CPU 202.

[0051] Perception system 200 also includes I/O devices 216, which may include, for example, a communication interface such as a network interface controller (NIC) 218, or a peripheral interface for communicating with a perception system peripheral device 220 over a peripheral link 222. I/O devices 216 may include, for example, a GPU for operating a display peripheral over a display link, a serial channel controller or other suitable interface for controlling a sensor peripheral such as one or more acoustic sensors, a LiDAR sensor or a camera, or a CAN bus controller for communicating over a CAN bus.

[0052] FIG. 3 is a depiction 300 of regions of coupled covariances that are to be boosted in response to outlier measurements. As shown in FIG. 3, regions marked 302 may be decreased or decoupled, regions marked 304 may not be modified, while regions marked 306, 308, and 310 may be boosted. The regions marked 306 and 308 may be boosted along a specific vector in ECEF and along a specific vector in FRD, respectively. The regions marked 310 may be boosted individually.

[0053] FIG. 4 is a depiction 400 of a multi-element mask. The multi-element mask may have 19 elements including 3 elements for attitude, 3 elements for velocity, 3 elements for position, 3 elements for A-bias and G-bias each, and 4 elements for wheel speed sensor (WSS) update. By way of a non-limiting example, the mask shown in FIG. 4 may be for WSS front wheel update. Rows and columns marked by 402 may be boosted, and rows and columns marked by 404 may not be modified.

[0054] FIG. 5 is a depiction 500 of regions of coupled covariances with the mask shown in FIG. 4 applied. As shown in FIG. 5, regions marked 502 may be decreased or decoupled, regions marked 504 may not be modified, while regions marked 506, 508, and 510 may be boosted. The regions marked 506 and 508 may be boosted along a specific vector in ECEF and along a specific vector in FRD, respec-

tively. The regions marked **510** may be boosted individually. Regions marked **512** may not be modified when the mask shown in FIG. **4** is applied.

[0055] FIG. **6** is a depiction **600** of boosting, decreasing, or decoupling of regions of coupled covariances applied to a two-dimensional shape representing $1-\sigma$ ellipsoid of a covariance with eigenvalues 1 and ¼, oriented at a 30° angle. As shown in FIG. **6**, regions of coupled covariances may be boosted in Y direction and shrink in X direction as shown by **602** and **604**, respectively. Similarly, regions of coupled covariances may be boosted along a random axis and a minor axis as shown by **606** and **608**, respectively.

[0056] FIG. **7** is a block diagram of an example Kalman filter error recovery system **200** implemented in accordance with the teachings of this disclosure. The example Kalman filter error recovery system **200** includes, in examples disclosed herein, example filter initiation circuitry **710**, example outlier detection circuitry **715**, example filter resetting circuitry **720**, example subspace projection circuitry **725**, example covariance resetting circuitry **730**, an example network **735**, and example data **740**. The example filter initiation circuitry **710** triggers the Kalman filter algorithm to run on a set of data (e.g., the example data **740**). The outlier detection circuitry **715** then analyzes the results of the algorithm triggered by the filter initiation circuitry **710** and determines which datapoints are outliers in need of removal. The filter resetting circuitry **720** then, upon determining that the number of flagged outliers exceed a maximum acceptable threshold value, initiates the Kalman filter resetting process to mitigate the excessive number of identified outliers. The subspace projection circuitry **725** then obtains the orthogonal subspace spanned by the original subspace H^+ from the decomposition of $H^+=QR$. The covariance resetting circuitry **730** then, in some examples, performs a covariance reset by rotating $P_{boosted'}$ by $V^{\beta-1}$ to obtain the reset Kalman filter. In some examples, the Kalman filter error recovery engine **705** may be communicably coupled with the example data **740** via the example network **735**.

[0057] FIG. **8** is an example flow-chart **800** of method operations performed by the Kalman filter recovery system shown in FIG. **7**. As shown in FIG. **8**, eigenvalues of a covariance matrix may be increased **802** to adjust probability distribution of a state vector error due to unmodelled process noise, unmodelled measurement errors in measurements from one or more position sensors. In some embodiments, and by way of a non-limiting example, the probability distribution may be adjusted of a state vector error due to unmodelled control vectors or unmodelled source of uncertainty that affects estimate of the state uncertainty. Further, position sensors may be sensors of a global navigation satellite system (GNSS). In some embodiments, a spectral theorem may be applied to the covariance matrix to cause the covariance matrix to include an orthogonal matrix of eigenvectors $V \in SO(n)$ and a diagonal matrix of non-negative real eigenvalues

$$\Lambda \in \left\{ \mathrm{diag}(\vec{x}) \mid \vec{x} \in R^n \right\}.$$

[0058] The method operations may include boosting **804** a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements. By

way of a non-limiting example, the boosting the plurality of covariances may include limiting a value corresponding to each respective diagonal element of the diagonal elements to a predetermined threshold value. Additionally, or alternatively, the boosting the plurality of covariances may include boosting the plurality of covariances based on a plurality of inputs corresponding to each outlier measurement. The plurality of inputs may correspond to each outlier measurement including a rotation from an eigenspace of the outlier measurement, an eigenvector to boost, and a mask that indicates a plurality of states of coupled covariances affected by the outlier measurements. As described herein, the mask may be a multi-element mask that may cause a first subset of the plurality of states of coupled covariances to be decreased, a second subset of the plurality of states of coupled covariances to be unmodified, and one or more subsets of the plurality of states of coupled covariances to be boosted. In some embodiments, boosted diagonal elements may be clipped or limited to predetermined threshold values.

[0059] An example technical effect of the methods, systems, and apparatus described herein includes at least one of: (a) improved performance of environmental sensing by autonomous vehicles; and (b) improved performance of autonomous vehicle maneuvering, routing, or operation more generally.

[0060] Some embodiments involve the use of one or more electronic processing or computing devices. As used herein, the terms "processor" and "computer" and related terms, e.g., "processing device," "computing device," and "controller" are not limited to just those integrated circuits referred to in the art as a computer, but broadly refers to a processors, a processing device, a controller, a general purpose central processing unit (CPU), a graphics processing unit (GPU), a microcontroller, a microcomputer, a programmable logic controller (PLC), a reduced instruction set computer (RISC) processor, a field programmable gate array (FPGA), a digital signal processor (DSP), an application specific integrated circuit (ASIC), and other programmable circuits or processing devices capable of executing the functions described herein, and these terms are used interchangeably herein. These processing devices are generally "configured" to execute functions by programming or being programmed, or by the provisioning of instructions for execution. The above examples are not intended to limit in any way the definition or meaning of the terms processor, processing device, and related terms.

[0061] The various aspects illustrated by logical blocks, modules, circuits, processes, algorithms, and algorithm steps described above may be implemented as electronic hardware, software, or combinations of both. Certain disclosed components, blocks, modules, circuits, and steps are described in terms of their functionality, illustrating the interchangeability of their implementation in electronic hardware or software. The implementation of such functionality varies among different applications given varying system architectures and design constraints. Although such implementations may vary from application to application, they do not constitute a departure from the scope of this disclosure.

[0062] Aspects of embodiments implemented in software may be implemented in program code, application software, application programming interfaces (APIs), firmware, middleware, microcode, hardware description languages (HDLs), or any combination thereof. A code segment or

machine-executable instruction may represent a procedure, a function, a subprogram, a routine, a subroutine, a module, a software package, a class, or any combination of instructions, data structures, or program statements. A code segment may be coupled to, or integrated with, another code segment or an electronic hardware by passing or receiving information, data, arguments, parameters, memory contents, or memory locations. Information, arguments, parameters, data, etc. may be passed, forwarded, or transmitted via any suitable means including memory sharing, message passing, token passing, network transmission, etc.

[0063] The actual software code or specialized control hardware used to implement these systems and methods is not limiting of the claimed features or this disclosure. Thus, the operation and behavior of the systems and methods were described without reference to the specific software code being understood that software and control hardware can be designed to implement the systems and methods based on the description herein.

[0064] When implemented in software, the disclosed functions may be embodied, or stored, as one or more instructions or code on or in memory. In the embodiments described herein, memory may include, but is not limited to, a non-transitory computer-readable medium, such as flash memory, a random access memory (RAM), read-only memory (ROM), erasable programmable read-only memory (EPROM), electrically erasable programmable read-only memory (EEPROM), and non-volatile RAM (NVRAM). As used herein, the term "non-transitory computer-readable media" is intended to be representative of any tangible, computer-readable media, including, without limitation, non-transitory computer storage devices, including, without limitation, volatile and non-volatile media, and removable and non-removable media such as a firmware, physical and virtual storage, CD-ROM, DVD, and any other digital source such as a network, a server, cloud system, or the Internet, as well as yet to be developed digital means, with the sole exception being a transitory propagating signal. The methods described herein may be embodied as executable instructions, e.g., "software" and "firmware," in a non-transitory computer-readable medium. As used herein, the terms "software" and "firmware" are interchangeable and include any computer program stored in memory for execution by personal computers, workstations, clients, and servers. Such instructions, when executed by a processor, configure the processor to perform at least a portion of the disclosed methods.

[0065] As used herein, an element or step recited in the singular and proceeded with the word "a" or "an" should be understood as not excluding plural elements or steps unless such exclusion is explicitly recited. Furthermore, references to "one embodiment" of the disclosure or an "exemplary embodiment" are not intended to be interpreted as excluding the existence of additional embodiments that also incorporate the recited features. Likewise, limitations associated with "one embodiment" or "an embodiment" should not be interpreted as limiting to all embodiments unless explicitly recited.

[0066] Disjunctive language such as the phrase "at least one of X, Y, or Z," unless specifically stated otherwise, is generally intended, within the context presented, to disclose that an item, term, etc. may be either X, Y, or Z, or any combination thereof (e.g., X, Y, and/or Z). Likewise, conjunctive language such as the phrase "at least one of X, Y,

and Z," unless specifically stated otherwise, is generally intended, within the context presented, to disclose at least one of X, at least one of Y, and at least one of Z.

[0067] The disclosed systems and methods are not limited to the specific embodiments described herein. Rather, components of the systems or steps of the methods may be utilized independently and separately from other described components or steps.

[0068] This written description uses examples to disclose various embodiments, which include the best mode, to enable any person skilled in the art to practice those embodiments, including making and using any devices or systems and performing any incorporated methods. The patentable scope is defined by the claims and may include other examples that occur to those skilled in the art. Such other examples are intended to be within the scope of the claims if they have structural elements that do not differ from the literal language of the claims, or if they include equivalent structural elements with insubstantial differences form the literal language of the claims.

We claim:

1. An autonomous vehicle, comprising:

a Kalman filter error recovery system including at least one processor and at least one memory storing instructions, which, when executed by the at least one processor cause the Kalman filter error recovery system to perform operations comprising:

increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or more position sensors; and

boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.

2. The autonomous vehicle of claim **1**, wherein the boosting the plurality of covariances comprises limiting a value corresponding to each respective diagonal element of the diagonal elements to a predetermined threshold value.

3. The autonomous vehicle of claim **1**, wherein the boosting the plurality of covariances comprises boosting the plurality of covariances based on a plurality of inputs corresponding to each outlier measurement.

4. The autonomous vehicle of claim **3**, wherein the plurality of inputs corresponding to each outlier measurement including a rotation from an eigenspace of the outlier measurement, an eigenvector to boost, and a mask indicating a plurality of states of coupled covariances affected by the outlier measurements.

5. The autonomous vehicle of claim **4**, wherein the mask is a multi-element mask.

6. The autonomous vehicle of claim **4**, wherein the mask causes a first subset of the plurality of states of coupled covariances to be decreased, a second subset of the plurality of states of coupled covariances to be unmodified, and one or more subsets of the plurality of states of coupled covariances to be boosted.

7. The autonomous vehicle of claim **1**, wherein the operations further comprising clipping or limiting boosted diagonal elements to predetermined threshold values.

8. A method performed by a Kalman filter error recovery system of an autonomous vehicle, the method comprising:

increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or more position sensors; and

boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.

9. The method of claim **8**, wherein the boosting the plurality of covariances comprises limiting a value corresponding to each respective diagonal element of the diagonal elements to a predetermined threshold value.

10. The method of claim **8**, wherein the boosting the plurality of covariances comprises boosting the plurality of covariances based on a plurality of inputs corresponding to each outlier measurement.

11. The method of claim **10**, wherein the plurality of inputs corresponding to each outlier measurement including a rotation from an eigenspace of the outlier measurement, an eigenvector to boost, and a mask indicating a plurality of states of coupled covariances affected by the outlier measurements.

12. The method of claim **11**, wherein the mask is a multi-element mask.

13. The method of claim **11**, wherein the mask causes a first subset of the plurality of states of coupled covariances to be decreased, a second subset of the plurality of states of coupled covariances to be unmodified, and one or more subsets of the plurality of states of coupled covariances to be boosted.

14. The method of claim **8**, further comprising clipping or limiting boosted diagonal elements to predetermined threshold values.

15. A non-transitory computer-readable medium (CRM) embodying programmed instructions which, when executed by at least one processor of a Kalman filter error recovery system of an autonomous vehicle, cause the at least one processor to perform operations comprising:

increasing eigenvalues of a covariance matrix to adjust probability distribution of a state vector error due to unmodelled process noise in measurements from one or more position sensors; and

boosting a plurality of covariances by increasing diagonal elements of an entire block corresponding to vector measurements.

16. The non-transitory CRM of claim **15**, wherein the boosting the plurality of covariances comprises limiting a value corresponding to each respective diagonal element of the diagonal elements to a predetermined threshold value.

17. The non-transitory CRM of claim **15**, wherein the boosting the plurality of covariances comprises boosting the plurality of covariances based on a plurality of inputs corresponding to each outlier measurement.

18. The non-transitory CRM of claim **17**, wherein the plurality of inputs corresponding to each outlier measurement including a rotation from an eigenspace of the outlier measurement, an eigenvector to boost, and a mask indicating a plurality of states of coupled covariances affected by the outlier measurements.

19. The non-transitory CRM of claim **18**, wherein the mask is a multi-element mask, and wherein the mask causes a first subset of the plurality of states of coupled covariances to be decreased, a second subset of the plurality of states of coupled covariances to be unmodified, and one or more subsets of the plurality of states of coupled covariances to be boosted.

20. The non-transitory CRM of claim **15**, wherein the operations further comprising clipping or limiting boosted diagonal elements to predetermined threshold values.

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