Recent Advances in Sensor Integrity Monitoring Methods - A Review

Felipe A. Costa de Oliveira, Frank Sill Torres, and Alberto García-Ortiz

***Abstract*—In face of the high complexity of modern systems and the increasing reliance on technology, the strategies and methods to evaluate the integrity of systems and the information they provide are of great importance. The use of sensors to provide important information in various applications has become ubiquitous, which puts more pressure on the accuracy of sensor measurements. In the navigation field, in particular, the integrity of positioning information provided by sensors can be critical, as failures can lead to fatalities and catastrophic damages. Extensive research has been done into methods to assess and improve the integrity of positioning information provided by GNSS receivers, led by the high safety requirements in the aviation field. More recently, a shift into the research of integrity solutions suitable for the challenging positioning requirements of autonomous vehicles in urban environment has been a trend. There have been extensive advancements in developing integrity monitoring algorithms for GNSS and navigation in general. However, these methods have not been sufficiently extended into other types of sensors, and the development of integrity methods outside the navigation field have been scarce and scattered. This work aims to provide an overview of recent advances in the integrity monitoring field, including research outside the navigation domain. The goal is to give an introduction to the integrity monitoring concept to a broader audience, as these techniques have been highly specialized by GNSS experts and navigation related research, fostering multi-disciplinary approaches and creative use of existing methods in different areas and applications.**

***Index Terms*—Integrity, integrity monitoring, navigation, review, sensor integrity, statistical methods.**

I. Introduction

THE past few decades have seen an unprecedented rise in technological development, driven by the advances in microelectronics, that led to exponentially increasing computational capabilities and miniaturized sensors, which are nowadays, cheaply and widely available. Although these advances have given enormous advantages, they are also responsible for an increased reliance on technology, raising the importance of assessing and improving the integrity of these complex systems, and of the information used and provided by them. However, due to the specific requirements of the immense multitude of systems, information types and sources, there is no standard approach for that integrity challenge.

The concept of integrity is used in various fields among the engineering and computer science disciplines, often having a different meaning depending on the context and application. The diagram in figure 1 gives an overview of selected areas and applications that interact with the integrity concept, showing how there are many different approaches to the integrity challenge arising from multiple fields. Despite having different context-dependent meanings, the integrity concept is fundamentally associated with trust. Whether is representing the correctness and accuracy of a information, or the integral functioning state of a system, or process, where expected performance and operation requirements are met, the underlying meaning of integrity can always be traced to trust. There are different definitions of integrity among these various fields, but it possible to distinguish two main categories and adapt those definitions accordingly, in a more generic way:

- **System integrity:** the assessment that a given system is performing according to expectation, with all operational and technical parameters used to evaluate the system falling within prescribed limits, and without any unauthorized access or spurious manipulation of its functionalities;
- **Information integrity:** the assessment of the correctness, veracity, and accuracy within prescribed or expected limits of a given information, often meaning that are no significant errors, faults or spurious manipulation of that data source.

The integrity aspects in the various fields and applications represented in figure 1 can be mainly associated with either one of these definitions, but there can be some overlap depending on the context and application. For instance, an information integrity aspect could be considered in a field that mainly focus on system integrity, and vice versa.

In the context of this review, the integrity concept is related to the integrity of the information provided by sensors. Since there are different approaches for the integrity concept, the methods used to o evaluate the integrity of measurements provided by sensors can differ from the strategies used for assessing the integrity of systems. The typical approach for sensor measurements is to derive a statistical model that relies on the estimated accuracy evaluation to determine if there

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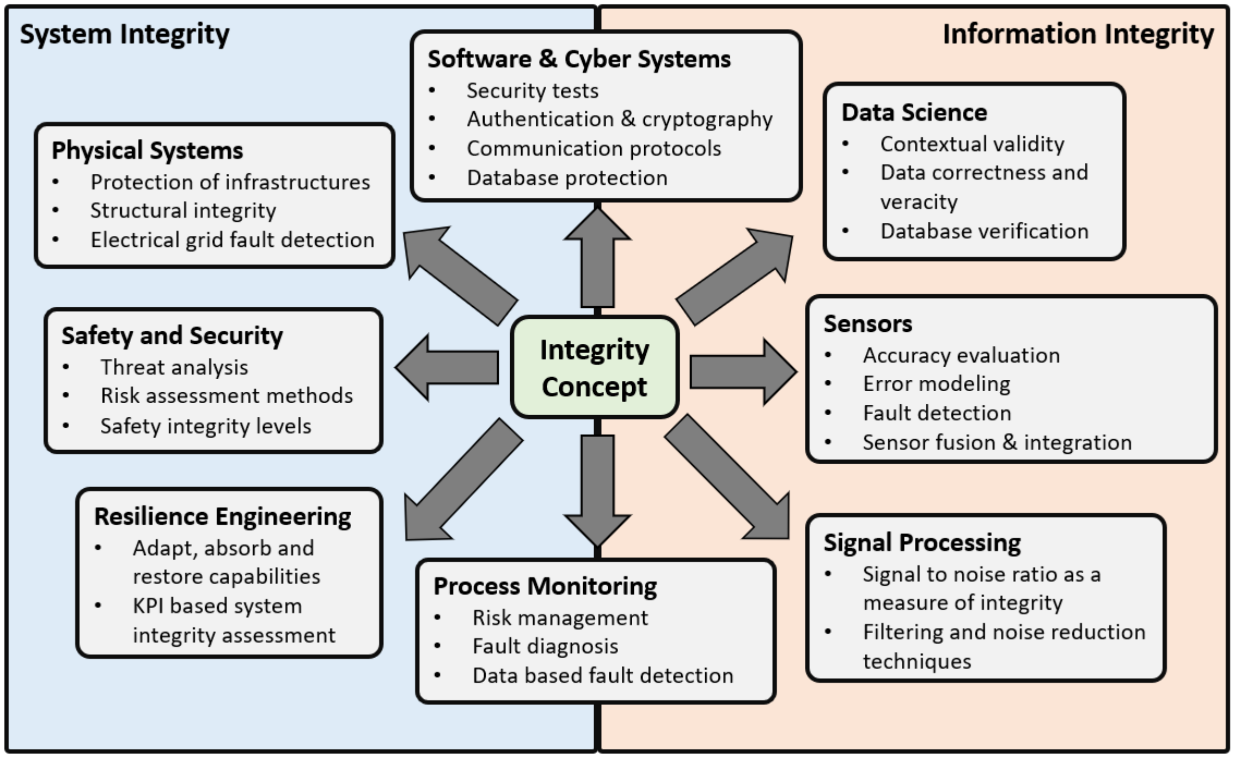

Fig. 1. Different fields in engineering and computer science where the concept of integrity is used.

is an integrity problem. The challenge of assessing system integrity might not have a standard approach, as there are a wide variety of systems with specific characteristics that would require different solutions.

The purpose of this work is to review the specific range of applications of the integrity concept that are relevant for assessing and assuring the integrity of sensor measurements. However, due to the vast multi-disciplinary aspect of the integrity challenge, it is necessary to give some perspective regarding depth of research involving these various areas. The identification and distinction of different fields that interact with the integrity concept should help guiding further research into the topic.

There is a wide variety of applications in which guaranteeing the correct behavior of a system and the accuracy of information is important. In particular, safety critical systems, as the ones described in [1], might require or benefit from an effective integrity monitoring strategy. As our reliance in technology increases, so the usage and accuracy requirements of several types of sensors that supports those various safety critical systems. One particular case in which the integrity of information provided by sensors is of critical importance is in transportation systems, such as aviation, autonomous vehicles and maritime navigation. Although extensive research has been done into improving and assessing the integrity in navigation systems [2], the development of similar strategies and standards for sensor integrity monitoring in other applications has not seen the same interest.

There have been recent reviews of the Global Navigation Satellite System (GNSS) integrity monitoring methods, such as [2], [3] and [4]. However, these works are highly specialized for GNSS users, and in [3] and [4], given the recent trend for autonomous vehicles, they focus on the specific GNSS integrity methods and challenges for ground vehicles in urban scenarios. The scope of this work is more general, and it is intended for a broader audience, in and outside the navigation field. The purpose is to incentivise the use and adaptation of these positional integrity monitoring techniques for other types of sensors and areas. Moreover, this review aims to provide insights regarding alternative methods in different applications, fostering new developments towards higher safety standards and information integrity.

The content of this work is divided into two main sections:

- **Theoretical Background**, containing an overview of navigation systems, which are the main application for the integrity monitoring methods; an outline of sensor integration techniques used for the navigation systems; an introduction to the two main estimation techniques that are used for integrity monitoring, the Least Squares method, and the Kalman Filter, which constitutes, respectively, the basis for the snapshot and sequential integrity monitoring schemes; a discussion of fault detection methods, with a focus on popular hypothesis testing approaches, such as the chi-squared and likelihood ratio tests; and an overview of important parameters for defining integrity specifications and evaluating the integrity solution performance.
- **Integrity Monitoring Methods**, divided into snapshot, sequential, hybrid and multi-strategy, and alternative methods, containing a review of recent works that features methods in each of these categories and summary tables to facilitate the consultation.

In the conclusion, a summary of the content is given, along

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with insights for future developments and trends for the research on the sensor integrity monitoring field. Additionally, a list of acronyms is provided in the nomenclature section, at the end of this work.

II. Theoretical background

Most integrity monitoring applications rely on two main steps: an estimation step, that can minimize the noise, provide a more accurate value for the states (the quantities of interest) along with a calculation of the error associated with that estimate; and a fault detection step, that evaluates the estimation error, with a test to decide if the estimated states are trustworthy or not. This section will provide an overview of a selection of topics that are necessary for understanding these two steps in the context of integrity monitoring. It also provides an introduction to navigation systems, as these are currently the most notorious application for integrity monitoring schemes, and an overview of sensor integration techniques that are used for navigation solutions.

A. Navigation Systems

The navigation systems are responsible for tracking the position and velocity of a vehicle, aircraft, ship, person or object, and, sometimes, they also include planning and maintaining a course between locations while avoiding obstacles and collisions. The term integrity monitoring is often associated with navigation systems, as it has been traditionally applied to GNSS positional integrity for the aviation sector. Therefore, a short overview of the inherit concepts in the field, the most common types of navigation systems, and its components will be given in this section.

There are basically two categories of techniques to provide a navigation solution: position fixing, that requires matching the current location to the known position of external references, such way-points; and dead-reckoning, that computes the new position based on the previous one, by calculating the change in position using distance, velocity, altitude and trajectory projection. The issue with the position fixing technique is that those external references might not be available at every time, and the main problem with the dead reckoning is that the position error tends to grow over time, since each measurement contains some degree of error and the new ones depends on the previous measurements. For that reason, in several modern navigation systems, since the two approaches are often complementary, they are used together.

1) Inertial Navigation System (INS): The INS, sometimes referred as INU (inertial navigation unit), is comprised of multiple sensors, usually a combination of orthogonal aligned accelerometers, gyroscopes and magnetometers, which is the typical constitution of a Inertial Measurement Unit (IMU) sensor, and a processing unit that calculates the relative position, velocity and altitude from the sensor measurements using a dead reckoning approach. Since the calculation of the position is derived from the acceleration and velocity integration, the navigation solution error grows over time. Therefore, its performance is highly dependent on the quality of the inertial sensors. Despite that issue, the INS can provide continuous measurements and are widely used as a part of the navigation system in ships, submarines, air-crafts and ground vehicles.

2) Range-based Navigation: There are various types of range based sensors, with particularities of functionality and operation that would make one type more suitable for specific applications. However, they all based on the principle of emitting a signal and extracting information about the environment from that signal echo (the reflected wave), by evaluating the time-of-flight, signal intensity, angle, frequency and phase change. An important type of ranging sensor is the Radio Detecting and Ranging, Radar, that uses Radio Frequency (RF) signals in the microwave spectrum to detect objects. Although there is a wide variety of Radar sensors with different performance characteristics, these devices are usually characterized by having a low spatial resolution, meaning they can not detect small objects or differentiate fine shape and format characteristics of the objects in view. However, they are very robust against challenging weather conditions and can offer a high detection range, with distances of up to dozens of kilometers. These devices are widely used in various applications, such as maritime surveillance, aerial traffic control, and measuring the speed of ground vehicles in urban scenarios.

The Light Detection and Ranging (LIDAR) sensors has a similar operation, but it uses a light source, typically a LASER, instead of the microwave signal. They can offer a much higher spatial resolution than Radar, being able to provide a 3D characterization of the scene and to accurately distinguish near-by objects. However, they operate on a much lower distance range, typically below 100 meters, and can be affected by weather and ambient light conditions. These sensors are gaining notoriety in autonomous driving applications, but they are usually used in combination with other sensors, such as a short-range Radar and cameras.

3) Satellite Navigation: The Global Satellite Navigation System (GNSS) has become one of the most popular navigation solutions, as the number of available satellites increases and the GNSS receivers becomes cheaper, smaller, and more widely available. The system is able to provide the position of the receiver in a global-referenced coordinate frame, and can be combined with map visualizations to enable tracking the user position anywhere on the planet, as long as sufficient satellite signal is available.

There are four main arrays of satellite navigation systems operating today, all using the same principle of broadcasting precise synchronized time information in the frequency range between 1000 and 2000 MHz. These systems operate with a constellation of up to dozens of satellites, most of which are orbiting the Earth in between the 20000 and 30000 km radius. The main satellite systems are: Global Position System (GPS); GLONASS; Galileu; and BeiDou Navigation Satellite System (BDS), and they were developed and are maintained, respectively, by the USA, Russia, European Union and China.

The GNSS data can contain a variety of signals in multiple frequency. Some of these signals are available for general use,

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and others are restricted to military application and commercial subscription. Despite various applications and specific purpose usage, the GNSS signal always contains the ranging codes, used for determining the time that the signal was transmitted from the satellite, and the data message, with information about the satellite orbits and timing parameters. The main goal of the GNSS is to provide the absolute global position of the receiver, by doing geometrical calculations from the synchronized time signal provided by multiple satellite sources. Since the GNSS signal propagates at a known speed (the speed of light), through time calculations, the pseudorange is able to provide the distance between the satellite and the receiver. Using that information from multiple satellites, it is possible to find the three-dimensional position of the receiver, considering a geo-referenced coordinate frame. Detailed information about these calculations can be found in [5] and [6].

Usually, the GNSS receivers are inexpensive and are able to provide the position with a radial and vertical accuracy around 5 meters. Although, there are several techniques and augmentation methods that can improve that accuracy to the centimeter scale. The drawbacks with the technology are the lack of signal continuity, interference vulnerability, and signal blockage and reflection. There are various error sources that can degrade the GNSS signal, such as: ephemeris (satellite orbit information) and clock errors, ionosphere and troposphere delays, radio frequency interference, multipath and no-line-of-sight (NLOS) errors. To ensure the usability of the position solution provided by the GNSS equipment an appropriate integrity monitoring strategy, that is able to detect, and ideally, correct, these errors, is necessary. Extensive research has been done into that topic, and a review of several works that deals with this challenge will be given in section III.

4) Sensor Integration in Navigation Systems: In some situations, combining measurements from different sensors is advantageous, with the possibility to mitigate or eliminate the issues of specific sensor types. In the context of integrity monitoring the most significant example is possibly for the position measurement in navigation systems, in which the integration of GNSS with INS is a popular approach. That integration can provide a more accurate and robust positioning and tracking solution, as the benefits and drawbacks of these two types of sensor are complementary. The GNSS receiver is able to provide a very accurate position, but it has a relatively low update frequency and since it depends on satellite signal, it can have continuity issues in bad weather and urban environments, where interference, NLOS and multipath errors can occur. The INS, conversely, does not suffer from any of these issues, as it is a standalone sensor system that calculates the position based on the inboard inertial measurement unit, which contains accelerometers and gyroscopes, integrating the acceleration and angle variations provided by those sensors. That strategy can output position measurements at a much higher rate than GNSS receiver can deliver, but it suffers from accuracy drift, as the integration process introduces errors that accumulates over time. For that reason, the integration of GNSS and INS is advantageous, as the INS can track the position during the events where GNSS signal is unavailable or is unreliable, and it is possible to periodically use the GNSS measurements to correct the INS position drift errors.

The differences between GNSS/INS integration schemes are mainly in three aspects: the way the INS corrections are applied; the types of GNSS measurements that are used; and how the integration algorithm interacts withe GNSS equipment. The three most common strategies for performing that sensor integration are:

- Loosely coupled integration: relies on the GNSS position and velocity solutions as inputs to the integration algorithm, providing the INS correction without regarding the INS measurements. It is a relatively simple solution, in which a navigation filter is incorporated in the GNSS equipment, with the advantage of being applicable to any type of GNSS and INS sensors.
- Tightly coupled integration: uses the GNSS pseudorange, pseudorange rate and accumulated delta range (ADR) measurements as the inputs for integration algorithm. In this case, a single navigation filter (such as the Kalman Filter) can be used to provide the GNSS solution and perform the integration. That approach mitigate time-correlation issues with the filter error output, but suffers from the fact that there might not be stand-alone GNSS solution, as the raw GNSS measurements are being directly processed by the integration algorithm.
- Ultra-tightly coupled integration: also referred to as deep-integration, it performs GNSS signal tracking inside the integration algorithm, using information from the GNSS correlation channels as inputs, controlling the code and carrier measurements within the GNSS receiver.

The information provided in this section is only meant to provide a brief overview of these techniques. The reader is advised to consult chapters 7 and 12 of [5], and refer to [7] for a comprehensive up-to-date review of these techniques.

B. Estimation Techniques

In statistical inference, an estimator can be considered as a rule (or set of rules) that specifies a way to use relevant data to calculate a plausible value for the variable of interest that the data is representing [8]. There are many different estimation techniques with specific characteristics to tailor different applications and requirements. However, all these techniques are meant to extract a suitable estimation for the unknown true value of a quantity of interest, that is represented by a set of measurements or data inputs. In the context of sensor accuracy evaluation, the assumption is that all measurements are imperfect and contain some noise. By applying an estimation algorithm it would be possible to reduce the measurement noise, get a better value for the quantity of interest, and, more importantly for integrity monitoring, have an assessment of the error associated with each measurement. In the context of integrity monitoring, there are two types of estimators and their variations that stand out in popularity and effectiveness, the Least Squares method and the Kalman Filter. An overview of these techniques will be given next.

1) Least Squares: The method is used to estimate the fitting parameters of a model that aims to represent a set of data (observations or measurements) by minimizing the sum, S, of the squared residuals, as shown in eq. 1. The residuals are the difference between the observed values of the dependent variable, y_i, and the ones calculated through the estimation using the model, $\hat{y_i}$. As stated by the Gauss-Markov theorem, the ordinary least squares method is an optimal[1] estimator for the fitting parameters, as long as the residuals are unbiased (mean value of zero), with the same variance, and uncorrelated. For a generic problem, consider the estimation function defined in eq. 2, [9].

$$S = \sum_{i=1}^{n} (y_i - \hat{y_i})^2 \tag{1}$$

$$\hat{y_i} = f(x_i, \beta) = \sum_{j=1}^{m} \beta_j \phi_j(x_i) \tag{2}$$

In this case, there are n observations (pairs of x, y), the model has m parameters in the vector β, and $\phi_j(x_i)$ is a function of the independent variable x_i according to the specific application. Expanding to the matrix form where all the observations, from $i = 1$ to $i = n$, are contained in the rows, the least squares solution for the β parameters is given by eq. 3, [10].

$$\beta = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y} \tag{3}$$

Where the matrix $\mathbf{X}$ is $n \times m$, with the elements $x_{ij} = \phi_j(x_i)$, and the matrix $\mathbf{Y}$ is $n \times 1$, containing the y_i observations. Note that this representation highlights one of the limitations of the method, that the coefficients being estimated are assumed to be linear in respect to the independent variable. There are non-linear variations to the LS method, but depending on the model used, a closed form solution does not exist and the estimation would be derived from numerical approximations.

An important variation of the LS method is the Weighted LS (WLS), in which the information about the variance of each measurement is incorporated into the solution. In the WLS, the sum of the weighted squared residues is minimized, as shown in eq. 4. In that case, the solution given by eq. 5 considers a $n \times n$ weighting diagonal matrix, $\mathbf{W}$, with its elements being the inverse of the variance of each measurement, $1/\sigma_i^2$, as shown in eq. 6.

$$S = \sum_{i=1}^{n} \frac{(y_i - \hat{y_i})^2}{\sigma_i^2} \tag{4}$$

$$\beta = (\mathbf{X}^T\mathbf{W}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}\mathbf{Y} \tag{5}$$

$$\begin{cases} \mathbf{W_{ij}} = 1/\sigma_i^2, \text{ if } i = j \\ \mathbf{W_{ij}} = 0, \text{ if } i \neq j \end{cases} \tag{6}$$

A particularly relevant application case of the LS and WLS estimator for integrity monitoring is in the estimation of the GNSS coordinates and clock offset from pseudorange observations, [11] and [12]. In that application, the same equations 3 and 5 are used, but the unknown parameter, β, is the correction vector for the GNSS user coordinates and receiver clock offset, $\delta\mathbf{X}$; the measurement vector, $\mathbf{Y}$, is the difference between the raw measured pseudoranges and a predicted noiseless one calculated based on an approximated receiver position, $\delta\rho$; the model matrix, $\mathbf{X}$, contains the information about the satellite to receiver relative positions, usually denoted by $\mathbf{H}$, $\mathbf{A}$ or $\mathbf{G}$, and referred as observation, or geometry, or design matrix. Note that in this case, the number of rows, n, represents the number of satellites available to the GNSS receiver, and the number of columns, for the matrix $\mathbf{H}$, represents the number of unknown parameters, which in this case are the receiver coordinates, x_r, y_r, z_r, and the clock offset. This calculation is the basis of one of the most popular integrity monitoring techniques, the Receiver Autonomous Integrity Monitoring (RAIM), which is widely used for GNSS positioning solutions and will be discussed in III.

[1]The best linear unbiased estimator.

2) Kalman Filter: The Kalman Filter (KF) is a recursive Bayesian estimator algorithm, initially proposed in 1960 [13], that has been used in a wide range of applications such as computer vision, signal processing, trajectory optimization, econometrics, integrity monitoring for navigation systems, among others. The method aims to provide an optimal estimation for the state vector, which contains the parameters or quantities of interest, generally combining the information from a prediction, made using the process or system model, with measurements of parameters that have a known relationship with the state vector. The filter operates recursively, taking the previous estimate to generate a new prediction, that gets updated with the new measurement results at each step. For that reason, the KF is memory efficient, being suitable for real time applications as it does not need to store all the measured values. When set up correctly, the KF is able to quickly reduce the uncertainty level of its estimations, getting close to the real value of quantities that are being monitored. The technique is widely used in integrity monitoring strategies due to its relatively low computational burden, being suitable for implementation in hardware level in real time applications, and its ability to provide optimal estimation under the right conditions, with an error output that can be used as a base for detecting faulty measurements.

There are several variations to the original algorithm that were derived to mitigate or overcome some of its limitations, to better target specific applications, or to improve the performance from a certain metric. For instance, the Extended Kalman Filter (EKF) is a popular variation used for non-linear systems. Despite the numerous KF variations, all of them share the underlying core elements and the base methodology of the original algorithm. An overview of the base algorithm will be given next.

The main elements of the Kalman filter are the following variables:

- State vector: the set of parameters being estimated by the KF. The true value for the parameters of interest, known as states, is typically represented by $\mathbf{x}$ and the KF estimation by $\hat{\mathbf{x}}$.

- Process covariance matrix: the errors associated with the state vector estimation and the level of correlation between them. It is typically represented as $\mathbf{P}$.
- System model: a deterministic model for the states and the associated errors, describing how those quantities vary over time. It is based on previous knowledge about the system and the interaction between parameters. It is partially implemented on the transition matrix, $\mathbf{F}$, which is used to generate the state vector prediction.
- Measurement vector: the set of ongoing measurements for the system parameters, from which the updated state vector is derived.
- Innovation: the main estimation error variable, usually denoted by δz, representing the difference between the measurement vector and the predicted states. Several integrity monitoring methods use this variable as the basis for detecting faulty measurements.

The KF uses the information about the system and the measurements to update the state vector, following a simple algorithm that can be implemented with a few linear algebra equations. Although the calculations can be easily conducted by a computer, setting up the filter parameters and matrices for a generic application can be a challenging task. The need for a good analytical model that can predict the current state based on the previous state, and having a good estimate for the expected variance of the model and measurements are the main difficulties for applying this technique. Additionally, the errors are assumed to follow a normal distribution. Although for many systems, a Gaussian distribution would not be an accurate representation of the real errors, in several cases, that assumption can provide a good approximation.

It is important to distinguish the state vector and the process covariance matrix in different phases of the calculation. Those variables before the update stage are called time propagated, a-priori, or predicted variables and can be represented with various notations in the literature. In this review, the notation convention used is with the superscript "$^-$", $\hat{\mathbf{x}}_\mathbf{k}^-$ and $\mathbf{P}_\mathbf{k}^-$, for the predicted, a-priori, variables, and with the superscript "$^+$", $\hat{\mathbf{x}}_\mathbf{k}^+$ and $\mathbf{P}_\mathbf{k}^+$, for the updated, a-posteriori, variables at the end of each estimation step. Note that the subscript "$_k$" represents the iteration number, and that one full iteration is commonly referred as an epoch.

The standard KF has basically three phases: initialization, which only occurs once when the process starts; prediction, in which the prediction for the state vector and the process covariance matrix is calculated; and update, that uses the combined information from the prediction and measurement to calculate a better estimate for the parameters of interest. The steps and equations to implement a standard KF are summarized in the following items and on the flowchart in fig. 2:

- Initialization phase: definition of the transition matrix, $\mathbf{F}$, which models how the state vector changes over time as a function of the inherent system dynamics; the control matrix, $\mathbf{B}$, in case there is a control input vector, $\mathbf{u_k}$, affecting the state vector; the process noise covariance matrix, $\mathbf{Q}$, containing the variance associated with the model; the measurement noise covariance matrix, $\mathbf{R}$, with the expected variance in the measurements; the measurement matrix, $\mathbf{H}$, which defines the relationship between the state vector and the measurement vector, according to eq. 7, where $\mathbf{w}_m$ is an additive measurement noise; and the initial guesses for the state vector and process covariance matrix to be fed in the first prediction step.

$$\mathbf{z_k} = \mathbf{H}\mathbf{x}_\mathbf{k}^- + \mathbf{w}_m \tag{7}$$

- Prediction phase: calculation of the predicted state vector and process covariance matrix using the updated estimations from the previous step, as shown in eq. 8 and 9.

$$\hat{\mathbf{x}}_\mathbf{k}^- = \mathbf{F}\hat{\mathbf{x}}_\mathbf{k-1}^+ + \mathbf{B}\mathbf{u_k} \tag{8}$$
$$\mathbf{P}_\mathbf{k}^- = \mathbf{F}\mathbf{P}_\mathbf{k-1}^+\mathbf{F}^\mathbf{T} + \mathbf{Q} \tag{9}$$

- Update phase: calculation of the innovation, eq. 10, using the predicted state and the new measurement; the system uncertainty, eq. 11, which encompasses both the system modeling and measurement errors; the Kalman gain matrix, eq. 12, representing the relative weights between the predicted state vector and the measurement vector; and finally, the calculation of the updated state vector and process covariance matrix, eq. 13 and 14, that will be propagated to the prediction phase in the next iteration. In some cases, the residual is also calculated, using the updated state and the measurement vector as shown in eq. 15.

$$\delta\mathbf{z}_\mathbf{k}^- = \mathbf{z_k} - \mathbf{H}\hat{\mathbf{x}}_\mathbf{k}^- \tag{10}$$
$$\mathbf{S_k} = \mathbf{H}\mathbf{P}_\mathbf{k}^-\mathbf{H}^\mathbf{T} + \mathbf{R} \tag{11}$$
$$\mathbf{K_k} = \mathbf{P}_\mathbf{k}^-\mathbf{H}^\mathbf{T}\mathbf{S}_\mathbf{k}^{-1} \tag{12}$$
$$\hat{\mathbf{x}}_\mathbf{k}^+ = \hat{\mathbf{x}}_\mathbf{k}^- + \mathbf{K_k}\delta\mathbf{z}_\mathbf{k}^- \tag{13}$$
$$\mathbf{P}_\mathbf{k}^+ = (\mathbf{I_d} - \mathbf{K_k}\mathbf{H})\mathbf{P}_\mathbf{k}^- \tag{14}$$
$$\delta\mathbf{z}_\mathbf{k}^+ = \mathbf{z_k} - \mathbf{H}\hat{\mathbf{x}}_\mathbf{k}^+ \tag{15}$$

The method is computationally efficient and relatively easy to implement in navigation systems, with well known model equations to track objects or vehicle position. The KF is able to provide an optimal estimation of the measured quantities, given that the linearity and Gaussian error modeling requirements are met. Consequently, the use of Kalman Filter in integrity monitoring schemes provides reduced noise and possibly higher accuracy values for the measured quantities, and through either residual or innovation monitoring, a fault detection strategy can be implemented.

C. Fault Detection

There are many systems and applications in which detecting faults is necessary to ensure safety and performance. In an industrial process, a undetected fault could lead to damaging goods and expensive equipment, and even to fatal accidents. In transportation systems, such as an airplane, where human lives are at risk, a critical component failure or a substantial error in the position estimate could have catastrophic results. Faults can occur as a result of malfunction in the system components and

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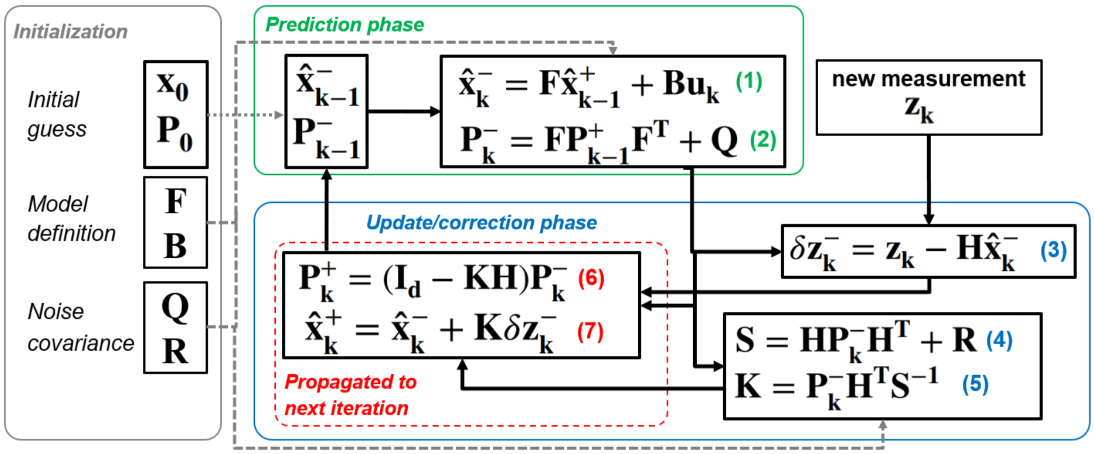

Fig. 2. Summary of the steps, phases and equations of a standard Kalman Filter algorithm.

sensors, or in case of a abnormal situation that the system can not deal with, such as human attacks. Specifically for sensor integrity monitoring, faults associated with sensor malfunction and hazardously inaccurate measurements will be the scope of interest.

The typical fault detection (FD) scheme for sensor integrity monitoring relies on a hypothesis test using a test statistic derived from the measurement errors, that are usually evaluated using an estimation method. Then, that test statistic compared with an appropriate threshold considering the integrity requirements. That approach can be referred as a model based fault detection, because it requires analytical models for the hypothesis testing, the error distribution and the construction of the test statistic. A different strategy, called data based fault detection, relies only on classified or fault free historical data. The data is then used to train an empirical model that would enable detecting faults and abnormal behavior. Sometimes both strategies can be used in combination, with data based techniques used as a framework to derive a model from the data, that is then applied to a model based method. A discussion of that hybrid approach can be found in [14], with a combination of Partial Least Squares (PLS) and Generalized Likelihood Ratio Test (GLRT).

In the following sections, an overview of the typical fault detection methods will be given, with a focus on model based approaches that are most commonly used for sensor integrity monitoring. The provision of comprehensive explanations of each method is outside the scope of this work. The goal of this overview is to present these techniques and give relevant references for the reader.

1) Hypothesis Testing for Fault Detection: Statistical hypothesis testing has been proved a reliable tool for model based fault detection. The objective is to determine if a fault is present (the rejection of the null hypothesis, $\mathcal{H}_0$, in favor of the alternative hypothesis, $\mathcal{H}_1$) while minimizing incorrect decisions such as false alarms and undetected faults. In cases where there is only one type of fault with a specific value being considered, a simple hypothesis test is used. However, in situations where different faults with different magnitude levels might occur, a composite hypothesis test is necessary. In another perspective, a simple hypothesis test is defined when the probability density function for the parameters being tested is fully known. On the other hand, a composite hypothesis test is used when the distribution of the parameters is unknown.

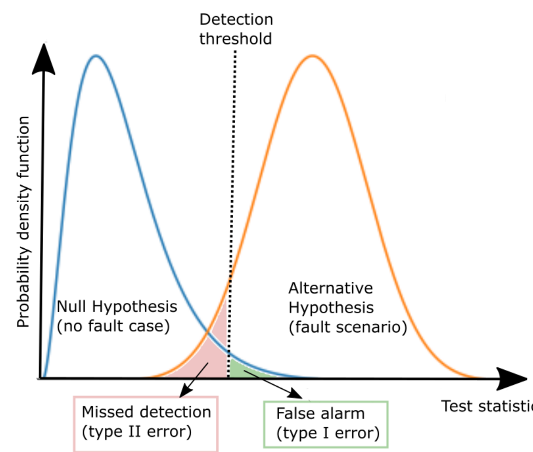

Fig. 3. Plot showing the performance compromise between type I and type II errors in a hypothesis test. For aesthetic purposes, the values in the vertical axis were normalized so that the the mean of both distributions would have the same height.

The quality of a specific hypothesis test can be quantified by measuring the probability of false alarms (type I error), α, and the test sensitivity, β, which represents the probability of rejecting the null hypothesis when the alternative is true. Note that the probability of missing a fault, a type II error, is defined by $1 - \beta$. A very low α, close to zero, and high β, close to 1, is the indication of a high quality hypothesis test. However, a trade-off must be made between those two quantities. Generally, a false alarm probability is specified, which defines the corresponding test sensitivity. That compromise in the test performance is outlined in figure 3. Here, the selection of the detection threshold, the parameter that is compared to the test statistic to decide if the null hypothesis will be rejected (fault detected), involves a decision between a higher probability of either type I or type II errors. In practice, the exact distribution of the test statistic under the normal scenario (null hypothesis) and in faulty conditions is unknown. However, there are various strategies to design a test statistic that would minimize the overlap between those distributions, enabling an effective test that mitigates the missed detection and false alarm issues. The next section will provide an overview of two important tests that have been successfully used for sensor integrity monitoring and for various other applications, the chi-squared test and the likelihood ratio test.

2) Chi-squared Test: The chi-squared test is based on assessing how well a sample of a random variable, representing the quantity of interest, fits a chi-squared distribution of which that variable is hypothesised to have. It is a very popular fault detection method used in combination with an estimation algorithm such as the Kalman Filter. The innovation produced at each KF step, which is the difference between the measurements and the predicted state, is used to form a test statistic that follows a chi-squared distribution, indicating a fault when that parameter is higher than a given threshold. That test statistic is often called normalized innovation squared, and it is defined by eq. 16. The detection threshold is usually defined in terms of the false alarm probability, as there is a compromise between test sensitivity and false alarms. To avoid false alarms due to outliers, an average test statistic comprised of innovations sampled over a specified time-window can be used, as shown in eq. 17 [15]. The choice of the size of the time window would take into account a trade off between low false alarm rates and undetected true failures.

$$s_k^2 = \delta\mathbf{z_k^-}^T \mathbf{S_k}^{-1} \delta\mathbf{z_k^-} \tag{16}$$

$$s_k^2 = \sum_{i=k-N+1}^{k} \delta\mathbf{z_i^-}^T \mathbf{S_i}^{-1} \delta\mathbf{z_i^-} \tag{17}$$

In this way, the fault is detected by comparing the s_k^2 test statistic with threshold T:

$$\begin{cases} \mathcal{H}_0 & \text{if } s_k^2 \leq T \\ \mathcal{H}_1 & \text{if } s_k^2 > T \end{cases} \tag{18}$$

The value of T can be computed using a look-up-table (see appendix D in [16]) for the chi-squared distribution, with the confidence level (p-value) determined by the false alarm probability and the degrees of freedom associated with the number of independent variables in the innovation or residual vector.

3) Likelihood Ratio Test: The likelihood ratio test (LRT) is able to give optimal results for a simple hypothesis test, maximizing the power function, or the detection ratio, for a given false alarm ratio. The Generalized likelihood ratio test (GLRT) is the similar approach for composite hypothesis testing, when there are multiple hypothesis to consider. In that situation, finding an optimal testing solution is oftentimes impossible, but the GLRT is able to provide a result which is close to the optimal test.

The GLRT is formulated by assuming that the measured quantity of interest can follow either one of two Gaussian distributions of known variance, one centered in zero, corresponding to the null hypothesis, and the other centered in θ, corresponding to the alternative hypothesis where a fault occurred. The test is based on the evaluation of the log-likelihood ratio between different hypothesis scenarios, detecting a fault in case that difference is above a set threshold level. A comprehensive explanation about the GLRT is outside the scope of this review. For more information, the reader is advised to refer to [17], and to [18] for an exemplary case in the context of integrity monitoring.

4) Data Based Fault Detection: There are many fault detection strategies that do not necessarily use a hypothesis testing scheme. These methods do not require a statistical model and rely on classified or fault free historical data to derive an empirical model that would assist the fault detection scheme. Several machine learning algorithms have been used for this purpose and these strategies are becoming more popular for industrial process monitoring. Some application cases found in the literature are given next.

The use of Principal Component Analysis (PCA) for fault detection has been reported in [19], [20] and [21]. In [22] and [23] methods based on Partial Least Squares (PLS) regression have been used. The authors in [24], [25] and [26] propose a Support Vector Machine (SVM) based fault detection. Examples of using Artificial Neural Networks (ANN) for that purpose have been found in [27], [28] and [29].

The advantage of this data based approach is that it supports the fault detection in highly complex scenarios, where developing an error model is not possible or feasible. The drawback is that it requires reliable historical data to train the algorithm, and since most faults are low probability events, the amount of faulty data to support that training might not be sufficient for a robust detection.

D. Fault Exclusion

Fault exclusion can be an effective strategy for improving or restoring the integrity of a set of measurements. It is necessary to have enough redundancy of sensors or measurements providing similar information to identify and exclude the faulty source. There are several methods for fault exclusion, but they are usually based on the same concept of conducting a global test to detect a fault, and then a local test to find the faulty measurement or sensor. Since it is necessary to detect a fault first, these methods are usually called fault detection and exclusion (FDE). The global test can be any kind of FD strategy, such as the chi-squared test, as previously discussed. The local test usually iterate through all measurements, calculating a local test statistic for each one and comparing them among each other to find the one that has the largest deviation, or the largest residual. In some cases, the local test statistic is simply the standardized residuals from the estimation process, defined as:

$$s_i = \left\| \frac{r_i}{\sqrt{\mathbf{P_{i,i}}}} \right\| \tag{19}$$

Where r_i is the residual for the i_{th} measurement and $\mathbf{P_{i,i}}$ is the diagonal element i, i from the residual's covariance matrix [30]. In this way, the local test is performed in each measurement, checking if the test statistic s_i is greater than a threshold specified by a quantile of the normal distribution associated to the confidence level, α, which is related to the pre-defined false alarm probability. Then, if the test statistic is greater than the threshold, the associated measurement is selected to be excluded if the residual associated to that measurement is the maximum residual in all measurements. In other words, the specific measurement k is excluded if the following two conditions are met:

$$\begin{cases} r_k & \geq r_i, \forall i \\ r_k & > T_\alpha \end{cases} \tag{20}$$

The implementation of this strategy to a batch of measurements, used, for instance, in the least squares estimation is straightforward. The method can also be applied to a recursive estimation, such as the Kalman Filter innovation, by performing the local test on a time-window of measurements, stored in a buffer, until no fault is left in that set of measurements.

E. Integrity Performance Evaluation and Related Parameters

The parameters used to define and evaluate the performance of an integrity solution are closely linked to the requirements for navigation systems, and were traditionally defined in standards for the aviation sector. However, these concepts can be extrapolated for sensor integrity monitoring in other scenarios. The following concepts and attributes can be used to specify the integrity requirements for a particular application, and, they can provide performance evaluation metrics for a given integrity monitoring solution:

- **Accuracy:** represents how close the measured or estimated value for the quantity of interest is to its true value. The true accuracy of a measurement is unknown, but it can be determined in terms of statistical confidence levels and in respect to the error distribution.
- **Continuity:** is related to the frequency of measurements and the sensor system capability of providing continuous data during operation within a certain accuracy level.
- **Availability:** a measure of the time ratio where the measurements are reliable, maintaining accuracy and continuity requirements.
- **Estimation error:** the difference between the estimation of the parameter of interest and its measured value.
- **Protection Level (PL):** represents statistical error bounds in which the true value of the quantity of interest is. It can be used to detect an integrity issue in case the bound is higher than an acceptable alert limit (AL) value. The PL is a common metric provided by the integrity monitoring algorithm in navigation systems, and it is usually divided into horizontal and vertical protection level, HPL and VPL, respectively, of the position solution. Note that, since the PL is an error bound, the higher its value, the more uncertainty there is regarding the value of the quantity of interest. There are several ways to calculate the PL, depending on the integrity monitoring method used and the application. The classic approach used in GNSS integrity monitoring algorithms is based on a slope parameter derived from the chi-squared test statistic [31].
- **Time to Alert:** it is the time between a sensor, or measurement, fault occurring, and the fault being detected and alerted to the user. Some applications, such as autonomous driving, might have very strict requirements in terms of this parameter.
- **Integrity Risk:** the probability of occurring a critical undetected fault in the quantity of interest, also represented by the probability of hazardous misleading information (HMI). Some applications have a user defined integrity risk requirement, P_{risk}, typically a very low value in the range of 10^{-5} to 10^{-7}, for which the actual integrity risk must not exceed. However, the direct calculation of the integrity risk is usually not possible, being instead represented by a statistical bound defined by the eq. 21, where r is the estimation error, s the test statistic, and T the detection threshold.

$$P(r > AL \text{ and } s < T) \leq P_{risk} \tag{21}$$

In the case where the error variable is independent from the test statistic, typically in snapshot integrity monitoring methods, that integrity risk compound probability can be calculated as the product of the two probabilities. However, if those variables are dependent, as in sequential methods, the calculation is not straightforward and the obtained integrity risk bound could be loose.

III. Integrity Monitoring Methods

As discussed in the theoretical background section, most sensor integrity monitoring schemes rely on applying an estimation technique to one or multiple sensors measurements, typically using a suitable model to make predictions with the estimator and to characterize the error distribution. Next, a fault detection scheme based on the results from the estimation is used, flagging erroneous measurements. In same cases, there can be a fault exclusion algorithm that would try to correct the estimation in case a fault is detected. The integrity is usually evaluated in terms of a protection level and the state estimation errors. A graphical representation of a generic sensor integrity monitoring scheme is presented in figure 4. Note that specific integrity monitoring strategies can differ from this generic approach, containing additional steps or omitting some of the parts. However, the presented diagram covers the typical approach and can be used as a guideline for deriving a specific sensor integrity monitoring strategy.

Despite the fact that there are innumerable different integrity monitoring methods, as recently observed in [2] and [11], there are basically two categories of integrity monitoring algorithms in the literature:

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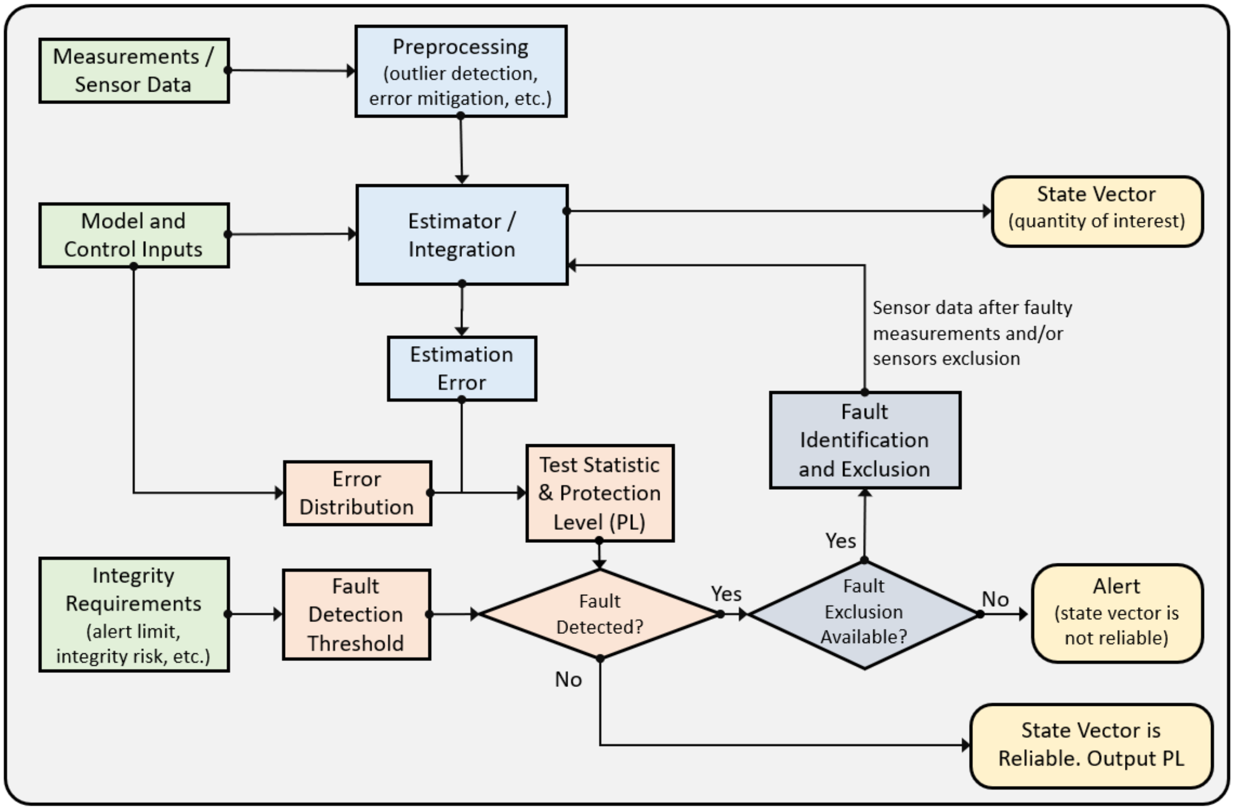

Fig. 4. Generic integrity monitoring scheme.

- **Snapshot methods**, with an error metric that only uses information about the present epoch or state, typically based on a test statistic derived from the residuals of the least-square estimator;
- **Sequential methods**, also referred as recursive methods, where the error variable is derived from present and previous state information, generally implemented with a test statistic based on the innovation from a Kalman Filter.

Usually, in the snapshot schemes, the error is derived either from the estimation using redundant information that is provided by different sources or sensors, from a single time-step (epoch), or from a fixed batch of measurements taken by the same sensor. In contrast, the sequential methods commonly use the estimation from the previous state to update the present error. In this way, the test statistic normally used along with KF, based on the innovation, is time-correlated to the previous measurement, as it was shown in eq. 10, while the batch-like residual based test statistic used in LS is only based on the variables from the current time epoch.

Some authors have presented a comparison of these two strategies or used them in combination, as will be discussed in section III-C. Therefore, for the purpose of organizing the different integrity monitoring literature, a multi-method or hybrid category will also be considered in this review. The snapshot and sequential methods assesses the integrity in terms of statistical evaluation of the measurement errors. They usually rely on a model for the distribution of values under faulty and fault-free condition. However, there are various other methods that evaluate the integrity from different perspectives, not necessarily checking if the measurements are faulty under rigorous statistical analysis. For that reason, works featuring those strategies will be grouped under the alternative methods category.

This section will provide a review of selected recent works (from 2016 to the present date, with only a few exceptions) in these four different categories of integrity monitoring methods. The development of these various integrity algorithms relies on formal mathematical representations that, for the purpose of this review, will be omitted. Most of these specific strategies can be interpreted as variations and extensions of the concepts that were presented in the Theoretical Background section of this work. Therefore, the readers who are interested in understanding the actual implementation of these methods should be able to interpret the equations provided in the original works having the background covered here as a reference.

A. Snapshot based IM

The snapshot methods rely on a test statistic that considers current[2] information about the monitoring quantity error. Therefore, this approach can be computationally efficient, and simplify the derived statistical analysis by disassociating time-correlated variables. The snapshot methods typically rely on monitoring the residual from a least-squares estimator, and they have been the basis for Receiver Autonomous Integrity

[2]Present time, or the latest measurements. However, some methods might consider a batch of measurements taken in a predefined time window.

Monitoring (RAIM) algorithms, which are popularly used for GNSS integrity monitoring. A summary of works that features snapshot integrity methods is given in table I, and next, a review of selected works will be given.

Snapshot RAIM Algorithms: The RAIM algorithm, first introduced in [39], is used in GNSS receivers to identify errors in the positional data. In essence, the method performs a consistency check using redundant positioning information from the multiple satellites that are in the view range of the receiver. Since there are basically four unknown variables to be checked, the receiver relative position in the 3-axis (x, y and z) and the clock offset, the method requires at least 5 satellites in view to be able to detect a fault, and in case a fault exclusion scheme is used, it needs a minimum of 6 satellites to perform the exclusion. The "autonomous" in the name means that the technique can be applied to a standalone receiver and does not require additional corrections from reference stations or augmentation systems that are used for GNSS accuracy improvement. Since the algorithm is implemented on the receiver, it is able to monitor local errors, and due to memory and processing speed restrictions, the method is designed to be computationally efficient. There are different implementations of the RAIM algorithm, but the LS residuals method is possibly the standard approach. There have been reports of sequential versions of the RAIM method, such in [40], but the typical algorithm is snapshot based.

There are several limitations with the standard RAIM implementation, such as:

- Restricted to a single satellite constellation;
- Only supports single frequency signals;
- Does not provide integrity monitoring for the vertical position (only outputs a HPL, horizontal protection level);
- Can only detect single fault cases (if there are multiple satellite failures the algorithm will fail to detect).

One way to deal with that last limitation is to consider multiple epochs for the integrity solution, as proposed in [41], but that could introduce a delay in the detection and the method would not be in the snapshot category. Other variants have been developed to improve the performance of the method:

- Advanced RAIM (ARAIM) [35], that addresses some of the traditional RAIM shortcomings providing vertical guidance, multiple-fault mode detection, dual frequency and multi-constellation GNSS signal [36];
- Relative RAIM (RRAIM) [42] and [43], which uses time differential carrier-phase measurements instead of ranging signals, being able to provide higher service availability;
- Extended RAIM (ERAIM), [44], that enables INS integration.

The ERAIM uses the innovation sequence provided by a Extended Kalman Filter, being, therefore in the sequential methods category, but the typical ARAIM algorithm is still based on the weighted least squares residuals of the current time measurements, therefore, defined as a snapshot method. Although, there have been proposals of sequential based ARAIM, such as in [45], the standard approach is snapshot based and it will be briefly discussed here.

The development of ARAIM is closely related to the navigation integrity requirements for the aviation sector, improving on the operational requirements specified by the International Civil Aviation Organization (ICAO) Standards and Recommended Practices (SARP), with a target of reaching LPV-200[3] [46]. Some of the important integrity performance parameters for that standard are summarized in table II. To reach those requirements, and to overcome the limitations in the standard RAIM method, the ARAIM was designed for dual-frequency, multi-constellation signals, with vertical protection and multiple fault-modes detection capabilities [35]. While those features are meant to improve the integrity monitoring performance, they also increase the likelihood of satellite fault detection, posing a higher risk for the continuity of the navigation solution. For that reason, the use of methods that can exclude the faulty measurements from the overall solution have been investigated. In [47] the authors compares two ARAIM methods with fault detection and exclusion (FDE) capabilities, one based on the chi-squared test for the worst-case fault, and another relying on solution separation (SS). The chi-squared and SS are the two main approaches for RAIM algorithms, and extensive works, such as in [46], [35], [47], [37], [48] and [36], have been published with performance evaluation and proposed variations from these methods. Due to the mathematical complexity involved in the formulations, a comprehensive explanation of these methods is outside the scope of this review. The reader is advised to refer to the recommended works on the field for additional details.

Snapshot Position Bonding using Non-Gaussian Error Distribution and MCMC: The authors in [32] propose a new integrity monitoring method that derives a tight position bond for GNSS measurements, modeling the pseudoranges and carrier phase observation errors as accurate non-Gaussian distributions. Typical snapshot methods rely on Gaussian over-bounding, a technique that is unable to accurately represent the tail of the error distribution, which is particularly problematic for NLOS and multipath errors that might be outside the protection bound. Another popular approach is the use of sequential methods, based on EKF, which has obvious accuracy advantages due to the accumulation of measurement information. However, the EKF methods suffers to provide a rigorous position bounding, due to the time-correlated aspect of the errors, and they assume Gaussian distributions for the errors and state noises, which are not always true and can led inconsistent results depending on the design of the filter. To address these problems, the authors developed a patent pending alternative method based on Bayesian inference, called Single Epoch Position Bond (SEPB). The method extracts an accurate non-Gaussian error distribution, using corrected GNSS measurements provided by a nearby reference station, and derives a bond for the protection level using Markov Chain Monte Carlo (MCMC) with parallel interacting chains to enable multi-modal sampling from the error posterior probability density function. The method targets automotive applications, which requires very tight position

[3]LPV Stands for Localizer Performance with Vertical Guidance, and the LPV-200 is a standard with high integrity requirements.

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Ref.	Method	Data Source	Validation	Comment
[32]	Single epoch position bond (SEPB)	GNSS	Experimental	Accurate non-Gaussian modeling of the pseudorange and carrier-phase error distribution, with the position bound calculation using a Monte Carlo method to sample from that error distribution.
[33]	Kalman Filter based solution separation (KFSS) with sensor exclusion upon fault detection	GNSS, INS, LIDAR and camera integration	Simulation and experimental	The comparison of the method, using both tight and loosely coupled integration, with baseline ARAIM approach, shows a better performance in terms of PL.
[34]	Multi-constellation WLS residual-based RAIM	GNSS	Simulation	Considered the effect of the spatial distribution of the navigation constellation, optimizing the integrity solution to decrease the false detection probability while meeting the LPV-200 performance standards.
[35]	Multiple hypothesis solution separation (MHSS) ARAIM with FDE capability and an additional chi-squared test	GNSS	None	Step-by-step formal definition of a multi-constellation, multiple-threat, SS-based RAIM algorithm, with a discussion of possible improvements.
[36]	ARAIM	GNSS	Simulation	Modified the baseline ARAIM with an improved fault mode determination scheme, named Feedback Structure with Probability Accumulation (FSPA).
[37]	Constellation Weighted ARAIM	GNSS	Simulation	Evaluation of single satellite outage scenario in different constellations and proposal of a constellation weighted non-least squares position estimator, for using with the ARAIM method to improve the integrity under those scenarios.
[38]	Satellite Based Augmentation Systems (SBAS) based maritime vessel protection area concept	GNSS with SBAS corrections	Simulation	Use of GPS positional data, along with correction messages provided by the European Geostationary Navigation Overlay Service (EGNOS), and 2D contour model of a ship to calculate protection boundary geometry that realistically accounts for the ship's dimensions.

TABLE I: Summary of Recent Snapshot Integrity Monitoring Works

Integrity Metric	LPV-200 Value
Time to Alert	6.2 s
Horizontal Alert Limit	40 m
Vertical Alert Limit	35 m
Integrity Risk	2×10^{-7} per approach
Horizontal Accuracy (95%)	16 m
Vertical Accuracy (95%)	4 m

TABLE II: Integrity requirements for the aviation LPV200 standard. Table adapted from [49].

bonds, using GNSS corrections from an augmentation system or physical reference station.

There are two underlining assumptions for using the SEPB method: that accurate measurement errors models are available; and that the measurements from different satellites are statistically independent. The latter can not be satisfied for errors that affect multiple satellites at the same time, which is the case for NLOS errors. For that reason, a measurement selection process that excludes invalid outliers is proposed. The process includes the investigation of two distinct consistency checks, one based on the Random Sample Consensus (RANSAC) technique and another based on a nonlinear least squares fit over a window of data.

The method was verified with experimental data, amounting 36.5 hours in a wide variety of environments, and the results were compared to a EKF based algorithm, similar to the one presented in [50]. The performance of the method was summarized in terms of the percentage of position bounds that were below a given threshold, meaning, the percentage of epochs in which the algorithm was able to output position with a given accuracy level defined by the threshold. The results showed that the proposed SEPB was able to provide tighter bonds than the EKF based methods, having about 62% of bonds below 0.5 m, while the EKF variant had no bounds below that level.

Solution Separation with Sensor Exclusion KF based Integrity Monitoring: The authors in [33] propose an integrity monitoring strategy for all source navigation based on the least square form of the EKF, and solution separation with sensor exclusion in case of detected faults. Their Kalman Filter Solution Separation (KFSS) approach has no limitation in type and quantity of sensors, or in number of faults, and they improve on the standard EKF to enable the integrity risk to be directly traceable in time by establishing a direct mapping function between the final state estimation and all input parameters. To accomplish that, it is proposed a new measurement model in which the measurement vector and the propagated state are combined. The authors use the weighted least square form of the KF, instead of using the Kalman Gain to update the state, and they show the mathematical equivalence of that method. That strategy enables the use of a KF based estimator without the drawback of having time-correlated errors, which poses difficulties for the integrity risk and protection bounding calculations. For that reason, the proposed method is compliant with the snapshot principle, even thought it uses a recursive estimator.

The integrity risk is defined in terms of the position estimation error, the alert limit, defined by the user, and the protection level. Note that the integrity risk might be an integrity requirement for a certain application, but evaluating if the integrity solution is able to satisfy that requirement might be challenging. The authors proposed a methodology to establish a bound for the integrity risk, with a solution separation method that considers the sum of the individual integrity risks in each fault hypothesis and calculates the state estimation separately for each hypothesis. Then, a fault detector based on the calculation of the minimal detectable bias (MDB) is applied, and the associated protection level is calculated. The authors presents a detailed algorithm to use the method and provide all the necessary equations. A summary of the procedure is given in the flowchart in figure 5, adapted from the diagram in the original paper. Note how the specific integrity monitoring scheme developed in that work is different from the generic method presented in figure 4 at the beginning of this section, but still have a similar structure, specially considering that the matrices correction steps are a part of the estimation block. The original diagram in [33] has a reference for the necessary equations to perform each step.

The authors tested the performance of their methodology using simulations and a field-experiment. The simulation was conducted with two scenarios, one using a tightly coupled INS and GNSS navigation system, and the other using a loosely coupled INS, Real Time Kinematics (RTK), LIDAR and Visual Inertial System (VINS). The sensor integration schemes were conducted based on the demos provided in [51]. They compared the results in terms of root mean square error (RMSE) and

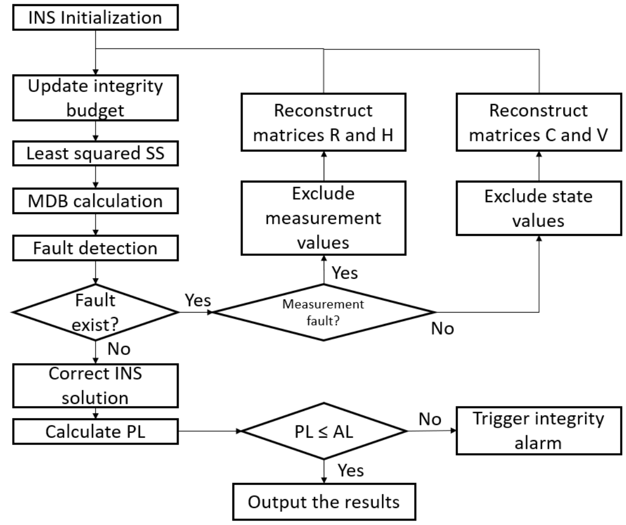

Fig. 5. KFSS integrity monitoring scheme. Figure adapted from [33].

horizontal and vertical protection levels to a baseline ARAIM method. The results showed the superiority of the KFSS method proposed, as the faulty sensors are excluded upon fault detection without loss of accuracy and the obtained protection levels were better than with the ARAIM. The field-experiment was conducted with a ground vehicle equipped with consumer grade IMU, GNSS, LIDAR and a fish-eye camera. A VINS-MONO algorithm was used to perform the integration of visual odometry, provided by the camera, with the IMU estimation to output an optimized localization result. In this way, the experiment used three independent sources of position data. The obtained results showed a very low position error, below 0.5 m, in each direction, and a HPL of less than 3.5 m and a VPL of less than 2 m in most cases.

The authors argue that the solution separation with sensor exclusion method proposed has two advantageous aspects: it is possible to analyze the impact of sensor fault on positioning result directly, without considering the measurement relevance inside a single sensor; and for a multi-sensor system, due to sensor exclusion the number of fault hypothesis considered is reduced, in comparison with measurement exclusion schemes. They propose using this method for safety-critical applications that uses multiple sources of navigation data, such as autonomous driving and unmanned aerial vehicles.

B. Sequential Methods

The sequential, or recursive, methods rely on a sequence of measurements to calculate the updated state vector and test statistic. In this way, instead of using redundant measurements to perform the estimation, these methods can use previous time measurements to update the estimation. Batch-based methods also rely on measurements from multiple time epochs, but differs from most sequential based algorithms by processing all these measurements together, or evaluating a number of epochs given a specified time window, typically being in the snapshot category. The use of Kalman Filter based innovation sequences to derive the test statistic is a common approach for sequential methods. Also, the integration of different sensor types, such as GNSS and INS, using a KF is possible with this strategy. These methods can have performance advantages in comparison to the snapshot approaches, being able to provide a better protection level and overall higher accuracy estimation of the quantity of interest. However, they are usually unable to detect slowly building faults and due to time-correlation the statistical analysis can be more complicated [33]. In particular, deriving the integrity risk and a tight bond for the protection levels can be difficult in sequential based methods.

The table III provides a summary of works featuring sequential integrity monitoring methods. Some of these references will be discussed in detail in this section.

Extended Kalman Filter with Interactive Multiple Model based Method for AIS data Positioning Integrity Monitoring: In [18], the authors propose an integrity monitoring scheme for the the positional information provided by the Automatic Identification System (AIS) data received from maritime vessels. The AIS data, which is broadcasted by vessels from a certain tonnage, gives important information for assessing the maritime traffic, giving periodic updates about the ships position. However, it is prone to faults, has a low update frequency and it is unreliable for collision avoidance. The integrity monitoring method proposed in the work is based on two different fault detection methods that use a test statistic derived from the innovation[4] of an Extended Kalman Filter (EKF), which is applied to the AIS positional information. The authors showed, by simulation and real-world results, that their suggested approach increases the integrity level of AIS data based positioning.

The EFK uses the course over ground (COG) and speed over ground (SOG) provided in the AIS data as inputs for two deterministic models in the prediction stage, namely, the constant velocity (CV) and constant turn ratio velocity (CTRV) which are integrated using the Interactive Multiple Model (IMM) framework [61]. The authors showed that by incorporating two complementary models to describe the vessel dynamics, one more suitable for straight line trajectory, CV, and the other being superior for describing maneuvering events, CTRV, the position error is minimized.

Moreover, the work compares the fault detection performance of two methods, the chi-squared test and the Generalized Likelihood Ratio Test (GLRT). The integrity monitoring scheme is based on the hypothesis test using these two methods, with test statistics derived from the IMM-EFK innovations at each step. The authors conclude that both chi-squared and GLRT methods are appropriate for failure detection in AIS. However, the GLRT was proved to be superior in isolating the time of failure, and therefore, worth the increased complexity associated with its implementation. Additionally, in the conclusion, the authors propose the idea of extending this study by fusing AIS and radar data to create a more reliable maritime surveillance system, improving safety by reducing the probability of collisions.

[4]The authors used the name residuals instead of innovation, which is very common on the literature. However, in this present work a distinction between the innovation and residual error is being considered, as shown in eq. 10 and 15, and therefore, the appropriate parameter name must be used.

Loosely Coupled BDS/INS Integrity Monitoring for Aircraft Applications, with multiple KF for the sensor integration and fault isolation: The work in [52] presents an integrity monitoring algorithm for a loosely coupled BDS (BeiDou Satellite Navigation System) and INS, using multiple Kalman Filters for integration and fault isolation of the measurements from redundant BDS receivers and INS units. The navigation system proposed is based on commercial aircrafts, that are normally equipped with two GNSS receivers and three INS units, and the goal is to develop a solution to enhance integrity monitoring for said application.

The measurements from the BDS and INS sensors are combined using a Kalman Filter in a loosely integrated scheme, where the INS calculation error is updated in a feedback loop. The fault detection is based on a chi-squared test using the KF innovation to form the test statistic. By using multiple filters, in the event of a fault, the faulty device can be isolated and the filter states restored to prevent fault propagation to the next states. The HPL and VPL are calculated at each step to verify the integrity algorithm performance and also to check its availability (if the HPL or VPL is above the alert limit, the integrity algorithm is not available). A convenient flowchart with the detailed fault detection processing and the schematic of the multiple KF and sensors architecture can be found in the original paper, in [52].

The authors verified their algorithm with a simulation, in which they obtained test data using a trajectory generator, a BDS, and a Strapdown Inertial Navigation System (SINS) simulator, and added artificial errors in the form of step and ramp disturbances, and their combination. The simulation results confirmed the adequate functioning of the their algorithm. A Monte Carlo simulation was conducted to verify the integrity risk, by running 10^6 random scenarios of different position information. The integrity monitoring scheme was applied to those scenarios to estimate the integrity risk. The results showed that only 2 exceptions where the alert limit was exceeded without detection occurred, indicating a very low integrity risk.

Landmark Reference Based Robot Positioning Integrity Monitoring: In [58] the authors propose an integrity monitoring method for robot localization in reference to established landmarks. They use the robot relative position measurement as input for an EKF, and then, evaluate the KF innovations with a fault detection scheme adapted from the chi-squared testing methodology presented in [62]. The landmark reference positioning is a type of fixed positioning technique that relies on feature mapping using objects that have a known position, defined as landmarks, to calculate the user relative position in regards to those. The technique requires sensors, such as LIDAR or cameras, that can be used for detecting the landmarks. The faults, modeled as deterministic shifts in the measurements means, occur when wrongly extracted features are identified as the mapped landmarks.

The authors present the integrity monitoring as an optimization problem in which the goal is to find the worst-case undetected fault that maximizes the estimation error. Since in a KF the error in the current state can be correlated to previous

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Ref.	Method	Data Source	Validation	Comment
[44]	Extended RAIM with EKF based GNSS/INS integration	GNSS/INS	Simulation	Use of accumulated pseudo and delta range measurements, INS driven dynamic model and GNSS/INS tightly coupled integration. The method works for detecting instantaneous bias but it is unable to flag slow growing errors.
[18]	Interactive Multiple Model (IMM) with EFK and Chi-squared and GLRT FD	AIS data	Simulation and experimental	Positional integrity monitoring of maritime vessels using AIS data. Two different dynamic models for ship movement are used and combined using the IMM framework and EKF.
[52]	Multiple KF with Chi-squared test	GNSS and INS	Simulation	Navigation solution for aircraft, with redundant GNSS receivers and INS sensors. Proposed a method for isolating faulty systems and to reconstitute (feedback reconstitution) the KF state after excluding the fault to maintain the availability of the integrity solution. Use of Monte Carlo (MC) simulation to verify the integrity risk.
[53]	KF adaptation of a Batch-based scheme, with residual based cumulative test statistic	GNSS	Simulation	The strategy enables the direct evaluation of the integrity risk. Integrity performance analysis for an aircraft approach and landing case, comparing the availability maps of the proposed method with standard techniques.
[54]	ARAIM with FDE and EKF based GNSS/INS tight integration	GNSS and INS	Simulation	Proposed method for meeting the high precision aircraft approach requirements in the CAT-I standard.
[55] and [56]	Cooperative integrity monitoring with EKF innovation-based Chi-squared testing that uses a global and local test statistic	GNSS and ultra wide band (UWB) inter-vehicle ranging sensor	Simulation	Strategy that combines the GNSS data from multiple vehicles and their respective distances from each-other, separating the errors into local and global components.
[57] and [58]	EKF with a sliding window Chi-squared innovation sequence based FD	LIDAR and IMU	Simulation and experimental	Robot localization safety based on landmark feature matching for GNSS-denied environments. Experimentally generated feature map, using trees as landmarks and data obtained from a fusion of IMU, GPS and LIDAR.
[59]	KF with chi-squared test and FDE	Integrated GNSS/INS	Simulation	Development of a analytical recursive expression for the worst case failure mode, and a computationally efficient integrity monitoring solution that uses a single KF for fault exclusion.
[60]	Extended H-infinity filter (EHF) for GNSS/INS integration, FD based on vehicle dynamic model and PL calculation using zonotopes	GNSS/INS	Experimental	The authors show, using data acquired from a land vehicle, that the EHF solution is more robust than the EKF for erroneous filter parameter initialization. They propose a non-probabilistic FD strategy to avoid statistical sensitivity issues.

TABLE III: Summary of Recent Sequential Integrity Monitoring Works

estimations, the authors propose evaluating the integrity in a user defined preceding horizon of size M, consisting of the range between the current epoch, k, and the epoch $k-M$. The integrity evaluation within a certain preceding horizon considers all fault hypothesis associated with each combination of landmark that could have been wrongly identified in that range.

Therefore, even for small horizons, the number of hypothesis could pose a significant computational burden. To solve that problem, the authors propose a hypothesis reduction strategy, monitoring only the faults that would have an occurrence probability higher than a predefined threshold. In their method, it is necessary to compute the probability of occurrence of each fault hypothesis, meaning that the probability of failure of each landmark association should be known. The authors assume those probabilities can be obtained from experimentation and that it is usually a low value, in the order of 10^{-3}.

Lastly, the proposed model was evaluated both in a simulated and real experimental environment. The simulation was conducted with three different values for the preceding horizon and the results confirmed that choosing a larger horizon reduces the integrity risk. The experimental map was generated using data fusion from IMU, Real Time Knematic (RTK) Differential Global Positioning System (DGPS) and LIDAR. The authors removed the DGPS data and artificially reduced the LIDAR range to conduct the actual integrity monitoring experiment. The test was conducted using tree trunks as landmarks and the robot followed a closed loop path between two sets of trees that were about 20 meters away. It was demonstrated that the reduction of the LIDAR range significantly increased the integrity risk, and the authors presented the contrasting results for two LIDAR ranges, in 20 m and 25 m. As expected, the results showed that the highest integrity risks were associated with the areas with fewer landmarks. The work can have significant impact for safety-critical applications, e.g. when mobile robots are operating among humans.

Batch-based Integrity Monitoring Adapted for Kalman Filter with Cumulative Test Statistic: The work in [53] proposes a integrity monitoring method using cumulative batch based Kalman filter that enables direct integrity risk evaluation, contrasting with most published methods that cannot accurately determine the integrity risk in real-time. The test statistic for fault detection is based on current and past-time KF residuals, which are defined as non-centrally chi-square distributed random variables. Since the residuals are proven to be independent from the state estimate error and that the current and past-time residuals are mutually independent, the test statistic can be recursively updated by adding the current residual contribution to a previously calculated weighted norm of past-time residuals. The approach is based on a batch Integrity Monitoring, in which the error estimation and fault detection methods are applied to a sequence of measurements over a finite window of time. The fact that the state estimation and the test statistic are independent and their probability distributions are known facilitates the evaluation of a tight bond for the integrity risk.

The authors provide an overview of a general batch based integrity monitoring method, first implemented in [63], including the mathematical details required to implement it. In the batch realization, all measurement and process equations are stacked in a single measurement equation, containing all state and measurement vectors within a specified time sequence. In that way, the number of measurements and states are equal to the size of these vectors multiplied by the size of the discrete time interval in which the batch realization is defined. The fault detection and the integrity risk evaluation is performed from the batch residual vector, defined as the difference between the batch measurement vector and the conditioned (by the measurement matrix) state estimate batch vector. Another fault-detection method, based on the forward-backward smoother (FBS), [64] and [40], is considered. The batch residual is partitioned into individual components at each sample time. Moreover, it should be noted that the starting point for the derivation of the cumulative KF-based integrity monitoring method presented in the work was motivated by the observation that the current-time component can be computed using a KF.

The cumulative KF-IM is based on the weighted norm of the current-time batch residuals, which is computed similarly as the innovation based test statistic used for chi-squared test presented in eq. 16. However, the authors use the residuals instead of the innovation because of the independence requirement, as the innovation is not independent from the state estimate. Therefore, the test-statistic used is the weighted norm of the current-time residuals, which is shown to enable a direct integrity risk bound evaluation. Instead of processing batch matrices, which is computationally expensive, the proposed recursive method only requires the storage of the weights and independent chi-square distributed random variables that are associated with the residuals. To evaluate the integrity risk bound, the authors propose a second KF, running in parallel, that uses the worst-case fault vector as input.

The method was evaluated in a precision navigation example for aircraft approach and landing, using simulated GNSS signals over a 5 by 7.5 deg latitude-longitude grid. The performance results were displayed as availability maps, which represents the percentage of time in which the integrity risk is below a predefined value associated with a certain location. The cumulative KF integrity monitoring method was compared to the batch-based approach, and also with a standard snapshot based algorithm. The availability map for the batch-based method was very similar to the KF approach, but the one based on KF was considerably more efficient, as the simulation running time for the higher sampling rates was several times lower than the batch-based method. The simulation also indicated a significant performance improvement of their method when compared to the standard snapshot algorithm, as in some locations the availability for the snapshot method was below 50% but with the cumulative KF algorithm it was never below 96%.

Collaborative Integrity Monitoring for Urban Transportation with Inter-vehicle communication: The authors in [55] and [56] propose a collaborative integrity monitoring strategy for vehicular navigation in dense urban areas, where using data outputs from multiple vehicles can effectively increase the detection of faulty GNSS measurements due to issues such as NLOS. The paper in [56] is an updated extended version of the work presented in [55]. The cooperative positioning method is based on decentralized Kalman Filter and innovation monitoring, which is applied to the measurements of a GNSS receiver, and a ultra wide band (UWB) transceiver, the inter-vehicle ranging sensor which is also responsible for the cooperative vehicular communication.

The measurement model proposed considers a separation between the common and specific types of errors, that are associated with errors that are common for all sensors in the area, or specific for one particular sensor. For the GNSS receiver, the common errors could be associated to tropospheric and ionospheric delays, ephemeris error and or satellite failure. The specific errors would be mainly due to NLOS or multipath issues, which are also issues that can affect the UWB measurements. The GNSS and UWB data are fused using an EKF and the chi-squared test is applied to the innovation, which is decomposed into global and local parcels associated with the common and specific errors.

Since different vehicles might track different satellite and ranging data, the Cooperative Integrity Monitoring (CIM) uses the concept of a *all-in-view* set, considering the group of satellites and UWB that is communicating with at least one of the collaborator vehicles. Therefore, the innovation for a given vehicle is the sum of the global innovation, which considers the errors in the *all-in-view* set, and the local innovation. That error metric is represented by a multi-dimensional Gaussian distribution with zero mean in the normal case, and non-zero mean for the faulty scenario. A diagram with an overview of the proposed integrity monitoring architecture is provided in fig. 6.

Based on the common and local innovations and the measurement error covariance matrices, the global and local test statistics are defined, following a chi-squared distributions with the number of degrees of freedom matching the corresponding innovation vectors sizes. The detection threshold is conditioned to a false alarm probability which should be a set requirement for a given navigation application. When a test statistic, associated either with the global or local errors, exceeds the detection threshold, a fault is detected. However, for fault exclusion, the authors rely on a greedy search method that is explained in [65], where in each fault exclusion iteration the measurement that has the largest effect on the test statistic is excluded.

In [55] the authors conducted simulations with GNSS only and GNSS plus UWB measurements under heavy GNSS multipath scenario to evaluate the CIM performance. For the GNSS only simulation, the results were compared with a baseline RAIM method, showing that the proposed CIM is more sensitive to faulty observations, having flagged 98.7 % of the GNSS errors, while the RAIM only detected 86.4 %. For the full simulation, with both GNSS and UWB measurements, a comparison with a baseline RAIM is not possible. However, the CIM was able to detect 98.5 % of the faulty measurements from both GNSS and UWB. The results were compared with and without the fault exclusion algorithm and the conclusion is that fault exclusion is necessary for maintaining position accuracy. The simulations conducted in [56] were more comprehensive, adding a comparison with the Collaboration-enhanced Receiver Integrity Monitoring (CERIM) presented in [66] and evaluating the common and specific errors separately. The performance under a more realistic dataset was evaluated, using a Navigation Constellation Simulator for the GNSS and UWB measurements containing real field trial noise. The simulation results showed that the proposed CIM achieves higher detection performance than the other methods in all investigated scenarios.

C. Hybrid and Multi-Method Integrity Monitoring

This section provides an overview of works that have used multiple integrity monitoring techniques, either as part of the same integrity solution, or as a means of performance comparison of different approaches for a specific application. Particularly for more complex sensor systems, it might be advantageous to combine different snapshot and sequential methods as a part of the overall integrity solution. A summary selected works that fit in this category is provided in the table IV.

Works Featuring Comparisons of Different Methods: In many works, such as in [55], [48], [47], [18] and [53], there are performance comparison of different approaches, which are interesting to assess the differences between different methods in a given scenario. It is important to point out that the results from such comparisons are biased by the setting, instrumentation or simulation strategy, choice of variables, etc. Therefore, they are not suitable so state objectively that one method is better than another. Nevertheless, these comparisons are useful when considering specific applications and are able to highlight strengths and weaknesses of the different techniques being addressed. For that reason, an overview of some interesting integrity performance comparisons found in the literature will be given here.

In [48] a formal comparison between the residual-based (RB) RAIM, which uses a single test-statistic, and the solution-separation (SS) RAIM, that has a test-statistic for each fault mode/satellite, was made. The authors showed that, although the SS approach has a superior performance, the RB is able to provide a tighter bond for the integrity risk. In [18], the IMM-EKF approach is used with two different fault detection strategies, namely the chi-squared test and the GLRT. For the AIS localization based solution investigated in the work, the two FD methods had comparable result. Although the GLRT was able to provide a slightly more robust solution, considering the much easier implementation, the chi-squared test performed well. The work in [50] uses a KF adaptation of the traditional snapshot RAIM with solution-separation and with the sum of the squared residuals FD approaches. The two strategies are compared using data from experiments with ground vehicle in a sub-urban area and with dynamic flight. The results showed that the solution-separation method is able to provide considerably lower protection levels, but the cost of running parallel filters for that approach has to be considered. In [11], the authors compare the performance of different snapshot, LS residual-based, and sequential, EKF innovation based, methods for GNSS integrity monitoring in harsh urban environments. They apply two different strategies for the characterization of the measurement errors, one based on the carrier-power to noise density ratio (C/N_0) variance model proposed in [73], and their own hybrid model, named urban multipath model (UMM), described in a previous work [74]. Additionally, the authors compared the results evaluating the

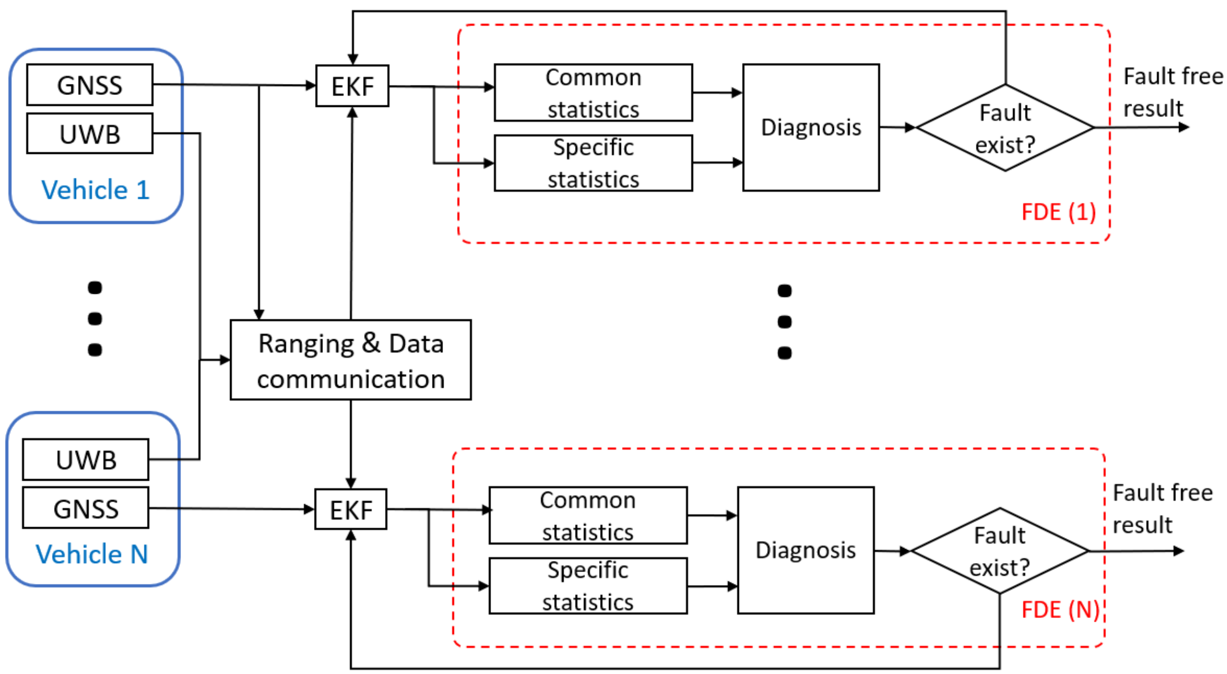

Fig. 6. Overview of the architecture of cooperative integrity monitoring solution. Diagram adapted from [56].

cumulative distribution function of the horizontal protection level derived from the various approaches. The results showed that the weighted version of the EKF with the UMM has the best performance, followed by the WLS also with the hybrid UMM. The classical EKF and LS methods had almost identical worse performances. In [60], the authors compared the standard GNSS/INS EKF integrated integrity monitoring scheme with a novel approach based on the Extended H-infinity Filter (EHF) and PL calculation using zonotope. The comparison is made for the scenarios in which the filters are initialized with bad parameters, in which the EHF is clearly advantageous. Instead of using the standard innovation based test statistic derived from the EKF, the authors propose a FD strategy that considers a dynamical model of the vehicle to avoid statistical sensitivity in the FD threshold calculation. Unlike the KF, the H-infiniy filter does not require Gaussian process and measurement noises, as those variables can follow an unknown statistical distribution.

PNT Integrity Monitoring Scheme for Maritime Navigation: The work in [72] presents a concept for an integrated Position, Navigation and timing (PNT) unit to be used on-board of vessels, relying on multiple sensors to provide accurate relevant position, navigation and timing data for maritime applications. To ensure the reliability of the information, the authors propose an integrity monitoring scheme on an architectural level, with different methods being applied to different sensors. Although the methods proposed are not a novelty, the use of multiple integrity monitoring techniques in a system level perspective is an interesting approach that can provide useful insights for designing integrity monitoring schemes in multi-sensor applications.

The PNT unit can be comprised of different sensors, but should be able to provide the following data: the vessel position, containing the latitude and longitude values, typically measured by a GNSS receiver but also tracked by a IMU in small time windows; the Under Keel Clearance, which is the distance between the lowest point of the ship and the ground of the sea, measured with a sonar sensor; the velocity vector, with the magnitude given by the Speed over Ground (SOG), and the direction by the Course over Ground (COG), which can be given by GNSS data and the IMU; the attitude, giving the orientation of the vessel relative to the true north, which can be measured by a gyrocompass and IMU; and timing, in UTC format, also given by the GNSS signal. The proposed PNT unit would have an integrity solution that monitors the information from each sensor, giving timely integrity messages to the user. A warning would be issued in case the accuracy of any given information is below an alert limit threshold, and therefore, the system would require a real time error estimation of all sensor relevant data.

The generic integrity monitoring steps for an Integrated Navigation System uses plausibility, validity and compatibility checks, respectively, if the data is within an acceptable range, with appropriate format, and with no discrepancies with redundant measurements of different sensors. For the PNT, the authors suggest a more comprehensive three steps integrity monitoring scheme, comprised of individual sensor data tests, compatibility checks for similar data of different sensors, and a fault detection after an integration algorithm that fuses the available data. The proposed strategy uses RAIM in the GNSS data to check for satellite faults, performs plausibility checks to the gyrocompass, speed log and IMU data, and also compares the similar variables with compatibility checks. A KF is used for integration, and multiple fault detection approaches that uses the KF output are suggested, including:

Ref.	Method	Data Source	Validation	Comment
[47]	Chi-squared and SS based RAIM with FDE	GNSS	Simulation	Model development for both chi-squared and solution separation test statistics, with derivations for faulty measurement detection and exclusion. Performance comparison between the two approaches indicated that the chi-squared method is able to provide a tighter protection bound, but at the cost of almost five times higher computational burden.
[67]	Fixed Lag Smoothing pose estimator with solution separation based FD	Ranging and odometer sensors	Simulation	Robot localization safety based on landmark feature matching. Comparison of the integrity risk bound using solution separation and a chi-squared integrity monitoring methods.
[11]	Comparison of snapshot Weighted Least-Squares residuals and sequential weighted EKF innovation	GNSS	Real Data Simulation	Error characterization for improved accuracy in urban environments, and use of the Danish Reweighting method, [68], for FDE.
[69]	EKF based sensor integration with a comparison of three different methods to compute the PL	GNSS, IMU and Odometry	Experimental	Evaluation of different integrity concepts for autonomous driving, under four different scenarios (airfield track, highway, country road and urban streets). Comparison of ARAIM, Kalman Integrated Protection Level (KIPL, based on the patent [70]), and the PL derived directly from the KF standard deviation.
[71]	Vector Delay Frequency Lock Loop (VDFLL) and comparison of RAIM and Isotropy-Based Protection Level (IBPL) techniques	Integrated GNSS/INS with camera aid	None	Fisheye camera based GNSS masking detection, with satellite exclusion based on sky visibility. The VDFLL tracks multipath errors and incoherent GNSS pseudo-range values.
[72]	Multi strategy, including plausibility and compatibility checks, RAIM and KF based FD approaches	Multi-sensors from a PNT system	None, architectural concept	Proposes using the classic snapshot RAIM for GNSS and KF bias, innovation and residual based FD for the integrated data from multiple sensors.

TABLE IV: Summary of Recent Multi-method Integrity Monitoring Works

- bias check, that monitors the errors in the navigation parameters against the maximum error specified by the sensor manufacturer;
- innovation filtering, that is sensitive to sudden large value discrepancies;
- innovation sequence monitoring, that detects smaller deviations over time;
- and residual based approaches, similar to innovation filtering and sequence monitoring.

It is important to note that the PNT unit was not implemented and the authors state that the work was a starting point towards the realization of such unit. The integrity monitoring strategy presented, although specific for that PNT unit, can be adapted for other multi-sensor systems in other applications and was, therefore, worth reviewing in this work.

D. Alternative methods and Integrity Aspects in other fields

As previously discussed, the research in the integrity monitoring field is closely related to navigation systems and the developed techniques are almost solely applied to improve and assess the integrity of positioning solutions. However, the integrity assessment goal is not exclusive of navigation systems and different strategies are used in other areas. Some examples of these strategies are:

- Data integrity checks based on logic formalism, and/or heuristic-rules, [75], [76] and [77];
- Data integrity verification based cyber-security techniques, [78] and [79];
- System integrity evaluation of infrastructures using the Analytical Hierarchy Process (AHP) and Key Performance Indicators (KPIs) [80];
- Data driven FD and fault diagnosis for industrial process monitoring, [81] and [82];

- Authentication protocols, cryptography methods, and software security tests for database and computer systems integrity assessment [83], [84] and [85].

The line between sensor integrity monitoring and data integrity might not be clear when the data of interest is being provided by sensors. For instance, a data integrity evaluation method for a Internet of Things (IoT) device, from which the information is being provided by one or multiple sensors, can be considered as a sensor integrity monitoring technique. However, there is typically a distinction between these two approaches. Integrity monitoring is concerned about the accuracy of sensor measurements, and data integrity simply checks for the validity of the sensor data itself, often disregarding any accuracy issues that may arise due to various sources of failures. Nevertheless, both strategies are important for guaranteeing the integrity of the sensor information, and therefore, selected works that presents data integrity solutions will be reviewed here.

With these considerations, this section aims to provide an overview of integrity evaluation techniques that are outside the typical navigation-based integrity monitoring approach. The idea of this overview is to foster the flow of multi-disciplinary insights for the development of new integrity monitoring strategies, aiming for higher safety and and resilience in the sensor systems operating in various areas. A summary of the reviewed works in this category, along with additional references that will not be discussed in detail, is provided in the table V.

Sensor Data Integrity Monitoring based on Heuristic Rules: In [76], a methodology for data integrity monitoring, applicable to IoT sensors, is presented. The strategy is based on a set of heuristic rules in combination with a variable-length data monitoring window (VLDMW) control mechanism that is able to recover from faulty data. The heuristic rules for sensor data integrity check are the following:

- Non-overflow: valid range check for the data fluctuation, according to the intrinsic characteristics of the sensor and monitored quantity;
- Inertia: assuming a high sampling rate, the variations between consecutive measurements should be small;
- Inequality: assuming a high enough accuracy level, it is unlikely that consecutive measures would be equal, as there should be a persistent random noise that would make the observations slightly different.

A failure model comprised of three types of failures, namely format, timing and value failure, and their superposition, is considered. Each data point, corresponding to a sensor measurement, is checked for format and timing failures and in case those faults are detected the faulty data is flagged. Next, a recovery strategy, using either interpolation or the proposed VLDMW method depending on the number of consecutive faulty points, is used. In summary, the VLDMW method is a adjustable length median filter that is applied to the flagged data points recursively until the faulty data is recovered. The authors provide a flowchart and a practical example that fully explains the method, but for the purpose of this review, a comprehensive explanation of the method will not be given.

The data integrity monitoring strategy was verified with both simulation and experimental results. The tests were made using a IMU unit, containing 3-axis magnetometers, gyroscope and accelerometers, in both static and dynamic scenarios. Different types of data failures and abnormalities, such as abrupt environmental changes, magnetic interference and loose data transmission connectivity, were introduced. The results showed that the proposed method has good robustness for detecting failures and recovering the data. Additionally, the performance of the strategy was strictly evaluated with turntable experiments, in which precise centripetal forces were introduced in a controlled manner. The root mean squared error (RMSE) of each sensor was calculated and compared with and without the data integrity method. The results showed that the RMSE with the data integrity method was, overall, orders of magnitude lower than without the use of the technique.

AIS Data Integrity Assessment for Maritime Anomaly Detection: The authors in [75] developed a AIS data integrity assessment method that uses logic rules, built from the case study specifications in conjunction with expert knowledge. The strategy relies on verifications that would trigger situation-specific alerts in case issues are found. The verification rules, divided into four layers of complexity, were established to assess the correctness of information, considering 935 integrity items were identified in AIS data. The integrity assessment was conducted in a sequential manner according to the layers, and considering the 27 different types of AIS messages, each containing several data fields. The summary of the four-order assessment is as follows:

1) Independent individual data field verification;
2) Independent individual message verification;
3) Grouped comparison of one or several fields of all messages of the same type;
4) Grouped comparison of several fields of all messages of all types.

The authors proposed the use of predicate logic to determine the integrity status of each item associated to the AIS messages. The logic relies on the corresponding data field values, the syntax and expert knowledge inference, and is able to assign a Boolean value for the integrity of each item in a rigorous and unambiguous manner. These integrity checks are constructed from logic statements about each data field or a combination of fields, being grouped into families of items which have been presented in detail in the original paper. A summary of these categories of integrity items, linked to the four-order assessment, is given in table VI, adapted from [75]. Then, a flag system, related to the integrity items, is proposed to highlight anomalies in the AIS data.

The authors have implemented and tested their data integrity monitoring system using about 24 million AIS messages, collected over a period of 6 months, and with added controlled degradation to evaluate rare occurring behaviours. The verification system was implemented in a web-based interface that displays the vessel traffic along with AIS messages that have been flagged with some integrity issues.

Ref.	Method	Data Source	Validation	Comment
[75]	Data integrity assessment based on predicate logic and rules defined by expert knowledge	AIS Data	Simulation with Real Data	Development of a GUI containing the vessels position in a map, with a flag system to indicate integrity issues in the respective AIS messages.
[76]	Data integrity assessment and recovery based on heuristic rules and a control strategy called variable-length data monitoring window	IMU	Simulation and Experimental	The method enables the detection and recovery from format, timing and value failure and can be, theoretically, applied to any digital sensor. Experiments with a IMU unit under static and controlled dynamic conditions are used to validate the strategy.
[86]	Continuity, plausibility and consistency checks based on sequential likelihood ratio	Multi-sensor, with AIS data, RADAR and camera	Simulation	Proposal of a multi-sensor verification architecture for sensor fusion with an example in maritime surveillance.
[87] and [88]	Multi-modal cross consistency integrity assessment	Spatial data sources (maps, camera and GNSS)	Simulation with real data	Alternative method for vehicle localization in highway and urban (extended the work in [88]) scenarios. Based on the comparison of the consistency fit between various data sources and the assignment of integrity markers to each source based on the consistency results.

TABLE V: Summary of Recent Alternative Integrity Monitoring Works

Integrity Item Family	Assessment Level(s)	Description
Conformity issues	1 and 2	Non compliance to the specifications
Inconsistent field values	2, 3 and 4	Inconsistency between two or more values, from the same or different messages
Data field evolution	3 and 4	Incoherent evolution of the value of a data field in several messages
Unusual values	3 and 4	The value of one given field is not in accordance with the usual values of the field when sent by the same vessel in other messages
Overabundant communication	4	Two stations communicate too often between themselves
Unexpected data field change	2, 3 and 4	The value of one given field has changed unexpectedly in comparison to the former message sent by the vessel

TABLE VI: Families of integrity items and their respective assessment levels. Table adapted from [75]. The original table contains more items.

IV. Conclusion

The rapid technological development in the past few decades increased the range of application for human and machine interactions. Through the use of advanced computation and various sensors, these interactions are becoming automated, requiring less or no human supervision. In order to enforce safety, this technological trend requires strict requirements regarding the trustworthiness of the sensor information, enforcing the relevance of the research in sensor integrity monitoring. The integrity monitoring methods, that have been traditionally developed for GNSS positional integrity in the aviation sector, are now evolving and being adapted to autonomous vehicles in urban environments, combining the information from various sensors to provide a high integrity positional solution under challenging scenarios. However, the adaptation of these methods for applications outside the navigation field has not seen the same interest.

As our reliance in technology increases, assessing and improving the integrity of information, in particular the one provided by various sensors, is of great importance. With this motivation, this work has provided an overview of the recent advances in the sensor integrity monitoring methods. A theoretical background section, with the fundamental topics for understanding these methods, was given with the intent of introducing this topic for a broader audience, as the discussions on the integrity monitoring field have been highly specialized by GNSS experts and users. In order to provide insights for the development of sensor integrity assessment methods for a wider range of applications, a review of alternative methods outside the navigation field was given, including selected works featuring strategies that assesses the correctness and veracity of the data. While sensor integrity monitoring techniques focus on accuracy of the measurements through statistical analysis and error distribution, a strategy that combines a data integrity verification could be beneficial for improving the integrity of the sensor information. As the complexity of systems relying on sensor information increases, and the human interactions with these systems becomes more frequent, the development of new integrity monitoring solutions is becoming more important. The vast research that was made into the navigation field can serve as a basis for expanding the integrity monitoring field for other areas. The overview provided in this work will hopefully serve as a foundation to facilitate that expansion.

V. Nomenclature

ADR Acumulated Delta Range
AHP Analytical Hierarchy Process
AIS Automatic Identification System
AL Alert Limit
ANN Artificial Neural Networks
ARAIM Advanced Receiver Autonomous Integrity Monitoring
BDS BeiDou Navigation Satellite System
CERIM Collaboration-enhanced Receiver Integrity Monitoring
CIM Cooperative Integrity Monitoring
COG Course over Ground
CV Constant Velocity
CTRV Constant Turn Ratio Velocity
DGPS Differential Global Positioning System
EGNOS European Geostationary Navigation Overlay Service
EHF Extended H-infinity Filter
EKF Extended Kalman Filter
ERAIM Extended Receiver Autonomous Integrity Monitoring
FBS Forward-backward Smoother
FD Fault Detection
FDE Fault Detection and Exclusion
FSPA Feedback Structure with Probability Accumulation
GLRT Generalized Likelihood Ratio Test
GNSS Global Navigation Satellite System
HMI Hazardous Misleading Information
HPL Horizontal Protection Level
IBPL Isotropy-Based Protection Level
ICAO International Civil Aviation Organization
IMM Interactive Multiple Model
IMU Inertial Measurement Unit
INS Inertial Navigation System
INU Inertial Navigation Unit
IoT Internet of Things
KF Kalman Filter
KIPL Kalman Integrated Protection Level
KFSS Kalman Filter Solution Separation
KPI Key Performance Indicator
LRT Likelihood Ratio Test
LS Least Squares
MC Monte Carlo
MCMC Markov Chain Monte Carlo
MHSS Multiple Hypothesis Solution Separation
MDB Minimal Detectable Bias
NLOS No-line-of-sight
PCA Principal Component Analysis
PL Protection Level
PLS Partial Least Squares
PNT Position, Navigation and timing
RANSAC Random Sample Consensus
RAIM Receiver Autonomous Integrity Monitoring
RB Residual Based
RTK Real Time Kinematic
RMSE Root Mean Squared Error
SARP Standards and Recommended Practices
SBAS Satellite Based Augmentation Systems
SI System Integrity
SINS Strapdown Inertial Navigation System
SEPB Single Epoch Position Bond
SOG Speed over Ground
SoS System of Systems
SS Solution Separation
SVM Support Vector Machine
UMM Urban Multipath Model
UWB Ultra Wide Band
VDFLL Vector Delay Frequency Lock Loop
VINS Visual Inertial System
VLDMW Variable-length Data Monitoring Window
VPL Vertical Protection Level
WLS Weighted Least Squares

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