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Author(s): Elsanhoury, Mahmoud; Koljonen, Janne; Välisuo, Petri; Elmusrati, Mohammed; Kuusniemi, Heidi

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Survey on Recent Advances in Integrated GNSSs Towards Seamless Navigation Using Multi-Sensor Fusion Technology

Mahmoud Elsanhoury, Janne Koljonen, Petri Välisuo, Mohammed Elmusrati, Heidi Kuusniemi, *University of Vaasa*

BIOGRAPHY

Mahmoud Elsanhoury is a doctoral student majoring telecommunications engineering at the University of Vaasa. He obtained his MSc degree in technology from Vaasa University in 2018, and BSc degree in telecommunications engineering from Alexandria University (Egypt) in 2013. His research interests are ultra-wideband localization, Kalman filters and machine learning algorithms.

Janne Koljonen was born in 1980. He received his M.S. and Ph.D. degrees in automation technology from the University of Vaasa, Finland, in 2004 and 2010, respectively. He has been working with the University of Vaasa since 2002. He is the author of more than 40 scientific articles.

Petri Välisuo is an Associate Professor at the University of Vaasa, Finland. He received MSc. in computer science from Tampere University of Technology and DSc. in automation technology from University of Vaasa, in 1996 and 2011 respectively. He co-authored 27 peer reviewed. His research interests cover machine learning, IoT, and positioning methods.

Mohammed Elmusrati received the D.Sc. degree in Control Engineering from Aalto University -Finland in 2004. Currently, he is a Full Professor in Communication, Automation, and Digitalization at University of Vaasa, Finland. Elmusrati is interested in wireless communications, machine learning, and applications. He has published more than 145 papers, books, and book chapters.

Heidi Kuusniemi is the Director of Digital Economy at University of Vaasa and a Professor at the Finnish Geospatial Research Institute. Possess more than 18 years of experience in research and development of positioning technologies. In 2016, she was selected as one of the 50 most inspiring technology leaders in Nordic countries.

ABSTRACT

During the past few decades, the presence of global navigation satellite systems (GNSSs) such as GPS, GLONASS, Beidou and Galileo has facilitated positioning, navigation and timing (PNT) for various outdoor applications. With the rapid increase in the number of orbiting satellites per GNSS, enhancements in the satellite-based augmentation systems (SBASs) such as EGNOS and WAAS, as well as commissioning new GNSS constellations, the PNT capabilities are maximized to reach new frontiers. Additionally, the recent developments in precise point positioning (PPP) and real time kinematic (RTK) algorithms have provided more feasibility to carrier-phase precision positioning solutions up to the third-dimensional localization. With the rapid growth of internet of things (IoT) applications, seamless navigation becomes very crucial for numerous PNT dependent applications especially in sensitive fields such as safety and industrial applications. Throughout the years, GNSSs have maintained sufficiently acceptable performance in PNT, in RTK and PPP applications however GNSS experienced major challenges in some complicated signal environments. In many scenarios, GNSS signal suffers deterioration due to multipath fading and attenuation in densely obscured environments that comprise stout obstructions. Recently, there has been a growing demand e.g. in the autonomous-things domain in adopting reliable systems that accurately estimate position, velocity and time (PVT) observables. Such demand in many applications also facilitates the retrieval of information about the six degrees of freedom (6-DOF - x, y, z, roll, pitch, and heading) movements of the target anchors. Numerous modern applications are regarded as beneficiaries of precise PNT solutions such as the unmanned aerial vehicles (UAV), the automatic guided vehicles (AGV) and the intelligent transportation system (ITS). Hence, multi-sensor fusion technology has become very vital in seamless navigation systems owing to its complementary capabilities to GNSSs. Fusion-based positioning in multi-sensor technology comprises the use of multiple sensors measurements for further refinement in addition to the primary GNSS, which results in high precision and less erroneous localization. Inertial navigation systems (INSs) and their inertial measurement units (IMUs) are the most commonly used technologies for augmenting GNSS in multi-sensor integrated systems. In this article, we survey the most recent literature on multi-sensor GNSS technology for seamless navigation. We provide an overall perspective for the advantages, the challenges and the recent developments of the fusion-based GNSS navigation realm as well as analyze the gap between scientific advances and commercial offerings. INS/GNSS and IMU/GNSS systems have proven to be very reliable

in GNSS-denied environments where satellite signal degradation is at its peak, that is why both integrated systems are very abundant in the relevant literature. In addition, the light detection and ranging (LiDAR) systems are widely adopted in the literature for its capability to provide 6-DOF to mobile vehicles and autonomous robots. LiDARs are very accurate systems however they are not suitable for low-cost positioning due to the expensive initial costs. Moreover, several other techniques from the radio frequency (RF) spectrum are utilized as multi-sensor systems such as cellular networks, WiFi, ultra-wideband (UWB) and Bluetooth. The cellular-based systems are very suitable for outdoor navigation applications while WiFi-based, UWB-based and Bluetooth-based systems are efficient in indoor positioning systems (IPS). However, to achieve reliable PVT estimations in multi-sensor GNSS navigation, optimal algorithms should be developed to mitigate the estimation errors resulting from non-line-of-sight (NLOS) GNSS situations. Examples of the most commonly used algorithms for trilateration-based positioning are Kalman filters, weighted least square (WLS), particle filters (PF) and many other hybrid algorithms by mixing one or more algorithms together. In this paper, the reviewed articles under study and comparison are presented by highlighting their motivation, the methodology of implementation, the modelling utilized and the performed experiments. Then they are assessed with respect to the published results focusing on achieved accuracy, robustness and overall implementation cost-benefits as performance metrics. Our summarizing survey assesses the most promising, highly ranked and recent articles that comprise insights into the future of GNSS technology with multi-sensor fusion technique.

I. INTRODUCTION

Global navigation satellite systems (GNSSs) is a key element for location-based services (LBS) that are playing an important role in today's smart cities and the futuristic internet-of-things (IoT) applications. With the quantitative and diversative growth of GNSSs constellations, the positioning, navigation and timing (PNT) capabilities were strengthened to new frontiers.

Seamless navigation is mostly demanded in various application where system integrity and reliability are paramount. Conventional GNSS stand-alone methodologies may fail to provide the required seamless navigation thus the researchers developed additional techniques to assist GNSSs, some are illustrated in figure 1.

The integrity of GNSS navigation systems, as defined by [1], is the trustworthiness of the information provided by the navigation engine. Additionally, the performance of GNSSs can be assessed using a pyramid-like scheme with system accuracy as the baseline, integrity as the second metric, continuity as the third, and availability as the peak paramount. System accuracy is the degree of conformance of the estimated positioning values to the ground truth. Continuity is the probability of the system to maintain the desired service level within the operation period while availability is the percentage of time in which the navigation system is usable.

GNSS performs well in non-urban environments mainly due to the user visibility from numerous satellites (more than four) in addition to the satellite-based augmentation system (SBAS) which ensures GNSS integrity, corrections and redundancy. While in urban environments, satellites visibility becomes a challenge hence, additional measures are required to maintain seamless navigation. The two major factors of signal impairments that contribute to the overall error in GNSSs are the multipath components and the non-line-of-sight (NLOS) occurrences. The multipath effects are mitigated via various techniques found in figure 1. Moreover, there exist few methods to combat or compensate the NLOS situations, the most highlighted method among them that provides the best compromise is the use of multi-sensor fusion technologies.

Multi-sensor fusion technology is becoming abundant in the navigation literature due to its many advantages. The use of multiple sensors for navigation can increase the positioning accuracy by mitigating the errors arouse from sensors thus increases the reliability of the system. Moreover, in some cases, multi-sensor fusion implementations can be presented as low-cost system in sensitive applications that require precision by utilizing low-cost multi-sensors however that can be on the account of computational complexity.

In this article, we survey the recent literature on seamless GNSS navigation in the context of multi-sensor fusion technique. After the introductory section, in section II, we provide brief descriptions about the principles of multi-sensor fusion, highlighting the structure of the fusion process, the commonly used sensors and algorithms. In section III, we present the most recent advances in the multi-sensor GNSS literature in a span of the previous five years focusing on the implementations in autonomous driving, pedestrian tracking and GNSS-denied situations. The selection criteria of articles were based on impact, relevance, higher ranking in the Finnish national system [2], novelty and citations score. Nevertheless, some older articles were also included in this review due to their importance and unchanged scientific principles.

II. MULTI-SENSOR FUSION APPROACH

Sensor fusion is a computational procedure to combine the measurements from multiple sources such that the output information after fusion is maximized. The sensor fusion technique is adopted in dynamic systems that require more precision and accuracy due to its capability of mitigating measurements errors which combat environmental impairments, an example is illustrated in figure 2. Moreover, the use of multi-sensors that complements each other (e.g. position and attitude) yields the best possible

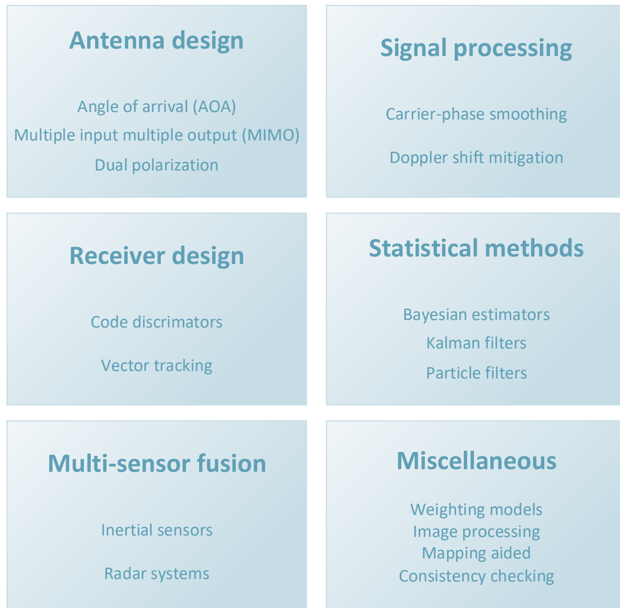

Figure 1: Approaches for multipath mitigation in GNSSs (adapted from [1])

results for PNT- based applications.

As sensor technology becomes more sophisticated (and its erroneous nature), multi-sensor fusion has been trending in recent years. In general, the reliance on multiple measurement devices in positioning applications will result in fewer uncertainties and greater reliability and accuracy than depending on a single measurement sensor [3].

The multi-sensors integration architecture may follow three schemes: loosely coupled (LC), tightly coupled (TC) and ultra-tightly coupled (UTC) as described in [4–6]. The LC system is the simplest architecture that provides good redundancy based on the duplicated measurements but requires good satellites visibility (four at least). The TC system can maintain navigation even when satellites visibility is poor (fewer than four) besides having better accuracy and immunity to jamming consequently the TC is widely adopted. In the UTC system, the GNSS receiver tracking loop is aided by a replicated software-defined radio (SDR) receiver that correlates and smooths the error between the received signal and the locally generated one.

1. Structure of the multi-sensor fusion approach

Numerous tracking systems can be fused with GNSSs to provide more accurate and reliable estimations. Common examples of these systems are radars, inertial navigation systems (INSs), inertial measurement units (IMUs), dead reckoning (DR) and computer vision (e.g. cameras). The optimal positioning estimations that result from fusing multiple positioning methods follow a unified framework, which is described in figure 3.

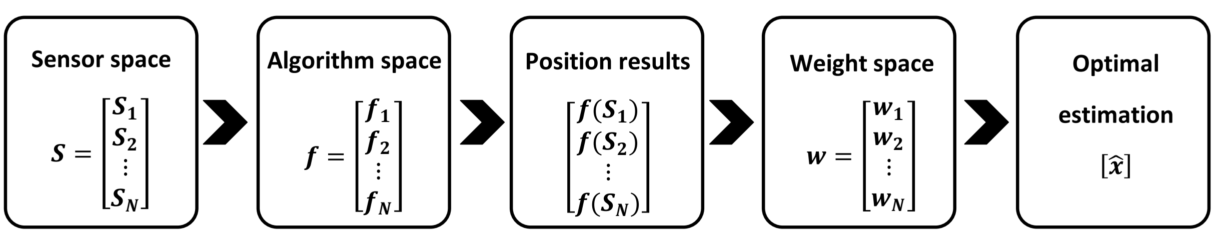

Figure 3: Fusion-based positioning framework (adapted from [3]).

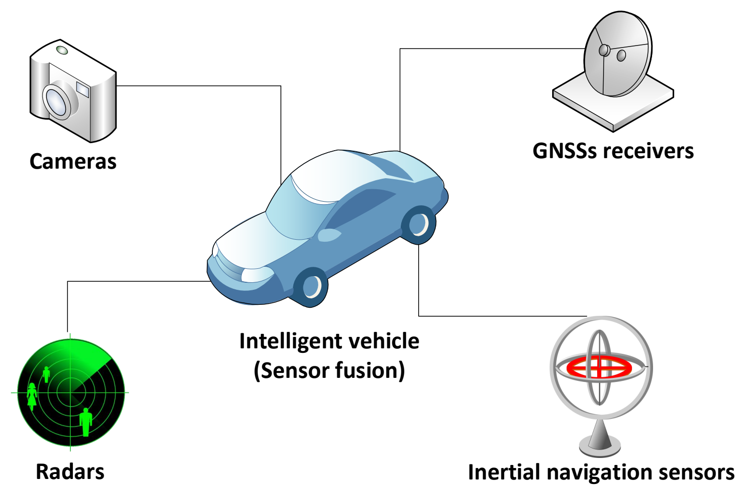

Figure 2: Illustration depicting the elements of multi-sensor system in intelligent vehicles.

In figure 3, the multi-sensor fusion framework comprise N sensors and same number of algorithms in which the PNT solution is obtained by solving local sensor data with the respective local algorithm. After that, a master fusion algorithm that comprise the weights vector of each sensor is responsible for fusing all input data to achieve the most optimal solution of the overall fusion-based system.

2. Fusion algorithms

Multi-sensor fusion of multiple technologies requires special algorithms to combine (fuse) all sensors data and produce the unified output estimations. Most commonly used algorithms capable of dealing with redundancy and overdetermined systems are Kalman filters, least squares algorithms and particle filter. Additionally, the algorithmic federation concept is recently trending throughout the recent literature. In this section, we provide a brief overall view about the most common algorithms.

a). Kalman filters

The Kalman filter algorithm is an iterative recursive estimation method to predict the new optimal states in linear state-space systems considering additive white Gaussian noise [7]. The algorithm is based on utilizing the priori knowledge to estimate the posterior states, calculate the Kalman gain and the measurements residual due to the mismatch error then calculate the new state and covariance vectors and use them as input to the next iteration [8–10]. The difference between all types of Kalman filters is showed in figure 4.

Extended Kalman filter (EKF) is an adapted version of the ordinary linear Kalman filter to estimate states in nonlinear dynamic systems [11]. A discrete-time Kalman filter has two steps: 1) prediction step, where the next state of the system is predicted given the previous measurements fed to the system, and 2) update step, where the current state of the system is estimated given the measurement at the active time step [10, 12].

In EKF, the state transition matrix and the measurement matrix in the linear Kalman filter are replaced by the nonlinear state transition function $f(.)$ and nonlinear measurement function $h(.)$ respectively in order to map the algorithm through Gaussian distribution to work in nonlinear conditions.

Unscented Kalman filter (UKF) Unlike EKF, the Unscented Kalman filter (UKF) employs the sigma-point Gaussian transformation to map the nonlinear state transition function of the system and tend to linearize it through the so called the unscented transform [10, 13, 14]. In other words, the UKF uses more than one point including the distribution mean, while EKF approximation relies only on one point, the mean. UKF selects additional weighted points (called sigma points) plus the mean for more accurate transformation. This procedure is called the unscented transform. As a result, UKF sometimes outperforms EKF in severely nonlinear systems, while EKF performs well in systems with modest nonlinearity [15]. There are other sigma-point Kalman filters which are widely adopted such as Cubature Kalman filter (CKF) and Gauss-Hermite Kalman filter (GHKF).

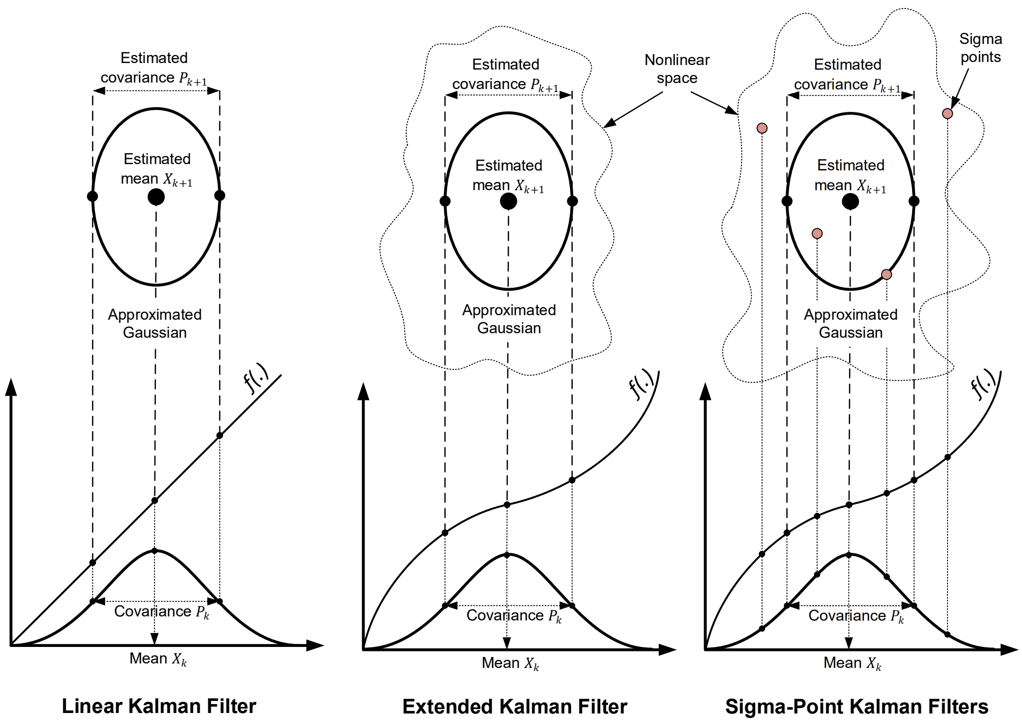

Figure 4: Illustration depicting a comparison between the different types of Kalman filter (adapted from [10]).

b). Particle filters

The position of an observer can be estimated using the discrete state-space model (DSS). In general case the process and measurement functions $f(.)$ and $h(.)$ can be nonlinear and process and measurement noise distributions, *q*, and, *r*, non-Gaussian noise sources. The problem of finding a position x_k can be seen as a filtering problem for estimating the posterior probability $p(x_k|y_k)$, which is often assumed to be Gaussian.

A closed form solution can be found only if DSS is linear and q and r are zero mean Gaussian noise sources. In practice these conditions do not hold very often. If the system function is well known, it can be linearized near an operating point and then linear methods be applied [16, 17]. EKF solves a Gaussian posterior estimation by linearization and UKF by using unscented transformation however the standard Particle Filter (PF) provides non-Gaussian posterior estimation iteratively by means of Sequential Monte Carlo (SMC) algorithm. A Gaussian variation of PF (GPF) solves Gaussian posterior distribution using SMC [16].

c). Federated filtering

The federated filtering concept first described by [18] in which the observations of subsystems are estimated locally as first step, then sent for general fusion using a master fusing filter [19]. Kalman filters are widely adopted as fusion filters especially the federated Kalman filtering (FKF) and the federated extended Kalman filter (FEKF) for multiple sensors, as illustrated in figure 5.

Kalman algorithms are the most commonly used filters for federation; ordinary Kalman filter for linear systems, extended (EKF) and unscented(UKF) Kalman filters for nonlinear systems [20].

The algorithmic behavior of FKF follows the state-space matrix equations of: [21]

$$X_{k+1} = \Phi_k X_k + U_k + W_k \tag{1}$$

$$Z_{k+1} = H_{k+1} X_{k+1} + V_{k+1} \tag{2}$$

where X_{k+1} and Z_{k+1} are the iterative global state vector and global measurements vector of the system at time step *k+1*, Φ_k and H_{k+1} are the diagonal state transition matrix and the observation matrix respectively. U_k is the global input matrix, W_k and V_{k+1} are the

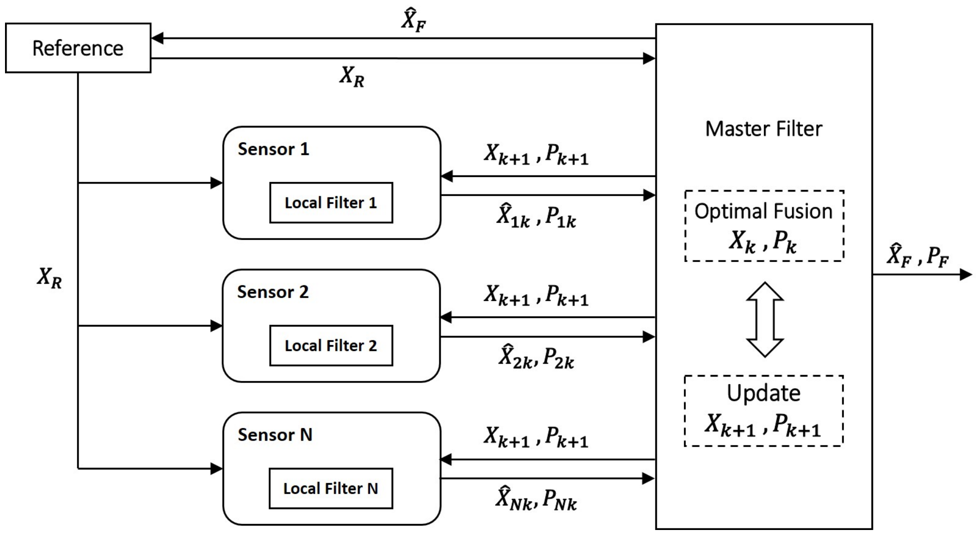

Figure 5: Structure of the federated Kalman filter (FKF).

Gaussian process and measurements noises respectively at time step *k* and *k+1* with covariances Q_k and R_{k+1}.

To obtain the Kalman gain, error residuals (innovation), final estimations for the optimal states and the optimal covariance, the FKF algorithm proceeds with the matrix-form sequence in two steps, as illustrated in table 1.

Moreover, the federated filtering principle can be applied to particle filter (FPF) as in [20, 22, 23] for nonlinear non-Gaussian estimations.

3. Types of commonly used multi-sensors

a). Inertial sensors

Inertial navigation sensors (INSs) are very reliable positioning systems, as they are not influenced by external factors. However, they accumulate significant errors over time [24, 25]. The main role of the primary positioning technology (e.g. GNSS) is to refine INS errors by tightening the position estimate to the absolute coordinate system while INS provides more accurate delta position updates in a short term.

An inertial measurement unit (IMU) differs from INS, as it is not an integrated dynamic system as an INS. However, IMU units are the main building block of INSs [26]. IMUs can still be utilized independently in fusion-based localization endeavors, but INSs have been widely adopted in positioning systems in the recent literature.

Globally, GNSS/INS fusion is a very common implementation due to the numerous advantages of this integration over utilizing each system solely [19]. As described in [4], both systems have complementary data to provide, GNSS estimates the PVT

Table 1: FKF algorithm for nonlinear multi-sensor fusion.

0 Initialization	for $k = 0$ set $\hat{X}_0, P_0^-, Q_0, R_0$
1 Prediction step	Prior estimate of the state: $X_{k+1}^- = \Phi_k X_k + U_k$ Prior estimate of the covariance: $P_{k+1}^- = \Phi_k P_k {\Phi_k}^T + Q_k$
2 Update step	Measurement residual update: $v_{k+1} = Z_{k+1} - H_{k+1} X_{k+1}$ Measurement covariance update: $S_{k+1} = H_{k+1}\, P_{k+1}^-\, {H_{k+1}}^T + R_{k+1}$ Kalman gain calculation: $K_{k+1} = P_{k+1}^-\, {H_{k+1}}^T\, S_{k+1}^{-1}$ Updating the posterior state: $X_{k+1} = X_{k+1}^- + K_{k+1} v_{k+1}$ Updating the posterior covariance: $P_{k+1} = P_{k+1}^- - K_{k+1} S_{k+1} K_{k+1}^T$ **Return to step 1, repeat until k iterations are consumed.**
Output	Estimated state vector: $\hat{X}_F$

measurements while INS provide the detailed information about the attitude which yield a 6-DOF system. Both systems can be utilized for mutual calibration hence reducing overall error components. The data rate of INS is higher than GNSS which produces better resolution for navigation in addition to exploiting previous features to achieve seamless navigation in GNSS-denied conditions. Consequently, the GNSS/INS multi-sensor fusion is suitable for aerial, terrestrial and extraterrestrial navigation on Earth and in Space.

b). Remote sensing

Remote sensing is the process of mapping the target environment by sending pilot signals and analysing the physical characteristics of the received signals. The pilot signals can be with different wavelengths, frequencies and types. Radars (Radio Detection and Ranging) is one type of remote sensing systems that utilizes low frequency RF signals as pilots, then detects the range of targets by analysing the frequency of the rebounded fraction of the signal. LiDAR (Light Detection and Ranging) is another type of remote sensors that employs high frequency light lasers in the same manner as Radars. Moreover, special types of Cameras can be considered as remote sensing systems when their functionalities are to map the topography of the surroundings, observe the heat maps of territories and so on. Other types of remote sensing can be acoustic like sonar systems, and can be ultra/infra sonic systems depending on the target application.

Radars and LiDARs are very common types of localization techniques that can be standalone systems and also can be used in multi-sensor fusion systems.

III. ADVANCES OF MULTI-SENSOR FUSION

In this section, we present a survey from the most recent literature that focus on the GNSS multi-sensor fusion approach. We highlight the implemented technologies within various applications. As the categorization of the multi-sensor literature is challenging, we present the in-text literature advances as application-based categorization while a summarized tabulation of references is presented from the perspective of quantity, integration and sensor types. The tabulated summary of sources is found in table 2.

Table 2: Summary of surveyed literature.

Dual integration	Triple integration	Quadruple and Quintuple integrations
GNSS/Inertial sensing [27], [28], [29], [5], [30], [31], [6], [32], [33], GNSS/Remote sensing [34], [35], [36]	GNSS/Inertial sensing/Remote sensing [36], [20], [37] GNSS/Inertial sensing/Visual [38], [39], [40], [41], GNSS/Inertial sensing/DR [42]	GNSS/Inertial sensing/Remote sensing/Visual [43], [44], [45]

1. Autonomous Driving and Intelligent Transportation Systems (ITS)

The authors of [36] validated an effective calibration method for the 6-DOF autonomous SLAM vehicles using LIDAR/GPS/IMU technique. The LIDAR error components originated from the deviations of point cloud measurements due to vehicle movement hence calibration became paramount. The GPS/IMU and LIDAR coordinate systems are matched by processing the time synchronization frames of LIDAR point cloud and corrected by the pose from GPS/IMU frame. The measurements of pitch and roll angles in addition to the Z-axis translation had transformed the 3-D positioning problem into 2-D problem. The ground truth data was used to solve the set of linear equations originated from sensors fusion thus obtain the optimal solution. The tests were held in a real vehicle by comparing the 3-D reconstruction results before and after the proposed calibration method. The verification results after calibration showed clearer views and more resolution than the views before calibration that were thicker in contours and more ambiguous.

In [38], the authors utilized triple fusion system GNSS/INS and optical velocity sensors (OVS) in addition to adaptive fault-tolerant fault detection and processing (FDP) algorithm to provide a continuous navigation information. The measurements of GNSS were judged against ground truth data to identify the observation outliers and biases that cross a preset threshold. Outliers were discarded and the biases were fed to the adaptive FDP (with varying covariance) for correction. The comparison was conducted at three scenarios: clear skies, semi clear skies and totally unclear skies. Moreover, the validation was set to compare between tightly-coupled (TC) and loosely-coupled (LC) triple-fusion GNSS/INS/OVS. The results based on real experiment showed that the TC integration was more accurate the LC integration hence the method was concluded to be suitable for continuous accurate navigation.

Another LC dual-integration method INS/GPS is described in [27], in which the authors utilized an EKF algorithm as a master fusion filter. The conducted simulations on datasets showed that the proposed method achieved better accuracy for attitude, velocity and time also ensured reliability and continuation.

Similar LC approach was developed by [6] using EKF and linear KF estimations to improve the overall accuracy, which was validated via MATLAB simulations.

The authors of [39] proposed a triple-fusion method comprising IMU/GNSS and map matching to integrate the location information of micro-electromechanical systems (MEMs) with commercial road maps. The method was developed to mitigate the uncertainty associated with GNSS positioning hence overcome the problem of lane-detection by providing more accurate location. From algorithmic perspective, the authors used the LC-EKF as the main fusing algorithm also used as a standalone local filter for the tracking step. Additionally, the hidden Markov (HMM) and LS algorithms were used to estimate the vehicle lane by map matching the input road maps using buffered records of the vehicle's poses. Based on real-time experiments in the open-sky scenario, the results showed that the proposed lane determination method achieved 97.14% success rate in detecting the correct lanes.

An UTC architecture was developed by [5] to implement a GNSS/INS integrated system for the navigation of autonomous ground vehicles. The authors compared the performances of the LC-GNSS vector tracking with the GNSS consumer-grade tracking of a smart phone in extreme scenarios. The RTK positioning results validated that the availability of the UTC method was better than other methods but the accuracy should be further improved.

Another UTC architecture is utilized by [31] to combat the nonlinearity introduced by the INS/GPS integration using the unscented particle filter (UPF). The nonlinear measurement equation was formulated using the second-order Taylor expansion of the pseudoranges while the UPF was employed for the dynamic state estimations. Results showed that the proposed method with UPF outperformed the same approach when Kalman filter is used.

Environmental disturbances (e.g. vibrations) can cause error drifts in the attitude measurements hence the issue was studied by [30] using micro electromechanical inertial sensors (MEMS-IMU) and GPS. The authors developed a dual-fusion GPS/MEMS-IMU system with EKF as fusion filter to study the effect of vibrations on attitude. The efficacy and reliability of the proposed method were validated as shown by the results.

Dynamic positioning in urban environments is challenging where GNSS satellites can experience frequent blockages, their carrier-phase reliability decrease or become insufficient in number of usable satellites. Hence, the authors of [28] proposed a TC integration of GNSS/INS sensors to mitigate the error divergence and improve the overall positioning accuracy in complex urban environments. The authors utilized a linear combination of triple-frequency GNSS, proposed an ambiguity fixed observation algorithm to compensate on and round the blocked epochs, and used the nonlinear Cubature Kalman filter (CKF) as the master fusion algorithm. In addition to utilizing two local Kalman filters for the ambiguity resolution and the inertial fusion with GNSS. A test vehicle was used to verify the proposed method. The results of testing several scenarios showed improved accuracies for minimal and maximal number of visible satellites (4 and 11 satellites) ranging from 4.1cm to 67cm for vertical and horizontal directions.

Similar approach (GPS/IMU) was utilized in [29] to mitigate the accumulated errors in IMU caused by the absence of GPS signal. The authors used the vehicle kinematics model (VKM) along with a Kalman filter for the fusion. High efficiency and high precision of the proposed method were validated through simulations.

2. Military Applications

The authors of [41] constructed a hardware-in-the-loop (HIL) simulation to test GNSS/MEMS-IMU system that is fused with fiber optic gyroscope (FOG) resulting in a compound navigation system (CPNS). The proposed GNSS/MIMU/FOG method is aimed at improving the navigation accuracy of smart ammunitions by calibrating the MEMS gyroscope and GPS lag values. The HIL simulations showed that the proposed CPNS had effectively improved the navigation accuracy and significantly reduced the fusion error.

3. Atmospheric Navigation in Space

Fusion-based navigation can solve complex problems for re-usable space crafts during re-entry by enhancing the accuracy of the on-board inertial system, as described in [40]. The authors proposed a triple-integration method INS/Star-tracker/GPS in which the INS measurements aided both GPS and the star tracker systems to correct the misalignment errors within a unified coordinal frame. Additionally, an EKF algorithm is used as a universal fusing filter to combine all the output estimations after being updated. The simulation results exhibited noticeable improvements in positioning accuracy, orientation accuracy, and overall efficiency.

4. Fusion with Radar systems

To achieve reliable object detection results for remote sensing, GNSS observables can be fused with radar systems to fine-tune the error drifts as in [34]. The authors proposed a theoretical GNSS/SAR approach using omnidirectional GNSS antenna operating at L1 frequency band, C/A code receiver and limited range field of view (FOV). The conducted experiment showed a probability of 0.1% as false alarm while the probability of detection was 95%, the FOV was restricted to 2 Km although theoretically the method should be able to detect objects from 5-8 Km away.

A quintuple-fusion system IMU/GNSS/Radar/Camera/LIDAR was proposed by [44] to provide precise environmental perception capabilities for automated-driving vehicles. The method used a 6-DOF kinematic model to produce PVT estimations which were corrected by the GNSS observations via LC error-state EKF algorithm. The observable measurements of radar, camera and LIDAR enhanced the overall perception of the surrounding environment using an outlier detection of optically impaired data. The conducted results showed that the redundancy of sensor data improved the robustness and the overall accuracy for 2-D and 3-D scenarios. Moreover, the scalability and precision were validated.

5. Pedestrian Tracking

A likelihood detection method was utilized in [20] using FPF approach for tracking in nonlinear non-Gaussian environment. The proposed method was a triple fusion system JIDS/SINS/GPS augmented by FPF algorithm as global fusion filter and local PFs for the three subsystems. After simulating the system, the results showed a high detection rate, low detection time and lower directional RMS values which achieved an improved performance of the fusion-fault tolerance.

6. Unmanned Aerial Vehicles (UAVs)

Ultra Wideband (UWB) is a wireless short-range radio-technology in which its communication channel propagates information over wide spectrum by modulating either a carrier-based waveform or carrier-less baseband signal in the form of short-width pulses [46].

The authors of [36], proposed a high-precision prototype for UAV traffic management (UTM) system. Besides the GPS, the authors utilized a novel method comprising an impulse radio (IR) calibrated UWB (Decawave) in addition to LoRa module. The implemented cost function of the proposed method GPS/UWB had reduced the GPS positioning error from 4.03 to 1.73 cm.

In [45], the authors designed a fusion positioning algorithm of GNSS/UWB/DR/VMM with a federated Kalman filter (FKF). Both the simulation and the results from real vehicle testing showed that the proposed intelligent vehicle localization accuracy was improved (MAE < 0.88 m). The positioning accuracy could be improved adaptive information distribution coefficient was established based on the FKF.

IV. CONCLUSION

Seamless navigation is a very crucial element for many PNT-dependent applications and future IoT implementations. GNSS standalone systems are providing acceptable level of integrity to many technologies especially in open-sky environments. Yet, they are not suitable for precise positioning and seamless navigation due to numerous factors such as: multipath fading, attenuation in dense environments, and signal obstruction in GNSS-denied conditions and urban environments. Multi-sensor fusion technologies are very promising candidates to mitigate positioning errors since they utilize additional navigational sensors that aid GNSSs in providing continuous navigation hence maintain integrity and the desired service level. Numerous applications are beneficiaries of precise multi-sensor fusion systems such as: autonomous self-driving vehicles, UAVs, mobile robots and smart machines. The capabilities of integrated GNSS fusion-based systems are maximized by the added multiple sensors hence meet the requirements of the beneficiary applications. In this survey, we presented a short review of the most recent literature that focus on the developing of dedicated multi-sensor systems in specific applications. We highlighted the use of inertial sensors, remote sensing devices, visual-based sensors, and RF-based navigational sensors to achieve seamless navigation for various scenarios. Moreover, we presented an overall view on the algorithmic implementations of multi-sensor fusion systems such as: Kalman filters, particle filters, and federal filters. We constructed the architecture of this article to be a short supporting tutorial for researchers seeking higher perspective on the GNSS multi-sensor fusion topic. In the future, we intend to design, implement, and develop our proposed fusion-based system that comprise GNSS, inertial sensors, UWB and low-earth orbit satellites (LEO) for seamless navigation.

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