Suez Canal Engineering
Energy and Environmental
Science Journal
Faculty of Engineering – Suez Canal University
Year, Volume 3, NO. 3 , pages 17– 30

Integrated INS/GNSS Navigation Systems: A Comprehensive Review of Filtering and AI-Based Fusion Techniques

Maher Tarek*[*1], Shady Zahran[2], EYAD S. ODA[1], Sherif F Nafea[1]

[1] *Electrical Engineering Department, Faculty of Engineering, Suez Canal University, Ismailia, Egypt.*
[2] *College of Computing and IT, Arab Academy for Science, Technology& Maritime Transport, Cairo, Egypt.*

**Corresponding author: Maher Tarek, Email address: maher.tarek@eng.suez.edu.eg*
DOI: 10.21608/sceee.2025.378670.1076

Article Info:

Article History:
Received: 24\04\2025
Accepted: 04\05\2025
Published: 30\07\2025

DOI: 10.21608/sceee.2025.378670.1076,

Abstract

Integrated Inertial Navigation System (INS) and Global Navigation Satellite System (GNSS) architectures have become essential for modern autonomous and navigation applications, offering complementary strengths to address the limitations of standalone systems. However, the fusion of INS and GNSS data presents several challenges, including handling sensor drift, nonlinearity, GNSS signal outages, and system uncertainties. This review systematically explores the current state of INS/GNSS integration, emphasizing the classification of fusion architectures (loosely, tightly, and ultra-tightly coupled) and the diverse inertial sensor technologies employed, including Micro-Electromechanical Systems (MEMS), fiber optic gyroscopes (FOG), and ring laser gyroscopes (RLG). Special attention is given to data fusion techniques, highlighting both classical model-based filters (e.g., Kalman Filter and its variants) and emerging artificial intelligence (AI)-based methods such as deep learning and recurrent neural networks. The paper also examines AI's role in replacing or augmenting traditional filters and the use of platform-specific motion constraints to improve localization accuracy. This review aims to guide researchers and engineers in designing robust, intelligent navigation systems suited for dynamic and GNSS-challenged environments by synthesising advancements in filtering algorithms, AI techniques, and sensor technologies.

Keywords: *Inertial and Satellite Navigation, INS/GNSS Integration, model-Based Navigation systems, AI-Based Navigation Systems, A*utonomous Navigation.
Suez Canal Engineering, Energy and Environmental Science Journal (2025), ***vol.3***, No.3.

1. Introduction

The rapid advancements in electronics technology significantly impact various engineering domains and industries, including aviation, maritime navigation, self-driving cars, military applications, surveying, mapping, precision agriculture, search and rescue operations, smart home devices, and robotics. All these applications rely on a navigation system, which serves as their "sense of perception" to navigate safely. This growing reliance on navigation systems has been further accelerated by the widespread availability of low-cost sensors and microcontrollers (Grewal, 2007).

Navigation systems are sophisticated technological solutions that gather data from various onboard navigation sensors to determine precise localization, which is crucial for mission success and operational efficiency. Figure 1 provides an overview of different types of navigation systems and highlights their diverse applications across multiple fields, emphasizing their significance and versatility.

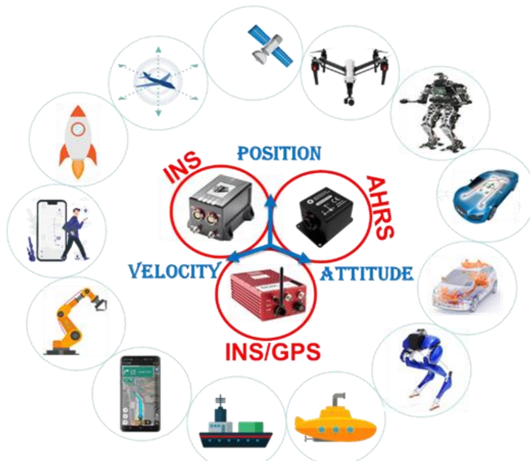

Figure 1: Various Navigation Systems and their diverse applications.

The fundamental navigation solutions are Inertial Navigation Systems (INS), Global Navigation Satellite Systems (GNSS), and their integrated INS/GNSS systems. INS provides self-contained navigation through inertial sensors, while GNSS offers global positioning based on satellite signals. Integrating these systems enables enhanced accuracy, robustness, and continuity, especially when using low-cost sensors.

The primary objective of this review is to explore recent research developments in INS, GNSS, and their integrated architectures. Emphasis is placed on system design methodologies, performance enhancement techniques, and practical applications. The review begins by categorizing inertial sensors such as mechanical gyroscopes, silicon and quartz Micro-Electromechanical Systems (MEMS), fiber optic gyroscopes (FOG), and ring laser gyroscopes (RLG) and analyzing their respective trade-offs in accuracy, size, cost, and environmental resilience.

A classification of INS/GNSS integration architectures into loosely coupled, tightly coupled, and ultra-tightly coupled configurations. These architectures are compared based on their fusion strategies, GNSS dependency, complexity, and suitability for different operational scenarios. Furthermore, model-based filtering techniques, including the Kalman Filter (KF) and its variants, are evaluated for their ability to estimate navigation states under dynamic and nonlinear conditions.

In Addition, the review addresses emerging artificial intelligence (AI)-based data fusion approaches that either replace or augment traditional filters. These include deep learning models, recurrent neural networks, and hybrid AI-KF frameworks designed to improve adaptability and performance, particularly in challenging real-time environments. The role of platform-specific motion constraints, such as those found in aerial, land-based, and underwater systems is also examined for their ability to enhance estimation accuracy and filter observability.

By synthesizing classical filtering methods, AI-driven strategies, and motion constraints, this review aims to provide a comprehensive resource for researchers and engineers developing robust and intelligent navigation systems for next-generation autonomous technologies.

The remainder of this paper is structured as follows. Section 2 discusses inertial navigation technologies. Section 3 reviews GNSS principles and challenges. Section 4 presents integrated INS/GNSS fusion techniques, including classical model-based methods and emerging AI-based approaches, and discusses platform-specific motion constraints. Finally, Section 5 concludes the paper and highlights future trends.

2. Inertial Navigation System (INS)

The operation of INS is fundamentally based on the principles of classical mechanics as formulated by Newton (Titterton, 2004). By measuring specific forces (linear acceleration) using accelerometers, it is possible to calculate changes in velocity and position through successive integration of acceleration over time. Additionally, by accumulating the integrated part of the angular velocity, attitude can be estimated. The INS device consists of inertial sensors (three accelerometers and three gyroscopes) and a computing unit.

Modern inertial sensors have significant advancements for a wide range of applications across industries with varying requirements for accuracy, size, weight, power consumption, cost, and robustness. One of the most prominent developments is MEMS, which are miniaturized (compact) sensors fabricated using semiconductor manufacturing techniques. These sensors are lightweight, tiny, low-cost, and consume minimal power, making them highly suitable for cost-sensitive and size-constrained applications such as smartphones, drones, and wearable devices. However, their performance is limited by high noise levels, bias instability, and sensitivity to environmental conditions such as vibration and temperature fluctuations (El-Sheimy, 2008).

For applications demanding higher precision and stability, FOG provide a robust solution. FOGs operate based on the Sagnac effect, where light propagating through optical fibers is used to detect rotation. They offer excellent bias stability, low drift, and high resolution, making them suitable for mission-critical applications such as aircraft navigation, space systems, and autonomous underwater vehicles. The trade-offs include their larger physical size, higher power consumption, and greater cost compared to MEMS sensors (Lefèvre, 2014).

An even more precise technology is the RLG, which also exploits the Sagnac effect but uses a ring-shaped laser cavity. RLGs provide exceptional accuracy, extremely low drift, and long-term stability, making them the preferred choice in high-end military, aerospace, and strategic-grade navigation systems. Their complexity, bulkiness, and high manufacturing cost, however, limit their usage to platforms where top-tier performance justifies these drawbacks (Lawrence, 1998).

Another important sensor technology is Quartz MEMS, which combines the miniaturization of MEMS with improved performance characteristics. Quartz MEMS sensors use piezoelectric quartz structures that offer better thermal stability, long-term reliability, and lower noise compared to silicon-based MEMS. These attributes make them ideal for demanding applications where space, weight, and power are constrained such as in satellites, precision agriculture drones, and compact guided munitions (Syed, 2007).

A comparative summary of inertial sensor technologies is presented in Table 1, outlining their core characteristics and typical applications to guide engineers and researchers in choosing suitable solutions based on mission demands.

Table 1: Inertial Sensor Technology Comparison

Sensor Type	Accuracy	Size/Weight	Cost	Power	Use Case
Mechanical Gyro	Low	High	Medium	High	Legacy systems (missiles, submarines)
Silicon MEMS	Low-Medium	Very Small	Low	Low	Drones, wearables, mobile and IoT devices.
Quartz MEMS	Medium	Small	Medium	Low	Aerospace, robotics, defense
FOG (Fiber Optic)	High	Medium	High	Medium	Aircraft, underwater, spacecraft
RLG (Ring Laser)	Very High	Large	Very High	High	Military, aerospace, precision nav

Although largely phased out in modern systems, mechanical gyroscopes based on spinning rotors were foundational in early navigation systems. Due to their mechanical nature, they are highly resistant to electromagnetic interference, offering robustness and reliability in harsh conditions. For this reason, they are still occasionally used in specific applications such as submarines and legacy missile systems where ruggedness and independence from electronic components are valued (Britting, 2010).

These varied sensor technologies enable the design of navigation systems that can be tailored to meet the specific tradeoff between cost, size, weight, power consumption, and performance, supporting a wide spectrum of applications from commercial to aviation-grade systems. The INS can be broadly categorized into two types: gimbaled and strap-down systems. Gimbaled INS employs gimbals with pivots to maintain the stability of the INS relative to the ground. However, this type of system is complex and rarely in use (mechanical gyroscopes, as mentioned before). In contrast, strap-down INS eliminates the need for gimbals, simplifying the motion analysis process. In strap-down systems (paul, 1991), the gyroscopes and accelerometers are directly mounted to the structure of the vehicle or body segment. new technologies rely on MEMS, and laser gyros use strap-down method.

The mechanization process in strap-down INS, also known as INS mechanization, involves determining the navigation state position, velocity, and attitude based on raw inertial measurements. This is achieved by solving the differential equations that describe the system's motion. These mechanization differential equations are typically framed in the local level coordinate system, allowing for accurate real-time navigation and orientation. The structure of the mechanization algorithm is given by scheme in Figure 2. This approach ensures that the INS provides precise and reliable navigation states for various dynamic applications, ranging from aerospace to autonomous vehicles. Despite its self-contained nature and robustness, INS suffers from accumulating errors over time, primarily due to deterministic biases and stochastic noise inherent in inertial sensors.

To address these limitations, numerous studies have proposed enhancement techniques for improving the accuracy of low-cost INS systems. For instance, Shin (Shin, 2001) introduced a field calibration method that significantly reduces positioning errors by compensating for accelerometer biases, enabling low-cost INS to operate independently during short GNSS outages. Nassar et al (Nassar, 2003) employed stochastic modeling and autoregressive techniques to better characterize sensor errors. Moreover, Chin (Chin, 2005) investigated the feasibility of a gyroscope-free INS, utilizing only accelerometer data and developing algorithms to mitigate errors associated with sensor placement and misalignment. Ding and Wang (Ding, 2007) leveraged vehicle dynamic constraints and integrated Kalman filtering (KF) to suppress sensor noise, achieving improved estimation stability.

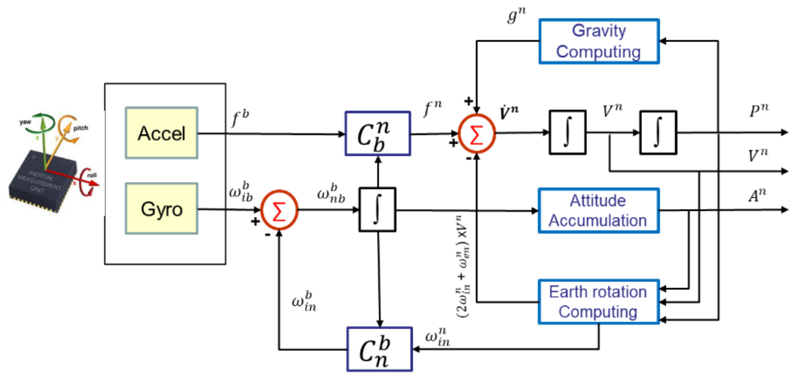

Figure 2: Schematic diagram of the Inertial Navigation System mechanization process.

While INS offers self-contained navigation, it suffers from cumulative drift errors over time. To mitigate these limitations, satellite-based navigation systems, notably GNSS, provide an essential complementary solution, as discussed in the following section.

3. Global Navigation Satellite System (GNSS)

GNSS is a constellation of satellites stationed at the Medium Earth Orbit (MEO) that transmits positioning and timing data to GNSS receivers and multiple satellites are observed simultaneously. The satellites' positions are forecasted and broadcast to the user along with the GNSS signals from many navigation satellite systems (GPS, GLONASS, Galileo, and BeiDou), as shown in Figure 3. By using the known positions of the satellites and the measured distances between the receiver and the satellites, the receiver's position can be accurately determined. Additionally, the receiver's velocity can be calculated based on changes in position over time. GNSS consists of three segments: the Space Segment (which includes multiple satellites distributed across various orbital planes), the Control Segment (which monitors satellite operations and ensures system functionality), and the User Segment (which comprises GNSS receivers and user communities). Despite its advanced technology, GNSS is subject to errors from several sources, including satellite clock errors, ionospheric and tropospheric delays, multipath interference, and receiver-related measurement noise. These errors can significantly degrade positioning accuracy, especially in challenging environments such as urban canyons, dense forests, or under intentional signal jamming.

Substantial research has been directed toward enhancing and mitigating these limitations and improving the reliability of GNSS as a standalone global navigation solution. The following literature review focuses on recent advancements in GNSS technologies and methodologies aimed at overcoming these challenges and using GNSS as a stand-alone navigation system.

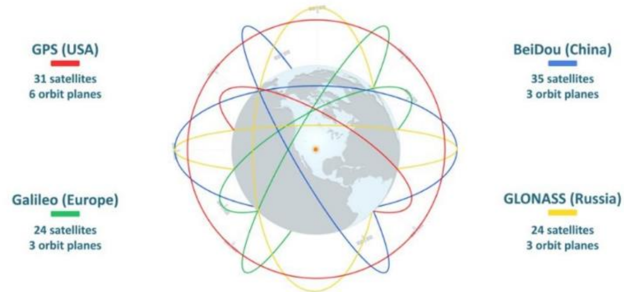

Figure 3: Global Navigation Satellite Systems (iLab, 2025)

Satellite positioning accuracy is susceptible to errors originating from satellite clock and ephemeris inaccuracies, ionospheric and tropospheric delays, multipath reflections, and receiver noise. Classical techniques have been widely adopted to counter these issues. Precise Point Positioning (PPP), which utilizes satellite clock and orbit corrections from the International GNSS Service (IGS), can achieve centimeter-level accuracy without a nearby base station (Zumberge et al., 1997). Satellite-Based Augmentation Systems (SBAS), such as WAAS and EGNOS, broadcast corrections to satellite ephemeris and clock errors (Kee et al., 2001). To mitigate ionospheric delays, dual-frequency receivers apply linear combinations of L1/L2 signals (Misra & Enge, 2006), while single-frequency systems rely on empirical models like Klobuchar and NeQuick. Tropospheric delay is addressed using models such as Saastamoinen (1972) or by estimating the delay as an unknown in high-precision solutions like PPP. Multipath interference is minimized through antenna design improvements such as choke ring antennas (Axelrad et al., 1996), and signal processing methods like Multipath Estimating Delay Lock Loops (MEDLL) (Van Dierendonck et al., 1992). Receiver noise is reduced using carrier-phase measurements (Leick, 2004), and through Kalman filtering when GNSS is integrated with Inertial Navigation Systems (INS) (Grewal et al., 2007; Titterton & Weston, 2004).

In recent years, advanced statistical and machine learning-based techniques have emerged to handle GNSS limitations more effectively in complex environments. Urban GNSS applications, especially those in signal-degraded areas, benefit from environmental modeling using ray tracing and heuristic estimations (Groves, 2013). Recent developments include enhancements to Real-Time Kinematic (RTK) systems. For instance, improved RTK algorithms exploit unused satellites to detect and reject incorrect integer ambiguities, resulting in improved positioning reliability in urban environments (MDPI, 2024). Similarly, ambiguity resolution has seen progress with the introduction of Laplacian Best Integer Equivariant (LBIE) estimation. LBIE integrates Laplacian distributions to outperform conventional estimators such as GBIE and ILS-PAR, reducing horizontal errors to below 0.5 meters in urban tests (Tech Xplore, 2024).

The newest frontier in GNSS enhancement involves deep learning and artificial intelligence. In 2024, researchers at Wuhan University and Baidu developed a Light Gradient Boosting Machine (LightGBM) model for detecting Non-Line-of-Sight (NLOS) signals by analyzing signal features like SNR and satellite elevation, achieving over 92% classification accuracy in urban environments (Highways Today, 2024). Additionally, a novel Graph Neural Network (GNN) approach replaced heuristic error mitigation in urban GNSS with a data-driven model, improving positioning accuracy by up to 80% (arXiv, 2024). On another front, a plug-in module incorporating Multipath Mitigation Technology (MMT) into Direct Position Estimation (DPE) frameworks was introduced to eliminate the intermediate step of measurement correction entirely, instead solving for position and time directly. This approach shows robust resistance to multipath and NLOS in urban environments (arXiv, 2024). These advancements represent a paradigm shift from traditional correction models to intelligent systems capable of learning and adapting to complex signal environments.

Despite offering global coverage, GNSS systems are vulnerable to signal degradation and outages. Therefore, integrating INS and GNSS provides a robust navigation solution, which will be explored in the next section.

4. INS/GNSS Integration

In INS/GNSS integration, the nominal trajectory is often unknown in advance. Therefore, the current best estimate of the actual trajectory is used as the nominal trajectory. When KF is applied to a system that has been linearized around this estimate, it is known as the Extended Kalman Filter (EKF). INS/GNSS integration can be performed in two modes: direct (state model) and indirect (error state model). In direct integration, the KF directly estimates states such as position, velocity, and attitude. In indirect integration, the KF is used to estimate the errors of the state vector of the inertial navigation algorithm. While direct mode offers higher accuracy and stability under dynamic conditions, indirect mode is preferred for static or low-speed scenarios due to its lower computational burden

(Li, 2014). Additionally, two types of error feedback mechanisms are employed: open-loop and closed-loop. In the open-loop configuration, corrections to position, velocity, and attitude are applied externally to the INS, with the estimated errors subtracted from the INS solution at each iteration. In contrast, the closed-loop configuration feeds the EKF error estimates back into the system, continuously correcting the INS solution. This feedback keeps the INS errors small, ensuring that the linearity assumption required for the EKF technique is maintained throughout the process (Groves, 2013).

4.1 Integration Architectures

Various INS/GNSS integration architectures have been developed to optimize performance based on specific applications and the balance between simplicity and robustness. The three primary integration architectures at (Noureldin, 2013) are Loosely Coupled Integration, Tightly Coupled Integration, and Ultra-Tightly Coupled Integration.

4.1.1 Loosely Coupled INS/GPS Integration

In this architecture, which is known as a decentralized integration, the GNSS and INS function independently and provide separate solutions for navigation states. To get the best of both solutions, this information is fused together by an optimal estimator to obtain a third and much-improved solution. This arrangement is shown in Figure 4. Although this approach was conceptually simple and easy to implement, it required a complete GNSS position solution to function effectively. This dependence on GNSS solution performance made loosely coupled systems unreliable in environments with degraded GNSS availability, such as urban canyons, high buildings or dense forests. Despite this limitation, loosely coupled systems were widely adopted in many applications, where GNSS signals were generally available (G. Lei, 2024).

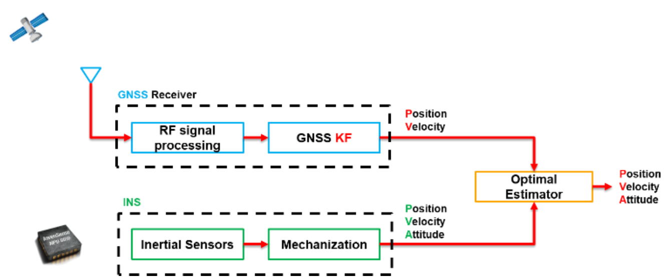

Figure 4: Basic diagram of loosely coupled INS/GNSS integration.

4.1.2 Tightly Coupled INS/GPS Integration

In this architecture, which is known as centralized integration, unlike the loosely coupled approach, tightly coupled systems fused raw GNSS pseudorange and Doppler measurements with INS data in a single estimation process as illustrated in Figure 5. This approach enhanced system robustness, enabling reliable navigation even with intermittent GNSS signals. Tightly coupled systems proved particularly effective in challenging environments, such as urban canyons and forested areas. The improved accuracy and reliability of tightly coupled architectures led to their widespread adoption in civil aviation, marine navigation, and advanced military applications (U. Muhammad, 2024).

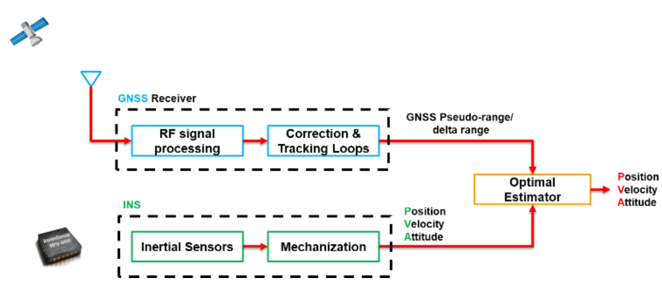

Figure 5: Basic diagram of tightly coupled INS/GNSS integration.

4.1.3 Ultra-Tightly Coupled Integration

Ultra-Tightly coupled integration provides an increased symbiosis between the INS and GNSS because the integration is at the tracking loop level. The main advantage of this is that the dynamics of the framework are estimated and compensated in the GNSS. tracking loops by using Doppler information. Various configurations of ultra-tight integration exist, and Figure 6 shows a basic one. The estimator combines either the pseudo-ranges/Doppler or I (in-phase) and Q (quadrature) measurements from the GNSS with the INS navigation parameters to render the estimated Doppler (D. Jwo, 2012). The estimated Doppler is used to remove the dynamics from the GNSS satellite signal entering the tracking loops, thereby reducing the carrier tracking loop bandwidth. Although this integration is more complex and requires access to the GNSS hardware, it can improve the quality of the raw measurements and also the anti-jamming performance of the signals (A. Elmezayen, 2021).

This integration is clearly at a deep level and requires access to the receiver's firmware, and so is usually implemented by receiver manufacturers or software receivers (C. Cristodaro, 2018). This makes the loosely and tightly coupled strategies the more common integration techniques. Also, this approach integrated GNSS and INS at the signal processing level, allowing for enhanced resistance to jamming and improved sensitivity in GNSS-denied environments. This period also marked a shift toward the use of low-cost MEMS sensors. Ultra-tightly coupled systems rise in applications in autonomous vehicles, UAVs, and portable navigation devices (H. Li, 2022).

Table 2 presents a structured comparison of INS/GNSS integration architectures, highlighting key differences in data fusion levels, dependency on GNSS signals, robustness against signal degradation, system complexity, and representative application domains.

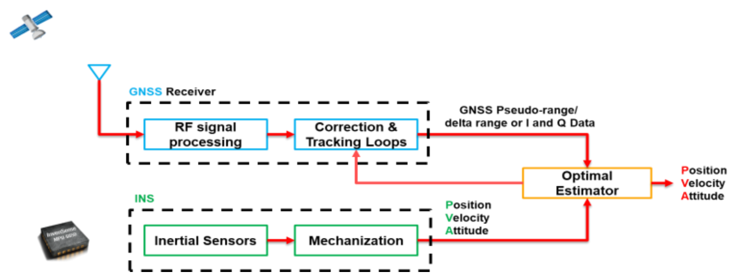

Figure 6: basic block diagram of an ultra-tightly coupled of INS/GNSS integration

Table 2: Comparison of INS/GNSS Integration Architectures

Integration Type	Data Fusion Level	GNSS Dependency	Signal Robustness	Complexity	Use Case
Loosely Coupled	Navigation solution level	High	Low	Low	Open environments, GNSS available
Tightly Coupled	Raw GNSS + INS data	Medium	Medium-High	Medium	Urban, obstructed GNSS
Ultra-Tightly Coupled	Signal tracking loop	Low	Very High	High	GNSS-denied, anti-jamming needed

Having classified the primary architectures, it is crucial to understand the estimation techniques that underpin their performance. The following section reviews model-based and AI-based filtering methods applied to INS/GNSS integration.

4.2 Filtering Techniques

INS/GNSS navigation systems rely on multi-sensor data fusion algorithms to achieve accurate and reliable localization. These algorithms can be broadly categorized into two approaches: Model-based methods and AI-based methods. Model-based methods, such as KF, use mathematical models to estimate and correct errors in the system, while AI-based methods leverage machine learning and deep learning techniques to learn patterns from data and enhance performance. **Figure 7** illustrates the classification of INS/GNSS navigation algorithms into model-based and AI-based methods, highlighting the most commonly used techniques within each category. The following section will provide a detailed discussion of these two approaches, and their applications in INS/GNSS integration.

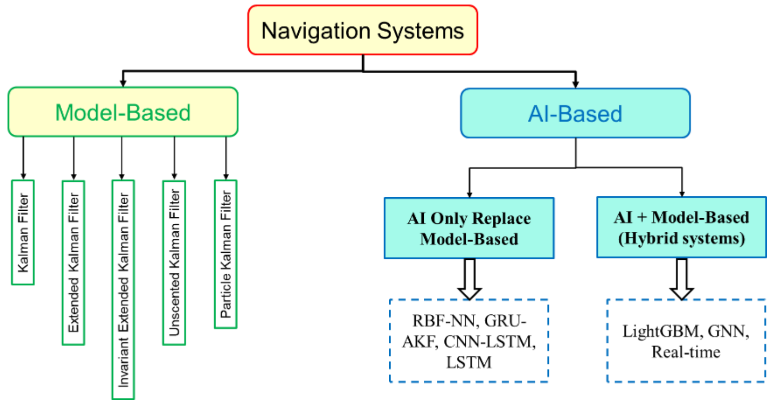

Figure 7: Model-based and AI-based estimation methods.

4.2.1 Model-based methods

The focus of research expanded beyond traditional INS/GNSS integration and fusion to include advanced multi-sensor fusion techniques. The standard KF is designed for linear systems and effectively integrates INS and fuses with GNSS measurements by combining high-rate, low-accuracy INS data with low-rate, high-accuracy GNSS data (M. Tarek, 2023), (Y. Yin, 2023). However, its performance relies on the assumptions of linear dynamics and Gaussian noise, which are frequently violated in practical navigation scenarios (J. Adalberto, 2024), (G. Gonggang, 2024), (Grewal, 2001). To overcome these limitations, the EKF, an extension of the KF, is widely employed in navigation systems to address non-linear system dynamics and measurement models. it linearizes the nonlinear function around the current estimate and truncates the first-order linearization of the Taylor expansion of the nonlinear function, thereby enhancing accuracy and robustness (X. Wang, 2022), (N. Allan, 2019).

Adaptive Kalman Filters dynamically adjust the process and measurement noise covariance matrices based on real-time data, improving accuracy in changing environments (A. H. Mohamed, 1999). Furthermore, Quaternion-based Kalman Filters use quaternions for attitude estimation, which avoids the singularities and inefficiencies associated with Euler angles. Quaternion-based methods are particularly useful for high-precision applications involving large rotations (Y. Yang, 2012). The EKF still has drawbacks where it does not guarantee convergence in general, as in the linear case (A. J. Krener, 2003). Also, it does not respect the geometry when the state space is a manifold, because it is designed in Cartesian coordinates (Y. Ge, 2023).

The Unscented Kalman Filter (UKF) improves upon the EKF by employing a deterministic sampling technique, which eliminates the linearization errors associated with the EKF. This makes the UKF more suitable for highly non-linear systems. However, its performance diminishes in high-dimensional cases due to reduced accuracy and increased computational complexity (Xuhua, Z, 2012), (M. N. Cahyadi, 2024).

The cubature Kalman filter (CKF) that is based on the spherical radial volume criterion is applied to data fusion, which can effectively approximate the Gaussian density function with higher accuracy, convenient parameter selection, and good convergence effect (I. Arasaratnam, 2009). In order to improve the fusion accuracy in complex measurement environments, robust Kalman algorithms have also started to attract the attention of researchers (J. Wu, 2024). To solve the problem of error model caused by measurement anomalies. (Taghizadeh, 2023) proposed a new cardinal maximum correlation entropy KF, which uses the robust maximum correlation entropy criterion (MCC) as the optimality criterion to solve the state estimation problem under outlier interference by maximising the correlation entropy between states and measurements. Yun et al. (B. Gao, 2023) proposed a variational Bayesian-based state estimation algorithm to improve the CKF accuracy under dynamic model mismatch and outlier disturbance.

The particle Kalman filter (PKF) offers even greater capabilities in managing highly non-linear dynamics and non-Gaussian noise, but it remains computationally intensive and sensitive to parameter selection (V. Khanaa, 2014), (F. Gustafsson, 2001). Despite these advancements, the EKF continues to be the preferred choice for INS/GNSS integration and sensor fusion due to its robustness, simplicity, computational efficiency, and established track record (A. Giremus, 2006). It strikes a balance between performance and complexity, making it a widely adopted algorithm in both industry and practical applications (H. Li, 2017), (Y. Kubo, 2008), (D. Bernal, 2008).

Integrating Lie group mathematics into navigation systems improves system accuracy by providing a mathematical framework to address non-linear manifold systems, especially rotational dynamics. The IEKF utilizes this approach for INS/GNSS integration, estimating rigid body orientation directly on the manifold of rotations (A. Barrau , 2018). This method avoids the linearization on traditional EKF, enhancing both accuracy and robustness, which is essential for high-update-rate navigation systems. The IEKF iteratively updates orientation estimates based on INS and GNSS data, ensuring consistency and validity in complex maneuvering scenarios and challenging environments (J. N. Maidens, 2017).

Bonnabel (S. Bonnabel, 2007) introduced the concept of left-invariant estimation errors, independent of the system trajectory, which was demonstrated in attitude estimation. This concept forms the foundation for applying these principles to various non-linear systems, such as non-holonomic land vehicles, chemical reactors, and aerial vehicle navigation (S. Bonnabel, 2008). The IEKF has been validated as a stable observer in these applications, demonstrating its effectiveness for inertial navigation (S. Bonnabel, 2009). Merging left-invariant dynamic systems with right-equivariant outputs ensures local convergence, and a federated structure of the IEKF has been proposed to enhance sensor fusion performance in complex scenarios (Barrau and Bonnabel, 2017), (N. Y. Ko, 2018). Table 3 provides a comparative overview of commonly used model-based filtering techniques in INS/GNSS integration, emphasizing their capabilities in handling nonlinearity, computational demands, robustness to outliers, and performance during GNSS outages.

Table 3: Model-Based Filtering Techniques

Filter Type	Handles Nonlinearity	Computational Cost	Robust to Outliers	GNSS Outage Handling	Remarks
KF	No	Low	No	Poor	Basic, linear systems
EKF	First-order approx.	Medium	No	Moderate	Widely used
UKF	Yes (via sampling)	Medium-High	Moderate	Moderate	Better than EKF for nonlinearity
CKF	Yes (cubature points)	High	Moderate	High	Accurate but complex
PKF	Yes (particles)	Very High	High	Very High	Best for non-Gaussian, nonlinear
IEKF	Yes (on manifold)	Medium	Moderate	High	Best for attitude and high dynamics

4.2.2 Artificial Intelligence-Based Methods

AI has been receiving more attention in the development of future technology, especially with the evolution of modern computer technology in hardware and software. AI has been verified as a successful and effective tool for solving certain engineering and science problems that cannot be solved properly using conventional techniques (Saifullah, 2023). The goal of AI technologies, which include artificial neural networks (ANNs) (M. Ünal,2013), Neuro-Fuzzy systems (R. Kruse, 2013), evolutionary computing (A. Hajian, 2018), expert systems (Goser, 1996), and genetic algorithms (GA) (L. Vanneschi, 2023), etc., is to provide some intelligence and robustness in the complex and uncertain systems similar to those seen in natural biological species (W. H. Hsu, 2009).

Many researches have been conducted to investigate the use of AI techniques in the field of INS/GNSS integration. The researchers have utilized various approaches for combining the AI module(s)with the rest of the INS/GNSS system. In fact, almost all architectures fall into two main categories:
(1) INS/GNSS integration using AI only in which the AI module is used as replacement of KF.
(2) INS/GNSS integration using AI and KF in which the AI module is combined with KF for improving the overall navigation accuracy.
Each of these two categories is also divided into subcategories according to the type of AI module or according to inputs/outputs(I/O) of AI module. The first category uses the separately scheme for integrating INS and GNSS while the second category uses loosely coupled integration scheme.

4.2.2.1 AI Only Replacing KF in INS/GNSS Integration

Several studies have investigated the use of AI as a standalone replacement for KF in INS/GNSS integration. (Uche Onyekpe et al, 2021) utilized artificial neural networks (ANNs) to directly estimate navigation states by learning the error characteristics of INS during GNSS signal outages, achieving better performance in highly dynamic environments compared to traditional KFs. Similarly, Zhang et al. (Alan Zhang, 2020) proposed a genetic algorithm (GA)-based model to optimize navigation parameters, showing its effectiveness in real-time applications with non-stationary noise conditions. Shuo Li et al (Shuo Li, 2023) developed a deep learning framework that integrated GNSS and INS data, demonstrating improved accuracy in nonlinear and uncertain environments where conventional KF methods struggle. While these approaches have proven the potential of AI in handling complex patterns and dynamics, their reliance on extensive training datasets and limited generalization capabilities remain challenges highlighted by researchers like Dah-Jing Jwo (Dah-Jing Jwo, 2023) and Nadav Cohen (Nadav Cohen, 2024).

4.2.2.2 AI Combined with KF in INS/GNSS Integration

When the GNSS signals are unavailable, model-based algorithms such as KF operates in predictive mode and corrects INS measurements according to the system error model. Currently, the accuracy of data fusion that relies only on the KF is not effective and navigation performance deteriorates rapidly. To improve the integrated navigation accuracy during GNSS outage, machine learning has started to be applied to integrated navigation systems. (Ning, 2019) proposed an optimal radial basis function (RBF)-based neural network that can improve the overall positioning accuracy during short-term GNSS signal outages. (Hang, 2020) proposed a new hybrid intelligence algorithm combining a discrete gray predictor (DGP) and a multilayer perceptron (MLP) neural network that provides pseudo-range positions during GNSS failures and uses GNSS position information from the last few moments to predict positions for future moments. Compared with traditional artificial neural networks, recurrent neural networks are more advantageous in combined navigation systems and can make full use of historical information (Jianguo Wang, 2020), (Ma Haibo ,2007). Liu et al. (Liu, 2021) proposed a multi-channel long-short term memory (LSTM) network to predict the increments of vehicle position, which reduces the navigation error in case of GNSS outages by an order of magnitude. In practical applications, a large amount of historical data before the GNSS outage needs to be trained when the GNSS outage occurs, so the training efficiency of neural networks also has high requirements. Tang et al. (Tang, 2022) proposed a hybrid algorithm that was based on the gated recurrent unit (GRU) and adaptive Kalman filter (AKF), and the experimental results showed that GRU outperformed LSTM in terms of prediction accuracy and training efficiency. Zhi et al. (Zhi, 2023) proposed a convolutional neural network-long short-term memory (CNN-LSTM) model, which uses convolutional neural network (CNN) to quickly extract the features of the input and LSTM network to output the pseudo-GPS signal, further improving the training efficiency. However, most of the current articles use the offline simulation, assuming that the GNSS failure time is known and do not consider the time that is required to train the model online. Al Bitar et al. (Al Bitar, 2023) proposed a novel real-time training strategy for regular training on the past one-minute data, with the disadvantage that only short historical data are used and the accuracy is poor when the time of GNSS outage is long.

Table 4: AI-Based Fusion Classification

Strategy	AI Role	Example Methods	Strength
AI-only Replacement	Replaces KF entirely	ANN, GA, DL models (Onyekpe, Zhang, Li)	Learns patterns during GNSS outage
AI + KF Hybrid	Assists the KF	RBF-NN, GRU-AKF, CNN-LSTM, LSTM (Tang, Zhi)	Improves accuracy during outages
Real-time AI Strategy	Online learning	LightGBM, GNN, Real-time LSTM (Al Bitar et al.)	Enhanced during unknown outages

Table 5 highlights the key distinctions between model-based filtering methods, such as the KF, and AI-based approaches, emphasizing differences in modeling requirements, adaptability, prior knowledge, and their ability to handle system nonlinearities.

Table 5 Model-Based vs AI-Based Approaches

property	Model-Based Approach	AI-Based Approach
Model dependency	Mathematical model: deterministic + stochastic	Empirical and adaptive model
Prior knowledge	Mainly require prior measurements, state vector and covariance matrices	No prior knowledge is required but requires prior training
Sensor dependency	System-specific; requires redesign or parameter tuning for different sensors	System independent algorithm (generalized algorithms can adapt to different platform)
Linearity	Relies on explicit system modeling to manage system nonlinearity	Naturally handles nonlinearities

Beyond filtering methods, leveraging the motion constraints inherent to specific platforms offers further opportunities to enhance navigation accuracy, which will be discussed in the next section.

4.3 Platform-Specific Considerations and Motion Constraints

Motion constraints play a critical role in shaping the performance and accuracy of INS/GNSS navigation systems, particularly when tailored to the specific dynamics of different platforms. By understanding and leveraging these constraints, especially nonholonomic ones, navigation systems can achieve enhanced robustness and precision in challenging environments. Nonholonomic constraints refer to constraints in a system that cannot be expressed as a direct function of the system's state variables and their derivatives. In navigation systems, these constraints arise when certain degrees of freedom (such as velocity) are restricted by the system's geometry and motion limitations. For example, in land vehicles, nonholonomic constraints prevent the vehicle from moving sideways without turning its wheels. These constraints are crucial for improving the accuracy and performance of INS/GNSS systems by leveraging platform-specific motion characteristics.

The classification of INS/GNSS frameworks into aerial, maritime, and land vehicle platforms reflects the different motion dynamics and constraints each platform experiences. In each of these platforms, nonholonomic constraints can enhance the INS/GNSS system as follows:

4.3.1 Aerial Platforms

Aircraft and UAVs are typically free from nonholonomic constraints. However, they are influenced by aerodynamic forces and require accurate models of attitude and dynamics for stable navigation. Nonholonomic constraints might be used in specific scenarios, such as for fixed-wing aircraft, which can't move sideways without turning or changing orientation. KF, EKF, and complementary filtering are often employed to integrate IMU and GNSS data with these dynamics, improving accuracy during flight.

4.3.2 Maritime Platforms:

Maritime vehicles (ships, boats, etc.) experience nonholonomic constraints in the form of limited sideways motion. Their motion is often constrained to forward or backward movement, with limited lateral motion due to the hydrodynamic forces and hull design. These constraints can be used to improve the navigation performance by reducing errors associated with lateral movement. Fusion techniques like KF and inertial navigation can benefit from incorporating these constraints, enhancing the fusion between IMU and GNSS data.

4.3.3 Land Vehicles:

Land vehicles are typically subject to more explicit nonholonomic constraints, such as the inability to move sideways without turning. These constraints are often modeled as part of the motion equations, allowing the INS/GNSS system to reduce lateral error growth. For example, odometry data can be used to enhance INS performance by imposing constraints that limit the vehicle's motion. Specialized filters like the UKF or the MEKF are often applied to take advantage of these constraints, improving both position and velocity estimates in urban or rural environments where GNSS signals may be weak or obstructed.

5. Conclusion

This review presents a comprehensive overview of integrated INS/GNSS navigation systems with a focus on sensor technologies, fusion architectures, and state estimation techniques. It classifies inertial sensors based on performance, size, and cost, and evaluates the trade-offs among different integration strategies, including loosely coupled, tightly coupled, and ultra-tightly coupled frameworks. The paper compares model-based filtering approaches such as EKF, UKF, CKF, PKF, and IEKF with recent advances in AI-based methods. It highlights the increasing potential of AI to either replace or enhance traditional filtering through data-driven learning, especially in environments with GNSS outages or high dynamics. Furthermore, the integration of platform-specific motion constraints is shown to improve estimation accuracy by leveraging domain knowledge. Collectively, the findings underscore that combining classical estimation theory with AI and domain-specific modeling enables the development of highly robust and intelligent navigation systems for next-generation applications.

References

Grewal, M. S., Weill, L. R., & Andrews, A. P. (2007). Global positioning systems, inertial navigation, and integration (2nd ed.). John Wiley & Sons.

Amean, Z. S. (2001). Development of GPS Navigation Aiding for a Ballistic Missile (Master's thesis). Department of Control and Computers Engineering, University of Technology.

Titterton, D. H., & Weston, J. L. (2004). Strapdown inertial navigation technology (2nd ed.). The Institution of Engineering and Technology.

El-Sheimy, N., Hou, H., & Niu, X. (2008). Analysis and modeling of inertial sensors using Allan variance. IEEE Transactions on Instrumentation and Measurement, 57(1), 140–149.

Lefèvre, H. C. (2014). The fiber-optic gyroscope (2nd ed.). Artech House.

Lawrence, A. (1998). Modern inertial technology: Navigation, guidance, and control (2nd ed.). Springer.

Syed, Z. F., Aggarwal, P., Niu, X., & El-Sheimy, N. (2007). Civilian vehicle navigation: Requirements and solutions. In IEEE/ION Position, Location and Navigation Symposium (pp. 1016–1025).

Britting, K. R. (2010). Inertial navigation systems analysis. Artech House.

Savage, P. G. (1991). Introduction to strapdown inertial navigation systems. Strapdown Associates.

Inertial Labs. (n.d.). GNSS and satellite navigation explained. Retrieved July 19, 2024, from https://inertiallabs.com/gnss-and-satellite-navigation-explained/

Zumberge, J. F., Heflin, M. B., Jefferson, D. C., Watkins, M. M., & Webb, F. H. (1997). Precise point positioning for the efficient and robust analysis of GPS data from large networks. Journal of Geophysical Research: Solid Earth, 102(B3), 5005–5017.

Kee, C., Parkinson, B. W., & Axelrad, P. (2001). Wide area differential GPS: Error sources and estimation. Navigation, 48(2), 85–102.

Misra, P., & Enge, P. (2006). Global positioning system: Signals, measurements, and performance. Ganga-Jamuna Press.

Saastamoinen, J. (1972). Atmospheric correction for the troposphere and stratosphere in radio ranging of satellites. Geophysical Monograph Series, 15, 247–251.

Axelrad, P., Comp, C., & MacDoran, P. F. (1996). GPS multipath mitigation using antenna back lobe cancellation. ION GPS, 96, 655–664.

Van Dierendonck, A. J., Fenton, P., & Ford, T. (1992). Theory and performance of narrow correlator spacing in a GPS receiver. NAVIGATION: Journal of the Institute of Navigation, 39(3), 265–283.

Leick, A. (2004). GPS satellite surveying (3rd ed.). John Wiley & Sons.

Grewal, M. S., & Andrews, A. P. (2007). Global navigation satellite systems, inertial navigation, and integration. Wiley.

Groves, P. D. (2013). Principles of GNSS, inertial, and multisensor integrated navigation systems (2nd ed.). Artech House.

Li, K. L., Hu, B. Q., Gao, J. D., & Li, Y. (2014). Direct navigation mode and indirect navigation mode for integrated SINS/GPS. Applied Mechanics and Materials, 958, 963–968.

Noureldin, A., Karamat, T. B., & Georgy, J. (2013). Fundamentals of inertial navigation, satellite-based positioning and their integration. Springer.

Lei, G., Fan, Z., He, T., Lv, J., & Zhang, X. (2024). A loosely coupled INS/BDS integrated navigation system.

Muhammad, U., Babri, B., Haider, I., Ahmad, R., & Alam, M. (2024). Tight coupling of GNSS and IMU using extended Kalman filtering.

Jwo, D., Yang, C. F., Chuang, C. H., & Lin, K. C. (2012). A novel design for the ultra-tightly coupled GPS/INS navigation system. The Journal of Navigation, 65(4), 717–747.

Elmezayen, A., & El-Rabbany, A. (2021). Ultra-low-cost tightly coupled triple-constellation GNSS PPP/MEMS-based INS integration for land vehicular applications. Journal of Navigation, 1(2), 258–286.

Cristodaro, C., Ruotsalainen, L., & Dovis, F. (2018). GNSS/INS/visual deeply coupled integration: Preliminary investigation on dynamic jammed datasets. In Proceedings of the 31st International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+), 3088–3097.

Li, H., Wang, S., Zhou, Y., Shen, Z., & Li, X. (2022). Tightly coupled integration of GNSS, INS, and LiDAR for vehicle navigation in urban environments. IEEE Internet of Things Journal.

Tarek, M., Zahran, S., Radi, A., Nafea, S. F., Oda, E. S., & Hafez, A. E.-D. S. (2023). Performance analysis of quaternion vs Euler-based approaches in reduced INS/GNSS fusion techniques. 2023 International Telecommunications Conference (ITC-Egypt), 530–537.

Yin, Y., Zhang, J., Guo, M., Ning, X., Wang, Y., & Lu, J. (2023). Sensor fusion of GNSS and IMU data for robust localization via smoothed error state Kalman filter. Sensors, 23(7), 3676.

Adalberto, J., Tavares, A., & Oliveira, N. M. F. (2024). A novel approach for Kalman filter tuning for direct and indirect inertial navigation system/global navigation satellite system integration. Sensors.

Gonggang, G., Zhikun, L., Zhonghong, L., Mu, P., Yuan, J., & Lin, W. (2024). Kalman filter state transformation application in INS/GNSS integrated navigation for polar navigation.

Grewal, M. S., & Andrews, A. P. (2001). Kalman filtering: Theory and practice using MATLAB. Wiley.

Wang, X., Zhao, Q., Lei, Y., & Li, T. (2022). EKF-based design of low precision INS-assisted GPS integrated navigation system. In Proceedings of the International Conference on Electronic Information Technology (EIT 2022).

Allan, N., & Jayaprasanth, D. (2019). Integration of inertial navigation system with global positioning system using extended Kalman filter. In Proceedings of the 2019 International Conference on Smart Systems and Inventive Technology (ICSSIT) (pp. 1–13).

Mohamed, A. H., & Schwarz, K. P. (1999). Adaptive Kalman filtering for INS/GPS. Journal of Geodesy, 73(5), 193–203.

Yang, Y., Zhou, J., & Loffeld, O. (2012). Quaternion-based Kalman filtering on INS/GPS. In Proceedings of the International Society for Optics and Photonics (SPIE).

Krener, A. J. (2003). The convergence of the extended Kalman filter. In Directions in Mathematical Systems Theory and Optimization (Vol. 286, pp. 173–182).

Ge, Y., van Goor, P., & Mahony, R. (2023). A note on the extended Kalman filter on a manifold. arXiv:2309.06008.

Xuhua, Z., Fengjun, Q., Hongtao, Z., & Haifeng, X. (2012). Application of unscented Kalman filter in GPS/INS. In 2012 Symposium on Photonics and Optoelectronics (pp. 1–3).

Cahyadi, M. N., Asfihani, T., Suhandri, H. F., & Erfianti, R. (2024). Unscented Kalman filter for a low-cost GNSS/IMU-based mobile mapping application under demanding conditions. Geodesy and Geodynamics, 15(2), 166–176.

Arasaratnam, I., & Haykin, S. (2009). Cubature Kalman filters. IEEE Transactions on Automatic Control, 54(6), 1254–1269.

Wu, J., Jiang, J., Tang, Y., & Liu, J. (2024). Gaussian–Student's t mixture distribution-based robust Kalman filter for global navigation satellite system/inertial navigation system/odometer data fusion. Remote Sensing, 16(24), 4716.

Taghizadeh, M., & Safabakhsh, R. (2023). Low-cost integrated INS/GNSS using adaptive H∞ cubature Kalman filter. The Journal of Navigation, 76(1), 1–19.

Gao, B., Gaoge, H., Zhang, L., Zhong, Y., & Zhu, X. (2023). Cubature Kalman filter with closed-loop covariance feedback control for integrated INS/GNSS navigation. The Journal of Navigation, 76(1), 1–19.

Khanaa, V., Thooyamani, K. P., & Udayakumar, R. (2014). An improved Rao-Blackwellized particle filter for GPS-INS integrated navigation. Middle-East Journal of Scientific Research, 20(9), 1111–1115.

Gustafsson, F., Gunnarsson, F., Bergman, N., Forssell, U., Jansson, J., Karlsson, R., & Nordlund, P.-J. (2001). Particle filters for positioning, navigation, and tracking. IEEE Transactions on Signal Processing, 49(10), 2191–2201.

Giremus, A., & Tourneret, J.-Y. (2006). Controlling particle filter regularization for GPS/INS hybridization. In Proceedings of the 2006 14th European Signal Processing Conference (EUSIPCO).

Li, H., Wang, S., Zhou, Y., Shen, Z., & Li, X. (2017). An unbiased homotopy particle filter and its application to the INS/GPS integrated navigation system. In Proceedings of the 20th International Conference on Information Fusion (Fusion) (pp. 1–8).

Kubo, Y., & Wang, J. (2008). INS/GPS integration using Gaussian sum particle filter. In Proceedings of the 21st International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2008), Savannah, GA.

Bernal, D., Closas, P., & Fernandez-Rubio, J. A. (2008). Particle filtering algorithm for ultra-tight GNSS/INS integration. In Proceedings of the 21st International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS 2008) (pp. 2137–2144).

Barrau, A., & Bonnabel, S. (2018). Invariant Kalman filtering. Annual Review of Control, Robotics, and Autonomous Systems, 1, 237–257.

Maidens, J. N., Barrau, A., Bonnabel, S., & Arcak, M. (2017). Symmetry reduction for dynamic programming and application to MRI. In Proceedings of the 2017 American Control Conference (ACC) (pp. 4625–4630).

Bonnabel, S. (2007). Left-invariant extended Kalman filter and attitude estimation. In Proceedings of the 46th IEEE Conference on Decision and Control (pp. 1027–1032).

Bonnabel, S., Martin, P., & Rouchon, P. (2008). Symmetry-preserving observers. IEEE Transactions on Automatic Control, 53(11), 2514–2526.

Bonnabel, S., Martin, P., & Rouchon, P. (2009). Non-linear symmetry-preserving observers on Lie groups. IEEE Transactions on Automatic Control, 54(7), 1709–1713.

Barrau, A., & Bonnabel, S. (2017). The invariant extended Kalman filter as a stable observer. IEEE Transactions on Automatic Control, 62(4), 1797–1812.

Ko, N. Y., Youn, W., Choi, I. H., Song, G., & Kim, T. S. (2018). Features of invariant extended Kalman filter applied to unmanned aerial vehicle navigation. Sensors, 18(5), 1400.

Khalid, S. (2023). Artificial intelligence (AI) in engineering and technology. International Journal of Future Research, 1(1), 1–10.

Ünal, M., Ak, A., Topuz, V., & Erdal, H. (2013). Artificial neural networks. In Optimization of PID Controllers Using Ant Colony and Genetic Algorithms (Vol. 449, pp. 5–17). Springer.

Kruse, R., & Nauck, D. (2013). Neuro-fuzzy systems. In Computational Intelligence: Soft Computing and Fuzzy-Neuro Integration with Applications (pp. 230–259). Springer.

Hajian, A., & Styles, P. (2018). Neuro-fuzzy systems. In Application of Soft Computing and Intelligent Methods in Geophysics (Vol. 449, pp. 375–395). Springer.

Goser, K., Schuhmacher, M., Hartung, K., Heesche, B., Hesse, A., & Kanstein, A. (1996). Neuro-fuzzy systems for engineering applications. In Proceedings of the 1996 American Control Conference (AFC) (Vol. 2, pp. 1234–1239).

Vanneschi, L., & Silva, S. (2023). Genetic algorithms. In Lectures on Intelligent Systems (pp. 45–103). Springer.

Hsu, W. H. (2009). Evolutionary computation and genetic algorithms. In J. Wang (Ed.), Encyclopedia of Data Warehousing and Mining (2nd ed., pp. 817–822). IGI Global.

Onyekpe, U., Palade, V., & Kanarachos, S. (2021). Learning to localise automated vehicles in challenging environments using inertial navigation systems (INS). Applied Sciences, 11(3), 1270.

Zhang, A., & Atia, M. M. (2020). An efficient tuning framework for Kalman filter parameter optimization using design of experiments and genetic algorithms. NAVIGATION: Journal of the Institute of Navigation, 67(4), 775–793.

Li, S., Mikhaylov, M., Mikhaylov, N., & Pany, T. (2023). Deep learning based Kalman filter for GNSS/INS integration: Neural network architecture and feature selection. In Proceedings of the 2023 International Conference on Localization and GNSS (ICL-GNSS) (pp. 1–7).

Jwo, D.-J., Biswal, A., & Mir, I. A. (2023). Artificial neural networks for navigation systems: A review of recent research. Applied Sciences, 13(7), 4475.

Cohen, N., & Klein, I. (2024). Inertial navigation meets deep learning: A survey of current trends and future directions. Results in Engineering, 24, Article 103565.

Ning, X., et al. (2019). Optimal radial basis function-based neural network for improving INS/GNSS integration accuracy. Journal of Navigation and Control Systems.

Hang, Y., et al. (2020). Hybrid intelligence algorithm with discrete gray predictor and multilayer perceptron for INS/GNSS navigation. IEEE Transactions on Aerospace and Electronic Systems.

Wang, J., Wang, J., & Sinclair, D. (2020). Neural network aided Kalman filtering for integrated GPS/INS georeferencing platform. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XXXVI(5), C55.

Ma, H. (2007). Recurrent neural network approaches for nonlinear filters of navigation systems. Journal of Systems Engineering and Electronics.

Liu, J., et al. (2021). Multi-channel LSTM networks for GNSS outage prediction in INS/GNSS navigation systems. Sensors, 21(8), 2681.

Tang, Z., et al. (2022). Hybrid GRU and adaptive Kalman filter algorithm for real-time GNSS outage prediction. Applied Soft Computing, 116, 108347.

Zhi, Q., et al. (2023). CNN-LSTM for pseudo-GPS signal generation to improve navigation accuracy during GNSS outages. International Journal of Navigation and Observation.

Al Bitar, F., et al. (2023). Real-time training strategy for INS/GNSS integrated navigation systems during GNSS outages. IEEE Transactions on Intelligent Transportation Systems.