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SENSOR FUSION TECHNOLOGY ADVANCEMENT IN GPS-AIDED LOCALIZATION FOR AUTONOMOUS MOBILE ROBOTS: A COMPREHENSIVE SURVEY

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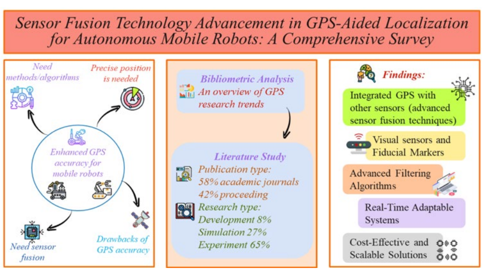
Graphical abstract



Abstract

Autonomous technology enables mobile robots to perform multiple functions, including navigation, decision-making, and automatic control, using sensors and advanced software. Localization, a key element of navigation, involves determining mobile robots' precise location and orientation. As most of the outdoor robots utilize Global Positioning System (GPS)-based data to navigate, this study surveys advancements in GPS (Global Positioning System)-assisted localization for autonomous mobile robots focusing on sensor fusion technology. The methodology includes collecting and analyzing papers from 2018 to 2024 using keywords such as GPS accuracy improvement, autonomous navigation, outdoor localization, autonomous vehicle, and autonomous mobile robot. The classification and examination of the chosen papers offer a comprehensive overview of the advantages and disadvantages of sensors and methods used to improve GPS accuracy, and the evaluation of these sensors and methods to identify the optimal solution available. Notably, several sensor fusion approaches have demonstrated substantial improvements, for instance, reducing localization errors from 79 to 3.7 meters which thereby highlighting the study's practical significance. The findings also indicate that visual sensors and fiducial markers are potential options to mitigate GPS signal loss, advanced filtering algorithms provide better accuracy and reliability, and real-time adaptive systems improve performance under various conditions, ensuring more reliable navigation. The integration of sensor fusion and advanced algorithms will provide significant technological progress in autonomous systems and intelligent environments.

Keywords: GPS accuracy, outdoor localization, sensor fusion, sensor integration, autonomous mobile robot, localization algorithm

Abstrak

Teknologi autonomi membolehkan robot mudah alih melaksanakan pelbagai fungsi, termasuk navigasi, membuat keputusan dan kawalan automatik, dengan menggunakan pelbagai penderia dan perisian lanjutan. Penyetempatan, elemen utama navigasi, melibatkan penentuan lokasi dan orientasi tepat robot mudah alih. Menurut kajian terdahulu, kaedah Correntropy Kalman Filter (CKF) meningkatkan ketepatan GPS sebanyak 34%. Oleh itu, kajian ini meninjau kemajuan dalam penyetempatan berbantu GPS (Global Positioning System) untuk robot mudah alih autonomi yang memfokuskan pada teknologi gabungan sensor. Metodologi termasuk mengumpul dan menganalisis kertas kerja dari 2018 hingga 2024 menggunakan kata kunci seperti peningkatan ketepatan GPS, navigasi autonomi, penyetempatan luar, kenderaan autonomi dan robot mudah alih autonomi. Pengelasan dan pemeriksaan kertas yang dipilih menawarkan gambaran menyeluruh tentang kelebihan dan kekurangan penderia dan kaedah yang digunakan untuk meningkatkan ketepatan GPS, dan penilaian penderia dan kaedah ini untuk mengenal pasti penyelesaian optimum yang tersedia. Terutamanya, beberapa pendekatan gabungan sensor telah menunjukkan peningkatan yang ketara, contohnya, mengurangkan ralat penyetempatan daripada 79 kepada 3.7 meter—dengan itu menonjolkan kepentingan praktikal kajian. Penemuan juga menunjukkan bahawa penderia visual dan penanda fidusia merupakan pilihan yang berpotensi untuk mengurangkan kehilangan isyarat GPS, algoritma penapisan lanjutan memberikan ketepatan dan kebolehpercayaan yang lebih baik, dan sistem penyesuaian masa nyata meningkatkan prestasi dalam pelbagai keadaan, memastikan navigasi yang lebih dipercayai. Penyepaduan gabungan sensor dan algoritma lanjutan akan memberikan kemajuan teknologi yang ketara dalam sistem autonomi dan persekitaran pintar.

Kata kunci: Ketepatan GPS, penyetempatan luar, gabungan sensor, penyepaduan sensor, robot mudah alih autonomi, algoritma penyetempatan

1.0 INTRODUCTION

The development of autonomous mobile robots (AMRs) has advanced significantly over the past few decades, driven by the increasing demand for intelligent systems capable of navigating and performing tasks in complex environments. One of the fundamental aspects of autonomous vehicles and robots is the ability to accurately determine their position and orientation within a given space, known as localization. Effective localization is crucial for deploying AMRs in various applications, including industrial automation, search and rescue operations, agricultural robotics, and urban mobility solutions [1].

GPS is a commonly used navigation sensor to determine location and direction in advanced vehicle and mobile robot systems [2], [3]. Originally developed to enhance military tactics, GPS relies on data from satellite to provide two or three-dimensional positioning on Earth. It operates through a constellation of satellites that transmit signals to GPS receivers, enabling accurate location determination. The accuracy of the determined position improves with the number of satellites used in the analysis [4], [5]. Typically, a GPS receiver tracks multiple satellites, although the actual number may vary depending on the time and geographical location.

While GPS offers advantages in global positioning, it also faces limitations, particularly in regions with poor satellite visibility. Positional inaccuracies of 10 to 15 meters are common, which can hinder precise navigation [6]. Additionally, GPS signals are often weak or unavailable in indoor environments or densely populated areas with tall buildings [7] [8], leading to challenges for AMRs navigating in such conditions [9]. Therefore, these limitations highlight the need for complementary technologies to enhance GPS accuracy and reliability.

This study addresses the research problems concerning the limitations of GPS and the need for supplementary sensors. What sensors can improve GPS precision? Sensor fusion techniques have been utilized to improve the accuracy of GPS-based localization and resolve these difficulties. In this technique, a GPS-aided localization system combines the GPS data with additional information from other sensors such as inertial measurement units (IMUs), inertial navigation systems (INS), magnetometers, LiDAR (Light Detection and Ranging), and radar [10] [11]. Sensor fusion integrates data from multiple sources to reduce uncertainty, minimize environmental interference, and improve the accuracy and reliability of localization systems [12], [13], [14], [15]. By leveraging sensor fusion, AMRs can maintain precise trajectories towards stationary or moving targets, even with minimal prior knowledge of their surroundings. This integration compensates for the weaknesses of standalone GPS systems, ensuring robust and accurate localization.

This study differs from existing literature in [16] by providing a detailed comparison of the sensor fusion technologies and methodologies for enhancing GPS accuracy. It evaluates the benefits and drawbacks of various sensor combinations and identifies the most effective approaches for improving localization accuracy in AMRs.

This paper aims to provide a comprehensive survey of the advancements in GPS-aided localization for autonomous mobile robots focusing on sensor fusion technology. It explores state-of-the-art techniques, discusses the integration of multiple sensors, and highlights the ongoing efforts to overcome the inherent limitations of GPS technology. By investigating various methodologies and their effectiveness in enhancing localization accuracy, this survey seeks to offer significant insights into the current state of autonomous vehicle and robot navigation.

Additionally, it proposes potential topics for future research and improvement, aiming to advance the reliability and precision of autonomous systems in diverse environments.

The contributions of this study can be further outlined as follows:

1. **Comprehensive Review of GPS-Aided Localization Technologies:** This study provides an extensive review of the current GPS-aided localization technologies employed in autonomous mobile robots. The review covers various methodologies, their applications, and the advancements in enhancing GPS accuracy for better navigation and localization performance.
2. **Evaluation of Sensor Combinations:** The study evaluates the effectiveness of different sensor combinations in enhancing GPS accuracy—including an in-depth analysis of how integrating multiple sensors, such as IMUs, LiDAR, and cameras, can improve the overall localization accuracy and reliability of autonomous systems.
3. **Assessment of Advanced Techniques:** A critical assessment of advanced techniques such as Kalman filters, AI-based methods, and Bayesian approaches is conducted to identify the most effective methods for improving GPS accuracy. The study compares these techniques based on their performance, computational efficiency, and practical applicability in real-world scenarios.
4. **Identification of Challenges and Limitations:** The study identifies the existing challenges and limitations in the current GPS-aided localization technologies. It highlights the areas where further research and innovation are needed, providing a roadmap for future studies to address these gaps and enhance the capabilities of autonomous mobile robots.

This paper is further organized to provide a comprehensive exploration of GPS-aided localization for autonomous mobile robots. Section 2 details the survey methodology, including bibliometric analysis that explains research performance, identifies trends and research impacts in the field of GPS improvement, and the literature study that explains the approach used to compile and analyze the most relevant literature. Section 3 provides an overview of current GPS localization technologies, highlighting key innovations and challenges specific to autonomous mobile robot applications. Section 4 examines auxiliary sensors that enhance GPS accuracy, exploring the critical role and interplay with GPS data. Section 5 focuses on sensor fusion techniques, illustrating how multiple sensors are combined to create robust and precise localization systems. Section 6 outlines future directions and potential gaps in GPS-aided localization, offering insights into emerging trends and research opportunities. Finally, Section 7 concludes with the key findings of this study.

2.0 METHODOLOGY

The methodology applied in this literature review integrates bibliometric analysis with a systematic approach to collecting, filtering, and analyzing research papers relevant to GPS-based accuracy within the domain of navigation, localization, vehicles, and outdoor robotics. The bibliometric analysis offered valuable insights into the evolving research trends and highlights areas of increasing academic interest related to GPS technologies. In this study, the bibliometric approach provided a broad overview of research trends regarding GPS technologies and applications without requiring extensive filtering.

During the literature review phase, the inclusion and exclusion criteria, presented in Table 1, were systematically applied. These criteria, guided by the research question "Which sensors and methods enhance GPS accuracy, and how do these sensors and methods compare to identify the optimal choice for improving GPS accuracy?" involved a structured evaluation of titles, abstracts, and full texts to ensure relevance to the research subject. An explicit exclusion criterion was the elimination of review papers, which ensured that the final selection consisted exclusively of research articles published in peer-reviewed journals and conference proceedings. All selected publications addressed development, simulation, and experimentation related to GPS accuracy improvements.

Table 1 Inclusion and exclusion criteria

Selection	Criteria
Inclusion	Peer reviewed Technical field Publication of 2018 – 2024 Academic publications (journal and conference proceedings)
Exclusion	Review articles Non-English language publications Inaccessible articles

The selection of publication data from 2018 to 2024 ensured that the review reflected the most recent technological development and trends in sensor fusion and GPS accuracy enhancement techniques. Moreover, publications from this period were readily accessible, ensuring the relevance and currency of the review. Figure 1 illustrates the literature collection process for obtaining papers relevant to the research focus. During the identification stage, a vast amount of data was gathered—using predetermined keywords—covering a wide range of topics. Then, further filtering processes were implemented to refine these data and acquire relevant literature by including specific terms such as GPS, IMU, INS, and odometry, as this research also focuses on using these sensors.

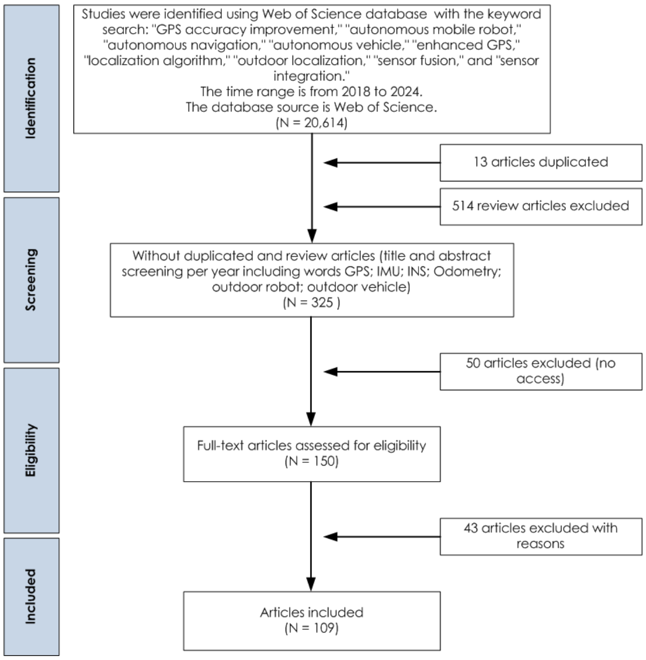


Figure 1 Literature collection process

2.1 Bibliometric Analysis

Before commencing the more in-depth literature survey, a bibliometric analysis was conducted, as it is a useful method for objectively assessing academic work and offering a comprehensive representation of the research topic [17].

Bibliometric analysis provides a comprehensive understanding of the progression and trends of research related to the subject area under investigation. For the purpose of this investigation, the Web of Science database was utilized, employing the following keywords: "GPS accuracy improvement," "autonomous mobile robot," "autonomous navigation," "autonomous vehicle," "enhanced GPS," "localization algorithm," "outdoor localization," "sensor fusion," and "sensor integration." The search query produced a total of 20,614 academic documents—including articles, conference papers, review articles, and early-access publications—published between 2018 and 2024. Then, these documents were exported into the RIS format for further analysis. The metadata extracted from these documents were subsequently analysed using VOSviewer, with a keyword occurrence threshold of 20. This threshold was selected to simplify visualization by ensuring only terms appearing more than 20 times were included, resulting in a manageable dataset of 813 keywords out of an initial 43,701. The implementation of this approach guarantees that only terms exhibiting a sufficiently high frequency are considered, hence facilitating the identification of significant research patterns and simplifying the visualization process.

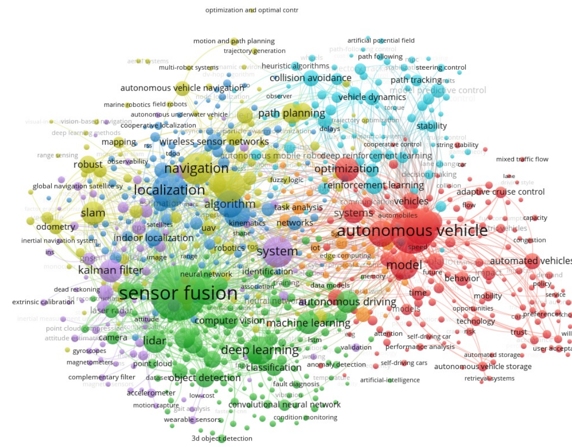


Figure 2 VOSviewer network visualization

Figure 2 presents seven clusters, each represented by a distinct color. The nodes with the largest size indicate the most frequently occurring terms in the analyzed documents. The dominant keywords frequently employed in academic literature are "sensor fusion," "autonomous vehicle," "localization," "navigation," "autonomous navigation," "system," "model," and "deep learning." Table 2 summarizes selected keywords that are closely associated with the current research under investigation. The visual size of the nodes correlates with the frequency of keyword occurrence, notably evident in keywords such as "sensor fusion," "autonomous vehicle," "navigation," and "localization."

Table 2 Keywords mapping

Keywords	Occurrences	Total link strength
sensor fusion	3,116	12,251
autonomous vehicle	3,458	13,730
navigation	1,054	5,489
autonomous navigation	1,076	3,503
localization	1,269	5,074
outdoor localization	31	86
system	978	4,637
model	810	3,764
deep learning	799	3,187
mobile robot	597	2,567
autonomous mobile robot	273	819
gps	197	865
global positioning system	97	747
accuracy	126	646
sensor integration	162	282
kalman filter	785	4,139
extended kalman filter	248	1,071

This paper specifically explores "GPS accuracy improvement," emphasizing the keywords "GPS or global positioning system" and "accuracy."

Figure 3 illustrates varying thicknesses of the labels for "accuracy" and "GPS" nodes, suggesting the frequency of use in the analysed documents. This analysis is also highlighted in Table 2, where the keywords "GPS" and "accuracy" appear only 197 and 126 times, respectively. Figure 4 illustrates the connection between the "GPS" node and the concurrent "sensor fusion," "navigation," "localization," and "GNSS" nodes, highlighting the use of GPS sensors as one of the employed sensors in research areas related to sensor fusion, navigation, and localization systems. Figure 5 further indicates stronger usage of GPS sensors in navigation compared to localization, as visually depicted by the thicker label for GPS in the navigation network versus the localization network (Figure 6).

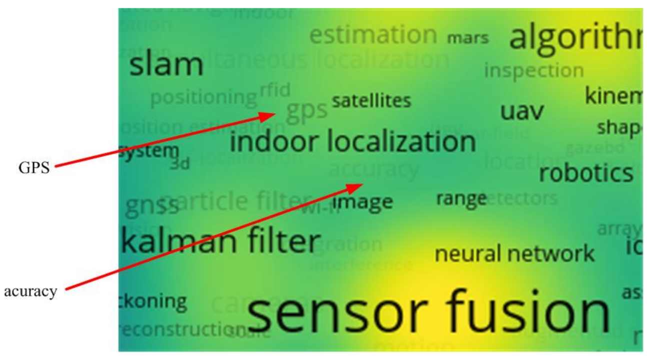


Figure 3 Visualization of GPS and accuracy labels

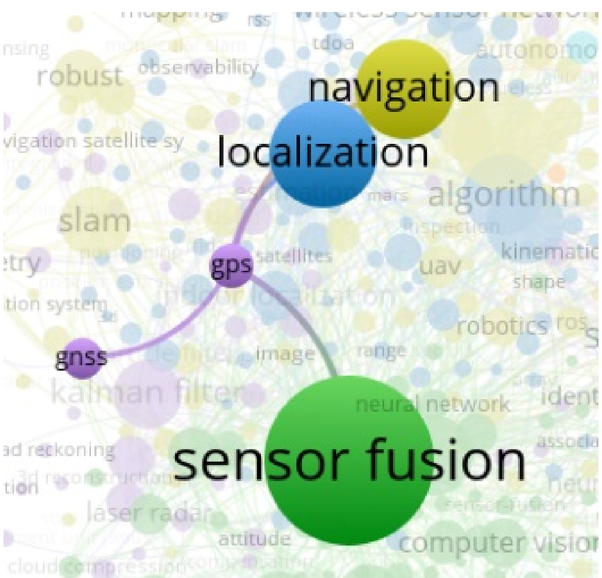


Figure 4 GPS network

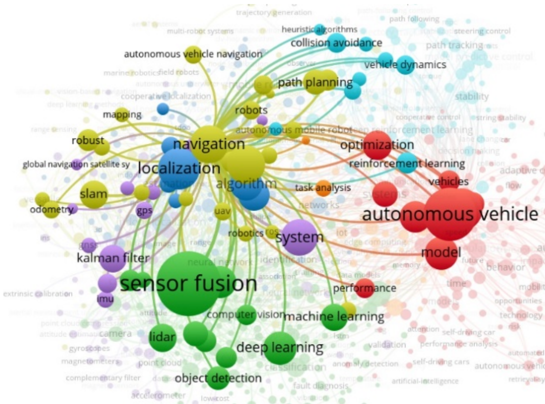


Figure 5 Navigation network

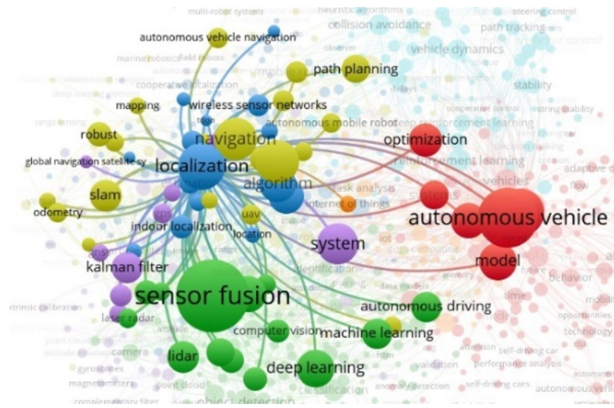


Figure 6 Localization network

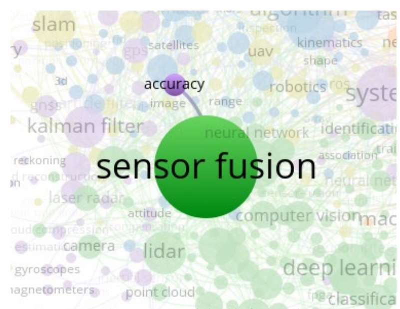


Figure 7 Accuracy network

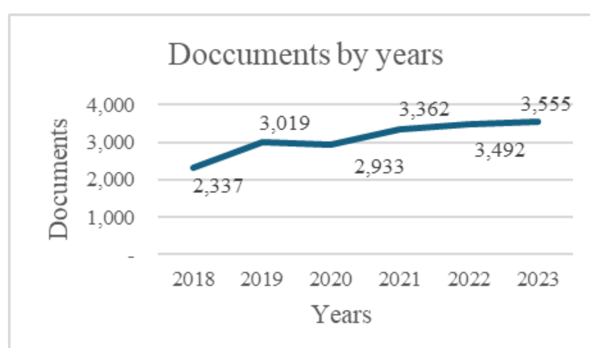


Figure 8 Current trend in GPS research (retrieved August 20, 2024)

Figure 7 highlights the association between "accuracy" and "sensor fusion" nodes, suggesting strong correlations between sensor fusion research and the accuracy of the employed sensors. Nevertheless, the lack of a direct connection between "accuracy" and the "GPS" indicates that investigations related to GPS rarely encompass an assessment of the accuracy of GPS sensors. This finding identifies a significant research gap, emphasizing opportunities for future investigations into "GPS accuracy improvement."

Figure 8 presents a statistical pattern from academic publications related to the aforementioned keywords, specifically focusing on the enhancement of GPS accuracy. The observed trend has exhibited a consistent upward trend over the years, suggesting that further investigation into enhancing GPS accuracy remains highly promising. The data analysis reveals that 63% of the publications are academic journals, while 37% are conference proceedings. Moreover, most of the research comprises 98% technical publications, whereas review articles constitute a mere 2% of the total.

2.2 Literature Study

The following outline clearly describes the steps undertaken to ensure a comprehensive and focused literature review, as well as highlighting the key contributions of the study:

A. Literature Search and Collection

The first step involves an extensive literature search to collect relevant research papers. This process included:

1. <u>Keywords Identification</u>: The keywords used for the search were "GPS accuracy improvement," "autonomous mobile robot," "autonomous navigation," "autonomous vehicle," "enhanced GPS," "localization algorithm," "outdoor localization," "sensor fusion," and "sensor integration." These keywords were specifically selected to cover a broad spectrum of research areas within the scope of GPS accuracy in autonomous systems.
2. <u>Databases and Sources:</u> The search used multiple academic databases, including IEEE Xplore, Google Scholar, Scopus, and Web of Science. These databases provided access to a wide range of peer-reviewed journals and conference proceedings.
3. <u>Initial Search Results:</u> The initial search yielded a large number of papers. These documents were then further screened based on titles and abstracts to assess their relevance to the topic of GPS accuracy improvement.

B. Filtering and Selection

A refined selection process was then applied to the initial pool of papers to specifically identify research addressing methods for improving GPS accuracy. The steps included:

1. <u>Relevance Screening:</u> Abstracts and conclusions were carefully examined to eliminate papers that did not directly address GPS accuracy enhancement within the targeted contexts.
2. <u>Full-Text Review:</u> The remaining papers underwent a full-text review to assess their contributions to the field. Only those that provide significant insights, methodologies, or experimental results related to GPS accuracy enhancement were included in the final selection.

C. Data Categorization and Analysis

The selected papers were categorized and analysed to provide a structured overview of the current research landscape:

1. Publication Type:
    - <u>Academic Journals:</u> 58% of the collected papers are from academic journals. These papers undergo rigorous peer-review processes, ensuring high-quality and reliable contributions.
    - <u>Conference Proceedings:</u> 42% of the papers are from conference proceedings. Conferences often present the latest research findings and emerging trends, making them a valuable source of current information.
2. Research Type:
    - <u>Development:</u> 8% of the papers focus on developing new technologies, algorithms, or systems to improve GPS accuracy. These contributions often include innovative approaches and theoretical advancements.
    - <u>Simulation:</u> 27% of the papers use simulation methods to model and test various hypotheses or systems related to GPS accuracy. Simulations provide a controlled environment for evaluating the effectiveness of different approaches.
    - <u>Experiment:</u> 65% of the papers are based on experimental research. These studies provide empirical data and practical insights by testing GPS accuracy improvements in real-world conditions or controlled experiments.

D. Temporal Analysis

Following initial keyword-based filtering, additional filtering was performed to specifically analyse research papers focused on GPS enhancement in mobile robots using sensor fusion, as shown in Table 3. This temporal analysis helps to identify research trends, advancements, and changes in research focus over time. Understanding the temporal distribution of research can highlight periods of increased interest or significant breakthroughs in the field of GPS accuracy for autonomous systems.

Table 3 Publications across the year

Year	Number of Papers	References
2018	13	[7], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29].
2019	12	[9], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41].
2020	14	[6], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [16].
2021	13	[55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [16], [65], [66].
2022	16	[67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82].
2023	19	[8], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100].
2024	20	[13], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119].

3.0 CURRENT GPS LOCALIZATION TECHNOLOGIES FOR AUTONOMOUS MOBILE ROBOTS

Localization refers to the process of accurately determining the position of an object within a predefined coordinate reference system utilyzing specialized technologies and methodologies, such as sensors, signal processing or sensor fusion. This capability is essential for tasks involving navigation, identification, or mapping in autonomous system. Localization is frequently employed in advance vehicle and mobile robot systems to precisely determine the whereabouts of vehicles or mobile robots.

Localization algorithms typically leverage sensor-derived measurements, including distance and bearing relative to known reference points (commonly referred to as anchors or beacons), to estimate the robot's or vehicle's position [120]. These anchors or beacons possess globally established coordinates and serve as fixed reference points for localization process.

Localization techniques can be broadly classified into two categories [121]: geometric and non-geometric approaches. Geometric approaches rely on spatial measurements such as distance, angles, or positional relationships with reference points to determine an object's relative position. Conversely, non-geometric methods use non-geometric data to determine position or location, such as radio signals, sensor data, image processing, fiducial markers, or advanced data analysis techniques.

GPS-based localization is a technique that uses data from the Global Positioning System (GPS) to accurately determine an object's location [122]. GPS offers notable benefits for robots [6], [7], [8], [83], [67], allowing them to navigate precisely even with limited knowledge of their surroundings. The location data provided by GPS is also vital for tracking vehicle or mobile robot movements in real-time. Additionally, the ability of robots to transmit their location through wireless signals facilitates effective remote monitoring and control. Although GPS has various advantages, it also has major limitations, including the possibility of losing GPS signals in heavily populated regions with tall structures and inherent positional inaccuracies. Consequently, integrating supplementary sensors is often necessary to refine GPS localization accuracy and mitigate these limitations.

This section reviews the state-of-the-art GPS-aided localization technologies and methodologies utilized in autonomous mobile robots.

Standard GPS: Geographical coordinates and time information are transmitted via satellites via the Global Positioning System (GPS), which operates regardless of the weather and in close proximity to any location on Earth. Standard GPS operates using a constellation of at least 24 satellites that orbit the Earth, transmitting signals to GPS receivers on the ground [123]. These receivers use the time delay between when a signal is sent and received to calculate the distance from multiple satellites and determine the precise location. Figure 9 illustrates the diagram of GPS constellation and signal transmission.

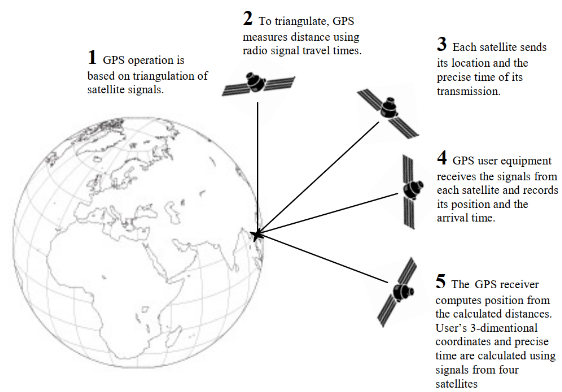


Figure 9 Standard GPS works (adopted from [124])

The accuracy of standard GPS is often limited to 10-15 meters due to various sources of error [6]. Atmospheric disturbances, such as ionospheric and tropospheric delays, can affect the speed of the GPS signals as they travel through the Earth's atmosphere. Multipath effects occur when GPS signals bounce off buildings or other structures before reaching the receiver, causing inaccuracies. In urban environments, non-line-of-sight (NLOS) signals caused by reflections from tall buildings remain a major source of positioning errors. A GPS receiver requires signals from at least four satellites to determine for accurate location determination. However, signals from NLOS satellites reflected by tall buildings can increase the pseudo-range, the estimated distance between the satellite and the GPS receiver, leading to errors in positioning [104]. Additionally, satellite clock inaccuracies and orbital errors contribute to the overall error margin. Despite these limitations, GPS remains a foundational technology for many localization systems, providing a global frame of reference and supporting a wide range of applications from navigation to timing services.

Differential GPS (DGPS): DGPS enhances the accuracy of standard GPS by using a network of fixed ground-based reference stations [125]. These stations are located at known positions and the difference between their true location and the location indicated by the GPS satellites is calculated. The reference stations then broadcast this correction data to DGPS receivers, which use the information to correct their GPS signals. This process significantly reduces errors, achieving an accuracy of 1-3 meters. Figure 10 illustrates the DGPS system that can give positional correction and better accuracy than standard GPS.

DGPS is particularly useful in applications where higher precision is required. Agriculture benefits from DGPS for precision farming techniques, such as planting and harvesting crops with minimal overlap or gaps [126]. Marine navigation uses DGPS for safe and efficient vessel navigation in crowded or hazardous waters [127]. Additionally, DGPS is used in surveying, where precise measurements are crucial for mapping and construction projects. By improving GPS data accuracy, DGPS helps autonomous mobile robots navigate more reliably and perform tasks with greater precision.

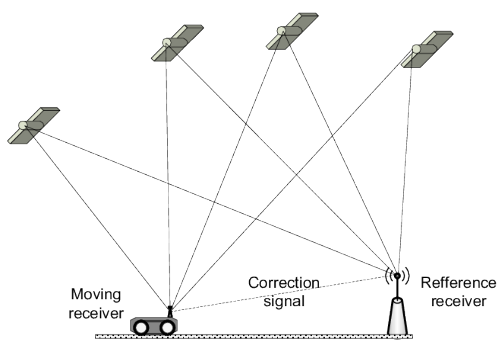


Figure 10 DGPS illustration (adopted from [128])

Real-Time Kinematic (RTK) GPS: RTK GPS provides centimetre-level accuracy by using carrier-based ranging and correction signals from a fixed base station [129], [130]. The RTK system comprises a base station and one or more rover units. The base station remains at a known, fixed position and broadcasts the carrier wave phase that the GPS satellites use. The mobile rover unit receives these signals from the base station and the satellites. By comparing the phase of the carrier wave from the base station with the phase received directly from the satellites, the rover can determine its position with high precision. Figure 11 illustrates the RTK-GPS system.

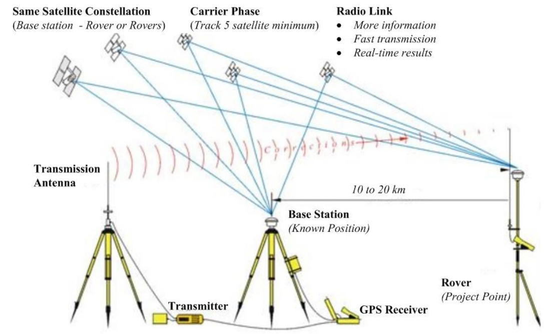


Figure 11 The idea behind RTK GPS surveying (adopted from [131])

RTK GPS is widely used in applications requiring high precision. Construction projects benefit from RTK GPS for tasks such as grading and excavation, where accurate positioning is critical. Surveying uses RTK GPS to create highly detailed and accurate maps and to lay out property boundaries. Precision agriculture employs RTK GPS for automated steering systems on tractors and other equipment, enabling precise planting, fertilizing, and harvesting.

Despite its high-level accuracy in localization systems, RTK systems also come with several disadvantages, including:

- Infrastructure Requirements: RTK requires a network of base stations to provide correction signals, which can be costly and complex to set up and maintain, especially in large or remote areas.
- Line-of-Sight Dependency: RTK performance relies on a clear line of sight between the base station and the rover receiver. Obstructions such as buildings, trees, or terrain can interrupt the correction signal, reducing accuracy.
- High Cost: RTK systems are generally more expensive than standard GPS receivers, which can be a barrier to widespread adoption, particularly in cost-sensitive applications.
- Data Transmission: RTK systems require a reliable data link between the base station and the rover receiver to transmit correction data. This requirement can be challenging in areas with poor coverage or during network outages.
- Susceptibility to Interference: RTK signals can be affected by radio frequency interference and atmospheric conditions, which can degrade performance and reliability.

Integrating these advanced GPS-aided localization technologies—standard GPS, DGPS, and RTK GPS—into autonomous mobile robots significantly enhances their navigation and operational capabilities. Each technology addresses specific limitations of standard GPS, providing varying levels of accuracy suitable for different applications.

In the next section, a comprehensive evaluation of various sensor combinations commonly used to aid GPS localization and their effectiveness in enhancing GPS accuracy will be presented. This includes an analysis of how these sensor combinations work together to overcome GPS's inherent limitations, thereby ensuring more reliable and precise localization for autonomous mobile robots in diverse environments.

4.0 AUXILIARY SENSORS FOR IMPROVING GPS ACCURACY

Various sensors can be integrated with GPS technology to enhance the accuracy of GPS-based localization for autonomous mobile robots. These sensors provide additional data that can be fused with GPS signals to correct errors and improve overall positioning accuracy. This section explores the commonly used sensors and their roles in enhancing GPS accuracy.

LiDAR, RADAR, ultrasonic sensors, and cameras are the primary sensors employed in autonomous mobile robots to enhance object recognition accuracy and localization. However, the detection, localization, and positioning capabilities of these individual systems are inadequate when used alone [132]. As a result, it is necessary to integrate these sensors with navigation and motion measurement sensors to improve the accuracy of position estimates and provide essential data for navigation purposes.

<u>LiDAR (Light Detection and Ranging)</u> [133]**:** LiDAR sensors use laser pulses to measure distances to surrounding objects, creating detailed 3D maps of the environment. A LiDAR system initiates the sensing process by generating laser pulses towards a specified location. When these pulses encounter barriers, they reflect a fraction of their emitted light to the LiDAR sensor. By calculating the duration of each laser pulse and leveraging the constant speed of light, LiDAR determines the distance to the target [134]. This technology is highly accurate, reaching centimetre-level accuracy [135] and can operate in various lighting conditions, making it an excellent sensor to be fused with GPS for both outdoor and indoor navigation. LiDAR provides high-resolution data that is critical for detecting and avoiding obstacles, mapping the environment, and performing precise localization. In addition, using LiDAR is also strongly recommended for precision measurements over long distances. However, LiDAR systems can be expensive and computationally intensive [136] and high-power consumption [137], requiring efficient processing algorithms to handle the large volumes of data generated.

<u>RADAR</u> [138]**:** RADAR sensors emit radio waves and measure the time it takes for the waves to bounce back from objects, providing information about the object's distance and relative speed. RADAR is particularly useful in adverse weather conditions, such as fog, rain, or snow, where optical sensors like cameras and LiDAR might struggle. RADAR's ability to penetrate certain obstacles and its robustness to environmental conditions make it a valuable addition to GPS for enhancing localization accuracy. However, RADAR typically offers lower resolution than LiDAR, necessitating the integration of multiple sensors for comprehensive environmental perception.

<u>Ultrasonic Sensors:</u> Ultrasonic sensors use sound waves to detect objects and measure distances, making them ideal for short-range obstacle detection and avoidance. They are commonly used in applications such as parking assistance and low-speed manoeuvring. Ultrasonic sensors are relatively low-cost and can operate in various lighting conditions [139]. However, their range and resolution are limited, and they are primarily effective for detecting large, solid objects rather than fine details in the environment.

<u>Cameras</u> [140]**:** Cameras capture visual information about the environment and are widely used for object recognition, tracking, and navigation. When combined with GPS, camera data can enhance localization by providing visual cues and landmarks that help correct GPS errors. Visual SLAM (Simultaneous Localization and Mapping) algorithms use camera data to build and update maps of the environment in real-time, offering precise localization even in GPS-denied areas. Cameras are relatively low-cost and provide rich environmental information, but their performance can be affected by lighting conditions and require significant computational resources for image processing.

<u>Inertial Measurement Units (IMUs)</u> [141]**:** IMUs consist of accelerometers and gyroscopes that measure linear acceleration and angular velocity, respectively. Another type of IMU is the Micro-Electro-Mechanical Systems Inertial Measurement Unit (MEMS-IMU), which uses MEMS technology to produce miniature sensors. The MEMS-IMU is extensively utilized in military and civilian applications due to its compact size, affordability, robust autonomy, and comprehensive navigation data [35]. The Inertial Navigation System (INS) integrates data from an IMU with sophisticated algorithms to deliver uninterrupted location and velocity estimates. These systems are beneficial in GPS-denied environments, such as tunnels or indoor areas. IMUs provide high-frequency data that can help bridge the gaps between GPS updates, particularly useful in environments where GPS signals are weak or intermittent. However, IMUs suffer from drift over time, leading to cumulative errors if not corrected by other sensors, such as GPS or magnetometers. INS can correct long-term drift in IMU measurements by integrating GPS data, offering a more stable and accurate localization solution. Advanced inertial navigation system (INS) implementations frequently include Kalman filters to effectively merge data from many sources, hence improving the overall precision and dependability of the navigation system [142].

<u>Odometry:</u> Odometry uses data from wheel encoders to estimate the distance mobile robots travel. It is a valuable short-term position estimation tool and particularly useful in structured environments

like warehouses or factories. Odometry is essential for robot navigation. It provides relative movement data that can complement GPS by filling in the gaps between GPS updates [134]. However, it is susceptible to errors due to wheel slippage, uneven terrain, and other factors affecting wheel-ground contact [143]. Integrating odometry with GPS helps mitigate these errors and improves overall localization accuracy.

5.0 IMPROVEMENT OF GPS BASED LOCALIZATION USING SENSOR FUSION

Even though GPS provides significant benefits for autonomous robot localization—especially in terms of global coverage and ease of integration—its reliability can be compromised by signal loss, multipath effects, and inaccuracies in dense urban areas. To address these limitations and improve GPS accuracy, integration with additional sensors becomes essential. Sensor fusion, which combines data from various sensors, has potential to improves overall precision, corrects errors, and provides more robust positioning across diverse environments.

5.1 Sensor Combinations Used in Autonomous Navigation

Table 4 summarizes various sensor combinations commonly used in autonomous navigation, emphasizing their respective benefits and drawbacks. In the following discussion, these methods are compared more directly, with illustrative real-world applications explicitly mentioning their limitations, computational considerations, and deployment requirements.

The integration of GPS with various sensors—such as IMU, MEMS-IMU, odometry, INS, ultrasonic, and LiDAR—enables the development of advanced navigation capabilities with exceptional precision in localization. Nevertheless, each sensor combination is associated with its own set of challenges, such as disruptions in GPS signals, inaccuracy of sensors in specific scenarios, exorbitant expenses, and complex installation procedures.

Table 4 Sensor combinations in autonomous navigation: advantages and disadvantages

Sensors used	Advantage	Disadvantage	Ref
GPS, IMU	GPS provides precise position accuracy that is critical for autonomous navigation, while IMU provides weather-resistant motion data that is essential for speed estimation and navigation in GPS signal-limited areas.	Building reflections and electronic noise can disrupt GPS accuracy, while IMU errors due to temperature and vibration can compound over time unless corrected by external data like GPS.	[18], [56], [77], [144], [145]
GPS, MEMS-IMU, odometry	The combination of GPS with MEMS navigation systems helps reduce position and velocity errors in navigation by improving inertial sensors, while odometry through wheel monitoring supports position estimation in environments with GPS signal disturbances.	GPS inaccuracies due to multipath effects and limitations in MEMS-IMU sensors contribute to navigation errors in position and orientation. Temperature changes and road conditions further affect odometry performance and position estimation accuracy.	[25], [33], [35]
GPS, IMU, Visual Odometry	The combination of GPS, IMU, and visual odometry (VO) help maintain localization when GPS data is unreliable. IMU and VO suffer from cumulative drift over time, but GPS corrects these errors, keeping the robot's position stable.	VO is sensitive to environmental changes (e.g., poor lighting, texture less surfaces) and can lose track of features, leading to errors. Sensor fusion requires precise calibration and time synchronization among GPS, IMU, and VO, which can be challenging in dynamic environments.	[41]
GPS, INS	GPS and INS integration enhances navigation accuracy by using GPS as a reference to correct INS errors, particularly in challenging environments with limited GPS signals. Its integration features small size, low cost, high precision, and strong autonomy. GPS enhances multi sensor navigation precision with reliable position data, while gyroscopes and accelerometers monitor orientation and motion when GPS is unavailable.	GPS accuracy can suffer from slow updates and signal disruptions, while INS may have errors, particularly in estimating yaw rotation angles. Impulsive non-Gaussian sounds can disrupt GPS signals, reducing navigation system reliability. Strong filtering techniques are needed, as traditional GPS algorithms may not suffice. Gyroscopes, which are prone to drift, require calibration to maintain accuracy.	[7], [9], [19], [23], [31], [54], [101]
GPS, INS, Odometry	The combination of INS and odometry improve the limitations of GPS, which can lose signal or experience multipath errors. While GPS assists INS and odometry in mitigating the accumulation of error (drift) that arises from prolonged use of INS or odometry.	Odometry can cause significant errors if the wheels move or slip on uneven surfaces.	[16]
GPS, ultrasonic/ detection sensors	GPS aids in determining the robot's position and destination; ultrasonic sensors prevent collisions by measuring distances, while detection sensors ensure safe and efficient movement by avoiding obstacles.	GPS devices with high energy consumption can decrease a robot's battery life, and adverse weather conditions can disrupt GPS signals, leading to difficulties in determining the robot's location.	[20], [57], [65], [69],
GPS, LiDAR	GPS provides accurate outdoor positioning	Indoor GPS accuracy can vary, often	[30],

Sensors used	Advantage	Disadvantage	Ref
	before entering indoor spaces, while LIDAR helps the robot achieve precise movement. Together, they ensure reliable navigation in open and enclosed environments, enabling robots to operate effectively and safely in various scenarios.	necessitating additional sensors like LIDAR for precise positioning. However, LIDAR's high cost and complex installation are notable drawbacks.	[55]

Simple pairings of GPS with an IMU provide a balance of precise position data and additional, continuous motion readings, making them particularly useful in scenarios where GPS signals intermittently degrade [18], [56], [77], [144], [145]. Nevertheless, building reflections and temperature-induced drift in the IMU can compound errors if external GPS corrections are not applied consistently. Some deployments extend this setup by including GPS, a MEMS-IMU, and odometry, where the lower-cost MEMS-IMU contributes compact inertial sensing and odometry bolsters position estimates in environments prone to GPS signal disturbances [24], [32], [34]. However, road condition changes, multipath effects, and inherent sensor limitations can degrade orientation accuracy unless robust calibration and error-filtering procedures are in place.

Other approaches merge GPS, IMU, and Visual Odometry (VO) to stabilize localization when GPS signals are unreliable [41]. GPS aids in correcting drift that accumulates from VO and IMU measurements, though effective time synchronization, precise calibration, and adequate environmental features are essential to avoid tracking failures—particularly in poorly lit or low-texture settings. A more integrated solution uses GPS and INS—where the IMU feeds into an onboard navigation system that tracks position, velocity, and orientation. This method helps correct INS errors via GPS signals in challenging or partially obstructed areas [7], [9], [19], [23], [31], [54], [101]. However, updating rates and signal disruptions can still pose accuracy challenges if gyroscopic drift or non-Gaussian noise is not properly handled through advanced filtering.

Some implementations add odometry to the INS-based setup to form a GPS, INS, and odometry combination, where INS drift is partially mitigated by odometry inputs when GPS quality declines [54]. If wheels slip or ground conditions vary, though, odometry errors can grow rapidly, highlighting the need for continuous calibration and appropriate filtering. Meanwhile, simpler obstacle-avoidance scenarios may only require GPS teamed with ultrasonic or detection sensors, ensuring fundamental collision warnings at low speeds or short ranges [20], [57], [65], [69]. Although this setup is relatively cost-effective and power-efficient, it offers limited mapping capacity and depends heavily on stable GPS power and signal availability.

At the higher end, GPS and LiDAR can be fused for accurate outdoor positioning and 3D mapping—an approach that proves valuable when robots move between open fields and enclosed areas [30], [55]. LiDAR captures high-resolution distance measurements, compensating for GPS reliability issues and enabling more precise indoor navigation. The associated cost, installation complexity, and data-processing overhead are notable disadvantages, requiring specialized hardware acceleration or efficient point-cloud algorithms to maintain real-time performance.

Overall, each of these sensor-fusion strategies aims to address the inherent weaknesses of standalone GPS, yet they differ in terms of cost, calibration requirements, computational overhead, and suitability for particular environments. Choice depends on operational constraints—whether indoor or outdoor navigation is prioritized, tolerance for drift, available processing resources, and the target level of localization accuracy.

By examining these sensor-fusion combinations—GPS + LiDAR, GPS + INS/IMU + odometry, GPS + camera, and GPS + detection systems—developers can select the most effective strategy based on cost, computational capacity, environment, and the required level of accuracy. Each combination addresses specific weaknesses in standalone GPS and delivers more reliable localization under variable conditions. Nevertheless, every additional sensor introduces new requirements for power, calibration, and data throughput, underscoring the need to balance hardware constraints with performance objectives.

5.2.3 Frequently Used Techniques for Sensor Fusion

Various methods and sensor fusion techniques have been developed for effective data integration. The primary goal of sensor fusion is to combine the data from multiple sensors in a way that minimizes the overall error and provides a more accurate estimate of the robot's position. This involves the use of sophisticated algorithms that can handle the uncertainties and noise associated with individual sensor measurements.

Table 5 illustrates the frequently used techniques for combining several sensor data with GPS to improve localization accuracy, with the Kalman filter-based method and its variations being the most utilized This section discusses various methods developed to enhance the accuracy of GPS-aided localization, highlighting algorithms extensively utilized in recent decades. Kalman filters are employed in various forms, often combined with other methodologies that integrate fuzzy logic, neural networks, and Bayesian algorithms. These integrated approaches aim to tackle issues such as measurement inaccuracies and rapid environmental changes.

While several of these systems provide significant performance improvements, they often have limitations such as high computational costs or reliance on specific navigation scenarios. Thus, this review offers a comprehensive perspective on the progress made in navigation technology and the continuous endeavours to improve the precision and reliability of autonomous navigation systems.

Table 5 Methods to solve GPS accuracy

Kalman Filter Approach	Kalman filter [21], [23], [24], [26], [31], [34], [37], [38], [44], [16], [74], [80], [82], [86], [88], [91], [92], [110], [113], [118]
	Extended Kalman filter (EKF) [7], [9], [13], [23], [29], [33], [36], [37], [39], [40],[41], [49], [53], [71], [75], [81], [85], [89], [93], [98], [99], [100], [103], [110], [114], [115]
	Adaptive Kalman filter (AKF) [18]
	Adaptive Extended Kalman filter (AEKF) [114]
	Adaptive and Robust Maximum Correntropy Extended Kalman filter (MCEKF) [119]
	Unscented Kalman filter (UKF) [28], [47], [53], [61], [64], [85], [95], [107]
	Augmented Quaternion Unscented Kalman filter (AQUKF) [112]
	Adaptive Robust UKF (ARUKF) [53]
	Mahalanobis Distance based Adaptive Unscented Kalman filter (MDAUKF) [35]
	Maximum Likelihood based Adaptive UKF (MLAUKF) [53]
	Federal Kalman filter (FKF) [23], [87]
	Cubature Kalman filter [81]
	$MH\infty\text{-}^{5th}CKF$ [102]
	Multiple Fading Factor Square Root Cubature Kalman filter (MSCKF) [60], [94]
	Distributed Kalman filter Data Fusion with Feedback (DKFDFWF) [29]
	Weighted Kalman filter [51]
	Interactive Multi-Model Kalman filter (IMMKF) [29]
	Correntropy Kalman filter [82], [78]
	Kalman and Complimentary filter-based Fusion Schemes [16]
	Adaptive Students T-based Kalman filter (STKF) [59]
	Minimum Error Entropy-Gauss Quadrature Kalman filter (MEE-GQKF) [54]
Artificial Intelligence Approach	Naive Bayes Prediction [57]
	Adam Optimizer [48]
	Backpropagation algorithm [48], [74]
	Back Propagation Neural Network (BPNN) [102]
	Gradient Boosting Decision Tree [31]
	Decision Tree Regressor [109]
	Random Forest Regressor [109]
	Automated ARIMA model [52]
	Neural Network [16], [73]
	Nonlinear Autoregressive Neural Networks with External Inputs (NARX) [47], [61]
	Extreme Learning Machine (ELM) Optimized by Minimum Learning Parameter (MLP) [101]
	Deep Neural Network (DNN) [104]
	CNN-LSTM model [56]
	Artificial Neural Network (ANN) [49], [16]
	Fully Convolutional Neural Network (FCNN) [106]
	ALSTM-GCN Networks [117]
	Fuzzy Inference System (FIS) [40], [68]
	Fuzzy Logic And Fuzzy Wall-Following Controllers [43]
	Intelligent Adaptive Kalman Filter Based on Deep Neural Network and Fuzzy Logic [48]
	Adaptive Fuzzy Neural Network-Aided Progressive Gaussian filter [73]
	Fuzzy Neural Network (FNN) model [60], [96]
	Fuzzy Logic System (FLS) [16]
	Adaptive Neuro Fuzzy Inference System (ANFIS) [68], [69]
	Adaptive Fuzzy Neural Network [74]
	Hybrid GPS-ANFIS method [42]
Statistical Approach	Gaussian Mixtures [27], [71]
	Mixture Of Gaussian and Cauchy Distribution [27]
	Gaussian Sum filtering [54]
	Progressive Gaussian Approximate filter (PGAF) [46], [74]
	Robust Bayesian filtering algorithm [27]
	Variational Bayesian approach [46], [66], [73]
	The Variance Accounted For (VAF) [22]
	Root Mean Square (RMS) [22], [92], [97], [100],
	Root Mean Square Error (RMSE) [107], [110]

	Mean Square Error (MSE) [109], [111]
	Kullback_Leibler Divergence [27]
	Least Square (LS) [34]
	Recursive Least Square (RLS) [34]
	Linear Interpolation [49]
	Linear Regression [109]
	Nonlinear Autoregressive (NAR) model [49]
	The Adaptive Factor Graph (AFG) [101]
	Hidden Markov model (HMM) [116]
	Particle Weighting Monte Carlo Localization (MCL) [45]
	Adaptive Monte Carlo Localization algorithm [45]
	Particle Generation approach [45]
Other Approach	Lidar-based SLAM method [30]
	Fiducial Augmented Global Positioning System (FAGPS) [6]
	Fusion Calculation of Angles and Vectors [19]
	Gauss-Kruger Projection Plane Rectangular Coordinate System [19]
	Fusion method combining RTK-GPS [30]
	Fusion Navigation algorithm [19]
	Dead Reckoning (DR) [7], [33], [44], [75]
	Non-Holonomic Constraint (NHC) model [33], [84]
	Dijkstra algorithm [43], [57]
	the B-spline method [43]
	Chord Secant method [35]
	Adaptive Decision-Making algorithm [108]
	FDE (Fault Detection and Exclusion) based on K-Means Clustering [110]
	RANSAC (Random Sample Consensus) algorithm [111]
	Simultaneous Localization and Mapping (SLAM) [116]
	Factor Graph Optimization (FGO) [118]
	Particle Swarm Optimization (PSO) [31]
	A* algorithm [13]
	Dynamic Window approach (DWA) [106]
	Pure Pursuit algorithm [106]

5.2.1 Kalman Filter based Fusion Approach

Kalman filters are widely used in sensor fusion due to their ability to provide optimal estimates by minimizing the mean squared error. Various forms of Kalman filters exist, including the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), each suited to different types of measurement inaccuracies and environmental conditions. Kalman filters are particularly effective in combining GPS data with inputs from IMUs and other sensors, significantly reducing drift and improving overall localization accuracy.

Kalman filter offer several advantages, including the ability to increase navigation accuracy in areas with restricted GPS visibility. Furthermore, by incorporating new constraints on vehicle position, this method can be integrated into existing localization methods to improve vehicle localization outcomes [21] [80]. However, Kalman filters also have limitations, particularly related to inaccuracies in computing the Kalman gain. Initially, the Kalman gain is calculated correctly, but inaccuracies can arise when gains from previous sensor measurements are incorrectly accumulated or integrated into their original positions within the gain matrix, leading to potential errors in the estimation process. [146].

According to prior research in [21] and [80], integrating Kalman filter methods with other sensors data and HD maps can minimize localization inaccuracy to less than half or even one-third of the original GPS position errors. In areas with low GPS visibility, the data integration strategy can greatly improve localization results and navigation accuracy. Despite their benefits, Kalman filter remains vulnerable to model flaws, incorrect starting estimates, and significant computational load.

The Correntropy Kalman Filter (CKF) is being compared to the Kalman filter in the study presented in [78] and [82]. The CKF demonstrates a substantial improvement in the accuracy of the GPS position estimate, exhibiting an improvement of up to 34% when compared to the conventional Kalman Filter. Nevertheless, it is crucial to acknowledge that this study exclusively assesses low-latitude regions, so the findings may not accurately represent the broader environmental circumstances.

Implementing the weighted Kalman filter [34], [51], can considerably improve the accuracy of GPS positioning through improved estimation of variance. This improvement is consistently observed in numerous motion scenarios, including straight and circular movements at varying speeds. This method performs better than compared to traditional recursive least squares (RLS) and standard Kalman filter algorithms. Nevertheless, it is important to acknowledge that this study has a restricted number of comparisons with alternative advanced filtering algorithms.

The fast indirect in-motion coarse alignment method, in conjunction with the adaptive Student's t-based

Kalman filter (STKF) method [59], provides a solution to minimize the computational load of current methods. This combination method performs more efficiently for real-time applications. The STKF method effectively handles non-Gaussian measurement noise and incorrect covariance matrices, enhancing navigation robustness. However, this study does not compare the proposed method to similar approaches or alternative state estimation methods, making it difficult to assess the superiority or advantages of the proposed methodology.

The implementation of the adaptively robust Kalman filter approach [26] greatly enhances the accuracy of GPS positioning. Furthermore, experimental results confirm their efficiency in managing measurement errors. Nevertheless, this study is flawed as it fails to perform a comparative analysis with other sophisticated filtering techniques and neglects to address the method's resilience against different forms of noise and interference.

The Federal Kalman Filter (FKF) outperforms the GPS-KF by utilizing the Kalman filter, extended Kalman filter, and Federal Kalman filter [23]. It achieves stability rapidly and provides a more accurate estimation of real values. The FKF algorithm is capable of accurately estimating the condition of vehicles even in situations where GPS signals are not available. Nevertheless, this study fails to investigate the constraints of the Federal Kalman Filter across different circumstances.

Using the extended Kalman filter (EKF) method [9], [36], [71], [75], integrating GPS with the EKF filter can enhance accuracy by around 10 % compared to GPS alone, resulting in more accurate location and velocity estimations and better long-term navigation accuracy. Nevertheless, employing low-cost sensors can compromise the precision and reliability of the measurements, particularly in situations where GPS signals are not accessible or lost, resulting in a reduction in horizontal accuracy by as much as 3 meters.

The Distributed Kalman Filter with Feedback (DKFDFWF), the Interactive Multi-Model Kalman Filter (IMMKF), the extended Kalman filter, and Differential GPS (DGPS) techniques [29] have effectively decreased maximum position errors by 22.96 % when compared to a single-point GPS Kalman filter. Additionally, these techniques have enhanced position accuracy by 48.59 % compared to the averaging method, which utilizes data from three GPS receivers. The feedback mechanism of DKFDFWF is essential for correcting significant estimation mistakes from GPS receivers, thereby improving the overall accuracy of location determination. Nevertheless, this approach has a disadvantage in that it raises computing complexity as a result of iterative computations, and its use may be restricted by the requirement for several GPS receivers, particularly in certain situations.

The system improves the unscented Kalman filter's (UKF) resilience by modifying the process noise covariance online. This is achieved by implementing the extended Kalman filter, unscented Kalman filter (UKF), adaptive robust UKF (ARUKF), maximum likelihood (ML), and maximum likelihood-based adaptive UKF (MLAUKF) [53]. This approach utilizes maximum likelihood estimation to handle the uncertainty in process noise for integrating the vehicle inertial navigation system (INS) and global positioning system (GPS). Empirical evidence shows that it outperforms conventional unscented Kalman filter (UKF) and augmented unscented Kalman filter (ARUKF) methods. Nevertheless, this approach also suffers from the disadvantage of imposing a substantial computing load due to the need to calculate partial derivatives.

The augmented quaternion unscented Kalman filter (AQUKF) approach [112] was created to improve the integration of loosely connected GPS/INS. This method specifically addresses the non-Euclidean unit quaternion mathematics, resulting in enhanced attitude estimation. The results derived from this approach successfully tackle the direct nonlinear estimate of vehicle states for the purpose of outdoor vehicle localization. During GPS outages, AQUKF can greatly decrease INS errors in comparison to indirect EKF and conventional UKF measurements. The intensity of this effect increases with a longer outage duration. This demonstrated the need to obtain highly precise estimations between GPS measurements to rectify bias in IMU sensors and minimize divergence in INS. Nevertheless, the existence of nonlinear INS state equations and the representation using unit quaternions can complicate the implementation and comprehension. Furthermore, the emphasis on locating vehicles outside may restrict the utility of the approach in certain situations or settings.

The integration of GPS with gyro uses a two-stage cascaded EKF method, where the first stage employs an adaptive extended Kalman filter (AEKF) [114] to process position, velocity, and attitude data from magnetometer, accelerometer, and gyroscope sensors. The second filter is an EKF that uses GPS data to update the INS velocity and position states. Due to drift, an INS with a low-grade IMU cannot serve as a precise position reference. The proposed two-stage EKF algorithm has a total execution time of 11.697 ms, which is faster than the standard EKF's execution time of 19.812 ms, which includes all attitude, velocity, and position states. Therefore, unmanned vehicles can implement the two-stage cascaded EKF in real-time, providing an optimal navigation solution. However, the discussion in this paper does not explore alternative navigation methods or technologies beyond GPS.

5.2.2 Artificial Intelligence based Approach

The KGP approach, which combines the Kalman filter, Gradient Boosting Decision Tree (GBDT), and Particle Swarm Optimization (PSO) methods [31], significantly improves positioning accuracy. It outperforms methods that utilize multi-layer perceptron neural networks and random forest regression by 28.20 % to 59.89 %. In addition, this technology effectively resolves the problem of nonlinearity between vehicle attributes and location data. It also corrects errors in the Inertial Navigation System (INS) caused by unstable GPS signals, resulting in a substantial improvement in positioning continuity and accuracy. Nevertheless, a disadvantage of this approach is the very high computing load resulting from the incorporation of numerous intricate techniques.

The AFNPGA-VS algorithm utilizes a Kalman filter, a progressive Gaussian approximate filter with variable step size (PGAFVS), and an adaptive fuzzy neural network controller with backpropagation based on PGAFVS [74]. This algorithm significantly enhances the reliability and accuracy of the system, particularly in situations where there has been uncertainty in the past. Simulations suggest that this approach surpasses existing methods, showcasing significant potential for enhancing overall system performance. Nevertheless, the practical efficiency of AFNPGA-VS has not been confirmed purely through simulations, and the algorithm's complexity necessitates significant processing resources.

By integrating the Kalman approach with a complementary filter-based fusion scheme, a neural network, and an expert fuzzy logic system [16], the neural network effectively represents GPS data and can make precise estimations of the robot's location in the absence of a GPS signal indoors. In outdoor environments, the Kalman fusion technique and complementary filter are effective at integrating data from proprioceptive sensors and GPS. In addition, the expert fuzzy logic system corrects positional inaccuracies caused by wheel slippage. Nevertheless, the disadvantage of this approach lies in its substantial dependence on GPS for outdoor positioning, which may not be reliable in all conditions or locations.

The integration of the multiple fading factor square root cubature Kalman filter (MSCKF) method and fuzzy neural network (FNN) model [60] significantly enhances the accuracy and speed of the navigation system by substantially reducing position and velocity errors, surpassing the performance of the pure inertial navigation approach. Furthermore, this approach can prevent issues with excessive training and overfitting in the network, as well as improve the speed at which the network reaches convergence. However, the performance in terms of training time relative to other models is not clearly defined.

The proposed methodology [47], [61] introduces a novel technique for selecting inputs from NARX networks based on mutual information (MI) criteria and lag-space estimation (LSE). The experimental findings clearly establish the superiority of this method over other approaches, such as UKF. This method has the ability to significantly improve the overall accuracy and performance of the system. Nevertheless, it is crucial to acknowledge that employing sophisticated methods like Unscented Kalman Filter (UKF) and Nonlinear AutoRegressive with External Inputs (NARX) networks can result in a rise in the intricacy of the system, requiring meticulous deliberation during practical execution.

When fuzzy logic is compared to the unscented Kalman filter (UKF) method [64], this system performs 69.2 % better than the unscented Kalman filter. The main benefit of this system is its superior capacity to handle fluctuations and uncertainties in GPS data. Logical operations enable the design of non-linear functions using the 'if else' structure. However, the quality and attributes of the datasets used might influence the system's performance, and it only compares with the unscented Kalman filter without evaluating its performance against alternative options.

The optimization of extreme learning machines (ELM) with minimal learning parameters (MLP) and the use of factor graph technology [101] for robust information fusion greatly enhance the navigation of the INS/GPS system during GPS outages. Empirical investigations conducted on ground vehicles demonstrated the approach's effectiveness in real-time applications by minimizing computational burden and improving system performance, particularly in difficult conditions without GPS signals. Nevertheless, the execution of this approach is more complex because it necessitates the use of several optimization methods. Furthermore, the system's success still depends on the quality of the sensors it implements.

5.3 Statistical based Approach

The Gaussian-based approach employs various advanced filtering techniques to enhance the performance and resilience of navigation systems, particularly in the presence of extreme noise and disturbances. This section elaborates on these methods and their contributions to improving localization accuracy and robustness.

Linear and Nonlinear Kalman Filters: These filters are foundational in sensor fusion and are used to provide optimal estimates by minimizing the mean squared error. Linear Kalman filters are suitable for systems with linear dynamics, while nonlinear Kalman filters, such as the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), are designed to handle nonlinearities in the system. These filters are effective in combining data from various sensors to improve the overall localization accuracy.

Minimum Error Entropy-Gauss Quadrature Kalman Filters (MEE-GQKF): The MEE-GQKF method is a significant advancement in dealing with non-Gaussian noise. It combines the principles of minimum error entropy and Gauss quadrature to improve the accuracy and robustness of state estimation in multisensory navigation systems. This approach is particularly effective in scenarios with heavy-tailed noise distributions, which are common in real-world applications.

Gaussian Sum Filtering: This technique approximates the probability distribution of the system's state using a sum of Gaussian components. Gaussian sum filtering is beneficial in managing non-linear and non-Gaussian processes, providing a more accurate representation of the state distribution than a single Gaussian assumption. This method enhances the system's ability to handle complex noise patterns and improves the overall accuracy of the state estimates.

Huber-Based Estimators: These estimators are designed to be robust to outliers and extreme noise by using Huber's criterion, which combines the best features of least squares and absolute value estimations. Huber-based estimators adjust the influence of outliers on the estimation process, making the system more resilient to unexpected and abnormal disturbances.

Maximum Correntropy Criterion (MCC): The MCC is an advanced approach used to handle non-Gaussian noise and outliers. It maximizes correntropy, a measure of similarity between two random variables, to improve the robustness of the estimation process. MCC-based methods are particularly effective in environments with impulsive noise, providing a higher level of resilience compared to traditional mean squared error minimization techniques.

Using various methods such as linear and nonlinear Kalman filters, Minimum Error Entropy-Gauss Quadrature Kalman Filters (MEE-GQKF), Gaussian sum filtering, Huber-based estimators, Maximum Correntropy Criterion (MCC), and Extended, Unscented, Cubature Kalman Filters [54], the system demonstrates superior performance in handling extreme noise, enhancing the system's resilience to unexpected and abnormal disturbances. The development of MEE-GQKF is a crucial step in strengthening multisensory navigation systems against non-Gaussian noise. Nevertheless, a disadvantage of this method is the increased computing complexity of direct filtering alternatives.

Combining the adaptive fuzzy neural network-aided progressive Gaussian filter method, Bayesian variational approach, and neural network model [73], the system outperforms existing advanced filters in terms of accuracy and reliability, as demonstrated by experimentation. This filter demonstrates exceptional precision and consistency in estimating values, particularly in the northern, eastern, and downward orientations. Nevertheless, its specialized design for GPS/INS integrated navigation makes it inappropriate for other navigation systems.

Technology enhances the precision of GPS by discerning multipath errors, particularly in urban areas. This is achieved by the utilization of a strong Bayesian filtering technique, multiple hypothesis tracking (MHT), Gaussian mixture reduction based on Kullback-Leibler divergence, and a combination of Gaussian and Cauchy distributions [27]. This method is more resilient than extended Kalman filters and other optimization algorithms, and it decreases computational complexity by employing Gaussian mixture reduction, although at a higher expense.

Robust Kalman filtering and ANN [49] are used to maintain location accuracy during GPS data interruptions in the extended Kalman filter, nonlinearauto-regressive (NAR) model, linear interpolation, and artificial neural network approaches. During these disruptions, the technique effectively improved the integrated GPS/INS system's accuracy by 67% on each axis. However, because this method was only evaluated in an outdoor area with a specified path and for a limited time, these constraints must be considered when assessing the system's accuracy and applicability.

5.2.4 Other Approach

Using the extended Kalman filter, Dead Reckoning (DR), and Non-Holonomic Constraint (NHC) approaches [33], the suggested system effectively reduces navigation errors on uneven terrain, such as slopes that go up and down. The proposed approach exhibits consistent performance in accurately determining horizontal locations, even in situations where GPS data is deliberately obstructed for a brief duration. Nevertheless, the performance of the system may differ among vehicles because of alterations in the odometer scale factor, and its effectiveness has not been evaluated across all varieties of terrain and driving circumstances.

Combining Unscented Kalman Filtering (UKF) with I-Q values [28] produces extremely precise carrier phase and frequency readings, particularly in rapidly changing settings. Its strengths are fast convergence and durable performance achieved through the implementation of the innovative I-Q combination approach. Moreover, the UKF loop effectively monitors and adjusts for fluctuations in carrier frequency, showcasing its capability to manage substantial alterations in the signal. Nevertheless, its disadvantage lies in the increased computing burden in comparison to conventional tracking techniques.

The integration of GPS and visual navigation result [106] indicate that combining navigation techniques can enhance the performance of autonomous robots in agricultural fields. The Pure Pursuit algorithm with GPS had a lateral deviation of 8.3 cm, while the deep learning model with Dynamic Window Approach (DWA) achieved a deviation of 4.8 cm. The integration of GPS with the deep learning model and DWA resulted in a lateral error of 9.5 cm, offering a more practical and effective navigation method. However, reliance on GPS can be problematic in areas with poor signal, and the complexity of integrating multiple navigation methods can complicate system design and require precise calibration. These points highlight both the advantages and potential limitations of navigation solutions in agricultural robotics.

5.3 Methods Summary and Discussion

The sensor fusion techniques discussed in the previous sections highlight a number of approaches widely used to enhance GPS-based localization techniques. Each approach is characterized by pros and cons, which are summarized in Table 6 and Table 7. This section briefly discusses and compares the four main approaches—Kalman filter-based, artificial intelligence (AI)--based, statistical-based, and other specialized methods—emphasizing their practicality, computational challenges, real-time feasibility, and implementation constraints.

It can be found in Table 6 that fusion approaches based on the Kalman filter technique offer strong real-time performance and efficient integration of sensor data (e.g., GPS and IMU). Widely used methods such as EKF and UKF effectively address sensor inaccuracies and nonlinear dynamics, significantly reducing localization errors across various scenarios. The work presented in [41], for example, demonstrates that utilizing EKF-based sensor fusion—which combines GPS, IMU, and odometry on autonomous vehicles—can significantly minimize localization errors from several meters down to just a few centimetres during urban navigation. While there is potential for enhancement, Kalman filters may exhibit inaccuracies due to model limitations and require rigorous initial calibration along with reliable sensor quality to maintain their accuracy. In addition, adaptive or complex variants like AQUKF also pose significant computational challenges, potentially straining the capabilities of real-time embedded systems [112].

AI-based techniques, such as neural networks and fuzzy logic, show significant promise in addressing complex nonlinear sensor data to outperform traditional techniques in terms of accuracy. For example, the work in [54] presents a combination of neural networks and fuzzy logic for a localization approach that could improve indoor robot localization accuracy, particularly when GPS signals are lost. Nevertheless, these approaches are constrained by notable limitations, including the requirement for extensive training data, substantial computational demands, and reliance on consistent sensor quality. These limitations constrain the methods from being deployed only to the systems with strong computational capabilities [31].

Statistical approaches—including Gaussian sum filtering and Bayesian techniques—are known for their adaptability in handling non-Gaussian and unpredictable noise. This noise is common in densely populated urban environments. These statistical approaches can enhance adaptability toward multipath errors affecting standard GPS performance. The work presented in [27] demonstrates that implementing the Gaussian mixture reduction method could enhance the accuracy of urban localization. While statistical methods are generally reliable, they demand significant computational resources and parameter tuning. Hence, they are not always the best choice, especially when dealing with situations that demand quick real-time updates or have limited hardware resources.

The other specialized techniques, including dead reckoning, LiDAR-based SLAM, and other tailored algorithms, have been effectively deployed in several controlled environments [30] [55]. For example, LiDAR-based SLAM methods enable highly accurate indoor localization for autonomous warehouse robots transitioning from GPS-based outdoor navigation [30]. Despite their precision, these approaches have significant limitations related to their environmental specificity, substantial calibration efforts, and high computational overhead due to real-time processing demands of dense sensor data.

A comparative analysis clearly indicates trade-offs between accuracy, computational complexity, and implementation constraints. The artificial intelligence approach and the statistical approach exhibit significantly higher than the Kalman filter approach. Statistical approaches like Gaussian mixture reduction techniques are particularly computationally intensive. On the other hand, the Kalman filter approach generally demonstrates lower computational demands but occasionally experiences inaccuracies related to calculating the Kalman gain. In terms of the improvements in GPS accuracy, the artificial intelligence approach has substantially higher accuracy than the other methods, but present greater implementation challenges in real world scenarios. Specialized techniques (e.g., LiDAR-based SLAM) offer exceptional accuracy in specific environments but lack generalizability and carry high implementation complexity.

Real-world case studies effectively illustrate these trade-offs between accuracy, computational complexity, and implementation constraints. For instance, research employing GPS, IMU, and visual odometry fusion processed with the EKF has demonstrated significant improvements in localization accuracy, reducing error from 79 meters down to 3.7 meters in urban autonomous vehicle applications [41]. This notable improvement is achieved through mutual sensor supports; if GPS signals are lost, the IMU and visual odometry data compensate for the positioning errors. Conversely, when visual odometry struggles due to lighting conditions or environmental obstacles, GPS provides reliable positional information. Additionally, the computational load associated with EKF-based sensor fusion is substantially lower than that of artificial intelligence methods, making it a more practical choice for real-world implementations. In addition, data processing using the EKF method is less computationally expensive than the artificial intelligence method, making it a more practical choice for real-world implementations.

In summary, sensor fusion methods need to balance accuracy, computational complexity, and practicality. Future research should optimize algorithms to decrease computational requirements, provide adaptive real-time sensor variance, and simplify sensor calibration. These improvements should make GPS-based localization better for autonomous systems.

Table 6 The summary of methods

Methods	Advantage	Disadvantage
Kalman Filter Approach	The Kalman filter has many advantages, including its ability to provide optimal estimates by improving navigation accuracy, especially in areas with limited GPS visibility. This filter, available in various forms such as EKF and UKF, is flexible in handling sensor inaccuracies and dynamic environments. Additionally, the Kalman filter is effective in combining data from GPS, IMU, and other sensors, significantly reducing localization errors. Some variants, like the two-stage EKF, are also efficient for real-time applications.	The Kalman filter is susceptible to model weaknesses, such as incorrect initial estimates or inaccuracies in calculating the Kalman gain, which can lead to suboptimal results. Some algorithms require intensive computations, especially when using adaptive variants or methods like AQUKF, which can slow down system performance. Although it improves accuracy, the Kalman filter still relies on GPS signals, and in situations where GPS signal loss occurs, its accuracy decreases over time.
Artificial Intelligence Approach	The artificial intelligence approach significantly improves the accuracy and speed of navigation systems by substantially reducing position and velocity errors, surpassing the performance of traditional navigation systems. Neural networks can effectively represent GPS data and accurately estimate the robot's location even without GPS signals. Additionally, the expert fuzzy logic system corrects positional inaccuracies caused by wheel slippage. The fuzzy neural network (FNN) prevents overtraining and overfitting in the network while also increasing the speed at which it reaches convergence.	This approach has a very high computational burden due to the integration of various complex techniques. Additionally, it relies heavily on GPS signals for outdoor positioning, which may be less reliable under certain conditions, and it also depends on the quality of the sensors used.
Statistical Approach	The statistical approach offers several advantages, including significantly enhancing multisensor navigation systems against non-Gaussian noise. This filter demonstrates exceptional accuracy and consistency, particularly in estimating north, east, and down orientations. Furthermore, this method is more robust than extended Kalman filters and other optimization algorithms, while also reducing computational complexity by using Gaussian mixture reduction techniques.	These methods have several drawbacks, including high computational complexity due to the use of advanced techniques such as Kalman filters and Huber-based estimators. Specific design for GPS/INS navigation systems renders variational Bayesian and fuzzy neural network approaches less suitable for other applications. Although techniques like Gaussian mixture reduction improve GPS accuracy, their computational costs remain high. Additionally, the limited evaluation of specific areas reduces the broader applicability of these methods.
Other Approach	This approach effectively reduces errors in uneven terrain, consistently achieving accurate horizontal location determination, even when GPS data is temporarily obstructed. Additionally, the combination with signal processing methods provides highly precise phase and carrier frequency readings, particularly in rapidly changing conditions, and achieves fast convergence. The integration of GPS and visual navigation also demonstrates improved performance for autonomous robots in agriculture, resulting in smaller lateral deviations.	The integration of GPS and visual navigation show potential for performance improvement; however, reliance on GPS signals poses challenges in areas with poor signal quality. The complexity of integrating multiple navigation methods can complicate system design and necessitate precise calibration, thereby hindering broader implementation. Additionally, there is an increased computational burden compared to conventional tracking techniques.

Table 7 Method comparison summary

Algorithm / Methods	Computational Complexity	Accuracy	Adaptability	Real-Worl Implement Ability
Kalman Filter Approach	Moderate	Moderate to High	Moderate	Moderate
AI-based Approach	Training: High Inference: Low	High	High	Difficult
Statistical Approach	High	High	Moderate	Difficult
Other / Specialized Approach	Moderate to High	High	Low	Moderate to Difficult

6.0 FUTURE DIRECTIONS IN GPS-AIDED LOCALIZATION FOR AUTONOMOUS MOBILE ROBOTS

Despite significant advancements in integrating GPS with other sensors like IMUs, LiDAR, and cameras, there remains a need for more advanced sensor fusion techniques. Future research should focus on developing robust algorithms that seamlessly combine data from multiple sources to enhance localization accuracy. These algorithms must effectively handle the uncertainties and inaccuracies inherent in each sensor type. For instance, while IMUs provide good short-term accuracy, they suffer from drift over time, which can be corrected using GPS data. Conversely, GPS inaccuracies can be mitigated using precise IMU data in short bursts, creating a balanced, reliable localization system.

Visual Sensors and Fiducial Markers: The visual sensor is another sensor with significant potential for use in autonomous mobile robots. This sensor has the ability to record more complex environmental data, such as the textures on walls that make perception easier [147]. Researchers have developed several approaches to improve mobile robot localization accuracy by integrating visual sensors with other sensors.

Another technique uses fiducial markers as a reference point for determining position and orientation. There are fiducial markers that have been installed along the route of the autonomous mobile robot, and the vision sensor is able to identify and extract them. A fiducial marker is a mechanism for identifying objects or locations in navigation systems or computer visual recognition. This approach is often used for augmented reality (AR), robot navigation, and object detection. Fiducial markers make use of specifically designed markers or things that computer systems can quickly detect and identify. These markers usually possess distinct visual patterns or attributes that are exclusive, such as checkerboard patterns, QR codes, or other symbols.

Fiducial markers offer several key benefits, including their user-friendly nature, the minimal expense associated with the markers themselves, and the affordability of cameras and computing equipment. Nevertheless, markers have other drawbacks, such as potential issues with camera resolution, limitations in marker size, and the dependence on favorable lighting conditions for reliable detection, identification, and localization of markers [148], [149]. To detect markers in low-light conditions, an IR camera can be used. Optimizing the size and contrast of the marker can overcome the problem of limited marker size.

Advanced Filtering Algorithms: Existing filtering methods, such as the Kalman filter, have shown promise in improving GPS accuracy but still face limitations, particularly in managing non-Gaussian noise and model uncertainties. Therefore, developing more sophisticated filtering algorithms that provide better accuracy and reliability under varying environmental conditions is crucial. Advanced variations of Kalman filters, such as the Unscented Kalman Filter (UKF) and Particle Filters, have been proposed. However, these methods often come with increased computational complexity and require further optimization for real-time applications.

Real-Time Adaptable Systems: Another potential research area is developing real-time adaptable systems. Many current approaches lack the ability to adjust dynamically to changing environmental conditions and sensor errors. Research should aim to create adaptive systems that can modify their parameters in real-time to improve localization accuracy. For instance, adaptive Kalman filters that adjust their noise parameters based on observed data can provide better performance in varying conditions, ensuring more reliable navigation.

Cost-Effective and Scalable Solutions: There is also a need for low-cost, scalable solutions that can be easily implemented in various autonomous mobile robots. This includes developing cost-effective sensor fusion techniques and algorithms that do not require extensive computational resources. Research should focus on optimizing existing algorithms to reduce computational load without compromising accuracy, making advanced localization techniques accessible for a broader range of applications, from small consumer robots to large industrial machines.

Comprehensive Testing and Validation: Many proposed methods and algorithms have not been extensively tested across different environments and scenarios. Comprehensive testing and validation of these techniques in diverse real-world conditions are essential to ensure their robustness and reliability. For instance, testing should cover a wide range of environments, including urban canyons, dense forests, and indoor settings, to evaluate the performance and limitations of the proposed solutions. Additionally, long-term field studies are necessary to assess the durability and consistency of these methods over extended periods.

By addressing these challenges and research gaps, the field of GPS-aided localization for autonomous mobile robots can make significant strides. Improved localization systems will lead to more accurate, reliable, and efficient navigation, enhancing the capabilities of autonomous robots in various applications, from urban delivery systems to agricultural automation and beyond. This progress will not only advance the state-of-the-art in robotics but also contribute to broader technological innovations in autonomous systems and smart environments.

In the localization of autonomous mobile robots, the main challenges include heavy computing (such as AI processing and deep learning), real-time processing, and implementation constraints. Therefore, to overcome high computing challenges, the algorithm used must be an optimizing algorithm, such as using EKF, particle filter, or graph-based SLAM. In addition, use hardware that has specific requirements (e.g., when processing data from Lidar or images), such as GPU or FPGA devices. To lighten the computational load, selection techniques can be employed to extract the relevant features from sensor data.

In real-time processing, the challenge is often high latency in sensor fusion processing; for that, hierarchical Kalman filters can be employed to accelerate data processing from sensor fusion. Furthermore, it can employ the factor graph optimization method to accelerate convergence in multi-sensor data processing. Machine learning algorithms can employ motion prediction models to reduce the necessity for excessive data processing.

To address the challenges in real-world implementation, it can use GPS, IMU, and Lidar sensors to ensure high accuracy in the event of GPS signal loss. Marker-aided localization techniques, such as AprilTag and ArUco, can enhance accuracy in environments with limited GPS visibility. Furthermore, the integration of robots and control systems is essential for facilitating communication between sensors and robot modules. This can utilize ROS (Robot Operating System) or RTOS (Real-Time Operating System). Before implementing it in the real world, simulate it in Gazebo or CARLA to detect potential field difficulties. In addition, implementation can be started from a small scale or limited area; if successful, then it can be applied to more complex areas.

7.0 CONCLUSION

Autonomous vehicles and mobile robots commonly rely on GPS as for determining their location, benefiting from its global positioning capabilities while facing inherent drawbacks such as signal disruptions and positional inaccuracies. To enhance GPS precision and mitigate its limitations, a number of works employ sensor fusion techniques to complement GPS system. This comprehensive survey has highlighted the strengths and limitations of current GPS-aided localization methods and the importance of sensor fusion techniques in overcoming these challenges.

This study has found that the integration of GPS with various sensors, such as IMUs, Odometry, LiDAR, cameras, and other advanced technologies, has significantly enhanced the localization capabilities of autonomous mobile robots, providing more robust positioning solutions. Advanced filtering methods, particularly the Kalman Filter and its variants, have proven its effectiveness in managing noises and uncertainties, further enhancing the reliability of GPS-aided systems.

This study provides a comprehensive evaluation of GPS-aided localization technologies and emphasizes the role of sensor fusion in addressing GPS limitations. It analyzes the effectiveness of sensor combinations in improving localization accuracy, assesses the performance of filtering algorithms, and identifies research gaps that require further exploration. In particular, the study highlights the need for more efficient algorithms, real-time adaptable systems, and cost-effective, scalable solutions for wider applications.

Future research should build on the findings of this study by developing more robust algorithms that can combine data from multiple sources to further enhance localization accuracy by effectively handling the uncertainties and inherent limitations in each sensor type. Based on the demonstrated potential of visual sensors and fiducial markers in reducing positional errors further exploration of these sensors, particularly in urban environments, is recommended. Additionally, advancements adaptive filtering methods like hierarchical Kalman filters are necessary to manage non-Gaussian noise and model uncertainties, improving the overall reliability of GPS-aided localization systems.

Developing cost-effective and scalable solutions using affordable sensors will require innovative sensor fusion algorithms that minimize reliance on expensive sensors while maximizing localization accuracy. Low-cost sensors combined with optimized algorithms can achieve reliable results for various applications, particularly in resource-constrained environments.

Given the computational challenges identified, future work should also focus on optimizing algorithms for real-time processing without sacrificing accuracy. Furthermore, to ensure practical applicability, testing these systems in realistic simulation environments such as CARLA or Gazebo, can effectively identify potential issues before the system is deployed in real-world environment.

By addressing these challenges, the development of more accurate, reliable, and efficient navigation systems will be possible, thereby significantly enhancing the capabilities of autonomous robots across various applications. Advancements in sensor fusion and algorithms development will not only contribute to broader technological innovations in autonomous systems but also support the growth of smart environments and intelligent mobility solutions.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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