Вестник РУДН. Серия: Инженерные исследования
RUDN Journal of Engineering Research

2023;24(4):305–322

ISSN 2312-8143 (Print); ISSN 2312-8151 (Online)
journals.rudn.ru/engineering-researches

DOI: 10.22363/2312-8143-2023-24-4-305-322
UDC 681.586
EDN: HMUNNV

Review / Обзор

Artificial intelligence-driven optimization of MEMS navigation sensors for enhanced user experience

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Article history

Received: June 9, 2023
Revised: August 21, 2023
Accepted: September 5, 2023

Conflicts of interest

The authors declare that there is no conflict of interest.

Authors' contribution

Undivided co-authorship.

Abstract. This review delves into the key area of artificial intelligence (AI)-driven optimization applied to Microelectromechanical Systems (MEMS) navigation sensors, with the primary objective of enhancing the user experience. Employing a comprehensive research methodology, it extensively explores AI-powered techniques, encompassing sensor fusion, adaptive filtering, calibration, compensation, predictive modeling, and energy efficiency. Through rigorous case studies and empirical evidence, this research provides substantial achievements, including enhanced accuracy, reduced power consumption, heightened reliability, and amplified user satisfaction, across diverse applications such as autonomous vehicles, indoor localization, wearable devices, and unmanned systems. In conclusion, this review highlights the transformative potential of AI-driven optimization in MEMS navigation sensors while acknowledging persistent challenges in computational complexity, data availability, and real-time processing. It advocates for future research focusing on innovative AI methodologies, integration with emerging technologies, adherence to human-centric design principles, and the establishment of rigorous evaluation standards. Such research promises to unlock the full potential of AI-driven optimization, ushering in advanced and user-centric navigation systems, and ultimately improving user experience across diverse areas.

Keywords: Microelectromechanical Systems, Artificial Intelligence, Mathematical Modelling, Optimization, Navigation Sensors

For citation

Alizadeh A, Saltykova OA, Novinzadeh AB. Artificial intelligence-driven optimization of MEMS navigation sensors for enhanced user experience. *RUDN Journal of Engineering Research.* 2023;24(4):305–322. http://doi.org/10.22363/2312-8143-2023-24-4-305-322

Оптимизация навигационных датчиков МЭМС с применением искусственного интеллекта для улучшения пользовательского опыта

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История статьи

Поступила в редакцию 9 июня 2023 г.
Доработана: 21 августа 2023 г.
Принята к публикации: 5 сентября 2023 г.

Заявление о конфликте интересов

Авторы заявляют об отсутствии конфликта интересов.

Вклад авторов

Нераздельное соавторство.

Аннотация. Рассмотрена ключевая область оптимизации на основе искусственного интеллекта (ИИ), применяемого к навигационным датчикам микроэлектромеханических систем (МЭМС). Основная цель — улучшение пользовательского опыта. Используя комплексный подход, исследуются методы, основанные на искусственном интеллекте, включающие слияние датчиков, адаптивную фильтрацию, калибровку, компенсацию, прогнозное моделирование и энергоэффективность. Через строгое проведение кейс-исследований и использование эмпирических данных данное исследование подтверждает значительные достижения, включая повышенную точность, снижение энергопотребления, увеличение надежности и усиление удовлетворенности пользователя, в различных приложениях, таких как автономные транспортные средства, внутреннее определение положения, носимые устройства и беспилотные системы. В заключении данное исследование подчеркивает трансформационный потенциал оптимизации на основе ИИ в навигационных датчиках МЭМС, признавая при этом наличие постоянных вызовов, таких как вычислительная сложность, доступность данных и обработка в реальном времени проведения дальнейших исследований, ориентированных на инновационные методологии ИИ, их интеграцию с передовыми технологиями с условием соблюдения принципов дизайна, ориентированных на человека, и установление строгих стандартов оценки. Подобные исследования позволят использовать весь потенциал механизмов оптимизации на основе методов ИИ, внедряя передовые и ориентированные на пользователя навигационные системы и в конечном итоге повышая уровень удобства пользователей в различных областях применения подобных систем.

Ключевые слова: микроэлектромеханические системы, искусственный интеллект, математическое моделирование, оптимизация, навигационные датчики

Для цитирования

Alizadeh A., Saltykova O.A., Novinzadeh A.B. Artificial intelligence-driven optimization of MEMS navigation sensors for enhanced user experience // Вестник Российского университета дружбы народов. Серия: Инженерные исследования. 2023. Т. 24. № 4. С. 305-322. http://doi.org/10.22363/2312-8143-2023-24-4-305-322

Introduction

MEMS (Microelectromechanical Systems) navigation sensors have become integral components in a wide range of applications, playing a crucial role in providing accurate and reliable navigation data [1]. These sensors, typically integrated on a small silicon substrate, offer a compact and lightweight solution for measuring various physical parameters, including motion, orientation, and environmental conditions [2]. The importance of MEMS navigation sensors extends across diverse domains such as autonomous vehicles, robotics, wearable devices, and augmented reality applications [3; 4].

In recent years, the convergence of MEMS technology with artificial intelligence (AI) has emerged as a transformative force, revolutionizing the optimization and capabilities of navigation sensors [5]. AI, encompassing advanced techniques like machine learning, deep learning, and data analysis, has unlocked new possibilities for enhancing the user experience and addressing the limitations of traditional MEMS navigation sensors [6]. By leveraging the power of AI, researchers and engineers are able to overcome challenges related to noise, errors, and environmental variations, thus optimizing the performance of MEMS navigation sensors [7].

The growing significance of AI in optimizing MEMS sensors is driven by its potential to revolutionize navigation systems and improve the user experience in various ways. By harnessing AI algorithms and methodologies, MEMS navigationsensors can be fine-tuned to achieve higher accuracy, reliability, and robustness [8]. The integration of AI-driven optimization enables navigation systems to provide precise position tracking, orientation estimation, and motion sensing, enhancing applications ranging from autonomous navigation in vehicles to immersive virtual reality experiences [9].

Furthermore, AI empowers MEMS navigation sensors to adapt and learn from real-time data, leading to dynamic adjustments that enhance their performance in ever-changing environments [10]. Sensor fusion, a key technique enabled by AI, allows the integration of data from multiple sensors, such as accelerometers, gyroscopes, and magnetometers, to derive more accurate and reliable navigation information [11]. This integration not only improves the accuracy of the sensor outputs but also reduces reliance on a single sensor, enhancing system robustness [12].

The optimization of MEMS navigation sensors through AI techniques also offers benefits in terms of energy efficiency and power consumption [13]. With AI-driven algorithms, sensor power can be intelligently managed, leading to optimized energy usage and extended battery life in portable devices. This becomes especially crucial in applications such as wearables and unmanned systems, where power constraints are critical [14].

In this review article, we delve into the realm of artificial intelligence-driven optimization of MEMS navigation sensors for an enhanced user experience. We explore the techniques, applications, and benefits of integrating AI methodologies with MEMS sensors in navigation systems. Through comprehensive analysis and examination of case studies and research findings, we aim to provide insights into the transformative potential of AI in improving the performance and usability of MEMS navigation sensors.

As the field of AI continues to evolve, with advancements in machine learning, deep learning, and data analysis, it is important to understand how these techniques can be effectively harnessed to optimize MEMS navigation sensors. By unlocking the full potential of AI-driven MEMS sensors, we can pave the way for a new era of navigation systems that offer unprecedented accuracy, reliability, and user-centric experiences.

In the subsequent sections of this review article, we will delve into the background of MEMS navigation sensors, discuss the role of artificial intelligence in optimizing these sensors, explore various optimization techniques, present applications and benefits, analyze case studies and research findings, and discuss the challenges and future directions in this exciting field.

Through this comprehensive research, we aim to provide a deeper understanding of the profound impact that artificial intelligence-driven optimization can have on MEMS navigation sensors, ultimately contributing to enhanced user experiences in navigation systems across a multitude of applications.

1. Background

MEMS (Microelectromechanical Systems) navigation sensors have emerged as critical components in various applications that require accurate and reliable navigation data. These sensors, based on microfabrication techniques, integrate mechanical elements, sensors, and electronics on a common silicon substrate, enabling compact and lightweight solutions for measuring motion, orientation, and environmental conditions [15]. MEMS navigation sensors have found widespread use in domains such as autonomous vehicles, robotics, wearable devices, and augmented reality applications [16; 17].

To understand the significance of artificial intelligence-driven optimization in MEMS navigation sensors, it is important to grasp their working principles and typical applications. MEMS sensors employ various transduction mechanisms to convert mechanical, thermal, or chemical stimuli into electrical signals [18]. In the context of navigation, commonly used MEMS sensors include accelerometers, gyroscopes, and magnetometers [19].

Accelerometers measure acceleration or changes in velocity, providing information about linear motion. Gyroscopes, on the other hand, sense angular velocity or changes in orientation, enabling measurement of rotational motion. Magnetometers detect changes in magnetic fields, aiding in compass-like functionality for determining heading or direction [20].

Traditionally, MEMS navigation sensors faced challenges and limitations that hindered their ability to provide highly accurate and reliable navigation data. One significant challenge is sensor noise, which can introduce errors and affect the accuracy of measurements. MEMS sensors are susceptible to noise sources such as thermal noise, quantization noise, and external disturbances, which can degrade their performance [21].

Additionally, MEMS sensors can experience errors due to factors like sensor bias, drift, and nonlinearity. Sensor bias refers to a systematic offset in the sensor output, even in the absence of motion or external stimuli. Sensor drift represents the gradual change in sensor characteristics over time, leading to inaccuracies in measurement. Nonlinearity refers to deviations from an ideal linear response, affecting the sensor's ability to accurately capture input stimuli [22].

Furthermore, MEMS navigation sensors can be influenced by environmental variations and external interferences [23]. Changes in temperature, humidity, and pressure can affect sensor performance, leading to inaccuracies in navigation data [24]. Interference from electromagnetic fields or magnetic materials can also impact magnetometer readings, affecting the accuracy of heading estimation [25].

These challenges and limitations have motivated researchers and engineers to explore the integration of artificial intelligence techniques to optimize MEMS navigation sensors. By leveraging the power of AI, it becomes possible to overcome these limitations and improve the accuracy, reliability, and robustness of MEMS navigation sensors, ultimately enhancing the user experience in navigation systems [26].

In the subsequent sections of this review article, we will delve into the role of artificial intelligence in optimizing MEMS navigation sensors. By exploring various AI-driven techniques such as machine learning, deep learning, and data analysis, we aim to shed light on how these methodologies can be effectively employed to address the challenges faced by traditional MEMS sensors. Through comprehensive analysis of optimization techniques, case studies, and research findings, we will demonstrate the transformative potential of artificial intelligence in elevating the performance of MEMS navigation sensors and delivering enhanced user experiences.

Stay tuned as we dive deeper into the realm of artificial intelligence-driven optimization of MEMS navigation sensors and explore the advancements that are reshaping the landscape of navigation systems.

2. Role of Artificial Intelligence in MEMS Navigation Sensors

Artificial intelligence (AI) has emerged as a transformative force in optimizing MEMS (Microelectromechanical Systems) navigation sensors, offering significant potential for enhancing their performance and improving the user experience. By harnessing AI techniques, such as machine learning and data analysis, researchers and engineers are able to overcome challenges associated with traditional MEMS sensors, including noise, errors, and environmental variations [27].

Fundamentally, artificial intelligence encompasses a range of techniques and methodologies that enable machines to simulate human intelligence and learn from data. Machine learning, a prominent subset of AI, involves training algorithms to recognize patterns and make predictions or decisions without explicit programming. Data analysis techniques complement machine learning by extracting meaningful insights from large datasets, aiding in decision-making processes [28]. In [29], have presented a clear classification for introducing sub-fields of AI that shown in Figure 1 also shows a Depicts a high-level overview of different components, types, and subfields of AI.

Artificial intelligence plays a crucial role in optimizing MEMS navigation sensors by addressing the inherent challenges they face. One such challenge is noise, which can introduce errors and degrade the accuracy of navigation data. By applying AI algorithms, MEMS sensors can effectively filter out noise sources and enhance signal-to-noise ratios, leading to more accurate and reliable measurements [30].

Several specific artificial intelligence algorithms and approaches have been successfully applied to optimize MEMS-based inertial navigation systems. For example, Kalman filtering, a widely used technique, combines measurements from multiple sensors with a mathematical model to estimate the true state of a system. Kalman filtering is effective in reducing noise, compensating for errors, and providing reliable navigation data [31].

Another approach is neural networks, which are artificial intelligence models inspired by the structure and function of the human brain [32]. Neural networks have shown promise in optimizing MEMS navigation sensors by learning complex relationships between sensor inputs and navigation outputs, improving accuracy and robustness [33].

Additionally, genetic algorithms, a form of evolutionary computation, have been employed to optimize MEMS navigation sensor parameters. By iteratively searching through a space of possible solutions, genetic algorithms can find optimal configurations for MEMS sensors, enhancing their performance and maximizing user experience [34].

In this review article, we have delving deeper into these specific artificial intelligence algorithms and approaches applied to optimize MEMS navigation sensors. Through comprehensive analysis and examination of case studies and research findings, we aim to demonstrate the efficacy of artificial intelligence in overcoming challenges and enhancing the capabilities of MEMS navigation sensors.

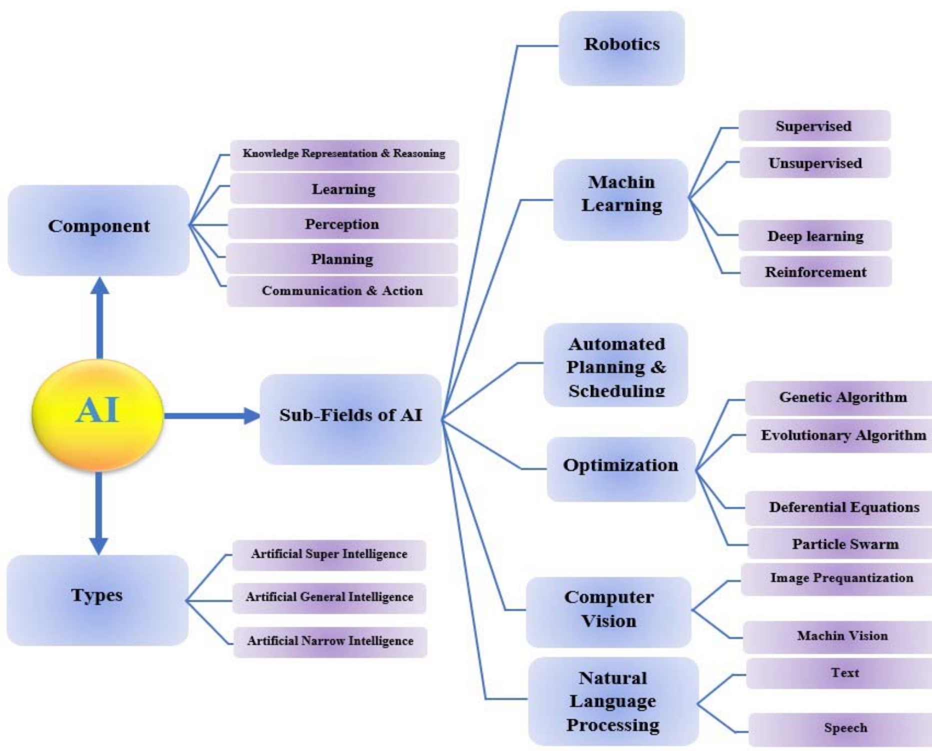


Figure 1. AI Components, Types, and Sub-Fields
S o u r c e : compiled by the author Ali Alizadeh

3. Optimization Techniques

Artificial intelligence (AI) has opened up a realm of possibilities for optimizing MEMS (Micro-electro-mechanical Systems) navigation sensors, ultimately enhancing the user experience in navigation systems. Through various AI-driven techniques, MEMS sensors can be fine-tuned and their performance optimized, addressing challenges such as accuracy, reliability, and power consumption. In this section, we have explored several optimization techniques facilitated by artificial intelligence for MEMS navigation sensors.

3.1. Sensor Fusion

Sensor fusion involves the integration of data from multiple sensors to improve accuracy and reliability. By combining measurements from different sensor modalities, such as accelerometers, gyroscopes, and magnetometers, sensor fusion algorithms can derive more accurate and robust navigation information. This integration reduces reliance on a single sensor and compensates for the limitations of individual MEMS navigation sensors, enabling more precise position tracking, orientation estimation, and motion sensing [35].

Due to the fact that MEMS navigation sensors consisting of gyroscopes, accelerometers and magnetometers can give us raw data at least in three X, Y, Z axes and provide access to the location and distance estimation through the existing technique. Many researchers are trying to create a three-dimensional perceptible space for the analysis of the target area or object with the fusion of real-time data received from these sensors with two-dimensional imaging [36].

It seems natural that according to the errors of MEMS sensors, special methods and algorithms should be provided to optimize these errors. Due to the existence of calibration errors and environmental disturbances and the sampling rate of these sensors, the received data usually does not coincide with the time of the imaging frames, so the estimation of the position of the desired points in the images is not very accurate. For this reason, Dong et al. [37] have investigated various methods for the fusion sensor, the summary of which can be seen briefly and comprehensively in Table 1.

Figure 2 shows an example of imaging data fusion based on Caruso's proposed algorithm with multi-IMU data that is being optimized with a Kalman filter [36].

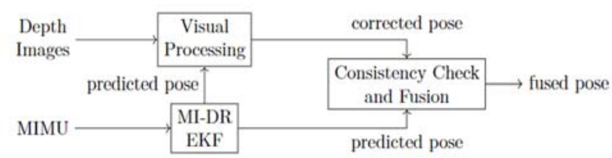


Figure 2. Sensor Data Fusion [36]

Table 1

Sensor Fusion Methods and Sub-Methods

Method	Sub-Method	Advantages/ Disadvantages
Standard fusion methods (SFA)	Principal component analysis (PCA) Intensity-hue-saturation (IHS)	• Co-registration of input images at sub-pixel level is required. • One of the main limitations of HIS and Brovey transform is that the number of input multiple spectral bands should be equal or less than three at a time. • SFA generate a fused image from a set of pixels in the various sources. These pixel-level fusion methods are very sensitive to registration accuracy, so that co-registration of input images at sub-pixel level is required.
	High-pass filtering	
	Different arithmetic combination: • Brovey transform	
Artificial Neural Networks (ANNs)	• BP • SOFM • ARTMAP • RBF neural network • Adaptive Resonance Theory (ART) neural networks	• Artificial neural networks (ANNs) have proven to be a more powerful and self-adaptive method of pattern recognition as compared to traditional linear and simple nonlinear analyses. • Many of applications indicated that the ANN-based fusion methods had more advantages than traditional statistical methods, especially when input multiple sensor data were incomplete or with much noises.
Multi-Resolution Analysis-Based Methods	Pyramid: • Gaussian Pyramid • Laplacian Pyramid	Laplacian Pyramid is used for image compression and has a low memory requirement which is its main advantage. On the other hand, the Gaussian Pyramid is used for multi-resolution analysis for image fusion. The Gaussian pyramid is computationally efficient and can be used to down sample an image by a factor of 2 at each level. However, it is not as efficient as the Laplacian pyramid in terms of memory usage.
	Wavelet transform	• Its computational complexity compared to the standard methods. • Spectral content of small objects often lost in the fused images. • It often requires the user to determine appropriate values for certain parameters (such as thresholds).

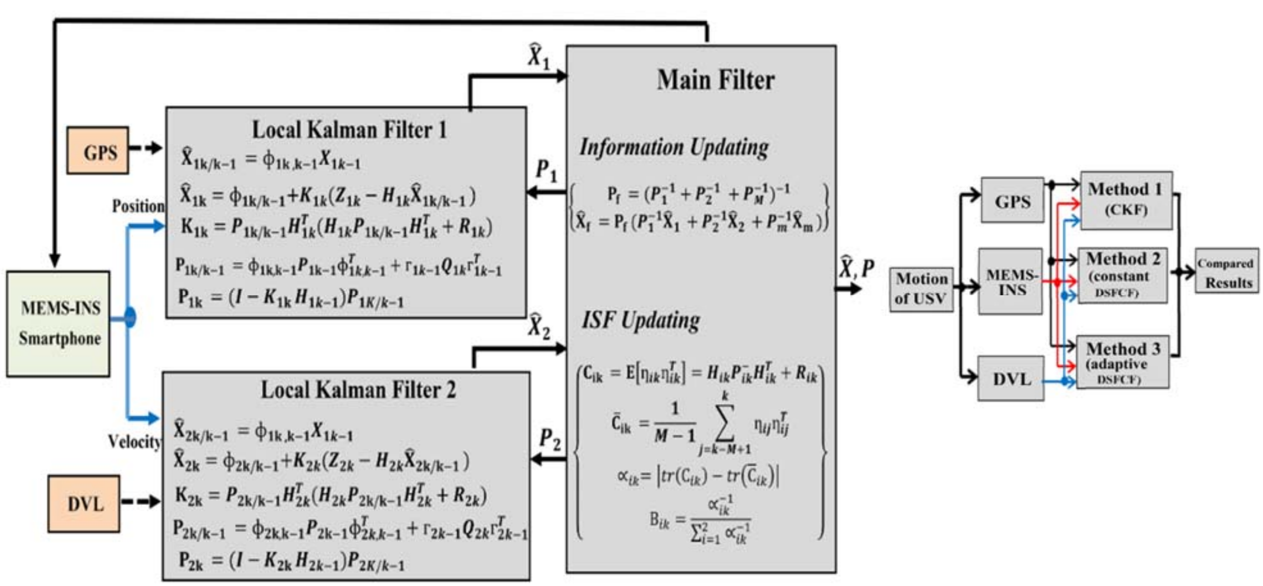
3.2. Adaptive Filtering

Adaptive filtering techniques play a crucial role in optimizing MEMS navigation sensors in real-time. These algorithms dynamically adjust sensor measure ments based on real-time conditions, allowing for accurate tracking and compensation of errors and variations. Adaptive filtering algorithms, such as Kalman filters or particle filters, continuously update sensor outputs based on incoming data, thereby improving the accuracy and reliability of navigation information.

As Bitar, Gavrilov and Khala mentioned [5], various fusion algorithms, such as Kalman Filters (KF) like Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), are commonly used for integrating INS and GNSS data. While KF can provide accurate geo-referencing solutions with continuous GNSS signal access, it has limitations such as the need for precise stochastic models for sensor errors, especially for low-end tactical grade and MEMS-based IMUs. Additionally, KF faces challenges related to sensor dependency and observability. To address these limitations, researchers have explored alternative methods based on AI, such as artificial neural networks (ANNs) and genetic algorithms (GA), which offer advantages such as intelligence and robustness in complex and uncertain systems. AI-based approaches aim to overcome the shortcomings of KF and have been increasingly investigated for INS/GNSS integration.

In order to achieve a more optimal solution, Mostafa et al. [38], has introduced a newly proposed method that enhances the navigation system of unmanned surface vehicles (USVs) by integrating MEMS-INS smartphone sensors with GPS and DVL. The accuracy of GPS and errors in DVL measurements directly impact the efficiency of existing methods. To address this, they have proposed an adaptive data sharing factor combined filter (DSFCF) method as an integrated solution. Their method detects and avoids the least accurate navigation subsystem while correcting USV navigation errors using the most accurate subsystem. Testing on a surface trajectory during GPS and DVL malfunctions has shown that proposed method significantly reduces position errors compared to two popular integrated methods.

Although three methods have been used for integration and integration at the same time, the problem of this combined method is that it does not have the ability to receive data for a cluster of inertial sensors. To accomplish and refine some dimensions of the previous proposed method, comprehensive investigations were conducted to address potential limitations and optimize its performance by Ma et al. [39] (Figure 3).



a *b*

Figure 3. Method structure:
a — Proposed GPS/DVL/MEMS based on adaptive DSFCF integrated method;
b — Block diagram of three integrated methods [39]

They have proposed an adaptive navigation algorithm with deep learning that has achieved accurate and robust navigation for autonomous underwater vehicles (AUVs). The algorithm has utilized deep learning to generate low-frequency position information and has corrected the error accumulation of the navigation system. The $\chi 2$ rule has been incorporated into the algorithm to identify and exclude outliers in Doppler velocity log (DVL) measurements. Furthermore, an adaptive filter based onthe variational Bayesian (VB) method has beenemployed to estimate navigation information and measurement covariance simultaneously, resulting in further improvements in accuracy. Experimental results using AUV field data have demonstrated that the proposed algorithm has significantly enhanced navigation performance and position accuracy. The algorithm has provided robustness and high accuracy navigation with a normal frequency, thereby meeting the requirements of various missions. Future work will involve exploring more complex integrated navigation system designs and evaluating the algorithm's performance with different acoustic equipment.

Figure 4 has depicted the position errors of various algorithms in comparison to the ground truth. The proposed method has outperformed others by compensating for sensor deviations and employing a data fusion strategy (Figure 4, *a*). In second test, the deep learning method has successfully enhanced navigation accuracy by addressing outliers in DVL measurements (Figure 4, *b*). The proposed method has demonstrated improved position accuracy when compared to the conventional EKF method (Figure 4, *c, d*). Furthermore, the RMSE results have indicated that the proposed algorithm has achieved robust navigation with enhanced accuracy, surpassing the conventional method by a minimum of 14.4 %.

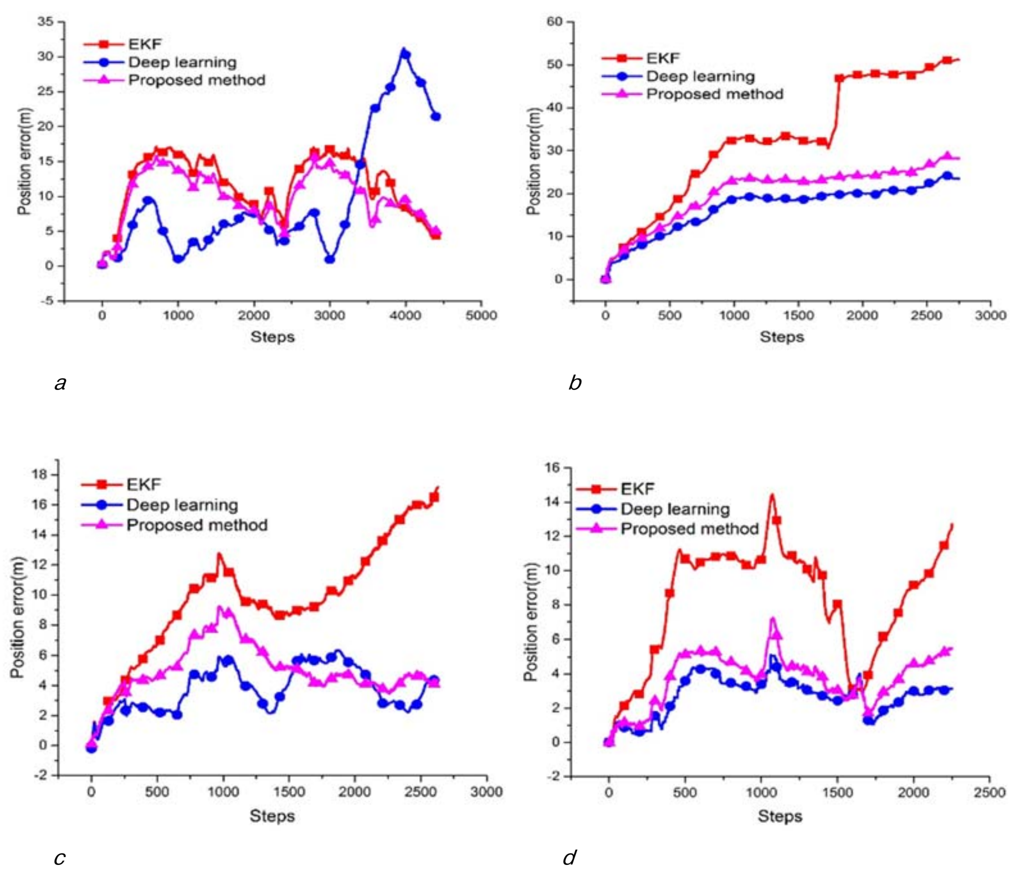


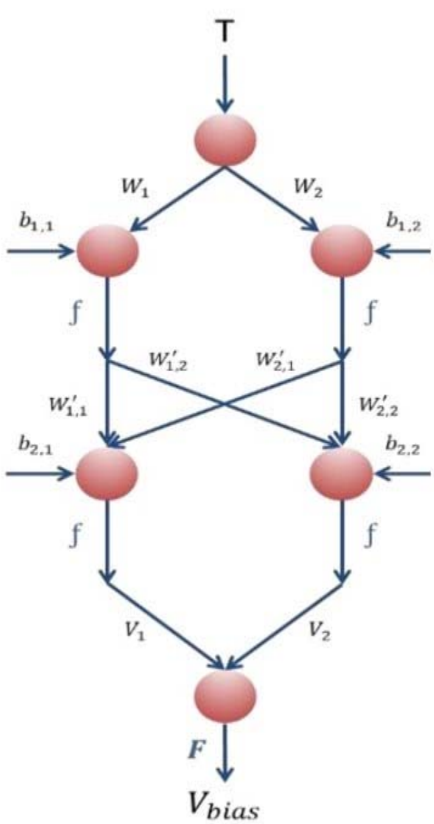
Figure 4. Position error between the ground truth and the estimation of different navigation methods:
a — Compares performance of various methods under sensor deviation, highlighting superior accuracy of the proposed method due to advanced data fusion strategy; *b* — Demonstrates error reduction in Test2 with DVL measurement outliers, showcasing the effectiveness of deep learning in enhancing navigation accuracy; *c, d* — Contrast the position accuracy of the proposed method against conventional EKF, indicating the proposed method's comparable accuracy to deep learning approaches [39]

3.3. Calibration and Compensation

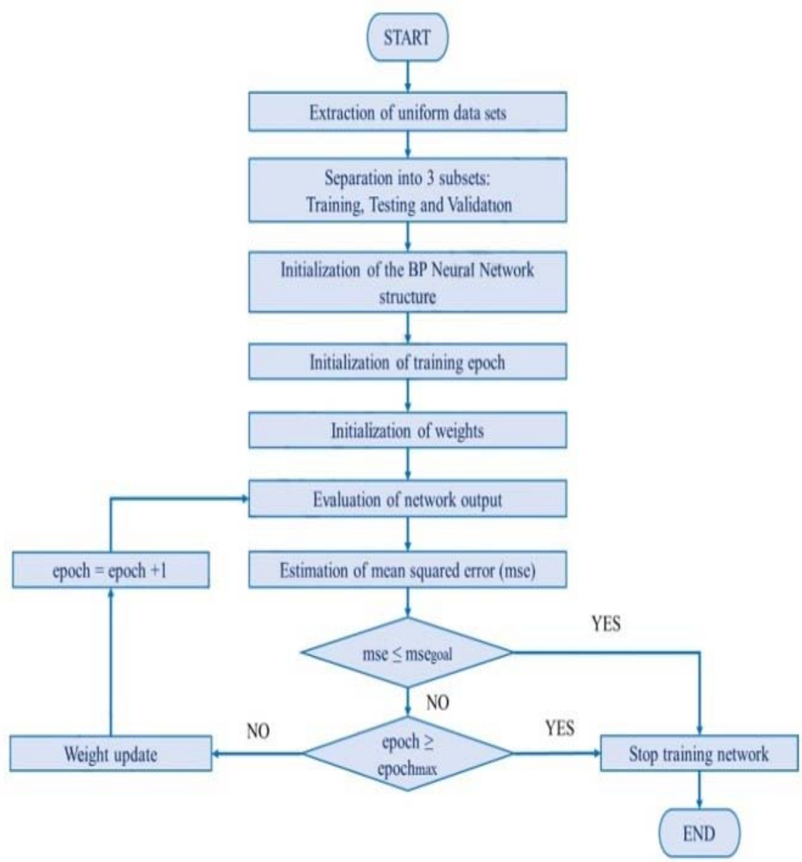
AI algorithms can be employed to calibrate and compensate for sensor biases and drifts, which can introduce errors in navigation data. Through calibration, ANN techniques determine the systematic offsets or biases in sensor outputs and apply correction factors to eliminate or minimize these errors. Similarly, Back Propagation Neural Network algorithms can track and compensate for sensor drift, which refers to the gradual change in sensor characteristics over time. By continuously monitoring and adjusting sensor parameters, AI-driven calibration and compensation techniques enhance the accuracy and long-term stability of MEMS navigation sensors [40].

Bias thermal calibration of micro-electromechanical gyroscopes has been a key issue in order to achieve optimal performance in demanding navigational environments, where GPS signals may encounter adverse conditions such as signal degradation, signal obstructions, or signal attenuation. The conventional modeling approach for capturing abrupt changes in direction within narrow temperature differentials and accounting for sensor hysteresis has not yielded satisfactory results. To address this issue, Fontanella et al. [24], have undertakenan investigation into employing a proposed backpropagation neural network (BPNN) with the Lorenzberg — Marquardt algorithm and the MATLABTM neural network toolbox for the process of polynomial fitting that shown in Figure 5.

Subsequently, by applying the Kolmogorov — Smirnov test, the adherence of this dataset to a uniform distribution was confirmed, thereby establishing the goodness-of-fit. The outcomes substantiated a remarkable 20 % enhancement in the precision of the flight attitude, aligning with the stipulated requirements mandated by prevailing regulations.



a



b

Figure 5. Back Propagation Neural Network:
a — Structure of the Back Propagation Neural Network adopted for modeling thermal drift;
b — Flow chart of the Back Propagation Neural Network training process [41]

In a study pertaining to the calibration of microelectromechanical sensors Huang et al [41], have introduced an innovative indoor positioning system that utilizes smartphone MEMS sensors. The system has employed a Pedestrian Dead Reckoning (PDR) algorithm, leveraging the accelerometer, gyroscope, and magnetometer sensors for continuous relative position information. It has incorporated an offline phase where sensor data has been collected to construct a training dataset, and a deep learning model has been developed using TensorFlow to detect indoor turning points. In the online phase, the trained model has been used to identify turning points, and a particle filter algorithm has been applied for error calibration. The system's performance has been validated through extensive experiments in a real indoor environment. However, limitations have included reduced accuracy in environments with few turning points and decreased computational efficiency when using a large number of particles in the filter algorithm.

3.4. Predictive Modeling

Machine learning techniques can be leveraged to develop predictive models that anticipate and compensate for sensor errors. By training algorithms on historical data, machine learning models can learn complex relationships between sensor inputs and outputs, enabling accurate prediction of sensor behavior. These predictive models can be used to estimate and correct for errors, improving the overall accuracy and reliability of MEMS navigation sensors [42].

Regarding this matter Nevlydov et al. [43] have explored the development of a predictive model for classifying the state of a robot using machine learning techniques and data from MEMS sensors. Through experiments, a three-axis MEMS gyroscope was used to investigate the effectiveness of various algorithms in real-time state classification. Supervised machine learning algorithms, including Support Vector Machines, k-nearest neighbors, and Decision Trees, have been evaluated, with weighted k-nearest neighbors and bagged trees showing the best performance, achieving an accuracy of approximately 89 %. The study highlights the potential of machine learning in developing accurate and reliable predictive models to enhance the decision-making system of robots.

3.5. Energy Efficiency

Artificial intelligence also offers opportunities to optimize power consumption and extend the battery life of MEMS navigation sensors. AI-based techniques can intelligently manage sensor power, optimizing energy usage based on the specific requirements and operating conditions. By dynamically adjusting power levels and sampling rates, AI algorithms can minimize power consumption while maintaining adequate performance. This becomes especially important in applications such as wearable devices and unmanned systems, where energy efficiency is critical [10; 11].

In this regard Fouché and Malekian [44], have developed a comprehensive system from first principles to enable autonomous navigation and remote fire detection. The system has utilized a low-cost inertial measurement unit with MEMS sensors to measure the aircraft's orientation, while line-of-sight guidance principles have facilitated real-time trajectory calculations for autonomous navigation. Stabilized flight has been achieved through the implementation of a stabilization control system with PID controllers. Fire detection has been accomplished by utilizing low-cost air composition sensors connected to an artificial neural network. For efficient flight planning, path-planning algorithms have been employed, utilizing equirectangular projection, terrain meshes, and AI techniques to minimize travel distance and maximize energy efficiency. The system has achieved the desired outcomes, surpassing specifications in fire detection and autonomous waypoint navigation. However, the system's applicability in challenging environments could be further enhanced by incorporating advanced attitude estimation approaches. The flight control has effectively stabilized the system, enabling it to operate under harsh conditions commonly experienced by unmanned aircraft.

4. Case Studies and Research Findings

AI-driven optimization of MEMS navigation sensors offers significant advantages across various applications, enhancing user experience. This section explores transformative impacts, including increased accuracy, reduced power consumption, improved reliability, and enhanced user satisfaction. Case studies and research findings demonstrate successful implementations, showcasing performance enhancements and real-world applications.

- Through AI-driven optimization, MEMS navigation sensors bring several benefits and improvements to these applications:

Table 2

Comprehensive Analysis of Case Studies and Optimization Results

Case	Research Objective	Approaches	Advantage	Ref
MEMS IMU De-Noising	The research tackles error divergence in standalone MEMS INS, focusing on weak or blocked GPS signals. It collects gyroscope data from a specific MEMS IMU model to improve accuracy.	Designing and training the LSTM-RNN model to effectively filter and de-noise the MEMS IMU gyroscope signals, thereby improving the accuracy of the MEMS INS.	• Enhancing the accuracy of a standalone MEMS Inertial Navigation System (INS) • Resulting in reduced standard deviation and attitude errors.	[45]
UAS (Drone)	Developed a flexible software framework for drones, enabling easy testing of AI-driven navigation and obstacle avoidance modules, while addressing limitations of existing frameworks like Ardupilot too.	A versatile obstacle avoidance library was developed with three modules: MEMS IMU sensor Module, Mavlink Communication Module, and Sensor Fusion Module. The research followed a methodology involving sensor selection, simulation testing, and open datasets. Optimization approaches were applied in software architecture, obstacle avoidance, and artificial intelligence.	• Reducing the probability of hitting the target. • Quick reaction to new obstacles. • A wide range of UAV environment settings is included in the designed library. • The library's flexibility and adaptability make it suitable for commercial drone applications, such as aerial photography, delivery services, inspection tasks, and more.	[46]
Human activity detection (wearable technologies)	Improving Human Activity Recognition (HAR) using MEMS sensor technology in smartphones. By applying ML techniques and a custom-built Bi-LSTM model, the study aims to accurately classify human motion activities. The goal is to develop a baseline-level technology for HAR with applications in healthcare and fitness industries.	The research proposed a custom-built DL model using the Bi-LSTM neural network architecture for human activity recognition. Through hyperparameter fine-tuning, the model achieved an accuracy of 98.1 % by accurately classifying nine different human motion activities. The implementation of this model using data from mobile phone sensors resulted in significant improvements in activity classification.	The proposed Bi-LSTM model achieves a high accuracy of 98.1 % in human activity recognition, outperforming other models. It effectively handles sequential motion data, identifies fine-grained patterns, and is practical using mobile phone sensors.	[47]
Human activity detection (Arm Motions)	Addressing sensor drift, noise, and calibration, handling data complexity, and optimizing the motion capture system for enhanced accuracy and applicability in different domains.	In the research, optimization approaches were used to improve the motion capture and recognition system. This involved designing and optimizing the MEMS sensor network system to address sensor drift, noise, and calibration. The convergence of the Kernel Perceptron Algorithm (KPA) was optimized to enhance its classification and recognition capabilities. The performance of KPA was compared with the Support Vector Machine (SVM) algorithm to balance speed and accuracy. The research aimed to optimize both hardware and software components for high-quality motion data and reliable arm motion recognition.	Improving the classification and recognition capabilities, allowing for accurate identification of different arm motions, including complex and dynamic movements.	[48]
Unmanned Aircraft Vehicle (UAV)	The main challenge for researchers in this research is to efficiently track and process the large volume of data generated by unmanned aerial vehicles (UAVs) at low cost and with high accuracy.	The researchers employ iterative learning control, Kalman filtering, and gradient descent algorithms to optimize data processing and achieve accurate trajectory tracking. The solution addresses the challenges of processing large volumes of data generated by UAVs in a cost-effective and efficient manner, providing improved accuracy and reduced time complexity.	Cost-effective UAV trajectory tracking, high accuracy with a low tracking error of 0.09 %, improved measurement accuracy of 92 %, reduced time complexity, and faster data processing. These advancements contribute to more affordable, accurate, and efficient UAV operations in various domains.	[49]
UAV	Developing accurate and efficient trajectory control systems for unmanned aerial vehicles (UAVs) in autonomous flight mode using neural network algorithms.	By using a numerical-analytical approach, suitable technical solutions are selected for constructing platformless inertial navigation systems (BINS) for micro and small UAVs. Through simulations and experiments with different neural network structures, such as ELM-Kalman and WANN-RNN-Madgwick algorithms, the aim is to improve navigation accuracy and adapt to the absence of GPS signals. The research aims to optimize the neural network architecture and parameters for precise trajectory control and error compensation in the UAV's navigation system.	The proposed technique and solution enhance UAV trajectory control during autonomous flight by utilizing neural network algorithms and advanced inertial navigation systems. It achieves superior learning accuracy and faster adaptation compared to alternative approaches. This research improves the precision and efficiency of micro and small UAVs in performing tasks without relying on GPS signals.	[50]

Continuation of the Table 2

Case	Research Objective	Approaches	Advantage	Ref
UAV	Limitations of low-cost IMUs, accurately modeling the vehicle dyna-mics, integrating machine learning techni ques, ensuring robustness and generalization, and conducting thorough performance evaluations. By overcoming these challenges, researchers aim to enhance UAV autonomous navigation in GNSS-denied environments without adding extra load to the vehicle.	This research proposes a hybrid machine learning approach to enhance unmanned aerial vehicle (UAV) navigation accuracy in GNSS-denied environments. The approach utilizes the UAV vehicle dynamic model and previous flight information during GNSS availability to train machine learning algorithms. These algorithms predict the vehicle states, such as position, velocity, and attitudes, during GNSS outages, mitigating the massive drift experienced by low-cost inertial measurement units (IMUs). The ML-VDM algorithm eliminates the need for modeling the UAV parameters, which can be time-consuming and prone to errors.	Test scenarios demonstrate the efecttiveness of the approach, achieving significantly reduced drift compared to standalone IMUs during outages, with RMSE values within an acceptable range for many UAV applications.	[51]
UAV (Multi-Rotor)	Developing a noninvasive hybrid computer interface (HCI) system using EOG and EEG signals for indoor target searching with a multi-rotor aircraft.	This research proposes a hybrid machine learning approach to enhance UAV navigation accuracy in GNSS-denied environments by utilizing the vehicle dynamic model and previous flight data. The ML algorithms predict vehicle states during GNSS outages, reducing drift in low-cost IMUs. The system also incorporates a hybrid computer interface for indoor target searching using EOG and MI EEG signals, with SVM for classification and obstacle avoidance. The solution combines signal processing, feature extraction, classification, and navigation techniques to achieve the objectives.	The proposed hybrid machine learning approach for UAV navigation in GNSS-denied environments offers advantages such as accurate prediction of vehicle states during GNSS outages, mitigating drift in low-cost IMUs. The ML-VDM algorithm eliminates the need for complex UAV parameter modeling. The hybrid computer interface system combines EOG and MI EEG signals, enabling effective human-computer interaction and improved navigation in complex environments.	[52]
UAV	The researchers face several challenges in this research. Their main goal is to accurately estimate air data parameters for a small fixed-wing UAV using low-cost pressure sensors and machine learning models. They need to address potential errors introduced during training with wind tunnel data and improve accuracy for the benchmark flight test.	The technique used in this research involves embedding low-cost pressure sensors into a small UAV's surface and employing machine learning algorithms (NNs and LR) to estimate air data parameters. The solution includes training the models using wind tunnel and flight data, considering factors like sensor placement and basis function expansions, and addressing potential errors in the wind tunnel data. The goal is to accurately estimate air data parameters for small UAVs in a cost-effective manner.	The technique and solution have several advantages. The machine learning algorithms enable accurate estimation of air data parameters. The flexibility in MEMS sensor placement allows for optimization. The method addresses potential errors in wind tunnel data and undergoes rigorous validation through extensive testing.	[53]
Cube Sat	The researchers in this study face several challenges. The first objective is to develop and validate algorithms for autonomous collision avoidance (CAM) in space missions. This involves implementing collision avoidance algorithms and using artificial intelligence for planning and decision-making during CAM operations. The second objective is to characterize untraceable space debris objects and improve the debris environmental model. The third objective is to model the upper atmosphere and thermomechanical loads for more accurate re-entry prediction. Additionally, selecting the operational orbit and disposal strategy, as well as ensuring compliance with space debris mitigation regulations, are crucial aspects of the mission design.	The research on e. Cube missions incorporates several optimizations approaches to enhance its objectives. One optimization approach is the development and implementation of efficient algorithms for debris analysis. These algorithms aim to improve the accuracy and speed of identifying and characterizing space debris. Another optimization approach involves optimizing the data collection process for upper atmosphere characterization. This includes designing sensors and instruments that can collect relevant data with high precision and minimal resource utilization.	The advanced collision avoidance system with optimized algorithms enhances the efficiency and effectiveness of avoiding potential collisions in space, reducing the risk of damage to satellites and spacecraft. Overall, these advancements contribute to improved sustainability and safety in space missions, making them more reliable and successful.	[54]

Ending of the Table 2

Case	Research Objective	Approaches	Advantage	Ref
Land Vehicle Navigation	The researchers aim to develop a reliable and accurate land vehicle navigation system by integrating MEMS-based GNSS and INS. The challenge lies in dealing with stochastic errors in inertial sensors and instability during GNSS outages.	The researchers employ a hybrid denoising algorithm, combining wavelet transform and support vector machine (SVM), to improve the signal-to-noise ratio of MEMS-INS measurements. This helps eliminate short-term and long-term errors while preserving vehicle dynamics. Additionally, they develop a data fusion method using SVM to predict and correct positioning errors during GNSS outages. By training the SVM model with simulated data, they achieve accurate positioning results even in the absence of GNSS. The proposed technique effectively reduces sensor noise, enhances positioning accuracy, and maintains real-time performance.	The technique's real-time performance and computational efficiency make it suitable for practical implementation. Overall, the approach enhances the reliability and accuracy of land vehicle positioning while mitigating the challenges posed by GNSS signal outages and stochastic error characteristics of inertial sensors.	[55]
CubeSat	Developing and validate a control approach that can effectively allocate efforts among actuators in an over-actuated system, specifically in the context of a space debris removal mission using a deployable net on a CubeSat, while considering failures and optimizing computational time.	The research utilizes a fuzzy controller combined with control allocation to stabilize the CubeSat and calculate thruster efforts. The controller considers disturbances from net-fired bullets and maintains stability. The proposed solution achieves stable recovery within a reasonable timeframe and shows comparable results to traditional control methods. It also demonstrates robustness in various scenarios, including thruster failure.	Simulation results show successful stability recovery within a reasonable time, comparable to a traditional control allocation method. The proposed approach demonstrates robustness in various scenarios, including a thruster failure.	[56]
Land Vehicle Navigation	This research addresses the challenge of effectively blending GNSS and INS data for accurate positioning in harsh environments.	The technique used in the research involves a two-tier robust fusion scheme. The first tier utilizes a Support Vector Regression-based Adapted Kalman Filter (SVR-AKF) to fuse GNSS and INS data and improve positioning accuracy. The SVR-AKF autonomously adjusts the covariance matrix to adapt to varying GNSS observation quality in complex urban environments. The second tier involves an Adaptive Neuro Fuzzy Inference System (ANFIS) to predict and compensate for INS errors during GNSS outages. This enhances the reliability of the positioning system. The solution proposed in the research significantly improves the overall reliability and positioning performance of land vehicle navigation in GNSS-challenged environments. Experimental tests validate the feasibility and effectiveness of the proposed methodology.	• Enhanced Positioning Accuracy • Robustness in Complex Urban Environ-ments • Compensation for GNSS Outages • Feasibility and Effectiveness Improving accuracy, robustness, and reliability for low-cost GNSS/INS integrated land vehicle navigation systems by addressing challenges of poor GNSS accuracy in complex urban environments and position errors during GNSS outages.	[57]

• *Increased Accuracy*: AI techniques enable improved sensor calibration, compensation for errors, and adaptive filtering, resulting in highly accurate navigation data. This accuracy translates into precise positioning, reliable motion tracking, and orientation estimation.

• *Reduced Power Consumption*: AI-based energy optimization techniques can intelligently manage power usage, reducing the energy footprint of MEMS navigation sensors. This leads to extended battery life in portable devices and efficient power utilization in resource-constrained systems.

• *Improved Reliability*: AI-driven optimization mitigates sensor noise, compensates for biases and drifts, and accounts for environmental variations. These improvements enhance the reliability of MEMS navigation sensors, ensuring consistent and trustworthy navigation information.

• *Enhanced User Satisfaction:* The combination of increased accuracy, reduced power consumption, and improved reliability contributes to an enhanced user experience. Users can benefit from precise navigation, seamless operation, and confidence in the performance of devices or systems relying on MEMS navigation sensors.

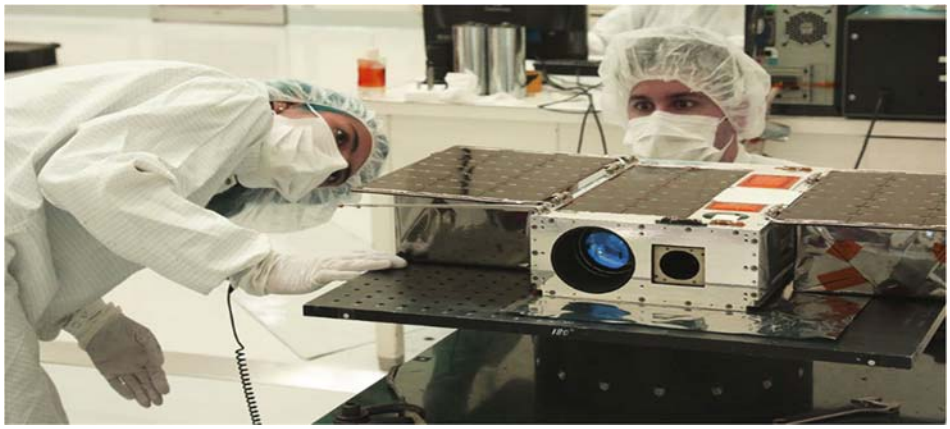


Figure 6. Nano Satellite. The ASTERIA Satellite. Credit: NASA/JPL-Caltech
Source: author's photo

Liddle et al. [58] have examined the challenges related to scientific missions utilizing the advantages of nanosatellites and CubeSats, including cost-effectiveness and the utilization of new technological advances. They have highlighted the importance of MEMS navigation sensors in supporting this strategy. Figure 6 has presented a view of a CubeSat, illustrating its integration within this framework [59].

5. Challenges and Future Directions

While artificial intelligence (AI)-driven optimization holds immense potential for enhancing the user experience with MEMS (Microelectromechanical Systems) navigation sensors, several challenges and limitations must be addressed. In this section, we will discuss the key challenges faced in implementing AI-driven optimization in MEMS navigation sensors and explore potential research directions and future developments that can further leverage AI techniques to improve user experiences.

5.1. Computational Complexity

One of the primary challenges in AI-driven optimization is the computational complexity associated with processing large volumes of sensor data in real-time. MEMS navigation sensors generate a continuous stream of data that needs to be processed and analyzed to extract meaningful information. Implementing complex AI algorithms, such as deep learning models, may require significant computational resources. Overcoming this challenge involves developing efficient algorithms, leveraging hardware accelerators, and exploring novel architectures tailored to the computational constraints of MEMS navigation sensors [60].

5.2. Data Availability and Quality

AI-driven optimization relies heavily on the availability and quality of training data. However, acquiring labeled and diverse datasets for training and validation purposes can be challenging in the context of MEMS navigation sensors. Additionally, ensuring the quality and reliability of collected data, especially in dynamic and unpredictable environments, is crucial. Future research should focus on developing methodologies for collecting and annotating high-quality datasets that reflect a wide range of real-world scenarios and sensor variations, enabling robust AI-driven optimization [60].

5.3. Real-Time Processing Requirements

MEMS navigation sensors are often used in applications that require real-time or near real-time processing of navigation data. However, many AI algorithms, especially those involving complex deep learning models, can introduce latency and computational overhead, making real-time processing challenging. Future research should aim to develop lightweight AI models and algorithms specifically designed for real-time applications, balancing the trade-off between accuracy and computational efficiency [41; 61].

5.4. Sensor Fusion and Integration

Integrating data from multiple sensors, also known as sensor fusion, is critical for optimizing MEMS navigation sensors. However, achieving seamless integration and synchronization of sensor data from different modalities can be challenging due to variations in data formats, sampling rates, and sensor characteristics. Future research should focus on developing standardized sensor fusion frameworks and techniques that can handle different types of sensors and facilitate efficient integration for improved accuracy and reliability [62].

5.5. Context Awareness and Adaptability

MEMS navigation sensors operate in diverse and dynamic environments where conditions can change rapidly. To enhance user experiences, AI-driven optimization should aim to make sensors context-aware and adaptable. This involves developing algorithms that can dynamically adjust sensor parameters, optimize sensor configurations based on environmental conditions, and adapt to user-specific preferences. Future research should explore techniques such as reinforcement learning and adaptive control to enable MEMS navigation sensors to continuously improve performance based on evolving contexts [62].

5.6. Interdisciplinary Collaboration

AI-driven optimization of MEMS navigation sensors requires interdisciplinary collaboration between experts in AI, MEMS technology, signal processing, and navigation systems. Collaboration and knowledge exchange between these domains are essential for developing comprehensive solutions that address the challenges faced by MEMS navigation sensors. Future research should encourage cross-disciplinary collaboration, fostering a deeper understanding of the unique requirements and opportunities for AI-driven optimization in MEMS navigation sensors [29; 64; 65].

Conclusion

In conclusion, this review has demonstrated the significant role of AI in optimizing MEMS navigation sensors to enhance the user experience.

Through the integration of AI techniques such as sensor fusion, adaptive filtering, calibration, compensation, and predictive modeling, MEMS navigation sensors can achieve improved accuracy, reduced power consumption, and enhanced reliability.

Case studies and research findings have showcased the successful implementation of AI-driven optimization in various applications, including autonomous vehicles, indoor localization, wearable devices, and unmanned systems. These applications have witnessed notable enhancements in accuracy, user satisfaction, and overall performance.

While challenges such as computational complexity, data availability, and real-time processing requirements exist, future directions in the field should focus on exploring novel AI techniques, integrating with emerging technologies, considering human-centric design principles, and establishing standards and benchmarks for evaluation. By continuing research and development efforts, the full potential of AI-driven optimization in MEMS navigation sensors can be realized, leading to advanced and user-friendly navigation systems that empower users in diverse domains.

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