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Review article

Inertial Navigation Meets Deep Learning: A Survey of Current Trends and Future Directions

Nadav Cohen *, Itzik Klein

The Hatter Department of Marine Technologies, Charney School of Marine Sciences, University of Haifa, Haifa, Israel

A R T I C L E I N F O

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A B S T R A C T

Inertial sensing is employed in a wide range of applications and platforms, from everyday devices such as smartphones to complex systems like autonomous vehicles. In recent years, the development of machine learning and deep learning techniques has significantly advanced the field of inertial sensing and sensor fusion, driven by the availability of efficient computing hardware and publicly accessible sensor data. These data-driven approaches primarily aim to enhance model-based inertial sensing algorithms. To foster further research on integrating deep learning with inertial navigation and sensor fusion, and to leverage their potential, this paper presents an in-depth review of deep learning methods in the context of inertial sensing and sensor fusion. We explore learning techniques for calibration and denoising, as well as strategies for improving pure inertial navigation and sensor fusion by learning some of the fusion filter parameters. The reviewed approaches are categorized based on the operational environments of the vehicles—land, air, and sea. Additionally, we examine emerging trends and future directions in deep learning-based navigation, providing statistical insights into commonly used approaches.

1. Introduction

Research on the concepts of inertial sensing has been conducted for several decades and has been used in the navigation process for a variety of platforms during the last century [1]. As of today, most inertial sensing relies on accelerometers, which provide specific force measurements, as well as gyroscopes, which provide angular velocity measurements [2]. An inertial measurement unit (IMU) typically consists of three orthogonal accelerometers and three orthogonal gyroscopes, with varying performance and cost [3,4].

The IMU readings are processed in real time to provide a navigation solution. Such a system, which executes the strapdown inertial navigation algorithm, is known as an inertial navigation system (INS) [5]. The INS provides the navigation solution consisting of position, velocity, and orientation as illustrated in Fig. 1a. The accuracy and efficiency of the navigation solution are affected by the duration of the mission, the platform dynamics, and the quality of the IMU. Using high-end sensors results in a more accurate navigation solution for extended periods of time, while using low-cost INS results in a much faster accumulation of errors. There is, however, a common approach for dealing with error accumulation in both cases, which is to use an accurate external aiding sensor or information aiding to ensure that the solution is bounded or the error is mitigated [6,7]. Sensors like the global navigation satellite system (GNSS), which provides precise position measurements, and the Doppler velocity log (DVL), which offers accurate velocity readings, are considered external aiding sensors. Additionally, supplementary information such as zero velocity updates (ZUPT) and zero angular rates (ZAR) can be utilized, either independently or in conjunction with physical sensors, to mitigate error accumulation in inertial navigation solutions. INS and aiding sensors are commonly fused using nonlinear filters, such as the extended Kalman filter (EKF) and the unscented Kalman filter (UKF). These filters are capable of accounting for model uncertainty by incorporating both process and measurement noise covariances. This allows them to provide valuable additional information while preventing error accumulation in inertial navigation algorithms [8]. A diagram of the sensor fusion is shown in Fig. 1b.

During the past decade, deep learning (DL) has made remarkable progress due to advances in neural network architectures, large datasets, and innovative training methods. In the field of computer vision, convolutional neural networks (CNNs) have revolutionized tasks such as image classification, object detection, and semantic segmentation [9]. It has been demonstrated that recurrent neural networks (RNNs), including long short-term memory (LSTM) networks, are particularly effective at modeling sequences and undertaking language-related tasks, such

* Corresponding author.
E-mail address: ncohe140@campus.haifa.ac.il (N. Cohen).

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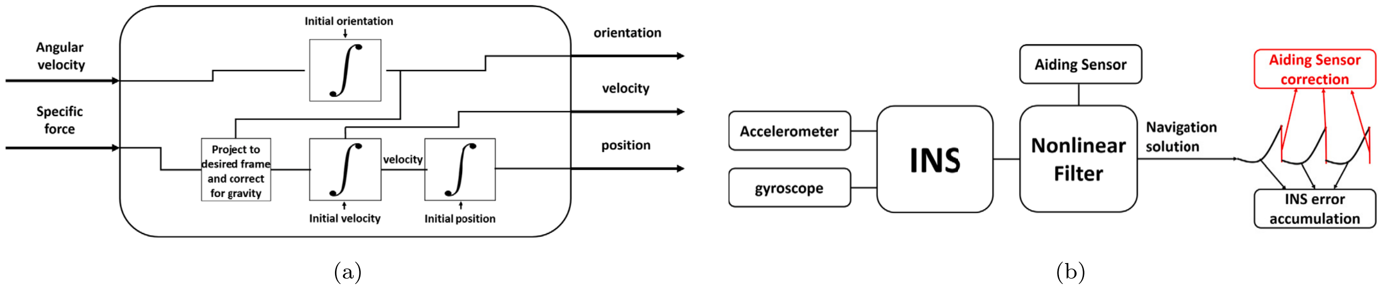


Fig. 1. (a) Strapdown inertial navigation algorithm. For a given initial condition, the gyroscope's angular velocity and the accelerometer's specific force measurements are integrated over time to calculate the navigation solution in the desired reference frame (local, geographic, and so on). (b) The process by which the navigation solution can be corrected using a nonlinear filter and an aiding sensor. The black diverging curve illustrates how the navigation solution accumulates error over time, while the red curve shows how the aiding sensor corrects this error, producing a chainsaw-like signal.

as translation and sentiment analysis, when used for natural language processing [10]. Moreover, techniques such as generative adversarial networks (GANs) and transfer learning have extended the capabilities of DL models to enable tasks such as image synthesis and the use of pre-trained models [11–13]. In light of these advancements, DL has been significantly enhanced, propelling it to new frontiers in the field of artificial intelligence.

The recent advances in hardware and computational efficiency have proven DL methods to be useful for dealing with real-time applications ranging from image processing and signal processing to natural language processing by utilizing its capabilities to address nonlinear problems [14–17]. As a result, DL methods began to be integrated into inertial navigation algorithms. One of the first papers to use neural networks (NNs) in inertial navigation was written by Chiang et al. [18] in 2003. A multi-sensor integration was proposed using multi-layer, feed-forward neural networks, and a back-propagation learning algorithm to regress the accurate land vehicle position. It demonstrated the effectiveness of the NN in addressing navigation problems.

Motivated by their success and impact, researchers published papers proposing utilizing deeper and more sophisticated neural networks. Noureldin et al. [19] designed a multi-layer perceptron (MLP) network to predict the INS position error during GNSS outages using the INS position component and instantaneous time. This work was continued and modified in [20], where the authors replaced the MLP network with a radial basis function (RBF) neural network to address the same scenario and successfully reduced the position error. In [21], further improvements were described, utilizing multi-layer feed-forward neural networks to regress the vehicle's position and velocity in an INS/differential-GNSS (DGNSS) integration by employing a low-cost IMU. Further research on GNSS outages and INS/GNSS fusion can be found in [22], where input-delayed neural networks are used to regress velocity and position through fully connected (FC) layers. Additionally, in [23], the development of fully connected neural networks with hidden layers constructed of wavelet base functions was proposed to develop INS/GNSS integration to eliminate the complexities associated with KF by providing a reliable positioning solution when GNSS signals are not available. In addition to position regression, Chiang et al. in [24–26] introduced NNs based on fully connected layers for the enhancement of orientation measurements provided by INS/GNSS fusions when using low-cost MEMS IMUs or when GNSS signals are not available. Another approach is to enhance a specific block within the KF. In [27], the authors proposed using a three-layer fully connected network to improve the innovation process in an adaptive KF for an integrated INS/GNSS system. Performance analysis for the networks above was conducted in [28] for INS/GNSS fusion. The aforementioned researchers were among the early adopters of using inertial data within deep neural networks (DNNs) to enhance navigation capabilities.

Aside from this paper, there are several other papers that conducted surveys on the general topic of data-driven navigation. Most of them looked at specific platforms or DL methods. In [29,30], a review of the navigation of spacecraft was made in addition to other concepts such as dynamics and control. Furthermore, approaches of only deep-reinforcement learning were reviewed for different platforms in [31–33]. In light of the significant advances in deep learning (DL) in the fields of image processing and computer vision, vision-based navigation surveys have been conducted for various platforms and more generally [34–38]. Some papers focused only on machine-learning-based navigation, which is based primarily on determining the features through preprocessing data analysis [39–41]. In [42] there is a discussion of end-to-end DL methods employed in autonomous navigation, including subjects other than navigation such as obstacle detection, scene perception, path planning, and control. A survey was conducted in [43] to examine inertial positioning using recent DL methods. It targeted tasks such as pedestrian dead-reckoning and human activity recognition. An overview of all the survey papers is provided in Table 1.

Table 1
A collection of fifteen surveys describing DL methods applied to various aspects of navigation, not solely focused on inertial navigation.

Paper	Topic
[29]	DL methods for spacecraft dynamics, navigation and control
[30]	DL methods of relative navigation of a spacecraft
[31,32]	DRL for mobile robot navigation
[33]	UAV autonomous navigation using RL
[34]	DL methods for visual indoor navigation
[35,37]	Visual navigation using RL
[36]	DL methods of perception and navigation in unstructured environments
[38]	DL for perception and navigation in autonomous systems
[39]	Machine learning for maritime vehicle navigation
[40]	Survey of inertial sensing and machine learning
[41]	Machine learning for indoor navigation
[42]	DL applications and methods for autonomous vehicles
[43]	DL methods for positioning including pedestrian dead-reckoning and human activity recognition

Contrary to the aforementioned approaches, this paper examines DL methods utilized exclusively in inertial sensing and sensor fusion algorithms, focusing entirely on vehicles regardless of their operating environment. The paper emphasizes why DL is well-suited for inertial navigation and provides insights into the common ways of integrating DL methods into the inertial navigation pipeline. The contributions of this paper are:

1. Provide an in-depth review of DL methods applied to inertial sensing and sensor fusion tasks for land, aerial, and maritime vehicles.
2. Examine DL methods for calibrating and denoising inertial sensor data suitable for any vehicle and any inertial sensor.
3. Provide insights into current trends on the subject and describe the common DL architectures for inertial navigation tasks.
4. Discussion of potential future directions for the use of DL approaches for improving inertial sensing and sensor fusion algorithms.

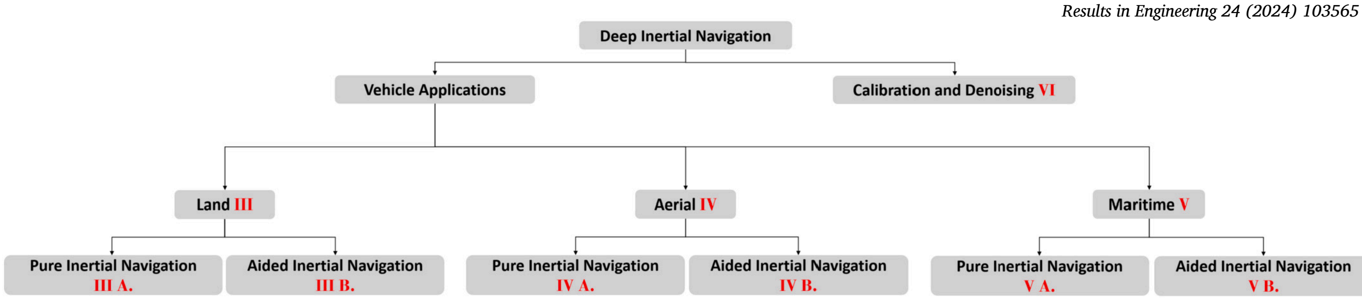


Fig. 2. Taxonomy tree of deep inertial navigation.

The paper begins with Section 2, which provides the motivation for utilizing deep learning (DL) in inertial navigation along with a discussion on its advantages and disadvantages. A taxonomy tree illustrating the structure of the paper is provided in Fig. 2. The rationale behind this structure is to first divide the inertial tasks into those related to inertial signals, such as calibration and denoising, discussed in Section 6, and those directly related to vehicle applications. In the latter category, we separately address works related to the vehicle operating environment, including land (Section 3), air (Section 4), and maritime (Section 5) domains. Within each operating environment, we further divide the survey into works focusing on pure inertial navigation and those concentrating on aided inertial navigation. Section 7 delves into the survey findings, exploring the pros and cons of employing DL in inertial navigation, and outlines future trends. Finally, Section 8 presents the conclusions of this survey.

2. Deep inertial navigation

The motivation for utilizing deep learning in inertial navigation arises from its capability to manage the complexity, variability, and nonlinearities inherent in inertial navigation tasks. This approach also benefits from the ability to leverage large volumes of data for learning and adaptation purposes. Model-based approaches for inertial navigation typically depend on intricate mathematical models and algorithms to accommodate factors like sensor noise, drift, and external disturbances. Deep learning holds promise in potentially managing this complexity more efficiently by learning pertinent features and relationships directly from the inertial sensor data. Additionally, inertial navigation systems function in dynamic environments that are prone to variation, where factors such as motion dynamics, sensor characteristics, and external disturbances may fluctuate unexpectedly. Deep learning models show potential in acquiring robust representations that can adapt across various operational conditions and adjust to environmental changes. There are additional advantages to using deep learning methods in inertial navigation, including:

A1. **Modeling of Nonlinear Problems** - Inertial navigation presents a nonlinear challenge since its model is based on the INS equations of motion. These nonlinear differential equations, combined with inherent stochastic noise characteristics, result in a complex system. DL approaches have demonstrated effectiveness in handling nonlinear and complex systems and, therefore, have the potential to improve inertial navigation performance and robustness. Additionally, DL methods have proven to be practical for real-life applications facing nonlinear setups [44].

A2. **Parameter Estimation** - In nonlinear inertial sensor fusion, the stochastic errors associated with the inertial sensors necessitate adaptive parameter estimation as they vary along the trajectory. DL methods, which excel in forecasting and regression problems based on feature extraction and time dependencies, have shown superior results in parameter estimation across various fields. These results could be leveraged to enhance inertial navigation and sensor fusion, thereby making the navigation filter more robust and preventing divergence, which could otherwise lead to mission failure. [45].

A3. **Robustness** - Variations in platform maneuvers, along with external factors like wind, waves, and obstacles, can significantly affect model-based inertial navigation. DL approaches have the ability to generalize across various scenarios, which is crucial for navigation tasks. Consequently, DL techniques can effectively learn, manage, and cope with these uncertainties [46].

A4. **Real-time Processing** - The advancement in computational hardware, coupled with the temporal nature of inertial data, makes DL methods particularly efficient. Unlike image processing tasks, which demand heavier computational loads (processing sequence of images), inertial data processing requires fewer computational resources (processing time-series data). Once trained, DL models can operate in real-time, offering swift and effective navigation solutions [17].

A5. **Multimodal Integration** - Inertial navigation often involves fusing inertial data with various sensors like GNSS and DVL, among others. DL approaches have demonstrated their ability to harness dependencies across different types of data, such as words and images, to solve specific tasks. This characteristic of DL can enhance sensor fusion by effectively integrating inertial readings with other aiding sensors or information data [47].

A6. **Sim-to-Real Transfer** - The IMU serves as the primary component for inertial sensing, measuring the specific force and angular velocity vectors. Its characteristics, including error models, are well-understood and can be accurately simulated, for example, through six degrees of freedom simulations. Data from these simulations can potentially be used to train a DL approach, which can then be applied to real-world scenarios. In that manner, the burden of recording huge amounts of data for the training process is no longer required [48].

A7. **Hybrid Approaches** - DL approaches can be embedded in the model-based algorithm while replacing or enhancing only a specific part of it. Thus, the solid theory beyond model-based approaches is maintained while a certain part can be replaced in order to leverage the benefits of DL, taking advantage of the best of both domains [49].

In addition to the benefits, DL approaches also have several disadvantages that need to be considered. Key challenges in DL and inertial sensing are discussed, along with strategies for addressing them:

D1. **Data Dependency** - DL models necessitate substantial amounts of high-quality data to effectively generalize the problem. Navigation presents a challenge as each platform exhibits unique dynamics and maneuvers. Training a model on specific dynamics may lead to overfitting, and variations in environmental conditions such as weather, wind, and temperature can influence sensor performance and dynamics, requiring adaptable learning approaches or additional data [50]. The data dependency for training can be avoided with sim-to-real approaches, as addressed in A6.

D2. **Computational Resources** - Training DL models typically require significant computational resources, such as high-performance GPUs or TPUs, which are often characterized by high costs and limited availability. This challenge is particularly relevant in the context of the increasing adoption of networks designed for large language models, such as transformers, in inertial sensing and sensor fusion applications. The requirement for high computational resources can be removed when using shallow or regular DL algorithms and avoiding the usage of approaches designed for large language models [51].

D3. **Interpretability** - A crucial aspect of applying a navigation system to a platform is understanding its characteristics. This knowledge allows users to anticipate when the system may excel and where it could potentially malfunction. DL models are often regarded as "Black Boxes," indicating that although the inputs and outputs are known, the internal workings of the learning system remain opaque. This is referred to as an end-to-end approach and poses a significant challenge in safety-critical navigation applications where users rely on understanding and trusting the system's behavior. To allow insight and understanding of the process, hybrid approaches can be implemented as discussed in A7 [52].

3. Land vehicle inertial sensing

3.1. Pure inertial navigation

One of the most researched aspects of land vehicle navigation is scenarios where GNSS signals are unavailable. Therefore, the use of deep learning methods has been explored to compensate for performance in these situations. Shen et al. in [53] presented an approach for improving MEMS-INS/GNSS navigation during GNSS outages. This article proposed two neural networks for a dual optimization process, wherein the first NN compensates for the INS error, while the second NN compensates for the error generated by a filter using the radial basis function (RBF) network for accurate position data. Recently, additional papers exploring the benefits of more complex DNNs in GNSS-denied environments began to emerge. Lu et al. [54] introduced a multi-task learning method, where initially, the inertial data undergo denoising through a convolutional auto-encoder, followed by temporal convolutional network (TCN) processing to address GNSS gaps and one-dimensional CNN (1DCNN) application for zero velocity scenario detection. Subsequently, this aiding data contributes to deriving an accurate navigation solution in Kalman filtering (KF). Additionally, Karlsson et al. proposed a CNN model for precise speed estimation solely relying on inertial data in the absence of aiding sensors like GNSS or wheel speed [55].

GNSS signals are not viable in all scenarios, such as indoor navigation or tunnel navigation, requiring not only compensation for gaps in GNSS signal availability but also accounting for the entire process. For example, in [56,57], Tong et al. regressed the change in velocity and heading of a vehicle in GNSS-blocked environments such as tunnels using a TCN architecture with residual blocks used from low-cost, smartphone mounted, IMU readings. Additionally, "DeepVIP", an LSTM-based architecture, was introduced for indoor vehicle positioning and trained on low-cost inertial data from smartphones. "DeepVIP" is available in two variations. The first approach achieves a higher level of positioning accuracy by estimating velocity and changes in heading, making it suitable for scenarios requiring the highest degree of positioning accuracy. The second approach, while slightly less accurate, is more appropriate for situations where computational efficiency is prioritized [58]. An illustration based on the DeepVIP model can be seen in Fig. 3.

The use of data-driven methods in inertial vehicle navigation also provides the benefit of improving the output of the inertial sensors independent of the other aiding sensors. Zhao et al. examined high-end sensors in [59] and proposed "GyroNet" and "FoGNet", which are based on bidirectional-LSTMs (bi-LSTMs). The first estimates the bias and noise of a gyroscope to improve angular velocity measurements, while the second corrects the drift of the fiber optic gyroscope (FOG) to improve vehicle localization. A similar approach was proposed in [60], where the authors introduced a novel method to generate IMU-like data from GNSS data to train a fully connected network. This network was designed to regress angular velocity and acceleration, leading to improved positioning based on MEMS IMU data. Gao et al. [61] introduced the "VeTorch," an inertial tracking system that employs smartphone-derived inertial data for real-time vehicle location tracking. Employing a TCN, they conducted acceleration, orientation sequence learning, and pose estimation. Another method to estimate the platform orientation was conducted in [62] using quaternion representation. The authors introduced a combined CNN and Bi-LSTM network, which receives data from a 6 DOF IMU and applies it to real-time vehicle navigation. A similar concept of an LSTM-based model was employed by Freydin and Or to forecast vehicle speed using low-cost IMU readings from smartphones [63].

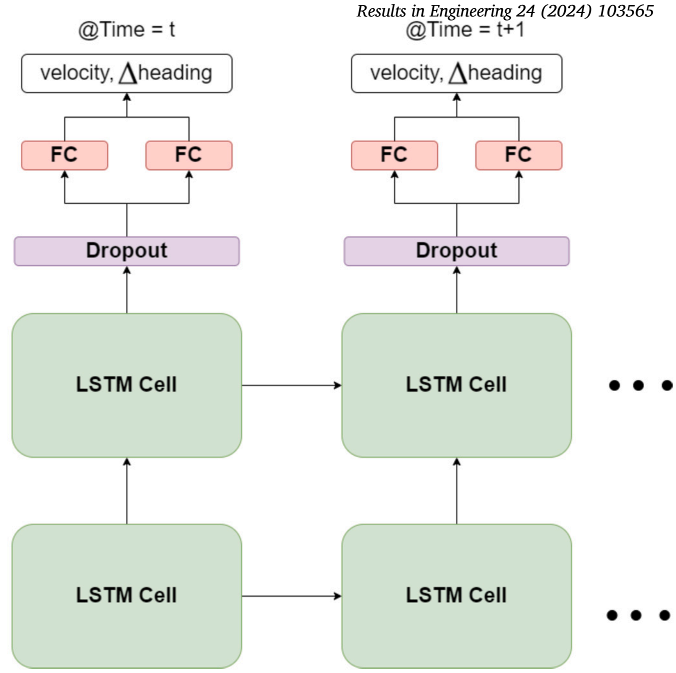


Fig. 3. The figure illustrates an LSTM architecture based on the DeepVIP architecture described in [58]. The DeepVIP architecture involves passing inertial readings and additional sensor data through LSTM cells to capture time dependencies. Subsequently, the data traverses dropout layers to prevent overfitting before being processed by FC layers to extract velocity and heading residual outputs.

3.2. Aided inertial navigation

Apart from enhancing inertial reading abilities for more accurate navigation, DL approaches have demonstrated a significant impact in improving sensor fusion. Li et al. [64] introduced a novel recurrent convolutional neural network (RCNN)-based architecture for scan-to-scan laser/inertial data fusion for pose estimation. Additionally, Srinivasan et al. [65] proposed an end-to-end RNN-based approach that utilizes IMU data along with wheel odometry sensor and motor current data to estimate velocity, following an investigation into the extreme dynamics of an autonomous race car. In the "GALNet" framework, the authors utilized inertial, kinematic, and wheel velocity data to train an LSTM-based network that regressed the relative pose of a car [66]. In [67], a smartphone gyroscope, magnetometer, and gravity sensor were integrated to train the "XDRNet" architecture. Using 1DCNN, the network regresses vehicle speed and heading changes and, as a consequence, reduces inertial positioning error drift. Moreover, Liu et al. presented a hybrid CNN-LSTM-based network that integrates a dual-antenna satellite receiver and MEMS IMU to forecast the residual of the position, velocity, and orientation at each time step [68]. An additional variation of a CNN-LSTM-based network was applied in [69,70] using 2D simulated data to estimate the Kalman gain and IMU errors. The CNN-LSTM can learn the accumulated IMU error in the strapdown computation and adapt the IMU error estimations to compensate for low-frequency IMU measurements. Additionally, it addresses system model deficiencies and handles unknown process and measurement noise. In the case of an agricultural wheeled robot, velocity estimation was achieved by integrating inertial readings, magnetometer data, and the absolute values of the mean discrete Fourier transform coefficients of accelerometer norms within a TCN architecture. These velocity estimates were subsequently utilized in INS/GNSS fusion to estimate 2D position and velocity, reducing the reliance on GNSS measurements, particularly in GNSS-denied environments, and demonstrating good performance in such scenarios [71]. Wang et al. [72,73] suggested a novel method that improves vehicle navigation using smartphones in GNSS-denied areas by automatically estimating smartphone installation angles using deep learning. Initially, an EKF integrates data from GNSS, IMU, and barometer to provide accurate position and attitude. Then, a trained deep learning network predicts the position from IMU and barometer readings using the attitude solution from the integrated system. Finally, another EKF estimates installation angles by comparing predicted and integrated positions. In addition to GNSS, other sensors fused with inertial sensors include radar and LiDAR. In [74], the authors combined low-cost mmWave radar with inertial data using attention-based mechanisms in a novel DL approach called milliEgo, which was designed to regress the position and orientation of a mobile robot. In addition, LiDAR-inertial odometry (LIO) has gained interest in land vehicle applications. Son et al. [75] proposed a deep learning framework that processes LiDAR data using a CNN-based network and IMU data using an RNN-based network, which is then combined to estimate the vehicle's position and orientation. A similar approach with a slightly different architecture, named DeepLIO, was proposed in [76]. In contrast, [77] introduced UnDeepLIO, which follows a similar framework but operates in an unsupervised manner. In a more recent study, Sun et al. [78] proposed TransFusionOdom, a transformer-based LiDAR-inertial fusion method that demonstrated superior position and orientation accuracy compared to the three deep LIO methods mentioned above.

It has been demonstrated that using a filter such as the EKF is a common approach to achieving a high level of accuracy and reliability in sensor fusion. Aside from providing a navigation solution, the filter also offers insight into the propagation of navigation uncertainty over time. Consequently, DL methods have shown great impact in addressing different aspects of the filter that significantly influence the solution. Hosseinyalamdary proposed a deep KF [79], which includes a modeling step alongside the prediction and update steps of the EKF. This addition corrects IMU positioning and models IMU errors, with GNSS measurements used to learn IMU error models using RNN and LSTM methods. In the absence of GNSS observations, the trained model predicts the IMU errors. Furthermore, SL-SRCKF (self-learning square-root-cubature KF) employs an LSTM-based network to obtain observation vectors during GNSS outages continuously, learning the relationship between observation vectors and internal filter parameters to enhance the accuracy of integrated MEMS-INS/GNSS navigation systems [80]. Additionally, DL methods identify specific scenarios in the inertial data that may prevent the navigation solution from accumulating errors. Using RNN, a zero velocity situation or no lateral slip could be identified and incorporated later on into a KF for localization processes [81].

The literature indicates that the covariance noise matrix plays an important role in the KF, and therefore, DL methods were employed to adapt it consistently. According to Brossard, Barrau, and Bonnabel, a CNN-based method was used to dynamically adapt the covariance noise matrix for an invariant-EKF using moderate-cost IMU measurements [82]. Previously, in [83], the authors devised a method that combined Gaussian processes with RBF neural networks and stochastic variational inference. This approach aimed to enhance a state-space dynamical model's propagation and measurement functions by learning residual errors between physical predictions and ground truth. Moreover, the study demonstrated how these corrections could be utilized in the design of EKFs. An alternative method of estimating the process noise covariance relies on reinforcement learning, as explained in [84], which uses an adaptive KF to determine position, velocity, and orientation. In [85], not only the parameters of measurement noise covariances but also the parameters of process noise covariances were regressed. These parameters can be more accurately estimated using a multitask TCN, resulting in higher position accuracy than traditional GNSS/INS-integrated navigation systems. The authors in [86] introduced a residual network incorporating an attention mechanism to predict individual velocity elements of the noise covariance matrix. As a result of the empirical study, it has been demonstrated that adjusting the non-holonomic constraint uncertainty during large dynamic vehicle motions rather than strictly setting the lateral and vertical velocities to zero could improve positioning accuracy under large dynamic motions. Table 2 categorizes the papers discussed in this section by their respective improvement goals.

Table 2
A summary of forty-one papers describing DL inertial sensing and sensor fusion for land vehicles, categorized by their improvement goals.

Improvement Goals	Papers
Pure Inertial Navigation	[18–26,28,53–61,63,62]
Aided Inertial Navigation	[27,64–86]

4. Aerial vehicle inertial sensing

4.1. Pure inertial navigation

In aerial navigation, as in other domains, GNSS signals are valuable when integrated with INS. However, in the absence of GNSS signals, the inertial navigation solution tends to drift. To achieve better performance than traditional GNSS/INS fusion, an LSTM-based network was proposed in [87] to estimate the 3D position of an aerial vehicle. When the aerial vehicle encounters GNSS-denied environments, DL approaches are used to compensate. Liu et al. [88] proposed a 1DCNN/GRU hybrid deep learning model that predicts the GNSS position increments for integrated INS/GNSS navigation in the event of GNSS outages [89–91]. A similar approach to deal with scenarios of denied GNSS environments was implemented in [92], in which a GRU-based network was used to estimate position and velocity. A novel method known as "QuadNet" was proposed by Shurin and Klein in [93]. They enforced the quadrotor motion to be periodic and utilized its inertial readings to develop 1DCNN and LSTM methods for regression of the distance and altitude changes of the quadrotor. In the study by Hurwitz and Klein, the "QuadNet" architecture was revisited to explore the benefits of using multiple IMUs and to devise effective methods for leveraging the excess inertial data [94].

For assessing a vehicle's attitude with only inertial sensing, Liu et al. employed an LSTM-based network based on IMU data from a UAV [88]. While in [95], the authors utilized a hybrid, more complex network that incorporates CNN and LSTM blocks to estimate MAV pose utilizing the current position and unit quaternion. Esfahani et al. introduced an inertial odometry network named "AbolDeepIO" [96]. Based on LSTM, this network architecture leverages IMU readings for inertial odometry in MAVs. In their study, they compared the performance of AbolDeepIO with that of "VINet" [97], demonstrating superior results in MAV data analysis. Seven sub-architectures were also tested and evaluated. As a follow-up to "AbolDeepIO", the authors brought forward "OriNet", which is also based on LSTM and capable of estimating the full 3D orientation of a flying robot with a single particular IMU

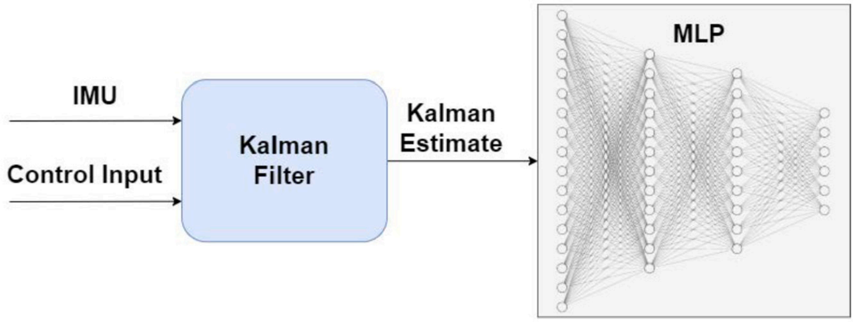


Fig. 4. The figure illustrates the architecture presented in [108], which is based on a simple MLP network. This network utilizes the estimated attitude states from the Kalman filter and enhances them through training with data containing accurate reference attitude information.

in the quaternion form [98]. A robust inertial attitude estimator called "RIANN" was also proposed, a network whose name stands for Robust IMU-based Attitude Neural Network. Several motions, including MAV motion, were regressed using a gated recurrent units (GRUs) network. As well as proposing three domain-specific advances in neural networks for inertial attitude estimation, they also propose two methods that enable neural networks to handle a wide variety of sampling rates [99]. It has been suggested by Chumuang et al. [100] that CNNs and LSTMs are both effective for predicting the orientation of a MAV, the former using the quaternions predicted from data from the IMU using Madgwick's adaptive algorithm [101], and the latter using raw gyroscope measurements. Recently, in [62] a CNN and Bi-LSTM network was proposed for estimating the quaternion representation of the MAV orientation, surpassing the performance of previously mentioned methods. For improving MAV navigation, rather than using two separate networks, the authors in [102] suggested three models, including CNN, RNN, and a CNN and LSTM hybrid model, and performed a comparison amongst them. Furthermore, Bajwa et al. [103] suggested an algorithm called DIVE, which employs a CNN to regress a velocity estimate from a history of IMU-derived inputs and applies it as a correction to an EKF.

4.2. Aided inertial navigation

A number of the papers examined visual-inertial odometry as a tool for aerial inertial navigation. Clark et al. [97] developed the "VINet" architecture. It comprises LSTM blocks that process camera output at the camera rate, and IMU LSTM blocks that process data at the IMU rate. This study used deep learning to determine an MAV's orientation. In [104], a similar approach was employed; however, the platform was not an MAV but rather a bigger and heavier unmanned aerial vehicle (UAV). Another vision-inertial fusion study was conducted in [105] in which a camera and IMU sensor fusion method were used to estimate the position of an unmanned aircraft system (UAS) using a CNN-LSTM-based network known as "HVIOnet", which stands for hybrid visual-inertial odometry network. A more complex method was introduced by Yusefi et al. where an end-to-end, multi-model, DL-based, monocular, visual-inertial localization system was utilized to resolve the global pose regression problem for UAVs in indoor environments. Using the proposed deep RCNN, experimental findings demonstrate an impressive degree of time efficiency, as well as a high degree of accuracy in UAV indoor localization [106]. In a different paper and scenario involving GNSS-denied environments, the researchers employed a combination of optical odometry, radar height estimates, and multi-sensory data fusion. To enhance optical flow velocity estimates in these challenging conditions, they utilized an LSTM network alongside angular velocity readings from the IMU to predict velocity increments [107].

Next, when examining data-driven approaches utilized to enhance the filtering in aerial vehicle navigation, Al-Sharman et al. proposed a fully connected network in [108] to improve the quality of Kalman attitude estimates. This network takes the Kalman state estimates, derived from inertial readings and control vectors, as inputs and regresses the UAV attitude. Fig. 4 illustrates the approach based on the one presented in the aforementioned paper. Another recurring approach involves predicting noise covariance information using DL. In [109], the authors introduced a CNN-based adaptive Kalman filter designed to enhance high-speed navigation with low-cost IMUs. Their approach employs a 1DCNN to predict noise covariance information for 3D acceleration and angular velocity, utilizing windowed inertial measurements. The aim is to outperform classical Kalman filters and Sage-Husa adaptive filters in high dynamic conditions. In a subsequent paper, Or and Klein [110] developed a data-driven, adaptive noise covariance approach for an error state EKF in INS/GNSS fusion. Using a 1DCNN, they were able to estimate the process noise covariance matrix and use the information to provide a better navigation solution for a quadrotor drone. Solodar and Klein [111] proposed VIO-DualProNet, consisting of two 1DCNNs tasked with estimating the covariance matrices of the accelerometer and gyroscope, respectively. These estimates are utilized to dynamically assess the process noise covariance matrix, enhancing the optimization process in visual-inertial odometry. Experimental findings on MAVs demonstrate a 25% enhancement in absolute trajectory error compared to the baseline approach. In [112], the authors introduce a learning-based method named "AirIMU," which captures the inherent nonlinearities of IMUs while ensuring accurate covariance propagation in a data-driven manner. This approach combines CNN and GRU. Performance testing was conducted on both MAVs and large-scale helicopters spanning over 262 km. Table 3 categorizes the papers discussed in this section by their respective improvement goals.

Table 3
A summary of twenty-seven papers describing DL inertial sensing and sensor fusion for aerial vehicles, categorized by their improvement goals.

Improvement Goals	Papers
Pure Inertial Navigation	[87–100,62,102,103]
Aided Inertial Navigation	[97,104–112]

5. Maritime vehicle inertial sensing

5.1. Pure inertial navigation

When evaluating maritime inertial navigation, it is important to distinguish between surface and underwater environments. An underwater environment is inherently considered a GNSS-denied environment, as GNSS signals cannot penetrate water. Zhang et al. [113,114] were among the first to apply deep learning techniques to autonomous underwater vehicle (AUV) navigation. To regress the position displacements of an AUV, the authors used an LSTM-based network trained over GNSS data that was utilized as the position displacement training targets. The output of this network is integrated into the EKF to make the position directly observable. Weizman et al. [115] investigated the maneuvers of ocean gliders and utilized their periodic motion to introduce GilderNet,

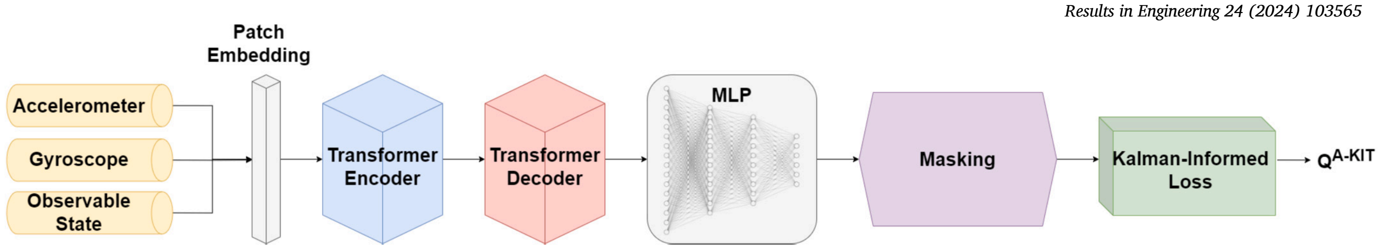


Fig. 5. The figure depicts the architecture based on A-KIT introduced in [133], where an adaptive Kalman-informed transformer is employed. In this approach, inertial data, along with observable states, such as position from GNSS, are fed through the block diagram presented. The output obtained from this process provides the scale factors required for dynamically estimating the process noise covariance matrix of the extended Kalman filter.

a 1DCNN that regresses glider distance and depth based solely on inertial sensors and inspired by methods from pedestrian dead reckoning. In [116], the authors investigate improving ship attitude estimation using an LSTM-based network. This network accepts the transformation matrix from the body frame to the inertial frame and can provide a reliable reference attitude for the strapdown INS when the celestial navigation system is invalid. Additionally, Li et al. [117] propose an underwater DI-EME navigation framework based on deep learning. This framework utilizes MEMS IMU and magnetic compass data to obtain displacements and headings. The network architecture comprises of CNN, attention, and fully connected layers, which accept raw IMU measurements as well as magnetometer data. Furthermore, in [118] the authors opted to estimate the displacement of an AUV using a transformer-based network, incorporating IMU data alongside additional redundant, more accurate, and precise accelerometer data.

5.2. Aided inertial navigation

A task such as navigation on or underwater may encounter difficulties due to the dynamics of the environment or the inaccessibility of GNSS signals. In [119], the authors used a hybrid TCN-LSTM network to predict the pitch and heave movement of a ship in different challenging scenarios. A fully connected network is suggested in [120] to improve AUV navigation in rapidly changing environments, such as in waves near or on the surface. This network is based on data from an accelerometer and is used to predict the pitch angle. The Kalman filter, neural network, and velocity compensation are then combined in the "NN-DR" method to provide a more accurate navigation solution.

The DVL is used in underwater applications as a sensor to assist in navigation, similar to GNSS data used by above-water applications. Several papers have been published examining scenarios of DVL failure. There was, for example, a proposal in [121] to aid dead-reckoning navigation for AUVs with limited sensor capabilities. Using RNN architecture, the algorithm predicts relative velocities based on the data obtained from the IMU, pressure sensors, and control actions of the actuators on the AUV. In [122], the Nonlinear AutoRegressive with Exogenous Input (NARX) approach is used in cases where DVL malfunctions occur to determine the velocity measurements using INS data. For receiving the navigation solution, the output of the network is integrated into a robust Kalman filter (RKF). Additionally, a system called "NavNet" utilizes data from the IMU and DVL sensors through a deep learning framework using LSTM and attention mechanisms to regress the position displacement of an AUV and compares it to the EKF and UKF [123]. Further improvements and revisions were made in [124], which used TCN blocks instead of LSTM blocks. Moreover, as a way of rectifying the error accumulation in the navigation system, Ma et al. proposed a similar procedure, as previously mentioned, and developed an adaptive navigation algorithm for AUV navigation that uses deep learning to generate low-frequency position information. Based on LSTM blocks, the network receives velocity measurements from the DVL and Euler angles from the attitude and heading reference system (AHRS) [125]. Cohen and Klein proposed "BeamsNet", which replaces the model-based approach to derive the AUV velocity measurements

Table 4
A summary of twenty-three papers describing DL inertial sensing and sensor fusion for maritime vehicles, categorized by their improvement goals.

Improvement Goals	Papers
Pure Inertial Navigation	[113–118]
Aided Inertial Navigation	[119–130,110,131–134]

out of the DVL raw beam measurements using 1DCNN that uses inertial readings [126]. The authors continued the work by looking at cases of partial DVL measurements and succeeded in recovering the velocity with a similar architecture called "LiBeamsNet" [127]. In the case of a complete DVL outage, in [128] the authors introduced "ST-BeamsNet", which is a Set-Transformer based network that uses inertial reading and past DVL measurements to regress the current velocity. By further examining challenging environments that may affect the performance of the DVL, Topini et al. [129] conducted an experimental comparison of data-driven strategies for AUV navigation in DVL-denied environments where they compared MLP, CNN, LSTM, and hybrid CNN-LSTM networks to predict the velocity of the AUV.

Moving to deep learning strategies aimed at enhancing the performance of the sensor fusion filter, according to the authors of [130], the RBF network can be augmented with error state KF to improve the state estimation of an underwater vehicle. By applying the RBF neural network, the proposed algorithm compensates for the lack of error state KF performance by enhancing innovation error terms. Or and Klein [110,131,132] developed an adaptive EKF for velocity updates in INS/DVL fusions. Initially, they demonstrated that by correcting the noise covariance matrix using 1DCNN to predict the variance in each sample time using a classification problem, they could significantly improve navigation results. In recent work, the authors introduced "ProNet", which uses regression instead of classification to accomplish the same task. In [133], an adaptive Kalman-informed transform (A-KIT) was presented. This method utilized inertial readings along with Kalman estimates of the velocity vector within a transformer-based network to regress the scale factors required for adjusting the process noise covariance matrix. The results demonstrated superior performance compared to standard EKF and various adaptive versions. Additionally, a Kalman-informed loss was introduced to ensure that the output aligns with the Kalman theory. The A-KIT approach is illustrated in Fig. 5. A similar endeavor was conducted in [134], however, this study introduces an integration of LSTM and EKF. It utilizes AUV speed and attitude information as inputs to the LSTM neural network. Subsequently, the network generates predicted process noise covariance, which serves as an input parameter for the subsequent EKF. Table 4 categorizes the papers discussed in this section by their respective improvement goals.

6. Calibration and denoising

Since the INS is based on integrating inertial data over time, it accumulates errors due to structured errors in the sensors. Calibration and denoising are crucial to minimizing these errors. In Chen et al. [135],

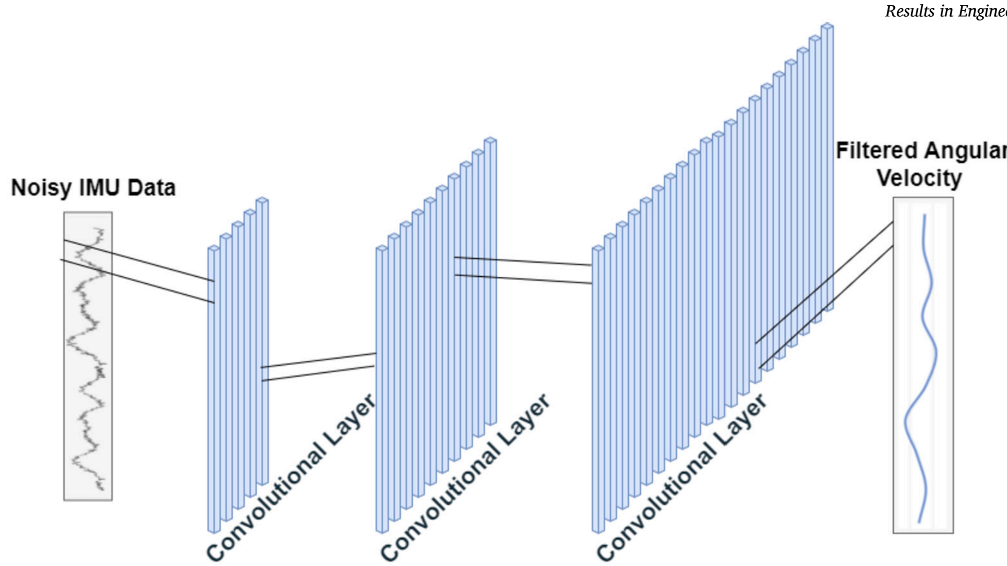


Fig. 6. The figure is based on the architecture introduced in [135], where a CNN architecture is proposed to address IMU errors by analyzing a window of inertial measurements, enabling the detection and removal of noisy features. The block diagram depicts noisy data passing through convolutional layers, with subsequent smoothing or filtering of the input.

deep learning was used for the first time to reduce IMU errors. IMU data, containing deterministic and random errors, is fed as input to CNN, which filters the data, an illustration van be seen in Fig. 6. According to Engelsman and Klein [136,137], an LSTM-based network can be used for de-noising accelerometer signals, and a CNN-based network can be used to eliminate bias in low-cost gyroscopes. In [138], a new calibration algorithm for inertial sensors is proposed based on CNN. The authors described how the challenge of lacking reliable ground truth data for the training step is addressed by employing visual-inertial integrated navigation with an error state EKF. They demonstrated that the first six seconds of integrated navigation offer adequate accuracy to serve as synthetic ground truth data for training the CNN. An additional method was proposed in [139], employing a deep learning architecture called DUET to calibrate gyroscope and accelerometer measurements in real-time. It comprises two dilated convolutional networks. The first processes raw IMU measurements to output calibrated angular velocity for the current frame. Subsequently, the second dilated convolutional network takes calibrated angular velocities and raw accelerations as inputs, providing calibrated acceleration for the current frame. Zhang et al. [140], proposed a method to improve the reliability of low-cost IMU applications in ship navigation. They utilize a Convolutional Autoencoder for dimensionality reduction and spatial feature extraction, while LSTM and Transformer multi-head attention mechanisms capture temporal correlations. The denoised IMU data is then reconstructed, enhancing the reliability of ship navigation systems.

Apart from the papers mentioned above, the majority of research focuses on the denoising and calibration of gyroscopes. A series of papers [141–143] examined the denoising of gyroscope data by utilizing various variations of RNNs. One paper demonstrated the performance of a simple RNN structure, while the others utilized LSTMs. A comparison was made between LSTM, GRU, and hybrid LSTM-GRU approaches for gyroscope denoising in [144]. Additional comparisons between GRU, LSTM, and hybrid GRU-LSTM were conducted in [145]. In Brossard et al. [146], a deep learning method is presented for reducing the gyroscope noise in order to achieve accurate attitude estimations utilizing a low-cost IMU. For feature extraction, a dilated convolutional network was used and for training on orientation increments, an appropriate loss function was utilized. Various CNN-based architectures have been explored to address gyroscope corrections. One study showcased a denoising autoencoder architecture constructed on a deep convolutional model to restore clean and undistorted output from corrupted data. It was found that the KF angle prediction was boosted in this scenario [147]. Furthermore, a TCN and 1DCNN were integrated for MEMS gyroscope calibration in [148]. Liu et al. introduced “LGC-Net” as a method for extracting local and global characteristics from IMU measurements to regress gyroscope compensation components dynamically. This model utilizes special convolution layers and attention mechanisms for this purpose [149]. Yuan et al. proposed “IMUDB” as a self-supervised IMU denoising method inspired by natural language processing techniques. This approach addresses the challenge of obtaining sufficient and accurate annotations for supervised learning while achieving promising results [150]. Engelsman et al. developed a bidirectional LSTM-based network specifically for gyrocompassing, particularly suitable for low-performance gyroscopes affected by the limited signal strength of Earth’s rotation rate, which is often overshadowed by gyro noise [151]. They subsequently demonstrated the effectiveness of this approach in unmanned underwater vehicle applications [152].

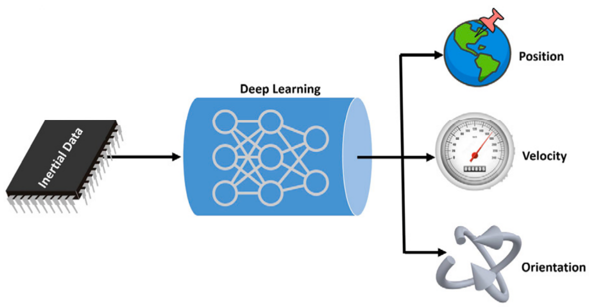
7. Discussion

In this section, we delve into the survey findings, summarizing the contributions, which encompass common techniques and approaches. Subsequently, we weigh the pros and cons of using DL approaches for inertial navigation tasks. Finally, we explore future trends in inertial navigation with deep learning.

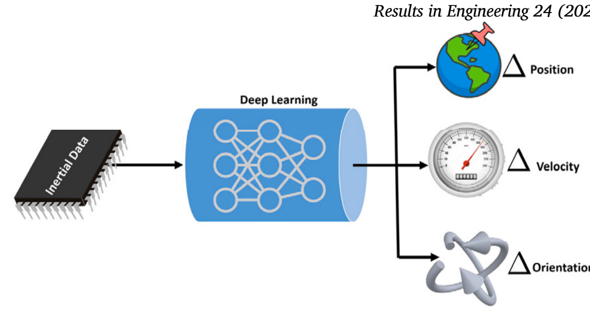
7.1. Summary

The purpose of this section is to provide a comprehensive analysis of the current trends in DL methods for inertial sensing and sensor fusion, drawing insights from previously discussed studies.

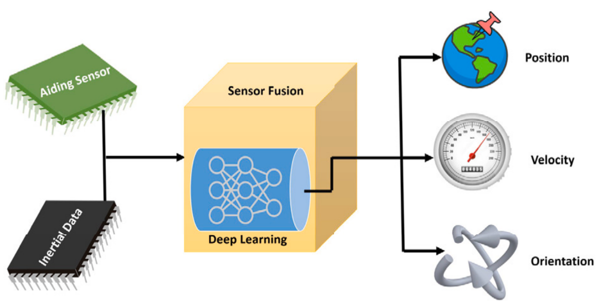
Taking a closer look at the most common courses of action, it appears there are four repeating baseline approaches to embed inertial sensing and DL, as illustrated in Fig. 7. The first approach involves inserting the inertial data into a DL architecture and regressing one or more states of the full navigation solution, as shown in Fig. 7a. Other studies took a different approach, focusing on analyzing the desired residual or delta required to update the current measurements rather than regressing the complete state of navigation components. Analyzing these residuals has proven to be more effective, particularly due to the high-rate solutions provided by the inertial sensors, which often hover close to zero with a small standard deviation, resembling a normal distribution. This characteristic makes it easier for the network to handle the problem efficiently.



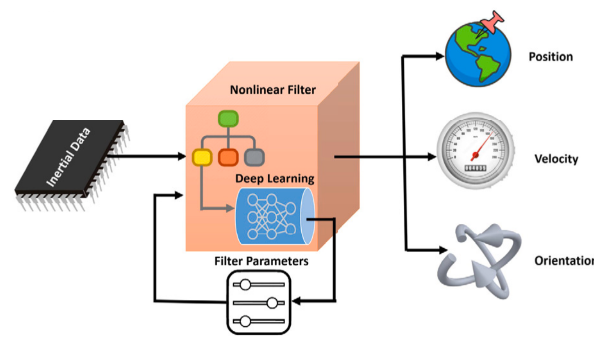
(a) Using an end-to-end DL approach to regress the full state of the vehicle.



(b) Using an end-to-end DL approach to regress the residual between the current state and the previous one of the vehicle.



(c) Implementing sensor fusing with an end-to-end DL block to regress the full state or the required in-crement.



(d) In sensor fusion scenarios, DL methods are ap-plied to obtain one or more filter parameters.

Fig. 7. Different techniques for improving inertial navigation using DL.

An illustration of this concept is depicted in Fig. 7b. Rather than relying solely on inertial data, and as discussed before, most navigation solutions integrate inertial data with other sensors to provide a more accurate result. Fig. 7c and Fig. 7d show how DL is incorporated within the sensor fusion operation. The former uses both the inertial data and the aiding measurements as input to the end-to-end network to give the navigation solution. The latter target parameters of the nonlinear filter, which are responsible for the sensor fusion, such as the noise covariance matrix estimation.

The methods outlined in this paper are applicable across all three domains: land, aerial, and maritime, as the navigation solution remains consistent regardless of the platform or environment. While the dynamics may vary between these domains, the fundamental navigation principles remain the same. Therefore, for example, DL-based orientation estimation developed for land vehicles could be adapted for use in aerial or maritime applications with appropriate adjustments for the specific dynamics of each domain. By analyzing the survey details, we identified the most common objectives that current research focuses on improving and presented them in a pie chart in Fig. 8. According to the chart, 81% of the papers focus on improving position, velocity, and orientation, while 19% addressed filter parameter improvement. Most of the latter papers were published within the past three years.

In addition to the initial analysis, we observed the general DL architectures that have been employed. We identified four distinct architectural streams: MLP, CNN, RNN, and others. MLP includes only fully connected networks, CNN includes networks such as 1DCNN and TCN, RNN includes LSTM and GRU, and 'others' encompass architectures such as transformers, reinforcement learning, and more, which are not included in the previously mentioned categories. As shown in Fig. 9, the networks are also divided into single and combined networks, where

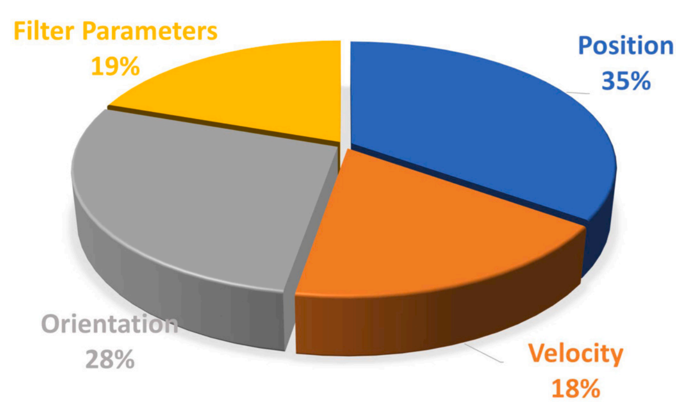


Fig. 8. DL goals in improving the navigation performance.

combined refers to architectures that comprise more than one method, such as CNN-RNN. The bar plot indicates that the primary architecture is RNN, along with its variations. This observation is sensible given that this architecture was explicitly developed for time-series problems, enabling it to detect temporal dependencies effectively. Furthermore, CNN methods play a significant role in deep inertial navigation, establishing themselves as the second most popular architecture in the field. In certain scenarios, they showcase superior accuracy when compared to RNNs. Their capability to excel at extracting informative features from small time windows, typically spanning just a few seconds, makes them particularly effective. Moreover, CNN architectures are the backbone for numerous denoising and calibration methods, underscoring their versatility and effectiveness within this domain. The MLP is a fundamental

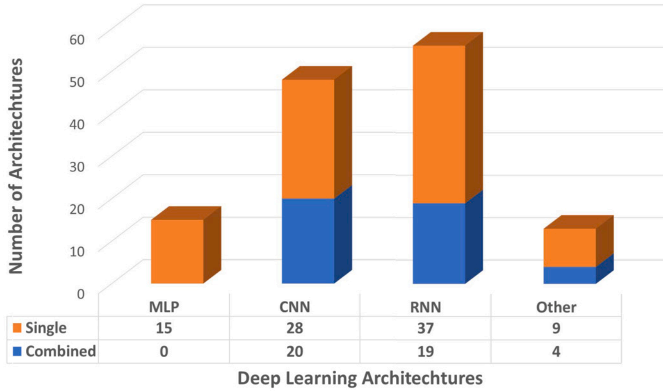


Fig. 9. Common deep learning architectures for enhancing inertial navigation are divided into single architectures and combined architectures. The “other” category encompasses methods such as attention mechanisms, transformers, and others.

architecture and was one of the earliest to be adopted in inertial navigation. However, while it is common for modern networks to incorporate FC layers in the final block, the MLP itself does not excel at extracting sufficient features independently. Its simplicity may limit its effectiveness in capturing complex patterns and relationships within inertial navigation data. Despite its current status as the least popular, the ‘others’ category is gaining momentum, largely due to its newfound recognition. With the advancements in natural language processing, architectures such as attention blocks, transformers, and bidirectional encoder representations from transformers (BERT) have started to surface in recent literature, displaying significant potential and delivering promising results. Notably, they have demonstrated superiority over MLPs, CNNs, and RNNs in various fields, marking a notable shift in the landscape of NN architectures.

7.2. Hardware considerations

This section addresses hardware requirements for both training, testing, and real-time applications. Training is a computationally intensive task that demands high-end hardware. Several factors must be considered when selecting hardware for training, including the complexity of the model architecture, the number of trainable parameters, and the size of the dataset. Simpler models, such as shallow convolutional networks or fully connected neural networks, generally require less computational power and can be trained efficiently on moderate hardware. In contrast, more complex models, such as transformers or deep recurrent networks, require significantly more resources. These larger models, especially when applied to large datasets, necessitate parallel processing capabilities and substantial memory to handle the increased volume of parameters and computations. A comparison of the performance of central processing units (CPUs), graphics processing units (GPUs), and tensor processing units (TPUs) can be found in [153].

Once the network is trained, only the weights are saved and later used in real-time applications. Therefore, the first consideration is that a deeper network will have more parameters, which in turn requires greater storage capacity. In addition to capacity, latency must also be considered, particularly in the context of real-time navigation or autonomous platforms. These systems must meet real-time navigation requirements, which can vary across platforms. Ensuring that the model’s processing time is sufficiently low is crucial to prevent delays, as any latency could negatively affect the overall performance of the navigation system. Once the deep learning approach is utilized, it is done by matrix multiplication and applying nonlinear activation functions according to the architecture. Although CPUs can perform these mathematical tasks, they do so more slowly than GPUs and TPUs, which are therefore preferred for such operations. The choice of hardware depends on various factors such as budget, platform size, energy consumption, and specific use case requirements. Several popular commercial platforms are available today, including NVIDIA Jetson modules [154], Intel neural compute stick [155], Google coral [156], Raspberry Pi AI kit [157], AMD Ryzen embedded V-series [158], Qualcomm Snapdragon platforms [159], and others.

7.3. Data collection and pre-processing

In data-driven approaches, data collection is crucial, especially in inertial regression, where the accuracy of the solution is mainly dependent on the precision of the reference system. There are two common methods for data collection. The first and preferred method is to deploy two systems: one as the unit under test, which may have slightly degraded performance, and the other as a reference system, which is more accurate to meet the required objectives. For example, a low-cost MEMS IMU combined with GNSS corrections can serve as the unit under test, while a navigation-grade IMU with RTK corrections providing centimeter-level accuracy can be used as the reference system.

The second approach, used when a unit under test is unavailable, involves taking accurate initial data and corrupting it with an error model. This model typically includes in-run bias, misalignment, scale factor errors, and noise. Since IMUs are distinguished by the magnitude of these errors, this approach simulates the deployment of a unit under test, with the reference data serving as the actual data.

Additionally, inertial data can be simulated either as it affects a point mass or as part of a complete system using six degrees of freedom simulations. This enables the newly emerging sim-to-real approach, where simulated data is used to train deep learning frameworks and then applied in real-life scenarios. Numerous platforms are available for such simulations, offering realistic environments across various domains, including land, aerial, and underwater. Some examples include MATLAB [160], Gazebo [161], Clara [162], and others.

7.4. Model deployment

Deploying trained DL models in real-world applications involving inertial navigation presents several challenges. A significant issue is the robustness of these models to noisy and drifting sensor data, which are common in INSs. While the data used for training is often clean and well-structured in controlled environments, real-world sensor inputs can vary significantly, potentially degrading the model’s performance and leading to inaccuracies in navigation. Additionally, models trained in one specific environment may struggle to generalize to new or unfamiliar conditions, such as varying terrains, sensor calibration differences, or changes in operational environments, including weather or lighting conditions. Ensuring that DL models can handle these variations is essential for successful deployment. Moreover, DL models can sometimes fail to provide reliable outputs, especially when encountering data distributions that deviate significantly from the training set. In such cases, it is crucial to have mechanisms in place to detect when the DL-based approach is underperforming.

To address these challenges, robust training techniques and fail-safe strategies are essential. Data augmentation can be used to simulate various real-world conditions during training, helping models generalize more effectively across diverse environments. A hybrid approach, combining DL models with classical inertial navigation algorithms, such as Kalman filters, can further enhance system performance. In this approach, the DL model works alongside the classical algorithm, refining estimates, while the traditional model serves as a fallback when the DL model’s output becomes unreliable. Incorporating fail-safe mechanisms that detect when the DL-based system is underperforming and automatically revert to a trusted, model-based approach ensures both robustness and reliability. Additionally, implementing continuous learning mechanisms enables the model to adapt to new sensor data over time, further improving its resilience as conditions evolve. These strategies enhance

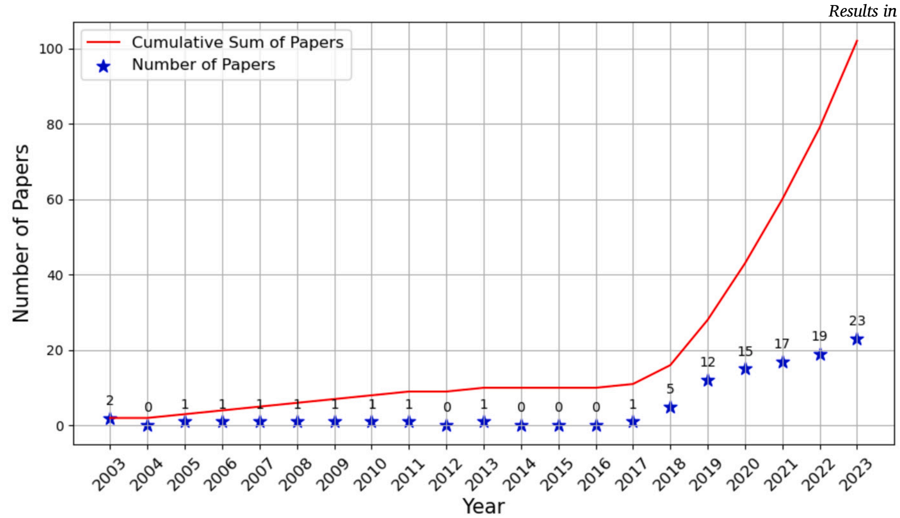


Fig. 10. The number of papers published from 2003 to 2023. Each year is represented by blue stars, while the cumulative sum of papers is depicted by the red curve.

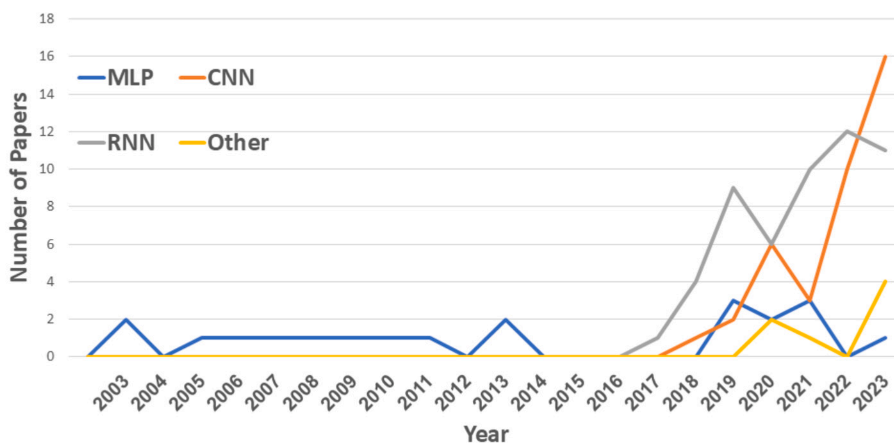


Fig. 11. The quantity and types of neural network architectures in deep inertial navigation research from 2003 to 2023. Notably, from 2019 onwards, a transition towards more complex architectures beyond MLPs, including RNNs and CNNs, is evident. Initially dominant, RNNs were later overtaken by CNN techniques around 2022. Furthermore, a positive trend is observed with the emergence of more intricate architectures inspired by NLP.

the deployment of DL models in inertial navigation systems, ensuring both innovation and safety.

7.5. Future trends

Fig. 10 depicts the burgeoning trend in the field of inertial navigation aided by DL. The significant increase in publications, evident from 2019 onwards and continuing to rise, underscores the growing integration of DL approaches in this domain. During the initial phase of this trend, from 2019 to 2022, conventional architectures such as MLP, CNN, and RNN predominated. However, from 2022 onwards, there has been a noticeable shift towards employing more complex architectures, aligning with the broader trend in DL research.

Upon reviewing the papers included in the survey, a clear trajectory emerges at the intersection of DL and inertial navigation. Previously, the focus was on employing end-to-end models to directly predict navigation states such as position, velocity, and orientation. However, there has been a notable shift in recent times towards leveraging the model itself. The shift towards leveraging DL techniques in inertial navigation is evident in the adoption of DL for denoising and calibration tasks, followed by the integration of refined inertial data into the navigation filter. Additionally, there is a growing trend towards enhancing filter parameters to achieve more accurate estimates of the navigation solution. Rather than directly estimating navigation components, improvements in filter parameters, such as estimating the process or measurement noise covariance, not only enhance the navigation solution but also contribute to the DL model's deeper understanding of the underlying model. Finally, while in the past, most models relied on RNNs, CNNs, and MLPs, there is now a trend toward employing more complex models derived from large language models. Specific adaptations of these models have shown significant improvements over the previously mentioned architectures. Fig. 11 provides an overview of how the field of deep inertial navigation has evolved over the years in terms of the neural network architectures used. Initially, the most common network was the basic MLP, demonstrating the potential for using DL to enhance inertial navigation solutions. From 2019 onwards, more complex architectures began to emerge, including RNNs and CNNs. RNNs dominated the field initially, but as we approached 2022, CNN techniques surpassed them. Additionally, more complex architectures inspired by NLP started to appear, showing a positive trend. Note that this survey addresses related works up to May 2024. Figs. 10-11 visualize works up to 2023 to ensure a comprehensive perspective, focusing on complete years for fair comparison.

8. Conclusions

Inertial navigation has garnered significant attention over the past decade due to the versatility of inertial sensors across diverse platforms and environments. Historically, navigation solutions have relied on model-based algorithms. However, there has been a notable shift towards data-driven methods, particularly with the increasing popularity and capabilities of DL techniques. This integration of DL represents a significant advancement in the approach to developing navigation solutions. This paper provides a comprehensive survey of DL methods applied to inertial navigation, specifically focusing on different platforms and practical applications. It reviewed research conducted across three distinct domains: land, aerial, and maritime. Additionally, the paper delves into calibration and denoising methods within the context of inertial navigation and DL. Furthermore, it offers insights into the trajectory of research in this area through statistical analysis.

Our findings indicate that the majority of research in this area has focused on land vehicles rather than aerial or maritime vehicles or calibration and denoising techniques. However, some papers suggest that despite differences in mechanics, maneuvers, etc., techniques can be adapted to various platforms, as the task of navigation remains consistent across all platforms, and data-driven networks can potentially learn these differences. While most reviewed papers aimed to enhance one or more aspects of the inertial navigation algorithm for improved solutions, recent years have seen a shift towards improving filter parameters for enhanced sensor fusion processes and increased reliance on the algorithm, incorporating mathematical models as well. Although leading DL architectures have traditionally been based on RNNs and CNNs, recent research has been inspired by approaches from natural language processing (NLP), importing and adapting leading architectures from that field, such as attention-based networks and transformers.

In conclusion, since 2019, there has been a notable surge in the utilization of DL methods for inertial navigation applications. These approaches have demonstrated superior performance compared to traditional model-based techniques, indicating significant potential for future research in inertial sensing. This evolution suggests a promising trajectory for further advancements in the field of inertial navigation aided by DL algorithms.

CRediT authorship contribution statement

Nadav Cohen: Writing – original draft. **Itzik Klein:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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