ORIGINAL

Robust ConvNet-Kalman Filter Integration for Mitigating GPS Jamming and Spoofing Attacks Basing on Inertial Navigation System Data

Integración Robusta de Filtro Kalman-ConvNet para Mitigar Ataques de Interferencia y Suplantación GPS Basados en Datos del Sistema de Navegación Inercial

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ABSTRACT

GPS (Global Positioning System) is the most accurate system for various applications, especially in transportation. However, GPS is critically vulnerable due to its reliance on radio signals, which can be exploited by hackers through intentional attacks like spoofing and jamming, leading to potentially dangerous disruptions for both humans and services. Moreover, GPS systems can also experience accidental disruptions in urban environments, where signals from multiple satellites may be blocked by buildings, severely affecting the receiver's accuracy. This paper presents a robust method designed to mitigate GPS outages caused by both jamming and spoofing by integrating inertial data. The proposed method leverages two key components: convolutional neural networks (ConvNet) and the Kalman filter (KF). A carefully optimized deep layer in the ConvNet is employed to correct errors in the inertial navigation system (INS). The findings indicate a considerable enhancement in accuracy, with the proposed method reducing the RMSE by 77,68 % compared to standalone GPS and by 98,34 % compared to standalone INS. This significant improvement underscores the proposed approach's performance in maintaining reliable navigation in environments where GPS signals are compromised.

Keywords: ConvNet; Kalman Filter; INS Errors; GPS Jamming and Spoofing.

RESUMEN

El GPS (Sistema de Posicionamiento Global) es el sistema más preciso para diversas aplicaciones, especialmente en el transporte. Sin embargo, el GPS es críticamente vulnerable debido a su dependencia de las señales de radio, las cuales pueden ser explotadas por hackers mediante ataques intencionales como el spoofing y el jamming, lo que puede llevar a interrupciones potencialmente peligrosas tanto para los humanos como para los servicios. Además, los sistemas GPS también pueden experimentar interrupciones accidentales en entornos urbanos, donde las señales de múltiples satélites pueden ser bloqueadas por edificios, afectando gravemente la precisión del receptor. Este artículo presenta un método robusto diseñado para mitigar las interrupciones del GPS causadas tanto por jamming como por spoofing, integrando datos inerciales. El método propuesto aprovecha dos componentes clave: redes neuronales convolucionales (ConvNet) y el filtro de Kalman. Se emplea una capa profunda cuidadosamente optimizada en el ConvNet para corregir errores en el sistema de navegación inercial (INS). Los resultados indican una mejora considerable en la precisión, con el método propuesto reduciendo el RMSE en un 77,68 % en comparación con el GPS autónomo y en un 98,34 % en comparación con el INS autónomo. Esta mejora significativa subraya el rendimiento del enfoque propuesto para mantener una navegación confiable en entornos donde las señales GPS están comprometidas.

Palabras clave: ConvNet; Filtro de Kalman; INS; Errores del INS; GPS; Interferencia y Suplantación del GPS.

INTRODUCTION

Continuous, precise, and reliable navigation output is a necessary condition to guarantee the safe operation of autonomous systems.[1,2,3] The lack of one of these conditions can threaten the safety of people and goods.

One of the precise and accurate solutions is the Global Positioning System (GPS)[4] which can deliver decimeter- to centimeter-level precision for determining precise positions across diverse applications from civil to military uses. However, this system suffers from numerous problems that can negatively impact its strengths. The key vulnerability of such a system lies in its reliance on radio signals radiated in all directions, which can be intercepted by both legitimate and illegitimate entities. This vulnerability is exploited by two types of threats: intentional and accidental. Hackers can conduct two types of attacks to disrupt the normal function of GPS. The first attack is GPS spoofing while the second attack is GPS jamming.[5,6] Additionally, natural phenomena also pose threats to the signals. Tall buildings, urban canyons, vegetation, and dense forests can block, attenuate, absorb, or reflect electromagnetic signals, which can affect the availability or reduce the accuracy of GPS.[7,8]

To surpass the problem of GPS unavailability, another system that can be utilized is the Inertial Navigation System (INS). INS presents many strengths; it delivers a wealth of information including 3D position, velocity around the three axes, and the attitude of the mobile platform.[9,10] Moreover, as a proprioceptive sensor, it continuously provides navigation information, ensuring good availability. However, this system is also influenced by various errors such as scale factor, bias instability, noise, and misalignment. These errors can generate significant deviations in the INS output[11] especially over long periods. Despite its strengths in delivering continuous navigation data and ensuring availability[12] INS precision degrades over time as these errors accumulate.[13]

This work deals with both GPS and INS to leverage the advantages of both systems (table 1). By integrating GPS and INS, the strengths of each system can be employed to compensate for the weaknesses of the other.[14]

System	Strengths	Weaknesses
GPS	Provides highly accurate position information. Delivers decimeter- to centimeter-level precision.	Susceptible to signal loss or interference. Vulnerable to spoofing and jamming attacks. Signal quality can be affected by natural phenomena.
INS	Provides continuous navigation data. Delivers 3D position, velocity, and attitude information. High availability. Independent of external signals.	Accumulates errors over time. Affected by the scale factor, bias, instability, noise, and misalignment. Requires regular calibration.

Table 1. GPS vs INS comparison

The overview of the authors' key contributions in this paper is as follows:
- They evaluated the impact of the layer depth of convolutional neural networks (ConvNet) in correcting INS errors, with a special focus on scale factor, bias, and noise.
- Through this evaluation, they determined the optimum configuration of ConvNet to reduce the influence of these errors;
- They integrated, for the first time, ConvNet architecture and a Kalman filter to achieve continuous and accurate navigation;
- Additionally, they overcame both the issues of INS and GPS by fusing their information.

Literature Review

Over the past few years, the field of intelligent systems has garnered significant interest due to the numerous opportunities it presents across various domains. However, this field has also introduced several challenges to the effectiveness of navigation. The reliance on radio frequency systems, such as GPS, and the rapid expansion of threats underscore the critical need for real-time navigation systems that can provide security, reliability, high availability, and high accuracy. Addressing these challenges is essential to ensure that navigation systems can operate effectively and safely in increasingly complex and hostile environments.

Mitigating this problem, Gao et al.[15] propose an adaptive Kalman filter navigation algorithm (RL-AKF) based on reinforcement learning for ground vehicles. The method uses the deep deterministic policy gradient to adaptively estimate the process noise covariance matrix, improving positioning accuracy under dynamic and complex environments. Results show that RL-AKF achieves average positioning errors of 0,6517 m within 10 s GNSS outage and 14,9426 m and 15,3380 m within 300 s GNSS outage for GNSS/INS/Odometer and GNSS/INS/Non-Holonomic Constraint systems, respectively.

Wu et al.[16] developed an improved adaptive federated Kalman filter (AFKF) for INS/GNSS/VNS integrated navigation to address the issue of low positioning accuracy in obstructed spaces. The method employs an adaptive information-sharing factor and combines residual chi-square and sliding-window averaging for fault

detection, significantly reducing root mean square errors in position and velocity compared to classic federated Kalman filtering. However, the method increases computational requirements, which may affect real-time performance.

Sun et al.[17] developed an improved innovation adaptive Kalman filter (IAKF) for integrated INS/GPS navigation. The method employs a chi-squared test to identify and adjust for measurement noise anomalies, enhancing filtering stability and positioning accuracy under disturbed conditions. Results demonstrate significant improvements in mean positioning errors and maximum error reduction compared to traditional Kalman filters. However, the method's complexity increases computational requirements, potentially impacting real-time performance.

Feng et al.[18] introduced an improved strong tracking cubature Kalman filter (IST-7thSSRCKF) for GPS/INS integrated navigation systems to enhance accuracy and robustness against process uncertainties. The method incorporates a hypothesis testing approach to detect process uncertainty and adjusts the prior state estimate covariance using an improved fading factor based on Cholesky decomposition, along with employing a seventh-degree spherical simplex-radial rule for higher accuracy in Gaussian integral computation. Results show superior accuracy and robustness in both simulation and car-mounted experiments compared to existing filters, though the method significantly increases computational complexity.

Abd Rabbou et al.[19] developed an unscented particle filter (UPF) to integrate GPS precise point positioning (PPP) and MEMS-based INS, addressing the limitations of extended Kalman filters (EKF) in nonlinear systems. The UPF, which combines the benefits of unscented Kalman filter (UKF) and particle filtering (PF), reduces the number of particles needed for accurate state estimation, enhancing navigation performance, particularly during GPS outages, achieving up to 15 % improvement in positioning accuracy compared to EKF. However, the method's increased computational burden remains a limitation.

Dong et al.[5] proposed a robust sequential Kalman filter for tightly coupled GNSS/INS integration, combining pseudorange, Doppler, and carrier phase observations to enhance vehicular navigation accuracy and robustness. The method sequentially processes high-dimensional observations to improve computational efficiency and employs a Gaussian test for fault detection in GNSS channels. Test results indicate significant improvements in velocity and attitude accuracy by up to 69,42 % and 47,16 % respectively, compared to loose coupling, though the method's computational burden is higher due to the increased number of observations.

Table 2. Summary of existing researches discussing GPS/INS integration system

Authors	Year	Model	Results
Alaeiyan et al.[10]	2024	Faded Memory Kalman Filter	45 % reduction in positioning errors, reliant on tuning fading factor
Wu et al.[16]	2023	Improved Adaptive Federated Kalman Filter	Significantly reduces RMSE in position and velocity, increases computational requirements
Yuan et al.[13]	2023	Kalman Filter with Singular Value Decomposition	45,77 % reduction in maximum error, increased computational burden
Sun et al.[17]	2022	Improved Innovation Adaptive Kalman Filter	Significant improvements in mean positioning errors increased computational requirements
Gao et al.[15]	2020	Reinforcement Learning Adaptive Kalman Filter	0,6517 m error in 10s outage, 14,9426 m and 15,3380 m in 300s outage
Dong et al.[5]	2020	Robust Sequential Kalman Filter	Improvement in accuracy of velocity and attitude by 69,42 % and 47,16 %, higher computational burden
Feng et al.[18]	2018	Improved ST-7thSSRC Kalman Filter	Superior accuracy and robustness significantly increased computational complexity
Abd Rabbou et al.[19]	2015	Unscented Particle Filter	15 % improvement in positioning accuracy, increased computational burden

Alaeiyan et al.[10] presented a GPS/INS integration method using a Faded Memory Kalman Filter (FMKF) to address the long-term degradation of positioning accuracy in traditional Kalman filters. This approach applies different weights to measurement updates, adapting to changes in system dynamics, significantly reducing positioning errors by an average of 45 % compared to the traditional Kalman filter. However, the method's effectiveness relies on accurately tuning the fading factor, which can be challenging in varying conditions. Yuan et al.[13] developed an improved Kalman filter algorithm based on singular value decomposition (SVD) for tightly coupled GNSS/INS integrated navigation systems. The method dynamically corrects the noise covariance matrix using a correction variable derived from the innovation and a new matrix obtained via SVD, enhancing robustness

and positioning accuracy. Experimental results show that the proposed algorithm reduces maximum error by 45,77 % compared to traditional Kalman filters; however, the increased computational burden due to dynamic correction is a limitation. Table 2 summarizes the existing researches discussing GPS/INS integration system.

Artificial intelligence

Artificial intelligence (AI) is an emerging domain with significant applications across various fields. It enables machines to perform tasks typically carried out by humans, granting them the ability to make decisions autonomously. These AI systems include industrial robots, drones, unmanned aerial vehicles (UAVs), autonomous vehicles, and other intelligent systems. AI is categorized into several types, including deep learning and machine learning, as depicted in figure 1.
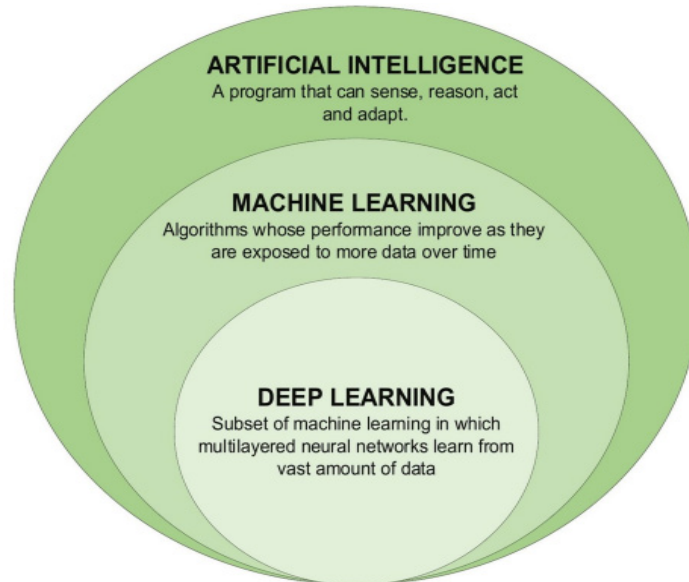

Fig. 2 Deep learning family

Figure 1. Family of artificial intelligence[20]

Deep learning, in particular, encompasses a range of algorithms such as RNNs (recurrent neural networks) and ConvNets (convolutional networks), as illustrated in figure 2. The ConvNets are the focus of this paper due to their demonstrated capacity to correct errors in inertial navigation systems (INS). There are two main approaches to employing ConvNet algorithms: supervised and unsupervised learning. This work specifically addresses the supervised approach, where the model is trained on labeled data to improve its performance in error correction tasks.3
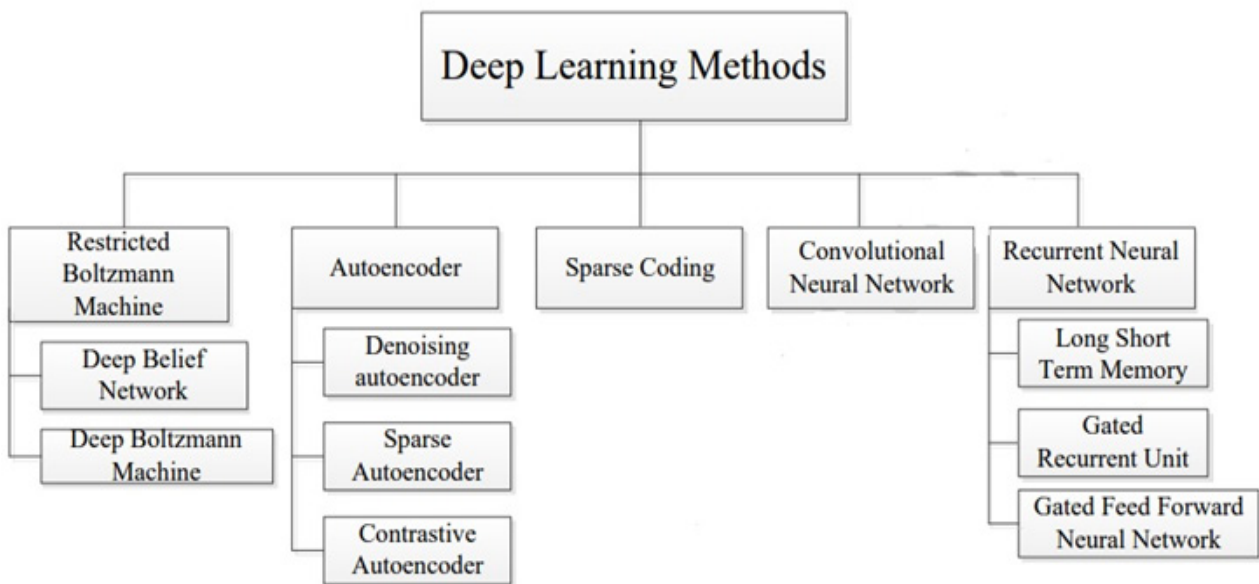

Figure 2. Deep learning different architecture, kindly taken from[21]

Fundamentals of GPS Technology

The Department of Defense of the United States developed the Global Positioning System (GPS) as a navigation system for both civilian and military applications. The constellation of 27 satellites orbiting the Earth forms the basis of this system (figure 3). Today, GPS is the most accurate navigation system available, providing 3D position information with an average error of approximately 3 to 5 meters and offering precise time information.
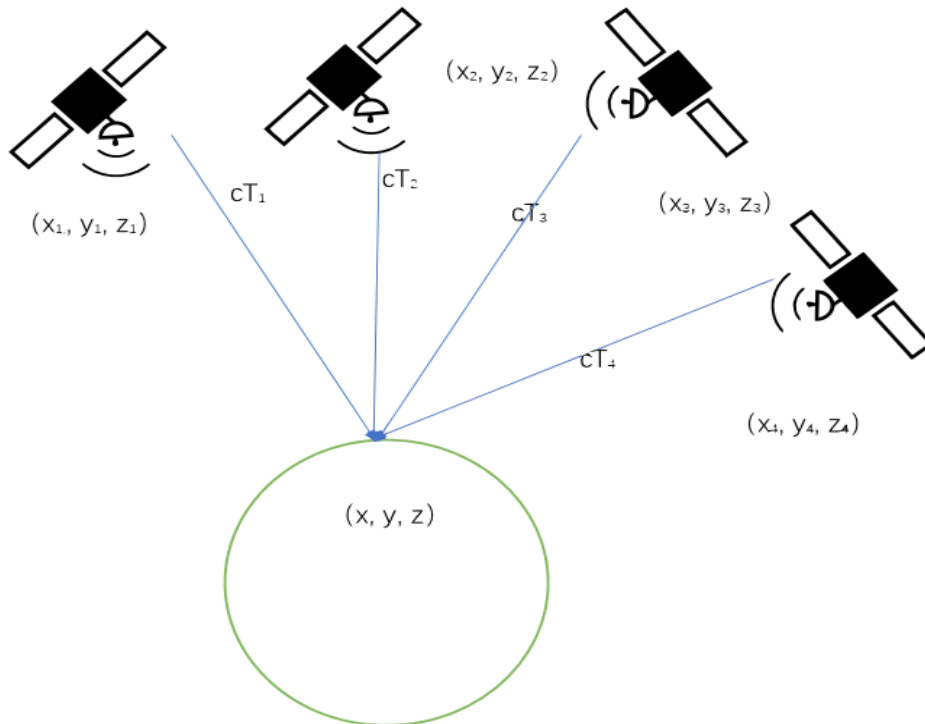

Figure 3. Principle of GPS point positioning

In GPS, localization is determined using the information from at least three satellites through a process called trilateration. The formula for trilateration involves solving a system of equations derived from the measurements of distances between each satellite and the GPS receiver. The basic formula used in GPS trilateration is given by (1):[22]

$$(px_r - px_s)^2 + (py_r - py_s)^2 + (pz_r - pz_s)^2 = D^2 \quad (1)$$

Where:
(PXr, PYr PZr)are the coordinates of the GPS receiver.
(PXrs PYs PZs) are the coordinates of the three satellites.
D are the distances from the receiver to each of the three satellites.

GPS vulnerabilities

The dependence on radio signals by the GPS presents a key vulnerability. Hackers exploit this vulnerability to attack this system using either spoofing or jamming. Another form of attack is accidental when tall buildings, tunnels, urban canyons, overpasses, dense vegetation, or even metallic obstacles block signals. These malicious intents and environmental factors lead to significant degradation in GPS signal quality, resulting in reduced accuracy and reliability of GPS-based applications.

GPS spoofing

GPS spoofing is an intentional attack that targets the GPS. The principle behind this attack is to create a fake GPS signal that will be used by the receivers, leading them to generate an erroneous location. The figure below (figure 4) illustrates the methodology employed by spoofers:

Consequently, this leads to significant inaccuracies in the computed location (figure 5), adversely affecting navigation, timing, and other critical applications that rely on precise GPS information.
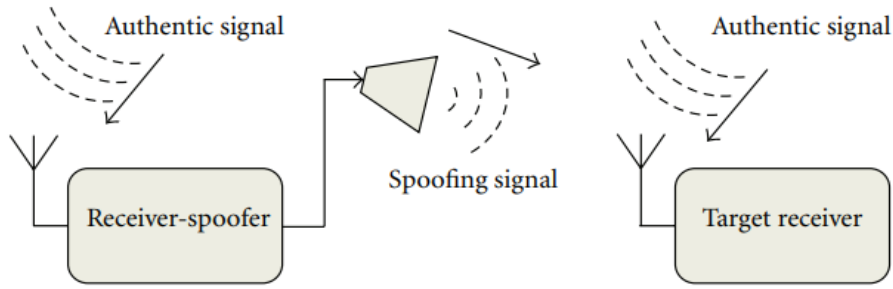
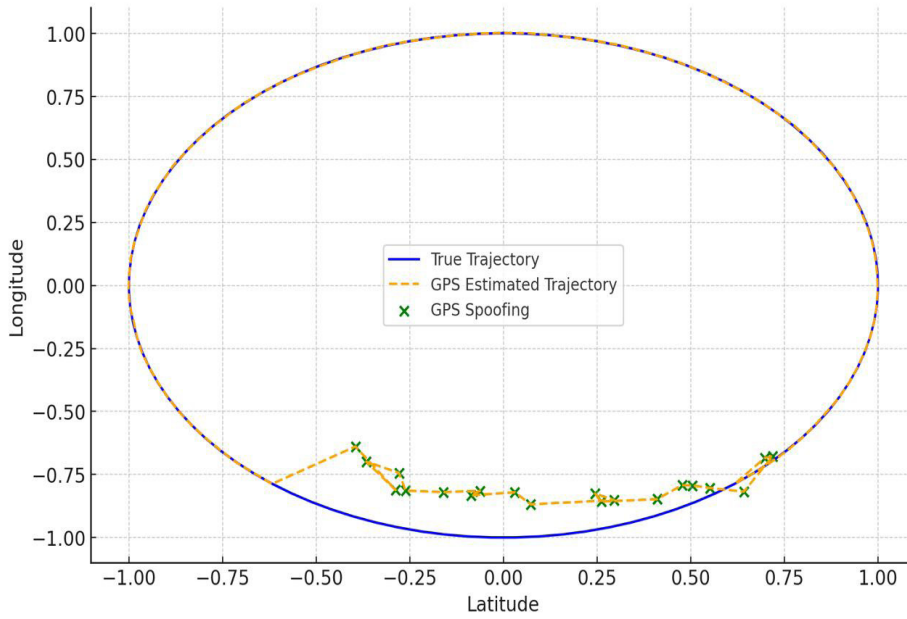**Figure 4.** GPS spoofing attack principle, kindly taken from[(23)]

Figure 5. Consequence of GPS spoofing on its accuracy

GPS jamming

GPS jamming is another malicious attack that relies on interference to disrupt the functioning of GPS systems. In this attack, jammers propagate intense signals at the same frequency as GPS signals. This interference overwhelms legitimate GPS receivers, preventing them from accurately calculating positions. Figure 6 details the methodology utilized by jammers.
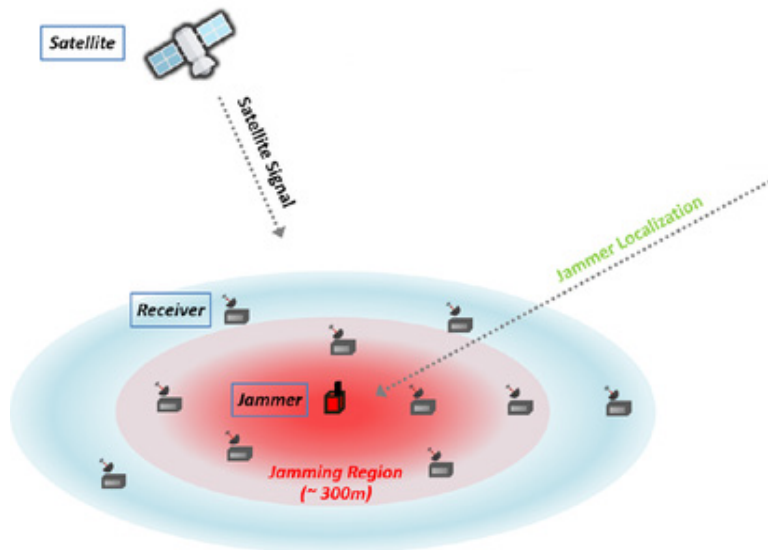

Figure 6. GPS jamming attack principle

As a result, GPS receivers may either fail to determine any position at all or exhibit a significant drift in the calculated position. Figure 7 below demonstrates these two abnormal situations.
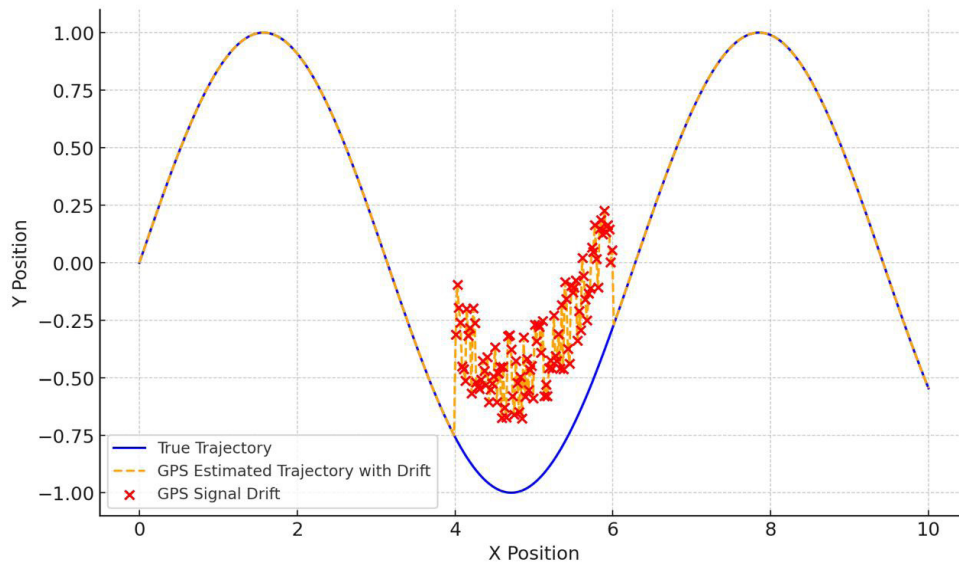

Figure 7. Impact of GPS jamming on its accuracy

Unintended obstruction of GPS signals
Unlike intentional attacks such as spoofing or jamming, this type of attack occurs naturally and without malicious intent. Common sources of unintended obstruction include tall buildings, which create urban canyons that physically create multipath, absorb signals, or block signal paths. The following figure (figure 8) provides an overview of this phenomenon.
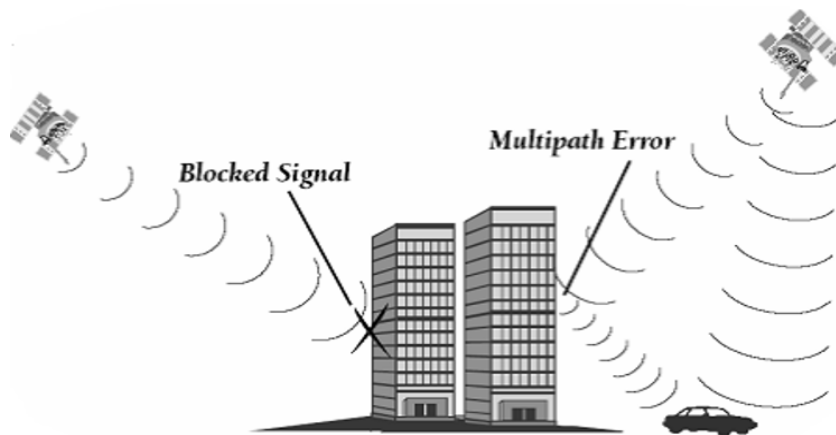

Figure 8. GPS signal reflection and multipath

In summary, the GPS offers significant strengths in terms of localization accuracy. However, it is vulnerable to both intentional and unintentional attacks, which target a fundamental element of the CIA triad: availability. Intentional attacks include spoofing and jamming, while unintentional obstructions can arise from environmental factors. To address these vulnerabilities, redundancy through the integration of other sensors, such as odometers, LiDAR, camera vision, or inertial navigation systems (INS), can be employed.

INS Technology: Fundamentals
Most inertial navigation systems contain three gyroscopes and three accelerometers, as demonstrated in figure 9, which are capable of measuring three-dimensional raw data. The gyroscopes measure angular velocities around three axes, while the accelerometers measure specific forces or accelerations in three dimensions. Two main types of INS are commercialized: strap-down INS and gimbaled INS. Strap-down INS are often preferred because they are more compact, have fewer moving parts, and are generally more robust and reliable. This type of INS directly integrates the sensor outputs into the navigation solution, making them ideal for several applications, from the electronics industry to defense and aerospace.
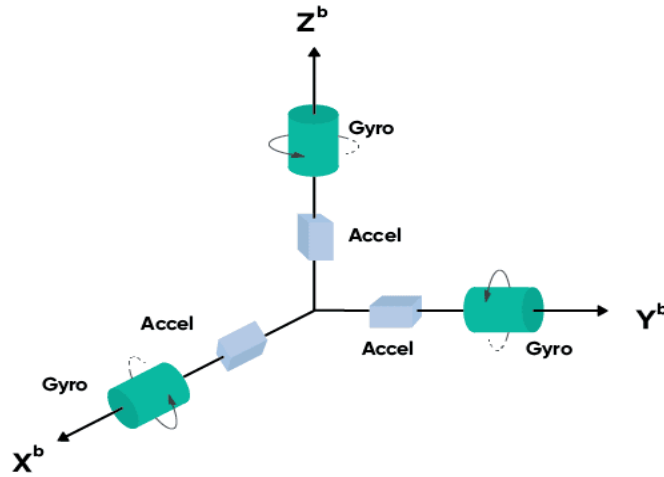
Figure 9. Three orthogonal gyroscopes and three orthogonal accelerometers

These measured raw data are then mechanized through the process of INS mechanization, detailed in figure 10, to determine the navigation information (position, velocity, and attitude) of the vehicle. This process involves solving the differential equations that describe the system's motion. By integrating the raw measurements of angular velocities and specific forces, the mechanization process translates these into meaningful navigation information. The differential equations of INS mechanization in the navigation frame are given by (2):[24,25,26]

$$\begin{pmatrix} \dot{r}^n \\ \dot{v}^n \\ \dot{C}_b^n \end{pmatrix} = \begin{pmatrix} D^{-1}v^n \\ C_b^n f^b - (2\Omega_{ie}^n + \Omega_{en}^n)v^n + g^n \\ C_b^n(\Omega_{ib}^b - \Omega_{in}^b) \end{pmatrix} \quad (2)$$

Where:
r^n presents the position components in term of latitude, longitude, and height.
v^n is the velocity;
C_n^b is a 3x3 conversion matrix from the ENU frame to the body frame.
f^b are the raw accelerations in the body frame.
g^n is the gravity.

These equations are fundamental in transforming sensor data into accurate navigational outputs, ensuring reliable tracking and positioning.
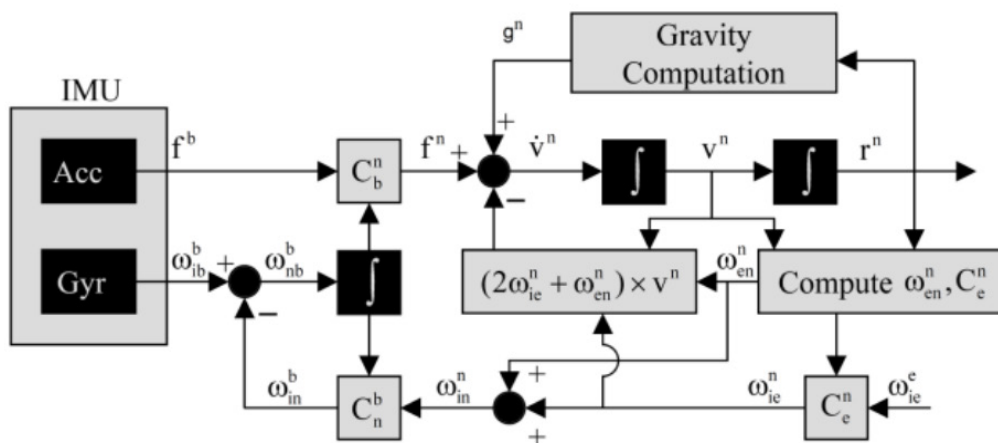

Figure 10. The process of INS mechanization[27]

INS inherent errors

The INS is an embedded system within intelligent systems, offering high availability as an alternative to GPS. However, this type of system presents a significant vulnerability. This vulnerability resides in the inherent errors due to various factors impacting its sensors, such as bias, noise, and scale factors.

These errors, along with the specific forces and angular velocities measured by the accelerometers and gyroscopes, are integrated twice, leading to a substantial drift that develops exponentially over time. This makes the INS a precise system only for short durations. This work focuses on three specific errors: noise, bias, and scale factor. Their modeling is given by the following (3 and 4):

$$\omega_{measured} = (1 + SF_{gyroscope}) * \omega_{true} + b_{gyroscope} + \eta_{gyroscope} \tag{3}$$

$$a_{measured} = (1 + SF_{accelerometer}) * a_{true} + b_{accelerometer} + \eta_{accelerometer} \tag{4}$$

Where:
a_{true} and ω_{true} are the true acceleration and angular rates.
While $N_{accelerometer}$ and $N_{gyroscope}$ represent noise in the measurements.
$b_{accelerometer}$ and $b_{gyroscope}$ represent the bias in the accelerometer and gyroscope respectively.
$SF_{accelerometer}$ and $SF_{gyroscope}$ the scale factor errors for accelerometers and gyroscopes, respectively.
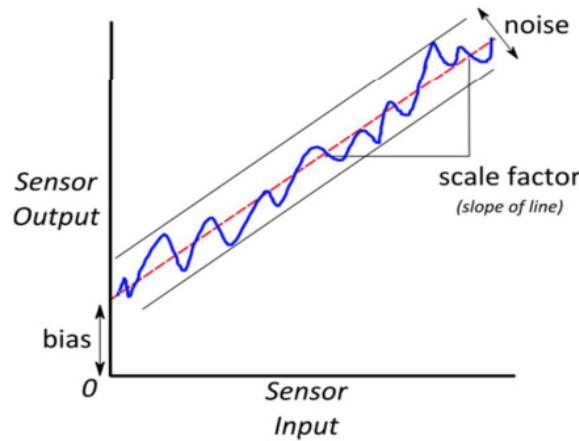

Figure 11. Illustration of Inertial sensor errors[28]

The following block diagram (figure 12) summarizes the phases carried out: first, modeling the accelerometer and gyroscope, and second, adding the three errors.
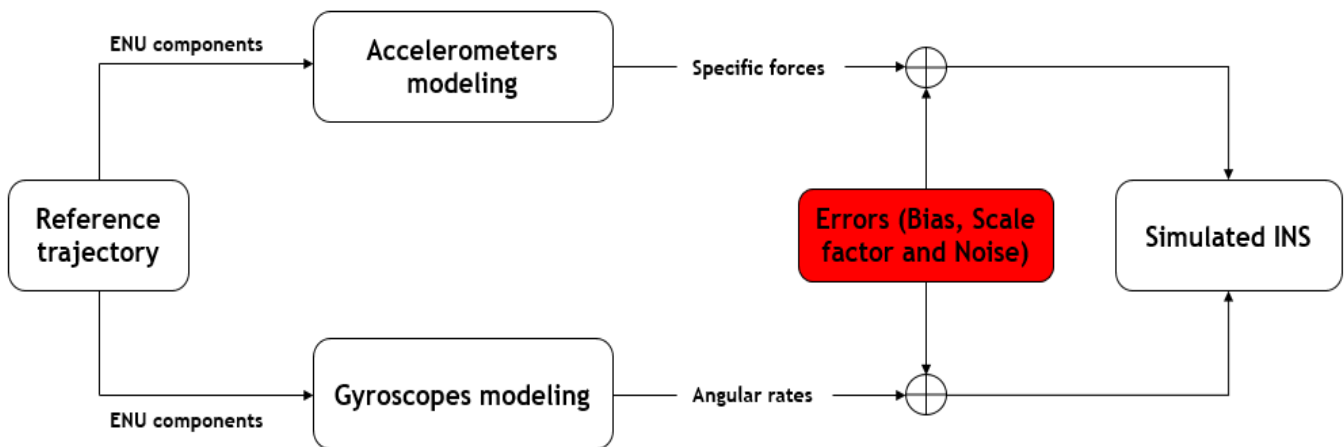

Figure 12. Block diagram of accelerometer and gyroscope modeling with error integration

METHOD

Our proposed approach involves the correctness of INS errors using a Kalman filter when the GPS signal is present and switching to a ConvNet algorithm when the GPS signal is unavailable to mitigate these errors. This hybrid approach leverages the strengths of both techniques to maintain accurate navigation. When GPS is available, the Kalman filter integrates GPS data with INS outputs to correct errors and provide accurate navigation information, and at the same time, accurate GPS positions are used to train the ConvNet algorithm. When GPS is unavailable, the pre-trained ConvNet algorithm is used to predict and correct INS errors based on historical patterns and sensor data.

INS error correction during GPS outages

To correct inherent INS errors, our group developed three architectures of convolutional neural networks (ConvNets) to determine the optimal depth of layers in terms of accuracy and computation time. We used the ReLU activation function due to its advantages over tanh and sigmoid functions. The MATLAB environment was employed to configure, train, and test the ConvNet algorithms. Each variant of the ConvNet includes a specific number of layers. The detailed configurations of these variants are presented in table 3.

Table 3. Three ConvNet variants configuration			
Variants	**Variant 1**	**Variant 2**	**Variant 3**
Configuration in term of layers number	2 Conv 2 Pooling 1 FC	4 Conv 2 Pooling 2 FC	8 Conv 4 Pooling 3 FC

GPS/INS fusion system when GPS signal is present

GPS and INS data are commonly integrated using KF trough three main schemes: loose coupling[29] tight architecture[30] and deep coupling.[31] In loose integration scheme, the output of INS mechanization is combined with the position data obtained from the GPS. In a tightly coupled scheme, raw data from the inertial sensors are integrated with the pseudoranges estimated by the GPS, allowing for better performance in challenging environments. The ultra-tightly coupled scheme goes a step further by integrating the raw inertial sensor data directly with the GPS signal processing.

Proposed GPS/INS fusion system

In this paper, the GPS/INS loosely integrated approach is adopted. Using this approach, the input of the filter is the errors between the accurate position estimated by GPS and the predicted values from the inertial system. Predicting the state based on the system model and updating the state based on the measurements are the two main phases of the proposed filter algorithm. The structure of the filter is detailed in figure 13.
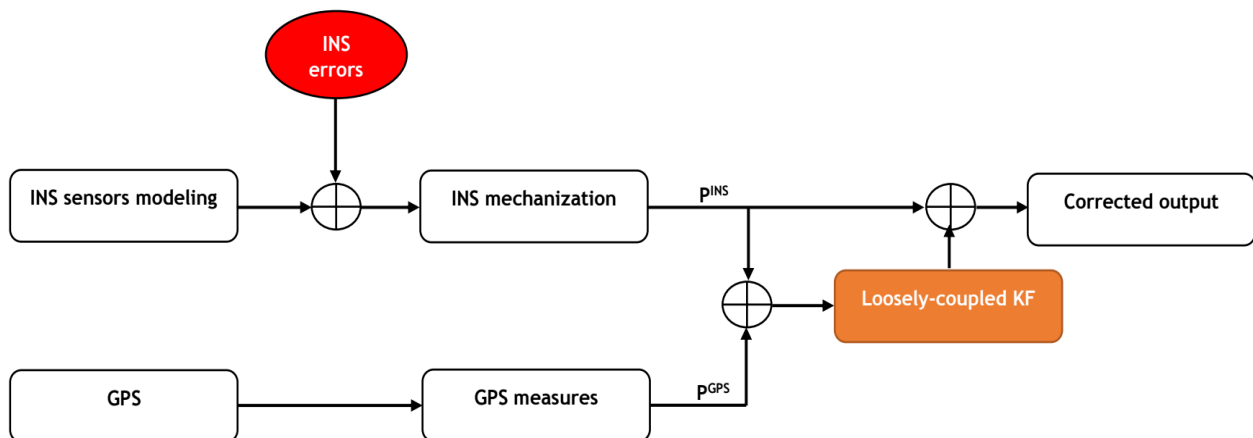
Figure 13. The proposed structure of the filter

Dynamic model

The dynamic model for integrated navigation utilizes the INS error equations. To optimize computational efficiency, the error state vector is reduced to six parameters, focusing on errors in position and velocity. This reduction aims the decrease of the computation time while capturing the essential dynamics of the navigation errors. This linearized model around the errors serves as the basis for the prediction step in KF. Equation 5 describes the continuous dynamic model.

$$\dot{X}(t) = F(t)X(t) + G(t)U(t) \qquad (5)$$

Parameter	Dimension	Description
		Table 4. Parameters
X	6x1	State vector including position and velocity errors.
F	6x6	System matrix that relates the state vector to itself.
G	6x3	Control input matrix that relates the control input (such as accelerometer and gyroscope measurements) to the state vector.
U	3x1	Control input vector, representing external inputs like accelerations or angular velocities.

Observation model

The update step refines the position and velocity estimates of the navigation system. Throughout this study, GPS is utilized to observe the position vector of the mobile unit. The observed GPS position is subtracted from the INS-derived position to form the measurement vector. The observation model of the GPS/INS loose architecture can be expressed as (6):

$$Z_k = H_{GPS}.X_k + V_k = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{pmatrix} \begin{bmatrix} X^{GPS} - X^{INS} \\ Y^{GPS} - Y^{INS} \\ Z^{GPS} - Z^{INS} \end{bmatrix}_k + V_k \qquad (6)$$

Where:

Z_k Is the observation vector.

H_{GPS} presents the observation matrix.
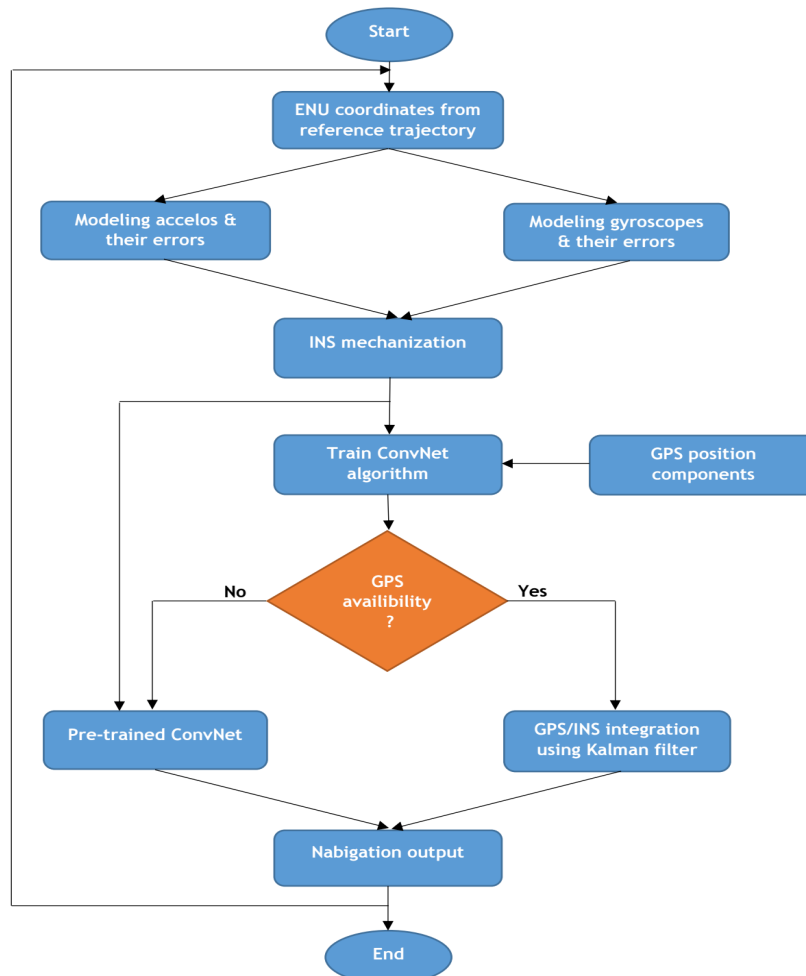
V_k Is white Gaussian noise.

Figure 14. The proposed algorithm flowchart

The figure (figure 14) details the steps of our proposed approach. Rectangles are used for steps, while diamonds are utilized when asking a question about GPS availability and determining the appropriate actions for navigation at decision points.

Experiment description

Simulated ground truth

Figure 15 illustrates the generated trajectory under the MATLAB environment, incorporating both straight segments and curves to emulate real urban trajectories. The true path consists of 3000 points, sampled at 1Hz, providing a total duration of approximately 50 minutes. To simulate realistic conditions, we introduced three zones where GPS signals are unavailable due to issues discussed in the first section. Each of these zones lasts for 1 minute. During these periods of GPS signal loss, the ConvNet algorithm takes over to estimate the navigation information, ensuring continuous and accurate positioning despite the lack of GPS data.
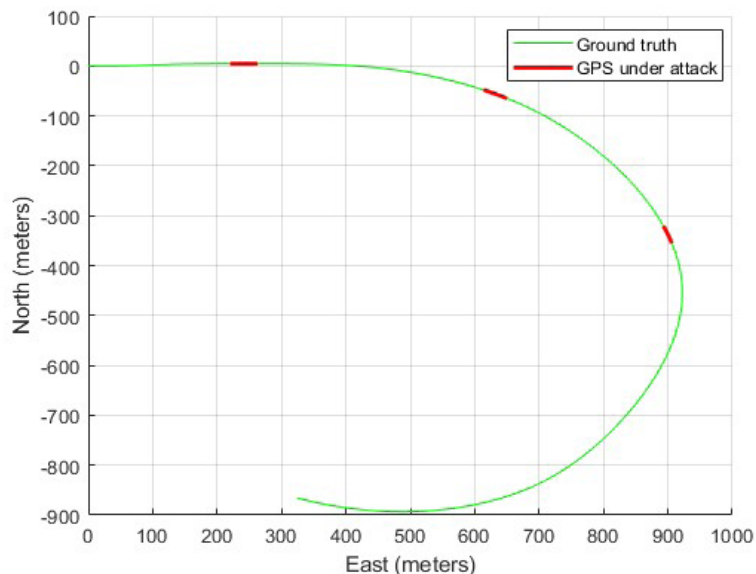

Figure 15. Overview of the 2D simulated ground truth

Simulated Inertial Measurement Unit (IMU)

Based on the ENU (East-North-Up) coordinates obtained from the simulated trajectory, we modeled the three accelerometers and three gyroscopes to obtain raw measurements, which are angular velocities and accelerations. These measures are affected by errors detailed in Section 1. To mimic a real Inertial Measurement Unit (IMU), we added error values that typically impact real low-grade IMUs. The added error values include biases, noise, and scale factors, which are summarized in the table below (table 5). This approach ensures that the simulated IMU measurements closely replicate the performance characteristics and limitations of actual low-grade IMUs.

Table 5. Calculated RMSE from the three ConvNet variants outputs		
Errors	**Simulated IMU**	**Real low-grade IMU**
On gyroscopes		
Scale factor	1 % to 5 %	5 %
Bias	10° to 100°/hour	100°/hour
Noise	0,01 to 0,1°/s/√Hz	0,1°/s/√Hz
On accelerometers		
Scale factor	0,1 % to 1 %	1 %
Bias	100 to 1 000 µg	1 000 µg
Noise	100 to 500 µg/√Hz	500 µg/√Hz

RESULTS AND DISCUSSION

This section aims evaluating the contribution of the developed method in terms of navigation accuracy and availability during GPS-denied environments, which may occur due to intentional or unintentional attacks.

Optimal ConvNet

The table below presents the calculated RMSE in the three dimensions: East, North, and Up, with the presence of GPS signals. Calculated positions based on triangulation are employed to correct INS errors. The table demonstrates that RMSE values inversely correlate with the depth of the ConvNet layers. Specifically, increasing the number of layers in the ConvNet algorithm results in smaller RMSE values. This finding indicates that the depth of the ConvNet can effectively enhance the accuracy of INS error mitigation. Additionally, the RMSE in the Up direction is observed to be greater than the RMSE in the East and North directions, which can be attributed to gravity fluctuations.

Table 6. Calculated RMSE from the three ConvNet variants outputs

RMSE (m)	Variant 1	Variant 2	Variant 3
East	23,63	5,08	2,39
North	22,10	6,93	6,31
Up	81,50	16,47	14,10

However, increasing the layer depth also increases computational time and resource utilization. In this study, Variant 2 was selected because it balances accuracy and computational efficiency. While Variant 3 offers slightly better accuracy, Variant 2 achieves nearly comparable accuracy with significantly lower resource consumption, making it a more efficient choice for practical applications.

GPS/INS data fusion

The Kalman filter estimates the state vector when GPS signals are present. At the same time, GPS positions are used to train the ConvNet variants. The estimation accuracy of the proposed GPS/INS integration algorithm is evaluated against the solutions provided by standalone GPS and standalone INS, both considered as benchmarks for this study. In this work, we modeled the disturbances of the GPS signal during three path segments, each lasting one minute. Furthermore, the INS errors were also modeled throughout the entire path. The reference trajectory and trajectories estimated by GPS, INS, and the proposed method are illustrated in Figure 16, with a zoom-in on these trajectories in figure 17 for greater clarity. The error statistics for GPS standalone, INS standalone, and our proposed method are detailed in Table 7, Table 8, and Table 9, respectively.

Table 7. Statistics of GPS standalone positioning error along the path

	Position error (m)		
	East	**North**	**Up**
RMSE	2,92	3,99	7,39
Max	43,32	50,34	81,17

From table 7, the calculated RMSE remains relatively moderate, particularly in the east and north directions, reaching 2,92 meters and 3,99 meters, respectively. However, a significant deviation is observed in the up direction, where a maximum error of 81,17 meters is calculated during the third zone of GPS under attack. This highlights the severe impact of such attacks on the accuracy of satellite-based systems, demonstrating how vulnerable these systems can be under intentional interference.

Table 8. Statistics of INS standalone positioning error along the trajectory

	Position error (m)		
	East	**North**	**Up**
RMSE	11,72	138,70	190,31
Max	17,52	237,81	342,00

Table 9. Performance of our proposed method along the trajectory

	Position error (m)		
	East	**North**	**Up**
RMSE	0,71	1,25	6,79
Max	2,51	3,11	8,40

In table 8, we observe that the situation is more complex concerning the INS system. The calculated RMSE is significantly higher, particularly in the north and up directions, reaching 138,70 meters and 190,31 meters, respectively. Additionally, the maximum difference from the ground truth is approximately 342 meters by the end of the estimated trajectory. This highlights the impact of accumulated errors over time, which increase exponentially, underscoring the inherent limitations of INS systems in maintaining accuracy over extended periods without external corrections.

The statistics in table 9 demonstrate an improvement in the performance of the proposed method compared to standalone GPS and INS. The RMSE in the north and east directions has decreased significantly, reaching approximately 0,71 meters and 1,25 meters, respectively. However, the RMSE calculated in the up direction remains moderate at 6,79 meters, which can be attributed to the accumulated errors related to gravity fluctuations along this axis. This improvement highlights the effectiveness of the proposed method in mitigating some of the key limitations of standalone systems.

The results demonstrate a significant enhancement in accuracy when using the proposed method compared to standalone GPS and INS systems. Overall, the proposed method achieved a total improvement of 77,68 % in RMSE compared to standalone GPS, indicating a substantial reduction in errors across all directions. The improvement is even more pronounced when compared to the INS system, with a total improvement of 98,34 %, highlighting the method's ability to effectively mitigate the accumulation of errors that typically plague inertial navigation over time.
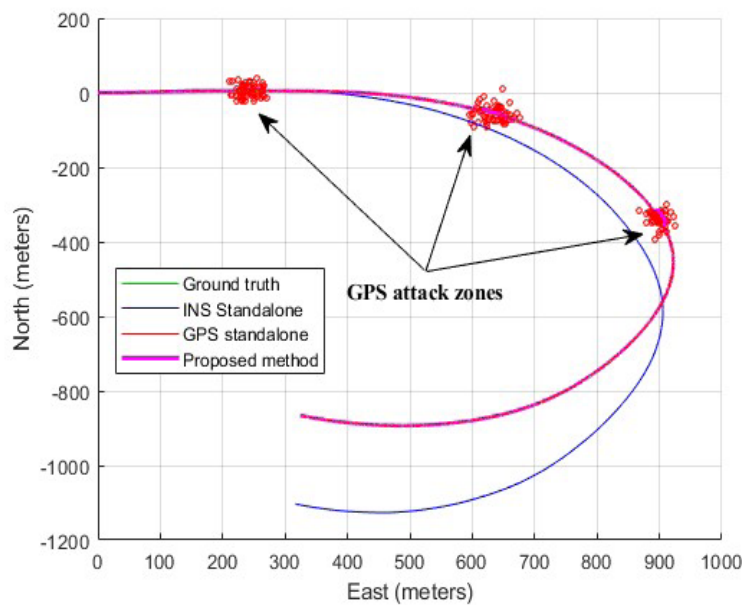

Figure 16. Comparison of reference, GPS standalone, INS standalone, and proposed method trajectories
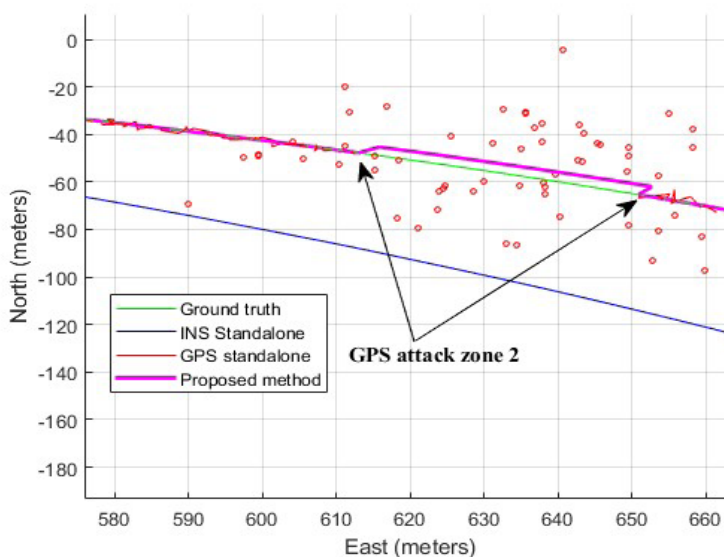

Figure 17. Zoomed-in analysis of trajectory comparison during GPS attack zone 2

The comparison reveals that the integrated approach significantly enhances positional accuracy compared to the individual systems. Specifically, while the standalone GPS and INS systems exhibit certain limitations in accuracy and reliability, the proposed integration algorithm effectively addresses these issues. This improved performance highlights the efficacy of combining the Kalman filter with ConvNet training in the GPS/INS integration framework, resulting in more accurate and reliable navigation solutions.

Figure 17 provides a detailed visualization of the reference, GPS, INS, and proposed method trajectories with a zoomed-in perspective for clearer comparison. The proposed method closely follows the reference trajectory, maintaining a high alignment throughout the observed path. In contrast, the INS trajectory diverges noticeably after a few initial points, demonstrating the cumulative effect of errors inherent in inertial systems over time. The GPS trajectory, while generally close to the reference, exhibits significant deviations in the zones under attack, where it produces points that are scattered and far from the reference trajectory, lacking any discernible order. This scattered pattern underscores the vulnerability of GPS to signal interference, further highlighting the superiority of the proposed method in maintaining trajectory accuracy under challenging conditions.

CONCLUSIONS

To conclude, this study has demonstrated the significant advantages of the proposed method over traditional standalone GPS and INS systems in reducing navigation errors. The results highlight the critical limitations of standalone systems, particularly under conditions of GPS signal degradation. The calculated RMSE for standalone GPS reached 3,99 meters in the north direction, 2,92 meters in the east direction, and a substantial 81,17 meters in the up direction during the simulated trajectory. The standalone INS system exhibited even higher errors, with RMSE values of 138,70 meters in the north direction, 190,31 meters in the up direction, and a maximum deviation from the ground truth of approximately 342 meters by the end of the trajectory, illustrating the exponential growth of errors over time. In contrast, the proposed method significantly reduced these errors, achieving RMSE values of just 0,71 meters in the north direction, 1,25 meters in the east direction, and 6,79 meters in the up direction. These improvements correspond to a total reduction in RMSE of 77,68 % compared to GPS and an impressive 98,34 % compared to INS. These findings underscore the effectiveness of the proposed method in providing more accurate and reliable navigation, particularly in challenging environments where GPS signals are compromised. The substantial improvement in error metrics across all directions affirms the robustness and potential of this approach for future navigation systems.

Previous research has shown that standalone GPS, while widely used, is prone to errors, particularly in environments where signal quality degrades due to interference or blockage.[32,33] Our findings corroborate these limitations, with GPS errors reaching as high as 81,17 meters in the vertical direction during the simulated trajectory. Similarly, standalone INS systems, despite their independence from external signals, exhibit error growth over time, as seen in the exponential increase in RMSE values in our simulation. This behavior is consistent with previous findings, where long-term INS operation without correction leads to substantial drift and inaccurate positioning.[34] The INS error of 342 meters by the end of the trajectory highlights this known limitation. In contrast, the proposed method significantly reduces navigation errors. The reduction in RMSE by 77,68 % compared to GPS and 98,34 % compared to INS demonstrates the potential of integrating machine learning and sensor fusion techniques for more robust navigation solutions. This aligns with recent advances in the field, where supervised learning algorithms have been successfully employed to correct sensor data and mitigate system drift.[15,35]

Future work

GPS is exposed to serious attacks that can threaten the safety of both humans and services, particularly through jamming and spoofing. Our upcoming work will explore artificial intelligence methods to detect the patterns of these external attacks. By leveraging AI, we aim to develop robust detection systems that can identify and mitigate the risks posed by these threats, ensuring the continued safety and reliability of GPS-dependent operations.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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