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Environment adaptive navigation (EAN): A data-driven approach for improved navigation accuracy

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ABSTRACT

The quality of GNSS-based navigation services is highly influenced by the type of operating environment. The urban environments with buildings and structures pose substantial challenges for GNSS navigation accuracy. To address this challenge, we propose a data-driven approach Environment Adaptive Navigation (EAN) because complex mathematical models for GNSS environments are impractical for real-time use due to their processing load. This data-driven approach analyzes real-time GNSS data to understand how the environment affects performance and optimize receiver settings for each scenario. Keeping this in view, raw GNSS data was collected through field trials including the three environments: clear sky, partially degraded, and highly degraded. We then analyzed this data to pinpoint factors affecting accuracy, such as the number of available satellites and standard error measurements. The proposed solution, the EAN algorithm, tackles these limitations of the GNSS due to the urban environments and improves the navigation performance. This data-driven approach analyzes real-time GNSS data to identify the specific environment (clear, partially degraded, or highly degraded). Based on this assessment, EAN dynamically adjusts receiver settings, like tracking loop bandwidth, to achieve optimal performance under those conditions. Integrating the EAN model into GNSS receivers allows for real-time environment detection and adaptive configuration. This EAN-based GNSS receiver holds significant promise for safety-critical applications like Intelligent Transportation Systems (ITS). Precise navigation is crucial for functionalities within ITS, such as route optimization and autonomous vehicle operation. The effectiveness of the EAN-based receiver was validated through a field experiment demonstrating a notable increase in tracked satellites and a substantial reduction in outages within a highly degraded environment.

1. Introduction

An accurate, precise and seamless navigation information is indispensable for a wide array of applications, especially in urban environments where precise navigation, emergency response, geo-fencing, Intelligent Transportation Systems, environmental monitoring and other location-based services require precise location data. [1]–[3]. Although GNSS provide ubiquitous coverage and GNSS data in real-time, but its performance degrades substantially in urban canyon due to satellite signal blockage, multipath, and non-line-of-sight (NLOS) reception [4]–[7]. These signal impairments collectively reduce accuracy and availability of GNSS-based navigation in urban environments, hindering the performance of location-based applications [8]. Existing studies for mitigation [9]–[13] such as NLOS detection and multipath exclusion can enhance the positional accuracy under particular situations, but their effectiveness is limited. For example reducing the multipath or NLOS measurements can enhance the positioning accuracy in partially degraded environments. However, this technique may rise the service interruptions in densely urban environment [14]–[16]. This type of the method may cause service interruptions in highly dense urban contexts due to reduced satellite visibility and limited satellite availability.

The traditional mathematical modelling of the environment in the context of GNSS is very complex due to its inherent randomness. While detailed 3D models exist in literature, those models have high computational load and are incapable of being employed in real-time GNSS receivers. Keeping this in view, a data-driven approach is adopted in the paper, which is the main contribution of this paper. The contribution of the paper is as follows:

- Initially to assess the GNSS performance across various contexts, real-time GNSS data is logged through rigorous field experimentation. The data acquired includes satellite availability, continuity, dilution of precision (DOP), and statistical accuracy measurements.
- Secondly, a data-driven approach is applied to GNSS raw data to interpret the potential anomalies that affect the GNSS in three distinct environments: open-sky, partially degraded with some obstructions, and highly degraded with minimal line-of-sight (LOS) reception.
- Based on the detailed assessment, a data-driven EAN algorithm is proposed to enhance the navigation accuracy. EAN algorithm optimize the receiver settings i.e. tracking bandwidth in real-time based on detected environment.

In a data-driven approach, decisions are made based on the data. The initial stage of data-driven approaches involves data analytics to analyze and interpret the data. Based on this, we have applied a data-driven approach on real-time GNSS data under different environments to interpret and quantify the stochastic behavior of the different environments. After detailed performance assessment, a data-driven environment adaptive navigation (EAN) algorithm is proposed to enhance the navigation accuracy. This approach utilized the real-time data from GNSS receiver to characterize the surroundings. Based on the environmental features detection by EAN algorithm like signal blockage, multipath, and NLOS reception the receiver can then optimize the settings in real-time. The optimization involves adjusting the parameters like noise bandwidth to enhance the processing of GNSS signals and restricts the consequences of deterioration. The EAN algorithm aims to enhance the positioning accuracy and reduce the limitations of traditional mitigation strategies specifically in complex urban scenarios.

Fig. 1. Three Distinct Environments for GNSS Performance Evaluation. (a) Open Sky Environment With Minimal Obstructions (b) Partially Degraded Environment With Some Building Blockage (c) Highly Degraded Environment With Significant Building Blockage And Limited Line-Of-Sight (LOS) Reception

2. Field Experimentation and Methodology

To precisely estimate the severity of GNSS inaccuracies in constrained environments, field experimentation is carried out on three different, pre-surveyed and carefully selected sites having different obstruction/blockage levels, as shown in Fig. 1 above. The three chosen sites reflect a wide range of GNSS reception conditions: open sky, slightly degraded, and severely degraded.

- Clear Open Sky Environment (Fig. 1(a)): This site, located on the roof of Academic Block-3, Sukkur IBA University, provides an uninterrupted view of the sky, reducing signal blocking and promising optimal reception conditions.
- Partially Degraded Environment (Fig. 1(b)): This site, located at the 1st Floor of Academic Block-3, Sukkur IBA University, presents a partially obstructed environment with a mix of line-of-sight (LOS) and non-line-of-sight (NLOS) reception.
- Highly Degraded Environment (Fig. 1(c)): This site, located inside the Academic Block-3, Sukkur IBA University, represents a challenging environment with a high probability of signal blockage and minimal LOS reception.

This study utilized a rigorous field experiment design to assess GNSS performance across diverse environments. Three separate trials were conducted, each lasting six hours. During each trial, a PolaRx5S multi-constellation GNSS receiver continuously collected navigation data at 10 Hz from all four GNSS constellations (GPS, GLONASS, BeiDou, and Galileo), providing a high-resolution record for analysis. Following data acquisition, GNSS performance was evaluated by analyzing key quality parameters: satellite availability (number of tracked satellites), satellite continuity (ability to maintain a valid position fix considering tracking and outage events - minimum of seven satellites required for 3D fix), positioning precision (PDOP, influenced by satellite geometry), and positioning accuracy (DRMS, a 2D horizontal accuracy measure). In practical world scenarios these measures plays an important part and utilized to extract the environmental factors that impact on GNSS performance. The PDOP and DRMS values can be estimated as

$$PDOP = \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2} \quad (1)$$

$$DRMS = \sqrt{\sigma_x^2 + \sigma_y^2} \quad (2)$$

where, σ^2 is the variance of estimated coordinates (x, y, z).

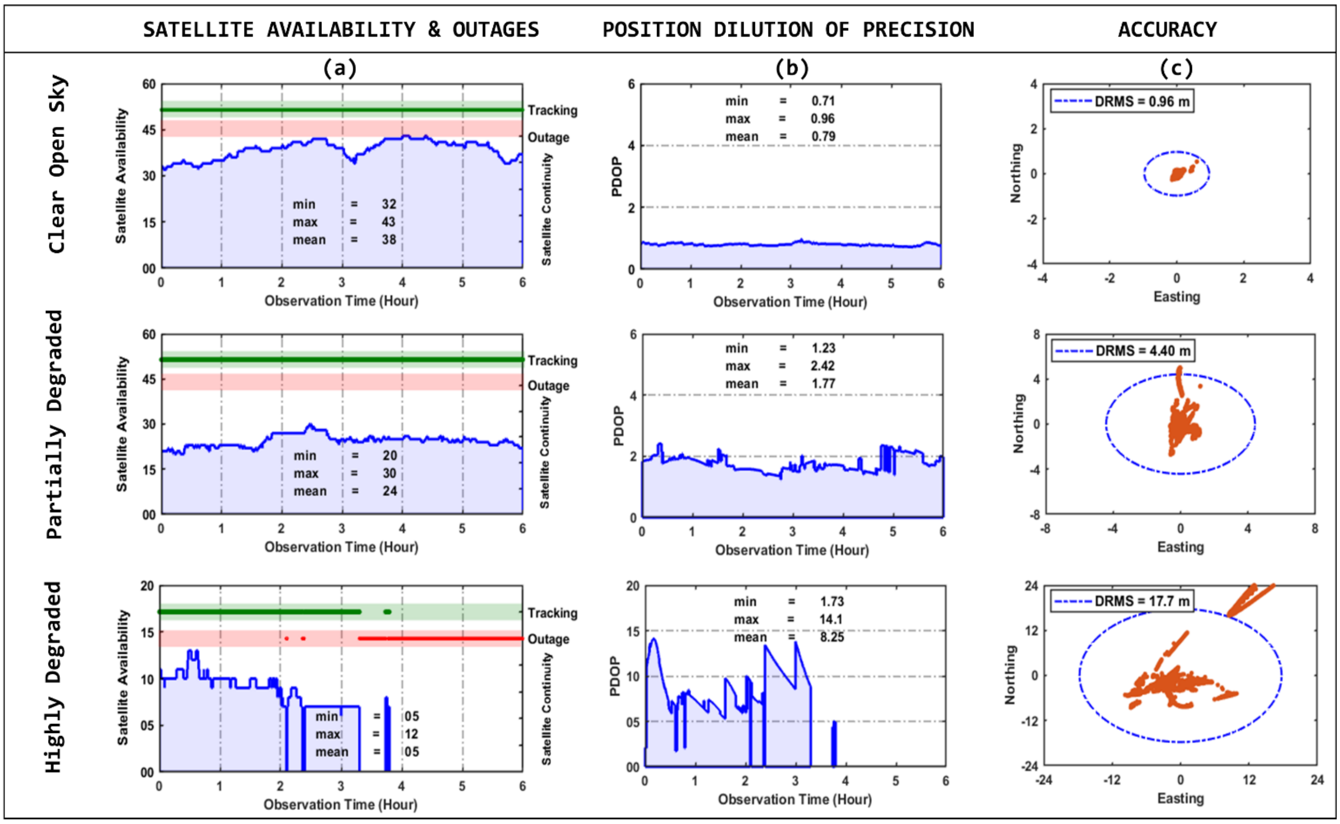

Fig. 2. GNSS Performance in Clear Open-Sky, Partially Degraded, And Highly Degraded Environment: (a) Satellite Availability and Outages; (b) PDOP; (c) Accuracy (DRMS)

3. GNSS Performance Evaluation in Different Environments

In this section, the results used for performance assessment of multi-constellation GNSS receiver across three diverse scenarios: clear open sky, partially degraded and highly degraded. The key GNSS quality parameters assessed are satellite availability (SW), continuity, Position Dilution of Precision (PDOP), and Distance Root Mean Square (DRMS) error.

The number of tracked satellites (satellite availability) significantly varied across the different environments, as shown in Fig. 2(a). In the open sky environment, the receiver consistently acquired and tracked a high number of satellites (average of 38, ranging from 32 to 43). This abundance of satellites, exceeding the minimum requirement of seven for a 3D position fix, ensures reliable positioning throughout the observation period. However, as the environmental conditions become more challenging, satellite availability deteriorates. In the partially degraded environment, the average number of tracked satellites drops to 24. While this is sufficient for a position fix, it represents a significant decrease compared to the open sky scenario. Importantly, no outages were observed in the partially degraded environment, indicating continuous tracking of the available satellites. The situation becomes most critical in the highly degraded environment. Here, the average number of tracked satellites plummets to just 5. This limited availability, coupled with frequent outages (resulting in a positioning solution for only 57% of the observation period), renders GNSS positioning unreliable and potentially unusable for safety-critical applications.

The blockage of GNSS signals by obstructions not only reduces satellite availability but also degrades the satellites' geometric distribution, quantified by PDOP. Lower PDOP values (less than 1) indicate a favourable constellation geometry with well-distributed satellites in the sky. Conversely, higher PDOP values signify a poor geometric distribution. Fig. 2(b) illustrates the PDOP values across the environments. In the open sky scenario, the PDOP values were consistently below 1, reflecting an excellent satellite geometry. The partially degraded environment exhibited fair PDOP values (average of 1.77). However, the highly degraded environment suffered from a severe increase in PDOP, with average and maximum values of 8.25 and 14.1, respectively. PDOP values exceeding 6 indicate poor satellite geometry and significantly contribute to degraded positioning accuracy.

Following the assessment of satellite continuity and geometry, the accuracy of the reported position was analyzed for all three cases. Positioning accuracy is highly dependent on the number and geometric distribution of tracked satellites. As expected, the significant satellite availability and excellent geometry in the open sky environment resulted in good positioning accuracy. Conversely, severe inaccuracies were observed in the highly degraded environment. The statistical accuracy, measured by DRMS, for all three environments is shown in Fig. 2(c). The radius of the confidence region depicted in Fig. 2(c) is directly related to positioning uncertainty. As the error increases, the radius of the confidence region expands. In the open sky case, the DRMS was found to be 0.96 meters. Approximately 70% of the position fixes fell within a 0.5-meter radius of the true position, which is considered an acceptable accuracy level for many navigation applications. However, in the partially and highly degraded environments, DRMS values increased significantly to 4.40 meters and 17.7 meters, respectively. These large errors indicate that the GNSS receiver's performance becomes unreliable in such challenging environments. Overall, these results clearly demonstrate the significant impact of environmental factors on GNSS performance. As the level of obstruction increases, satellite availability decreases, outages become more frequent, PDOP values worsen, and DRMS errors increase, leading to degraded positioning accuracy.

4. Environment Adaptive Navigation

With the growing reliance on GNSS for safety-critical applications requires dependable and precise positioning across diverse environmental conditions [11], [17]–[19]. Many researchers have explored the environment recognition using factors like signal strength, number of satellites, and DOP (Dilution of Precision) to identify the environment (indoors, outdoors, etc.).

Some studies [7, 10, 14] achieved this with a single GNSS constellation, focusing on classifying environments rather than improving accuracy. Others [13, 20] used dual constellations and showed accuracy improvements of up to 15%. Table 1 enlists the previous studies of the environment recognition. The prior performance assessment clearly demonstrated a substantial impact of environmental factors on GNSS performance. Even minimal deviations in accuracy can lead to significant legal or financial consequences [20]–[22]. The limitations of the previous studies are as:

- However, these approaches may not be sufficient with the emergence of new GNSS constellations (BeiDou and Galileo) that significantly increase the number of available satellites.
- Relying solely on CNR or similar metrics can be inaccurate because environmental impact varies with frequency, and monitoring CNR for each frequency in a multi-constellation system that can increase the processing load on the receiver.
- Additionally, these studies are based on complex mathematical models and 3D models, which are computationally extensive and may not be practically feasible to incorporate in real GNSS designs.

The key quality indicators exhibited significant variations between open sky, partially degraded, and highly degraded environments. These observations highlight the need for additional mechanisms to mitigate inaccuracies and maintain the required navigation performance in challenging environments. This paper proposes a data-driven Environment Adaptive Navigation (EAN) algorithm designed to enhance the availability and accuracy of positioning solutions. The primary principle of EAN is data-driven environment detection using GNSS measurements. This technique takes use of the inherent changes in GNSS quality metrics across different contexts. The EAN algorithm can use these changes to determine thresholds or statistical connections for environment categorization. The complete flowchart of the EAN algorithm is shown in Fig. 3. The process initiates with the signal acquisition and tracking, then certain parameters as in Table 2 are extracted and feed to the EAN algorithm for environment detection. The EAN method uses a data-driven strategy for environment characterization, as illustrated in Table 1. The table outlines thresholds for key GNSS quality indicators, including satellite availability (SA), satellite geometry (PDOP), and accuracy (DRMS). These thresholds are determined by study of a large GNSS dataset that includes a variety of environmental conditions. In real-time operation, the EAN algorithm continuously tracks and compares live GNSS data to the specified thresholds. Based on which thresholds are met, the EAN algorithm can then classify the surrounding environment as open sky, partially degraded, or highly degraded.

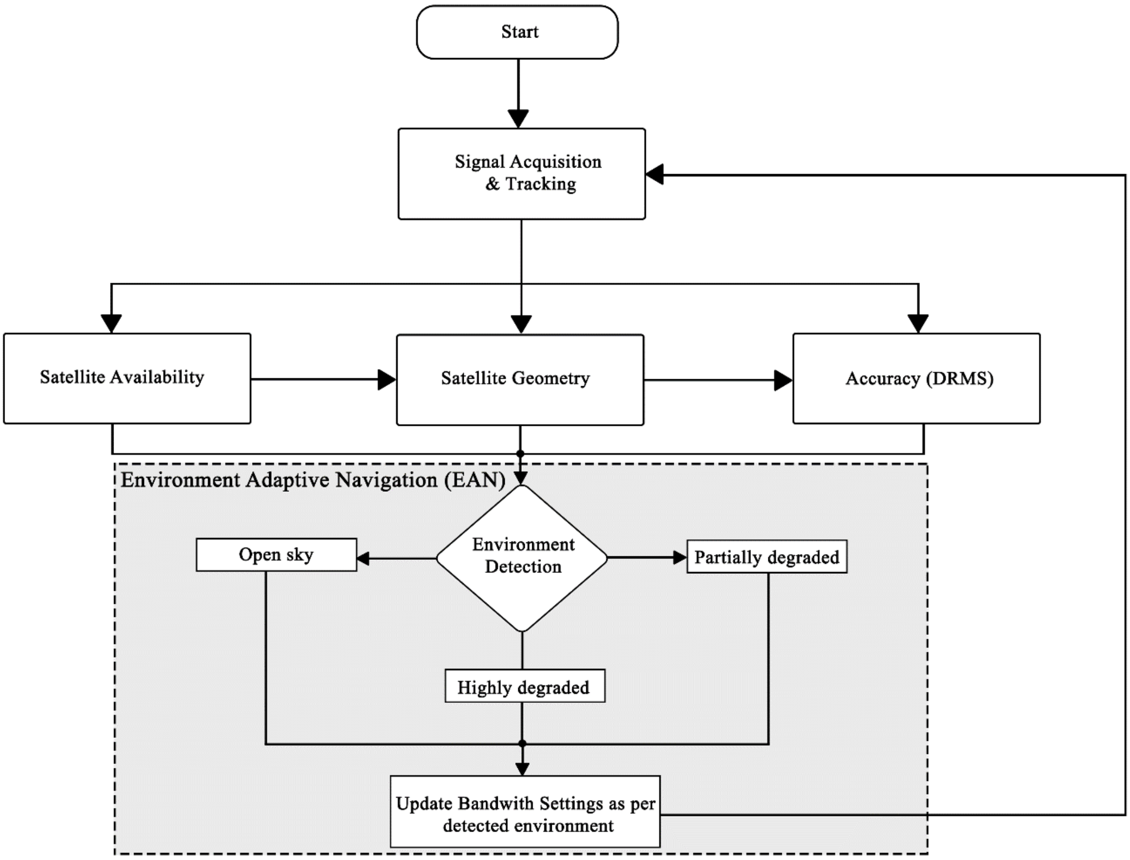

Fig. 3. The Complete Workflow of The Proposed EAN Algorithm

Table 1

Environment characterization literature

Parameter	Environment Characterization	Constellation	Performance Improved	Source Year
CNR, CNR Sum	Indoor/Outdoor	Single	Not Discussed	[07] 2020
Signal Strength, No. of Satellites	Indoor/Intermediate/Outdoor	Single	Not Discussed	[14] 2018
Signal Strength, No. of satellites, DOP, Blockage coefficient	Urban/Suburban/Indoor/Open sky	Single	Not Discussed	[10] 2020
CNR, Height	Urban/Suburban/Indoor/Open sky	Dual	15%	[20] 2013
CNR, Satellite Geometry	Urban/Nominal	Dual	Not Discussed	[13] 2022

Once the environment is detected by EAN, an optimal mitigation strategy as per detected environment can be initiated to enhance the GNSS performance. While this study utilizes a post-processing approach for environment detection, the strategy can be directly incorporated into the GNSS receiver during real-time operation.

To establish the effectiveness of the EAN algorithm, a field experiment was conducted at a highly degraded site. This experiment involved adjusting the receiver's tracking loop parameters based on the environment detected by EAN. GNSS receivers utilize tracking loops, such as Phase Locked Loops (PLLs) and Delay Locked Loops (DLLs), to maintain signal lock with detected satellites. These loops precisely estimate the carrier frequency and code phase of the received signal.

Table 2

The environment characterization model of EAN

S.No	Satellite Availability	Satellite Geometry	Accuracy (m)	Environment Detection
01	SA ≥ 30	PDOP ≤1.5	DRMS ≤2	Open Sky
02	15 ≤ SA < 30	1.5<PDOP ≤1.5	2<DRMS ≤6	Partially Degraded
03	SA < 15	PDOP >3	DRMS >6	Highly Degraded

A crucial factor influencing their performance is the noise bandwidth, which controls the trade-off between noise filtering and tracking precision. The performance of these loops is highly dependent on the noise bandwidth, which controls the amount of noise and tracking precision. A tracking loop with a large noise bandwidth exhibits a higher capability of satellite acquisition but with low precision while small noise bandwidth leads to precise tracking. However, the main drawback of small noise bandwidth is that a tracking loop becomes very sensitive and cannot handle larger dynamics in different environments. The EAN algorithm overcomes these limitations by proposing adaptive noise bandwidth settings. By leveraging the environment detection capability, EAN can adjust the noise bandwidth based on the surrounding conditions. For instance, in a highly degraded environment with weak signals and potential dynamics, the EAN algorithm might recommend a wider noise bandwidth to prioritize satellite acquisition while managing noise to a certain extent. Conversely, in a stable open-sky environment with strong signals, a narrower noise bandwidth might be chosen to achieve the highest possible tracking precision. Table 3 presents the specific tracking loop settings, including the chosen noise bandwidth, employed for the highly degraded environment during the field experiment. The GNSS performance evaluation results at the highly degraded site with and without EAN are shown in Fig. 4. As the figure illustrates, significant improvements were observed in all the aforementioned metrics due to the optimal bandwidth settings recommended by the EAN model. At the highly degraded site, the limited satellite visibility and reliance on fixed/compact bandwidth settings (without EAN) resulted in substantial outages. This may be due to the inability of the fixed bandwidth to effectively handle the signal variations of such environments.

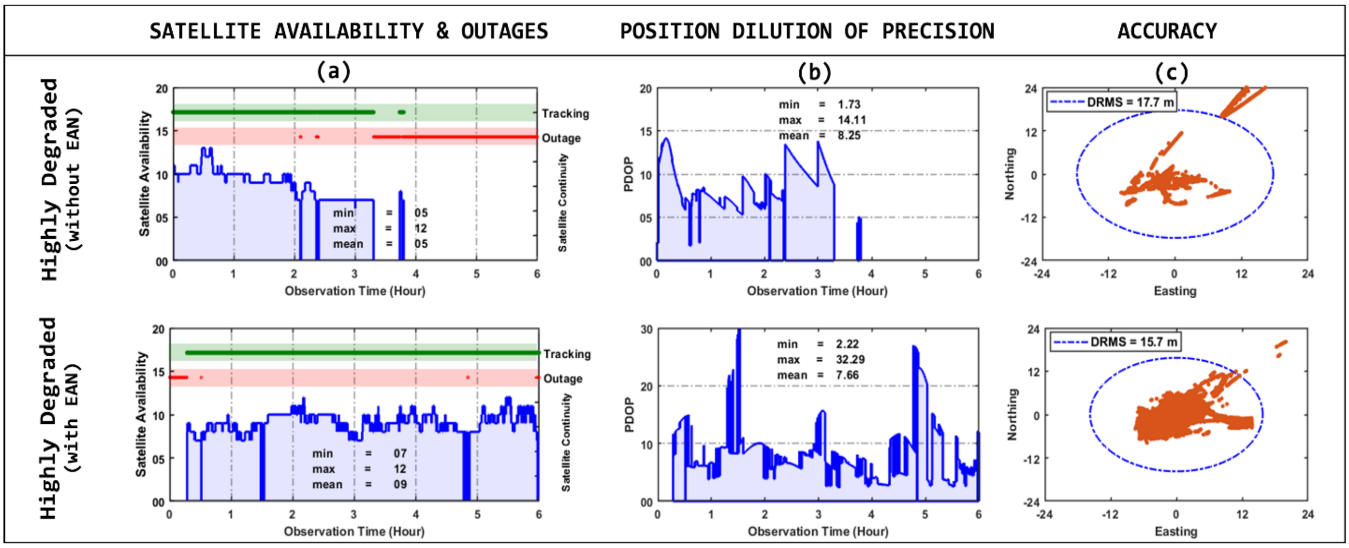

Fig. 4. GNSS Performance in A Degraded Environment with and Without EAN model: (a) Satellite Availability and Outages; (b) PDOP; (c) Accuracy (DRMS).

Table 3

Receiver parameters settings

Parameter	Without EAN	With EAN
DLL Bandwidth (Hz)	0.25	1.0
PLL Bandwidth (Hz)	15.0	15.0
CNR Mask (dB)	10.0	10.0

Conversely, EAN-enabled receivers achieved a significant increase in the average number of tracked satellites (Avg = 09) and a substantial reduction in outages (i.e., 6%). Furthermore, the EAN model led to a reduction in the average PDOP value (to 7.66) and an improvement in DRMS accuracy by 2 meters. These enhancements indicate that the EAN-enabled receivers achieved not only better satellite visibility but also more precise positioning within the highly degraded environment.

5. Conclusion

This paper investigated the environmental impact on GNSS accuracy through field experiments in contrasting environments (open sky, partially degraded, highly degraded). The results confirmed significant accuracy variations depending on the surroundings. To address these challenges, a novel Environment Adaptive Navigation (EAN) algorithm was proposed. EAN utilizes real-time GNSS measurements for environment detection and adjusts receiver settings (tracking loop bandwidth) to optimize performance. This data-driven approach prioritizes satellite acquisition in challenging environments and enhances tracking precision in favourable conditions. Field validation demonstrated that the EAN-based receiver significantly improved GNSS performance, particularly in highly degraded environments. This improvement highlights the potential of the EAN algorithm for mitigating environmental effects on GNSS accuracy.

Future research should focus on examining the effectiveness of this method in scenarios with more complex and complicated environments. Furthermore, the development of a more robust EAN algorithm, potentially leveraging machine-learning techniques, could enhance the capability to detect and mitigate GNSS signal anomalies. Additionally, the integration of artificial neural networks presents a promising future direction for data exploration and minimizing the impacts of random environmental errors in navigation and ultimately results in subsequent improvements in navigation performance.

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