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Performance Enhancement of Low-Cost INS/GPS Navigation System Operating in Urban Environments

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As a result of the increasing usage of UAVs (Unmanned Air Vehicles) in urban environments for UAM (Urban Air Mobility) applications, the preciseness and reliability of PNT (Positioning, Navigation and Timing) systems have critical importance for mission safety and success. With its high accuracy and global coverage, GNSS (Global Navigation Satellite System) is the primary PNT source for UAM applications. However, GNSS is highly vulnerable to Non-Line-of-Sight (NLoS) blockages and multipath (MP) reflections, which are quite common, especially in urban areas. This study proposes a machine learning-based NLoS/MP detection and exclusion algorithm using GNSS observables to enhance position estimations at the receiver level. By using the ensemble machine learning algorithm with the proposed method, overall 93.2% NLoS/MP detection accuracy was obtained, and 29.8% accuracy enhancement was achieved by excluding these detected signals.

I.Nomenclature

UAV	=	Unmanned Air Vehicle
UAM	=	Urban Air Mobility
PNT	=	Positioning, Navigation and Timing
GNSS	=	Global Navigation Satellite System
NLoS	=	Non-line-of-sight
MP	=	Multipath
GPS	=	Global Positioning System
DOP	=	Dilution of precision
PVT	=	Position, Velocity, and Timing
INS	=	Inertial Navigation System
LoS	=	Line-of-sight
RHCP	=	Right-handed Circular Polarization
LHCP	=	Left-handed Circular Polarization
CNR	=	Carrier-to-noise ratio
mRMR	=	Minimum Redundancy — Maximum Relevance

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II.Introduction

It is seen that the applications of UAM, which is a subject that attracts a lot of attention from both industry and academia, are increasing rapidly [1]. As a result of the increasing usage of UAVs in urban environments for UAM applications, the preciseness and reliability of PNT (Positioning, Navigation and Timing) systems have critical importance for mission safety and success. Currently, GNSS (Global Navigation Satellite Systems) is the primary PNT source in either civilian or military applications with its high accuracy and global coverage. However, GNSS is highly vulnerable to line-of-sight (LoS) blockages and multipath reflections, which are especially common in urban areas.

Since urban environments contain many flat surfaces that reflect GPS signals, two major signal reception issues are experienced: NLoS reception and MP interference. MP and NLoS are the major error sources that have the most detrimental effect on urban environment conditions [2], [3]. Although both are frequently grouped as multipath issues, they cause very different ranging errors, as illustrated in Figure 1.

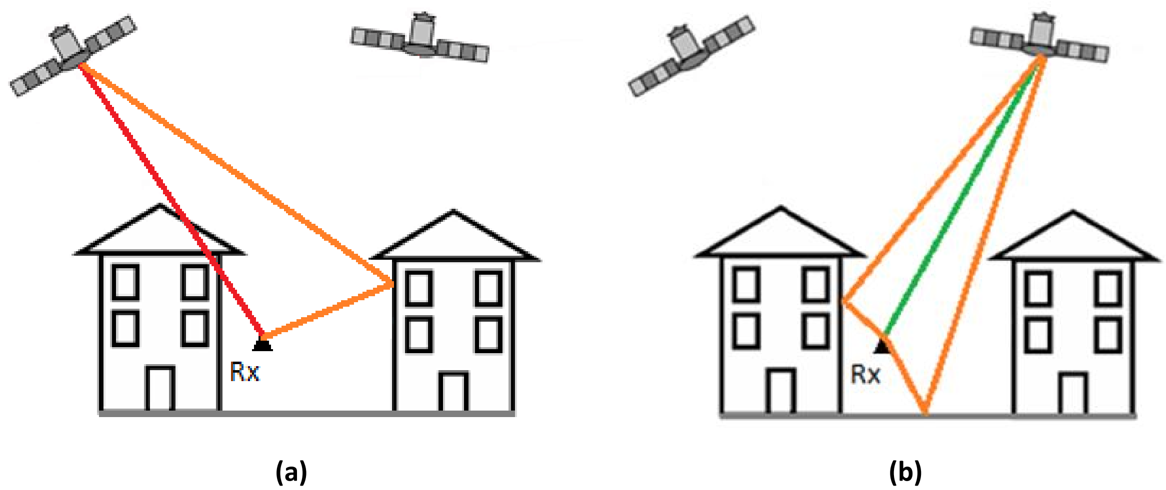

Figure 1 (a) NLoS reception (b) Multipath interference

A signal reception issue is called NLOS, where only a multipath reflection is received while the LoS signal is blocked. On the other hand, multipath interference occurs if both direct LoS signal and reflection(s) are received by a receiver. GPS data associated with these signals cause severe positional errors in urban environments due to the additional delay introduced by the reflected signal [2].

INS (Inertial Navigation System)/GPS integration is the most common multi-sensor navigation approach and is widely used even in low-cost navigation systems. INS offers highly accurate Position, Velocity, and Timing (PVT) measurements which is beneficial for aiding temporary GPS inaccuracies and unavailabilities. However, GPS is still the main PNT source, and a consumer-grade INS can only remain reliable for a few seconds in the absence of satellite navigation [4].

In order to mitigate the impact of GPS error sources, satellite-based and ground-based augmentation strategies and RAIM (Receiver Autonomous Integrity Monitoring) methods have already been investigated in the literature. The classical RAIM fault detection and exclusion (FDE) algorithm work based on monitoring Dilution of Precision (DOP) coefficients, representing how good satellite geometry is [5]. Since these methods are designed considering open sky error characteristics, they are not convenient to use in urban environments due to the intense LoS (Line of Sight) blockages and signal reflections [3]. After applying RAIM FDE procedures in urban environments, an insufficient number of satellites remains, or the remaining satellites have a bad satellite geometry to conduct accurate position estimations. Therefore, this study proposes a solution where only reflected components of received signals are removed rather than completely rejecting a satellite. So that sufficient GPS availability and satellite geometry can be maintained after FDE.

The overall aim of this study is to enhance the performance of low-cost INS/GPS navigation systems operating in urban environments. In order to achieve this aim, we propose eliminating NLoS and MP signals from position estimation calculation. In this study, LoS signals are referred to as direct signals, and NLoS and MP signals are referred to as indirect signals. Because of the difficulty of predicting and modelling MP and NLoS errors, utilizing machine learning was considered a suitable approach. After detecting and excluding faulty GPS signals, the enhanced PVT estimations are provided to INS/GPS fusion block. GPS and INS position estimates are fused with a loosely coupled Extended Kalman Filter (EKF). Finally, enhanced GPS position estimations are obtained.

In the literature, there is no classification algorithm with the features utilized in our study that has ever been designed and collected training data with GPS simulation, which is able to simulate real environments like the GSS7000 GNSS Simulator. In addition, although previous studies have investigated the success and suitability of machine learning algorithms for classification, the effect of signal elimination based on this classification on the static and dynamic positioning performance has not been examined in detail. Our research aims to contribute to the existing literature on these topics.

III.Related Studies

For urban mobility applications, INS and GPS complement each other as the navigation system. Both systems have advantages over each other. While INS is able to provide high-frequency position estimation, the long-term content of the information is insufficient since the system drifts slowly due to sensor characteristics. On the other hand, GPS requires receiving GPS signals in order to remain accurate over the long term. The master aim of using INS/GPS combined navigation systems is to estimate the better position of the system by taking advantage of both systems [6].

It is crucial to keep the cost and weight low for the tools used in urban mobility applications. However, advanced sensors used in complex systems can be very expensive and heavy. For this reason, the Micro-Electro-Mechanical System IMU is often used in these applications. These systems are also known as low-cost IMU [7]. The critical disadvantage of this type of sensor is that the noise in the sensor measurements is high. Therefore, the time to make a reliable prediction before the correction data is received is very short.

In order to have one estimation from two different data, a fusion algorithm is utilized. GPS and INS data are utilized by Kalman filters to estimate the system's position continuously.

In urban environments, there are significant difficulties with satellite-based navigation. This is due to the dependence of GPS location calculation on received signals. Signals coming from satellites could be deflected, diffracted, and blocked on the ground by buildings, trees, and other objects. As a result of the limited satellite sight and multipath impact, the accuracy of location estimation could be significantly reduced [3], [8].

In the literature, there are studies to enhance position estimation by mitigating the effect of MP and NLOS signals at different levels in urban environments. These studies are listed into three groups according to their levels: antenna-based techniques, additional sensor-based techniques, and receiver-based techniques.

A. Antenna-Based Techniques

Antenna-based techniques propose to mitigate MP and NLoS effects by examining antenna numbers and types. Paul [9] has suggested designing a dual-input GPS front end based on direct RF sampling. Because GPS signal coming from a direct satellite has right-handed circular polarization (RHCP), commercial GPS antennas are more sensitive to RHCP signals. In this study, also left-handed circular polarization (LHCP) is utilized, and carrier power to noise density, C/N0, measurements were obtained separately. It has been proposed that the differences between RHCP and LHCP can be used to detect MP signals.

In another study [10], by utilizing differences between RHCP and LHCP, a weighting and exclusion system is proposed to mitigate the effects of multipath and enhancement of the system on final PVT calculation. The effectiveness of the established technique in the positioning solution was evaluated through real-world testing.

B. Additional Sensor-Based Techniques

In literature, there are studies proposing to use of different additional sensors to detect the environmental obstacle and obtain which satellite signals should be blocked from these obstacles and which signals should reach the receiver directly. Tang [11] used a fisheye camera and projection of the satellite position to obtain visibility of the satellite. Using the information on which satellite is blocked could be determined, and a User Equivalent Range Error (UERE) calculation was proposed to predict the positioning error with the Horizontal Dilution of Precision (HDOP) estimation approach. In another study [12], carrier-to-noise ratio (CNR) and image-based methods were investigated to detect multipath and NLOS signals by Marais. It has been proposed that image processing and CNR-based approaches could provide complementary information to use the benefits of the two approaches while trying to minimize the disadvantages of each one.

C. Receiver-Based Techniques

Even antenna-based techniques and additional sensor-based techniques are successful to some extent. They offer to use more than one antenna or another sensor, which increases the weight and cost of the aircraft. In urban mobility, especially for the Low-Cost INS/GPS Navigation System, it is important to keep weight and cost low. That is why, in our study, the main focus is on receiver-based techniques, which can improve performance estimation without it increases cost and weight.

Mubarak [13]proposed using the combination of L1 and L2C signals. Even though this method helps to detect multipath signals more correctly than one single frequency, it is observed that it could cause to increase in false detection.

In another study [14], a convolutional neural network-based method has been proposed for detecting multipath using information obtained from the correlator output of a GPS receiver's tracking loops. The author suggests verifying the proposed algorithm with ground truth information. Another study by Ozeki [15] offers NLOS and MP detection approach which utilizes machine learning techniques, namely, one using a support vector machine (SVM) and the other using a neural network (NN). Signal strength against elevation angle outputs distribution of the delay of the maximum correlation, and the number of local maxima of the correlation was utilized as features for the machine learning model. These models were trained, and their performance levels were compared. NN had slightly better classification accuracy compared to SVM, and the system is able to classify 97.7% of NLOS MP signals.

Also, there are studies utilizing GPS observable data to classify signals. Gong [16] utilized carrier-to-noise ratio (CNR) and pseudorange to distinguish between direct and MP signals by training K-means Clustering Algorithm, and their classification accuracy reached 90.5%. In another study [17], C/No, elevation and pseudorange residuals are used to train with a binary decision tree. And this algorithm slightly gives better results than the standard C/No and Gaussian-based approach. Hsu [17] trained and tested support vector machine models with different observable features and found C/No, the difference between delta pseudorange and pseudorange rate, as optimum features. Sun [18] proposes a gradient-boosting decision tree method to classify signals using the satellite elevation angle, signal strength and pseudorange residual features. Outcomes indicate that MP/NLOS signal elimination, although enhancing performance, is vulnerable to both the receiver's proximity to signal reflector blocks and geometrical configuration.

Jiang [19] proposes an unsupervised algorithm that detects indirect signals by utilizing a clustering method. GPS data in an offline system are categorized as normal or abnormal when an indirect signal reaches the receiver. Satellite elevation angle, C/No, pseudorange residual and pseudorange rate consistency are considered features for this model. It is observed that while systems that detect and eliminate indirect signals can improve positioning estimation, removing indirect signals can also reduce the number of available GPS satellites and degrades their geometric distribution, which impacts positioning performance.

After analyzing the studies, it was determined that multipath detection at the observation deck level, which does not require an additional cost or sensor, is appropriate for low-cost navigation solutions.

When reviewing previous studies conducted at the observables level, it has been noticed that C/No and satellite elevation have a direct relationship with the signal type, and the methodology section in our study examined the effect of other observable features to determine the features of the system.

IV.Methodology

This section provides a detailed analysis of the technique used to meet the objectives of the study. In the subsequent sections, every aspect of this research will be presented.

In this study, LoS signals are referred to as direct signals, and NLoS and MP signals are referred to as indirect signals. The main aim of this study is to enhance position estimation in urban environments. First of all, for this purpose, the signal classifier system was developed to classify the received GPS signals as direct and indirect signals. Because of the difficulty of predicting and modelling undirect signals, utilizing machine learning was considered a suitable approach. The proposed method's main concept is to evaluate received signals with GPS receiver observables values to determine signal types. Spirent GSS7000 simulator is utilized with SimSENSOR to obtain realistic training and test scenarios. GPS observables values are collected from a U-Blox receiver by connecting the output of this simulation with the real receiver. Collected GPS observables values are labelled with the developed algorithm using simulator output, and machine learning models are trained with these data sets. Also, the simulation provided ground truth information and signal type information. Figure 2 shows the high-level structure of the proposed enhancement system.

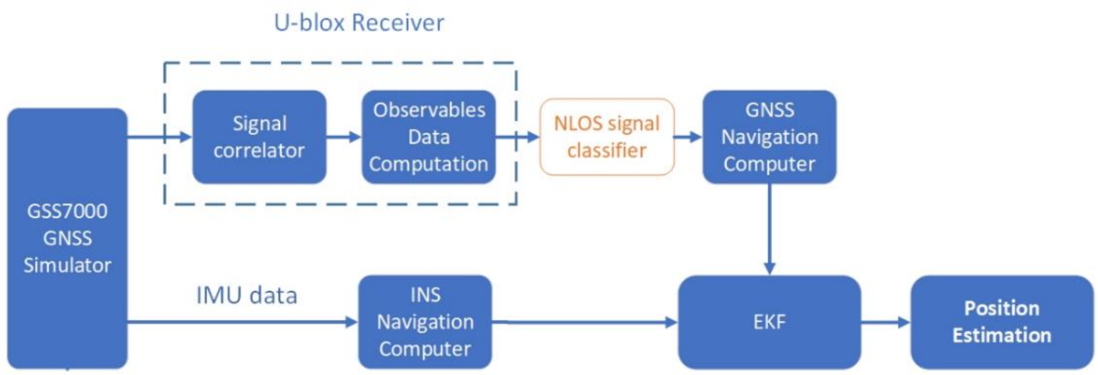

Figure 2 High-level architecture of the proposed system

EKF is the non-linear version of Kalman Filter, which linearize a continuously updated trajectory based on measurement state estimation[20]. The most popular INS/GPS integration technique is loosely coupled integration, and the primary benefit of loosely connected integration is its simplicity of setup and operation. In loosely coupled integration, the sensors are fully independent of one another [21]. In our study, a loosely coupled EKF integration method is preferred in order to fuse INS and GPS positions since it is commonly used for low-cost navigation applications due to its simplicity and compatibility.

A. Simulation Setup and Data Collection

The data collection stage is critically important for the success of the proposed solution in this study. The type of the received signals (LoS, NLoS or MP) should be known for training a signal classifier with supervised learning algorithms. Even though the most realistic data would be acquired by conducting an actual flight, it is difficult to distinguish actual signal classes at the receiver level. Since errors in the labelling process would impair the classifier's performance, Spirent's GSS7000 GNSS Simulator [22] which is able to simulate GPS signals and IMU data realistically in varied environmental conditions, was utilized to generate training and testing data. Figure 3 illustrates urban environment types defined in the simulator while generating the data set.

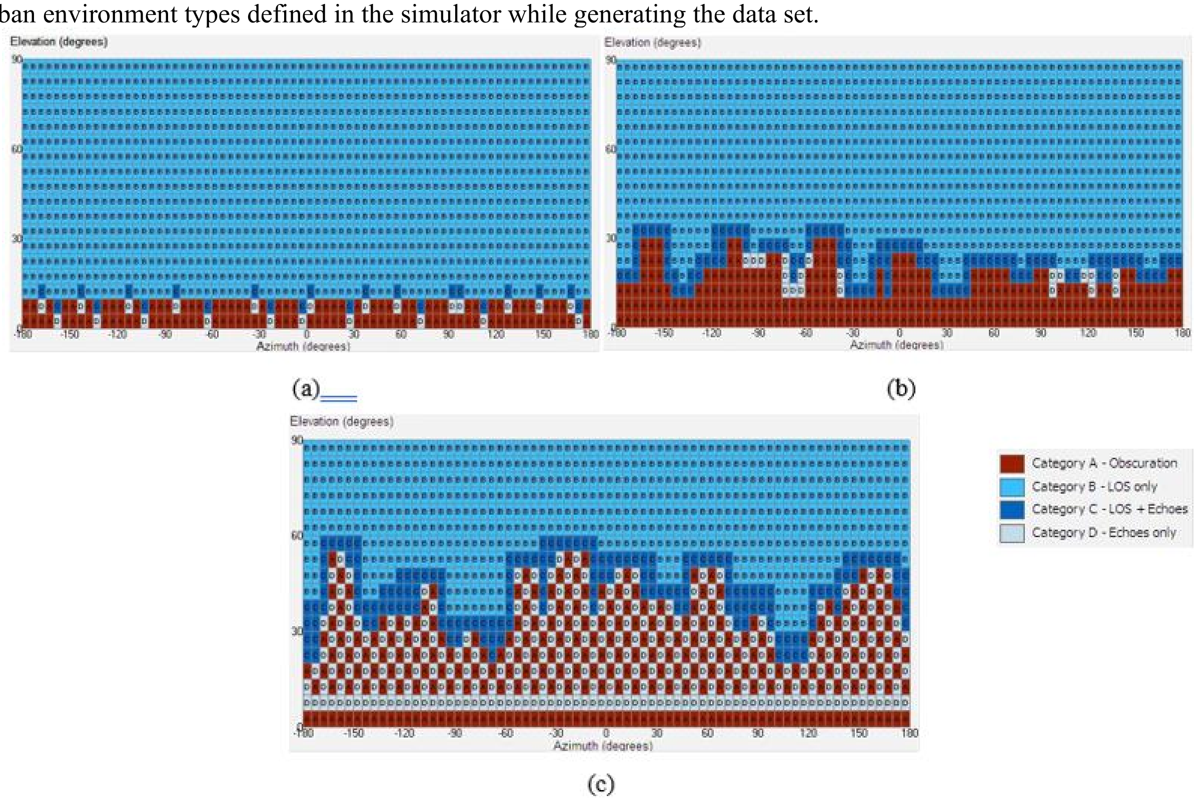

Figure 3 Simulation environments: (a) Suburban (b) Urban (c) Urban Canyon

In order to generate our training data set, the synthetic data is received by a U-Blox ZED-F9P [23] GNSS receiver, which is capable of providing GPS observables in addition to PVT information, and estimated positions and GPS observables are recorded at the receiver's output in NMEA format by using U-Centre [24] GPS evaluation software. The simulation architecture set up for data collection can be seen in Figure 4.

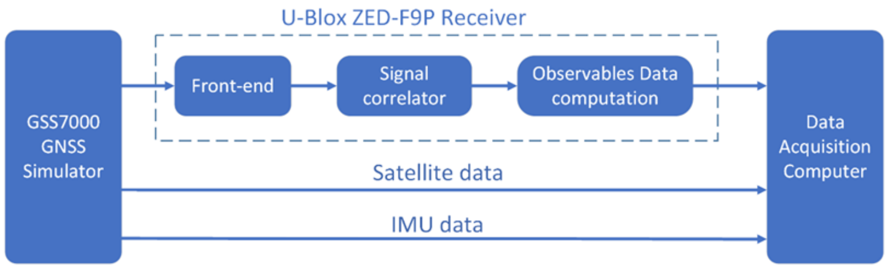

Figure 4 The simulation architecture

Thanks to the simulator, the ground truth labels are available for all data and set as NLoS, LoS or multipath. Different environmental conditions, urban canyon, urban and suburban, were created for data collection. In these environments, 6 pieces of 12-hour data, static and dynamic, were collected. After data collection with U-blox receiver and u-centre software, it is necessary to label which signals are clean and which signals are multipath. A labelling script was developed in the MATLAB environment to complete this task. With this script, signals extracted from NMEA messages were labelled as direct or indirect signals based on satellite data at the same UTC from the simulation. Table 1 shows how many signals are collected in static and dynamic scenarios and how many are labelled as direct signals and indirect signals as a result of the labelling process.

In order to increase the indirect signal detection success of the system, it was decided to train and test different models as stationary and dynamic. Therefore, the test data were also collected differently.

Table 1 The number of signals collected for training data

	Total Number of Signals	Total Number of Direct Signals	Total Number of Indirect Signals
Stationary	763650	577781	185869
Dynamic	736532	623388	113144

For testing the performance of the proposed system, additional 12-hour test data was generated. These test data were collected statically and dynamically by simulating a different day from the day the training data was collected. Training data was labelled using the developed labelling script based on NMEA messages and satellite data at the same UTC from the simulation, whether they were direct or indirect signals. Table 2 summarizes the number of signals collected in stationary and dynamic situations, as well as the number of direct and indirect signals labelled as a result of the labelling procedure.

Table 2 The number of signals collected for testing data

	Total Number of Signals	Total Number of Direct Signals	Total Number of Indirect Signals
Stationary	304836	236503	68333
Dynamic	304366	236524	67842

After extracting the NMEA data, pseudorange, carrier phase, doppler shift, carrier-to-noise ratio and elevation values were obtained for each signal value. The minimum redundancy — maximum relevance (mRMR) algorithm was used to see the effect of these values on the output. The reason for using the mRMR approach is that it efficiently reduces redundant features while holding the relevant features for the model [25]. By using mRMR algorithm, every feature's importance score was plotted [26].

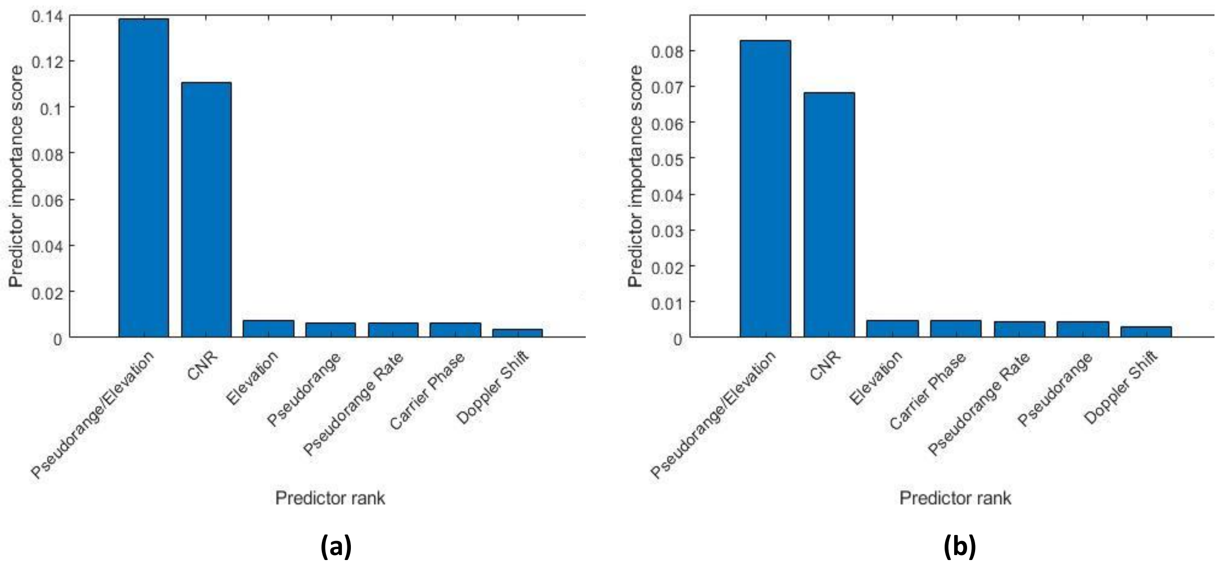

Figure 5 Bar plot of features importance scores: (a) Stationary (b) Dynamic

Figure 5 indicates that pseudorange/elevation and CNR features are the most remarkable indicators for the signal type. In addition, as seen in Figure 5, it has been observed that the pseudorange feature has low relation with the signal type, and the importance is low because of the pseudoranges in different bands for different elevation degrees. Therefore, the pseudorange value of the relevant signal was divided by the elevation value, and the mRMR algorithm was used again with the obtained data set.

In order to evaluate the performance of the trained model, there are different approaches. Our study uses accuracy, precision, recall and F-score as performance indicators. Following the classification, the confusion matrix was used to evaluate the classifier's performance [27].

Table 3 Validation results of optimized classifiers with different features

Features	Accuracy (%)	Precision	Recall	F1 Score
CNR and Pseudorange/Elevation	84.7	0.8541	0.4120	0.5558
CNR, Pseudorange Rate, Pseudorange/ Elevation, Carrier Phase, Doppler Shift	91.5	0.8841	0.7301	0.8001
CNR, Pseudorange Rate, Pseudorange/ Elevation, Carrier Phase, Elevation	95.9	0.9286	0.8937	0.9108
CNR, Pseudorange Rate, Pseudorange/ Elevation, Carrier Phase, Elevation, Doppler Shift	99.2	0.9871	0.9789	0.9830
CNR, Pseudorange Rate, Pseudorange/ Elevation, Carrier Phase, Elevation, Doppler Shift, Pseudorange	**99.5**	**0.9934**	**0.9845**	**0.9890**

Even though the correlation of features such as carrier phase and doppler shift in the mRMR algorithm seems low, when the optimized classifiers are compared, it is observed that all features are beneficial for obtaining more accurate classification. For this reason, all features, CNR, pseudorange rate, pseudorange/elevation, carrier phase, elevation, doppler shift and pseudorange were used as features for training the classifier.

B. Model Optimization and Training

After extracting the NMEA data, randomly separated 10% of the data is used to optimize all algorithms because training with the full data set took a very long time. After the optimization process with the limited parameter, the algorithm showing the best performance was optimized with the full data set. In all optimization and training processes, 80% of the data is randomly selected for training the signal classifier, and the remaining 20% is allocated for validation. It has been seen that the training data is highly variable when used for testing [28], [29]. Therefore, these data sets were collected separately.

Machine learning algorithms help us with classification problems as an effective and efficient method. Machine learning algorithms can generally model complicated class signatures, accept a range of predictor data as input, and make no assumptions about the data distribution. Numerous studies have usually demonstrated that these algorithms provide greater accuracy than classic parametric classifiers, particularly for complex data with a high-dimensional feature space [30].

The optimization and training procedure was carried out by utilizing the Classification Learner in the MATLAB environment [31]. For stationary and dynamic data, optimization progress was performed with different algorithms, namely, decision trees, discriminant analysis, support vector machines, nearest neighbours, naive Bayes, ensemble, and neural network classification. In the sub-headings, the results obtained from these optimization processes are presented and compared.

Classifier options were tuned before starting the optimization. The random search method was selected as the optimizer option, and the iteration number was set as 30. After these settings, the optimization process is carried out with the specified features.

The previous section explains how the data was collected and labelled to train the classifier in stationary and dynamic scenarios. This section presents the validation results of the optimized classifiers evaluated with accuracy, precision, recall, and F1-score evaluation metrics.

1. *Classifier Optimization and Training for Stationary Scenarios*

The results of the evaluation for optimized classifiers in the stationary scenarios are presented in Table 3.

Table 4 Validation results of optimized classifiers in the stationary scenarios

Algorithm	Accuracy (%)	Precision	Recall	F1 Score
Decision Trees	98.57	0.9763	0.9620	0.9698
Discriminant Analysis	81.83	0.6140	0.5937	0.6037
Naive Bayes	81.97	0.5998	0.6161	0.6078
Support Vector Machines	97.66	0.9581	0.94067	0.9493
Nearest Neighbors	99.44	0.9892	0.9867	0.9880
Ensemble	**99.77**	**0.9968**	**0.9933**	**0.9950**
Neural Network	99.49	0.9934	0.9845	0.9889

As can be seen in Table 3, according to the validation results with 10% stationary data, it was observed that the best performance values were achieved with the ensemble algorithm. The ensemble algorithm was optimized with a full dataset for the system to be trained to perform the highest classification performance. Table 4 shows the best point hyperparameters of the optimized ensemble classifier with full parameters.

Table 5 The best point hyperparameters of the optimized classifier in the stationary scenarios

Algorithm	The Best Point Hyperparameters	Observed Minimum Classification Error
Ensemble	Ensemble Method: GentleBoost Number of Learners: 121 Learning Rate: 0.020235 Maximum Number of Splits: 122	0.0023048

The validation result of that classifier can be seen in Table 5. As expected, the system optimized with full parameters showed a better result.

Table 6 Validation result of the optimized classifier in the stationary scenarios

Algorithm	Accuracy (%)	Precision	Recall	F1 Score
Ensemble	99.96	0.9993	0.9992	0.9992

Later in the study, the classifier obtained from this optimization is used to enhance stationary position estimation.

2. *Classifier Optimization and Training for Dynamic Scenarios*
   The results of the evaluation for optimized classifiers in the dynamic scenarios are presented in Table 6.

Table 7 Validation results of optimized classifiers in the dynamic scenarios

Algorithm	Accuracy (%)	Precision	Recall	F1 Score
Decision Trees	99.48	0.9850	0.9813	0.9831
Discriminant Analysis	88.42	0.8019	0.3271	0.4646
Naive Bayes	87.95	0.6916	0.3887	0.4977
Support Vector Machines	95.37	0.9652	0.8100	0.8809
Nearest Neighbors	99.37	0.9813	0.9777	0.9795
Ensemble	**99.73**	**0.9911**	**0.9916**	**0.9913**
Neural Network	94.47	0.8463	0.7824	0.8131

As can be seen in Table 6, according to the validation results with 10% stationary data, it is observed that the best performance is achieved with the ensemble algorithm. The algorithms were optimized with the entire dataset for the system to be trained to perform the highest classification performance. Table 7 shows the best point hyperparameters of the optimized ensemble classifier with full parameters.

Table 8 Validation result of the optimized classifier in the dynamic scenarios

Algorithm	The Best Point Hyperparameters	Observed Minimum Classification Error
Ensemble	Ensemble Method: GentleBoost Number of Learners: 79 Learning Rate: 0.0055994 Maximum Number of Splits: 10572	0.0018193

The validation result of that classifier can be seen in Table 8. As expected, the system optimized with full parameters showed a better result.

Table 9 Validation result of the optimized classifiers in the dynamic scenarios

Algorithm	Accuracy (%)	Precision	Recall	F1 Score
Ensemble	99.82	0.9943	0.9938	0.9941

Later in this study, the classifier obtained from this optimization is used to enhance dynamic position estimations.

C. INS/GPS position estimation

In this section, our propsed method to estimate position is explained. Figure 6, the blue blocks illustrate the functional diagram of a standard GPS user equipment to perform PNT estimation [32] and the green blocks illustrate the proposed system architecture added to enhance GPS performance. Signal classification and navigation processor blocks coded in MATLAB environment.

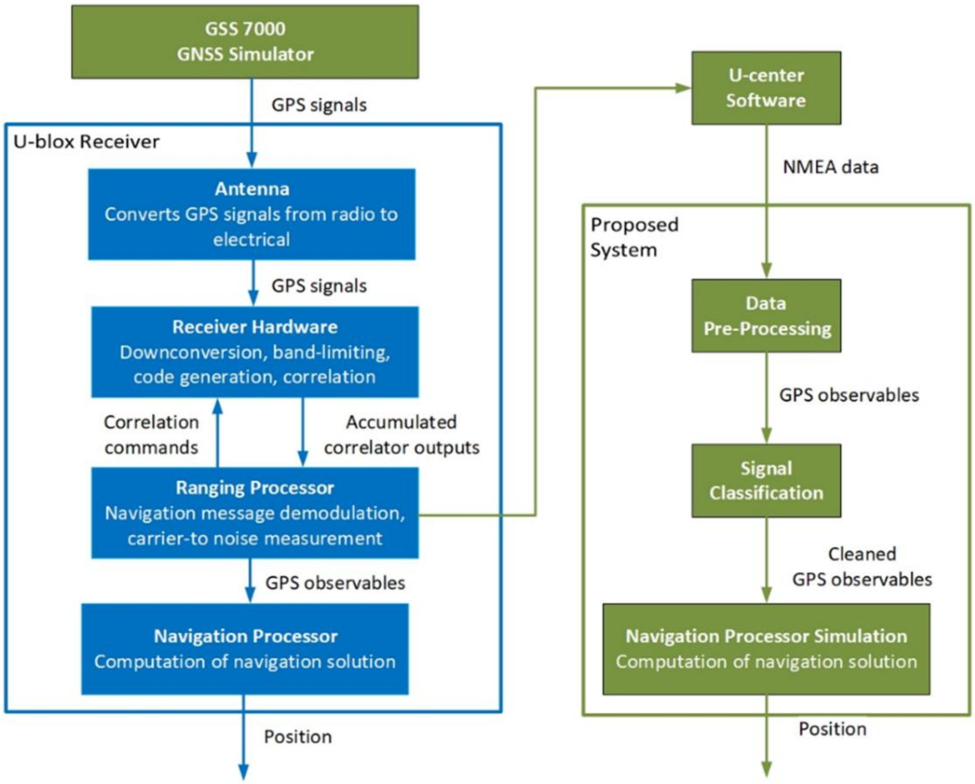

Figure 6 Standard GPS user equipment functional diagram [32] **and our proposed method**

Our classification system extracts the recognized signals according to the fault detection results and uses only the clean signals for the GPS calculation to enable the system to estimate position with less error. For position calculation after extracting faulty signals, the data free from multipath is processed with a GPS receiver model coded in the MATLAB environment since we are not allowed to modify the U-blox receiver according to our needs. In order to test the performance of our proposed solution, first, the position estimations are carried out without any signal elimination. Afterwards, the signals determined to be indirect according to the signal classifier results are excluded from the NMEA message and positions are estimated again. These position estimations were made with a receiver model provided by MATLAB Navigation Toolbox [33].

After estimating GPS positions, the INS and fusion steps were performed to see the effect of the classification system on the resulting position estimation. GSSS 7000 could also provide accelerometer and gyroscope data. To make this data realistic, noise has been added in accordance with a low-cost IMU characteristic.

In order to estimate the INS position and fuse this position with the GPS position, a loosely coupled EKF was utilized. As mentioned in the previous section, The Global Positioning System and Inertial Navigation Systems are technologies that complement one another. INS provides high-frequency data. However, due to sensor features, the system drifts, which will cause big errors in the long term. Also, GPS is long-term accurate but requires access to GPS signals [6].

V. RESULTS & DISCUSSION

In this section, the classification system performance and its effect on enhancing position estimation are presented. After that, the system performance of the classification process, enhancing accuracy at various levels, its limitations, and what should be done to improve this system were discussed.

A. Classification Process

In order to test the performance of the classifier, test data is generated in the simulation that is not used for training. When simulating test data, another day was simulated from the day the training data were collected. Two different 12-hour test data, stationary and dynamic, were collected. In these data, as in the previous sections, the necessary labelling was done with the help of simulation data. The performance of the classification algorithm developed with these labelled data has been tested in this section, and the results are presented.

In order to test the performance of the system, the system was tested with 12-hour-long test data that is not used in training and was collected as described in the data collection section. The performance of the classifier can be seen in Table 10.

Table 10 Test result of the ensemble classifiers

Model	Algorithm	Accuracy (%)	Precision	Recall	F1 Score
Stationary	Ensemble	94.56	0.8266	0.9593	0.8881
Dynamic	Ensemble	91.75	0.8428	0.7741	0.8070

Looking at the results, as expected, it has been observed that the classifier in the dynamic scenario performs less effectively than the stationary one. However, we obtained an efficient overall accuracy of 94.57% for stationary and 91.75% for dynamic. The following sections will further discuss how classification performance affects the proposed GPS performance enhancement method.

B. GPS Performance Enhancement

95th percentile errors are investigated in this section for six scenarios (3 dynamic and 3 stationary scenarios) to assess the performance of the proposed enhancement method. These test scenarios were designed as 15-minute scenarios at different times of the day where data was collected for testing. For a more effective performance evaluation, the position accuracy is calculated by considering three cases. In the first case, the accuracy was calculated without applying signal exclusion. The outputs provided by the proposed classification algorithm were used in the second one. And in the last case, the ideal condition is taken into account, assuming that all indirect signals are classified correctly. The results from these three cases are presented and discussed for each scenario in the following sections.

1. Stationary Scenario Horizontal Error

In this section, the horizontal position enhancement obtained with the proposed system for the static scenario is presented.

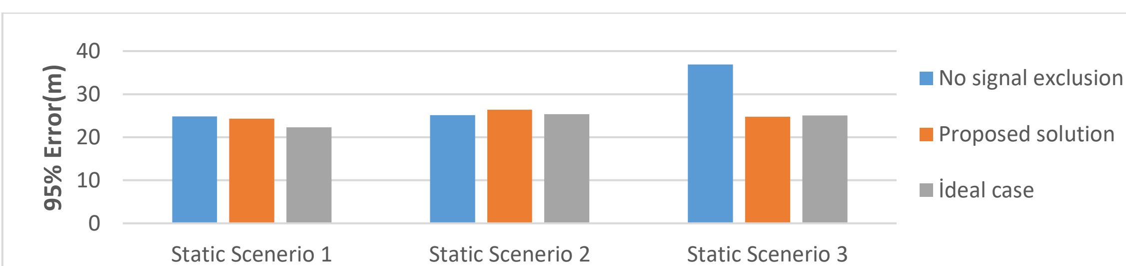

Figure 7 Horizontal error values for stationary scenarios

In Figure 7, horizontal error values can be seen for all static scenarios. While the system developed in the third scenario succeeded in reducing the error significantly, the situation was not the same in other scenarios. The positional error was slightly improved in the first scenario, while in the second scenario, a slight increase in the error was observed. Overall, the proposed method is able to reduce 10.7% of error I horizontal axis for stationary scenarios. In order to understand whether the error increases are due to misclassification, the results were compared with the absolute accuracy of signal elimination, and it was seen that the results were similar to the developed system. HDOP values can be seen in Figure 8 to examine this situation in more detail.

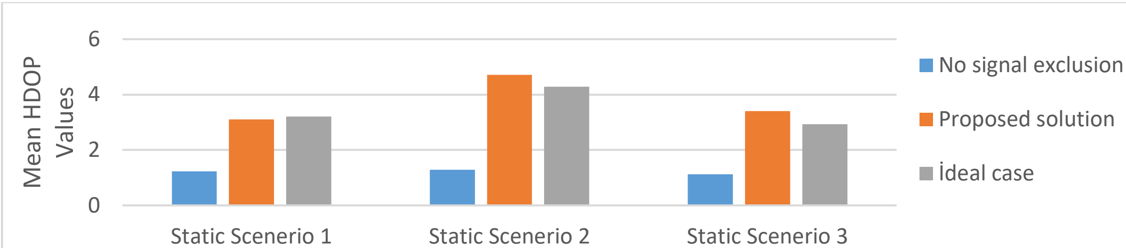

Figure 8 Mean HDOP values for stationary scenarios

As it can be understood from the HDOP values in figure 8, when the signal is eliminated, the satellite constellation deteriorates as the number of satellites from which the signal is received decreases. Especially in the second case, the HDOP value increased significantly, so the error increased instead of decreasing with the developed system.

2. Stationary Scenario Vertical Error

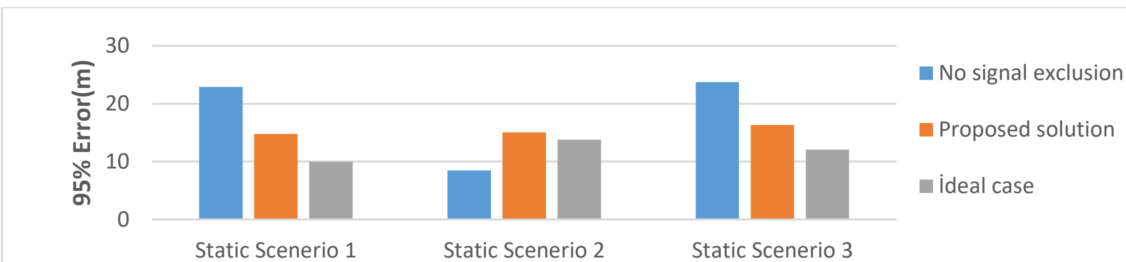

Figure 9 Vertical error values for stationary scenarios

Considering the error values on the vertical axis, the proposed system significantly reduced the error in the position estimation in the first and third scenarios, but in the second scenario, the error value increased. On the vertical axis, the proposed method was reduced by 16.4% error based on the average of these scenarios. In addition, it was determined that the developed system had a higher absolute accuracy than the elimination system due to some misclassification operations. It has been observed that this misclassification is more specific on the vertical axis than on the horizontal axis. When examining the cause of the increase in the second scenario, it is observed that the VDOP value rises 269% after signal elimination.

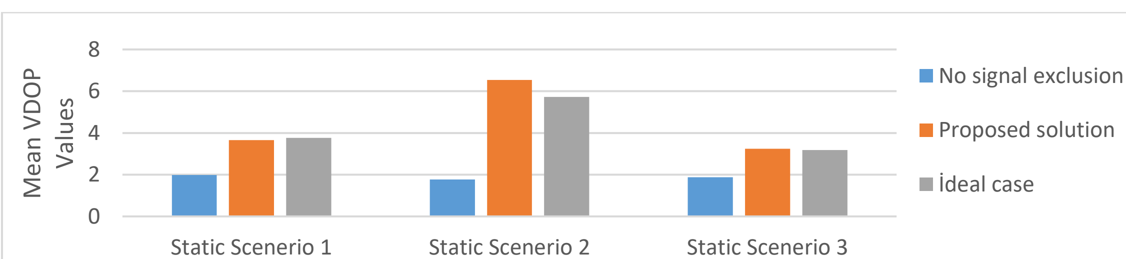

Figure 10 Mean VDOP values for stationary scenarios

When examining the cause of the increase in the second scenario, the increase in the VDOP value once again stands out.

3. Dynamic Scenario Horizontal Error

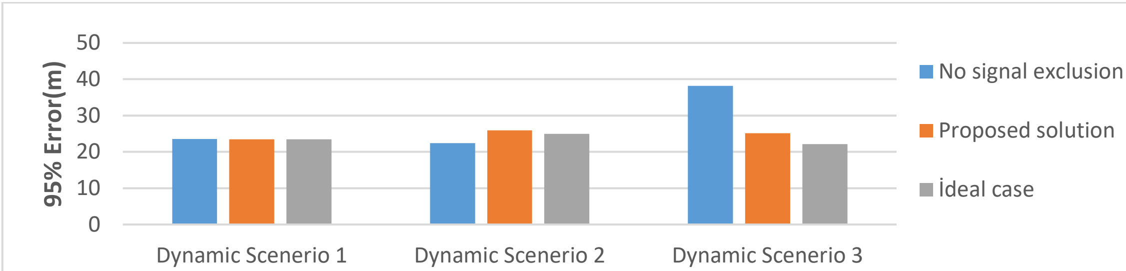

Figure 11 Horizontal error values for dynamics scenarios

When examining the results on the horizontal axis in the dynamic scenario, the proposed system revealed no noticeable change in the first scenario, whereas it slightly increased the error in the second scenario. In scenario 2, when we examine the increase in HDOP values, the HDOP value before elimination is very close to 1. Overall, the proposed system is able to reduce by 10 % error. In this instance, good satellite consolation was not significantly impaired by signal loss, but it did increase the system position estimation error. In scenario 1, the HDOP values for all compared systems are nearly the same. In scenario 3, although DOP values increased as a result of signal elimination, the system significantly improved position estimation.

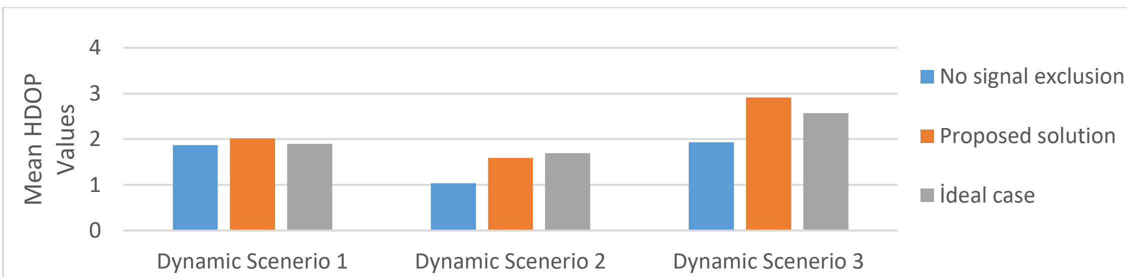

Figure 12 Mean HDOP values for dynamics scenarios

Although satellite correlation observed in DOP values in system position improvement is an important parameter, it is insufficient to explain the entire system's performance.

4. Dynamic Scenario Vertical Error

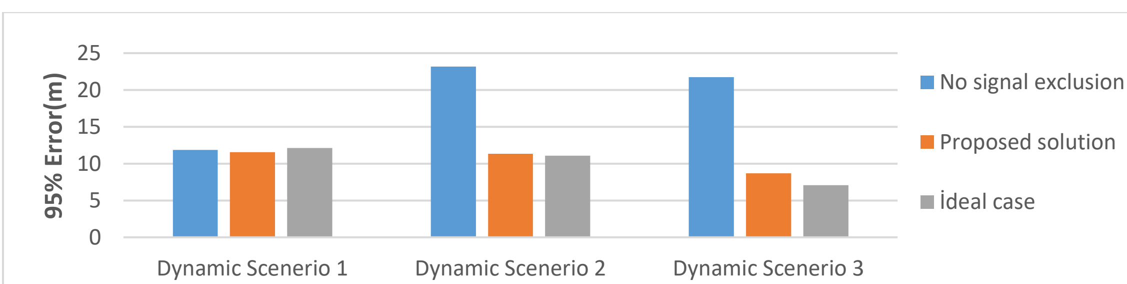

Figure 13 Vertical error values for dynamics scenarios

The system developed in scenario 1 was able to achieve a very low error reduction. In dynamic scenarios, the system is able to reduce 43% error for position estimation. In addition, it is seen that the error of position estimation made by signal elimination using absolute correct data is higher. The underlying reason is that some indirect signals are misclassified as direct signals and included in position estimation. Also, it has been observed that when these signals are eliminated, the DOP value deteriorates, and the error increases instead of decreasing.

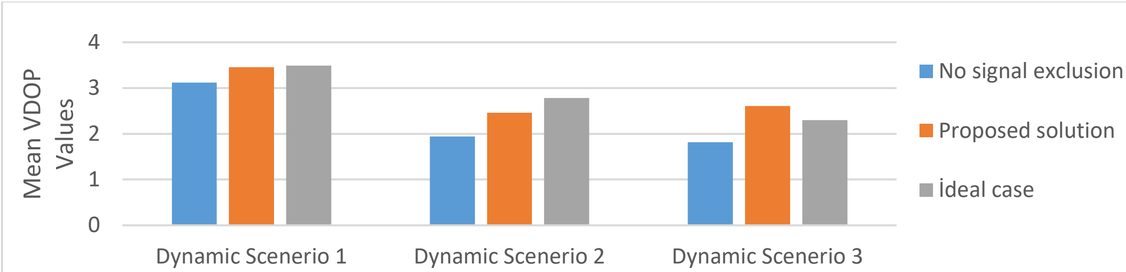

Figure 14 Mean VDOP values for dynamics scenarios

C. INS/GPS Integration

The system, which was developed to enhance position estimation in the urban environment, first classifies signals with GPS observables values. That is why the entire system's success is dependent on the classifier's accuracy. It was observed that the classifier provided accurate results in the tests. In addition, the performance of the proposed solution was similar to ideal cases in many scenarios.

The performance of the system as a result of the classification, detection, and elimination of indirect signals, as well as the utilization of direct signals and GPS location, was presented and discussed. However, since the system will use the position information obtained after INS/GPS integration, the performance of the system as a result of this integration is crucial. In this section, the effect of the proposed system on the estimation of the final position in various scenarios is discussed.

Figure 15 contrasts the GPS performance of the developed system with that of the standard system. In two of the six scenarios, it significantly improved the system's position estimation. In the two scenarios, the system's performance is slightly lower than its overall performance, and there is no noticeable difference between the two scenarios.

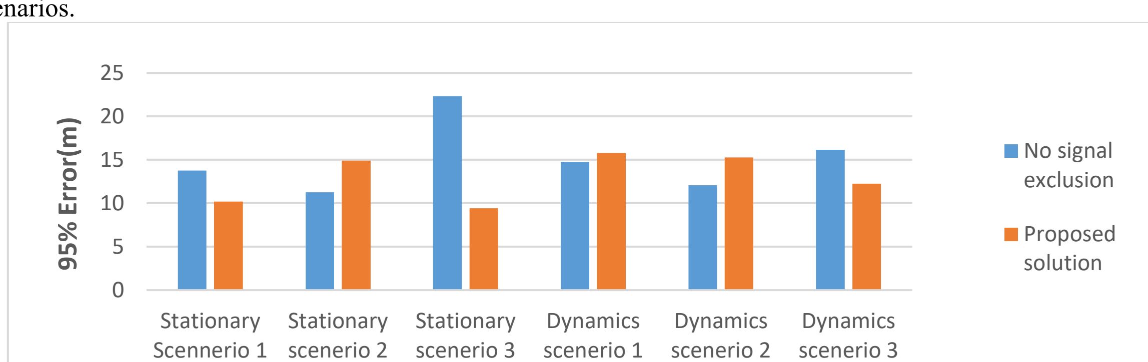

Figure 15 INS/GPS horizontal errors

The performance of the system decreased in two of the six scenarios on the horizontal axis, whereas the position estimation performance of the system increased in three scenarios. In addition, there was no significant change in the first scenario. It has been determined that the performance of the horizontal system as a result of INS/GPS fusion is related to the GPS performance and HDOP. However, as seen in static scenario 1, even though the GPS error is comparable, the performance of the system developed after INS/GPS fusion has improved. It was hypothesized that the developed system's error value was less than the standard deviation and that this could have been the cause.

Regarding error values along the vertical axis, the proposed system is more effective by reducing %13.9 errors along this axis than along the horizontal axis.

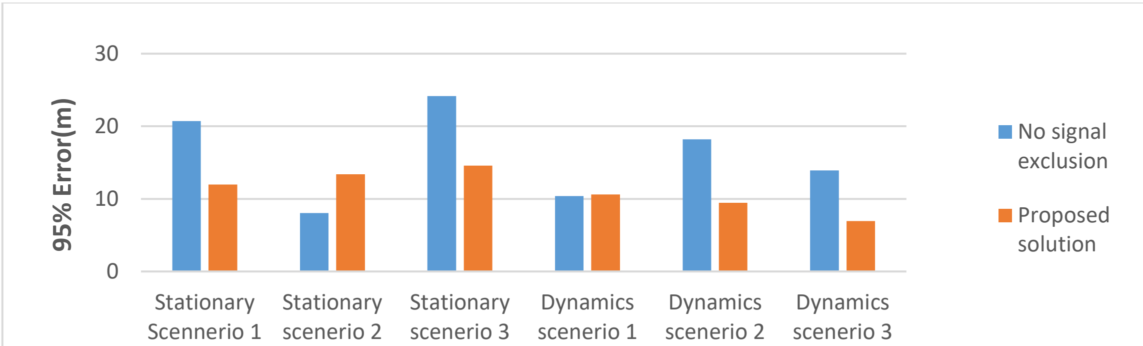

Figure 16 INS/GPS vertical errors

When examining the INS/GPS fusion results for the vertical axis, similar results to the GPS only are observed. The proposed system was able to enhance position estimation resulting in an error reduction of 29.8%. In situations where the system cannot improve or where the error value increases, it is believed that the observed increase in VDOP values is due to visible satellite configuration.

VI. Conclusion

This paper proposes classifying and eliminating indirect signals from position estimation to enhance INS/GPS performance in urban environments. In order to see the effect of direct and indirect signals on final position estimation, position estimation was made without signal elimination and with signal elimination, using the receiver model in MATLAB environment, and error values were compared at different levels such as GPS position and INS/GPS position.

After the data collection and labelling process, different machine learning algorithms were optimized and trained to determine which algorithm shows the best performance. It was observed that the ensemble classification algorithm showed the best performance among compared algorithms, with 94.57% accuracy for the stationary scenarios and 91.75% accuracy for the dynamic scenarios.

Before investigating the horizontal and vertical results, the reasons why vertical accuracy is better than horizontal ones in some scenarios need to be addressed for a better discussion. Ideally, the horizontal accuracy of the GPS is expected to be more reliable than the vertical accuracy. However, in this study, some vertical accuracy results are better than horizontal ones. It can be caused for two reasons. The first one is insufficient data scattering in the vertical axis. Since the selected flight trajectories have a fixed altitude, the vertical position of the UAV remains constant without error in the simulation environment, while the horizontal position changes according to the flight trajectory during the simulation. Consequently, the training and test data consist of repeated values at the same altitude, which is why GPS estimation showed better performance in the vertical axis. The second reason might be that the receiver model, which is coded in MATLAB, does not reflect GPS error model realistically in position estimations. Under normal circumstances, position estimation should not be relied on in such cases, but in this study, it was thought that this would have a similar effect on the comparison results since the scope of the study was not integrity but indirect signal detection and elimination of them from position estimation.

Using the proposed solution, received signals were classified with the developed ensemble algorithm, and the system success was evaluated by estimating the position with and without signal elimination. Overall, the proposed system is able to reduce position error by 25.68% for stationary scenarios and 17.71% for dynamic scenarios for low-cost INS/GPS navigation systems without increasing the weight and cost of the aircraft.

Despite the successful performance of the classification algorithm, it was observed that the error of the system increased in some scenarios tested. Even if signals are eliminated using labelled true data, it is observed that in these cases, the error is still higher than the system without signal elimination. When the DOP values are considered as the error increases, it is observed that these values increase significantly as a consequence of signal elimination. Therefore, it has been decided that the increase in error is related to the geometry of the satellite. That is why it has been observed that performing an elimination without taking satellite constellations into account will have limited success in enhancing system accuracy.

References

[1] A. Straubinger, R. Rothfeld, M. Shamiyeh, K. D. Büchter, J. Kaiser, and K. O. Plötner, "An overview of current research and developments in urban air mobility – Setting the scene for UAM introduction," *J Air Transp Manag*, vol. 87, 2020, doi: 10.1016/j.jairtraman.2020.101852.

[2] J. Zidan, E. I. Adegoke, E. Kampert, S. A. Birrell, C. R. Ford, and M. D. Higgins, "GNSS Vulnerabilities and Existing Solutions: A Review of the Literature," *IEEE Access*, vol. 9, pp. 153960–153976, 2021, doi: 10.1109/ACCESS.2020.2973759.

[3] N. Zhu, J. Marais, D. Betaille, and M. Berbineau, "GNSS Position Integrity in Urban Environments: A Review of Literature," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 9, pp. 2762–2778, Sep. 2018, doi: 10.1109/TITS.2017.2766768.

[4] O. K. Isik, J. Hong, I. Petrunin, and A. Tsourdos, "Integrity Analysis for GPS-Based Navigation of UAVs in Urban Environment," *Robotics*, vol. 9, no. 3, p. 66, Aug. 2020, doi: 10.3390/robotics9030066.

[5] V. G. Virball, W. R. Michalson, P. L. Levin, and P. K. Enge, "A GPS integrity channel based fault detection and exclusion algorithm using maximum solution separation," in *Proceedings of 1994 IEEE Position, Location and Navigation Symposium - PLANS'94*, pp. 747–754. doi: 10.1109/PLANS.1994.303385.

[6] Y. Li and X. Xu, "The application of EKF and UKF to the SINS/GPS integrated navigation systems," *2nd International Conference on Information Engineering and Computer Science - Proceedings, ICIECS 2010*, 2010, doi: 10.1109/ICIECS.2010.5678253.

[7] S. Achanta, S. T. Watt, and E. Sagen, "Mitigating GPS Vulnerabilities," *Power and Energy Automation ConferenceSpokane*, 2015.

[8] T. Lan, A. Dodinoiu, A. Geffert, and U. Becker, "3.1 Machine-Learning-Based Position Error Estimation for Satellite-Based Localization Systems," in *Proceedings - ettc2020*, 2020, pp. 89–97. doi: 10.5162/ettc2020/3.1.

[9] P. D. Groves *et al.*, "Novel Multipath Mitigation Methods using a Dual-polarization Antenna," *International Technical Meeting of the Satellite Division ofThe Institute of Navigation*, 2014, [Online]. Available: https://www.researchgate.net/publication/265035422

[10] B. Guermah, H. el Ghazi, T. Sadiki, and H. Guermah, "A Robust GNSS LOS/Multipath Signal Classifier based on the Fusion of Information and Machine Learning for Intelligent Transportation Systems," *2018 IEEE International Conference on Technology Management, Operations and Decisions, ICTMOD 2018*, pp. 94–100, Jul. 2018, doi: 10.1109/ITMC.2018.8691272.

[11] D. Tang, D. Lu, B. Cai, and J. Wang, "GNSS Localization propagation error estimation considering environmental conditions," in *Proceedings of 2018 16th International Conference on Intelligent Transport System Telecommunications, ITST 2018*, 2018. doi: 10.1109/ITST.2018.8566771.

[12] J. Marais, S. A. Kazim, Y. Cocheril, and C. Meurie, "Multipath and NLOS detection based on the combination of CN0 values and a fish-eye camera," in *2020 European Navigation Conference, ENC 2020*, 2020. doi: 10.23919/ENC48637.2020.9317408.

[13] O. M. Mubarak and A. G. Dempster, "Analysis of early late phase in single-and dual-frequency GPS receivers for multipath detection," *GPS Solutions*, vol. 14, no. 4, pp. 381–388, Sep. 2010, doi: 10.1007/s10291-010-0162-z.

[14] E. Munin, A. Blais, and N. Couellan, "Convolutional neural network for multipath detection in GNSS receivers," *2020 International Conference on Artificial Intelligence and Data Analytics for Air Transportation, AIDA-AT 2020*, Feb. 2020, doi: 10.1109/AIDA-AT48540.2020.9049188.

[15] T. Ozeki and N. Kubo, "GNSS NLOS Signal Classification Based on Machine Learning and Pseudorange Residual Check," *Front Robot AI*, vol. 9, May 2022, doi: 10.3389/FROBT.2022.868608/FULL.

[16] J. Gong, R. Ma, D. Li, and J. Zhao, "GNSS Multipath Mitigation Method Based on K-means Classification in Urban Environment," *Journal of the Indian Society of Remote Sensing*, vol. 50, no. 5, pp. 805–813, May 2022, doi: 10.1007/S12524-022-01494-Y.

[17] L. T. Hsu, "GNSS multipath detection using a machine learning approach," *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, vol. 2018-March, pp. 1–6, Mar. 2018, doi: 10.1109/ITSC.2017.8317700.

[18] R. Sun *et al.*, "Improving GPS Code Phase Positioning Accuracy in Urban Environments Using Machine Learning," *IEEE Internet Things J*, vol. 8, no. 8, pp. 7065–7078, Apr. 2021, doi: 10.1109/JIOT.2020.3037074.

[19] C. Jiang *et al.*, "Multipath/NLOS Detection Based on K-Means Clustering for GNSS/INS Tightly Coupled System in Urban Areas," *Micromachines 2022, Vol. 13, Page 1128*, vol. 13, no. 7, p. 1128, Jul. 2022, doi: 10.3390/MI13071128.

[20] L. Zhao, W. Y. Ochieng, M. A. Quddus, and R. B. Noland, "An Extended Kalman Filter Algorithm for Integrating GPS and Low Cost Dead Reckoning System Data for Vehicle Performance and Emissions Monitoring," *Journal of Navigation*, vol. 56, no. 2, pp. 257–275, May 2003, doi: 10.1017/S0373463303002212.

[21] Y. Li and X. Xu, "The Application of EKF and UKF to the SINS/GPS Integrated Navigation Systems," in *2010 2nd International Conference on Information Engineering and Computer Science*, Dec. 2010, pp. 1–5. doi: 10.1109/ICIECS.2010.5678253.

[22] "GNSS Simulator, Reliable Results, Faster - GSS7000 - Spirent." https://www.spirent.com/products/gnss-simulator-gss7000 (accessed Aug. 06, 2022).

[23] "ZED-F9P module | u-blox." https://www.u-blox.com/en/product/zed-f9p-module (accessed Aug. 06, 2022).

[24] "u-center | u-blox." https://www.u-blox.com/en/product/u-center (accessed Aug. 06, 2022).

[25] Z. Zhao, R. Anand, and M. Wang, "Maximum Relevance and Minimum Redundancy Feature Selection Methods for a Marketing Machine Learning Platform," *International Conference on Data Science and Advanced Analytics*, 2019.

[26] "Rank features for classification using minimum redundancy maximum relevance (MRMR) algorithm - MATLAB fscmrmr - MathWorks United Kingdom." https://uk.mathworks.com/help/stats/fscmrmr.html (accessed Aug. 07, 2022).

[27] F. Demir, "Deep autoencoder-based automated brain tumor detection from MRI data," *Artificial Intelligence-Based Brain-Computer Interface*, pp. 317–351, Jan. 2022, doi: 10.1016/B978-0-323-91197-9.00013-8.

[28] M. Millidere, F. S. Gomec, H. B. Kurt, and F. Akgul, "Multi-Fidelity Aerodynamic Dataset Generation of a Fighter Aircraft with a Deep Neural-Genetic Network," in *AIAA AVIATION 2021 FORUM*, Aug. 2021. doi: 10.2514/6.2021-3007.

[29] M. Millidere, H. B. Kurt, H. Balli, and O. Ugur, "Kalman Based Neural Network Model Analysis with Resampling Methods for Longitudinal Aerodynamic Coefficient Estimation," in *AIAA AVIATION 2020 FORUM*, Jun. 2020. doi: 10.2514/6.2020-3197.

[30] A. E. Maxwell, T. A. Warner, and F. Fang, "International Journal of Remote Sensing Implementation of machine-learning classification in remote sensing: an applied review Implementation of machine-learning classification in remote sensing: an applied review," *Int J Remote Sens*, 2018, doi: 10.1080/01431161.2018.1433343.

[31] "Train models to classify data using supervised machine learning - MATLAB - MathWorks United Kingdom." https://uk.mathworks.com/help/stats/classificationlearner-app.html (accessed Aug. 07, 2022).

[32] P. D. (Paul D. Groves, *Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems*, vol. Second Edition. 2013.

[33] "Navigation Toolbox Documentation - MathWorks United Kingdom." https://uk.mathworks.com/help/nav/index.html?s_tid=CRUX_lftnav (accessed Aug. 09, 2022).

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