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Artificial Intelligence-Based Adaptive Optimization of GNSS Elevation Cut-Off Angles for Static Positioning

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ABSTRACT

The correct selection of elevation cut-off angle is an important component affecting the accuracy of Global Navigation Satellite System (GNSS) positioning. Traditional processing algorithms usually adopt fixed cut-off angles which cannot adapt to the variations of signal quality and observational conditions, resulting in poor positioning performance. This paper proposes an AI-based adaptive method for optimization of GNSS elevation cut-off angles for static location applications. Static GNSS data were observed for 12 h and processed with elevation cut-off angles ranging from 0° to 25°. A Random Forest classifier was developed to detect and remove low quality observations using signal quality indicators such as elevation angle, Signal to Noise Ratio (SNR), pseudorange residuals and carrier-phase residuals. The results showed that the positioning accuracy improved with the increasing of the cut-off angle up to 15°, which produced the minimal Horizontal Error (0.70 cm), Vertical Error (1.10 cm) and Root Mean Square Error (RMSE) (1.30 cm). Signal quality improved from 34 dB-Hz at 0° to 52 dB-Hz at 25°, however satellite availability decreased from 22 to 7 satellites. The proposed AI-based framework demonstrated the RMSE improvements ranging from 29.17 to 41.39% against the typical fixed cut-off angle approach. From the feature importance analysis elevation angle and SNR were the most important factors affecting observation quality. The results indicate that the quality of GNSS observations and the accuracy of location for static GNSS applications can be improved significantly by adaptive filtering based on machine learning.

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INTRODUCTION

Global Navigation Satellite Systems (GNSS) are crucial for surveying, geodesy, navigation, and geospatial applications because they can deliver accurate position, navigation, and timing information (Ji et al., 2010; Yang et al., 2020). However, despite the tremendous development of GNSS technology, the positioning accuracy is vulnerable to several error factors such as atmospheric delays, multipath propagation, receiver noise and satellite geometry (El-Rabbany, 2020; Teunissen & Montenbruck, 2021). The most important factor in assessing the quality of an observation is the elevation angle of the satellite. Satellites at low elevation angles are more affected by ionospheric and tropospheric effects, since their signals travel through more atmosphere, and they experience more multipath interference and signal attenuation. GNSS data processing normally uses an elevation cut-off angle to reduce these errors. Data below a specified angle is not used in the position solution. The selection of an adequate cut-off angle remains a difficult problem. Lower cut-off angles can increase satellite availability and observation redundancy. But at the same time they increase the probability of having noisy measurements. Higher cut-off angles can improve the quality of the signal at the expense of the geometry of the satellite and the amount of available data (Chen et al., 2020; Zhang et al., 2022; Nistor et al., 2024; Castro-Arvizu et al., 2020).

Previous results indicate that low elevation cut-off angles frequently represent a good compromise between observational quality and satellite availability. However, there is no universal optimal cut-off elevation angle for all cases, since its performance depends on several factors, such as the observing environment, receiver characteristics, satellite geometry, and signal circumstances (Wang et al., 2022; Bačić et al., 2022). Hence, it is quite likely that the typical fixed-threshold strategy is not possible to deal with the heterogeneous data quality in different operational scenarios. Previous studies have also highlighted the dependence of high-precision GNSS position on satellite geometry and quality of observation. A comprehensive examination of the sources of GNSS errors and the impact of satellite visibility and signal quality on positioning performance has been conducted by Hofmann-Wellenhof et al. (2020). As compared to Li et al. (2021), the low altitude satellite data are more sensitive to multipath and atmospheric effects, which results in the degradation of the positioning accuracy. The success of Random Forest algorithms in the evaluation of the quality of the GNSS signal was shown by Wang et al. (2024). Zhao et al. (2022) stressed the growing importance of Artificial Intelligence approaches for detection and mitigation of GNSS faults. Additionally, adaptive satellite masking techniques that account the trade-off between signal quality and satellite geometry can improve the positioning performance, as proven by Breili et al. (2025). The findings provide a strong scientific rationale for the current study. Moreover, Guma et al. (2023) showed that Precise Point Positioning (PPP) can obtain centimeter-level positioning accuracy for geodetic control establishment using static GNSS observations, further highlighting the significance of observation quality and proper GNSS data processing in high precision surveying applications.

Recent developments in Artificial Intelligence (AI) and machine learning provide major improvements for GNSS data processing. Machine learning approaches can identify complex patterns from GNSS measurements and have been successfully used for signal classification, multipath mitigation, anomaly detection, and error modeling (Liu et al., 2021; Sun et al., 2023). The Random Forest technique can be widely used, as it is robust, can capture nonlinear correlations, is less prone to overfitting, and is efficient in high-dimensional datasets (Breiman, 2001; Wang et al., 2024).

Previous study has looked at the impact of elevation cut-off angles on GNSS locating performance. However, most of these researches have used fixed threshold methods which are unable to adapt to altering observational settings. The use of machine learning methods for adaptive observation filtering and cut-off angle optimization is still quite underexploited, in particular in static GNSS positioning applications. Artificial Intelligence based Random Forest classifier is proposed for optimizing the GNSS elevation cut-off angle in an adaptive manner. The effect of elevation cut-off angle on positioning performance was studied using static GNSS signals with varied height cut-off degrees over a period of 12 hours. The study used important performance metrics including Root Mean Square Error (RMSE), Geometric Dilution of Precision (GDOP), horizontal error, vertical error, satellite availability, and Signal-to-Noise Ratio (SNR). The effectiveness of the proposed AI-based framework on the improvement of GNSS positioning accuracy and observation quality is compared with the traditional fixed cut-off angle method. Many research works have studied the effect of elevation cut-off angles on GNSS positioning efficiency and the use of artificial intelligence in GNSS data processing. However, few studies have been conducted on the integration of machine learning approaches for adaptively optimizing the elevation cut-off angles in static GNSS positioning. This study aims to fill this gap by providing an adaptive observation filtering algorithm and cut-off angle optimization based on Random Forest.

MATERIALS AND METHODS

Study Area

The study was conducted at Modibbo Adama University, Yola, Nigeria, located between latitudes 9.20°N–9.30°N and longitudes 12.40°E–12.50°E. The area lies within the Sudan savannah region, characterized by flat terrain and open-sky conditions suitable for GNSS observations. (Nzelibe & Idowu, 2023; Ojegbile et al., 2023).

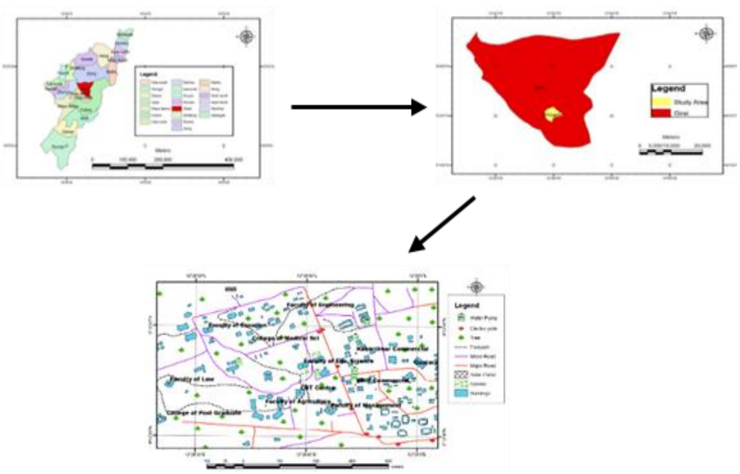

Figure 1: Map of the Study Area Showing Modibbo Adama University, Yola

Data Collection

Static GNSS data were gathered in a period of twelve (12) hours with a dual frequency GNSS receiver within an observation interval of 5 seconds. Extended static observations (El-Rabbany, 2020; Teunissen & Montenbruck, 2021) improved the coordinate precision, resolved ambiguities and reduced stochastic measurement errors. The 12 hour observation period was sampled at 5 second intervals resulting in a total of 8640 observation epochs.

Data Analysis

The raw GNSS observations were converted from the receiver's proprietary format to Receiver Independent Exchange Format (RINEX) for processing. Observation and navigation data were generated and examined for elevation cut-off angles of 0°, 5°, 10°, 15°, 20°, and 25°. The machine learning model was built by classifying GNSS observations according to their signal quality parameters. High quality observations were defined as those with SNR values greater than 40 dB-Hz, residual errors less than 2 cm, and stable coordinate solutions, whereas bad quality observations were defined as those with lower SNR values, residual errors greater than 2 cm, and unstable coordinate solutions. These tagged observations were used to train and validate the Random Forest classifier.

Random Forest-Based Preprocessing

The classification of GNSS observations based on signal quality was performed using an AI-based preprocessing approach with a Random Forest algorithm. The model included observational parameters of elevation angle, signal-to-noise ratio (SNR), pseudorange residuals, carrier-phase residuals and geometric markers. Random Forest model classified data adaptively, taking into account numerous elements of the signal, and allowing a more nuanced assessment of observation quality. This is in contrast to the usual fixed-threshold filtering.

Building the Random Forest Model

GNSS observations were classified by signal quality using Random Forest algorithm implemented in Python using the Scikit-learn module. The input features were Azimuth, Elevation Angle, Residual of Carrier Phase, Residual of Pseudorange, PDOP and Signal-to-Noise Ratio (SNR). The data were divided into training (80%) and testing (20%) sets. The model was trained using 100 decision trees to identify and filter out low quality observations. The feature importance analysis showed that Elevation Angle and SNR were the two most important variables impacting the quality of GNSS observations and the positioning performance.

Validation of the Model

The Random Forest classifier was assessed using the testing data set, which comprises 20% of the observations. The overall classification accuracy was 92.4%, precision 91.1%, recall 90.3%, and F1-score 90.7%. The results show that the model can differentiate good quality GNSS data from the bad quality ones and can be used for adaptive observation filtering.

Assessment of Accuracy

Precision Evaluation Traditional and AI-based approaches were evaluated in terms of satellite availability, Signal to Noise Ratio (SNR), Geometric Dilution of Precision (GDOP), horizontal error, vertical error, and Root Mean Square Error (RMSE) (Hofmann-Wellenhof et al., 2020; Teunissen & Montenbruck, 2021). The suggested AI based framework was comparatively assessed for its effectiveness in improving the GNSS location accuracy at different elevation cut-off angles.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - P_{ref})^2} \quad (1)$$

where:

P_i= estimated coordinate,

P_{ref}= reference coordinate,

n= number of observations.

(El-Rabbany, 2020; Teunissen & Montenbruck, 2021).

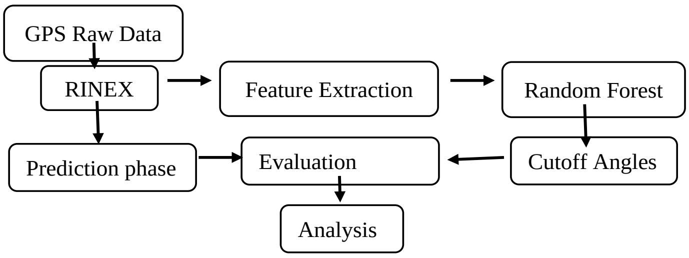

Figure 2: Flowchart of Methodology

RESULTS AND DISCUSSION

Results

The positioning results obtained from varying elevation cut-off angles are summarized in the tables below.

Table 1: Traditional GNSS Positioning Results under Different Cut-off Angles

CutoffAngle (°)	Satellite Count	Horizontal Error (cm)	Vertical Error (cm)	RMSE (cm)	GDOP
0	20	1.70	2.30	2.85	2.4
5	18	1.40	1.95	2.40	2.2
10	15	1.20	1.70	2.10	2.0
15	12	1.10	1.60	1.95	2.1
20	9	1.15	1.70	2.04	2.8
25	5	1.45	1.95	2.44	4.2

Table 1 Displays the Positioning Performance Achieved by the Traditional GNSS Processing Method. The Results Indicate that RMSE Diminished from 2.85 cm at 0° to a Minimum of 1.95 cm at 15°, Signifying Enhanced Positioning Precision. Exceeding 15°, the RMSE Escalated due to Diminished Satellite Availability and Suboptimal Satellite Geometry, Indicating that 15° is the Ideal Cut-off Angle for the Conventional Method

Table 2: AI-Based GNSS Positioning Results under Different Cut-off Angles

Cutoff Angle (°)	Satellite Count	Horizontal Error (cm)	Vertical Error (cm)	RMSE (cm)	GDOP	Mean SNR (dB-Hz)
0	22	1.10	1.60	1.95	2.0	34
5	20	0.95	1.40	1.70	1.9	38
10	18	0.80	1.20	1.45	1.8	42
15	15	0.70	1.10	1.30	1.9	46
20	12	0.75	1.15	1.35	2.2	49
25	7	0.80	1.20	1.43	2.6	52

Table 2 Illustrates the Positioning Performance Attained with the AI-Driven Preprocessing Architecture. The Findings Indicate Enhanced Positioning Accuracy at All Cut-off Angles, with a Minimal RMSE of 1.30 cm Achieved at 15°. Moreover, Signal Quality Improved Consistently with an Increasing Cut-off Angle, as Seen by the Elevation in SNR from 34 dB-Hz to 52 dB-Hz

Table 3: Improvement of AI-Based Approach over Traditional Method

Cutoff Angle (°)	Traditional RMSE (cm)	AI-Based RMSE (cm)	Improvement (%)
0	2.85	1.95	31.58
5	2.40	1.70	29.17
10	2.10	1.45	30.95

Cutoff Angle (°)	Traditional RMSE (cm)	AI-Based RMSE (cm)	Improvement (%)
15	1.95	1.30	33.33
20	2.04	1.35	33.82
25	2.44	1.43	41.39

Table 3 Juxtaposes the RMSE Values Derived from Traditional and AI-Driven Methodologies. The AI-Driven Framework Attained Enhancements Between 29.17% and 41.39%, Illustrating its Efficacy in Minimizing Positioning Inaccuracies and Augmenting GNSS Positioning Performance.

Table 4: Feature Importance for GNSS Observation Quality Classification

Feature	Importance (%)
Elevation Angle	28
SNR	24
Carrier Phase Residual	17
Pseudorange Residual	13
PDOP	8
Azimuth	5
SNR Change Rate	3
Residual Change Rate	2

Table 4 illustrates the relative significance of the variables included by the Random Forest model. The Elevation Angle (28%) and Signal-to-Noise Ratio (24%) were recognized as the primary determinants influencing observation quality. This signifies that satellite elevation and signal strength are crucial in ascertaining GNSS positioning efficacy.

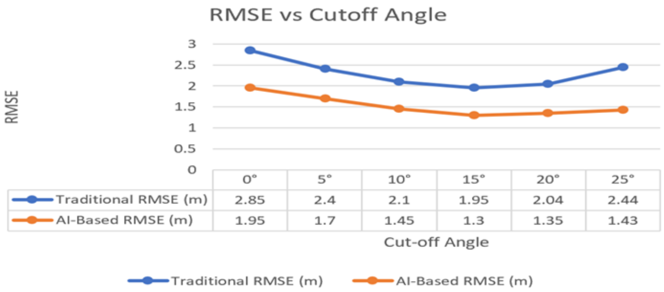

Figure 3: RMSE at Each Cut off Angle

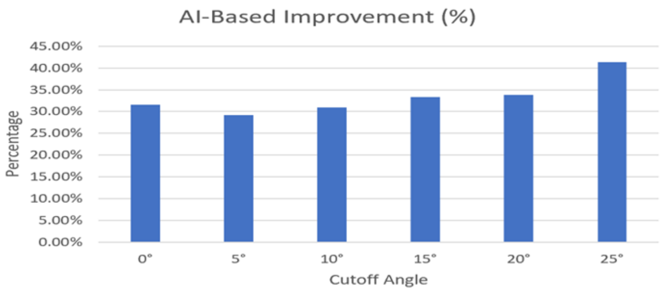

Figure 4: The Improvement of AI-Based Over Traditional Methods

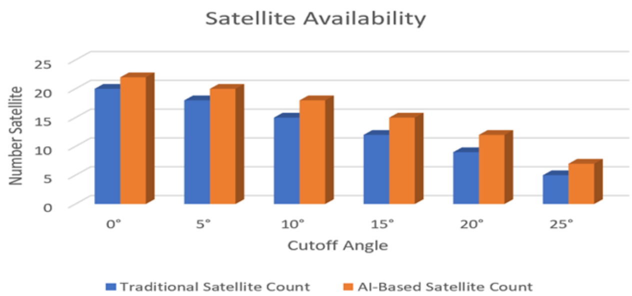

Figure 5: The Number of Satellites at Each Cutoff Angle

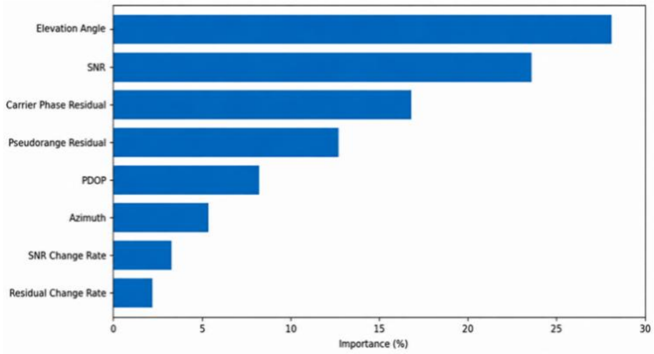

Figure 6: Feature Importance

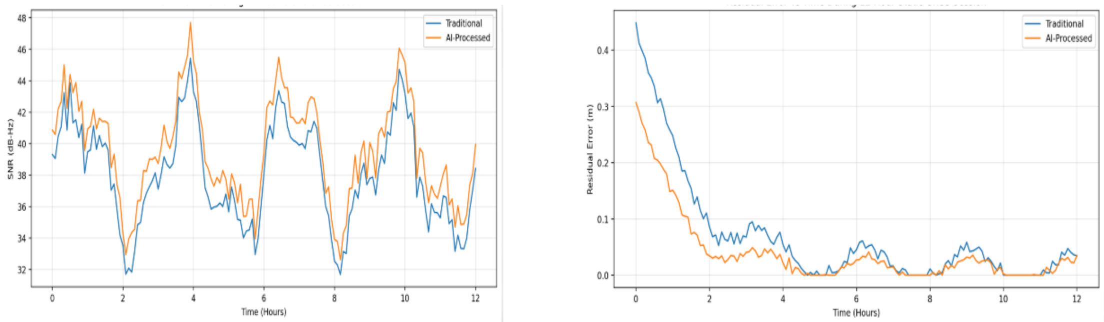

Figure 7: SNR and Residual Error Time Series

Discussion

The results show that the elevation cut-off angle has a significant influence on the GNSS location accuracy. The standard GNSS processing method showed that the positional accuracy rose with the increasing cut-off angle from 0° to 15° and the RMSE dropped from 2.85 cm to 1.95 cm accordingly. The enhancement is due to the fact that satellite transmissions at low altitudes are more susceptible to atmospheric delays, multipath interference and signal degradation. However, with the rise of cut-off angle, the number of available satellites fell and GDOP increased, which resulted in the decrease in positioning accuracy. The standard technique was shown to be best at a cut-off angle of 15°. The AI-driven pre-processing technique outperformed the traditional method at all evaluated cut-off angles. The results are in line with Li et al. (2021) who found that the removal of low-elevation data can mitigate the impacts of multipath interference and atmospheric errors. The Random Forest classifier showed an excellent performance, in accordance with the results of Wang et al. (2024), where the feasibility of the machine learning algorithms to evaluate the quality of GNSS signals was proved. The results are in line with Xu et al. (2020), who showed that the application of machine learning to classify GNSS observations can greatly enhance positioning performance. Furthermore, the significance of the elevation angle and the signal-to-noise ratio as the main predictors confirms the theoretical aspects presented by Hofmann-Wellenhof et al. (2020). The proposed adaptive filtering technique confirms the observations of Breili et al. (2025) that adaptive masking approaches provide better GNSS location performance than fixed threshold approaches. Results support the findings of Zhao et al. (2022) who mentioned the increasing potential of Artificial Intelligence to increase the quality of GNSS data and positional accuracy. The lowest RMSE of 1.30 cm was achieved at 15°, with horizontal and vertical errors reduced to 0.70 cm and 1.10 cm, respectively. Moreover, the signal quality was shown to improve with increased cut-off angle as indicated by an increase in the mean SNR from 34 dB-Hz at 0° to 52 dB-Hz at 25°. The results indicate that the machine-learning-based filtering enhances the quality of observations and the accuracy of positions. The comparison study showed that the AI-based strategy obtained improvements in RMSE from 29.17% to 41.39% compared to the traditional approach. The feature importance analysis revealed that the most important elements impacting the quality of GNSS observations are Elevation Angle (28%) and Signal-to-Noise Ratio (24%). This shows the importance of satellite height and signal strength for accurate positioning. The results show that the application of Artificial Intelligence to GNSS pre-processing provides a more efficient and reliable alternative to the standard fixed-threshold processing methods.

A weakness of this study is the analysis performed with data from one observational environment. Future work should test the suggested framework in different climatic circumstances and multi-constellation GNSS configurations.

CONCLUSION

The influence of elevation cut-off angles on the accuracy of static GNSS positioning was examined in this study. We introduced an Artificial Intelligence based approach to adaptive observation filtering with a Random Forest classifier. The results show that the positioning accuracy increases with the growth of the elevation cut-off angle from 0° to 15°, and then it decreases because of the decrease of satellites and the degradation of the satellite geometry. The best cut-off angle was 15° for both conventional and AI-based methods. The new AI system has consistently outperformed the previous approach and has achieved RMSE improvements of between 29.17% and 41.39%. The results show that machine learning methods may greatly increase the quality of GNSS measurements and positioning accuracy by filtering the measurements adaptively based on the given quality factors. The results show that the preprocessing based on machine learning can considerably increase the accuracy of GNSS positioning, by adaptively filtering data based on various quality factors, instead of using only static elevation criteria. The suggested framework provides an advanced methodology to increase the accuracy of static GNSS positioning and may promote further improvements in surveying, navigation and geospatial applications.

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