Short Communication
Volume 14:01, 2025

Journal of Telecommunication System and Management

ISSN: 2167-0919

Open Access

Soft-decision GNSS Multipath Detection and Mitigation Using Deep Learning

Shanshan Min*

Department of Data Science and Information Engineering, Guizhou Minzu University, Guiyang, China

Introduction

Global Navigation Satellite System (GNSS) technology is widely used in various applications, including autonomous vehicles, precision agriculture, aviation, and geolocation services. However, one of the major challenges in GNSS signal processing is multipath interference, which occurs when satellite signals reflect off nearby surfaces such as buildings, trees, or the ground before reaching the receiver. This phenomenon leads to errors in positioning accuracy, making it crucial to develop effective detection and mitigation techniques. Traditional methods for multipath mitigation rely on signal processing techniques and hardware-based solutions, but these approaches often fall short in complex environments. Recent advancements in deep learning have introduced new possibilities for addressing this issue. A soft-decision GNSS multipath detection and mitigation framework using deep learning offers a promising solution by leveraging data-driven models to enhance positioning accuracy. Deep learning models, particularly neural networks, have demonstrated exceptional capabilities in recognizing patterns in large datasets. In the context of GNSS multipath detection, deep learning can analyze signal characteristics and distinguish between direct Line-Of-Sight (LOS) signals and reflected Non-Line-Of-Sight (NLOS) signals. A soft-decision approach enables the system to estimate the likelihood of multipath interference rather than making hard binary decisions. This probabilistic assessment improves the reliability of GNSS positioning by allowing for adaptive corrections rather than outright rejection of affected signals.

Description

The implementation of deep learning-based soft-decision GNSS multipath detection involves several key steps. First, raw GNSS signals and metadata, such as pseudorange measurements, Doppler shifts, and signal-to-noise ratios (SNR), are collected. These data points serve as input features for training a deep learning model. A supervised learning approach is commonly used, where labeled datasets containing both LOS and NLOS signals are utilized to train the model. The model learns to differentiate between direct and reflected signals by identifying subtle patterns that are difficult to detect with traditional techniques. A Convolutional Neural Network (CNN) or a Recurrent Neural Network (RNN) architecture can be employed to process GNSS data. CNNs are effective in feature extraction and can detect spatial patterns in signal characteristics, making them suitable for analyzing GNSS spectrograms and signal correlation functions. On the other hand, RNNs, particularly Long Short-Term Memory (LSTM) networks, are beneficial for capturing temporal dependencies in GNSS signals, as they can analyze time-series data and detect changes in signal patterns over time. One of the advantages of deep learning-based multipath detection is its ability to generalize across different environments. By training the model on diverse datasets collected from urban, suburban, and rural areas, the system can adapt to varying multipath conditions. Data augmentation techniques further enhance robustness by simulating different multipath scenarios and improving the model's ability to handle unseen data [1].

Once the deep learning model is trained, it is deployed in a real-time GNSS receiver system. The receiver continuously processes incoming GNSS signals and feeds them into the model for soft-decision classification. Instead of discarding suspected NLOS signals entirely, the system assigns a probability score to each signal, indicating the likelihood of multipath interference. These probability scores are then integrated into a positioning algorithm, such as a Kalman filter or a machine learning-based fusion technique, to refine position estimates. The mitigation process involves adjusting the weight of each satellite measurement based on its probability score. Signals with a high likelihood of being affected by multipath are downweighted, while more reliable signals contribute more to the final position computation. This adaptive weighting approach improves overall accuracy without completely disregarding useful information from NLOS signals, which may still contain valuable positioning data. Performance evaluation of the proposed method is conducted using real-world GNSS datasets and simulated environments. Standard benchmarks such as root mean square error (RMSE), mean absolute error (MAE), and horizontal positioning error are used to compare the accuracy of deep learning-based soft-decision GNSS multipath mitigation against traditional techniques. Experimental results demonstrate that the deep learning model outperforms conventional methods by reducing multipath-induced errors and improving positioning stability [2,3].

One of the challenges in implementing deep learning for GNSS multipath detection is the requirement for large labeled datasets. Data collection and annotation can be time-consuming, especially in dynamic environments where multipath conditions change rapidly. To address this limitation, transfer learning techniques can be employed, where a pre-trained model is fine-tuned using a smaller dataset specific to the target application. Additionally, semi-supervised learning and self-supervised learning approaches can reduce the dependency on labeled data by leveraging unlabeled signals for training. Another consideration is the computational complexity of deep learning models, which may introduce latency in real-time GNSS applications. To mitigate this issue, lightweight neural network architectures such as MobileNet and EfficientNet can be explored. These models offer a trade-off between computational efficiency and accuracy, making them suitable for embedded GNSS receivers and edge computing devices [4,5].

Conclusion

Beyond GNSS, the principles of deep learning-based multipath detection can be extended to other positioning technologies, such as LiDAR and ultra-wideband (UWB) systems. The integration of multi-sensor fusion techniques, where GNSS data is combined with other sensor inputs, can further enhance positioning accuracy in complex environments. Future research directions include improving the interpretability of deep learning models for GNSS applications. Explainable AI (XAI) techniques can provide insights into how neural networks classify signals as LOS or NLOS, increasing trust and transparency in decision-making. Additionally, the incorporation of reinforcement learning can enable adaptive tuning of mitigation strategies based on real-time environmental conditions. In conclusion, deep learning-based soft-decision GNSS multipath detection and mitigation represent a significant advancement in satellite-based positioning systems. By leveraging probabilistic assessments and adaptive corrections, this approach enhances accuracy while maintaining robustness in challenging environments. The integration of deep learning into GNSS signal processing opens new possibilities for improving navigation

***Address for Correspondence:** Shanshan Min, Department of Data Science and Information Engineering, Guizhou Minzu University, Guiyang, China, E-mail: minshan@gmail.com*

Received: 02 January, 2025, Manuscript No. jtsm-25-162625; **Editor Assigned:** 04 January, 2025, PreQC No. P-162625; **Reviewed:** 17 January, 2025, QC No. Q-162625; **Revised:** 23 January, 2025, Manuscript No. R-162625; **Published:** 31 January, 2025, DOI: 10.37421/2167-0919.2025.14.475

reliability in urban canyons, indoor environments, and autonomous systems. As research continues to refine these techniques, the adoption of AI-driven GNSS solutions will play a pivotal role in the evolution of modern geolocation technologies.

Acknowledgment

None.

Conflict of Interest

None.

References

1. Munin, Evgenii, Antoine Blais and Nicolas Couellan. "Convolutional neural network for multipath detection in GNSS receivers." *Sens* 11 (2020): 1-10.
2. Suzuki, Taro and Yoshiharu Amano. "NLOS multipath classification of GNSS signal correlation output using machine learning." *Sens* 21 (2021): 2503.
3. Blais, Antoine, Nicolas Couellan and Evgenii Munin. "A novel image representation of GNSS correlation for deep learning multipath detection." *Array* 14 (2022): 100167.
4. Guillard, Anthony, Paul Thevenon and Carl Milner. "Using convolutional neural networks to detect GNSS multipath." *Front Robot AI* 10 (2023): 1106439.
5. Alzubaidi, Laith, Jinglan Zhang, Amjad J. Humaidi and Ayad Al-Dujaili, et al. "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions." *J Big Data* 8 (2021): 1-74.

How to cite this article: Min, Shanshan. “Soft-decision GNSS Multipath Detection and Mitigation Using Deep Learning.” *J Telecommun Syst Manage* 14 (2025): 475.