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Possibilities of AI Algorithm Execution in GNSS

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Abstract

A large number of studies were obtained to validate the opportunity of using Artificial Intelligence (AI) algorithms in the field of the Global Navigation Satellite System (GNSS). There are two ways to achieve intelligence: one is through Machine Learning (ML) and another is through Deep Learning (DL). Most commonly, Support Vector Machine (SVM) and Convolutional Neural Network (CNN) are the important algorithms of AI which is used in the literature to enhance the position accuracy of GNSS system. Here, the literature review has been done by considering the different stages of GNSS receivers at the Radio Frequency (RF) Front End level, at the pre-correlation level, at the post-correlation level, and at the Navigation level which will provide a better understanding of the implementation of AI in this domain. The major research work is done at the post-correlation stage where different data formats like correlation outputs, National Marine Electronics Association (NMEA) data, and Receiver Independent Exchange Format (RINEX) data have been utilized. Along with that, threats and risk factors associated with the application of AI algorithms have been discussed in this paper.

1. Introduction

The GNSS provides global and real-time services using precise timing information, positioning, and synchronization technologies. Currently, the United States' Global Positioning System (GPS), Russia's GlObal NAvigation Satellite System (GLONASS), European GALILEO, and china's BeiDou Navigation Satellite System (BDS) are the fully operational GNSS systems. Furthermore, India's Navigation with Indian Constellation (NavIC) and Japan's Quasi-Zenith Satellite System (QZSS) are independent and autonomous regional navigation systems. In recent years, GNSS applications have become more and more precise, and their precision has opened the door to a wide range of applications. [1]. Satellite navigation systems are designed according to the discovered laws of physics [2].

• The basic idea behind GNSS systems is that satellites transmit signals in space. Here, the position of satellites in an orbit follows Kepler's laws of planetary motion.

• These signals are received by the receivers on or near the surface of the earth. The spread-spectrum technique is used to acquire very weak satellite signals transmitted from the Earth's orbits.

• Doppler effects and tracking loops to track signals and decode navigation messages, then use a trilateration model to obtain a fix and use least squares to estimate the receiver's position.

• With advanced technologies like DGPS (Differential GPS), AGPS (Assisted GPS), RTK (Real-Time Kinematic), and e-Dif (extended Differential), GNSS could be able to achieve centimeter-level positioning.

After all these concepts and scientific theories, it is difficult to obtain a perfect GNSS position. The main reason behind this is that different layers in the atmosphere can diffract the signal as well as multipath effects and non-line-of-sight (NLOS) reception caused by buildings and obstacles on the ground [1]. Fortunately, some smart models have been generated to mitigate the range error caused by the delay of the troposphere and ionosphere transmission. But again, it is difficult to get the perfect positioning due to their high nonlinearity and complexity. The concept of artificial intelligence as shown in Figure 1 is very useful to solve the above problems. There are many fields of GNSS where AI can be utilized to enhance position accuracy [3]. This paper reviews all major fields related to this concept.

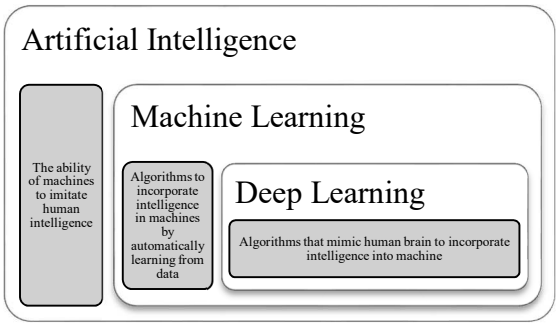

Figure 1. Concepts of AI, ML, and DL

Section 2 gives the details regarding the possible approaches based on intelligence in GNSS. Section 3 discusses the major risk and threats to applying AI in the GNSS domain. Finally, Section 4 focuses on the conclusion.

2. Possible approaches based on intelligence in GNSS

The addition of AI with GNSS can improve the overall performance of the GNSS in various applications. In many domains of GNSS, AI has been implemented. The functionality of a basic GNSS receiver has been studied in [4]. Here the utilization of AI in the GNSS field has been

reviewed by considering the four stages of any GNSS receiver as shown in Figure 2:
Stage I: At RF Front End
Stage II: At Pre-correlation Level
Stage III: At Post-correlation Level
Stage IV: At Navigation Level

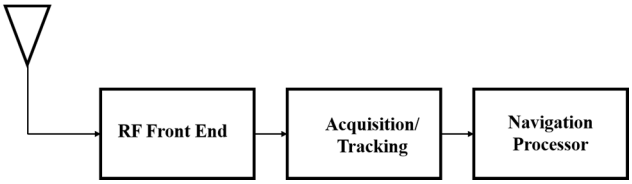

Figure 2. Basic Block Diagram Of GNSS Receiver [4]

2.1 Stage I: At RF Front End

Mostly at this level, the DL-based antenna beamforming concept is utilized in the GNSS receiver. Although few papers are available on this technique. In [5], the authors employ an emerging class of beamforming techniques that utilize Neural Networks (NNs) to detect the most appropriate features of a wanted signal in the presence of noise and interference. Here, neural processors have been used as an alternative to classical beamforming, even at low Signal-to-Noise Ratios (SNRs) and a limited number of snapshots of the received signal. In this paper, the authors evaluate the performance of CNNs in suppressing narrowband and wideband interference.
One author proposes an artificial NN fusion model that combines positioning data from multiple sources, such as Radio Signal Strength (RSS) and GNSS, to improve positioning accuracy in a 5G environment [6].

2.2 Stage II: At Pre-correlation Level

Generally, GNSS software receivers are used to process AI algorithms at the pre-correlations level. The training and testing datasets are generated using Intermediate Frequency (IF) signal and then the IF signal is further processed in SDR. Some papers are reviewed in Table 1 with such kinds of techniques.

Table 1 Literature Review at Pre-correlation Stage

Ref.	Application	AI Algorithm & Features	Key observations
[7]	Indoor NLOS & Multipath Detection	NN-based approach based on receiver tracking loop outputs	It provides an improvement of 20-45% in overall classification accuracy compared with SVMs. NLOS usually causes more serious range errors than multipath.
[8]	Detection of multipath, interference and scintillation	K-means clustering, SVM	The author has compared the PVT solutions obtained by processing all the tracked satellites with PVT solutions after excluding multipath-affected satellites.
[9]	LOS/Multipath/NLOS Classifiers	SVM	IF data is processed in SDR to get correlator output, NMEA, and RINEX files and it is proved that correlator-level the classifier is more robust against NMEA/RINEX-level classifiers.

2.3 Stage III: At Post-correlation Level

Many research papers have been published at this level in different domains of GNSS. Mostly RINEX, raw data, and NMEA data have been utilized as input to AI algorithms. Likewise, a great deal of research has been done using correlation outputs from GNSS receivers. This section is summarized in Table 2 to understand the impact of AI algorithms in various GNSS domains.

Table 2. Literature Survey at Post-correlation Stage

Ref.	Application	AI Algorithm & Features	Key observations
[10]	Multipath Detection	CNN and SVM using correlator output	CNN performs better than SVM. But the complexity is increased.
[11]	Ionosphere modeling and prediction	RBF-NN for modeling and Long- and Short-Term Memory Neural Network (LSTM-NN) for predicting using Vertical Total Electron Content (VTEC) values	The dual-frequency observations of 62 stations around China are used for regional ionospheric modeling and RBF-NN is a superior regional ionospheric model than traditional models
[12]	Estimating the air temperature from GNSS data	Support Vector Regression (SVR) using zenith tropospheric delay (ZTD), temp., and day-of-the year	The SVR algorithm can be used to predict temperature only from the ZTD of the GNSS signal without overfitting or underfitting the regressor.
[13]	Improving GPS Code Phase Positioning Accuracy	Gradient Boosting Decision Tree (GBDT) using satellite elevation, C/N_0, and pseudo-range residuals	Using the GBDT algorithm, the positioning accuracy has been greatly improved.
[14]	GNSS Signal detection and classification	CNN using Scalogram images	The DL-based approach is used to recognize the GPS signal in the high-power AWGN and the different jammers with an accuracy of 99.8%.
[15]	Estimating GNSS Position Corrections	Deep Neural Networks (DNNs) using GNSS pseudorange residuals and LOS vectors	The approach is not verified with diversity datasets and it depends on the initial position guess which is to be solved.

[16] [17]	Spoofing Detection	C-SVM using correlation output	The correlation analysis seems a good approach as an input for the SVM approach to detect spoofing signals.

2.4 Stage IV: At Navigation Level

Usually, Receiver Autonomous Integrity Monitoring (RAIM) and Integrated Navigation Systems (INS) approaches are utilized at this level.

Table 3 Literature Review at Navigation Level

Ref.	Application	AI Algorithm & Features	Key observations
[18]	Hurricane Tracking	CNN-based Approach and estimated wind speed values and locations as input	CNN model has achieved 96.6% predictability, with 3.6% relative absolute error.
[19]	Accuracy Improvement of INS During GNSS Signal Outages	Radial Basis Function Neural Network (RBFNN), Multilayer Perceptron (MLP) and Adaptive Neuro-Fuzzy Inference System (ANFIS)	Here AI module(s) is proposed as a replacement for KF for INS/GNSS integration.
[20]	Automatic water detection on the Earth surface,	Low-cost GNSS-R mounted onboard a small UAV and CAF is utilized as an input feature for K-Means Unsupervised Learning	Priori calibration of a threshold limitation of GNSS-R is resolved with the help of this proposed work based on AI.

Some papers have been reviewed in Tables 1 to 3, but a similar kind of research can be found in various articles. Lots of work have been done in the direction of GNSS signal classification using ML and DL algorithms [21-23] to enhance position accuracy in urban areas. Rather than this, ML or DL is applied to the different sectors of the GNSS domain. In [24], landmark detection for mobile robot outdoor localization has been proposed based on DL algorithms. For multiuser detection in Satellite Mobile Communication Systems, the authors have proposed DL Network [25].

3. Threats and Risk-factors Using AI Algorithms in GNSS

Geographical diversity: Merging of AI with GNSS, the major problem associated with data diversity across the globe if considering GPS/GLONASS system or regional if taking NavIC and QZSS systems. Generally, the ML/DL models are trained with the help of limited regional data [15]. It may be possible that some models give the best performance only with that set of trained data but are not suitable for another set of trained data. like if the ionosphere model is trained with AI algorithms using Total Electron Count (TEC) values for one particular state/country, then it might be possible that it will not give good performance for another state/country as the input TEC values depend upon the atmospheric condition of the particular location. Hence, this is the biggest issue associated with AI algorithms.

Data Security and Storage: AI models can learn from massive amounts of data and make intelligent decisions that create storage issues. Additionally, data-driven automation can lead to threats related to sensitive data security.

Infrastructure: Most AI-based solutions require high computing speeds and high-end processors to perform tasks. AI-based systems will be able to achieve faster speeds. If any field planning to implement AI should consider building a robust environment and flexible infrastructure that is fully compatible with AI-based solutions or applications.

The Choice of Inputs/Outputs of AI Modules: As observed in Section 2, various types of inputs have been used to implement AI algorithms in the GNSS domain. The quality of AI algorithms depends on the data they train on. Large amounts of structured or standardized data are key factors in getting good AI outputs. Currently, it is impossible to configure AI algorithms to control the flow of low-quality and inaccurate data; therefore, the collection of datasets and selection of features should be done correctly.

Lack of transparency: It is popularly called the black box problem. A level of transparency that can explain the process behind its predictions is required in the AI field. It is imperative that AI models which can make high-impact decisions have the highest standards of transparency and accountability.

Among other things, non-representative samples used for training data, bias, system parameters, feedback loops, overfitting and underfitting, misinterpretation of the resulting model, and contaminated reference data or data biases are related to risk factors associated with AI Algorithms [3].

4. Conclusion

In recent times, AI algorithms are utilized in space exploration, robotics, agriculture, education, automobile, social media, surveillance, finance, healthcare, entertainment, etc. The review has been done by considering the different stages of the GNSS receiver where the AI algorithms have been applied. It will provide a better understanding of the input data format or features generated by GNSS receivers on which AI algorithms can be applied. The major work that has been done at the post-correlation stage includes signal acquisition, NLOS/multipath/LOS detection and classification, GNSS positioning error estimation, indoor navigation, detection of GNSS ionospheric scintillations, detection of GNSS spoofing attacks, and jammer classification, GNSS/INS integration, etc. From the literature survey, it is concluded that SVM and CNN algorithms have been used in the GNSS domain to improve the overall performance of

GNSS accuracy. Although, high complexity is required to implement CNN algorithms. The previous section discussed the challenges and risk factors that AI algorithms need to address.

5. Acknowledgements

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