International Journal of Multidisciplinary Research and Growth Evaluation.

Utilizing MIMO neural networks for wireless signal surveillance

Nguyen Van Hieu [1], Truong Van Thu [2], Le Ngoc Giang [3*]
[1] Inspection and Repair Station for Measuring Devices, Logistics and Technical Department, AD-AF Academy of Vietnam
[2] Faculty of National Defense- Security Education, HaNoi University of science and Technology, Vietnam
[3] Faculty of Fundamental Technical, AD-AF Academy of Vietnam

* Corresponding Author: **Le Ngoc Giang**

Article Info

ISSN (online): 2582-7138
Volume: 05
Issue: 04
July-August 2024
Received: 16-05-2024;
Accepted: 19-06-2024
Page No: 613-617

Abstract
The integration of IoT technology into wireless signal monitoring presents significant opportunities for both military and civilian applications, such as signal reconnaissance, anti-jamming, and device identification. Traditional methods for modulation recognition, which rely on likelihood estimation and manual feature extraction, often encounter challenges related to computational complexity and the need for expert knowledge. In contrast, machine learning (ML) and deep learning (DL) models, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), deliver superior performance without the need for manual feature extraction.
In this paper, we propose the utilization of a Multiple Input Multiple Output (MIMO) neural network model for automatic modulation classification and direction of arrival (DOA) estimation. The proposed system is elaborated through functional block diagrams and comprises key components such as antenna arrays, analog preprocessing units, radio signal receivers, digital signal processors, MIMO neural networks, data processors, and display units. By integrating these components, the model is capable of simultaneously performing modulation classification and DOA estimation, thus providing an efficient and cost-effective solution for real-time signal monitoring. The proposed approach not only enhances the accuracy and efficiency of signal analysis but also reduces the overall system cost, making it highly suitable for diverse applications in the evolving landscape of wireless communications.

Keywords: IoT, MIMO neural networks, wireless monitoring

1. Introduction

With the rapid advancement of information and communication technology, the monitoring and identification of wireless signals have become crucial for both military and civilian applications. Tasks such as signal reconnaissance, anti-jamming, and signal identification demand sophisticated systems to ensure high efficiency and accuracy. The complexity of modern communication systems and military electronic warfare has increased the difficulty of signal identification, particularly in environments with multiple coexisting signals [2].
Digital transformation in radio monitoring is essential for developing automated systems capable of identifying radio signal sources. IoT technology, which enables connection and data collection from various sensors, offers a robust platform for the continuous and accurate monitoring of wireless signals.
Recent studies have highlighted the significant potential of ML and DL models in signal recognition. Traditional methods, based on hypothesis testing and feature extraction, while effective, are limited by their computational complexity and reliance on expert knowledge. In contrast, ML and DL algorithms, such as CNNs, have demonstrated superior performance across many domains without the need for manual feature extraction [3].

This paper introduces a MIMO neural network model designed to address two primary challenges: automatic modulation classification and DOA estimation of radio signals. This model offers high efficiency in monitoring and identifying wireless signals while reducing costs and hardware requirements. Additionally, the paper explores the challenges associated with implementing IoT technology, including investment costs, cybersecurity concerns, and the skill requirements for operators [1, 4].

Through this research, the authors aim to advance the development of cutting-edge solutions in wireless signal monitoring, thereby creating new opportunities for both military and civilian applications.

2. Two Main Challenges in Wireless Signal Monitoring Systems

Wireless signal monitoring systems primarily address two significant challenges: the classification of signal modulation and the estimation of the DOA of radio signals.

The first challenge involves classifying signal modulation types. In wireless communications, modulation techniques include amplitude modulation (AM), frequency modulation (FM), and phase modulation (PM), as well as more complex methods like quadrature amplitude modulation (QAM) and phase-shift keying (PSK). The aim is to correctly identify the modulation type to interpret the transmitted information. However, this task becomes more challenging in complex transmission environments where noise and signal fading are prevalent, making the accurate classification of modulation types more difficult [5].

The second challenge is estimating the DOA of radio signals. This involves determining the direction from which a signal originates as it reaches the monitoring system. DOA estimation is crucial for applications ranging from tracking the source of signals to improving detection capabilities in military contexts. The primary difficulty in DOA estimation arises from the need to process data from multiple antennas to accurately determine the signal's angle of arrival. Additionally, the presence of noise and signal reflections can distort the received data, complicating the estimation process.

3. Application of AI Algorithms in Wireless Signal Monitoring

To tackle the primary challenges in wireless signal monitoring, the use of AI, especially ML and DL techniques, is becoming increasingly prominent. These advanced AI methods offer promising solutions to the complex issues associated with monitoring wireless signals. Machine learning models such as SVM are employed to classify various modulation types by analyzing features extracted from signals. While SVMs are capable of achieving high classification accuracy, they are often limited by computational demands and the necessity for expert intervention in feature extraction [6].

On the other hand, deep learning, a specialized area within machine learning, utilizes models like CNNs to achieve even better performance in tasks such as signal modulation classification. CNNs are advantageous as they can automatically derive features from raw data, eliminating the need for manual feature extraction and thereby reducing reliance on expert knowledge while improving classification efficiency.

Despite their advantages, AI algorithms encounter several challenges. Firstly, deep learning models require substantial computational resources to handle large and complex datasets efficiently. Secondly, these models need to be adaptable to the varied conditions encountered in real-world wireless environments. Additionally, the high cost of the necessary hardware for deploying AI algorithms can make monitoring systems more expensive. Finally, real-time operation is crucial for signal monitoring systems, which must analyze and classify signals promptly as they are received.

4. Wireless Signal Monitoring System Using MIMO Neural Networks

To overcome the challenges associated with wireless signal monitoring, we propose employing a MIMO neural network model. This approach specifically targets two critical aspects: the analysis and classification of signal modulation and the estimation of the DOA of radio emissions [7].

The proposed system, utilizing MIMO neural networks, is illustrated through a functional block diagram as depicted in Figure 1. The system is comprised of the following key components:

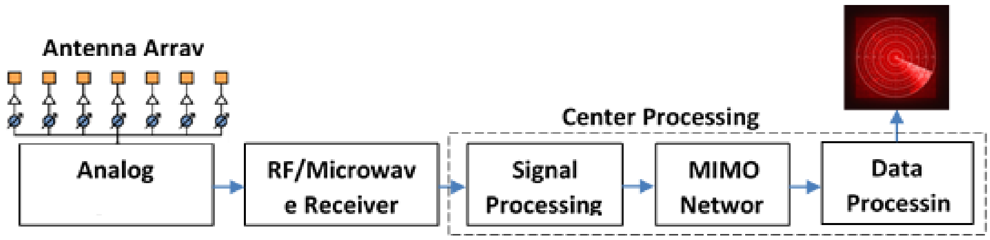

Fig 1: Wireless Signal Monitoring System Using MIMO Neural Networks

4.1. Antenna Array

The antenna array is an essential component in the wireless signal monitoring system, serving as a key electromagnetic sensing module. Its main role is to convert incoming electromagnetic waves into electrical signals that can be processed by the system. The antenna array enables functionalities such as spatial and frequency filtering, which are crucial for determining the direction of the signal, also known as DOA estimation.

Various antenna array configurations are available, each with distinct features and applications. The primary configurations include:

Linear Array: This straightforward setup arranges antennas in a straight line. It simplifies the design by reducing the number of elements while providing a large aperture in a two-dimensional plane. However, it limits DOA estimation to either horizontal or vertical directions within a -90° to +90° range, making it unsuitable for simultaneous multi-direction estimation.

Circular Array: In this arrangement, antennas are positioned in a circular pattern. This setup allows for comprehensive DOA estimation in both horizontal and vertical planes, covering a 360° azimuth and 180° elevation range. Nevertheless, the circular array's smaller aperture can limit angle estimation accuracy and resolution. Additionally, this configuration can be more expensive to produce due to the increased number of antennas required.

Rectangular Array: Combining elements of linear and circular arrays, the rectangular array features antennas arranged in a grid pattern. This design enhances DOA estimation accuracy by covering both spatial dimensions more effectively than circular arrays. However, it also faces challenges such as a limited aperture and higher production costs due to the larger number of elements involved.

Beyond these primary configurations, alternative setups like spherical arrays or dome arrays are also explored. These configurations may offer additional benefits for specific applications, and their suitability will be evaluated to identify the best solution for the wireless signal monitoring system. The goal is to achieve accurate DOA estimation while balancing cost and production efficiency.

4.2. Analog Signal Processor

The analog signal processor is a pivotal element in the wireless signal monitoring system, tasked with preparing the signals received from the antenna array for digital conversion and subsequent processing. This component predominantly comprises high-frequency elements and associated controllers.

Each antenna element in the array is linked to a quadrature channel, commonly referred to as an I/Q (in-phase/quadrature) channel. This channel encompasses several critical components:

Filters: These are used to eliminate unwanted frequency components from the received signal, ensuring that only the relevant frequencies are preserved.

Amplifiers: Their role is to boost the signal strength to an appropriate level for the next stages of processing.

Mixers: Mixers combine the incoming signal with a local oscillator signal to shift the signal's frequency to an intermediate level, facilitating further processing.

Phase Shifters: Phase shifters adjust the phase of the signal to synchronize all signal channels, which is essential for maintaining coherence among signals from various antenna elements.

Local Oscillator: Serving all channels, the local oscillator generates the necessary frequency for the signal mixing process.

For optimal performance, the signal channels must meet several critical criteria. They should be uniform in terms of time delay and designed to minimize signal distortion. Ensuring precise time synchronization among channels and minimizing distortion are crucial for maintaining the integrity and accuracy of the signal prior to its digital conversion.

4.3. Radio Signal Receiver

The radio signal receiver is a vital component of the wireless signal monitoring system, tasked with capturing and converting signals from analog to digital form for further processing.

The primary functions of the radio signal receiver include:

Signal Reception from the Antenna Array: The receiver gathers signals from the antenna array elements. At this stage, the signals are still in their analog form, having been amplified and phase-adjusted but not yet digitized.

Initial Signal Processing: The received analog signals undergo preliminary processing, which may involve filtering, additional amplification, and noise reduction to enhance signal quality.

Analog-to-Digital Conversion: Following preliminary processing, the analog signals are converted into digital format.

Provision of Digital Data: The processed digital data is then forwarded to the digital signal processor, where it will be utilized for subsequent tasks such as signal analysis, modulation classification, and DOA estimation.

4.4. Digital Signal Processor

The digital signal processor (DSP) is a vital component of the wireless signal monitoring system, tasked with the swift and efficient processing of digital signals. It utilizes FPGA chips to deliver high-speed processing capabilities and adaptability.

The processing sequence in the DSP includes the following

Temporary Storage: Once converted from analog to digital, the signal is temporarily stored within the processor to ensure readiness for immediate processing.

Signal Formatting: The digital signal is organized according to a specific format, aligning with the requirements for further processing stages.

Algorithm Execution: The DSP runs various algorithms for real-time processing, including filtering, Fourier transforms, and other signal processing techniques to enhance signal quality and performance.

Data Transfer to the MIMO Neural Network: After processing, the digital signal is forwarded to the MIMO neural network, which is essential for tasks such as modulation classification and DOA estimation.

The DSP is crucial for the efficient and rapid handling of signals, supporting the subsequent analysis and classification steps within the wireless signal monitoring system. The use of high-speed FPGA chips ensures that the system maintains high performance and flexibility, facilitating the timely processing of all incoming signals.

4.5. MIMO Neural Network

The MIMO neural network serves as the central software module within the wireless signal monitoring system, fulfilling two key functions:

Modulation Classification: The MIMO neural network employs advanced deep learning algorithms to analyze and categorize the modulation schemes of incoming wireless signals. This enables the identification of specific signal attributes and the determination of modulation types such as AM, FM, PSK, QAM, and others.

Direction of Arrival Estimation: Beyond classification, the MIMO neural network estimates the direction from which the signal originates. This process provides crucial information about the signal's source location.

Advantages of the MIMO Neural Network

High Precision: By leveraging deep learning techniques, the MIMO neural network achieves exceptional accuracy in both modulation classification and DOA estimation tasks.

Real-Time Capability: The network is optimized for fast and efficient data processing, meeting the real-time demands of the wireless signal monitoring system.

Adaptability: The MIMO neural network can manage a wide range of signal types and varying environmental conditions, enhancing the system's versatility and expanding its potential applications.

Improved Performance: As a core component of the monitoring system, the MIMO neural network enhances signal classification and DOA estimation. Its deep learning and sophisticated data analysis capabilities significantly boost the system's overall performance and reliability.

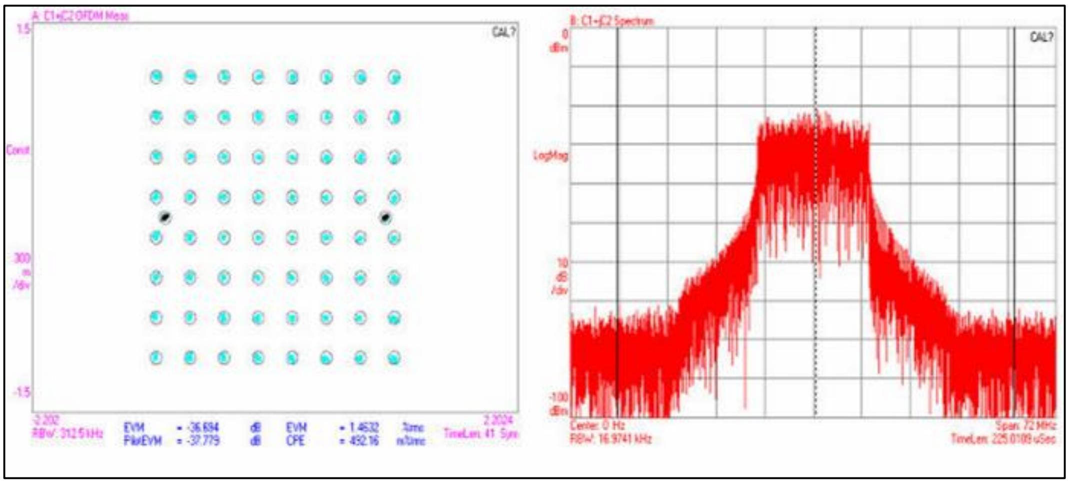

Fig 2: Analysis Results of the 64 QAM Modulated Signal

The proposed design of the MIMO neural network model is illustrated in Figure 3

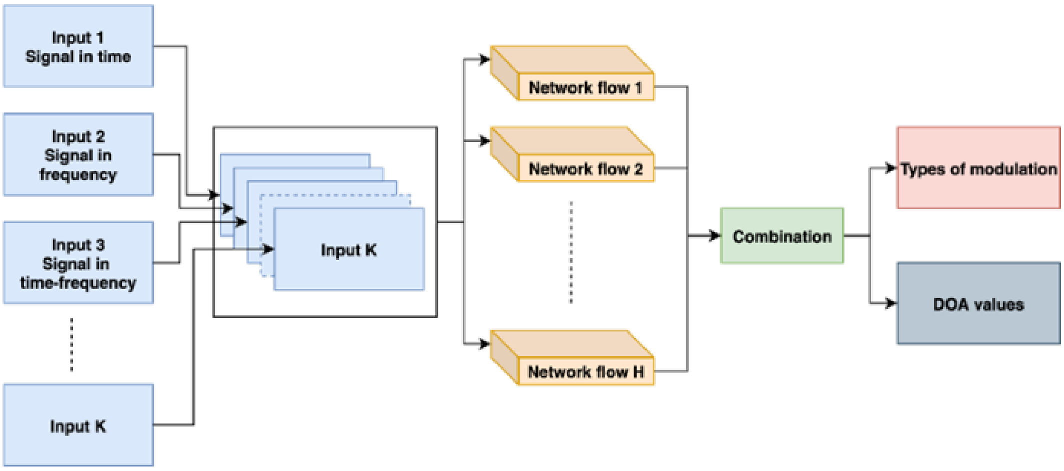

Fig 3: MIMO Neural Network Model for Modulation Classification and DOA Estimation

4.6. Data Processor

Once the wireless signal parameters, such as frequency spectrum, signal characteristics, modulation type, and DOA, are gathered, they are sent to the data processor. The data processor performs several critical functions to analyze and utilize this information, including:

Data Collection: With an antenna array consisting of M elements, M signal channels are collected. When a wireless signal is detected by a trigger pulse, the signal processor synchronizes and gathers samples from all M channels.

Data Storage: The collected signal samples are saved in RAM with a predefined window size, such as N. This storage results in a matrix of dimensions M×N.

Digital Processing: The digital processor transforms the time-domain signal into the frequency domain using Fourier transform techniques or into a time-frequency representation using the STFT.

Input to CNN: The CNN can process input data from various domains, including the time domain, frequency domain, time-frequency spectrum, or constellation diagrams, depending on the data format.

CNN Classification: The CNN analyzes the signal, classifies its modulation type, and provides a classification result. It is trained using a labeled dataset and applies learned weights to perform real-time signal classification.

MIMO Neural Network Optimization: To enhance resource efficiency and reduce hardware costs, the MIMO neural network is designed to handle both modulation classification and DOA estimation simultaneously. This integration into a single hardware platform helps economize resources and lower costs.

Versatility of the MIMO Neural Network: The MIMO neural network is capable of processing various input data formats and providing results for multiple tasks. It handles signals from different domains, and outputs include the modulation type and DOA of the signal source.

The data processor, supported by the MIMO neural network, is crucial for synthesizing and analyzing wireless signal parameters. This setup enables accurate and efficient modulation classification and DOA estimation while optimizing resource usage and minimizing hardware costs, thereby enhancing the performance and reliability of future wireless signal monitoring systems.

5. Conclusion

The advancement of wireless signal monitoring systems is becoming increasingly crucial in the era of sophisticated communication and electronic warfare technologies. The ongoing digital transformation, driven by AI, has significantly improved the capabilities of signal classification and recognition.

This paper introduces an advanced MIMO neural network model that addresses two pivotal tasks: modulation classification and DOA estimation of radio emissions. The proposed system integrates several key components, including antenna arrays, analog and digital signal processors, MIMO neural networks, and data processors.

The MIMO neural network model enhances the system's accuracy and efficiency while optimizing resource use and reducing hardware costs by performing both modulation classification and DOA estimation concurrently. This integration of advanced hardware and software components ensures robust performance across complex and diverse environments.

The findings suggest that this model holds substantial promise for applications in both military and civilian contexts, including signal reconnaissance, anti-jamming, and device identification. The progress in AI, particularly through machine learning and deep learning techniques, has unlocked new possibilities for enhancing the performance and reliability of wireless signal monitoring systems.

Looking ahead, further research and development of AI algorithms, alongside advances in hardware technology, are expected to drive additional breakthroughs in this field. Future work will continue to build on these results, further advancing the technology of wireless signal monitoring.

6. References

1. Le Ngoc Giang, Vương Thuy Linh, Phuong Nhat Minh. Research and application of IoT technology for food warehouse monitoring. International Journal of Multidisciplinary Research and Growth Evaluation. 2022;03(06):662-668, DOI: 10.54660/anfo.2022.3.6.20.
2. X Hong, J Wang, CX Wang, J Shi. Cognitive radio in 5G: A perspective on energy-spectral efficiency trade-off IEEE Communications Magazine. 2014;52(7):46-53.
3. AA Khan, MH Rehmani, A Rachedi. Cognitive-radio-based internet of things: applications, architectures, spectrum related functionalities, and future research directions, IEEE Wireless Communications Magazine. 2017;24(3):17-25.
4. M Nekovee. Dynamic spectrum access-concepts and future architectures. BT Technol J. 2006;24:111-116. https://doi.org/10.1007/s10550-006-0047-4.
5. S Pandit, G Singh. An overview of spectrum sharing techniques in cognitive radio communication system." Wireless Netw. 2017;23:497-518. https://doi.org/10.1007/s11276-015-1171-1.
6. A Hazza, M Shoaib, SA Alshebeili, A Fahad. An overview of feature-based methods for digital modulation classification, in 2013 1st International Conference on Communications, Signal Processing, and their Applications (ICCSPA); c2013, doi: 10.1109/iccspa.2013.6487244.
7. OA Dobre, A Abdi, Y Bar-Ness, W Su. Survey of automatic modulation classification techniques: classical approaches and new trends, IET Communications. 2007;1(2):137. Doi: 10.1049/iet-com:20050176.