

Enhancing Modulation Classification in OFDM System using Radial Basis Functional Neural Network (RBFNN)

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ABSTRACT: Orthogonal Frequency Division Multiplexing (OFDM) has emerged as a dominant modulation technique in modern wireless communication systems due to its high spectral efficiency and resilience to multipath fading. This project proposes an enhanced modulation classification framework utilizing Radial Basis Function Neural Networks (RBFNN) for robust channel estimation and symbol detection in OFDM systems. The proposed approach integrates data-driven learning through RBFNN with traditional channel estimation techniques to improve symbol detection accuracy and mitigate the effects of noise and channel distortions. The system architecture incorporates Quadrature Amplitude Modulation (QAM) for data transmission, followed by encoding and symbol mapping, while the receiver leverages RBFNN-assisted channel estimation to optimize symbol DE mapping and decoding. Simulation results demonstrate that the RBFNN-based classification method significantly enhances classification accuracy, reduces bit error rates (BER), and outperforms conventional estimation techniques in various signal-to-noise ratio (SNR) conditions. This project paving the way for improved wireless communication reliability and efficiency.

1. Introduction

Orthogonal Frequency Division Multiplexing (OFDM) is a widely used digital modulation technique that enhances data transmission efficiency by dividing a high-rate data stream into multiple lower-rate subcarrier. OFDM has become the foundation for modern communication standards, including Wi-Fi (IEEE 802.11a/g/n/ac/ax), LTE, DVB-T, and 5G NR, due to its superior spectral efficiency, robustness against multipath fading, and ease of equalization.

A wireless channel refers to the medium through which wireless signals are transmitted between devices such as smartphones, laptops, routers, and other wireless-enabled devices., wireless communication relies on the transmission of electromagnetic waves through the air or free space.

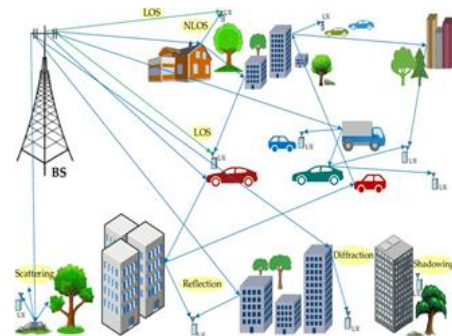


Figure 1: Wireless Channel

Interference can be caused by other wireless devices operating in the same frequency band or by external sources such as electronic devices or atmospheric conditions. Fading result in signal loss & reduced communication range. Noise can degrade the signal quality and increase the bit error rate, leading to reduced data throughput. Multipath propagation can lead to signal fading, Inter symbol interference, and reduced signal quality.

1.1 Basic Principles of OFDM

The fundamental principle of OFDM is based on the concept of orthogonality, where subcarriers are mathematically arranged to avoid overlapping and eliminate inter-carrier interference (ICI). This unique characteristic allows OFDM to achieve high spectral efficiency, making it widely used in modern wireless communication standards such as Wi-Fi, LTE, DVB-T, and 5G networks. OFDM enables subcarriers to overlap while maintaining orthogonality, thereby optimizing bandwidth utilization. The implementation of OFDM involves several key steps, starting with serial-to-parallel conversion, where incoming data is split into multiple streams to be transmitted on different subcarriers. Each of these subcarriers is then modulated using conventional schemes like Quadrature Amplitude Modulation (QAM) or Phase Shift Keying (PSK), ensuring flexibility in adapting to varying channel conditions. The next step involves the application of the Inverse Fast Fourier Transform (IFFT) at the transmitter, which converts frequency-domain subcarriers into a time-domain signal suitable for transmission.

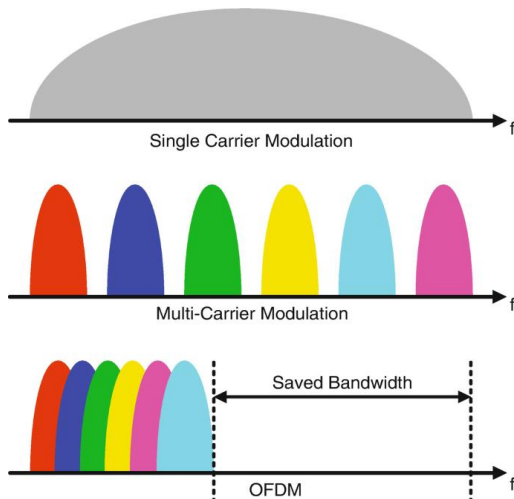


Figure 2: Basic Principles of OFDM

OFDM divides the entire bandwidth into narrow subcarriers, only a small subset of subcarriers is affected by fading, allowing adaptive modulation and coding (AMC) to adjust transmission parameters dynamically for enhanced performance. Additionally, OFDM supports

Multiple Input Multiple Output (MIMO) technology, where multiple antennas at the transmitter and receiver further improve spectral efficiency and link reliability.

1.2 Channel Estimation and Equalization

In wireless communication, transmitted signals propagate through a dynamic channel characterized by multipath fading, Doppler shifts, and frequency-selective attenuation, which distort the received signal and degrade system performance. To counteract these effects, OFDM receivers employ channel estimation to model the channel's response and equalization techniques to compensate for distortions, restoring the transmitted signal. Channel estimation is the process of determining the channel impulse response (CIR) or channel frequency response (CFR) using known reference signals, typically called pilots.

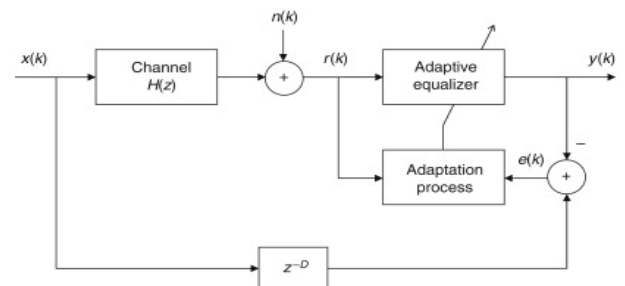


Figure 3: Channel Estimation and Equalization

1.3 Objectives

To implement enhancing modulation classification in OFDM systems using radial basis function neural networks (RBFNN). To develop a robust classification model that effectively handles noise, interference, and channel impairments. To enhance the generalization ability of the classification system for varying wireless channel conditions. To compare the performance of RBFNN with conventional classification techniques in OFDM systems.

1.4 Advantages

The RBFNN-based framework enhances modulation classification accuracy by effectively learning complex signal patterns. The proposed

approach minimizes BER by mitigating the impact of noise and channel distortions in OFDM systems. The system outperforms conventional methods, ensuring reliable communication even in challenging signal-to-noise ratio environments.

2. Proposed System

2.1 Introduction

Mobile wireless communication systems have rapidly evolved, with new generations of mobile technology emerging approximately every decade. Each generation, from the first (1G) to the fifth (5G), has been carefully developed to meet the changing demands of both end-users and network operators. The first generation (1G), deployed in the 1980s, relied on analog communication and was primarily designed for

voice calls. The second generation (2G), introduced in the 1990s, marked the transition to digital cellular technology, significantly improving performance, reliability, and capacity. The third generation (3G), launched in 2000, introduced multimedia capabilities, enabling data services alongside voice communication. The fourth generation (4G), which emerged in 2014, was designed to support wireless mobile internet and advanced multimedia services, including video chat, digital video broadcasting (DVB), mobile TV, and high-definition television (HDTV). It offered peak data rates ranging from 100 Mbps to 1 Gbps, with latency between 40 milliseconds (ms) and 60 ms. One of the most widely adopted 4G standards is Long-Term Evolution-Advanced (LTE-A), developed by the 3rd Generation Partnership Project (3GPP).

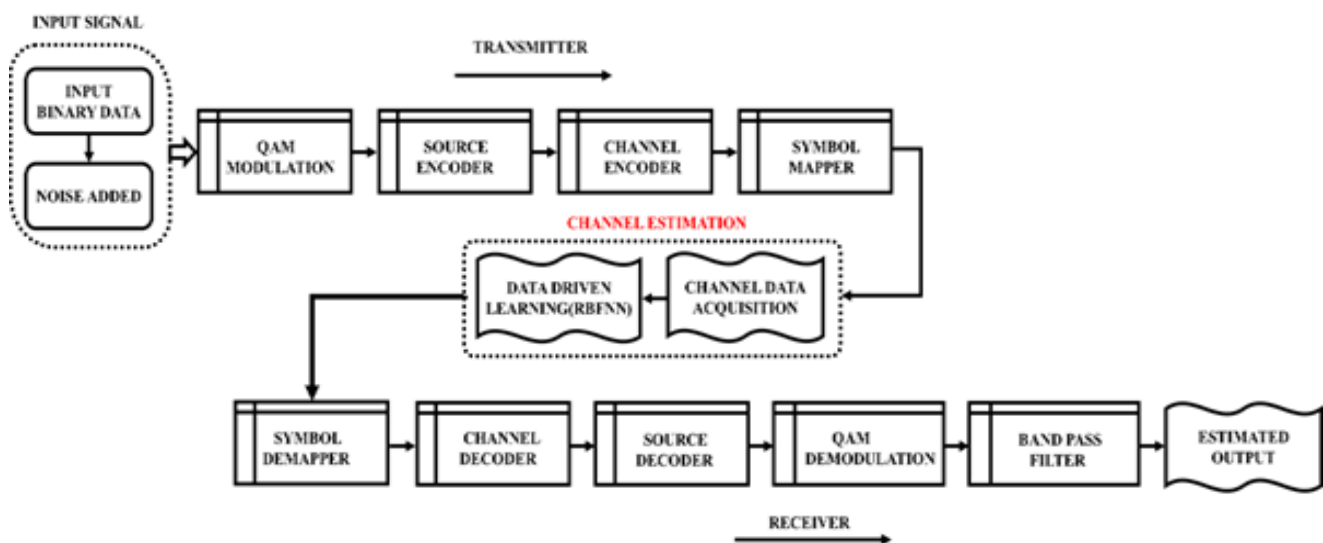


Figure 4: Block Diagram of Proposed System

2.2 QAM Modulation

In 6G communication, Quadrature Amplitude Modulation (QAM) enhances data transmission efficiency by varying the amplitude of two carrier waves that are phase-shifted relative to each other. QAM in 6G is integrated with deep learning-based channel state estimation. The deep learning model continuously analyses the channel conditions and dynamically adjusts QAM parameters in real time, minimizing errors and maximizing data throughput.

2.3 Source Encoder

The source encoder plays a crucial role in enhancing the efficiency and reliability of wireless communication systems by transforming input data typically binary sequences or symbols—into a more compact and optimized format for transmission. This process reduces redundancy. In the context of 6G communication, where ultra-fast and reliable data transmission is critical, source encoding is instrumental in maximizing spectral efficiency and minimizing latency. Advanced

encoding techniques such as Huffman coding, arithmetic coding, and entropy coding significantly reduce the size of transmitted data streams, optimizing resource utilization and improving overall system performance.

2.4 Channel Encoder

The channel encoder plays a crucial role in enhancing communication reliability by introducing redundancy into transmitted data, enabling error detection and correction at the receiver. In 6G communication, where ultra-reliable and low-latency communication (URLLC) is paramount, the channel encoder is essential for maintaining data integrity and ensuring robust system performance. By employing advanced error-correcting codes such as Reed-Solomon, convolutional, and turbo codes, it effectively mitigates channel impairments, enhancing overall communication reliability.

2.5 Symbol Mapper

The symbol mapper plays a critical role in wireless communication by converting encoded data into modulated symbols for transmission. It assigns each encoded bit sequence to a specific modulation scheme, such as Quadrature Amplitude Modulation (QAM) or Phase Shift Keying (PSK), ensuring efficient data representation. In 6G communication, where high data rates and reliability are paramount, the symbol mapper is key to maximizing throughput and minimizing transmission errors. Advanced modulation schemes and adaptive mapping techniques can dynamically adjust symbol allocation based on channel conditions, optimizing performance across diverse communication scenarios.

2.6 Data Driven Learning (RBFNN)

Data-driven learning using Radial Basis Function Neural Networks (RBFNN) is an effective approach for pattern recognition, classification, and function approximation in various applications, including wireless communication

and signal processing. RBFNN utilizes radial basis functions as activation functions, enabling efficient mapping of input data to output classes with minimal error. Unlike traditional machine learning techniques, RBFNN excels in handling non-linear relationships and high-dimensional data, making it well-suited for complex signal classification tasks. In communication systems, RBFNN is particularly beneficial for modulation classification, channel estimation, and symbol detection, where it learns from real-time data to optimize performance. Enhances system accuracy and robustness against noise and distortions. Moreover, its faster convergence and lower computational complexity compared to conventional neural networks make it suitable for real-time applications. RBFNN's structure, consisting of an input layer, hidden layer with radial basis functions, and an output layer, allows efficient processing and decision-making with minimal training time. In the context of OFDM systems, RBFNN-driven learning improves modulation classification accuracy, reduces bit error rates, and enhances overall communication reliability. The integration of data-driven learning with RBFNN provides a powerful tool for improving system efficiency, offering a balance between accuracy and computational feasibility. With its adaptive nature and superior performance, RBFNN continues to be a promising approach for advancing intelligent communication and signal processing technologies.

2.7 Symbol Demapper

Symbol de mapping is the process of translating modulated symbols received from a wireless channel back to their original encoded form. Deep learning methods can significantly improve symbol remapping by utilizing learned representations of channel characteristics, thereby enhancing decoding performance in complex wireless scenarios.

2.8 Channel Decoder

A channel decoder is a critical component in communication systems, tasked with recovering the original data transmitted over a channel, despite distortions and errors introduced during transmission. The process begins when the received signal, which has been corrupted by noise and interference, is passed to the channel decoder. Techniques such as Maximum Likelihood Decoding (MLD) and Soft Decision Decoding are commonly used.

These methods perform multiple iterations of decoding, exchanging information between different decoding components to refine the estimates of the transmitted code words. The channel decoder outputs the decoded data, which ideally matches the original transmitted information. Effective decoding is essential for ensuring data integrity and reliable communication, particularly in noisy and challenging transmission environments.

2.9 Source Decoder

A source decoder is responsible for reconstructing the original data from its encoded form after it has been transmitted and possibly compressed. The process begins when the encoded data, which might be compressed to reduce its size, is received by the decoder. The source decoder first reverses the compression process applied by the source encoder. This involves decoding the compressed data, which could be in formats such as Huffman coding, arithmetic coding, or run-length encoding.

2.10 QAM Demodulation

QAM demodulation is essential for retrieving transmitted symbols from the received signal. The demodulation process involves extracting the amplitude and phase information of the modulated symbols through techniques like coherent or differential demodulation. Accurate QAM demodulation is crucial for precise channel state estimation and data decoding. Deep learning approaches can significantly enhance QAM

demodulation by optimizing demodulation parameters and adapting to changing channel conditions, thus boosting the reliability and performance of communication systems, particularly in 6G networks.

2.11 Band Pass Filter

A band-pass filter is essential for isolating the desired frequency range from a received signal. This filtering process reduces interference and noise from adjacent frequency bands, thereby improving channel state estimation and signal recovery accuracy. Deep learning techniques can refine band-pass filter design by adapting filter parameters to changing channel conditions, thus enhancing the performance and reliability of communication systems, especially in 6G networks.

3. Estimated Output

The estimated output represents the inferred channel state information obtained from deep learning models. This process involves training neural networks on extensive datasets of channel measurements to learn intricate relationships between received signals and their associated channel parameters. By doing so, the neural network can accurately estimate key channel characteristics, including amplitude, phase, and noise levels. These estimates are crucial for refining signal processing algorithms, enhancing data transmission reliability, and facilitating adaptive modulation and coding schemes in 6G communication systems.

3.1 Introduction

MATLAB (Matrix Laboratory) is a high-level programming environment primarily designed for numerical computing and data visualization. Developed by MathWorks, MATLAB is widely used in various fields, including engineering, physics, finance, and biology, due to its ability to handle complex mathematical calculations, algorithm development, data analysis, and graphical representations. One of its core strengths

lies in its matrix-based structure, which makes it particularly well-suited for solving linear algebra problems, a common task in scientific computing. MATLAB provides an extensive library of built-in functions and toolboxes that facilitate the implementation of advanced algorithms, including signal processing, control systems, machine learning, and deep learning. These toolboxes enable users to quickly prototype and test ideas without needing to write extensive code from scratch.

4. Results and Discussions

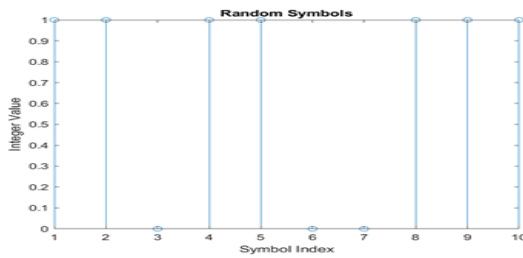


Figure 5: Random Symbol

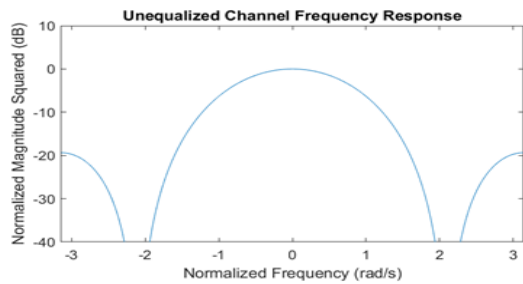


Figure 6: Unequalized Channel Frequency

Response displays an unequalized channel frequency response graph, illustrating the normalized magnitude squared (in dB) versus normalized frequency (in rad/s).

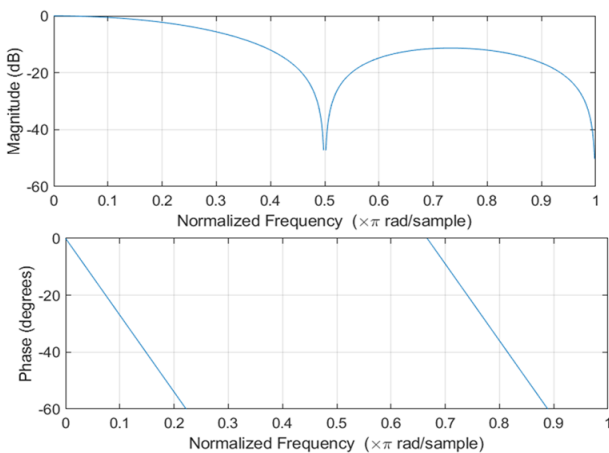


Figure 7: Normalized Frequency

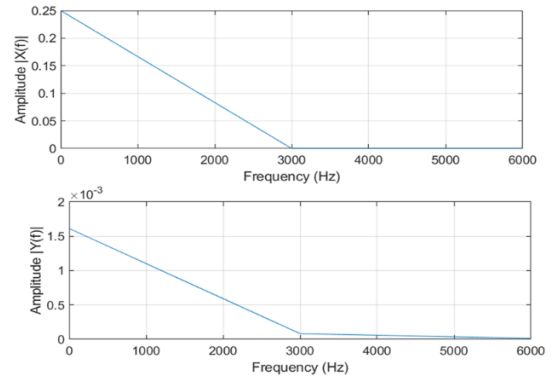


Figure 8: Frequency Range

A signal with a frequency is shown in figure 8 range of frequencies that a signal or system function across is referred to as its frequency range. It establishes the minimum and maximum frequencies that are used for efficient transmission, reception, or processing.

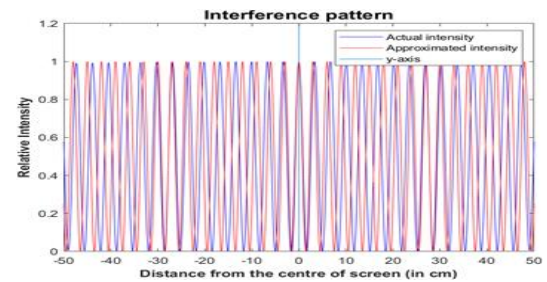


Figure 9: Interference Pattern

When two or more waves superimpose on one another, either constructive or destructive interference results, creating an interference pattern. Regions of alternating high and low intensity are what define it. Many phenomena, like double-slit interference in optics and multipath interference in radio waves, exhibit interference patterns.

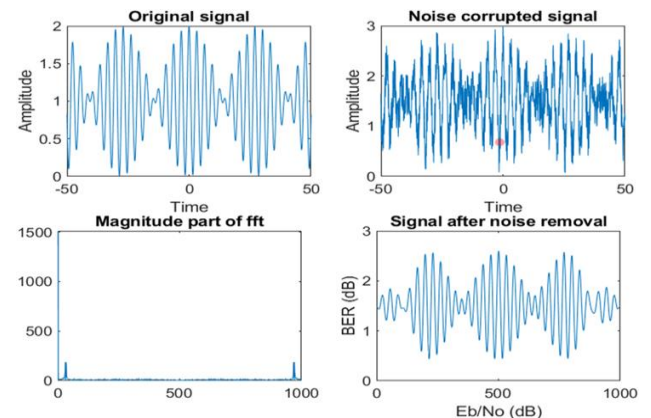


Figure 10: Noise Signal

Any undesired or random variation that tampers with a signal's accuracy or quality is referred to as noise. A signal with undesired random fluctuations is called noise. Many things can produce noise, including background radiation, electrical interference, and temperature variations. It can impair a signal's quality and have an impact on how well communication systems operate.

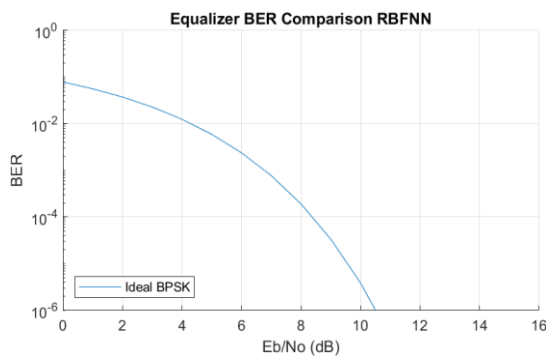


Figure 11: BER Value

A BER value is shown in figure 5.7. In a communication system, the transmitted and received data are compared to determine the BER value. Both the total number of bits sent and the number of bit errors are counted and analyzed during the output process. The system's performance is gauged by the resulting BER value, which is utilized for optimization, troubleshooting, or comparison with predetermined performance standards.

5. Conclusion and Future Scope

The RBFNN-based modulation classification framework effectively enhances channel estimation and symbol detection in OFDM systems. By integrating data-driven learning with traditional techniques, the system improves classification accuracy and minimizes bit error rates, ensuring reliable communication even in challenging noise conditions. The use of QAM modulation, combined with RBFNN-assisted estimation, optimizes signal processing efficiency. Simulation results confirm the superiority of this approach over conventional methods, particularly in varying signal-to-noise ratio environments. The framework's adaptability and computational

efficiency make it suitable for real-time applications. This research contributes to advancing OFDM-based communication systems, paving the way for future enhancements. The implementation in MATLAB 2021a b further validates its practicality and effectiveness.

5.1 Future Scope

Future advancements focus on improving the adaptability of RBFNN for dynamic and real-time communication environments, ensuring better performance under varying channel conditions. The application of RBFNN in 6G networks, IoT, and satellite communication further enhance signal processing efficiency and reliability in next-generation communication systems.

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