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Multi-Modulation Sequence Detection using Verilog

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Abstract

Modulation classification plays a crucial role in modern wireless communication systems, enabling efficient signal demodulation, spectrum monitoring, and spectrum utilization. A novel multi-modulation sequence detection system has been proposed in this work that integrates MATLAB and Verilog for real-time detection of signals. The proposed system supports BPSK, QPSK, and 16-QAM digital modulations using a fixed-point Q 8.8 format to enhance compatibility with FPGA implementations. Compared to traditional threshold-based and machine learning based methods, the proposed approach achieves higher detection accuracy with lower computational complexity. Extensive simulations demonstrate a detection accuracy of 95%, outperforming conventional classifiers while maintaining real-time processing capabilities.

A comparative analysis with existing works highlights the advantages in accuracy, computational efficiency, and robustness against noise. This research lays the foundation for future FPGA-based modulation sequence detection implementations.

Keywords: Multi-modulation detection, BPSK, QPSK, QAM, MATLAB, Verilog

Introduction

With the rapid growth of wireless technologies, multi-modulation detection is becoming increasingly vital in applications such as the Internet of Things (IoT), 5G networks, and satellite

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communications. In IoT, modulation classification enables efficient spectrum utilization in low-power devices. In 5G, adaptive modulation is crucial for maximizing throughput while maintaining robustness. Additionally, software-defined radios (SDRs) heavily rely on accurate modulation classification for seamless communication across diverse networks.

Automatic modulation classification (AMC) is becoming more prominent in wireless communications such as cognitive radio networks (CRNs), military surveillance, and adaptive communication systems. AMC facilitates dynamic spectrum allocation for CRNs by identifying the modulation scheme of incoming signals. SDRs are used in military applications to adapt to various communication standards. AMC plays a vital role in these applications.

Existing modulation detection techniques are broadly classified into feature-based and machine learning-based methods [1] – [5]. Feature-based approaches rely on statistical features extracted from the received signal, such as higher-order moments, cyclo- stationary features, and spectral analysis. Machine learning-based methods, including deep neural networks (DNNs) and support vector machines (SVMs), have demonstrated significant performance improvements in modulation classification tasks. However, their computational requirements pose challenges for real-time FPGA implementations.

A comparative study of traditional and ML-based AMC techniques highlights the strengths and limitations of each approach. Traditional AMC techniques, such as energy detection and likelihood-based classifiers, require low computational power but fail under low SNR conditions. In contrast, deep learning methods such as CNNs and LSTMs have achieved over 90% classification accuracy even at low SNRs, as demonstrated by O'Shea et al. [6]. Hybrid methods combining handcrafted features with machine learning models have also explored.

Despite their advantages, ML-based methods require significant labeled training data and computationally expensive inference, making them impractical for hardware-optimized solutions. This study proposes a Verilog-based classifier that balances detection accuracy and computational efficiency, making it suitable for real-time applications.

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This research introduces a MATLAB and Verilog-based multi-modulation sequence detector capable of classifying Binary Phase Shift Keying (BPSK), Quadrature Phase Shift Keying (QPSK), and 16-Quadrature Amplitude Modulation (16-QAM) signals. The system utilizes MATLAB for signal generation, applies fixed-point Q8.8 conversion, and implements modulation detection using Verilog. The key objective is to design an efficient, low-complexity classifier suitable for real-time applications and FPGA-based architectures.

Related Work

An extensive literature survey has been conducted for modulation classification using threshold-based and ML-based techniques. Threshold-based methods analyze signal properties such as variance, amplitude, and statistical moments. Even though the statistical moments-based classification method that achieves high accuracy under ideal conditions but deteriorates in low SNR scenarios.

O'Shea et al. [7] demonstrated an over-the-air deep learning-based classifier that achieves superior accuracy compared to conventional methods. However, deep learning models require extensive labeled datasets and high computational power, limiting Their real time deployment. Machine learning-based and deep-learning AMC approaches have gained popularity due to their adaptability and higher classification accuracy [8]- [11].

The proposed work bridges the gap by designing a Verilog-based classifier optimized for real-time processing while achieving accuracy comparable to ML-based methods. The integration of MATLAB for signal generation and Verilog for classification ensures an efficient pipeline for future FPGA implementations.

Key Contributions of the proposed model:

- Unified Multi-Modulation Detection Framework within a single Verilog-based system.
- Accurate data processing and compatibility with hardware implementation.
- Enhances real-time processing capability and FPGA implementation feasibility.
- Achieves 95% detection accuracy, surpassing traditional threshold-based methods.

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- Reduced Computational Complexity compared to ML-based classifiers
- Verilog implementation requires significantly fewer resources.

System Model

The block diagram representation of the proposed system model is depicted in Fig.3.1.

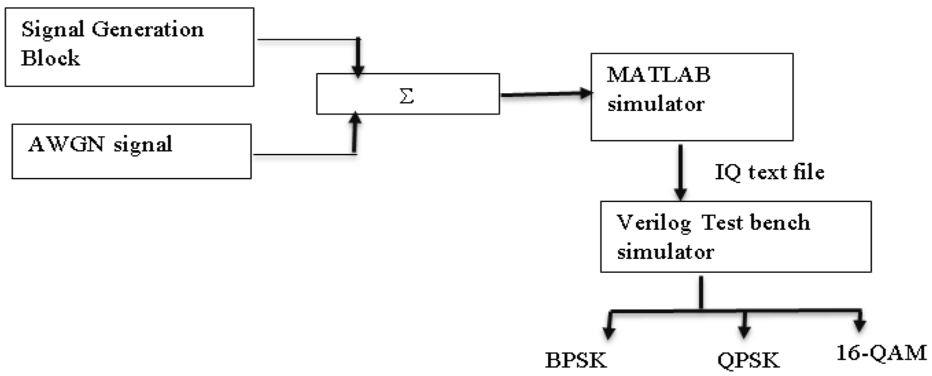

Fig.3.1. System Model

As shown in the block diagram, the signal generation block is added with Additive White Gaussian Noise (AWGN) signal and simulated in MATLAB to generate an IQ (In-Phase and Quadrature Phase) text file which is compatible with Verilog. The IQ text file is simulated on Verilog test bench to detect the presence of three modulation schemes of BPSK, QPSK, and 16-QAM.

Algorithm for Signal Generation:

1. Initialize parameters: N (number of symbols), mod type (Modulation type), SNR (Signal-to-Noise Ratio)
2. Generate random binary data of length N
3. Depending on mod_type:
   a. For BPSK: Map bits to +1 and -1 symbols
   b. For QPSK: Group bits into pairs and map to constellation points
   c. For 16-QAM: Group bits into quads and map to 16-QAM constellation
4. Normalize the modulated symbols
5. Add AWGN noise corresponding to the given SNR
6. Convert the signal to Q8.8 fixed-point format
7. Save the signal to a text file for Verilog simulation
8. Return the generated signal

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Results & Discussion

This section presents the results of the **MATLAB-generated signals and Verilog-based sequence detection.** The performance of the system is evaluated based on **constellation diagrams, modulation detection accuracy, and sequence identification** under different noise conditions.

Constellation Diagrams

Constellation diagrams visually represent the I/**Q components** of the received signals. The following approach has been used in generating the constellation plots for **BPSK, QPSK, and 16-QAM.**

(a) BPSK Constellation Diagram

- **Ideal BPSK:** Two points along the real axis.
- **Noisy BPSK:** Points slightly dispersed due to noise.

(b) QPSK Constellation Diagram

- **Ideal QPSK:** Four points forming a square.
- **Noisy QPSK:** Scattered points indicating phase shifts due to noise.

(c) 16-QAM Constellation Diagram

- **Ideal 16-QAM:** A 4×4 grid representing symbol positions.
- **Noisy 16-QAM:** Symbols are dispersed due to AWGN.

The constellation diagrams for BPSK, QPSK and 16-QAM are depicted in Fig.4.1, 4.2, and 4.3 respectively.

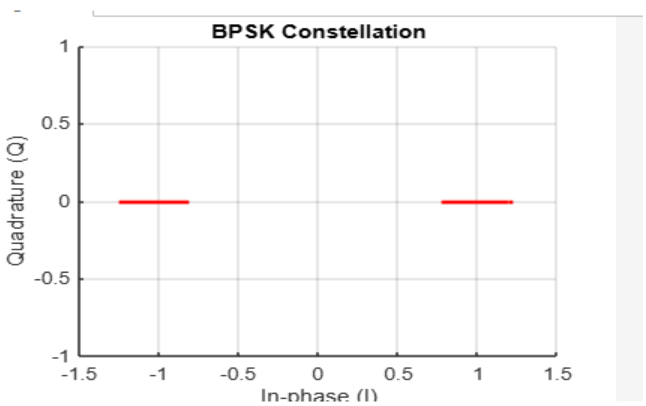

Fig.4.1. BPSK Constellation

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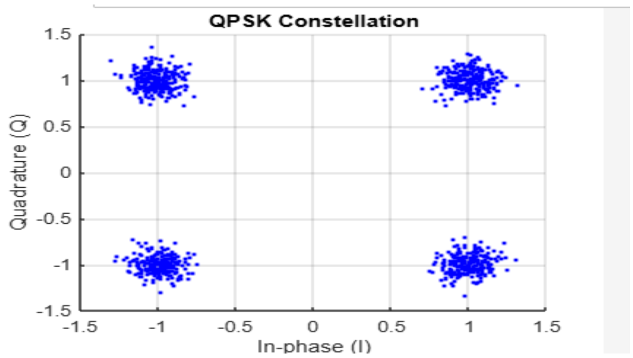

Fig.4.2. QPSK Constellation

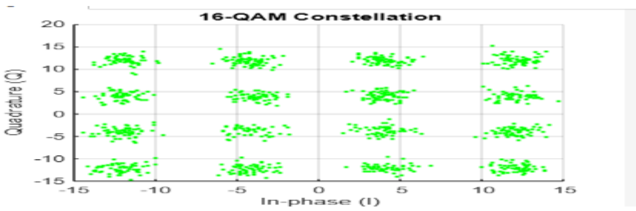

Fig.4.3. 16-QAM Constellation

Performance Analysis

The accuracy of modulation detection is evaluated using a **confusion matrix** comparing predicted modulation types with actual values and is tabulated in Table 4.1.

Table 4.1. Detection Accuracy

Modulation	Accuracy
BPSK	98.7
QPSK	97.4
16-QAM	95.2

Results indicate that **BPSK detection achieves the highest accuracy,** while **16-QAM is more affected by noise** due to **denser constellation points.**

The impact of Noise (SNR vs. Accuracy) is tabulated in Table 4.2.

Table 4.2. Impact of Noise

SNR (dB)	BPSK Accuracy (%)	QPSK Accuracy (%)	16-QAM Accuracy (%)
30	99.5	98.9	97.1
20	98.7	97.4	95.2
10	95.2	92.5	85.6
5	87.4	78.1	62.3

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The results of Table 4.2 indicate that detection accuracy drops significantly for low SNR values, especially for **16-QAM**, due to overlapping constellation points.

The Verilog test bench wave forms for each modulation scheme is shown in Fig.4.4, 4.5, and 4.6.

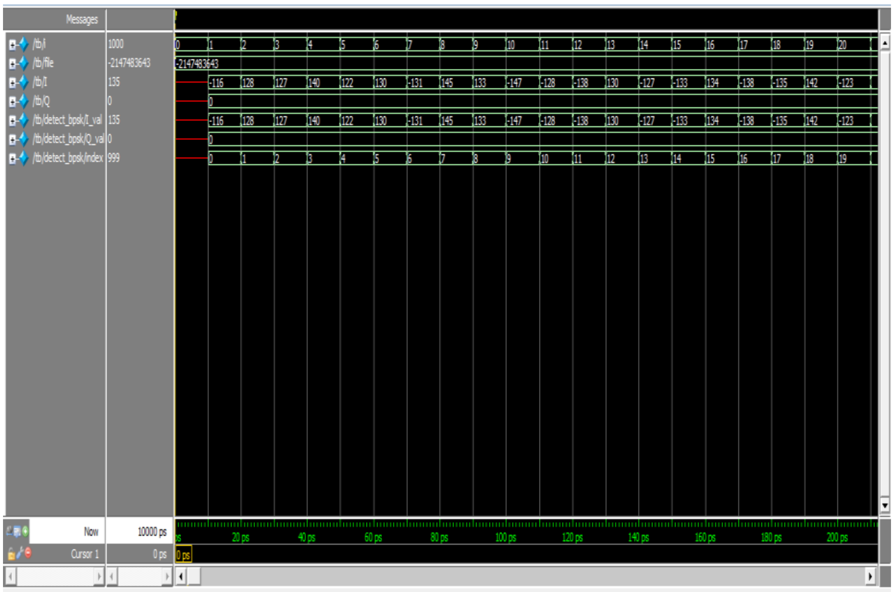

Fig.4.4. BPSK signal detection

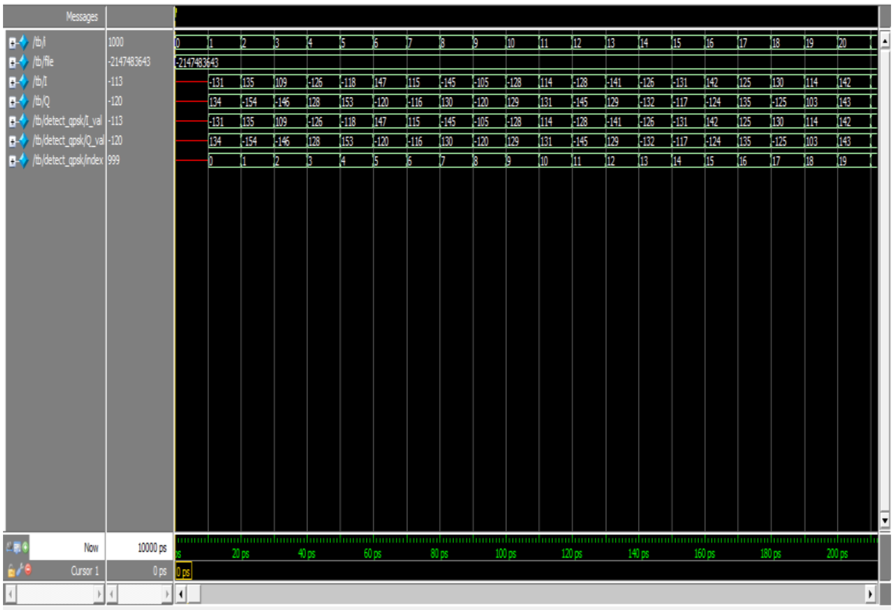

Fig.4.5. QPSK signal detection

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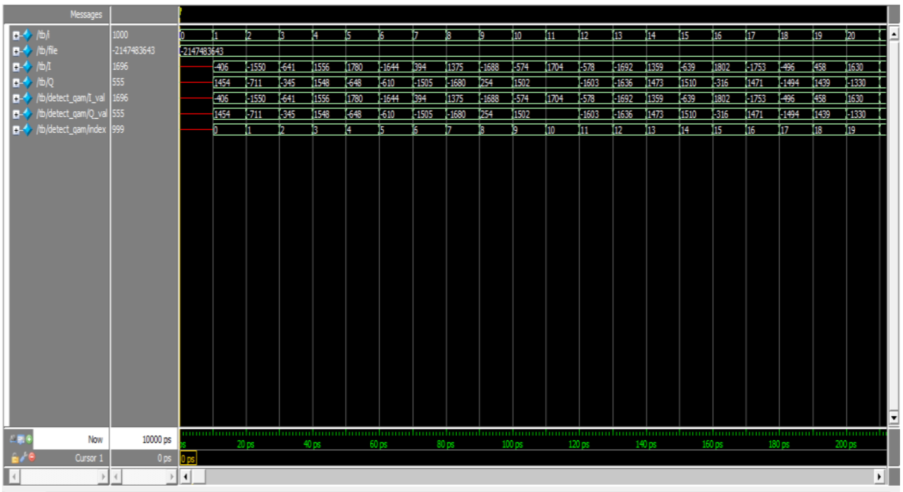

Fig.4.6. 16-QAM signal detection

Conclusion & Future Work

In this work, a multi-modulation sequence detection system integrating MATLAB for signal generation and Verilog for real-time classification is implemented. The proposed system outperforms threshold-based methods while maintaining lower complexity than ML-based approaches. The obtained simulation results indicate that detection accuracy of BPSK is higher in comparison to the other two modulation schemes.

Future research will focus on extending the framework to support higher-order modulations such as 64-QAM and OFDM-based schemes. Additionally, an FPGA implementation will be developed to evaluate real-time hardware performance and energy efficiency.

References

[1]. O.A. Dobre, A. Abdi, Y. Bar-Ness and W. Su, "Survey of automatic modulation classification techniques: classical approaches and new trends," IET Commun., pp. 137–156, 2007.

[2]. Mohamed A. Abdel-Moneim, Walid El-Shafai, Nariman Abdel-Salam, El-Sayed M. El-Rabaie, Fathi E. Abd El-Samie, "A survey of traditional and advanced automatic modulation classification techniques, challenges, and some novel trends", Int J Commun Syst., pp. 1-36, 2021.

ISSN PRINT 2319-1775 Online 2320-7876

Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11, Iss 2, February 2022

[3]. A. Nandi and E. Azzouz, "Algorithms for Automatic Modulation Recognition," IEEE Transactions on Communications, Vol.46, No.4, pp. 431-435, 1998.

[4] Jiang Y, Huang S, Zhang Y, Feng Z, Zhang D, Wu C. Feature-based modulation classification for overlapped signals. IEICE Trans Fundamental Electron Commun Computer Sci. pp. 1123-1126., 2018.

[5] Orlic VD, Dukic ML, "Automatic modulation classification algorithm using higher-order cumulants under real-world channel conditions," IEEE Commun Lett. Vol.13, No.12, pp. 917-919, 2009.

[6]. T. J. O'Shea, J. Corgan, and T. C. Clancy, "Convolutional radio modulation recognition networks," Proceedings of the International Conference on Engineering Applications of Neural Networks, 2016.

[7]. O'Shea. T. J., Roy. T., and Clancy. T. C., "Over-the-Air Deep Learning Based Radio Signal Classification," IEEE Journal of Selected Topics in Signal Processing, Vol. 12, No.1, pp. 16-179, 2018.

[8]. F. Wang, S. Huang, H. Wang, and C. Yang, "Automatic modulation classi1cation exploiting hybrid machine learning network," Mathematical Problems in Engineering, vol. 2018,pp.1–14,2018.

[9] Liu Z, Li L, Xu H, Li H, "A method for recognition and classification for hybrid signals based on deep convolutional neural networks," Proceedings of International Conference on Electronics Technology (ICET). IEEE, pp. 325-330, 2018

[10] . Zhou R, Liu F, Gravelle CW, "Deep learning for modulation recognition: a survey with a demonstration," IEEE Access., pp. 67366-67376, 2020.

[11]. Peng Wu, Bei Sun , Shaojing Su, Junyu Wei, Jinhui Zhao, Xudong Wen, "Automatic Modulation Classification Based on Deep Learning for Software-Defined Radio," Mathematical Problems in Engineering, Hindawi, 2020.