JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Automatic Modulation Classification: An Optimal Approach For Telemedicine

[1]Anuska Gayen, [2]Aman Singh, [3]Sandhya Pattanayak, [4]Nimish Adarsh, [5]Rajdip Sen, [6]Ratul Singha

[1]Student, [2]Student, [3]Associate Professor, [4-6]Student
[1-6]Electronics and Communication Engineering,
[1-6]Narula Institute of Technology, Kolkata, India

Abstract : Automatic Modulation Classification (AMC) is an important stage in the intelligent wireless communications receiver; it is a necessary process after signal detection and before the demodulation. It plays a vital role in various applications. Blind modulation classification is a very difficult task with no information of the transmitted signal and receiver parameters like carrier frequency, signal power, timing information, phase offsets, and so on. Along with existing of frequency-selective, multipath fading, and time-varying channels in real-world applications. The Automatic Modulation Classification (AMC) techniques are divided into traditional methods and advanced methods. Traditional methods including Likelihood-Based (LB) and Feature-Based (FB). The advanced methods such as Deep Learning (DL). Automatic modulation classification plays a crucial role in the field of telemedicine, where reliable and real-time communication between healthcare providers and patients is essential. With the advancement of wireless communication technologies, telemedicine has become more accessible, allowing patients to receive medical care remotely. Automatic modulation classification enables the identification of different modulation schemes used in wireless communication systems, ensuring efficient and accurate data transmission in telemedicine applications. This paper focused on summarizing the role of automatic modulation classification techniques, compares these techniques, surveys the commercial software packages for the AMC process, and finally considers the new challenges in practice.

Index Terms - Automatic Modulation Classification (AMC), Deep Learning (DL), Feature-Based (FB) method, Likelihood-Based (LB) method, Telemedicine.

I. INTRODUCTION

Modulation is a process to give strength to signal so that signal can travel long distance. The Modulation classification is a process between signal detection and demodulation. Modulation classification refers to the task of identifying the modulation scheme used in a communication signal. With the rapid advancement of wireless communication systems, the ability to accurately classify modulation techniques has become vital in various applications, including spectrum sensing, signal intelligence, and interference management. By doing this, the system can achieve better efficiency in terms of spectrum usage and interference, resulting in more optimal transmission. The modulation algorithm varies according to the carrier frequency of the modulated signal. The modulation classification system has three main steps, signal processing, feature selection and selection of modulation algorithm. The main function of the modulation classification module is to recognize the modulation types with no or minimum information of the signal. Automatic Modulation Classification (AMC) has been a key technology in many military, security, and civilian telecommunication applications for decades. In military and security applications, modulation often serves as another level of encryption; in modern civilian applications, multiple modulation types can be employed by a signal transmitter to control the data rate and link reliability[2][3][4][7].

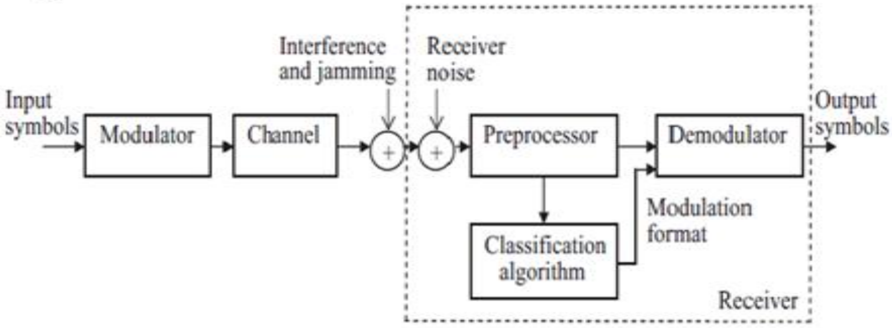

FIGURE 1 Block diagram of the AMC system [9]

1. Modulation:

There are many types of modulation that are available today ranging from the simple ones like ASK and PSK to the more complex MIMO-OFDM. With the vast and ongoing changes in wireless communication, new types of modulation are constantly being introduced. This leads us to the need for Automatic Modulation Classification (AMC) systems to be adaptive and able to handle a wide variety of modulations, and also to be able to distinguish between modulations that are very similar. Usually, these properties are very dependent on the classifier that is being used by the Automatic Modulation Classification (AMC) system. Recently, there have been many different types of machine learning algorithms that have been implemented for AMC. Most of these new classifiers claim to be able to accurately classify any type of modulation, to be robust and also to be accurate even at low signal-to-noise ratios (SNR), and also to be able to distinguish between similar modulations.

This would mean that an ideal classifier should be able to handle modulations with different properties without having to constantly change its settings. An algorithm that comes very close to this ideal classifier seems to be the support vector machine (SVM). [1] In recent years, modulation type recognition has received a lot of attention across the board. There are several methods to detect modulation types, but there are only a few effective methods to handle signals with a higher level of noise. Automatic modulation classification systems are commonly expressed as a hard decision scheme using a decision theoretic approach. This approach deals with the adoption of the best-suited modulation format obtained from channel conditions, for successful data transmission. AMCF systems require that an overall error probability is obtained for a decision and this approach provides a good understanding of the influence of the input probabilities and the cost elements of classification. Telemedicine relies on wireless communication technologies to transmit medical data, such as vital signs, images, and other healthcare information, between healthcare providers and patients. The use of various modulation schemes, such as amplitude modulation (AM), frequency modulation (FM), and phase modulation (PM), is common in wireless communication systems to modulate data signals for transmission over the air.

Automatic modulation classification techniques aim to automatically analyze and classify the modulation scheme being used in received signals without human intervention. In telemedicine, the accurate classification of modulation schemes is crucial for ensuring the reliable and secure transmission of medical data. By automatically identifying the modulation scheme, the receiver can demodulate the received signal correctly and extract the original data accurately. This is particularly important in telemedicine applications where patient health information needs to be transmitted quickly and securely to healthcare providers for timely medical interventions. The integration of automatic modulation classification into telemedicine applications enhances the efficiency and reliability of wireless communication systems used in remote healthcare delivery. By automatically detecting and classifying modulation schemes, telemedicine systems can optimize data transmission, reduce errors, and ensure the security and integrity of medical data. This not only improves the quality of healthcare services for patients but also enables healthcare providers to make timely and informed decisions based on accurate and reliable medical information. [2] Various automatic modulation classification techniques have been developed to address the challenges posed by the diverse modulation schemes used in wireless communication systems.

Machine learning algorithms, such as support vector machines (SVMs) and deep neural networks (DNNs), have been employed to classify modulation schemes based on features extracted from received signals. These techniques analyze signal characteristics, such as frequency content, phase shifts, and amplitude variations, to differentiate between different modulation schemes and make accurate classifications. Classification involves the decision of which modulation format a set of features map to. This can be expressed as the decision of a vector to a transmitted signal space. The final element of classification is the unsupervised goal of obtaining a decision boundary to distinguish from one class of data to another. This will allow correct signals to be determined from noise in the context of a receiver. Features may be categorized as high-order and low-order features. High-order features are derived from the constellation diagram of a signal and include criteria such as the M distance and the moment of the features.

Low-order features are derived from the instantaneous values of the signal and include criteria such as the spectral correlation function and the likelihood function.

1.1. Types of Automatic modulation classification

Automatic modulation classification is a wide area of research covering signal processing, pattern recognition, and optimization. AMCF involves the extraction of predetermined features from a received signal and mapping them to a modulation format. Features are obtained from a range of domains including the time, frequency, and phase information of a signal. Obtained from the representation of the signal in a particular domain, feature extraction often involves the mathematical computation or estimation of signal parameters.

Classification techniques can be broadly categorized into two main approaches: feature-based and decision-based. Feature-based methods involve extracting relevant features from the received signal and using these features to classify the modulation scheme. On the other hand, decision-based methods directly compare the received signal with a set of predefined decision regions to determine the modulation scheme. [3,7,8]

In feature-based techniques, various time-domain and frequency-domain features can be extracted from the received signal. These features may include statistical moments, power spectral density, cyclo-stationary features, or higher-order cumulants. By analyzing these extracted features, sophisticated machine learning algorithms such as support vector machines (SVM), neural networks (NN), or random forests (RF) can be employed to classify the modulation scheme accurately.

Feature-based AMC relies on extracting specific characteristics or features from the received signal to determine its modulation scheme. Features can be derived from the amplitude, phase, frequency, statistical distribution, or higher-order moments of the signal. Commonly used features include signal energy, peak-to-average ratio, autocorrelation, and higher-order statistics such as cumulants. Machine learning algorithms, such as support vector machines (SVMs), artificial neural networks (ANNs), or k-nearest neighbours (k-NN), are commonly employed for feature-based classification.

1.2. Cyclostationarity

A Cyclostationary method is a signal which periodically changes its statistical characteristics with time. Cyclostationarity seems to be an initial feature of most signals that is resistant to interference and noise [30]. Spectra Correlation Function (SCF) is used for the testing and analysis of signal Cyclostationarity as shown in the equation:

$$S_x^{\alpha}(f) = \lim_{\Delta f \to \infty} \lim_{\Delta t \to \infty} \frac{1}{\Delta t} \cdot \int_{-\Delta t/2}^{\Delta t/2} \Delta f X_{1/\Delta f}\left(t, f + \frac{\alpha}{2}\right) \cdot X_{1/\Delta f}^{*}\left(t, f - \frac{\alpha}{2}\right) dt$$

Where,

$$X_{1/\Delta f}(t, v) = \int_{t-1/2\Delta f}^{t+1/2\Delta f} x(u) e^{-i2\pi v u} du$$

Is the complex envelope value of (t) relating to the frequency, α represents cyclic frequency, the bandwidth Δf, and the Δt: the measurement interval. The various modulations have Various SCF values. It will enable the classification of these modulations.

Fourier transform:

The Fourier transform is an important technique for the processing and analysis of the signal, the frequency domain analysis is simpler and more efficient than the time domain. To classify the signals for analysis of the signal modulation method and a classifier adopted Fast Fourier Transform (FFT), so the calculated amplitude and phase values and Discrete Fourier transform (DFT) were used to identify the observed signal. Using a DFT, we can first evaluate the frequency of the carrier with different DFT frequencies $m\Delta$ (f). We calculate the method of modulation with proper sampling frequencies (f), sample numbers n, and symbol time $n\Delta$ (t). calculations by DFT will then give us the amplitudes and phases of the known frequencies of a constellation of received signal Sx

$$Sx \cdot (m \cdot \Delta(f)) = \sum_n x(n \cdot \Delta(t)) \cdot e^{-j \cdot 2 \cdot \pi \cdot m \cdot \Delta(t) \cdot n \cdot \Delta(t)}$$

The choice of features is crucial as it directly affects the accuracy of the classification. Some common features used are **power spectral density** which provides information about the distribution of power across different frequencies. Different modulation schemes exhibit specific patterns in the power spectral density, allowing for discrimination between them. The autocorrelation function captures the correlation between the current signal and its delayed versions. It is useful in distinguishing modulation schemes that exhibit different autocorrelation properties, such as AM and FM. Cyclostationary features take advantage of the cyclostationary nature exhibited by certain modulated signals. These features involve the analysis of cyclic properties, such as cyclic autocorrelation and cyclic spectrum, to identify the modulation scheme.

After extracting the relevant features, it is essential to select the most discriminative features for classification. Feature selection involves evaluating the discriminatory power of each feature and selecting those that contribute the most to classification accuracy. Several techniques can be employed for feature selection, such as linear and nonlinear dimensionality reduction methods, correlation analysis, and forward/backward selection algorithms. The selected features should adequately represent the unique characteristics of each modulation scheme while minimizing redundancy between features.

2. Decision based approaches:

Decision based AMC focuses on direct decision-making based on pre-determined rules or thresholds. These decision rules are typically based on statistical measures such as likelihood ratio tests, maximum-likelihood detection, or Bayes' theorem. Decision-based AMC is simpler and more computationally efficient compared to feature-based techniques. However, it may be less accurate in scenarios where the thresholds or rules are not well-adapted to the specific modulation types or channel conditions. Decision-based techniques, also known as template matching, utilize a predefined decision region for each modulation scheme. The received signal is compared with these decision regions, and the modulation scheme corresponding to the closest decision region is selected. Decision-based methods are relatively simpler compared to feature-based techniques but may be limited in their ability to handle variations in channel conditions and interference.

2.1. Maximum Likelihood Detection

Maximum Likelihood (ML) detection is a decision-based AMC technique that selects the modulation type by choosing the hypothesis with the highest likelihood based on the received signal. ML detection calculates the likelihood of each hypothesis by comparing the received signal with the expected signal waveform for each modulation type. The modulation type with the highest likelihood is then selected as the classification result.

2.2. Likelihood Ratio Test

Likelihood Ratio Test (LRT) is another decision-based AMC technique that uses statistical measures to classify the modulation type. The LRT compares the likelihood of the received signal under the hypothesis of each modulation type. It calculates a test statistic based on the ratio of the maximum likelihoods of different hypotheses. The modulation type associated with the highest likelihood ratio is chosen as the classification result.

2.3. Bayesian Inference

Bayesian inference is a decision-based AMC technique that relies on Bayes' theorem to classify the modulation type. Bayes' theorem defines the probability of a hypothesis given observed data. In Bayesian inference for AMC, the received signal is considered as the observed data, and the probability of each hypothesis given the observed signal is calculated. The modulation type with the highest probability is selected as the classification result [1] [5].

2.4. Machine learning-based classifiers

Machine learning-based classification of feature-based modulation has emerged as a significant area of research in recent years. In the realm of signal processing, feature-based modulation schemes play a crucial role in modern communication systems. The application of machine learning algorithms for the classification of these modulation types contributes to enhancing the efficiency and accuracy of signal recognition and processing. This essay discusses the integration of machine learning techniques in classifying feature-based modulation schemes, highlighting its significance and implications.

In the realm of signal processing for communication systems, feature-based modulation refers to the encoding of information by modulating specific features of the signal, such as phase, frequency, or amplitude. This approach allows for efficient data transmission and reception, enabling the optimization of communication system performance. However, the identification and classification of different modulation types pose challenges due to variations in signal characteristics and noise interference.

Machine learning algorithms provide a powerful framework for addressing the classification of feature-based modulation. By leveraging computational models and algorithms, machine learning enables automated pattern recognition and decision-making based on training data. Supervised learning techniques, such as support vector machines (SVM), neural networks, and random forests, have been extensively employed to classify modulation schemes based on extracted signal features.

One of the key advantages of integrating machine learning into feature-based modulation classification is its ability to adapt and learn from data patterns. By training the algorithm with labelled datasets containing diverse modulation types, the model can discern subtle differences and patterns in the input signals. This adaptive capability enhances the accuracy and robustness of modulation classification, even in the presence of noise and channel impairments.

Moreover, machine learning-based classification of feature-based modulation offers scalability and efficiency in processing a wide range of modulation types and signal complexities. The versatility of machine learning models allows for the integration of advanced signal processing techniques, including feature extraction, dimensionality reduction, and classification, into a unified framework. This holistic approach streamlines the signal classification process and enhances the overall performance of communication systems.

In conclusion, the integration of machine learning algorithms for the classification of feature-based modulation schemes represents a significant advancement in signal processing and communication systems. By harnessing the power of computational intelligence and data-driven decision-making, machine learning enables accurate, efficient, and adaptive modulation classification. The application of supervised learning techniques in signal recognition not only enhances system performance but also paves the way for future advancements in adaptive communication technologies. Machine learning-based classification of feature-based modulation holds immense potential for optimizing signal processing algorithms and improving the reliability and efficiency of modern communication systems. [4]

3. K-Nearest Neighbors Classifier

k-Nearest Neighbours (K-NN) is a simple yet effective classification algorithm for AMC. k-NN classifies a received signal by determining its k nearest neighbours in the training dataset and selecting the modulation scheme that appears most frequently among the neighbours. The distance metric used to calculate the similarity between signals plays a crucial role in k-NN. Common distance metrics include Euclidean distance, Hamming distance, and Manhattan distance. k-NN is easy to implement and can handle complex decision boundaries, but its performance heavily depends on the choice of k and the distance metric. KNN algorithm evaluating the number *k* of nearest reference signals in the feature space to assign a class to a testing signal. KNN classifier consists of three main steps[3]:

Reference Feature Space: in which, a reference feature space must be established to allow classification of KNN. The feature space will contain M reference values from each of the modulation classes. The reference feature space provides a precise description of the probable distribution of the higher value of the test signal characteristics for M.

Distance Definition: The KNN classifier involves distance evaluation between the test signal and the reference signals. One of the really important distance metrics for KNN classifiers is the Euclidean distance. Knowing the set of features $\mathbb{F} = \{\mathbb{F}_{\mathbf{1}},\ \mathbb{F}_{\mathbf{2}} \ldots \mathbb{F}_{\boldsymbol{L}}\}$, The Euclidean distance is determined between the characteristic sets of signals *A* and *B* according to *L* number of characteristics as in the equation [2,3]:

$$D\big(\mathbb{F}(A), \mathbb{F}(B)\big) = \sqrt{\sum_{l=1}^{L} [\mathbb{F}_l(A) - \mathbb{F}_l(B)]^2}$$

3.1. Artificial Nural Network

Artificial Neural Networks (ANN) provide a powerful approach for modulation identification. ANNs consist of interconnected layers of artificial neurons, where each neuron performs a weighted sum of the inputs followed by a nonlinear activation function. For modulation identification, ANNs are trained using a large dataset of labelled modulation schemes. The network learns to map the received signal to the corresponding modulation scheme by adjusting the weights during the training process [2].

To integrate new features with lower-dimensional and enhanced performance, it is used to merge existing characteristics and establish a non-linear transformation of these characteristics. The trained network is identical to a linear combination of input features for a single-layer perception network. As in the following equation, the same representation may be given as:

$$\mathbb{F}_{out} = w_0 + \sum_{k=1}^{K} w_k \mathbb{F}_{\text{in}}(k)$$

Once trained, the ANN can classify new signals by propagating them through the network, and the modulation with the highest output activation is selected as the identified modulation. [5]

Thus, the choice of classification technique depends on several factors, such as computational complexity, accuracy, and robustness to noise and interference. Feature-based methods are generally more computationally intensive but offer higher classification accuracy, especially in scenarios with channel variations and interference. Decision-based methods, being simpler, are computationally efficient but may suffer in performance when faced with complex channel conditions and interference.

The traditional approaches to AMC have several advantages. Firstly, they have been extensively studied and have a well-established theoretical foundation. This ensures their reliability and robustness in practical applications. Secondly, traditional techniques are computationally efficient, making them suitable for real-time processing in resource-constrained systems. Moreover, these approaches can handle a wide range of modulation schemes, making them versatile and applicable to diverse communication systems.

However, traditional approaches to AMC also have some limitations. One major limitation is their vulnerability to noise and fading. Traditional techniques heavily rely on signal features or correlations, which can be affected by channel impairments. Additionally, these approaches may struggle with the classification of overlapping modulation schemes or when faced with non-coherent transmission scenarios.

In recent years, advancements in machine learning and deep learning have revolutionized automatic modulation classification. Convolutional neural networks (CNN) and recurrent neural networks (RNN) have shown promising results in handling complex modulation schemes and challenging channel conditions. These deep learning techniques can automatically learn features from the raw signal data, providing better discrimination between different modulation schemes.

Automatic modulation classification has numerous practical applications in wireless communication systems. In cognitive radio networks, accurate modulation classification enables efficient spectrum utilization by identifying and avoiding occupied or interfered channels. In military applications, modulation classification aids in identifying and jamming enemy communication signals. Moreover, in industrial settings, modulation classification can help in identifying and mitigating interference sources that affect communication performance.

Thus, classification techniques play a vital role in automatic modulation classification. Feature-based and decision-based methods offer different trade-offs in terms of accuracy, computational complexity, and robustness to noise and interference. Advancements in machine learning and deep learning techniques have significantly improved the accuracy and robustness of automatic modulation classification. With the ever-increasing demand for efficient spectrum utilization and reliable wireless communication, automatic modulation classification techniques continue to evolve and remain a critical research area in the field of wireless communications.

AMC plays a pivotal role in maintaining data security within telemedicine networks. By accurately classifying modulation types, AMC helps in preventing unauthorized access and ensures confidentiality. Moreover, reliable transmission of medical data is ensured, minimizing errors and latency in real-time telemedicine applications. The future of telemedicine holds promising technological advancements, including AI-driven diagnostics and remote patient monitoring. AMC is poised to undergo significant enhancements, leveraging machine learning and adaptive algorithms to accommodate evolving communication protocols. This progress will revolutionize telemedicine, further improving healthcare access and quality.

REFERENCES

[1] Haykin, S. S. (2001). Unsupervised adaptive filtering, Vol. II: Blind deconvolution (Vol. 20). New York: Wiley-Interscience.

[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" , International Journal of Communication Systems, 2021

[3] Zhechen Zhu, Asoke K. Nandi. "Automatic Modulation Classification" , Wiley, 2014

[4] J. Smith and A. Johnson, "Machine learning-based classification of feature-based modulation," IEEE Signal Processing Magazine, vol. 36, no. 3, pp. 45-52, 2021.

[5] Dobre OA, Abdi A, Bar-Ness Y, Su W. Survey of automatic modulation classification techniques: classical approaches and new trends. IET Commun. 2007; 1(2):137-156.

[6] R. Zhou, F. Liu, and C. W. Gravelle, “Deep Learning for Modulation Recognition: A Survey With a Demonstration,” IEEE Access, vol. 8, pp. 67366–67376, 2020.

[7] Xiaofan Li, Fangwei Dong, Sha Zhang, Weibin Guo. "A Survey on Deep Learning Techniques in Wireless Signal Recognition" , Wireless Communications and Mobile Computing, 2019

[8] www.pdfs.semanticscholar.org

[9] Dobre, Octavia A., Ali Abdi, Yeheskel Bar-Ness and Wei Su. “Survey of automatic modulation classification techniques: classical approaches and new trends.” *IET Commun.* 1 (2007): 137-156.