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Research Article

M-ary Pulse Ampplitude Modulation Recognition Using Discrete Meyer Wavelet and Reverse Biorthogonal Wavelet

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Abstract:

Automatic modulation recognition (AMR) is a fundamental task in communication systems. Feature extraction (FE) is an essential part in the recognition system,the proper selection of FE will enhance the recognition accuracy, and reduce the complexity of the system. In this paper, Reverse Biorthogonal wavelet (RBW), andDiscrete Meyer Wavelet (DMW), followed by standard deviation are used for FE. They are used to reduce the FE sets, and complexity of the recognition system.Adaptive Neuro Fuzzy Inference system is used as a classifier, to classify the,M-ary Pulse Amplitude Modulation (PAM) signals (i.e.4PAM, 8PAM, 16PAM, 32PAM, 64PAM, and128PAM), in a wide range of signal to noise ratio (SNR). MATLAB programs were used to fulfill all the requested tasks.The results show that the recognition system of M-ary (PAM) signals exhibits a satisfactory level under low SNR, and the system can achieve success rates over 98% in SNR (from -2 to 12) dB.

1. Introduction

Automatic modulation recognition (AMR), a system that can detect automatically the modulation scheme from a received modulated signals without a priori information of the received signals parameters [1], AMR is important to recognize the transmitted modulated signal and, then determine the appropriate demodulation method to recover the transmitted signals correctly and accurately [2]. It is widely used in military, and civilian applications, and commercial scenarios [3], IOT [4], and spatial cognitive communication systems [5].It can be split into likelihood-based AMR (LB-AMR), and relies upon feature based AMR (FB-AMR), the (LB-AMR) exploits the recognition of a combination of hypothesis and testing problems, it suffers from hardness to implementation, high computational complexity, and lack of robustness [6]. In (FB-AMR), the recognition based on feature extraction (FE) and classifier [7], review of signal features and classifiers are demonstrated in [8- 10]. Selection of FE is a big challenge in the recognition of the modulated signals.There is a trade of number of extracted features and complexity of the recognition system, increasing the numbers of extracted features improve the accuracy of the system, but increase the complexity of the system, thus will increase the recognition time (training and classification times), that is very important in signals recognition [11], the AMR is useless if the recognition time is more than the signal period. In order to tackle these matters, Discrete Meyer wavelet (DMW) transform and reverse biorthogonal wavelet (RBW) followed by standard deviation for dimensionality reduction were used in this paper as features extraction. In [12], Continuous WT, Haar type was employed to classify the signals 4QAM, 8QAM, 16QAM, 2PSK, 4PSK, 8PSK, 2FSK, 4FSK, 8FSK, the percentage of recognition is more than 65% at (SNR) less than 5dB, the algorithm presents low computational complexity and small calculation amount. The authors in [13] use continuous WT to extract features for analyzing and classifying the signals BFSK, QFSK, 8FSK, 2ASK, 4ASK, 8ASK, QPSK, 8PSK, 16QAM, 32QAM, 64QAM.Binary digital modulation signals were analyzed in the presence of additive white Gaussian noise (AWGN) using Haar wavelet, the results show a high average accuracy of classification especially at low SNR [14]. In [15], discrete WT was used and 4th, 6th, 8th order moment for FE to identify MFSK signals. Continuous WT was used to analyze the parameters of signal characteristic in the AMR system, the proposed system grants high recognition rate to identify eight kinds of signals including MPSK, MASK, MFSK, and MQAM [16]. This paper reduces the complexity of the system by applying the standard deviation to the DWT and RBW, as well as improving the recognition efficiency especially at low SNR. While reducing the complexity and getting a high recognition ratio at low SNR were difficulties in previous researches.

The proposed classifier sub system is adaptive neuro fuzzy inference system [17] for training and decision- making. The proposed AMR can detect the type of modulation scheme automatically. The proposed algorithm is evaluated on M-ary pulse amplitude modulation (MPAM) types: 4PAM, 8PAM, 16PAM, 32PAM, 64PAM, 128PAM.

Following this introduction, section 2, discusses the mathematical model. section 3 gives the proposed AMR system, section 4, presents the simulation results and analysis. section 5 the conclusion is drawn.

2. Mathematical Model

2.1 Signal Modulation Recognition Model

This article specifies the modulation signal briefly namely M-ary Amplitude pulse modulation (MPAM). MPAM is a kind of modulation scheme that controls the different amplitude of carrier to attain the digitally modulated signal. MPAM is a good candidate for use in orthogonal frequency division multiplexing, it's minimum subcarrier frequency separation is 1/2T instead of 1/T for QAM, or MPSK, where T is symbol duration, then MASK is considered for bandwidth efficient applications [18].

The general mathematical expression of digital MPAM signal waveforms can be expressed as:

$$x(t) = \tilde{x}(t)e^{j(\omega_c+\theta_c)} \qquad 0 \le t \le T \qquad (1)$$

Where

x(t) is the modulated MPAM signal, $\tilde{x}$ is the envelope, ω_c and θ_c are the carrier frequency and carrier phase respectively.

$$\tilde{x}(t) = \sum_{i=1}^{M} A_i h_T(t-iT)$$

$$A_i = 2i - 1 - M \qquad i = 1,2,\dots,M$$

A_i represents the signal amplitude, and M= 2k, k refers to number of bits for each symbol. h_T is the standard unit pulse with duration T [19].

The mathematical expression of the received signal can be written as:

$$y(t) = x(t) + n(t) \qquad (2)$$

Where $n(t)$ is AWGN.

2.2 Discrete Meyer and Reverse Biorthogonal WT

Both continuous and discrete WT are powerful techniques with the ability to analyze and filter non stationary signals. Continuous WT is the basis of wavelet analysis. In case of discrete WT, digital filtering techniques are used to analyze the signals, the input signal is filtering by a high pass filter and low pass filter. The two filters compose the analysis filter bank, while the inverse discrete WT can reconstruct the original signal by a synthesis filter [20]. Meyer wavelet (MW) has many advantages like smoothness, derivation infinitely, its spectrum is finite, and attenuates fast, thus it is valuable to numerical calculation.MW spectrum is given by:

$$\hat{\psi}(W) = \begin{cases} e^{j\frac{W}{2}} \sin\left(\frac{\pi}{2}\vartheta\left(\frac{3|W|}{2\pi}-1\right)\right) \frac{2\pi}{3} \le |W| \le \frac{4\pi}{3} \\ e^{j\frac{W}{2}} \cos\left(\frac{\pi}{2}\vartheta\left(\frac{3|W|}{4\pi}-1\right)\right) \frac{4\pi}{3} \le |W| \le \frac{8\pi}{3} \\ 0 \qquad otherwise \end{cases} \qquad (3)$$

$$\vartheta(y) = \begin{cases} 0 & if \quad y < 0 \\ y & if \ 0 \le y \le 1 \\ 1 & if \quad y > 1 \end{cases}$$

Where $\vartheta(y)$ is a smooth function [21], [22].

Biorthogonal wavelet (BW), shows the property of linear phase, two sets of symmetric wavelets are required, $\varphi_{L,M}$ and its dual $\tilde{\varphi}_{L,M}$, one set is utilized for analysis of the signal and the other to reconstruct it [23]. Reverse biorthogonal wavelet (RBW) family is got from BW. BW fulfills the biorthogonality condition

$$\int_{-\infty}^{\infty} \varphi_{L,M}, \tilde{\varphi}_{L',M'}(t)\,dt = \begin{cases} 1 & if \ L = L' \ and \ M = M' \\ 0 & other\ wise \end{cases} \qquad (4)$$

The number which follows the BW and RBW symbolize the number of vanishing moment [24].

2.3 Standard Deviation

The sample standard deviation (SSD) can be expressed as:

$$SSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (5)$$

Where:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{N} x_i$$

N is the sample size.x_i is the ith point in the data set. $\bar{x}$ is the mean [25].

3. Proposed AMR System

A developed AMR was designed to recognize the MPAM signals, 4PAM, 8PAM, 16PAM, 32PAM, 64PAM, and 128PAM. The signals are corrupted with noise through AWGN channel. DMW and RBW were utilized followed by standard deviation, the selection of FE reduces the complexity of the system, and enhance the performance of the classifier. The features extraction were arranged as matrices for classification process. Classification sub system is based on adaptive neuro fuzzy inference system. Figure 1shows the proposed system. MATLAB programs were designed to produce each stage in the system.

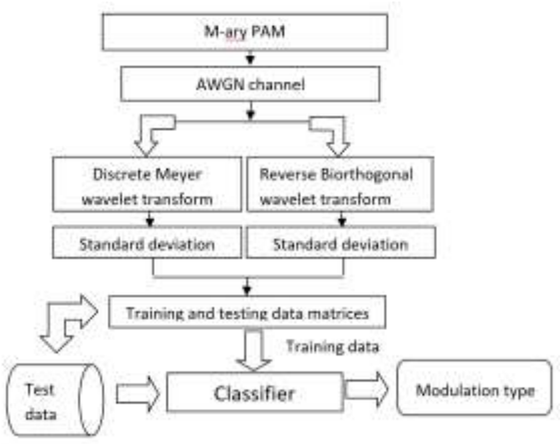

Figure 1. *Proposed AMR system.*

4. Simulation Results and Analysis

The AMR proposed system was simulated in MATLAB. The simulation was performed for recognition of MPAM signals. The results were obtained with 1680 bits for each modulation type at each signal to noise ratio (SNR), and AWGN was added according to specified SNR. Features of signals were extracted using approximation coefficients of DMW, and RBW, followed by standard deviation for each to decrease the computational complexity of the AMR, Figure 2 and 3 demonstrate the FE for each MPAM signal with specified SNR using DMW, and RBW respectively. The figures shows a high discriminating facilities of the FE of the system, thus improve the efficiency of the classifier. Adaptive neuro fuzzy inference system was utilized as a classifier.The input member ship function type is generalized bell, a number of member ship function =3, the output member ship function is linear, and the hybrid (gradient descent and least square) learning algorithm. After 1000 epochs the training error was =0.014912. Table 1 shows the classifier parameters, which were generated and copied from MATLAB program through recognition processes. The FEs are arranged as a matrices to train and test the classifier using MATLAB programs, The first two numbers of each row represents the input and

Table 1. *Classifier parameters.*

Classifier Parameters	Numbers
Nodes	35
Linear parameters	27
Nonlinear parameters	18
Total parameters	45
Training data pairs	48
Fuzzy rules	9

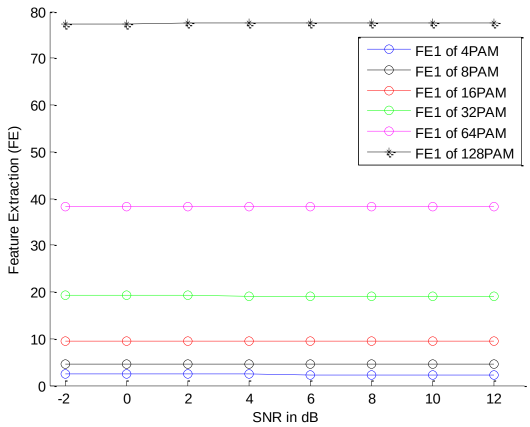

Figure 2. *FE of the modulated signals using discrete MW.*

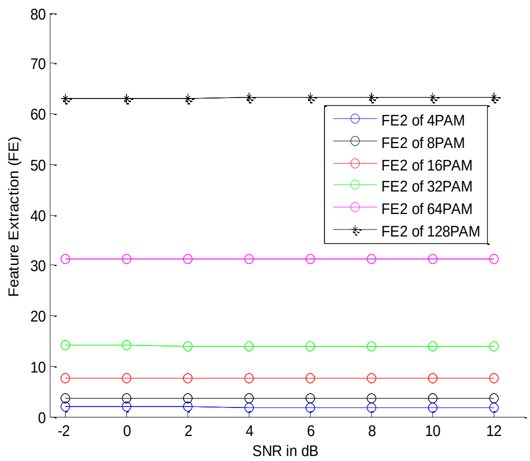

Figure 3. *FE of the modulated signals using RBW.*

the last number represent the output. Choice of the signal scheme type was represented by a numeric value; table 2 shows these choices. The program was run 1000 iteration for each test. The system encounters all the types of the MPAM signals, if the choice number and the decision numbers had the same value, then the classification was correct,

Table 2 the output numbers of classifier represent the signals

Choice Number	Modulation Type
1	4PAM
2	8PAM
3	16PAM
4	32PAM
5	64PAM
6	128PAM

However, if the choice and classifier decision were not the same, then the results represent incorrect classification. Figure 3 demonstrate the output of AMR system. From the results the system offers high recognition ratio close to 98.5%, robust and low complexity. Figure 4 shows classification of MPAM signals.

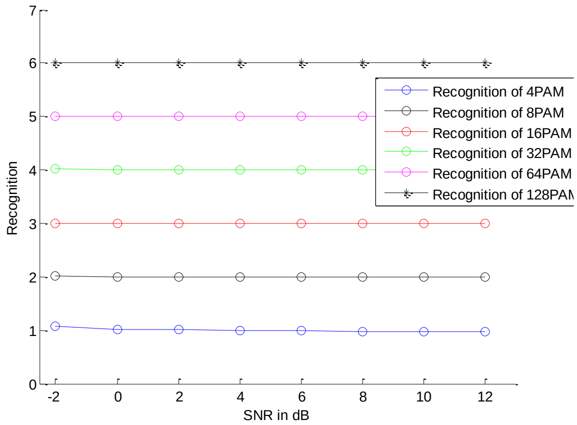

Figure 4. *Classification of MPAM signals.*

5. Conclusion

MPAM schemes are proposed to identify modulated signals in the presence of AWGN channel. DMW and RBW were used for FEs followed by standard deviation to reduce the complexity of the system, and classifier training time. The classifier is based on neuro fuzzy inference system. The structure of the system is robust against AWGN of channel, as well as high recognition ratio. The simulation results exhibits the high performance of the proposed AMR system. Applying the proposed recognition system for other digitally modulated signals are suggested for future work. IoT applied in different works as reported in literature [26-37].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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