A New Method of Automatic Modulation Recognition Based on Dimension Reduction

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***Abstract*—To improve the recognition rate of signal modulation recognition methods under the low Signal-to-noise ratio (SNR), a modulation recognition method is proposed. In this paper, we study an automatic modulation recognition through the Artificial Neural Network (ANN). Implement and design 7 digital modulations are: 2FSK, 4FSK, 8FSK, BPSK, QPSK, MSK and 2ASK. The cyclic spectrum after reducing dimension via Principle Component Analysis (PCA) is chosen as key feature for digital modulation recognizer based on the ANN. We corrupted the signals by additive White Gaussian Noise (AWGN) for testing the algorithm. The simulation results show that the ANN could classify the signals in its current state of development.**

Keywords- automatic modulation recognition; Artificial Neural Network; cyclic spectrum; Principle Component Analysis

I. INTRODUCTION

Since the spectrum is limited, in order to meet the needs of various users, and utilize the frequency resource more adequately, signals are modulated in different ways. Modulation recognition is increasing in importance for a number of years [1]. Extensive work has been carried out in both military and commercial applications [2], and it is also a key technology in the intelligence signal analysis and processing [3].

In general, the modulation recognition methods are divided into two main categories: artificial recognition method and automatic modulation recognition method. The artificial recognition method means to transform the signals from high-frequency to mid-frequency, and use the modem to demodulate the signal, then judge the demodulation results using related instruments, such as headphones and spectrum analyzer. However, the artificial recognition method needs great experience and knowledge, and the recognition rate is not accurate when the symbol rate is high. The automatic modulation recognition method is divided into three main processes: data pre-processing, feature extraction, and classificatory decision. Data pre-processing is the estimation of carrier and symbol rate after signal has been down-conversion. The use of feature extraction is to transform original data to extract some features which could be classified more easily. Classificatory decision is to judge the modulation type according to the features extracted.

Many features have been adopted for the automatic modulation recognition, including wavelet coefficients, higher order statistics (HOS), etc. Meanwhile, different methods are also employed for classificatory decision, such as probability density function (PDF) matching methods, unsupervised clustering techniques, and support vector machine (SVM). However, the aforementioned modulation recognition techniques are either computationally cumbersome or lead to unsatisfactory performances and hence new robust efficient modulation recognition schemes are still in demand.[4]

In this work, we proposed a method on automatic recognition of signal modulation based on cyclic spectral feature and artificial neural network. As the characteristics of the signal, the cyclic spectrum is not sensitive to noise, which is helpful for signal modulation recognition in low SNR environment. However, the cyclic spectrum of the signal is a large number of data, there are a lot of redundant information if it is directly recognized as the feature. On the one hand, it increases the complexity, and on the other hand, it may interfere with the final recognition. Therefore, this paper uses the PCA dimension reduction method to reduce the dimension of the cyclic spectrum feature. For the classifier, we choose artificial neural network as classifier. The neural network classifier has a strong pattern recognition ability, which can cope the complicated nonlinear problem well. Meanwhile, it has better robustness, and it is generally applied in the modulation recognition.

The remainder of this paper is organized as follows. Section II is the system model in which we introduce the signal expression and the environment of our study. Section III describes the cyclic spectrum after dimensionality reduction as features. Section IV introduces the classifier of the automatic modulation classification based on the neural network, and argues with some parameters of network. Experiments are conducted in Section V, and finally Section VI concludes the paper.

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II. SYSTEM MODEL

Like in many studies, in this paper too, we will assume perfect frequency offset and time offset recovery. We will also assume the channel to be frequency nonselective with additive white Gaussian noise (AWGN) [5]. A general expression for the received signal is $x(t)$, which is given by:

$$x(t) = h(t) + n(t) \tag{1}$$

where $h(t)$ is the noise-free received signal, $n(t)$ is the white Gaussian noise. The received signals are given into our automatic modulation classification system, through feature extraction and classification decision (the preprocessing will be left out because of the simulation), modulation type can be output from the system. The system block diagram is as Fig.1.

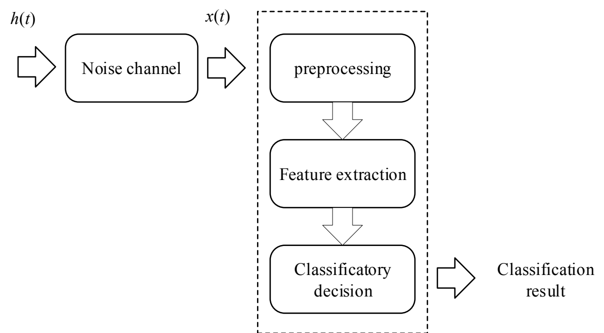

Fig. 1. system block diagram

III. FEATURE EXTRACTION

The feature extraction plays a very important role directly related to the feasibility of signal recognition algorithm in CR. Those features must be sensitive to the digital modulation types and insensitive to the SNR variation.[6] In this Section, we reduce the size of the cyclic spectrum projection by extracting some distinct component. These components can be represented as d-dimensional vectors, and we regard the vectors as the feature.

A. Cyclic Spectrum

The first step of the automatic modulation recognition is to estimate the cyclic spectrum, $\hat{S}_x^{\alpha}(f)$, of the received signal. It has been demonstrated that cyclic spectrum detection can be used for many types of modulation [7]. We express the autocorrelation of a signal as R_x, which is periodic when the signal $x(t)$ is a cyclostationary signal, so we know follows according to above:

$$R_x(t;\tau) = R_x(t+T;\tau) \tag{2}$$

where, T is the period and τ is the lag. The cyclic autocorrelation function for $x(t)$ is written as R_x^{α}:

$$R_x^{\alpha}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} R_x(t;\tau)e^{-j2\pi\alpha t}dt \tag{3}$$

where $\alpha = m/T$. Finally, the cyclic spectrum $S_x^{\alpha}(f)$ can be obtained by Fourier transforming the cyclic autocorrelation:

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau)e^{-j2\pi f\tau}d\tau \tag{4}$$

where α and f are cyclic frequency and spectrum frequency respectively. To extract the feature further, we need to get the cyclic frequency domain profile, which is just the largest value of the cyclic spectrum at each value of α. The formula can be written as follows. This can invert the cyclic spectrum from matrix to a vector, and reduce the computation of the subsequent recognition.

$$I(\alpha) = \max_f \left|S_x^{\alpha}(f)\right| \tag{5}$$

Fig. 2 shows the cyclic frequency domain profile of 7 types of signals, and there is no noise.

B. Feature Dimension Reduction

After getting the cyclic frequency domain profile, the feature vector still has a large length. Principal component analysis (PCA) is a good method to reduce the dimension. PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of correlated variables into a set of values of uncorrelated variables called principal components. PCA plots the data into a new coordinate system where the data with maximum covariance are plotted together and is known as the first principal component. Similarly, there are the second and third principal components and so on. The first principal component has the maximum energy concentration [8].

The data table to be analyzed by PCA comprises I observations described by J variables and it is represented by the $I \times J$ matrix $\mathbf{X}$, each observation is a cyclic frequency domain profile $I(\alpha)$. The matrix $\mathbf{X}$ has rank L where $L \le \min\{I,J\}$ [9].

In general, the data table will be pre-processed before the analysis. Almost always, the columns of $\mathbf{X}$ will be centered so that the mean of each column is equal to 0. In addition to centering, when the variables are measured with different units, it is customary to standardize each variable to unit norm. This is obtained by dividing each variable by its norm [9]. In this case, the correlation matrix can be written as:

$$C_X = \mathbf{X}^T\mathbf{X} \tag{6}$$