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Automatic Recognition of Communication Signal Modulation based on Neural Network

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***Abstract*—In order to solve the problem of low modulation recognition rate of digital communication signals and the difficulty of selecting the appropriate decision threshold, the paper features a recognition method for communication signal modulation. The paper constructs characteristic parameters for recognizing signals in the cyclic frequency domain, and uses a 3-layer neural network as a classifier to identify the modulation mode. The experiment indicates that it can recognize 2FSK, 4FSK, 8FSK, BPSK, QPSK, MSK and 2ASK. When signal to noise ratio (SNR) is higher than 0 dB, the recognition rate achieves 95%. The results suggest that recognition of communication signal modulation based on neural network is accurate and feasible.**

Keywords- modulation recognition; cyclic feature; neural network

I. INTRODUCTION

Communication environment has been more and more complex with the developing of communication, and the signal modulation mode becomes multitudinous to satisfy a large number of user's requirement. The automatic recognition of signal modulation refers to identification of a modulated signal with noise, and to ensure demodulation and feature extraction, which plays an important role in the military intelligence intercepted, electronic warfare, electronic reconnaissance, and other areas [1]. In the military field, we must judge the enemy's signal modulation type and estimate some critical parameters to disturb and intercept enemy's information. There are also many significant use in civilian areas such as detect the illegal radio and surveillance whether the parameter configuration of legal radio follows standard. For the more, automatic recognition of signal modulation is vital in cognitive ratio.

The modulation recognition is mainly divided into three 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, providing several appropriate data for follow-up operate. 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 mode according to the features extracted. In this paper, features in cyclic frequency domain are regarded as characteristic parameters, and the classifier is designed based on neural network.

The rest of this paper is organized as follows. In section 2, we briefly introduce the cyclic spectrum and characteristic parameters that we would use in the next process. Section 3 describes a BP network as a classifier. The simulation and analysis are presented in section 4. Section 5 concludes this paper.

II. CHARACTERISTIC PARAMETERS

A. The Definition of Cyclic Spectrum

Cyclostationarity is a kind of stochastic process in which the statistical characteristics periodic change with time [2]. We know by the definition of a cyclostationary signal that the mean of a signal, M_x, and the autocorrelation of a signal, R_x, are periodic [3]. Let's define the period by being T and the lag being τ, then:

$$M_x(t) = M_x(t+nT) \tag{1}$$

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

Since $R_x(t;\tau)$ is periodic, it can be expressed as a sum of a series of Fourier series, and Fourier series coefficients could be written as is shown in the following formula [4].

$$R_x(t;\tau) = \sum_{\alpha=-\infty}^{+\infty} R_x^{\alpha}(\tau) e^{j2\pi\alpha t} \tag{3}$$

$$R_x^{\alpha}(\tau) = \frac{1}{T}\int_{-T/2}^{T/2} R_x(t;\tau) e^{-j2\pi\alpha t} dt \tag{4}$$

where $\alpha=m/T$, and Fourier series coefficients $R_x^{\alpha}(\tau)$ are called cyclic autocorrelation function. We can get following formula by expanding the autocorrelation function:

$$R_x^{\alpha}(\tau) = \lim_{T\to 0}\frac{1}{T}\int_{-T/2}^{T/2} X(t+\tau/2) X^*(t-\tau/2) e^{-j2\pi\alpha t} dt \tag{5}$$

The spectral correlation function which is also known as the cyclic spectrum, can be obtained by Fourier transforming the cyclic autocorrelation [4]:

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-j2\pi f \tau} d\tau \qquad (6)$$

where α and f are cyclic frequency and spectrum frequency respectively.

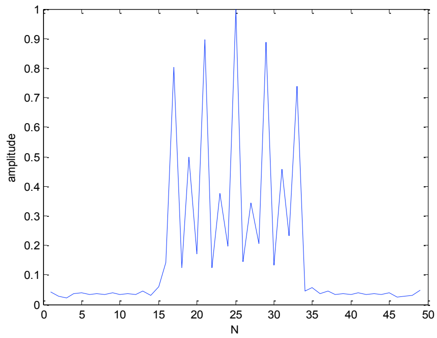
B. The Reduction of Cyclic Spectrum

Since cyclic spectrum yields large arrays that require significant post-processing in order to extract features of interest, the feature entered into the classifier in this paper is the cyclic frequency domain profile which is simply the largest spectral correlation function component at each value of α. The cyclic frequency domain profile is defined as follows [2]:

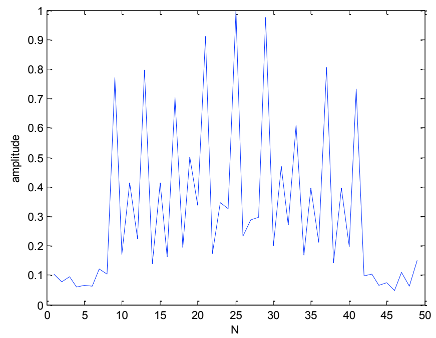
$$I(\alpha) = \max_{f} \left| S_x^{\alpha}(f) \right| \qquad (7)$$

According to projection, signal features in cyclic domain range from two-dimensional cyclic spectrum to one-dimensional cyclic frequency domain profile.

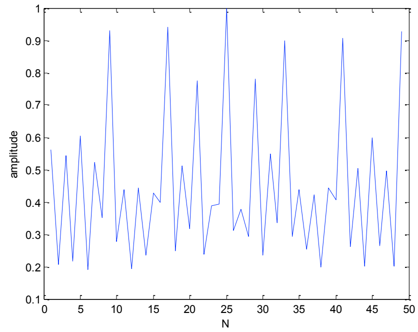
In order to reduce the complexity of the neural network, the cyclic frequency domain profile $I(\alpha)$ can multiply by a matrix



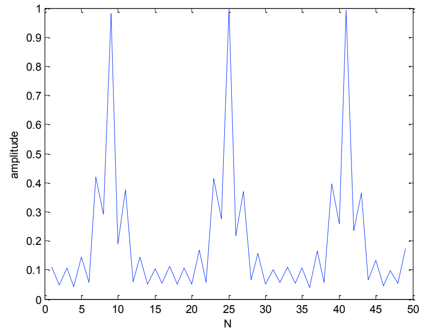
(a)The simulation profile of 2FSK.



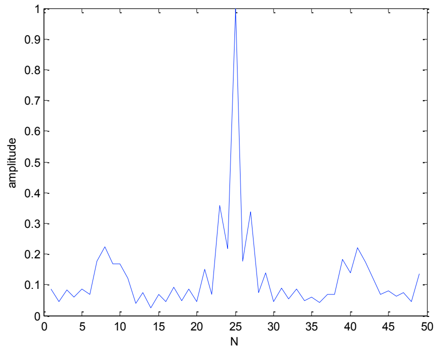
b) The simulation profile of 4FSK.



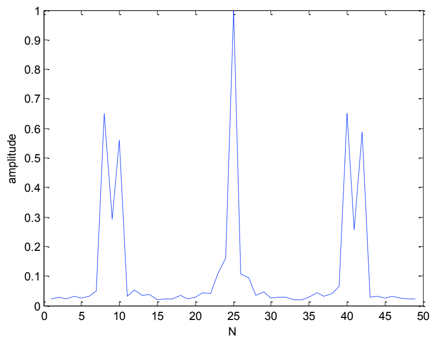
(c) The simulation profile of 8FSK.



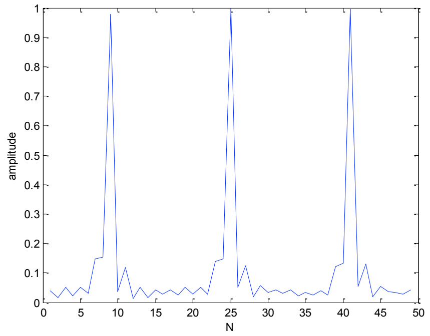
(d)The simulation profile of BPSK.



(e) The simulation profile of QPSK.



(f) The simulation profile of MSK.



(g) The simulation profile of 2ASK.

Fig. 1. The Cyclic Frequency Domain Profile of 7 Types Signal.

A can reduce the length of the cyclic frequency domain profile without the loss of sensitivity.

$$G = A \times I \qquad (8)$$

In the formula, the length of $I(\alpha)$ is q, and the size of A is $p \times q$, where $p < q$. G is the final feature which we will enter into the neural network. Seven types of signals' cyclic frequency domain profile are presented in Fig.1.

III. Classifier

The neural network is one kind of machine learning, which has characteristics of self-studying, self-adaptation, and high stabilization and can improve the autoimmunization and intelligence of recognition [5]. The neural networks improve the classification performance by changing the node weight, just like people's brain. In This paper, BP neural network is used as a classifier.

The cyclic frequency domain profile that we extracted after reducing the length should enter the network as the feature, so the number of input layer nodes is the length of the feature, p, which we set as 49. The network for the classify problem consists of only one hidden layer.

The output layer nodes number is set as the type number of signals that we intend to classify. In the paper, seven kinds of signals will be classified, so the output nodes are seven. Every node represents one kind of signal, and the value of the node which represents the current signal type is 1, others are 0.

The number of hidden nodes is designed according to the experience formula method. There are two common experience formula:

$$m = \sqrt{n+l} + a \qquad (9)$$

$$m = \log_2 n \qquad (10)$$

where n is the number of input nodes and l is the number of output nodes, a is an integer range from 1 to 10. In the paper, the hidden nodes number is set as 15.

The training of BP network needs mounts of samples as input dot. We get 100 signals each modulation type, and signal to noise ratio ranges from -10 dB to 20dB, thus, we obtain 700 signals in simulation, then we get the sample data according to cyclic feature extraction.

IV. Simulation Results and Analysis

Simulated parameters are represented by: the symbol rate is 1000bps, carrier frequency is 4 kHz, and sampling rate is 16 kHz. Each signal modulation mode to be identified should be sampled 500 times at each SNR, totally we have 15500 samples from -10 dB to 20 dB. The simulation results of one type recognition rate are shown in Fig.2. While the number of signal at each SNR will be 1000 when putting all types of signal together, and the comprehensive recognition rate is presented in Fig. 3.

From the Fig.2 and Fig. 3 we can see that the extracted characteristic parameters can effectively distinguish the signal to be recognized. There are excellent performance when SNR is higher than -5 dB when 2FSK, 8FSK, QPSK, 2ASK is to be identified solely, the recognition rate of signals is more than 95%. The comprehensive recognition is more than 90% when SNR is higher than 0 dB.

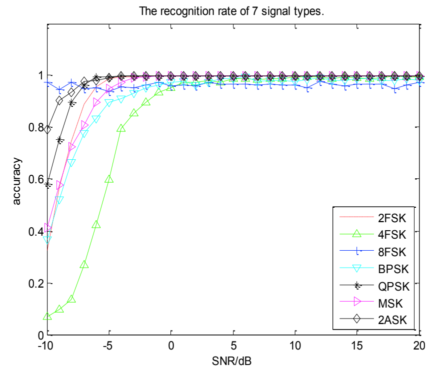


Fig. 2. The Recognition Rate of 7 Signal Types

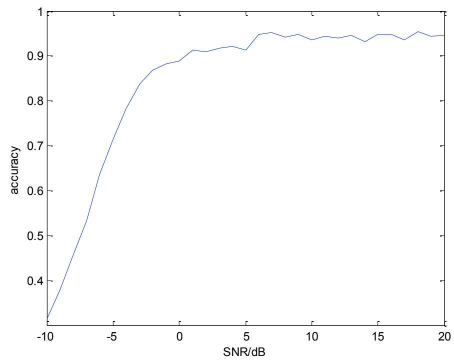


Fig. 3. The Comprehensive Recognition Rate

V. Conclusion

The paper outlined a method for recognizing the communication signal modulation mode. The use of the neural network makes the recognition process more effective and fast. It has been demonstrated, via simulation, the cyclic frequency profile is a type of good characteristic parameter in the recognition process.

Work is now needed to improve the design of neural network, which would make the recognition more accurate.

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