An Improved Communication Signal Recognition Algorithm Based on Extreme Learning Machine

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***Abstract*—In the modern information warfare, the requirements for the reliability and real-time performance of the communication signal recognition technology are getting more and more strict. Although a great number of studies have been conducted in the reliability of communication signal recognition, few studies have been performed in the speed of communication signal recognition. The purpose of this study is to explore an improved feature extraction methods based on extreme learning machine (ELM) which has the advantage of higher speed in communication signal recognition. The results of simulations show that the approach in this paper not only improves the speed of recognition and ensures a high reliability, but also reach an ideal recognition accuracy at a low SNR.**

Keywords—Communication signal recognition; ELM classifier; Feature extraction; Holder coefficient; Cloud features

I. INTRODUCTION

At present, enough attention has been aroused in feature extraction and many literatures [1] have studied the feature extraction algorithm, including the time domain feature extraction algorithm, the transform domain feature extraction algorithm and the time-frequency feature extraction algorithm. In addition, the entropy feature [2], the Holder coefficient feature [3] and other feature extraction algorithms in the communication signal recognition have also been a certain application. In the classifier design, the most common classification algorithm is the classification and recognition algorithm based on decision tree [4] which requires some prior information and the threshold is difficult to set accurately. In recent years, the development of artificial neural network has also made a significant contribution to the classification of signals. In [5], the BP neural network classifier is used to classify and recognize the extracted signal features. However, since the BP network is apt to fall into a local minimum and has the defect of longer time in calculation. In this paper, the rectangular window function and the Gaussian window function are used as a reference sequence to extract the two-dimensional Holder coefficient distribution characteristics and then the two-dimensional Holder coefficient features were extracted again to obtain the three-dimensional features [6] of the signals, then the ELM [7,8] classifier is introduced into the recognition of signals.

The structure of the paper is as follows: Section Two introduces Communication signal recognition model, Section Three illustrates the designed method presented in this paper, Section Four provides the simulation results and analysis.

II. COMMUNICATION SIGNAL RECOGNITION MODEL

The communication signal recognition system mainly consists of two parts: feature extraction and classifier designing as is shown in Figure 1. The innovation of this paper is to propose a new method to extract the feature based on the Holder coefficient. Then, extract the feature again by using cloud model theory to get the three-dimensional features of signal. Finally, the ELM classifier is introduced for signal recognition.

In this research, six different communication signals-Amplitude Modulation (AM), Frequency Modulation (FM), Phase Modulation (PM), Amplitude Shift Keying (ASK), Frequency Shift Keying (FSK), Phase Shift Keying (PSK) are taken as samples of communication signals to be recognized.

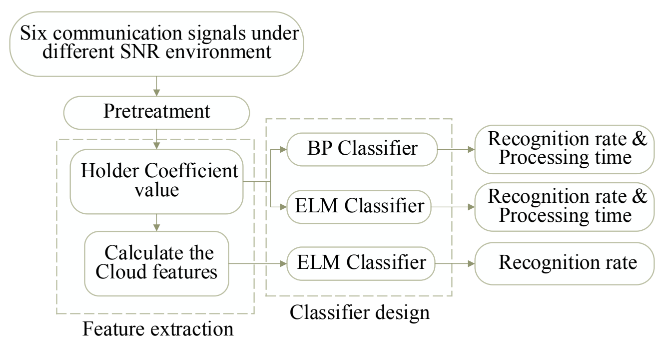


Fig 1 Communication signal recognition model

III. METHODOLOGY

A. Basic theory

According to the definition of the Holder inequality, Holder coefficient of the two communication signals can be defined as:

$$H = \frac{\sum s(i) s_n(i)}{\left(\sum s^p(i)\right)^{1/p} \cdot \left(\sum s_n^q(i)\right)^{1/q}} \tag{1}$$

where $n=1,2$, $p,q>1$, $\frac{1}{p}+\frac{1}{q}=1$, $0 \le H \le 1$, and $\{s(i)\}$ is signal sequence need to recognize. The basic definition of the Holder coefficient shows that the Holder coefficient represents the degree of similarity between two signals [9]. According to the definition of Holder coefficient, the rectangular window function and Gaussian window function were taken as reference sequences and they can be set as:

$$S_1(i)=\begin{cases} s, & 1\le f\le N \\ 0, & 其他 \end{cases} \tag{2}$$

$$S_2(i)=e^{-\frac{1}{2}\left(\frac{i-(N-1)/2}{\sigma(N-1)/2}\right)^2}, \sigma\le 0.5 \tag{3}$$

where N represents the number of discrete points of the signal.

B. Design process of improved algorithm

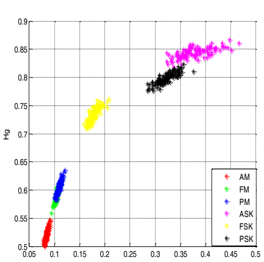
Step 1 – Obtaining the Holder coefficients of the signal and the rectangular window function H_r, the Holder coefficients of signal and Gaussian window function H_g to form a two-dimensional features vector, that is, $H=\left[H_r, H_g\right]$.

Step 2 - Under the low SNR environment, cloud model theory was used to extract the Holder coefficients distribution characteristics again and obtain the three-dimensional signal features- expectation Ex, entropy En and hyper-entropy He.

Step 3 - Introducing ELM classifier to recognize the six communication signals by using the two-dimensional characteristics and three-dimensional characteristics described above.

IV. SIMULATION RESULT AND ANALYSIS

In this section, we simulate the performance of the proposed algorithm, the simulation environment is as follows: SNR(dB)=[10,5,0,-5,-10], classifier training sampling number is 1000, classifier testing sampling number is 100.



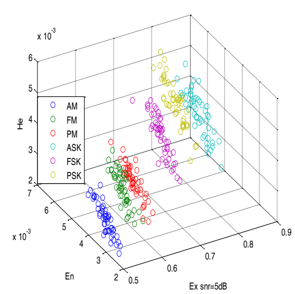


Fig 2 Holder coefficient characteristics of six communication signals

Fig 3 Holder cloud characteristics of six communication signals

Figure 2 shows the two-dimensional characteristics distribution of different signals at 5dB. Figure 3 displays the three-dimensional characteristics distribution of different signals at 5dB. We can observe that the Holder cloud characteristics are superior to Holder coefficient characteristics especially between FM and PM.

Table 1 Average recognition accuracy of two kinds of classifiers based on Holder coefficient characteristics under different SNR

SNR(dB)	10	5	0
BP(%)	100	90.8	75.1
ELM(%)	100	90.3	81.9

Table 2 Simulation time of different classifiers

Classifier	BP network	ELM
Simulation time(s)	2.8	0.9

From the Table1 and Table 2, we can see that ELM classifier has the advantages of the slightly higher recognition accuracy and shorter simulation time in comparison to the BP network classifier.

Table 3 Average recognition accuracy of ELM based on Holder cloud characteristics under different SNR

SNR(dB)	10	5	0	-5	-10
ELM(%)	100	100	100	98.3	74.7

After the above two-dimensional features are extracted again by using the cloud model to obtain the three-dimensional features, ELM classifier is taken to recognize the six signals. The simulation results are shown in Table 3, the recognition accuracy is improved obviously, the recognition accuracy can reach 74.7% even when the SNR is -10dB.

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