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# A Communication Signal Recognition Algorithm Based on Holder Coefficient Characteristics

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***Abstract*—**Communication signal modulation recognition technology is one of the key technologies in the field of modern information warfare. At present, communication signal automatic modulation recognition methods are mainly divided into two major categories. One is the maximum likelihood hypothesis testing method based on decision theory, the other is a statistical pattern recognition method based on feature extraction. Now, the most commonly used is a statistical pattern recognition method, which includes feature extraction and classifier design. With the increasingly complex electromagnetic environment of communications, how to effectively extract the features of various signals at low signal-to-noise ratio (SNR) is a hot topic for scholars in various countries. To solve this problem, this paper proposes a feature extraction algorithm for the communication signal based on the improved Holder cloud feature. And the extreme learning machine (ELM) is used which aims at the problem of the real-time in the modern warfare to classify the extracted features. The algorithm extracts the digital features of the improved cloud model without deterministic information in a low SNR environment, and uses the improved cloud model to obtain more stable Holder cloud features and the performance of the algorithm is improved. This algorithm addresses the problem that a simple feature extraction algorithm based on Holder coefficient feature is difficult to recognize at low SNR, and it also has a better recognition accuracy. The results of simulations show that the approach in this paper still has a good classification result at low SNR, even when the SNR is -15dB, the recognition accuracy still reaches 76%.

***Keywords*—**Communication signal, feature extraction, holder coefficient, improved cloud model.

## I. Introduction

MODULATION recognition of communication signals is increasingly significant in non-cooperative communication [1]. At present, communication signal automatic modulation recognition methods are mainly divided into two major categories. One is the maximum likelihood hypothesis testing method [2] based on decision theory, the other is a statistical pattern recognition method [3] based on feature extraction. Now, a statistical pattern recognition method based on feature extraction is used commonly. At present, there have been many studies on feature extraction in many literatures, including time domain [4], frequency domain, time-frequency domain [5]. For example, feature extraction based on instantaneous information, feature extraction methods based on high-order cumulants, feature extraction based on wavelet transform [6]. In addition, a great number of scholars have studied the signal complexity features, including the Holder coefficient [7] feature of the signal, the entropy feature [8] of the signal, the box dimension [9] of the signal. These features that can represent the signal are saved to the database as characteristic parameters of the signal. The feature extraction method based on signal complexity features is widely used among them due to it has the advantages of simple calculation. However, as the electromagnetic environment becomes more and more complex and the noise in the channel becomes larger and larger, the features mentioned in the above-mentioned literatures have randomness and fuzziness at low SNR that cannot represent a signal clearly. In the classifier design, the most common classification algorithm is the classification and recognition algorithm based on decision tree which requires some prior information and its threshold is difficult to set accurately. It is difficult to achieve satisfactory results at lower SNR. In recent years, with the development of artificial intelligence and machine learning, the BP neural network [10] classifier has also made a significant contribution to the classification of signals due to its strong self-adaptive ability and good classification effect, but the major defects about this method are as follows: weak generalization performance, longer time in calculation and it is easy to fall into a local minimum during the search process. Aiming at the above mentioned problems, in this paper, the rectangular window function and the Gaussian window function are used as reference sequences to extract two Holder coefficient features. Then, each Holder coefficient feature is transformed into a three-dimensional cloud feature using a one-dimensional cloud model [11] that does not require certainty information. Next, a comprehensive cloud model formula is used to get the last three-dimensional cloud features which have better intra-class aggregation and inter-class separation. Finally the ELM [12] which has a faster calculation speed is used to classify the above features. The rest of this paper is organized as follows: Section II introduces algorithm model, Section III illustrates the designed method presented and innovation in this paper, Section IV provides the simulation results and analysis, Section V gives the conclusion.

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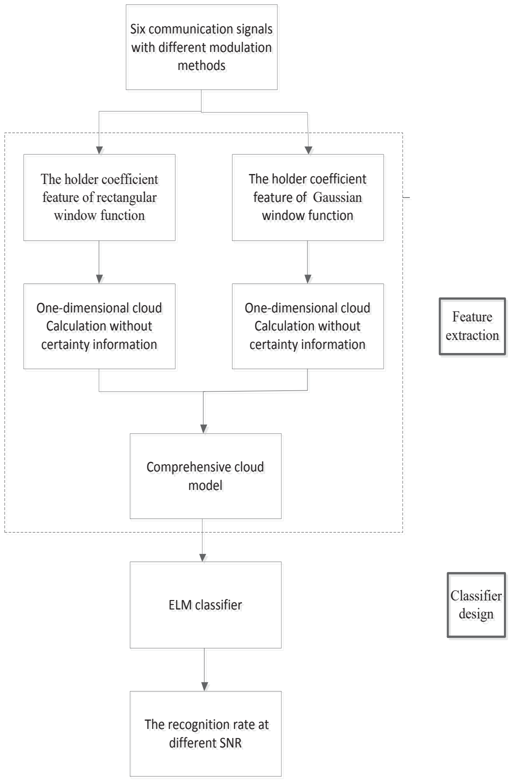


Fig. 1 Algorithm Model

## II. Algorithm Model

The communication signal modulation recognition system mainly consists of two parts: feature extraction and classifier designing. The feature extraction part is mainly to extract the stability characteristic that can represent the signal, and the classifier design part is mainly to classify the signals to be recognized according to the provided features. The innovation of this paper is to extract two kinds of Holder coefficient features firstly and to use one-dimensional cloud model that does not need to certainty degree information to extract the quadratic features of the Holder coefficient features, then the comprehensive cloud formula is used to obtain the final three-dimensional features of the signals. Finally, the ELM [13] classifier is introduced for signal recognition. The algorithm model of this paper is shown in Fig. 1. 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.

## III. Methodology

### A. Holder Coefficient Algorithm

For any vector $X = (x_1, x_2, ..., x_n)^T$, $Y = (y_1, y_2, ..., y_n)^T$, $X \in C^n$, $Y \in C^n$, the definition of Holder inequality [15] can be described as follows:

$$\sum_{i=1}^{n} |x_i \cdot y_i| \le (\sum_{i=1}^{n} |x_i|^p)^{1/p} \cdot (\sum_{i=1}^{n} |y_i|^q)^{1/q} \tag{1}$$

where, $p, q > 1$, $\frac{1}{p} + \frac{1}{q} = 1$. Holder coefficient can be used to measure the degree of similarity between two sequences from the basic definition of the Holder coefficient. The Holder coefficients between different kinds of signals and reference sequences are different, so it is possible to identify communication signals by using this method. The algorithm implementation process is as follows:

1.Let the signal to be identified is $S$, and the signal is sampled and converted into a discrete sequence $s(i), i = 1, 2, ...N$, $N$ represents the number of discrete sequence. Then analyze the signal by Fourier transform and obtain the signal sequence represented as $S(f)$.

2.Two different reference sequences are selected, this paper choose rectangular window function $S_1(f)$ which has the best effect compared with other window function and Gaussian window function $S_2(f)$ which is easier to implement in practice. Calculating the Holder coefficient value between the communication signal to be identified $S(f)$ and the two reference sequences separately. Then Holder coefficient of the two communication signals can be defined as:

$$H = \frac{\sum S(f) S_n(f)}{(\sum S^P(f))^{1/p} \cdot (\sum S_n^q(f))^{1/q}} \tag{2}$$

where $n$=1, 2, $p, q > 1$, $\frac{1}{p} + \frac{1}{q} = 1$, $0 \le H \le 1$. The basic definition of the Holder coefficient shows that the Holder coefficient represents the degree of similarity between two signals, where the rectangular window function and Gaussian window function were taken as reference sequences and they can be set as:

$$S_1(f) = \begin{cases} s, 1 \le f \le N \\ 0, others \end{cases} \tag{3}$$

$$S_2(f) = e^{-\frac{1}{2}\left(\frac{i-(N-1)/2}{\sigma(N-1)/2}\right)^2}, \sigma \le 0.5 \tag{4}$$

3. The obtained Holder coefficient can be constituted a two-dimensional joint feature vector which prepares for the subsequent secondary feature extraction, that is, $H = [H_c, H_t]$.

### B. Cloud Model Theory

Due to the complexity of modern communication environment, the feature parameters of communication signals are random and ambiguous. Cloud model can describe the randomness and ambiguity of features. The literature [14] uses two-dimensional cloud model to extract the expectation, entropy and hyper-entropy of the features of Holder coefficient. The specific algorithm of the above literature is to use the Holder coefficient feature of the triangular window function as the certainty information of the rectangular window function. This paper presents an improved Holder cloud feature extraction algorithm which extracts two sets of Holder cloud features by using one-dimensional cloud model with no certainty information for two Holder coefficient features, respectively. Then, the expectation $Ex$, entropy $En$ and hyper-entropy $He$ of the corresponding Holder coefficients are obtained to improve the recognition accuracy. $Ex$ indicates the center of gravity of the cloud cluster, $En$ indicates the degree of uncertainty of the feature, $He$ is the degree of uncertainty of entropy, reflecting the degree of cloud droplet condensation. One-dimensional cloud calculation formulas without certainty information are as follows:

1.Find the expectation of $n$ cloud drops:

$$Ex = \frac{\sum\limits_{i=1}^{n} x_i}{n} \tag{5}$$

2. Find intermediate variables:

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - Ex)^2 \tag{6}$$

3. Find the value of cloud entropy:

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{n}\sum_{i=1}^{n}|x_i - Ex| \tag{7}$$

4. Find the value of cloud entropy hyper-entropy:

$$He = \sqrt{S^2 - En^2} \tag{8}$$

The points in the cloud model satisfy the normal distribution, and the eigenvalues of the signal fluctuate around a certain stable value that also satisfy the normal distribution, which is consistent with the cloud model theory. Let the coordinates of cloud droplets be two Holder coefficient eigenvalues respectively, to find the expectation $Ex_m$, entropy $En_m$, and hyper-entropy $He_m$ of the one-dimensional cloud model by using (5)-(8), $m = 1, 2$. The specific formula are as follows:

$$Ex_m = \frac{\sum\limits_{i=1}^{n} H_m(i)}{n} \tag{9}$$

$$S_m^2 = \frac{1}{n-1}\sum_{i=1}^{n}(H_m(i) - Ex_m)^2 \tag{10}$$

$$En_m = \sqrt{\frac{\pi}{2}} \times \sum_{i=1}^{n}|H_m(i) - Ex_m| \tag{11}$$

$$He_m = \sqrt{S_m^2 - En_m^2} \tag{12}$$

where $n$ represents the number of calculation times of the Holder coefficient of the same signal, and the size of $n$ depends on the size of the recognition accuracy we need. The larger $n$ is, the higher the precision is and the larger the required cost is. That is, we get the expectation $Ex_1$, entropy $En_1$, and hyper-entropy $He_1$ of $H_c$ and the expectation $Ex_2$, entropy $En_2$, and hyper-entropy $He_2$ of $H_t$.

The final three-dimensional cloud features of the signals can be obtained by using the comprehensive cloud formula [15], that is,

$$Ex = \frac{Ex_1 En_1 + Ex_2 En_2}{En_1 + En_2} \tag{13}$$

$$En = En_1 + En_2 \tag{14}$$

$$He = \frac{He_1 En_1 + He_2 En_2}{En_1 + En_2} \tag{15}$$

Using the obtained expectation $Ex$, entropy $En$, and hyper-entropy $He$ to construct a three-dimensional joint feature vector which prepares for the design of the following classifier, that is, $F = [Ex, En, He]$.

### C. Classifier Design

ELM is an easy-to-use and effective single-layer hidden feed-forward neural network learning algorithm. Traditional neural network learning algorithms such as BP algorithm need to set a large number of network training parameters artificially, and it is easy to produce local optimal solutions. The ELM has the advantages of faster speed and good generalization performance due to it only needs to set the number of hidden nodes in the network and it does not need to adjust the input weight of the network and the offset of the hidden element during the execution of the algorithm to generates a unique optimal solution. Therefore, ELM has the advantages of fast calculation speed and better generalization ability. So this paper uses ELM classifier to recognize the six communication signals by using the two-dimensional Holder coefficient features, the features of original cloud model algorithm and the features of algorithm proposed in this paper.

## IV. Simulation Results and Analysis

In this section, this paper simulates the performance of the proposed algorithm, the simulation environment is as follows: SNR(dB)=$[10, 5, 0, -5, -10, -15]$, classifier training sampling number is 200, classifier testing sampling number is 100.

Fig. 2 shows the two-dimensional features distribution of different signals at SNR from 10 to $-5dB$. Fig. 3 displays the three-dimensional features distribution of different signals obtained by the improved algorithm described above at SNR from 0 to $-15dB$. We can observe that the improved Holder cloud features are superior to Holder coefficient features especially between ASK and FSK. When the SNR is 0 dB, the features of the ASK signal and the PSK signal substantially overlap, so that the classifier cannot accurately classify them. The improved three-dimensional Holder cloud features by the proposed algorithm still has good intra-cluster aggregation degree and inter-class separation degree when the SNR is $-10dB$. However, when the SNR is $-15dB$, the features of some signals overlap together.

Table I shows the results of using the ELM classifier to classify the two-dimensional Holder coefficient features of

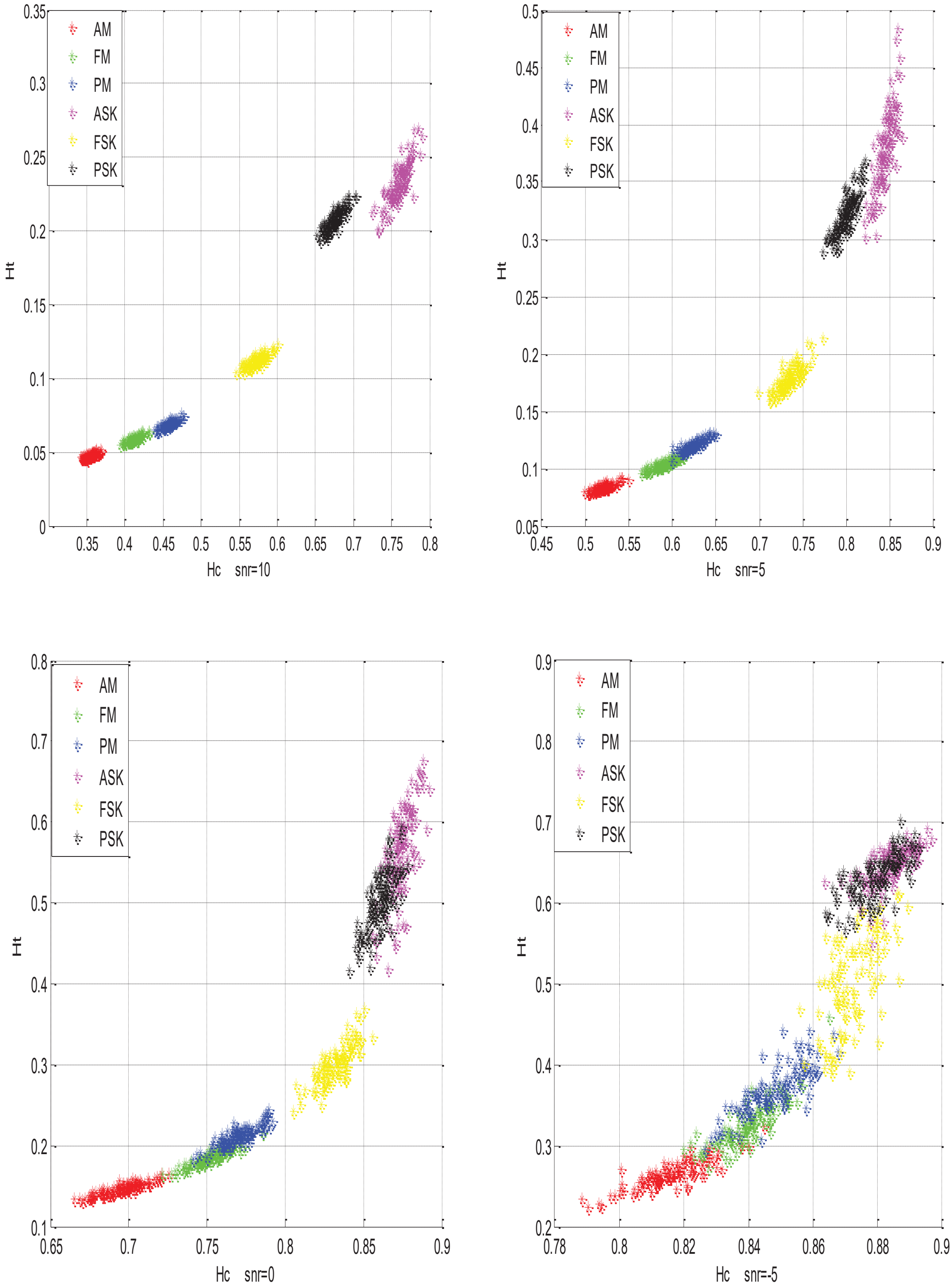


Fig. 2 Holder Coefficient Features of Six Communication Signals

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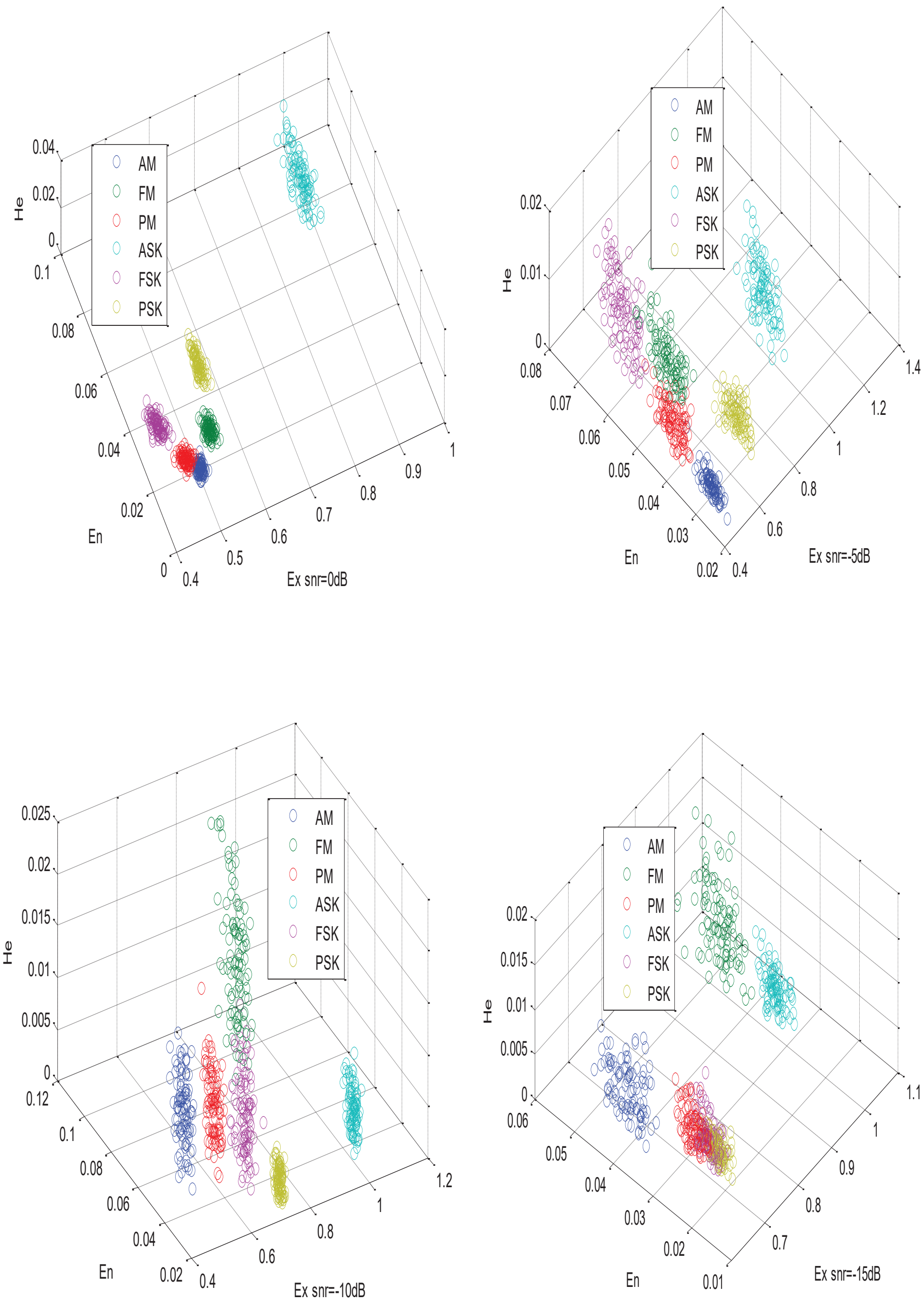


Fig. 3 New Holder Cloud Features of Six Communication Signals

different signals at different SNR. From Table I, we can see that an ideal recognition accuracy can be obtained when the SNR is high, but when the SNR is lower than 0dB, the classification effect is poor.

Table II shows the results of using the ELM classifier to classify the original Holder cloud features and the improved Holder cloud features of different signals in the case of lower SNR. We can see that the improved Holder cloud features have the advantages of the higher recognition accuracy in comparison to the original Holder cloud features. From Table II, we can see that the recognition accuracy is improved obviously when the SNR is low, it can achieve 76% even when the SNR is $-15dB$.

TABLE I
AVERAGE RECOGNITION ACCURACY OF ELM BASED ON HOLDER COEFFICIENT FEATURES UNDER DIFFERENT SNR

| SNR(dB) | 10 | 5 | 0 | $-5$ |
|---|---|---|---|---|
| Holder features(%) | 100 | 98.5 | 78.3 | 46.1 |

TABLE II
AVERAGE RECOGNITION ACCURACY OF ELM BASED ON HOLDER CLOUD FEATURES AND NEW HOLDER CLOUD FEATURES UNDER DIFFERENT SNR

| SNR(dB) | 0 | $-5$ | $-10$ | $-15$ |
|---|---|---|---|---|
| Holder cloud features(%) | 100 | 98.5 | 74.5 | 33.2 |
| improved Holder cloud features(%) | 100 | 100 | 100 | 76.0 |

## V. CONCLUSION

This paper proposes an improved feature extraction algorithm for the communication signal based on the improved Holder cloud feature. This algorithm addresses the problem that a simple feature extraction algorithm based on Holder coefficient feature is difficult to recognize at low SNR, and it also has a better recognition accuracy than the original Holder cloud feature extraction algorithm. In this paper, six common communication signals are taken as examples. For the features of Holder coefficient features with unstable eigenvalues at low SNR, three-dimensional cloud features of two kinds of Holder coefficients are obtained to describe the ambiguity and randomness of the basic characteristics of the signal by using a one-dimensional cloud model with no certainty information. Then the final three-dimensional cloud features of the signals can be obtained by using the comprehensive cloud formula. Because the ELM has the advantages of faster learning speed and better generalization performance, this paper uses the ELM classifier to classify the improved three-dimensional Holder cloud features of the above-mentioned different signals to verify the reliability of the algorithm. The simulation results show that the features extracted by the improved algorithm have better intra-class aggregation degree and inter-class separation degree so that it will have better application value in the recognition of communication signals.

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