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Research Article

A New Feature Extraction Algorithm Based on Entropy Cloud Characteristics of Communication Signals

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Identifying communication signals under low SNR environment has become more difficult due to the increasingly complex communication environment. Most relevant literatures revolve around signal recognition under stable SNR, but not applicable under time-varying SNR environment. To solve this problem, we propose a new feature extraction method based on entropy cloud characteristics of communication modulation signals. The proposed algorithm extracts the Shannon entropy and index entropy characteristics of the signals first and then effectively combines the entropy theory and cloud model theory together. Compared with traditional feature extraction methods, instability distribution characteristics of the signals' entropy characteristics can be further extracted from cloud model's digital characteristics under low SNR environment by the proposed algorithm, which improves the signals' recognition effects significantly. The results from the numerical simulations show that entropy cloud feature extraction algorithm can achieve better signal recognition effects, and even when the SNR is −11 dB, the signal recognition rate can still reach 100%.

1. Introduction

Signal recognition [1, 2] is a considerable intermediate step between signal detection and signal demodulation, which has been widely used in electronic reconnaissance, electronic jamming, electronic warfare, and other areas. At present, signal recognition algorithms can be broadly categorized as decision theory based algorithm [3] and statistical pattern recognition based algorithm [4]. Decision theory is usually required to get a theoretically optimal classification based on the minimum cost under a certain assumption. However, this algorithm needs to get much priori knowledge, and the calculation is complex and large. Pattern recognition algorithm based on feature extraction and classifier design does not need large amounts of known parameters, which could achieve the blind modulation recognition. Therefore, it has been more widely used in communication fields.

With the development of communication technology, the electromagnetic environment is increasingly complex. The noise is often superimposed on the signals, which leads to a low SNR and makes the waveform of the signals difficult to identify. Simply relying on a feature extraction algorithm is difficult when extracting better signal characteristics under lower SNR, which makes it difficult to achieve satisfactory recognition results. The existing recognition algorithms such as the recognition algorithm based on decision theory [5] is simple, and it can identify many types of signals and real-time process the data. However, the classification threshold values are changing with SNR which increases the difficulties of setting the threshold values. So its adaptability is poor. Recognition algorithm based on spectral analysis [6] extracts the power spectrum [7] and cyclic spectrum [8] characteristics of the signals in frequency domain to recognize the signals, which can reduce the impact of noise in the channel. However, it needs much priori knowledge of the signals, and the calculation is relatively complex. Constellation map [9] displays the structure characteristics of the signals, with the advantage of simple, intuitive, and low dependence on SNR.

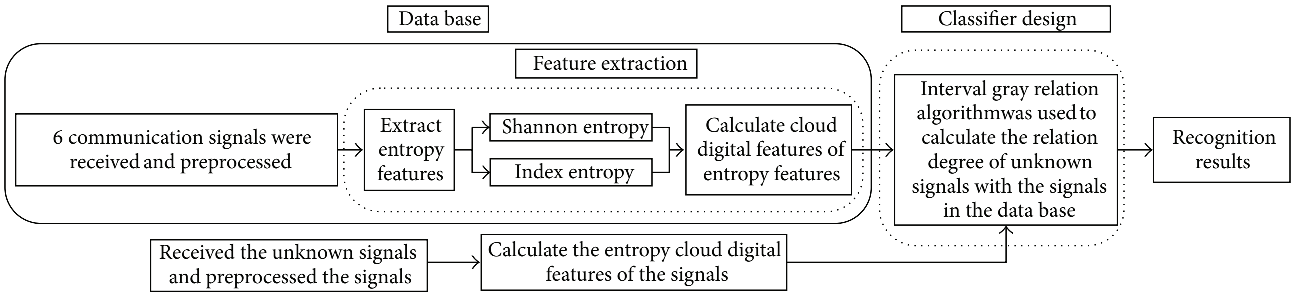


Figure 1: Recognition system based on entropy cloud characteristic of communication signals.

However, it requires strict synchronization with the receiving system and also needs to estimate, synchronize, and correct the initial phase and carrier of the signals.

To overcome the above disadvantages of the algorithms, we proposed a novel feature extraction algorithm based on entropy cloud characteristic of the communication modulation signals. First, the two-dimensional characteristics, Shannon entropy and index entropy of the signals in frequency domain, were extracted. Due to the existence of noise, the distribution of the extracted characteristics possesses fuzzy property. Then three digital characteristics of cloud model were used to further extract the three-dimensional entropy distribution characteristics of the signals, in order to extract the signal distribution characteristics in details to achieve the purpose of identifying the signals under low SNR environment.

2. Recognition System Model

Automatic identification of communication modulation signals is a relatively new research direction in the field of signal analysis, which has a great application prospect. According to the received signals, automatically recognizing the modulation types of the signals is referred to as signal modulation recognition or modulation classification. The communication signal recognition system block diagram based on entropy cloud characteristics is shown in Figure 1, which can be divided into two parts, feature extraction [10] and classifier design [11].

In the feature extraction module, six different communication signals were preprocessed first; then the entropy features of the signals need to be extracted, which includes Shannon entropy and index entropy. Considering the existence of noise, the signal characteristic values are not a constant value, but fluctuating within a certain interval. Given the distribution of entropy characteristics which is similar to the distribution characteristics of cloud model, the digital characteristics of cloud model were employed to extract the distribution characteristic of the entropy features, which provides a good database for the second module—classifier design.

In the classifier design module, interval gray relation algorithm [12] was adopted to calculate the relation degrees of entropy cloud characteristic values of the signal to be recognized with the known characteristic values in the database. Then the modulation type of the signal in the database with the maximum relation degree value was selected as the recognition result of the signal to be identified, eventually to achieve the purpose of classifying and recognizing the signals with higher accuracy.

3. Methodology

3.1. Entropy Theory. In information theory, "entropy" [13] can measure the uncertainty of the things. It can be used to describe the uncertainty distribution and the complexity characteristics of the signal, which can quantitatively describe the internal information characteristics that contain in the signal. Therefore, entropy characteristic can be used to extract the internal features of the signals.

In the entropy theory, the most commonly used Shannon entropy [14] can be defined as

$$H_1(p) = H(p_1, p_2, \ldots, p_n) = -\sum_{i=1}^{n} p_i \log_2 p_i, \tag{1}$$

where $p = (p_1, p_2, \ldots, p_n)$ represents the existing probability of every event in the collection, and it satisfies

$$0 \le p_i \le 1, \quad \sum_{i=1}^{n} p_i = 1. \tag{2}$$

The index entropy [15] algorithm adopt in this study can be defined as

$$H_2(p) = \sum_{i=1}^{n} p_i e^{1-p_i}, \tag{3}$$

where $\Delta I(p_i) = e^{1-p_i}$ represents the amount of information of the event with the probability of p_i.

Compare the amount of information $\Delta I(p_i) = e^{1-p_i}$ of index entropy defined above with $\Delta I(p_i) = \log(1/p_i)$ of Shannon entropy; the meaning of them is unified by definition. The amount of information defined by index entropy $\Delta I(p_i)$ is a monotonically decreasing function in the domain of $[0, 1]$ while the value range is $[1, e]$. For Shannon entropy, its value range is $[-\infty, +\infty]$. Only when $p_1 = p_2 = \cdots = p_n$ can the two entropies both take the maximum values.

Feature extraction algorithm based on entropy theory can distinguish different communication signals through describing the distribution state characteristics of the signals. The details of the signal's characteristics are unnecessary, and calculation is relatively simple. Feature extraction algorithm based on entropy is suitable for the signal recognition under higher SNR environment. However, when the signal is completely submerged in the noise, the recognition method based on the complexity of the signals by entropy characteristics is difficult when accurately identifying the signal due to the big overlap interval between different signal entropy characteristics.

3.2. Cloud Model Theory. Cloud model [16] is an uncertainty reasoning systems based on language rule, which can describe the randomness and fuzziness between uncertainty language characteristics and precisely numerical values on the basis of statistical mathematics and fuzzy mathematics. Based on this feature, cloud model can describe the concept of the multilevel perspective. The expectation curve of cloud model follows normal distribution characteristic, which reflects the fuzzy states. The distribution of cloud model concept has a certain cohesion property which is consistent with the distribution characteristics of signals affected by noise. Therefore, the digital characteristics of normal cloud model can be used to reveal the relevance between the randomness and fuzziness property of the entropy characteristics. We add hyper entropy into the normal distribution function to measure the deviation of signal characteristic samples from the normal distribution samples, taking expansion of the normal distribution to Pan-normal distribution, in order to more accurately describe the statistical properties of the signal's characteristics.

Cloud model can be divided into two types, forward cloud model and backward cloud model. The basic principle of forward cloud model is a process to produce cloud droplets which satisfy the distribution characteristics according to the known digital distribution of cloud droplets group. The basic principle of inverse cloud model is a process to calculate the digital characteristics of cloud droplets distribution characteristics based on the known data values of cloud droplets.

The digital characteristic of inverse cloud model was adopted in this study, effectively converted the exact data which is the distribution of cloud droplets to its digital characteristics—mean value Ex, entropy En, and hyper entropy He in order to concretely express the concepts of the cloud model. The distribution of the cloud droplets and its digital characteristics can be illustrated in Figure 2.

The digital characteristics can be used to represent overall cloud droplets which are reflected by the exact data. Thus the purpose of accurately describing the fuzziness and randomness of the signal characteristics can be achieved. The basic process of inverse cloud model can be described as follows.

(1) Suppose the two-dimensional position coordinates of every cloud droplet are $S(i) = (x(i), y(i))$ and calculate the mean value Ex of cloud droplets according to $\mathrm{Ex} = (1/n)\sum_{i=1}^{n} x(i)$, where $x(i)$ represents the value of ith cloud droplets and $i = 1, 2, \ldots, n$, n is the number of cloud droplets.

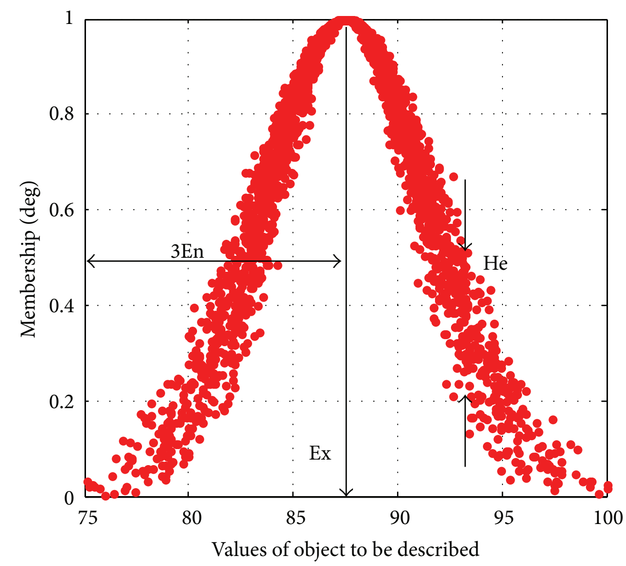


FIGURE 2: Distribution of cloud model and its digital characteristics.

(2) For each cloud droplet $S(i) = (x(i), y(i))$, the entropy value $\mathrm{En}(i)$ can be calculated according to $\mathrm{En}(i) = \sqrt{-(S(i) - \mathrm{Ex})^2 / 2\ln y(i)}$.

(3) The average entropy En of cloud droplets with the number of n can be calculated by $\mathrm{En} = (1/n)\sum_{i=1}^{n} \mathrm{En}(i)$.

(4) The hyper entropy He can be calculated by $\mathrm{He} = \sqrt{(1/(n-1))\sum_{i=1}^{n} (\mathrm{En}(i) - \mathrm{En})^2}$, which is the mean square error of $\mathrm{En}(i)$.

The distance between the test sample $S(i)$ and the center of gravity value Ex of cloud droplet group determines the possibility of the sample belonging to the category. The entropy value $\mathrm{En}(i)$ reflects the range of cloud droplets group that can be accepted by signal characteristic sample in the data space. Hyper entropy is the measure of the uncertainty of entropy value, which represents the laxity of entropy.

4. Proposed Algorithm

In feature extraction process, the target signal could be affected by the noise, and the amplitude of signal has a certain fuzziness and randomness property. The extracted characteristic of the signal is not stable but fluctuates in a certain range. It is difficult to accurately and completely describe the characteristics of the target signal. In order to improve the recognition accuracy, it is often needed to increase the number of the extracted features and thus to achieve the purpose of extracting the signal's characteristics more accurately. However, in this case, it often results in the excessive characteristic dimensions which increase the computational time forming "curse of dimensionality." To solve this problem, feature extraction algorithm based on entropy cloud model was proposed which described the fuzziness and randomness property of the extracted characteristics to more accurately extract the features of the signals. The steps of the proposed algorithm are as follows.

(1) Suppose the signal to be identified is $s(n)$ and make use of FFT transformation to transform the signals from time domain to frequency domain:

$$S(i)=\sum_{n=0}^{N-1}s(n)\exp\left(-j\frac{2\pi}{N}ni\right). \tag{4}$$

(2) Calculate the energy value of every frequency spectrum point in the frequency domain:

$$E(i)=\frac{1}{N}\sum_{i=0}^{N-1}|S(i)|^2. \tag{5}$$

(3) Calculate the sum of all the points of the energy spectrum:

$$E=\sum_{i=1}^{N}E(i). \tag{6}$$

(4) Calculate the probability of every spectrum point's energy in the total energy:

$$P(i)=\frac{E(i)}{E}=\frac{E(i)}{\sum_{i=1}^{N}E(i)}. \tag{7}$$

(5) Calculate the Shannon entropy of the signal's spectrum point:

$$H_s=H(p(1),p(2),\dots,p(n))=-\sum_{i=1}^{n}p(i)\log_2 p(i). \tag{8}$$

(6) Calculate the index entropy:

$$H_i=\sum_{i=1}^{n}p(i)e^{1-p(i)}. \tag{9}$$

Two-dimensional feature vector $H=[H_s,H_i]$ can be constituted by the Shannon entropy and index entropy. The Shannon entropy and index entropy characteristics of the signals were extracted repeatedly under different SNR. Due to the presence of noise, the entropy values of the signals stay unstable and fluctuate in a certain range. Thus it is better to apply digital characteristics of cloud model to further extract the entropy distribution under instability noise environment. In accordance with calculation methods of cloud model given in Section 3.2, the distribution characteristics of different modulation signal should be extracted to achieve the purpose of signal recognition.

5. Simulation Results and Analysis

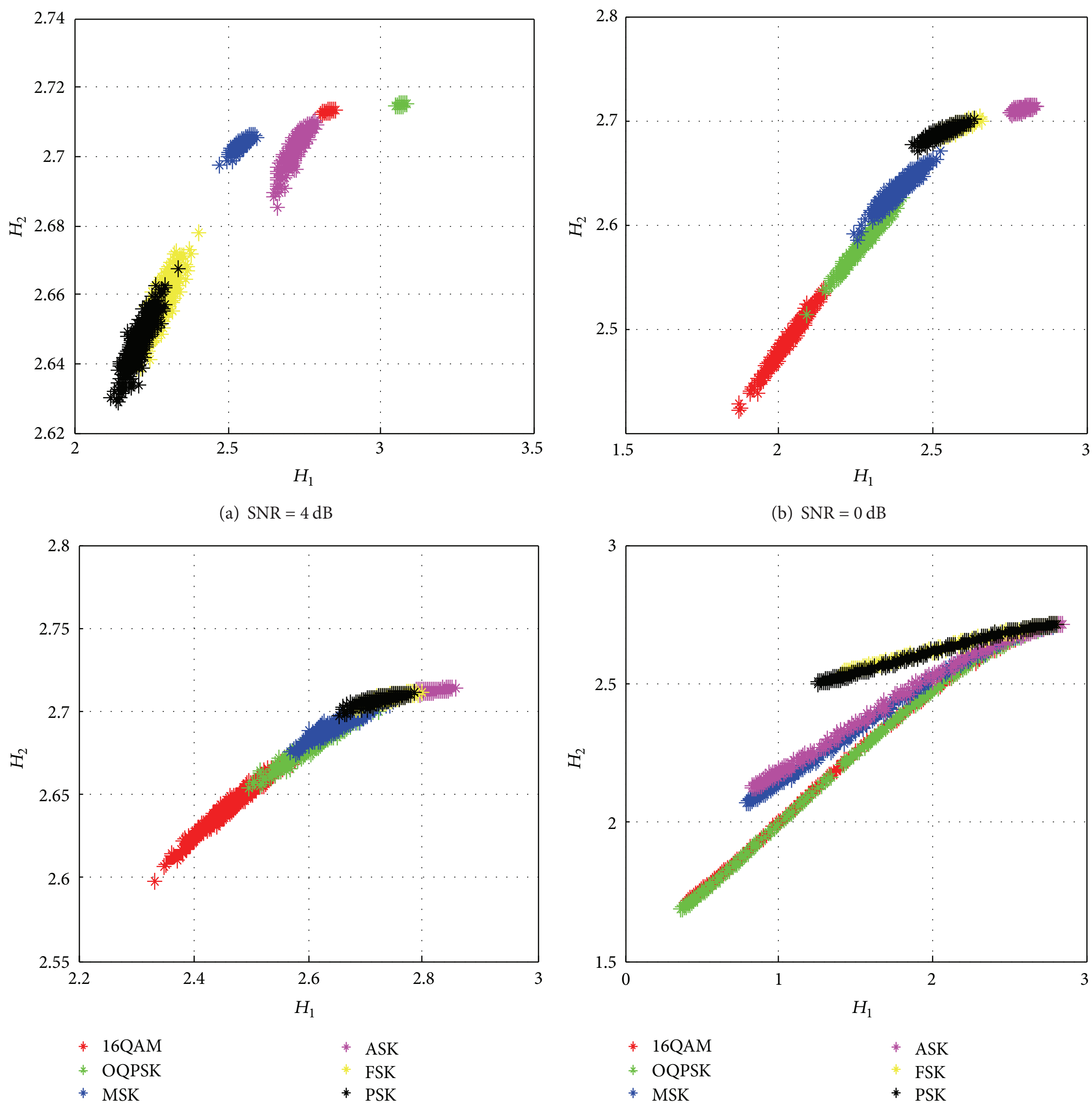
Take the six kinds of communication modulation signals: 16 quadrature amplitude modulation (16QAM), offset-quadrature phase shift keying (OQPSK), minimum shift keying (MSK), amplitude shift keying (ASK), frequency shift keying (FSK), and phase shift keying (PSK) as example, and then Shannon entropy and index entropy characteristics of different modulation signals under different SNR were calculated, which consist of two-dimensional feature vectors. Under the influence of noise, the two-dimensional entropy characteristic values are not fixed but changing with the SNR within a certain range. Meanwhile, with the increase of noise, the fluctuation ranges of the entropy characteristic values are becoming larger. Simulation results are shown in Figure 3, where the abscissa represents the Shannon entropy of the signal characteristics and the ordinate represents the index entropy of the signal characteristics. Simulation results under different SNR are, respectively, shown in subgraphs (a), (b), (c), and (d).

The aggregation of signal characteristics is better when the SNR is 4 dB, which has the smaller overlap among different types of modulated signals characteristic values. When the SNR is decreased to −8 dB, there is some separation among different signal characteristic values. The overlap intervals among different characteristic values of modulation signals become larger. Therefore, a better design of the classifier is required in order to achieve a higher recognition rate.

In order to improve the aggregation degree of the same signals' characteristics and the separation degree of different signals, entropy distribution characteristics of different modulated signals were extracted again based on the digital characteristics of cloud model, that is, the mean value, entropy, and hyper entropy. Simulation results are shown in Figure 4, in which Ex represents the mean of the signal characteristics (x coordinate axes), which is the central value of the signal characteristic values; En represents the entropy distribution of the signal characteristics (y coordinate axes), which is the discrete property of the signals' feature distribution; He represents the hyper entropy of the signal' characteristics distribution (z coordinate axis), which is the dispersion degree of entropy characteristic distribution of the signals. The same as in Figure 3, Figures 4(a), 4(b), 4(c), and 4(d), show the simulation results under different SNR, respectively.

It can be seen from Figure 4 that extracting the distribution characteristics of the signals' entropy the second time and transforming the two-dimensional distribution of entropy characteristics into three-dimensional cloud model characteristics have better aggregation degree among the same signals and separation degree among different signals. We can also see that only one feature (Ex) from three cloud model characteristics (Ex, En, He) has some discriminative power, but it only works well under higher SNR environment; at this time, the rest two features can be neglected to save the recognition time. While with the decreasing of SNR, the noise become larger, features (Ex) of some signals stay the same; thus only one feature to classify the signals is not enough. Given that entropy feature distributions of these signals are different, the other two features (En, He) that are used to reveal the relevance between the randomness and fuzziness property of the entropy characteristics will also be different. Therefore, three-dimensional features are essential for the signal recognition.

Gray relation theory based classifier [12] was selected to calculate the recognition rate of each simulation graph under



(a) SNR = 4 dB

(b) SNR = 0 dB

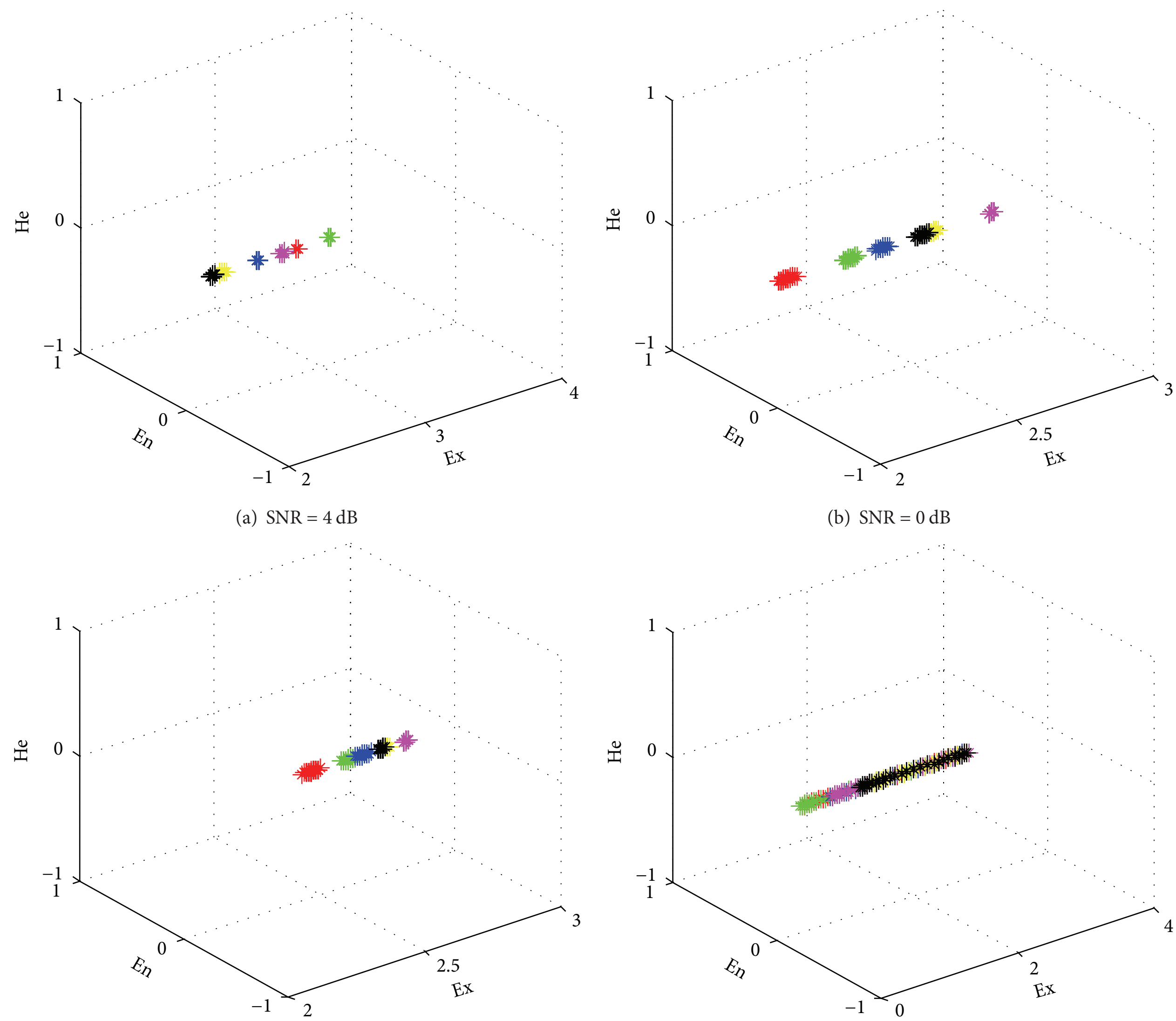
(c) SNR = −4 dB

(d) SNR = −8 dB

Figure 3: Feature extraction based on entropy under different SNR.

different SNR environment and compare the proposed algorithm with the method that only extracts the entropy characteristics [17, 18], the traditional cyclic spectrum entropy characteristics [19, 20], and wavelet transform characteristics [21]; the results are shown in Table 1.

Simulation results in Table 1 show that when the SNR is 4 dB, the recognition rates based on entropy and entropy cloud feature extraction algorithms can both reach 100%, but for cyclic spectrum entropy features, the recognition rate is only 87% and wavelet transform based features are 98%. Thus we conclude that cyclic spectrum entropy and wavelet transform based algorithm is not suitable for signal recognition under low SNR environment. When the SNR is decreased to 0 dB and −4 dB, the proposed method based on entropy cloud algorithm can still achieve the recognition rate of 100%. However, the recognition rates of the methods based on other algorithms are decreasing to some extent. When the SNR is reduced to −8 dB, the recognition rate of the improved



(a) SNR = 4 dB (b) SNR = 0 dB

(c) SNR = −4 dB (d) SNR = −8 dB

Figure 4: Feature extraction based on entropy cloud under different SNR.

Table 1: Recognition rate of different algorithms under different SNR.

SNR (dB)	4	0	−4	−8
Recognition rate of wavelet transform based features (%)	98	84.6	74.5	62.5
Recognition rate of cyclic spectrum entropy based features (%)	87.5	78.5	67.0	59.5
Recognition rate of entropy based features (%)	100	97.5	96.0	78.5
Recognition rate of entropy cloud model based features (%)	100	100	100	100

algorithm is significantly better than the original algorithm, wavelet transform based algorithm, and the traditional cyclic spectrum algorithm.

In order to compare the recognition effects of the improved algorithm with the original algorithm and some traditional algorithms, the recognition rates of six types of signals were calculated under different SNR. Simulation results are shown in Figure 5. It can be seen that the four feature extraction algorithms can all reach the recognition rate of 100% under high SNR environment. However, with the decreasing of SNR, the method based on entropy cloud algorithm can still maintain a higher recognition rate, while the recognition rates of the methods based on entropy algorithm, wavelet transform based algorithm, and cyclic spectrum entropy algorithm are decreasing. The results verified the effectiveness of the improved algorithm.

6. Conclusion and Discussion

The novel feature extraction algorithm proposed in this study based on entropy cloud characteristics of communication

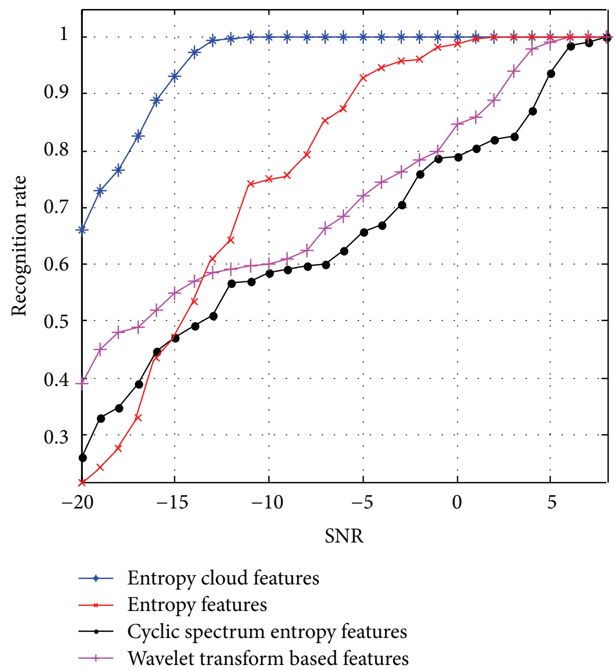


Figure 5: Recognition rate curves of entropy cloud based algorithm and other traditional algorithms.

signals solves the problem existing in the traditional algorithm based on entropy algorithm, cyclic spectrum entropy algorithm, and wavelet transform algorithm, which are difficult when identifying the signals under low SNR. Given that entropy characteristic is unstable under low SNR, we suggest applying the digital characteristics of cloud model and describing the unstable distribution characteristics of the entropy characteristics to identify communication signals accurately. Simulation results show that feature extraction algorithm based on entropy cloud characteristic, using three-dimensional digital characteristic of cloud model to describe the fuzziness of entropy characteristic, has better antinoise performance. It can still achieve the recognition rate of 100% even in the SNR of −11 dB. Obviously, it has better application value in today's complex electromagnetic environment.

Until now, some prior knowledge needs to be known for many communication signal recognition algorithms. The potential drawback of this new algorithm proposed in this research is that it also needs a certain prior knowledge of the signals to constitute a characteristic database. Therefore, blind signal recognition remains to be a future work to explore.

This work is rather new. We are the first to apply the basic property of cloud model into communication signals' recognition and achieve amazing signal recognition results. Although the cloud model theory has developed to a mature theory today, it has not fully broadened its application value in communication field. Thus how to make full use of cloud model and apply it into the area of signals' feature extraction is what we plan to study in future work.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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