A Novel Recognition Algorithm Based on Holder Coefficient Theory and Interval Gray Relation Classifier

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Abstract

The traditional feature extraction algorithms for recognition of communication signals can hardly realize the balance between computational complexity and signals' interclass gathered degrees. They can hardly achieve high recognition rate at low SNR conditions. To solve this problem, a novel feature extraction algorithm based on Holder coefficient was proposed, which has the advantages of low computational complexity and good interclass gathered degree even at low SNR conditions. In this research, the selection methods of parameters and distribution properties of the extracted features regarding Holder coefficient theory were firstly explored, and then interval gray relation algorithm with improved adaptive weight was adopted to verify the effectiveness of the extracted features. Compared with traditional algorithms, the proposed algorithm can more accurately recognize signals at low SNR conditions. Simulation results show that Holder coefficient based features are stable and have good interclass gathered degree, and interval gray relation classifier with adaptive weight can achieve the recognition rate up to 87% even at the SNR of -5dB.

Keywords: Communication signal recognition; Feature extraction algorithm; Holder coefficient; Interval gray relation classfier

1. Introduction

Communication signals' recognition technology[1, 2] is a major research topic in the field of electronic warfare. Feature extraction[3] and classifier design[4] are the two key links. With the rapid development of communication technology, the types of communication signals and the complexity of modulations are gradually increasing, which require more high-level modulation recognition algorithms. How to extract modulation characteristics of the signals effectively and design efficient classifier become important issues no matter in military or civilian areas.

In recent years, researchers[5-6] have made great progresses in communication signal recognition. Some traditional algorithms such as Higher order cumulants algorithm, wavelet transform based algorithm and spectrum analysis based algorithm have been widely used in the field of signal recognition. While, higher order cumulants algorithm[7] is limited to the recognition at white noise conditions. Wavelet wave based algorithm[8] is simple, but it is difficult to recognize the singals at low SNR. Spectral analysis[9] can extract the power spectrum[10] and cyclic spectrum[11-12] characteristics of signals in frequency domain, which can reduce the impact of noise in the channel. However, it needs much priori knowledge of the signal, and the calculation process is relatively complex, which greatly limits the application of it. The traditional method, decision theory[13] based algorithm is simple, but the key parameter, threshold value is sensitive to noise, which increases the difficulties of setting threshold value. So its anti-noise ability is poor. Constellation map[14] displays the structure characteristics of signals. It has the advantage of simple, intuitive, and low dependence on SNR. However, it requires strict synchronization with the receiving system, and also needs to estimate, synchronize and correct the initial phase and carrier wave of signals, which make it difficult to recognize the signals. Wang Hai-hua[15] used Holder coefficient method in radar signal for intra-pulse feature extraction, and neural network algorithm for identification. However, they had no further discussion about how to determine the values of the important parameters p and q in Holder coefficient algorithm, which could affect signal recognition results directly. Moreover, the application of Holder coefficient was limited in radar signal intra-pulse feature extraction[16], and was never applied in the field of communication modulation signal recognition. Similar coefficient[17] has been widely used in radar signal feature selection, and some achievements have been made. However, similar coefficient limited the value selection of p and q [18] in Holder coefficient formula, which affects the clustering features of the characteristic values to some extent. This research discussed the values of p and q in Holder coefficient algorithms which affected the characteristic values' distances among different communication modulation signals. Based on the theory above, Holder coefficient features were extracted. According to the distribution of the extracted features, interval gray relation algorithm with improved adaptive weight was adopt to classify the features. Simulation results showed that, the proposed recognition algorithm based on Holder coefficient theory and interval gray relation classifier had better recognition results at low SNR conditions and good application value in the field of pattern recognition.

2. Holder Coefficient Algorithm

2.1 Basic Theory

Let $\frac{1}{p}+\frac{1}{q}=1$ with $p,q>1$, for arbitrary vector $X=(x_1,x_2,\cdots,x_n)^T$, $Y=(y_1,y_2,\cdots,y_n)^T$, and $X\in C^n, Y\in C^n$, Holder inequality states that [19]:

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

Based on the definition above, Holder coefficient for two discrete signals $\{f_1(i)\ge 0, i=1,2,\cdots,N\}$, $\{f_2(i)\ge 0, i=1,2,\cdots,N\}$ can be defined as:

$$H=\frac{\sum f_1(i)f_2(i)}{\left(\sum f_1^p(i)\right)^{1/p}\cdot\left(\sum f_2^q(i)\right)^{1/q}} \tag{2}$$

where the values of discrete positive signals $\{f_1(i)\}$, $\{f_2(i)\}$ are not always equal to zero, and $0\le H\le 1$ .If $p=q=2$, it becomes similar coefficient [20]. Similar coefficient is a special example of Holder coefficient.

2.2 Feature Extraction Steps

Holder coefficient represents the similar relevance degree of two signals. When $f_1^p(i)=kf_2^q(i)$, $i=1,2,\cdots,N$, and k is a real number, H gets the maximum value $H_{\max}=1$, as the two signals have the greatest similar relevance, which means that they belong to the same type of modulation. Only when $\sum f_1(i)f_2(i)=0$, H_c gets the minimum value $H_{c\min}=0$, as the two signals have the least similar relevance, which shows that the two types of signals are uncorrelated. That is to say the two signals belong to different types of modulations.

The above theoretical analysis shows that, it is possible to analysis clustering features of Holder coefficient based feature extraction algorithms of different communication modulation signals. The algorithm processes are demonstrated as follows:

(1) Suppose the communication modulation signal to be identified is s, and its bandwidth and carrier frequency are known. After sampling the signal, the discrete signal sequence $s(i)$, $i=1,2,\cdots N$ is obtained. And then transform the sequence from time domain to frequency domain by FFT, and normalize it. Suppose the signal sequence after pretreatment is $\{S(f)\}$.

(2) After the pretreatment, the spectrum characteristics of different signals are obtained. Then, two different reference sequences are chosen to calculate Holder coefficient features to constitute a two-dimensional distribution vector, which possesses good interclass gathered degree.

Rectangular window function $\{S_1(f)\}$ and triangle window function $\{S_2(f)\}$ are used as reference sequences in this research. On one hand, rectangular and triangular waves are the most basic signals in practical engineering application, and they are easy to generate. On the other hand, reference signals are just used to get the holder coefficient values of the signals to be identified. The more simple the reference signals, the more uncomplicated the Holder algorithm. Then, Holder coefficient values of the signal to be identified with the two reference signal sequences are calculated.

According to formula (2), Holder coefficient value H_c of the signal sequences $\{S(f)\}$ with rectangle signal sequences $\{S_1(f)\}$[15] is calculated as:

$$H_c = \frac{\sum S(f)S_1(f)}{\left(\sum S^p(f)\right)^{1/p} \cdot \left(\sum S_1^{\,q}(f)\right)^{1/q}} \tag{3}$$

where rectangle signal sequences $\{S_1(f)\}$ is：

$$S_1(f) = \begin{cases} 1\,, & 1 \le f \le N \\ 0\,, & \text{else} \end{cases} \tag{4}$$

where N is the number of nonzero points of rectangular signal sequences.

Similarly, Holder coefficient value H_t of the signal sequences $\{S(f)\}$ with triangle signal sequences $\{S_2(f)\}$[15] can be calculated as：

$$H_t = \frac{\sum S(f)S_2(f)}{\left(\sum S^p(f)\right)^{1/p} \cdot \left(\sum S_2^{\,q}(f)\right)^{1/q}} \tag{5}$$

where triangle signal sequences $\{S_2(f)\}$ can be expressed as：

$$S_2(f) = \begin{cases} 2f/N\,, & 1 \le f \le N/2 \\ 2-2f/N\,, & N/2 \le f \le N \end{cases} \tag{6}$$

where N is the number of nonzero points of triangle signal sequences.

(3) Based on the Holder coefficient value H_c and H_t, a two-dimensional characteristics vector is formed $H = [H_c, H_t]$, which is the result of feature extraction.

3. Interval Gray Relation Classifier

Due to the complexity of communication signal, the uncertainty of noise, and the existence of counting error, Holder coefficient characteristic value is not always a steady value, but fluctuated in a certain interval, which can be expressed by interval value. If we use the points in the interval to classify the signals, such as the classifiers of support vector machine or neural network, with the reduction of SNR, the recognition results will be low. So it is difficult to realize the exact identification at low SNR conditions. Thus, interval gray relation algorithm [21] was adopted in this research to classify the Holder coefficient characteristics, which had better classification effect for overlapping features. Meanwhile, entropy weight algorithm was adopted to calculate the weight of characteristic parameters according to the important degree of the characteristics, in order to improve the adaptability of the algorithm. Compared with neural network classifier and the traditional gray relation classifier, the classification algorithm in this research has better recognition results for this kind of overlapping characteristics. According to the characteristic vector $H = [H_c, H_t]$ extracted in part 2, the procedure of this algorithm can be described below:

(1) After repeatedly extracting the Holder coefficient features of communication signals, record the fluctuating interval of each Holder coefficient value, which means that record the maximum and minimum values of the characteristics. And then, feature interval matrix can be

developed, namely:

$$H = \begin{bmatrix} [H_{1c\min} & H_{1c\max}] & [H_{1t\min} & H_{1t\max}] \\ [H_{2c\min} & H_{2c\max}] & [H_{2t\min} & H_{2t\max}] \\ \vdots & & \vdots & \\ [H_{nc\min} & H_{nc\max}] & [H_{nt\min} & H_{nt\max}] \end{bmatrix} \tag{7}$$

where $H_{nc\min}$ and $H_{nc\max}$ are respectively the minimum and maximum values of features H_c of the *nth* communication signal in formula (3). $H_{nt\min}$ and $H_{nt\max}$ are respectively the minimum and maximum values of features H_t of the *nth* communication signal in formula (5). Thus, the characteristics' interval matrix H can be obtained.

(2) Normally, after getting the characteristics' interval matrix, first process the matrix interval characteristics [22] to make it dimensionless. However, dimensionless processing often makes the characteristics varying in a small area which make the feature distances of different signals small. Correspondingly, the calculated amount will also increase. Due to that the reference matrix belong to the same magnitude for different communication modulation signals, and the characteristics' values also belong to the same level, dimensionless processing is not needed for this proposed algorithms. Interval leave degree[23] formula was directly used to calculate the interval distance.

Suppose the characteristic's interval matrix that calculated with rectangular wave of the signals to be identified is $H_{0c\min}$. The Holder coefficient interval leave degree d_{nc} of the unknown signal's feature matrix with the *n*th known communication signal can be calculated as:

$$d_{nc} = \frac{1}{\sqrt{2}}\sqrt{(H_{nc\min} - H_{0c\min})^2 + (H_{nc\max} - H_{0c\max})^2} \tag{8}$$

Similarly, with triangular wave, d_{nt} can be defined as:

$$d_{nt} = \frac{1}{\sqrt{2}}\sqrt{(H_{nt\min} - H_{0t\min})^2 + (H_{nt\max} - H_{0t\max})^2} \tag{9}$$

(3) According to the formula of interval gray relation algorithm [24], the gray relation coefficient matrix is calculated as:

$$\varepsilon_{nm} = \frac{\min\limits_n \min\limits_m \{d_{nm}\} + \rho \max\limits_n \max\limits_m \{d_{nm}\}}{d_{nm} + \rho \max\limits_n \max\limits_m \{d_{nm}\}} \tag{10}$$

where, the meaning of n is the same with the former n which represents the *n*th communication modulation signal. $m = c, t$ represent the two Holder coefficient characteristics mentioned above. ρ is resolution coefficient, which usually equals to 0.5.

Thus we can get the interval gray relation coefficient matrix ε_{nm}:

$$\varepsilon_{nm} = \begin{bmatrix} \varepsilon_{1c} & \varepsilon_{1t} \\ \varepsilon_{2c} & \varepsilon_{2t} \\ & \vdots \\ \varepsilon_{nc} & \varepsilon_{nt} \end{bmatrix} \tag{11}$$

Using the obtained Holder coefficient characteristic matrix $H = [H_c, H_t]$ to calculate the gray relation degree of the unknown signal with all known signals in the data base, the most basic relation algorithm[25] is to calculate the average value of the relation coefficients as the relation degree of the signal, it averages the contribution of various characteristics, which can not get the optimal choice of the characteristics. Therefore, in this research, corresponding weight values were given to each of the relation coefficient matrix's value, which means that larger weight was given to the characteristics that have both larger interclass gathered degree and larger outclass separated degree. Conversely, small weight was given to the characteristics with opposite property. This process can select the optimal features so that to improve the adaptive ability of the classifier. The specific steps of weights assignment can be performed as follows:

Take the weight value of relation coefficient ε_{ic} of signal *i* as an example, the weight value calculation method of ε_{it} is the same as ε_{ic}. The normalized entropy value h_{ic} of relation coefficient ε_{ic} can be defined as:

$$h_{ic} = -\frac{1}{\ln(n)}\sum_{i=1}^{n} p_{ic} \ln p_{ic} \tag{12}$$

where, n is the *nth* modulation signal, $p_{ic} = \frac{\varepsilon_{ic}}{\sum_{i=1}^{n}\varepsilon_{ic}}$, and define that if $\varepsilon_{ic} = 0$, $p_{ic} \ln p_{ic} = 0$。

Thus, the weight value a_{ic} of the feature ε_{ic} is defined as:

$$a_{ic} = \frac{1-h_{ic}}{(1-h_{ic})+(1-h_{it})} = \frac{1-h_{ic}}{2-h_{ic}-h_{it}} \tag{13}$$

So the relation degree r_i is:

$$r_i = \varepsilon_{ic}\cdot a_{ic} + \varepsilon_{it}\cdot a_{it} \tag{14}$$

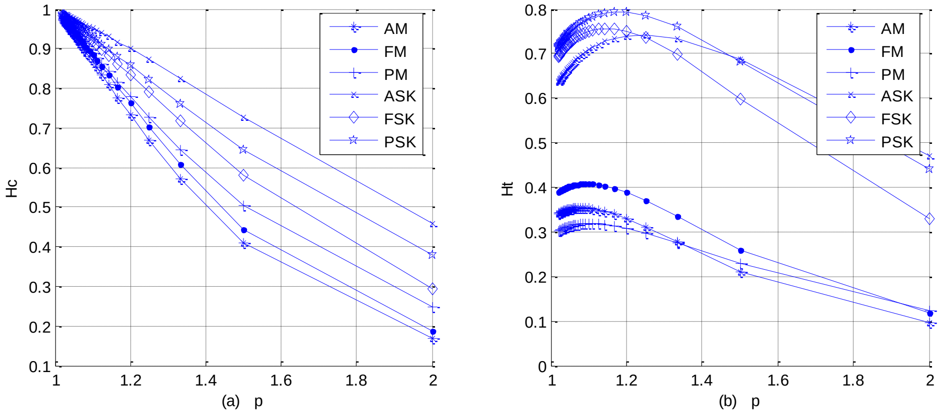
The value of r_i reflects the similarity degree of the unknown signal sequences' characteristics to be identified with the known signal sequences'. The larger the value of r_i is, the greater probability the unknown signal belongs to the *ith* sequence of the signal. Hence, using this theory can achieve the purpose of identification.

4. Simulation Results and Analysis

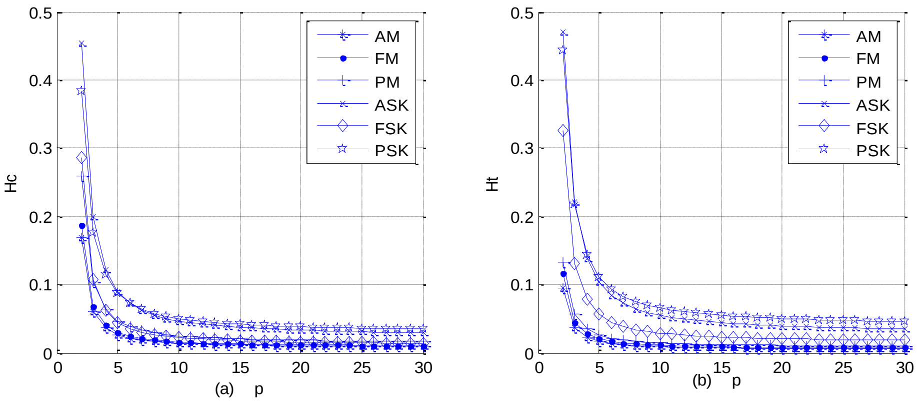
Holder coefficient features have good clustering degree and can reflect the modulation characteristics of different communication signals well. This research just adopted this kind of clustering feature for the identification of different modulation signals. However, the definition of formula (2) explains that, the values of p and q that selected in Holder coefficient calculating process directly affects the calculation results and the clustering level of features. Therefore, the selection of value p and q is also a novel key issue that discussed in this research. In this study, all the simulation results were calculated using a household computer with an Intel 2.4 GHz dual processor.

The Holder coefficient value curves of different communication signals with changing value p 、 q are shown in **Fig. 1** and **Fig. 2**. They are the variant values of Holder characteristic coefficient when $1 < p \le 2$ ($p = 1.1, 1.2, \cdots, 1.9, 2$) and $2 < p \le 30$

($p = 2,3,\cdots,30$) respectively. Specially, $p = 2$ is the definition of similar coefficient. It can be seen that the curves of Holder coefficient in two intervals are apparently different, while the situations of $p > 1$ that defined in Holder inequality can be considered comprehensively. Due to the existence of noise under the realistic environment, the simulation condition is at the SNR of 20dB. Besides the interclass gathered degree, anti-noise ability is also need to be considered when select the value of p and q.



a. Holder coefficient value curves associated with rectangle wave
b. Holder coefficient value curves associated with triangular wave
Fig. 1. Holder coefficient characteristic value curves of different modulation signals ($1 < p \le 2$)



a. Holder coefficient value curves associated with rectangle wave
b. Holder coefficient value curves associated with triangular wave
Fig. 2. Holder coefficient characteristic value curves of different modulation signals ($2 < p \le 30$)

Comparing the curves in **Fig. 1** and **Fig. 2**, we select the p value with greater distance of different signal characteristics and the values that have best anti-noise ability as the final value . Paradigm distance algorithm was used to calculate the distances of corresponding feature points' values of different signals repeatedly. Due to the existence of noise, the points in the curves are not fixed values but fluctuated in a certain interval. So the distances calculated are also not stable. Therefore, Monte Carlo experiment was adopted to calculate the distances 500 times, then select the p value whose corresponding features has the best anti-noise ability and separated degree. After calculating we choose $p1=2$ for rectangular wave, while for triangle wave, we choose $p2=5$.The two dimensional Holder coefficient characteristics curves of different modulation signals under the environment of different SNR were shown in **Fig. 3**.

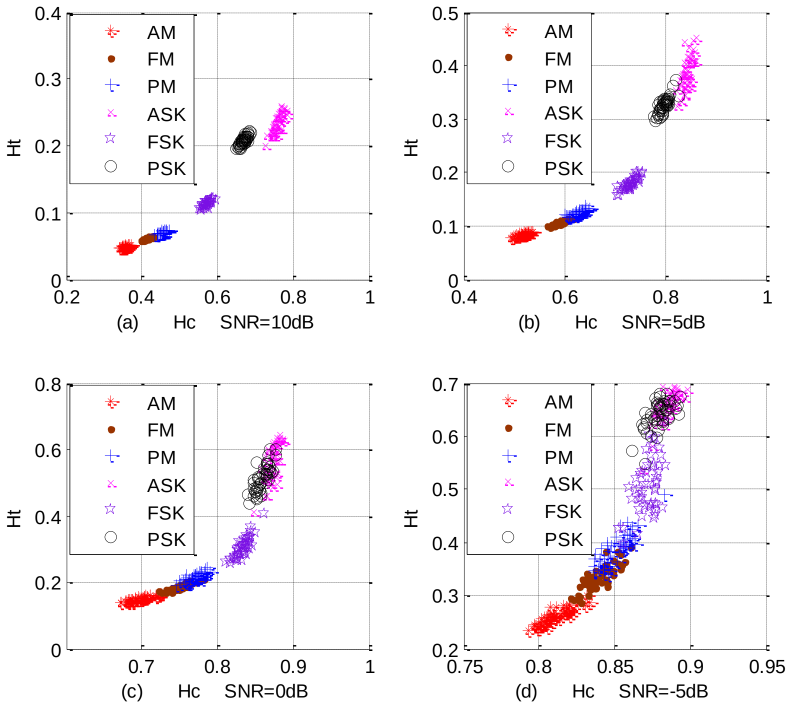


Fig. 3. Holder coefficient characteristics' curves of different signals at different SNR conditions (a) SNR=10dB (b) SNR=5dB (c) SNR=0dB (d) SNR=-5dB

It can be seen that two dimensional Holder coefficient characteristic values of different modulation signals are not fixed but fluctuated in an interval. They only have good separating degree among different signals at high SNR conditions. But with the reduction of SNR, especially when SNR = 0dB, the characteristics' intervals of PSK, ASK signals have great overlap, and the characteristics of FM signal also have a certain overlap with PM, AM signals. When SNR=-5dB, there are different levels of overlaps among the six types of signals. In this case, better design of classifier is in great need. Neural network classifier[15] is widely used in signal classification due to its strong adaptive ability. Gray relation algorithm was applied in classifier design [25], which also got a good classification effect compared with neural network. In recent years, some improved gray relation algorithm[26] was proposed, which had better recognition effect at low SNR. According to the overlapping distribution characteristics extracted in this research, interval gray relation algorithm with improved adaptive weight was adopted to recognize the signals. Although the overlapping phenomena appear in **Fig. 3**, the signal's characteristics are not overlapped completely. So, recognition using different features' distribution intervals can be achieved. Compared the classifier adopted in this research with the above traditional methods, simulation results were shown in **Fig. 4**.

In order to show the performance of Holder coefficient based feature extraction algorithm, compare the anti-noise ability time of recognition process of the algorithm in this research with the traditional decision tree algorithm[27] and cyclic spectrum based algorithm[28], the results are shown in **Table 1** and **Table 2**.

Table 1. Recogniton rates of three algorithms under different SNR

SNR	10dB	5dB	3dB	0dB	-5dB
Traditional decision tree algorithm(%)	96.5	80.9	63.5	34.9	23.6
Cyclic spectrum based algorithm(%)	100	100	98.9	90.6	82.5
Holder coefficient based algorithm(%)	100	100	99.8	99.4	86.9

Table 2. Calculation time of three algorithms

Name of algorithm	Traditional decision tree algorithm	Cyclic spectrum based algorithm	Holder coefficient based algorithm
Calculation time	9.6ms	20.5ms	12.5ms

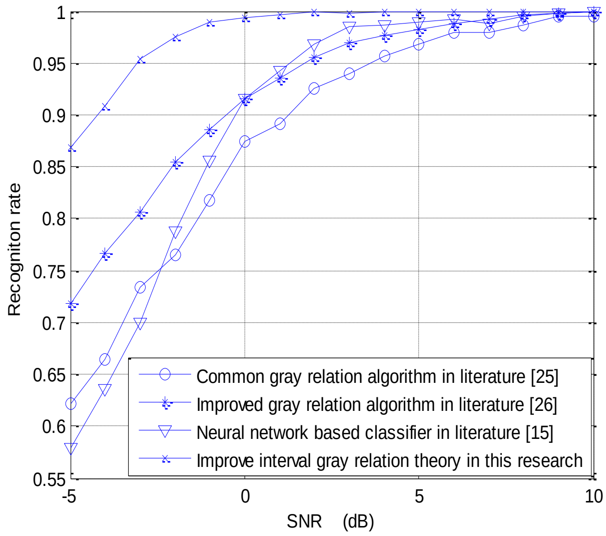


Fig. 4. Recognition rates of different classifiers at different SNR

It can be seen that when the SNR is high, all different signals have better separating degree, and all the four classifiers can achieve the recognition rate of 100%. However, with the reduction of SNR, different features' intervals have overlaps to some extent. When the overlap spaces become larger, recognition rate falls rapidly [15,25,26]. Only the proposed classifier can still maintain high recognition rate.

In order to verify the properties of the obtained value p, three groups of p values were selected to compare . Recognition rate curves of different signals at different SNR conditions were simulated and shown in **Fig. 5**. Similarly, $p1$ and $p2$ represent the parameters of Holder coefficient formula with rectangle wave and triangle wave respectively.

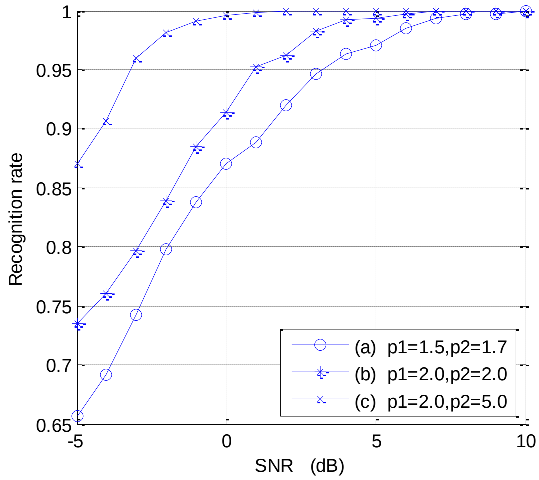


Fig. 5. Recognition rates of different values of p at different SNR

The value of p in curve (a) was selected by maximizing paradigm distance according to **Fig. 1**. In curve (b), it was selected based on similar coefficient which is the special case of Holder coefficient function. Curve (c) selected the optimal value by maximizing paradigm distance and anti-noise ability, which combined **Fig. 1** with **Fig. 2** together it had the highest recognition rates under different SNR. Simulation results show that, the recognition rate in Curve (c) stays relatively stable at low SNR conditions.

5. Conclusion

Feature extraction and classifier design are the two important parts of signal recognition. Nowadays, varies kinds of algorithms have been proposed for better recognition results at low SNR conditions and low computation to realize the real time recognition, which make it became a hot issue in the field of pattern recognition.

A new feature extraction method based on Holder coefficient features was proposed in this research. And the selection of parameter value p was discussed in detail. Then an improved adaptive interval gray relation algorithm was adopted to recognize the extracted characteristic parameters effectively. Simulation results show that, Holder coefficient theory can be used to extract features of communication signals and has good aggregation degree. The improved classifier has better recognition performance at low SNR compared with other classifiers. This research provides a good basic theory for communication signal modulation recognition in engineering at low SNR conditions.

Prior knowledge needs to be known in most signals recognition algorithms including the algorithm improved in this research, which is the potential drawback of this study. Hence, blind recognition algorithms are still the focus need to be explored in this field.

The selection of p value is discussed in this research. And there is an another issue we want to discussed that whether we can choose some other referenced waveform to achieve better recognition results, it is the work we will do in future work.

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