Weak Signal Acquisition and Recognition Method for Mobile Communication Based on Information Fusion

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Abstract. In traditional communication signal acquisition, the effect of weak signal recognition is poor. Therefore, a weak signal acquisition and recognition method for mobile communication based on information fusion is designed. The mobile communication signal location model is established; the TDOA algorithm is used to locate the mobile communication signal; the receiver is used to capture the mobile communication signal. M-QAM modulation technology is used to modulate the parameters of mobile communication signal transmission mode, and the feature classification model of mobile communication signal is established. The modulation types of mobile communication signals are identified by using cyclic spectrum, and the simulation is carried out. The modulation types are classified by using mobile communication signal feature classifier and information fusion technology, and the recognition of mobile communication signals is completed. Experimental results show that the recognition rate of this method is 24% higher than that of traditional method 1 and 34% higher than that of traditional method 2. This method is based on information fusion. The information is fused by combining classifiers to classify modulation types, which significantly improves the recognition accuracy.

Keywords: Information fusion · Mobile communication · Weak signal acquisition · Recognition

1 Introduction

Communication signal transmission has a wide range of applications in many fields, but there are also many challenges. As an important part of communication countermeasure, the acquisition and identification of communication signal is more and more difficult. The specific reason is that with the application of communication if, frequency hopping and spread spectrum technology, the signal may be submerged in noise, which makes the signal-to-noise ratio of the received signal at the communication signal acquisition and identification receiver very low, and if it is a weak signal in the communication signal, This situation will get worse [1–3]. With the increase of traffic, the communication system needs to process the weak signal under the condition of big data samples.

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In addition, in the modern high-tech war, the electromagnetic environment is becoming more and more complex. In addition to the conventional mobile communication signals, some uncommon and new modulation types of mobile communication signals appear from time to time. Usually, the characteristics of these new modulation types of mobile communication signals are complex and difficult to identify, but the threat level is relatively high, here referred to as the weak signal of mobile communication. It is of great significance to capture and recognize them.

Data fusion is a comprehensive information processing technology about how to use multi-source information in collaboration to obtain more objective and essential knowledge of the same thing or objective. In recent years, researchers have put forward a variety of information fusion algorithms from different perspectives. Because of the different starting point and destination of the problem, different methods of information fusion algorithm processing are different. The fusion information of weak signals in mobile communication is from multiple classifiers. Traditional classification methods mostly use feature extraction or neural network classifier. For the case of sufficient samples, neural network classifier has good effect, but the actual samples collected in communication confrontation environment are often limited, and the problem of poor generalization ability of neural network leads to its limited application in radiation source identification.

Relevant scholars have conducted research on this and made some progress. Li Kun et al. proposed a narrow-band power line carrier communication signal recognition algorithm [1], which uses the wavelet transform amplitude variance value and high-order cumulant of the carrier communication modulation signal as the identification feature parameters, and uses an improved support vector machine method to design signal recognition It improves the robustness of power line noise signal removal and avoids problems such as under-learning and over-learning in the signal processing process. This method can improve the accuracy of signal capture, but it takes longer to capture the signal. Li Changba et al. proposed an automatic modulation recognition method for communication signals based on deep learning [2], which extracts communication signal features based on feature extraction, uses self-encoding technology to obtain spectrum in complex electromagnetic environments, and conducts feature set training based on deep learning technology. Automatic recognition of MQAM communication signal modulation mode. The method in this paper has better classification anti-jamming recognition ability, but poor signal capture ability.

For the above methods, there is a poor signal capturing ability. Problems such as low signal recognition accuracy. For this reason, this article introduces the information fusion method to capture the weak signal of mobile communication. The signal feature classifier is established according to the conventional features, the modulation pattern is recognized through multiple classifiers, and the information fusion technology is adopted to use the complementarity and redundancy of the performance of each classifier to improve the accuracy and anti-interference of the capture and recognition results. Effectively enhance the mobile communication weak signal capture and recognition effect.

2 Weak Signal Acquisition and Recognition Method for Mobile Communication Based on Information Fusion

2.1 Mobile Communication Signal Location

The apparatus and method for searching signals in a mobile communication system can process input signals in a parallel manner. A signal searcher device in a mobile communication system may include a first sequential storage device and a second sequential storage device for storing codes and input signals, respectively. The signal searcher may include a plurality of despreading devices capable of despreading input signals containing components in a parallel manner using codes. When the length of coherent accumulation is multiple of the number of despreading devices, the additional buffer will store the accumulated despreading signal with sum component whose number is equal to the number of offsets searched. The system completes the positioning of air targets through the cooperation of different mobile base stations and a system receiver. When the target enters the detection area, the base station radiation signal that irradiates the target will be reflected, and part of the energy of the reflected wave signal will be received by the receiving station. The time delay of target echo signal can be obtained by generalized correlation between direct wave signal and target reflection signal. As shown in Fig. 1, the radar target positioning model based on mobile communication signal at a certain time is presented.

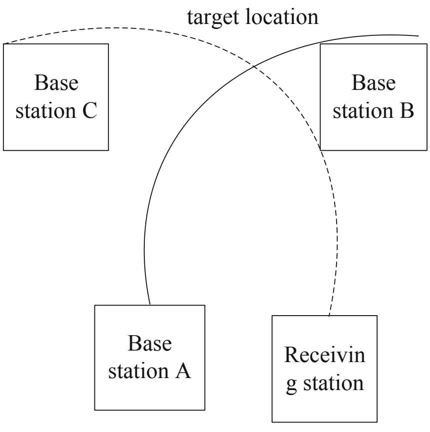


Fig. 1. Passive location model of mobile communication signal

When the echo signal of each base station is delayed, TDOA algorithm can be used to locate the target. At the same time, the coordinates of base station i are defined as $X_i = \left[x_i, y_i\right]$ and $i = 1, 2, \cdots, N$ (N is the number of base stations), and the target is located at $x = \left[x, y\right]$. Without considering the noise, it is assumed that the arrival time difference between the signal transmitted by base station i and that transmitted by base station j is $\sigma^*_{i,j}$. since the propagation speed of electromagnetic wave in the air is constant, it can be concluded that:

$$r^*_{i,j} = c\sigma^*_{i,j} = R_i - R_j \times \|x - X_i\| - \left\|x - X_j\right\| * \tag{1}$$

In formula (1), $R_i = \|x - X_i\|$ represents the distance from the target to base station i, $R_j = \|x - X_j\|$ represents the distance from the target to base station j, and $*$ represents the actual value without noise. $r^*_{i,j}$ represents the distance difference formed by multiple base station pairs. Since the echo time delay of each base station is known, the distance difference formed by multiple base station pairs can be obtained without considering the noise, thus forming a hyperbolic equation group. By solving the equation group (that is, finding the focus of the hyperbola), the position of the target can be obtained. According to the properties of the equations, the hyperbolic equations constructed by using different base stations as reference base stations to calculate the delay difference are equivalent to the equations constructed by using a specific base station as reference base station. By solving the equations, the target mobile communication signal can be located. After positioning, the receiver is used to capture the mobile communication signal.

2.2 Mobile Communication Signal Acquisition

For most of the mobile communication signals, coherent integration and incoherent integration are used for acquisition, while for the signals which only contain Doppler shift, two-dimensional search is used for acquisition. Generally, the carrier to noise ratio of strong signal in mobile communication is 40 dB·Hz. But when users use mobile communication, mobile communication signal receiving devices are often in weak signal environment, such as indoor, garage, forest and so on. The signal is weakened due to occlusion and multipath effect, which leads to the decrease of receiver sensitivity. The receiver needs to extend the dwell time to improve the processing performance. The main methods include coherent integration and incoherent integration. Coherent integration can improve the sensitivity of receiver acquisition by extending the signal length, but the signal length will be affected by the mobile communication signal message data bits. Incoherent integration is not affected by data information, but it will produce square loss. Therefore, when processing a certain segment of target signal, the receiver can design different integration strategies, and reasonably combine coherent integration and incoherent integration, so as to coordinate the shortcomings between them and obtain the optimal acquisition performance of the receiver. The general capture process diagram is shown in Fig. 2.

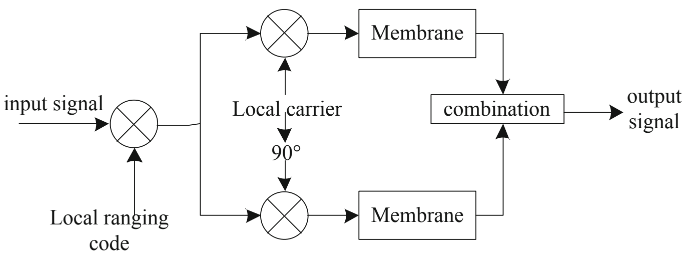


Fig. 2. Coherent/incoherent acquisition process

In some environmental conditions, when the signal quality is weak, extending the length of the signal sequence can improve the signal-to-noise ratio, which is the principle of coherent integration. Assuming that the signal is converted to baseband, only the complex number of signals with Doppler shift is included. Because the received signal has the uncertainty of Doppler frequency shift and code delay, the carrier tracking loop can not track the signal change directly. Because the received signal is a spread spectrum signal formed by the direct sequence spread spectrum modulation and carrier modulation of the communication data, the signal receiving power is very small, so the signal must be de expanded firstly. At the same time, due to the dynamic of the receiver carrier, the Doppler frequency shift is uncertain, and the code acquisition must be searched in the whole code phase and frequency domain at a fixed interval. Therefore, the acquisition of spread spectrum signal must complete the initial synchronization of pseudo code phase and the initial estimation of carrier frequency difference. During the search process, the code phase stepping amount is half code phase unit, and Doppler frequency step amount is a Doppler frequency shift unit, then a code phase search unit and a Doppler search unit constitute a search unit in the two-dimensional search space, as shown in Fig. 3.

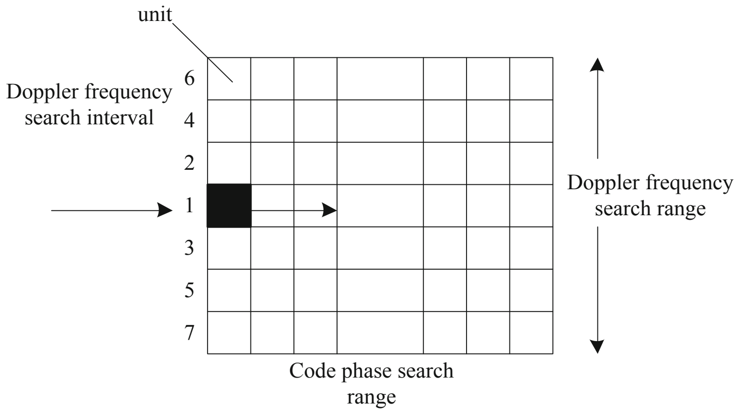


Fig. 3. Two dimensional sequence search

As shown in Fig. 3, through two-dimensional sequence search, when the correlation result is higher than the preset signal detection threshold, the mobile communication signal acquisition is completed.

2.3 Parameter Modulation of Mobile Communication Signal Transmission Mode

After the acquisition of signal is completed, m-QAM modulation technology is used to modulate the transmission mode parameters of mobile communication signal. In modulation, besides the system transmission BER and band utilization rate with general significance, other parameters related to modulation methods should be considered, such as: peak to average ratio of m-QAM modulation signal, Euclidean distance between constellation points and minimum phase offset of signal. For different transmission systems, the requirements for these parameters are different. The peak to average ratio of m-QAM signal: the magnitude of the peak to average ratio of m-QAM signal reflects the anti-linear distortion ability of m-QAM signal, especially the nonlinear distortion caused by the nonlinear power amplifier. The larger the peak to average ratio of m-QAM signal, the worse its anti-linear distortion performance. Minimum Euclidean distance of m-QAM signal: the minimum Euclidean distance is the minimum distance between constellation points on m-QAM signal constellation. This parameter reflects the ability of m-QAM signal to resist Gaussian white noise. The maximum of m-QAM signal can be obtained by optimizing the constellation distribution of m-QAM signal, and thus the m-QAM modulation scheme with better anti-interference performance can be obtained. Minimum phase offset of m-QAM signal: the lowest phase offset is the minimum offset of constellation phase of m-QAM signal. This parameter reflects the phase jitter ability of m-QAM signal and sensitivity to clock recovery accuracy. It can also modulate the transmission formula parameters of mobile communication signal by optimizing m-QAM signal. After the parameter modulation of the transmission mode of mobile communication signal is carried out by m-QAM modulation technology, the classification model of mobile communication signal characteristics is established.

2.4 The Feature Classification Model of Mobile Communication Signal is Established

In the complex environment of communication electronic countermeasure, the intercepted communication signals need to be preprocessed. Based on the determination of the modulation type of communication signals, the steady-state classification features are extracted by using the time domain, frequency domain and time-frequency domain methods, so as to establish the steady-state Feature Classification Library. The communication signal feature classification model is shown in Fig. 4.

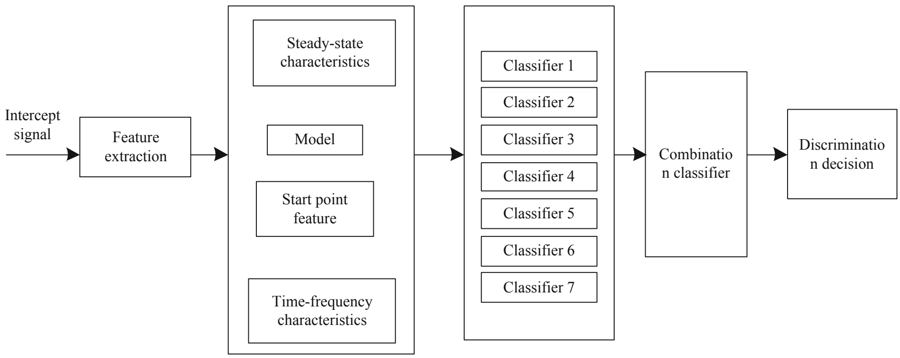


Fig. 4. Communication signal feature classification model

Secondly, according to the signals classified by steady-state features, the instantaneous phase variance method, recursive graph method and phase variance method based on higher-order cumulant are used to detect the starting point of the communication signals classified by steady-state features, so as to realize the further classification of communication signals. Then, in the process of feature analysis and extraction of communication emitter signal, it is usually necessary to convert the measured values reflecting the characteristics of communication emitter signal into feature space. However, this conversion process is usually not linear, which makes the features of communication emitter signal are usually high-dimensional feature vectors, which mainly show time-frequency image features, high-order statistics features and high-order spectrum features, and these feature vectors may overlap in the high-order feature space, resulting in the reduction of classifier efficiency and classification probability. Therefore, by using the time-frequency image feature analysis and extraction method, the high-order features of the intercepted communication signal are further extracted by selecting the time-frequency image features with less dimension and low complexity, so as to form a transient feature classification library, which can improve the classification efficiency of the classifier and the classification probability. Finally, the classifier design method of combining single feature classifier and combined feature classifier is adopted to improve the classification performance of multi feature vectors of the designed classifier, so as to improve the classification and recognition ability of communication emitter signals. After the feature classification model of mobile communication signal is established, the modulation type of mobile communication signal is identified.

2.5 Modulation Type Recognition of Mobile Communication Signal

Modulation type is the main steady-state feature of signal differentiation. Therefore, the same type of signal is selected by modulation type, and prior information for other feature parameters is extracted and classified. Because the cyclic spectrum can show better noise resistance on non-zero cycle frequency and Gaussian white noise only appears on the zero cycle spectrum, the cyclic spectrum can be used to recognize different modulation types of signals [11]. If the mean $j(t)$ of continuous time stochastic process $a(t)$ and the autocorrelation function $H(t, \varepsilon)$ of random process $a(t)$ are periodic and the period is T, then $a(t)$ is called generalized cyclic stationary random process, namely:

$$\begin{cases} j(t+T) = j(t) \\ H(t+T, \varepsilon+T) = H(t, \varepsilon) \end{cases} \tag{2}$$

As shown in formula (2), the process is a random cyclic process, then the autocorrelation function $H(t, \varepsilon)$ can be expanded by Fourier series:

$$H(t, \varepsilon) = \sum_{\beta} H^{\beta}(\varepsilon) \exp(k2\pi\beta t) \tag{3}$$

In formula (3), $\beta = \frac{n}{T}, n = 0, 1, 2, \cdots$ and β represent the cyclic spectrum. $H^{\beta}(\varepsilon)$ is the cyclic autocorrelation function, k is a Fourier parameter [12], where the cyclic autocorrelation function can be expressed as:

$$H^{\beta}(\varepsilon) = \frac{1}{T} \int_{-T/2}^{T/2} H\left(t + \frac{\varepsilon}{2}, t - \frac{\varepsilon}{2}\right) \exp(k2\pi\beta t) dt \tag{4}$$

The results of Fourier transform for $H^{\beta}(\varepsilon)$ are as follows:

$$D^{\beta}(f) = \int_{\infty}^{\infty} H^{\beta}(\varepsilon)\exp(-k2\pi\beta t)d\varepsilon \tag{5}$$

In formula (5), $D^{\beta}(f)$ represents the cyclic spectral density function of cyclic autocorrelation function [13]. The modulation type of mobile communication signal is identified by cyclic spectral density function. Then, the mobile communication signal features are classified by the classifier.

2.6 Classification and Recognition Using Mobile Communication Signal Feature Classifier

Firstly, the intercepted signal individuals in the communication countermeasure environment are extracted from the multi angle feature analysis. Firstly, through preprocessing, the signal sequence (interval) which is stable and suitable for feature analysis is extracted. For the obtained signal analysis interval, the frequency domain analysis method can be used to extract the frequency domain characteristics of the individual signal. However, because the small characteristics of the communication signal radiation source are more irregular non-stationary, nonlinear and non Gaussian, it is difficult to use the traditional signal processing method for the characteristics of spurious components and parasitic modulation, while small wave analysis and time-frequency distribution are very good tools for non-stationary signal analysis. Therefore, the transient characteristics are extracted by fractal method in time domain, and then a small sample classifier is designed. Aiming at the results of small sample condition and statistical learning theory, single classifier and combined classifier are mainly used to improve the classification ability of signal feature vector under small sample condition. The information of different classifiers is fused to classify the characteristics of mobile communication signals. The recognition of L modulation pattern can be regarded as a pattern recognition problem of L category $\phi_i(i = 1, 2, \cdots, L)$. Suppose that each class has N_i M dimensional samples indicating the class, φ_i is the mean value of ϕ_i, $\sum$ is the covariance matrix of all class samples, the sample set composed of all class ϕ_i samples is U_i, B_i^l is the $l(l \leq N_i)$ sample in U_i, B is the sample with unknown style, and the classifier settings are as follows. If the maximum value of the sample in U_i in the $l(l = 1, 2, \cdots, M)$ coordinate is $\max il$ and the minimum value is $\min il$, then there is a "super box" in M dimensional space composed of $[\min i1, \max i1] \times [\min i2, \max i2] \times \cdots [\min iM, \max iM] \in R^M$. It defines the possible areas of class ϕ_i samples in the feature space. However, in many cases (for example, the samples are arranged along the volume diagonal of the "super box"), the "super box" obtained by the above method will include large adjacent areas while surrounding the sample set. We use B_i to transform the coordinate system of the space, and find the "super box" in the transformed space to make it "tight" as much as possible. The "super box" classifier will contain L "super boxes" corresponding to each type. When the unknown sample B falls into the "super box" surrounding the class ϕ_i sample, it is considered that it may belong to the ϕ_i class. If no "super box" is included, it will be rejected. It is sent to the nearest neighbor classifier. Suppose that the Mahalanobis distance from B to ϕ_i is:

$$d_i(B) = \sqrt{(B - \varphi_i)^T \sum^{-1} (B - \varphi_i)} \tag{6}$$

The mahalanobian distance between Class B and class ϕ_i is calculated by formula (6). The Markov distance classifier uses the minimum distance criterion to judge the unknown sample category. The Markov distance is used to improve the reliability of the recognition results. According to the recognition results of all training samples by using the criterion of Markov distance and minimum distance, a maximum E_i of Markov distance is calculated for each class ϕ_i, so that the samples identified as ϕ_i in the training set and the Markov distance of ϕ_i is less than 95% of the samples in the subset of E_i belong to class ϕ_i. The Markov distance classifier uses E_i to verify the recognition result ϕ_i, and when $d_i(B) \geq E_i$, it refuses to recognize the sample. In conclusion, the feature vector B with length 20 extracted from the signal segment with unknown modulation style is first sent to the "super box" classifier. If the sample is not rejected, it is sent to the nearest neighbor classifier. Nearest neighbor classifier either refuses B, or identifies it as an ϕ_i class. If the latter situation occurs, the result of the "super box" classifier should be referred to. If B is not included in the "super box" of corresponding ϕ_i, B is rejected, otherwise it will be sent to the Markov distance classifier. The Markov distance classifier will calculate the Markov distance from class ϕ_i. if it is greater than or equal to the threshold E_i, B will be rejected, otherwise, the class of B is determined as ϕ_i. After selecting the modulation styles to be identified, collect the communication signals (mobile communication weak signals) belonging to these styles. After preprocessing, a series of signal segments are obtained, each segment contains 4000 sampling points, and then, according to the feature extraction method in the feature library, each signal segment is extracted, and a 20-dimensional feature vector is formed and the corresponding modulation category is given. The vector obtained is composed of the original training sample set. The "super box" classifier is established according to the training sample set. The nearest neighbor classifier and Markov distance classifier can recognize the modulation pattern within the set range, and realize the weak signal recognition of mobile communication based on information fusion.

3 Experiment

The proposed method based on information fusion for mobile communication weak signal acquisition and recognition is compared with the traditional acquisition and recognition method 1 and the traditional acquisition and recognition method 2 to compare the recognition accuracy of different methods in the process of acquisition and recognition.

3.1 Experimental Process

In order to ensure the smooth progress of the experiment, TDOA measurement algorithm is used to test the accuracy of signal location. The results are shown in Fig. 5.

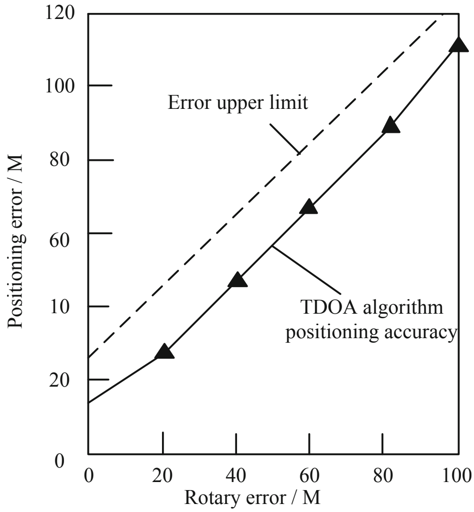


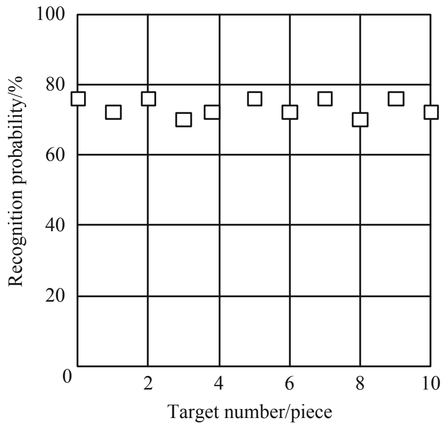
Fig. 5. Positioning result of mobile communication signal

It can be seen from Fig. 5 that the positioning results of mobile communication signals tested by TDOA measurement algorithm are within the allowable error range, which meets the experimental requirements. The experiment is further carried out by using the method of weak signal acquisition and recognition based on information fusion. Firstly, the intercepted radiation source signals are classified and classified. Then, the instantaneous and transient features such as the starting point feature and time-frequency image feature are used respectively. The combined classifier is used to recognize and classify the intercepted radiation source signals. It is assumed that the signals from 10 different sources intercepted are continuous phase, the sampling frequency is 600 MHz and the sampling signal is 10 ms. When the SNR of intercepted signal is 10 dB, the intercepted radiation source signal is identified by using the above characteristics, and the recognition accuracy results are obtained, and compared with the traditional method 1 and traditional method 2.

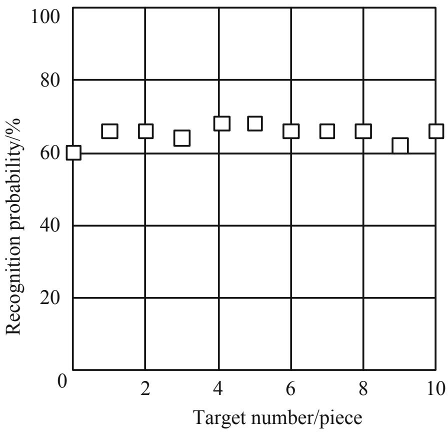
3.2 Experimental Results and Analysis

The recognition results obtained by using the proposed weak signal acquisition and recognition method of mobile communication based on information fusion, traditional method 1 and traditional method 2 are shown in Fig. 6.

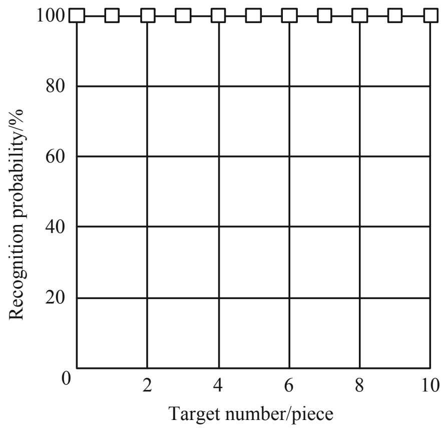
It can be seen from Fig. 6 that the recognition accuracy of traditional method 1 is about 75%, that of traditional method 2 is about 65%, and that of the proposed method is about 99%. Through the analysis, it is found that the proposed method is based on information fusion, through the combination of classifiers to fuse the information and classify the modulation types, the recognition accuracy is significantly improved, which is about 24% higher than the traditional method 1 and 34% higher than the traditional method 2.



(a) Traditional method 1



(b) Traditional method 2



(c) A weak signal acquisition and recognition method for mobile communication is proposed

Fig. 6. Comparison results of recognition accuracy

4 Concluding Remarks

Aiming at the low recognition accuracy in the acquisition and recognition of weak signal in mobile communication, a method of weak signal acquisition and recognition based on information fusion is designed. Through the design and comparison experiment, the proposed method based on information fusion has higher recognition accuracy. It is hoped that the method can provide reference for the research of weak signal acquisition and recognition in mobile communication.

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