A Cooperative Spectrum Sensing Method Based on Feature Extraction and Fusion Clustering

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Abstract. To improve the performance of spectrum sensing at low SNR, a collaborative spectrum sensing method based on feature extraction and fusion clustering is proposed (FEFC). First, the sampling matrix of the received signal is vectorially decomposed to obtain the I and Q component signals. Second, Cholesky decomposition is applied to the covariance matrices of the I and Q signals to fully extract their features and construct the two dimensional feature vectors. The K-Means clustering algorithm is used to optimize the initial parameters of the Gaussian Mixture Model (GMM), effectively preventing it from falling into local minima under low SNR. Finally, the feature vectors of the signals are classified using GMM clustering optimized by the K-Means algorithm to obtain the final spectrum sensing results. Simulation results show that this method reduces the convergence time of GMM and improves the accuracy of model classification. It effectively enhances the performance of spectrum sensing compared to other mainstream methods.

Keywords: cooperative spectrum sensing · Cholesky · K-Means · Gaussian mixture model

1 Introduction

In recent years, the rapid development of wireless communications and the surge in spectrum demand have outpaced the available spectrum resources, which can no longer meet user needs. Cognitive Radio (CR) technology is a key solution to alleviate spectrum resource scarcity. This technology intelligently detects unused frequency bands, efficiently allocates and fully utilizes spectrum resources, and enhances band utilization. Traditional spectrum sensing techniques include Energy Detection (ED), Matched Filter (MF) detection, and

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Cyclostationary Feature (CF) detection [1]. However, traditional spectrum sensing techniques have shortcomings. For example, ED cannot distinguish between signal and noise at low SNR [2]. MF requires prior knowledge of the primary user signal and the channel response [3]. CF is characterized by high complexity and latency [4]. Stochastic theory based and machine learning based methods are employed for spectrum sensing.

1.1 Random Matrix Theory Based Approaches

Spectrum sensing schemes based on random matrix theory have been applied [5], such as Ratio of Maximum and Minimum Eigenvalue (MME), Difference between the Maximum Eigenvalue and the Average Eigenvalues (DMEAE), Difference of Maximum and Minimum Eigenvalues (DMM), and Ratio between Maximum Eigenvalue and the Trace (RMET). These blind spectrum sensing methods extract eigenvalues from the received signal covariance matrix to obtain statistical properties, without requiring any prior information about the PU signal and noise variance. However, these schemes require the calculation of precise judgment thresholds in practice.

1.2 Machine Learning Based Approaches

Machine Learning (ML) based spectrum sensing techniques avoid the issue of judgment threshold calculation [6]. Recent studies have combined covariance based spectrum sensing techniques with ML by extracting eigenvalues from the covariance matrix to generate a training set, thus obtaining a spectrum sensing model. An unsupervised spectrum sensing technique based on K-Means, using the MME of the covariance matrix as the training input for the classifier [7]. In [8], eigenvalues are extracted through the covariance matrix after I Q decomposition and a perception scheme based on K-Means clustering is analyzed with different statistical properties. In [9], eigenvalue computation are realized using the Decomposition and Reorganization (DAR) method for random matrices, increasing the amount of SUs from the theoretical derivation by constructing two covariance submatrices. In [10], the received signal is first preprocessed to generate a feature vector, which is then classified using a Support Vector Machine (SVM), and this approach ultimately yields an effective spectrum sensing result.

1.3 Our Contributions

In order to solve the problem of poor sensing ability and inaccurate threshold estimation at low SNR in traditional spectrum sensing system. This paper proposes a cooperative spectrum sensing method based on feature extraction and fusion clustering (FEFC). The main components are as follows:

1. Vector decomposition is performed on the acquired signals to obtain I and Q components.

2. Construct the I and Q signals feature matrices, and use Cholesky to decompose the feature matrices to fully extract the features of the signals and construct two dimensional feature vectors.
3. Optimization of the GMM using the K-Means algorithm can effectively prevent the GMM from falling into local minima at low SNR, thus improving the performance of spectrum sensing under low SNR conditions.

In the experimental part, we compare the method of this paper with other spectrum sensing methods. Experimental results show that the algorithm avoids the setting of classification thresholds and exhibits good perceptual performance at low SNR compared to traditional algorithms, and the improvement in perceptual performance is more significant in the case of fewer secondary users.

2 System Model

In cognitive radio, the secondary user (SU) senses the primary user (PU) signal, which is easily affected by multipath effects, shadowing, and channel fading, increasing the detection difficulty. To address this, a multiuser collaborative spectrum sensing model is proposed. Signal sensing through multiple users and paths reduces environmental influences and improves system performance. The model is illustrated in Fig. 1.

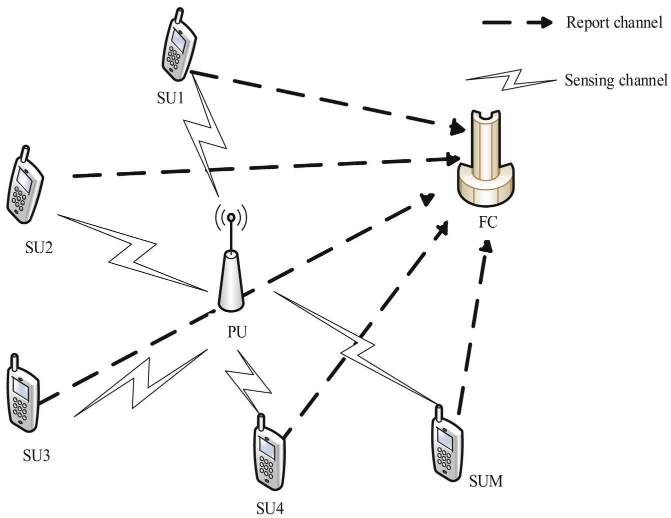

Fig. 1. Cooperative spectrum sensing model

The cognitive radio network consists of 1 PU and M SUs. The detection of the PU signal by the SU can be expressed as a binary hypothesis model.

$$x(t) = \begin{cases} w(t), & H_0 \\ s(t) + w(t), & H_1 \end{cases} \tag{1}$$

In Eq. (1), $x(t)$ represents the received signal of the SU at time t, $s(t)$ represents the PU signal at time t, and $w(t)$ represents additive Gaussian white noise with a mean of 0 and a variance of δ_x^2. The PU signal and the noise are independently distributed. H_0 indicates that the PU signal is absent, while H_1 indicates that the PU signal is present. Assuming S=0 and S=1 correspond to the channel's available states, respectively, they can be represented as:

$$S = \begin{cases} 0, H_0 \\ 1, H_1 \end{cases} \tag{2}$$

Thus, the false alarm probability (P_f) and the detection probability (P_d) are defined as:

$$\begin{aligned} P_f &= p[S = 1\, S = 0] \\ P_d &= p[S = 1\, S = 1] \end{aligned} \tag{3}$$

In a spectrum sensing system, the signals sensed by M SUs form a vector matrix $\mathrm{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_M]^T$, where the signal sensed by the mth SU is $\boldsymbol{x}_m = [\boldsymbol{x}_m(1), \boldsymbol{x}_m(2), ..., \boldsymbol{x}_m(N)]$, and N is the number of samples. This results in an $M \times N$ dimensional signal matrix.

$$\mathbf{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_M]^T = \begin{bmatrix} x_1(1) & x_1(2) & \cdots & x_1(N) \\ x_2(1) & x_2(2) & \cdots & x_2(N) \\ \vdots & \vdots & \ddots & \vdots \\ x_M(1) & x_M(2) & \cdots & x_M(N) \end{bmatrix} \tag{4}$$

3 Feature Extraction

3.1 Signal Decomposition

In signal analysis, the signal is typically decomposed into two components with the same peak amplitude and frequency but with a 90° phase difference, known as I Q decomposition. This method provides a comprehensive description of the signal's amplitude, frequency, and phase. To fully utilize the received signal information, the signal matrix X is vectorially decomposed:

$$\begin{aligned} \mathrm{X}^{\mathrm{I}} &= \sin(\tfrac{2\pi f_c n}{f_s})\mathrm{X} \\ \mathrm{X}^{\mathrm{Q}} &= \cos(\tfrac{2\pi f_c n}{f_s})\mathrm{X} \end{aligned} \tag{5}$$

In Eq. (5), f_c and f_s denote the carrier frequency and sampling frequency, respectively. Thus, the signal matrix X is vectorially decomposed into two $M \times N$ signal matrices:

$$\mathrm{X^I} = \begin{bmatrix} x_1^I(1) & x_1^I(2) & \cdots & x_1^I(N) \\ x_2^I(1) & x_2^I(2) & \cdots & x_2^I(N) \\ \vdots & \vdots & \ddots & \vdots \\ x_M^I(1) & x_M^I(2) & \cdots & x_M^I(N) \end{bmatrix} \quad (6)$$

$$\mathrm{X^Q} = \begin{bmatrix} x_1^Q(1) & x_1^Q(2) & \cdots & x_1^Q(N) \\ x_2^Q(1) & x_2^Q(2) & \cdots & x_2^Q(N) \\ \vdots & \vdots & \ddots & \vdots \\ x_M^Q(1) & x_M^Q(2) & \cdots & x_M^Q(N) \end{bmatrix} \quad (7)$$

3.2 Feature Extraction

Using the $\mathrm{X^I}$ and $\mathrm{X^Q}$ matrices from Eq. (6) and (7), we can calculate the corresponding covariance matrices $\mathrm{R^I}$ and $\mathrm{R^Q}$ as follows:

$$\begin{aligned} \mathrm{R^I} &= \tfrac{1}{N}\mathrm{X^I}(\mathrm{X^I})^{\mathrm{H}} \\ \mathrm{R^Q} &= \tfrac{1}{N}\mathrm{X^Q}(\mathrm{X^Q})^{\mathrm{H}} \end{aligned} \quad (8)$$

In Eq. (8), $(\cdot)^{\mathrm{H}}$represents the conjugate transpose operation, and the covariance matrices $\mathrm{R^I}$ and $\mathrm{R^Q}$ are both $M \times M$ dimensional. Next, the two matrices undergo Cholesky decomposition, as shown in Eq. (9).

$$\begin{aligned} \mathrm{R^I} &= \mathrm{Y^I}(\mathrm{Y^I})^{\mathrm{T}} \\ \mathrm{R^Q} &= \mathrm{Y^Q}(\mathrm{Y^Q})^{\mathrm{T}} \end{aligned} \quad (9)$$

Both $\mathrm{Y^I}$ and $\mathrm{Y^Q}$ are lower triangular matrices, expressed as:

$$\mathrm{Y^I} = \begin{bmatrix} y_{11}^I & 0 & \cdots & 0 \\ y_{21}^I & y_{22}^I & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ y_{M1}^I & y_{M2}^I & \cdots & y_{MM}^I \end{bmatrix} \quad (10)$$

$$\mathrm{Y^Q} = \begin{bmatrix} y_{11}^Q & 0 & \cdots & 0 \\ y_{21}^Q & y_{22}^Q & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ y_{M1}^Q & y_{M2}^Q & \cdots & y_{MM}^Q \end{bmatrix} \quad (11)$$

The signal features G^I are extracted using the lower triangular matrix $\mathrm{Y^I}$ after Cholesky decomposition, represented by Eq. (12) as follows:

$$G^I = \frac{\sum_{1 \le i \le j \le M} \mid y_{ij}^I \mid}{\sum_{1 \le i \le M} \mid y_{ii}^I \mid} \quad (12)$$

$y_{ij}^{I} \geq 0$ is calculated by Eq. (13).

$$\begin{cases} y_{ij}^{I} = \sqrt{\left(r_{ij}^{I} - \sum_{k=1}^{i-1} \left(y_{ki}^{I}\right)^{2}\right)} & i = j \\ y_{ij}^{I} = \left[r_{ij}^{I} - \sum_{k=1}^{j-1} \left(y_{ki}^{I} y_{kj}^{I}\right)\right] / y_{jj}^{I} & i > j \end{cases} \tag{13}$$

where r_{ij}^{I} represents the element in the ith row and jth column of matrix $\mathrm{R^I}$. Similarly, Cholesky decomposition of the covariance matrix $\mathrm{Y^Q}$ is performed, and the signal feature $\mathrm{G^Q}$ is extracted, represented as:

$$G^{Q} = \frac{\sum_{1 \leq i \leq j \leq M} \mid y_{ij}^{Q} \mid}{\sum_{1 \leq i \leq M} \mid y_{ii}^{Q} \mid} \tag{14}$$

Thus, based on G^{Q} and G^{Q} , the two dimensional feature vector G of the signal can be constructed.

$$\boldsymbol{G} = [G^{I}, G^{Q}] \tag{15}$$

Since many training feature vectors are needed to train the clustering algorithm, all training feature vectors **G** must first be constructed as a training feature vector set $\tilde{\mathrm{G}}$:

$$\tilde{\mathrm{G}} = \{\boldsymbol{G}_1, \boldsymbol{G}_2, ..., \boldsymbol{G}_B\} \tag{16}$$

where $\boldsymbol{G}_b$ $(b = 1, 2, \ldots, B)$ is the two dimensional feature vector computed in Eq. (16), and B denotes the number of feature vectors in the training set.

4 A Fusion Clustering-Based Approach to Spectrum Sensing

In this paper, the K-Means clustering algorithm is used to optimize the initial parameters of the Gaussian Mixture Model (GMM), effectively preventing it from falling into local minima under low SNR. The optimized GMM model is then used to classify the constructed signal feature vectors, yielding the spectrum sensing results. Figure 2 shows the system modeling based on the fusion clustering algorithm.

4.1 Training Process of K-Means Clustering Algorithm

For the input set of training feature vectors $\tilde{\mathrm{G}} = \{\boldsymbol{G}_1, \boldsymbol{G}_2, ..., \boldsymbol{G}_B\}$, the K-Means clustering algorithm divides the set into multiple clusters. The objective function of the K-Means clustering algorithm is as follows:

$$J = \sum_{i=1}^{k} \sum_{\boldsymbol{G}_b \in C_i} \|\mathbf{G}_b - \boldsymbol{\beta}_i\|^2 \tag{17}$$

Here, k is the number of clustering centers, which is set to 2. C_i represents the ith cluster, $\boldsymbol{G}_b$ denotes the sample points in the C_i cluster, and $\boldsymbol{\beta}_i$ is the center

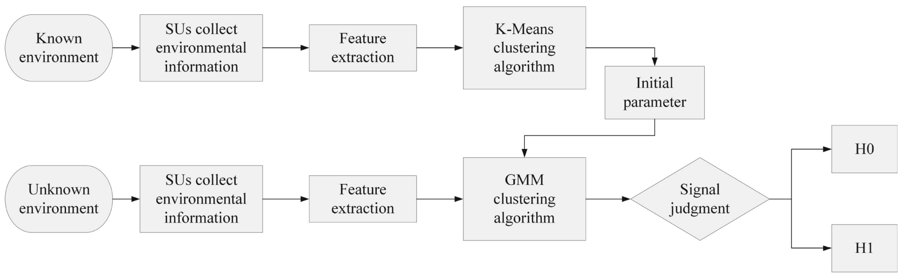

Fig. 2. System modeling based on fusion clustering algorithm

of mass of C_i. The final division of clusters is achieved when the iterative results of the algorithm no longer produce significant changes. At this point, the optimal center of mass $\boldsymbol{\beta}_k^{\psi}$ is calculated using Eq. (18).

$$\boldsymbol{\beta}_k^{\psi} = \frac{1}{|C_k|} \sum_{\boldsymbol{G}_b \in C_k} \boldsymbol{G}_b \tag{18}$$

In the final clustering result, cluster k contains B_k data points out of a total of B data points. The weight of the cluster corresponding to the best quality center is calculated using Eq. (19):

$$\alpha_k^{\psi} = \frac{B_k}{B} \tag{19}$$

The corresponding covariance matrix of the corresponding K-Means is as follows:

$$\Sigma_k^{\psi} = \frac{1}{N_k - 1} \sum_{i=1}^{B_k} (\boldsymbol{G}_i - \boldsymbol{\beta}_k^{\psi})(\boldsymbol{G}_i - \boldsymbol{\beta}_k^{\psi})^T \tag{20}$$

4.2 Training Process of Fusion Clustering Algorithm

The GMM clustering algorithm is initialized using the optimal centroids, weights, and covariance matrices obtained from the convergence of the K-Means clustering algorithm. The GMM measures the affiliation category of each data point in terms of probability, with its probability density distribution given by the following form:

$$q(\boldsymbol{G}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\boldsymbol{G}|\boldsymbol{\mu}_k, \Sigma_k), \sum_{k=1}^{K} \pi_k = 1 \tag{21}$$

where K is the number of models, π_k denotes the mixture weights, $\mathcal{N}(\boldsymbol{G}|\boldsymbol{\mu}_k, \Sigma_k)$ denotes the kth Gaussian distribution, $\boldsymbol{\mu}_k$ is the mean vector, Σ_k is the covariance matrix of the GMM, and the D-dimensional Gaussian distribution takes the following form:

$$\mathcal{N}(\boldsymbol{G} \mid \boldsymbol{\mu}_k, \Sigma_k) = \frac{1}{(2\pi)^{D/2}} \frac{1}{|\Sigma_k|^{1/2}} \exp\left\{-\frac{1}{2}(\boldsymbol{G} - \boldsymbol{\mu}_k)^T \Sigma_k^{-1} (\boldsymbol{G} - \boldsymbol{\mu}_k)\right\} \tag{22}$$

The GMM determines the parameters of each distribution using the maximum likelihood function, which is formulated as follows:

$$\ln q(\boldsymbol{G}|\pi, \boldsymbol{\mu}, \Sigma) = \sum_{b=1}^{B} \ln(\sum_{k=1}^{K} \pi_k \mathcal{N}(\boldsymbol{G}_b|\boldsymbol{\mu}_k, \Sigma_k)) \tag{23}$$

The maximum likelihood function is solved using the Expectation -Maximization algorithm (EM), and the specific implementation process is shown in Table 1:

Table 1. GMM Expectation-Maximization algorithm

Expectation-Maximization algorithm steps	
Step 1	Use the K-Means clustering algorithm to initialize the GMM algorithm
	$\boldsymbol{\mu}_k = \boldsymbol{\beta}_k^{\psi}, \Sigma_k = \Sigma_k^{\psi}, \pi_k = \alpha_k^{\psi}$
Step 2	Desired Steps :
	$\gamma(z_k \mid \boldsymbol{G}_b) = \frac{\pi_k \mathcal{N}(\boldsymbol{G}_b|\boldsymbol{\mu}_k, \Sigma_k)}{\sum_{j=1}^{k} \pi_j \mathcal{N}(\boldsymbol{G}_b|\boldsymbol{\mu}_j, \Sigma_j)}$
Step 3	Maximization step:
	$\boldsymbol{\mu}_k = \frac{1}{B} \sum_{b=1}^{B} \gamma(z_k \mid \boldsymbol{G}_b) \boldsymbol{G}_b$
	$\Sigma_k = \frac{1}{B} \sum_{b=1}^{B} \gamma(z_k \mid \boldsymbol{G}_b)(\boldsymbol{G}_b - \boldsymbol{\mu}_k)(\boldsymbol{G}_b - \boldsymbol{\mu}_k)^{\mathrm{T}}$
	$\pi_k = \frac{B_k}{B}$
	$B_k = \sum_{b=1}^{B} \gamma(z_k|\boldsymbol{G}_b)$
Step 4	until the parameters converge, otherwise return to step 2.

4.3 Perceptual Decision

The optimal solutions $(\boldsymbol{\mu}_k^*, \Sigma_k^*, \pi_k^*)$ for the relevant parameters of the $\tilde{\mathrm{G}}$ training vectors are obtained using Expectation-Maximization algorithm. The test vectors are then partitioned using the final clustering model, represented by the following mathematical model of perceptual judgment:

$$\omega = \ln \frac{\pi_1^* N(Q|\boldsymbol{\mu}_1^*, \Sigma_1^*)}{\pi_2^* N(Q|\boldsymbol{\mu}_2^*, \Sigma_2^*)} \tag{24}$$

In the above equation, Q is the test vector, ω denotes the detection probability, and β is the threshold which controls the false alarm probability P_f. The detection and judgment process does not require retraining the model. If $\omega > \beta$, the judgment is H_1. Here, H_0 and H_1 denote channel unavailability and availability.

4.4 Complexity Analysis

The model training time overhead of this paper's approach consists of the computation of the covariance matrix, the feature extraction and the computation of fusion clustering,the complexities are $O(M^2N)$, $O(M^3)+O(M^2)$ and

Table 2. Comparison of complexity of different methods

Methods	Complexity
DMM+IQ	$O(N^2L) + O(M^3) + O(CdL)$
DMEAE+DAR	$O(M^2L) + O(M^3) + O(CdL)$
GMM	$O(M^2N) + O(M^3) + O(M^2) + O(CdL + CL) + O(2CdL)$
FEFC	$O(M^2N) + O(M^3) + O(M^2) + O(CdL) + O(2CdL)$

$O(CdL) + O(2CdL)$, where d denotes the dimension, C is the number of clustering centers and L is the length of the training data.

We also compare the complexity of the method in this paper with other methods with better performance, as shown in Table 2. The clustering method in this paper has lower complexity compared to traditional GMM clustering, comparing with the other two algorithms, the complexity of this paper's method is higher, but the proposed method has better detection performance due to the use of GMM clustering.

5 Simulation Experiments

To demonstrate the spectrum sensing performance of the proposed method, its performance is analyzed through MATLAB simulations and compared with other spectrum sensing techniques. To ensure the accuracy and reliability of the experimental results, the simulated primary user signal used in the experiments is a BPSK signal, with a signal activity probability of 0.5. Additionally, a flat Rayleigh fading channel is assumed between the primary user (PU) and the secondary user (SU). The noise is an additive white Gaussian noise (AWGN) signal with a mean of 0 and a variance of 1, and it is independently distributed with ideal Gaussian white noise. Experimentally, 2000 signal feature vectors were extracted for clustering to obtain a classification model, and another 1000 signal feature vectors were extracted to analyze the perceptual performance of the model.

5.1 Classification Effect Based on Feature Extraction and Fusion Clustering

Figure 3 shows 2000 feature vectors that have not been classified by the clustering algorithm, with 1000 being noise feature vectors and the remaining 1000 being signal plus noise feature vectors. Figure 4 shows the results of clustering 2000 feature vectors using the proposed method. In the figure, red indicates the channel available class, while blue represents the channel unavailable class.

5.2 Spectrum Sensing Performance Comparison

Figure 5 compares the channel classification accuracy of the proposed fusion clustering method with traditional GMM clustering at different SNR. The SNR

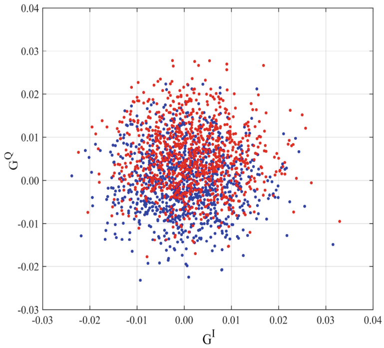

Fig. 3. Raw signal feature vector (Color figure online)

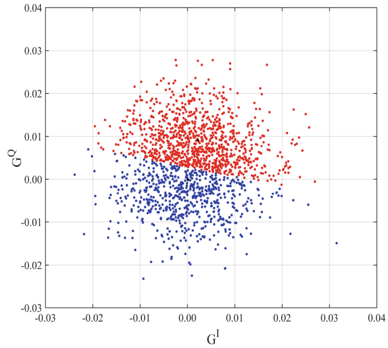

Fig. 4. Clustered signal feature vector (Color figure online)

was varied from −20 dB to −6 dB, with the number of SUs $M = 5$ and the number of samples N=2000. From the figure, it can be seen that the classification accuracy of this paper's algorithm is close to 100% when $SNR = -8$ dB, 97.6% when $SNR = -$ 10 dB, and 62.75% in the worse environment with SNR of −20 dB. When the SNR is higher than −10 dB, the accuracy of the two algorithms in the figure is comparable. However, when the SNR is lower than −12 dB, the classification accuracy of the proposed method is significantly better than that of traditional GMM clustering.

To evaluate the performance of our proposed method, we compare it with other mainstream spectrum sensing techniques, including the Maximum to Minimum Eigenvalue ratio (MME), the Difference between Maximum and Minimum Eigenvalues (DMM), and the Ratio of Maximum Eigenvalue to Trace (RMET).

Figure 6 shows the spectrum sensing performance of various algorithms with the number of SUs $M = 5$, the SNR is set to be −12 dB and the number of samples N equals 2000. When the false alarm probability P_f is 0.1, the detection probability P_d reaches 89%, representing a 9% improvement over the DMM based K-Means clustering method. Figure 7 shows the spectrum sensing performance of various algorithms at an SNR of −14 dB. When the false alarm probability P_f is 0.1, the detection probability P_d reaches 78.5%, representing an 8% improvement over the DMM based K-Means clustering method.

Figure 8 shows the performance analysis of different number of SU with SNR = −16 dB and N = 2000. From Fig. 8, it can be seen that the number of secondary SUs M is highly related to the detection probability of the algorithm, and the perceived performance of the FEFC algorithm improves with the increase of M.

Figure 9 shows the performance analysis of different sampling points with $SNR = -16$ dB and $M = 5$. From Fig. 9, it can be seen that the perceptual performance of the FEFC algorithm improves with the increase in the number of sampling points.

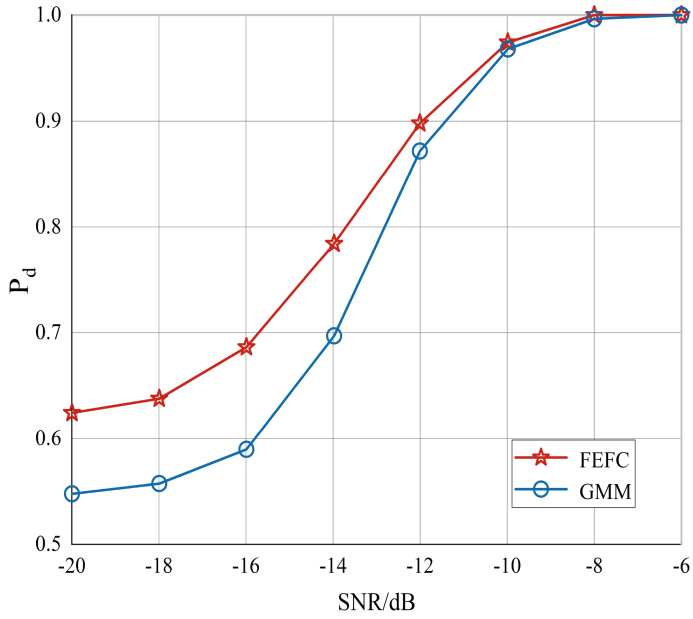

Fig. 5. Comparison of classification accuracy

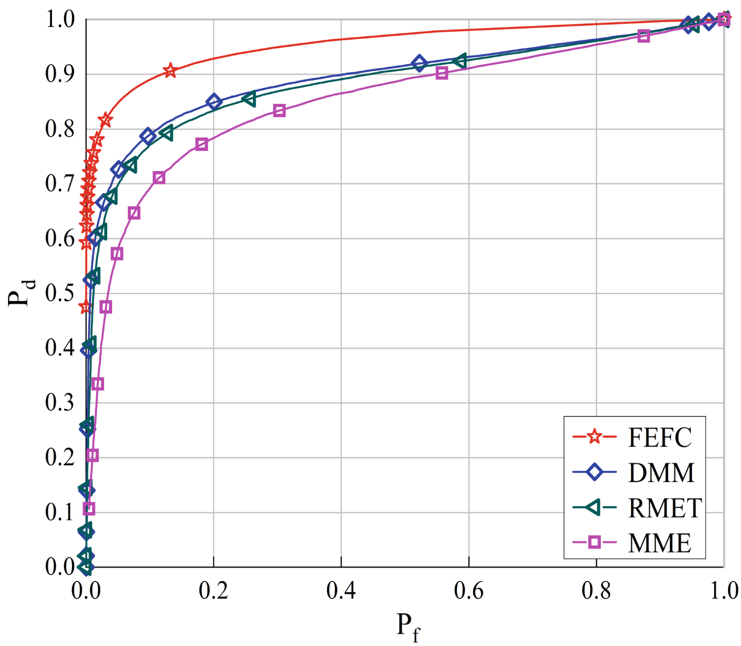

Fig. 6. ROC curves for each algorithm with $SNR = -12$ dB and $M = 5$

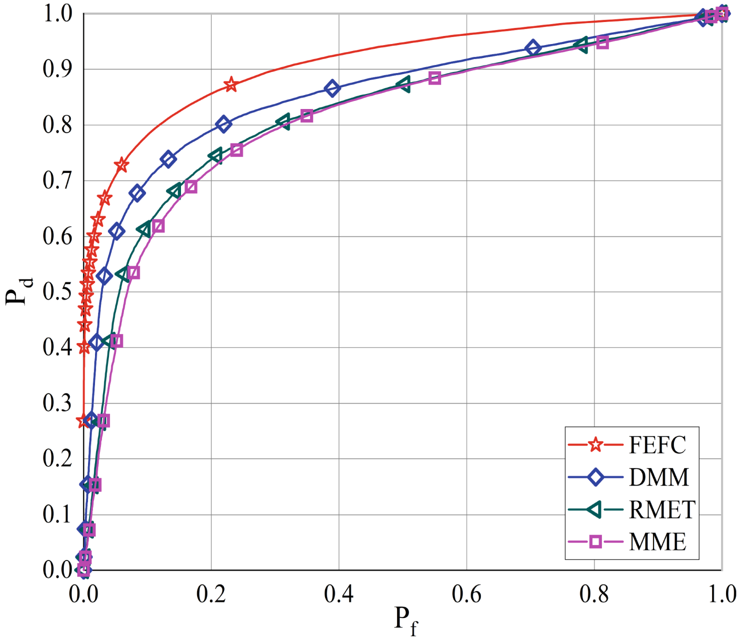

Fig. 7. ROC curves for each algorithm with $SNR = -14$ dB and $M = 5$

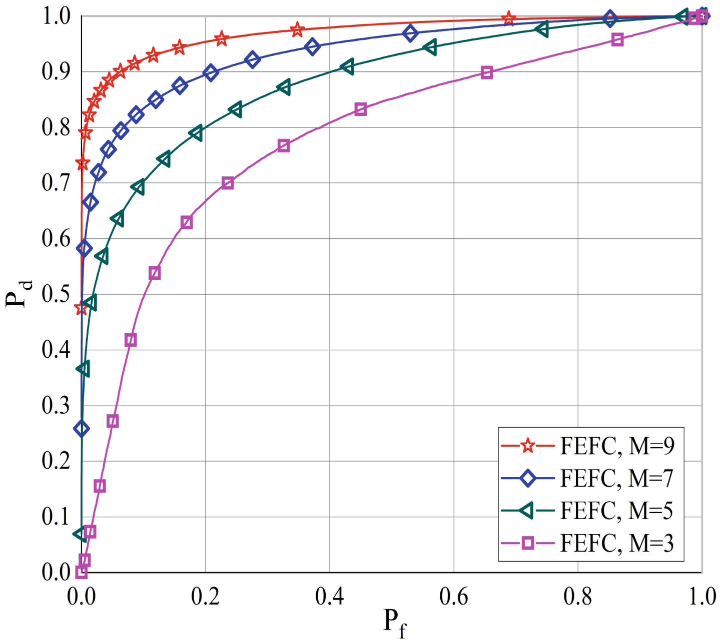

Fig. 8. Performance analysis of different number of SU with $SNR = -16$ dB

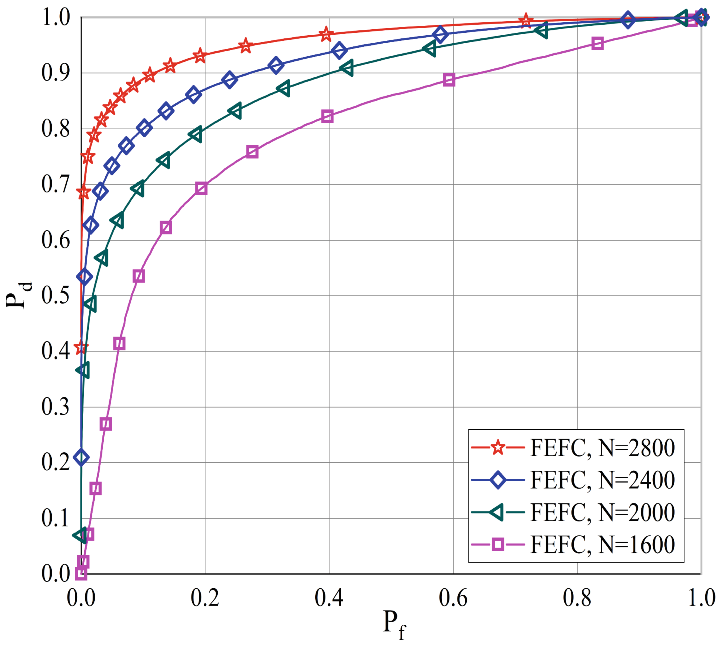

Fig. 9. Performance analysis of different sampling points with $SNR = -16$ dB

The experimental results indicate that the detection performance of the method proposed in this paper is significantly improved compared to other spectrum sensing methods across a range of SNR.

5.3 Conclusions

This paper proposes a spectrum sensing method based on feature extraction and fusion clustering to address spectrum sensing problem under low SNR conditions. First, the sampling matrix of the received signal is vectorially decomposed to obtain the I and Q component signals. Then, the information of the signal matrix is fully extracted using the cholesky decomposition of the covariance matrix of the I and Q signals. Finally, the GMM model, optimized by the K-Means algorithm, is used to classify the signal samples and determine the channel state. Simulation results indicate that the algorithm exhibits good perceptual performance. In this paper, we have not considered the problem of forging data by malicious users in the system, which can generate outliers and thus affect the performance of clustering, and further research will be conducted on this issue in the subsequent work.

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