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Robust Spectrum Sensing for Blind Multiband Detection in Cognitive Radio Systems: A Gerschgorin Likelihood Approach

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Abstract

Energy detection is a widely used method for spectrum sensing in cognitive radios due to its simplicity and accuracy. However, it is severely affected by the noise uncertainty. To solve this problem, a blind multiband spectrum sensing scheme which is robust to noise uncertainty is proposed in this paper. The proposed scheme performs spectrum sensing over the total frequency channels simultaneously rather than a single channel each time. To improve the detection performance, the proposal jointly utilizes the likelihood function combined with Gerschgorin radii of unitary transformed covariance matrix. Unlike the conventional sensing methods, our scheme does not need any prior knowledge of noise power or PU signals, and thus is suitable for blind spectrum sensing. In addition, no subjective decision threshold setting is required in our scheme, making it robust to noise uncertainty. Finally, numerical results based on the probability of detection and false alarm versus SNR or the number of samples are presented to validate the performance of the proposed scheme.

Keywords: Cognitive radio, spectrum sensing, energy detection, multiband detection, likelihood function

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1. Introduction

Cognitive radio (CR) [1][2] is a promising technology for future wireless communication systems which has received much attention in the recent years. It aims at improving spectral efficiency by allowing secondary users (SUs) to opportunistically access the vacant spectrum bands which are originally allocated to primary users (PUs) without inducing any interference. A comprehensive review of recent advances in CR is investigated, including its fundamentals, architectures and applications [3]. Spectrum sensing, which deals with the opportunistic spectrum access, is an essential step in CRs. In general, spectrum sensing techniques can be classified into three categories: energy detection, matched filter detection and cyclostationary feature detection [4][5]. These techniques can be applied to an individual SU or multiple SUs in a collaborative way to make the final decision [6][7]. However, some prior knowledge should be assumed at the CR, such as PU signals, channels gains or the accurate noise power. Such limitation would greatly influence their application scenarios.

The characteristics of low complexity for implementation and no needs of PU signals information have made energy detection the most widely used spectrum sensing method and fairly appropriate for blind spectrum sensing. Furthermore, it has been proved that energy detection is optimal for white Gaussian noise if the noise variance is known [8]. However, noise variance generally cannot be accurately estimated due to the fluctuation of noise power. This is the so-called noise uncertainty, which leads to a high false alarm probability and severely deteriorates the performance of energy detection [9][10][11].

In order to deal with the multiband spectrum sensing for CR, an early approach is to use a tunable narrowband bandpass filter at the radio frequency front-end to sense one narrow frequency band at a time [12], over which the existing narrowband spectrum sensing techniques can be applied. Similar to that, energy detection can be applied to multiband case, where the multiband is divided into multiple subbands and detection is performed in each subband independently [13]. One way to operate over multiple frequency bands at a time is to use the wavelet transform [14][15], which estimates the power spectral density over a multiband frequency range. Optimal multiband joint decisions are made over multiple frequency bands by a class of optimization problems in [16], where the decision thresholds are designed to maximize the aggregated opportunistic throughput while keeping the aggregate interference under a certain value.

Distinct from the above methods, this paper deals with the multiband sensing problem from another perspective. The proposed scheme first estimates the number of occupied channels and then determines the corresponding locations. This paper exploits the characteristic that sampling power of the busy channel is the addition of noise and signal while idle channel only corresponds to noise. Thus channel with larger sampling power is more likely to be a busy one. On condition that the sampling powers of each channel are sorted in descending order, the first couple of channels are more likely to be the busy channels while the rest are the idle ones. Therefore the estimation of the number of occupied channels becomes a critical issue. In this way, the multiband spectrum sensing problem becomes the estimation of the number of occupied channels, which can be viewed as the issue of estimating the number of signal sources. Thanks to the fruitful achievements in source number estimation [17][18][19], we can get the estimation of the number of occupied channels.

This paper proposes a robust spectrum sensing scheme for blind multiband detection in CR systems. Due to the fact that the noise eigenvectors of the sampling covariance matrix are

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orthogonal to the steering matrix while the signal eigenvectors are not, the proposed scheme can utilize the transformed Gerschgorin radii to distinguish noise from signal. The likelihood function combined with Gerschgorin radii of unitary transformed covariance matrix is employed to improve the detection performance. The proposed scheme performs spectrum sensing over the total frequency channels simultaneously instead of a single channel each time to make an estimation of the number of occupied channels and then determine the corresponding locations. Besides, having no prior knowledge requirements of the PU signal, the proposed scheme possesses a wide practical applicability. Numerical results verify that our approach is robust to noise uncertainty and outperforms energy detection with noise uncertainty.

The rest of the paper is organized as follows. In Section 2, the system model for multiband spectrum sensing in CR is described. In Section 3, we develop the robust multiband spectrum sensing scheme. Numerical results are shown in Section 4 and conclusions are drawn in Section 5.

2. System Model

It is assumed that CR system operates over a wideband channel which can be divided into Q nonoverlapping subbands and the system usually has very low utilization of spectrum radio [20]. K out of Q channels are occupied by PUs and the rest of them are vacant channels. The total frequency band ranges from f_s to f_e Hz and each channel's bandwidth is W Hz. **Fig. 1** depicts a spectrum usage pattern at a particular time in a particular area. We use $\mathbf{R}=\{1,2,\cdots,Q\}$ to denote the index set of total channels. $\mathbf{R}_1=\{q_1,q_2,\cdots,q_K\}$ denotes the index set of occupied channels (the grey rectangles in **Fig. 1**) and $\mathbf{R}_2=\mathbf{R}\text{-}\mathbf{R}_1$ denotes the index set of vacant channels (the white rectangles in **Fig. 1**).

The purpose of spectrum sensing is to determine the number and locations of occupied channels, namely, to estimate K and $\mathbf{R}_1$.

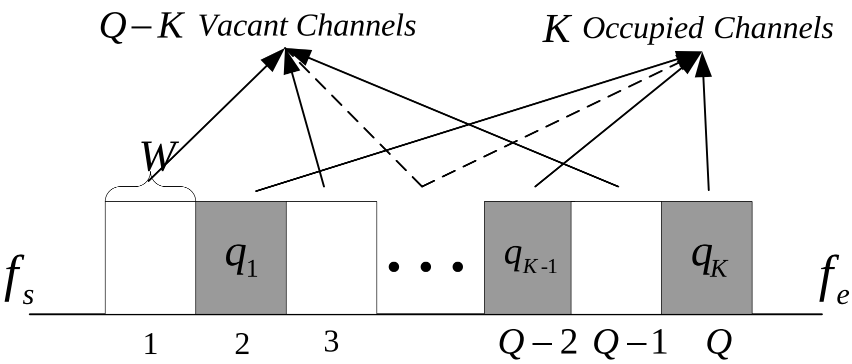

Fig. 1. Spectrum usage pattern

The binary hypothesis test for spectrum sensing is formulated as follows:

$$\begin{aligned} &H_0 : \mathbf{r}(n) = \boldsymbol{\varepsilon}(n) \\ &H_1 : \mathbf{r}(n) = \mathbf{s}(n) + \boldsymbol{\varepsilon}(n) \end{aligned}, \qquad (1)$$

where H_0 denotes that PU is absent, i.e. the channel index belongs to $\mathbf{R}_2$ and H_1 denotes that PU is present, i.e. the channel index belongs to $\mathbf{R}_1$. The sources that emit powers are considered to be PUs. $\boldsymbol{\varepsilon}(n)$ is the additive noise at the CR receiver, modeled as an independent identical distribution (i.i.d.) circularly symmetric complex Gaussian (CSCG) vector with zero mean and the covariance matrix $\sigma^2\mathbf{I}$ while $\mathbf{s}(n)$ is the received PU signals to be detected. Here $\mathbf{I}$ denotes an identity matrix and σ^2 represents the noise power. Noise power density is constant with frequency, and so the noise powers are identical in different channels. $\mathbf{s}(n)$ is modeled as an i.i.d. CSCG random vector with zero mean and the covariance matrix $\mathbf{C}_s = E\left[\mathbf{s}(n)\mathbf{s}^H(n)\right]$, where $E[\cdot]$ denotes expectation and $(\cdot)^H$ denotes the Hermitian transpose. It is also assumed that the received PU signal is uncorrelated with the noise. SUs make the decisions according to the observation data $\mathbf{r}(n), n=1,\cdots,N$ where N represents the sampling number.

The covariance matrix of the observation data $\mathbf{r}(n)$ can be represented as

$$\mathbf{C}_r = E\left[\mathbf{r}(n)\mathbf{r}^H(n)\right] = \mathbf{C}_S + \sigma^2\mathbf{I}. \tag{2}$$

However, in practice, the covariance matrix can only be estimated from a finite set of sampling numbers, which is called sampling covariance matrix and is represented as

$$\hat{\mathbf{C}}_r = \frac{1}{N}\sum_{n=1}^{N}\mathbf{r}(n)\mathbf{r}^H(n). \tag{3}$$

When in the limit $N \to \infty$, $\hat{\mathbf{C}}_r$ will become $\mathbf{C}_r$.

3. Proposed Spectrum Sensing Scheme

3.1 Principle Analysis

For the multiband spectrum sensing problem, there are multiple channels to be detected and we must detect the presence or absence of PUs in each channel. So multiband spectrum sensing is to find out the exact locations of the channel occupied by PUs and then SUs can make use of the idle channels after spectrum sensing. On the other hand, note that sampling power of the busy channel is the addition of noise and signal while idle channel only corresponds to noise, and hence, received signal with larger sampling power is more likely not to be pure noise. As a result, sampling powers of the idle channels are approximately identical and lower than those of the busy channels. Exploiting this characteristic, if we sort the sampling powers of each channel in descending order, the first coming $\hat{K}$ channels correspond to the busy channels while the rest Q-$\hat{K}$ channels correspond to the idle channels. In other words, the knowledge of $\hat{K}$ is the key issue that needs to be settled. So the multiband spectrum sensing problem shifts to be the estimation of the number of occupied channels, which can be seen as the subject of estimating the number of signal sources.

Source number estimation with no prior knowledge of the signals has already been widely investigated in radar array processing. Akaike's Information Criterion (AIC) and Minimum

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Description Length (MDL), the two common information theoretic criteria, are proposed to estimate the number of signal sources [17]. However, AIC and MDL only employ the information of the eigenvalues of the covariance matrix but do not exploit any other information, such as the eigenvectors and signal subspace components. There exists a more robust method applying Gerschgorin likelihood function called Gerschgorin likelihood estimator (GLE) [18]. It enhances the detection performance by jointly utilizing the likelihood function combined with Gerschgorin radii of unitary transformed covariance matrix. In this method, different hypotheses on the number of signal sources are assumed first. Then several competing models and the corresponding modeling functions are constructed under these hypotheses by using Gerschgorin AIC (GAIC) or Gerschgorin MDL (GMDL). The number of sources is determined when the modeling function, i.e. GAIC or GMDL, is minimized. Motivated by source number estimation, we can get the estimation of the number of occupied channels utilizing the GLE method. Details are given below.

Before the discussion of our proposed scheme, we shall make a brief review of Gerschgorin's disk theorem [21]. The theorem gives an easy approach to estimate the locations of the eigenvalues of a matrix by its elements since there is no need to perform precise calculation in general.

3.2 Gerschgorin's Disk Theorem

Specifically, for a complex $L \times L$ matrix $\mathbf{A}$, whose (i, j) th element is denoted as $a_{i,j}$. The Gerschgorin radius, the sum of the magnitudes of the elements of the i th row, excluding the i th element, which is the Gerschgorin center, is defined as

$$r_i = \sum_{j=1, j\neq i}^{L} \left| a_{i,j} \right| \quad i = 1, 2, \cdots, L . \tag{4}$$

Gerschgorin disk, the collection of points in the complex plane whose distance to the Gerschgorin center is not larger than the Gerschgorin radius, is defined as

$$\left| z - a_{i,i} \right| \leq r_i \quad i = 1, 2, \cdots, L . \tag{5}$$

Gerschgorin's disk theorem tells that the eigenvalues of a matrix locate in the union of the Gerschgorin disks. Furthermore, if m Gerschgorin disks are separated from the other disks, then there exist exactly m eigenvalues locating in the union of the m disks. However, the Gerschgorin radii and the Gerschgorin centers of the sampling covariance matrix usually tend to be large and close, respectively, making it difficult to distinguish noise from signals.

3.3 Proposed Scheme

With the previous limitations in mind, we employ a likelihood approach called GLE to estimate the number of occupied channels similar to that of [18]. Before introducing GAIC and GMDL, we first make some transformations with Eq. (3).

The binary hypothesis test (1) can be rewritten as

$$\mathbf{r}(n) = \mathbf{P}\mathbf{s}(n) + \boldsymbol{\varepsilon}(n) , \tag{6}$$

where $\mathbf{P}$ is a $Q \times K$ matrix with its (i, j) th element shown as

$$p_{i,j}=\begin{cases}1 & i\in R_1, j=k\\ 0 & others\end{cases}. \tag{7}$$

In this way, $\mathbf{P}$ can be seen as the steering matrix.

The covariance matrix depicts the statistical behavior of the received signals. A unitary transformation is performed at first. The sampling covariance matrix of the received signals can be first partitioned as

$$\mathbf{C_r}=\begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1Q}\\ c_{21} & c_{22} & \cdots & c_{2Q}\\ \vdots & \vdots & \vdots & \vdots\\ c_{Q1} & c_{Q2} & \cdots & c_{QQ}\end{bmatrix}=\begin{bmatrix}\mathbf{C_r'} & \mathbf{c}\\ \mathbf{c^H} & c_{QQ}\end{bmatrix}, \tag{8}$$

where $\mathbf{C_r'}$ is a $(Q-1)\times(Q-1)$ leading principal submatrix of $\mathbf{C_r}$,which is obtained by deleting the last row and column of $\mathbf{C_r}$ .It is noted that $c=\left[c_{1Q},c_{2Q},\cdots,c_{(Q-1)Q}\right]^T$.

The reduced covariance matrix $\mathbf{C_r'}$ can be decomposed by its eigenvalues as

$$\mathbf{C}_r'=\mathbf{U}'\mathbf{D}'\mathbf{U}'^H, \tag{9}$$

where $\mathbf{D}'$ is a diagonal matrix constructed from the corresponding eigenvalues of $\mathbf{C_r'}$ as

$$\mathbf{D}'=diag\left[\lambda_1'\ \lambda_2'\cdots\lambda_K'\cdots\lambda_{Q-1}'\right], \tag{10}$$

and $\mathbf{U}'$ is a $(Q-1)\times(Q-1)$ unitary matrix ($\mathbf{U}'\mathbf{U}'^H=\mathbf{I}$) constructed from the corresponding eigenvectors of $\mathbf{C_r'}$ as

$$\mathbf{U}'=\left[\mathbf{q}_1'\ \mathbf{q}_2'\cdots\mathbf{q}_K'\cdots\mathbf{q}_{Q-1}'\right]. \tag{11}$$

Here λ_i' shown in descending order denotes the eigenvalues and $\mathbf{q}_i'$ represents the eigenvectors of the corresponding eigenvalues. For the true covariance matrix, it can be proved that

$$\lambda_{K+1}'=\cdots=\lambda_{Q\text{-}1}'=\sigma^2, \tag{12}$$

since the smallest eigenvalues correspond to the noise variance.

An important unitary transformation matrix is constructed, represented by

$$\mathbf{U}=\begin{bmatrix}\mathbf{U}' & \mathbf{0}\\ \mathbf{0}^T & 1\end{bmatrix}. \tag{13}$$

Then the transformed covariance matrix is given by

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$$\begin{aligned}\mathbf{S} &= \mathbf{U}^H \mathbf{C}_r \mathbf{U} \\ &= \begin{bmatrix} \mathbf{U}'^H \mathbf{C}' \mathbf{U}' & \mathbf{U}'^H \mathbf{c} \\ \mathbf{c}^H \mathbf{U}' & c_{QQ} \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{D}' & \mathbf{U}'^H \mathbf{c} \\ \mathbf{c}^H \mathbf{U}' & c_{QQ} \end{bmatrix} \\ &= \begin{bmatrix} \lambda_1' & 0 & 0 & \cdots & 0 & \rho_1 \\ 0 & \lambda_2' & 0 & \cdots & 0 & \rho_2 \\ 0 & 0 & \lambda_3' & \cdots & 0 & \rho_3 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \lambda_{Q-1}' & \rho_{Q-1} \\ \rho_1^* & \rho_2^* & \rho_3^* & \cdots & \rho_{Q-1}^* & c_{QQ} \end{bmatrix},\end{aligned} \tag{14}$$

where $\rho_i = \mathbf{q}_i'^H \mathbf{c} \quad i = 1, 2, \cdots, Q-1$.

According to Gerschgorin's disk theorem, the Gerschgorin radius of $\mathbf{S}$ is

$$r_i = \sum_{j=1, j\neq i}^{Q-1} |a_{i,j}| = |\rho_i| = |\mathbf{q}_i'^H \mathbf{c}| \quad i = 1, 2, \cdots, Q-1. \tag{15}$$

Based on Schmidt's concept [22], it is important to verify that $\rho_i = 0$ when $i = (K+1), \cdots, (Q-1)$ due to the fact that the noise eigenvectors are orthogonal to steering matrix of $\mathbf{C}_r'$. Additionally, $\rho_i \neq 0$ when $i = 1, \cdots, K$ since the signal eigenvectors are not orthogonal to steering matrix of $\mathbf{C}_r'$ and $\mathbf{C}_s$ is full rank.

Using the similar procedures established by Wax and Kailath [17] in conjunction with Schmidt's concept, we obtain the Gerschgorin log-likelihood function as

$$\Psi_Q(k) = -N \log\left[\det\left(\mathbf{S}^{(k)}\right)\right] - tr\left[\mathbf{S}^{(k)-1}\hat{\mathbf{S}}\right], \tag{16}$$

where $\hat{\mathbf{S}}$ denotes the estimated transformed sampling covariance matrix and $\mathbf{S}^{(k)}$ represents the true transformed covariance matrix if there exists k occupied channels.

Based upon the derivations in [17] and by ignoring the constant terms, the Gerschgorin log-likelihood function can be approximately expressed as

$$\Psi_Q(k) = N(Q-1-k)\log\left[\frac{\alpha_{Q-1}'(k)}{\beta_{Q-1}'(k)}\right] - N\log\left(c_{QQ} - \sum_{i=1}^{k}\frac{r_i^2}{\lambda_i'}\right), \tag{17}$$

where

$$\alpha_{Q-1}'(k) = \left(\prod_{i=k+1}^{Q-1} \lambda_i'\right)^{1/(Q-k-1)} \tag{18}$$

and

$$\beta'_{Q-1}(k) = \frac{1}{Q-k-1}\sum_{i=k+1}^{Q-1}\lambda'_i . \tag{19}$$

It can be seen that the first term of Eq. (17) is an eigenvalue based log-likelihood function, describing the ratio of the arithmetic mean of the noise elements to their geometric mean. The second term of Eq. (17) is contributed by the Gerschgorin radii weighting by their corresponding eigenvalues. This Gerschgorin term is a measure of the distance between the elements in the signal subspace.

Combining the above Gerschgorin likelihood function and a penalty function, the GLE becomes

$$GLE(k) = -\Psi_Q(k) + P(N,k,Q), \tag{20}$$

where $P(N,k,Q)$ represents the penalty function.

According to [23], the number of free parameters in Eq. (17) is k^2 for signal subspace components and k for Gerschgorin radii. Hence, the GLE criterion can be further illustrated as

$$GAIC(k) = -N(Q-1-k)\log\left[\frac{\alpha'_{Q-1}(k)}{\beta'_{Q-1}(k)}\right] + N\log\left(c_{QQ} - \sum_{i=1}^{k}\frac{r_i^2}{\lambda'_i}\right) + k^2 + k \tag{21}$$

and

$$GMDL(k) = -N(Q-1-k)\log\left[\frac{\alpha'_{Q-1}(k)}{\beta'_{Q-1}(k)}\right] + N\log\left(c_{QQ} - \sum_{i=1}^{k}\frac{r_i^2}{\lambda'_i}\right) + \frac{1}{2}(k^2+k)\log N . \tag{22}$$

The number of occupied channels K is then estimated by the value which minimizes the GAIC or GMDL criterion. That is to say,

$$\hat{K} = \arg\min_{k=0,1,\cdots,Q-1} GAIC(k) \tag{23}$$

or

$$\hat{K} = \arg\min_{k=0,1,\cdots,Q-1} GMDL(k). \tag{24}$$

Note that the diagonal elements of $\mathbf{C}_r$ corresponds to the sampling power of each channel. After estimating the number of occupied channels, the index of the largest $\hat{K}$ elements of the sampling powers correspond to the index set of occupied channels. In other words, we use φ_q to denote the sampling power, $q=1,2,\cdots,Q$. If $\varphi_{q_1}, \varphi_{q_2}, \cdots, \varphi_{q_{\hat{K}}}$ are the $\hat{K}$ largest elements of $\{\varphi_1, \varphi_2, \cdots, \varphi_Q\}$, then $\hat{\mathbf{R}}_1 = \{q_1, q_2, \cdots, q_{\hat{K}}\}$ is the estimated index set of occupied channels.

In summary, the steps of the proposed schemes are shown below.

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Step 1: Estimate the sampling covariance matrix $\mathbf{C}_r$ and transformed covariance matrix $\mathbf{S}$.
Step 2: Perform eigenvalue decomposition and calculate the Gerschgorin radii.
Step 3: Estimate the number of occupied channels using GAIC Eq. (23) or GMDL Eq. (24).
Step 4: The indexes of the $\hat{K}$ largest diagonal elements of $\mathbf{C}_r$ correspond to the indexes of the occupied channels.

3.4 Discussions of The Proposal

- From Eq. (23) and Eq. (24), it seems that our GAIC/GMDL scheme cannot deal with the special case when there are Q occupied channels. Under this circumstance, all the channels are occupied. From another perspective, it can be viewed as a single-band spectrum sensing problem and abundant conventional methods have already emerged on this topic. So the proposed method can estimate the number of occupied channels in all cases and make the appropriate judgment.
- The proposed method does not need to set any subjective threshold or estimate the noise power, which avoids the interference of the inaccurate estimation. Hence, the proposal is more robust to noise uncertainty than energy detection.
- To reach the final decisions, unlike the conventional spectrum sensing methods, the proposed GAIC/GMDL method jointly utilizes the information of Gerschgorin radii, signal and noise subspace components together with the likelihood function. In this way, the detection performance would be greatly improved.

4. Numerical Results

In this section, some numerical results are provided to validate the proposal's performance. Detection probability P_d and false alarm probability P_f are used to scale the performance. In IEEE 802.22, $P_d \geq 0.9$ is the generally required detection probability and $P_f \leq 0.1$ is the generally required false alarm probability for ideal CR systems [11]. These two key parameters are used for performance evaluation. Meanwhile, noise uncertainty is also considered here. The estimated noise power is uniformly distributed in an interval $\left[\sigma^2/A, A\sigma^2\right]$. Thus the noise uncertainty is $\delta = 10\log_{10} A\ dB$. Consequently, energy detection with noise uncertainty has to set the threshold by using the estimated noise variance to meet the given P_f.

It is assumed that there are Q=40 channels to be detected in total, among which K=10 channels are occupied by the PUs. Our goal is to find out the exact locations of the occupied channels, and thus SUs can make full use of the vacant ones. It is noted that PUs' signal powers are generally various in different channels, and SNR in the following numerical results is the average SNR. 500 independent Monte Carlo runs are carried out in each procedure. For the energy detection, there are two cases: without noise uncertainty, i.e. $\delta = 0$, and with 1 dB noise uncertainty, i.e. $\delta = 1$. Energy detection with $P_f = 0.1$ is used in the following Sections.

4.1 Detection Performance with Varying Channel Condition

In this section, the detection performance comparison of our proposed GAIC/GMDL method and energy detection in the case of varying channel condition resulting in changing received SNR. **Fig. 2** depicts the probability of detection and false alarm against SNR when N=200.

It follows from the figure that when $N = 200$, the ideal energy detection reaches $P_d = 0.9$ at approximately 2 dB lower SNR than energy detection with 1 dB noise uncertainty, which indicates a perfect P_d performance. Furthermore, P_f of the energy detection with 1 dB noise uncertainty is approximately 0.2, which is not accepted in CR systems while the ideal energy detection remains the preset value 0.1. It implies that noise uncertainty severely degrades the performance of energy detection. Similarly, we can conclude that the proposed GAIC scheme outperforms energy detection with noise uncertainty as well no matter whether P_d or P_f performance is concerned.

The proposed GMDL scheme seems to have a poor P_d performance. However, note that it can almost achieve a perfect P_f performance, which indicates that no false alarm event occurs under this circumstance. This is even better than the ideal energy detection. Meanwhile, a perfect P_d performance is also achieved at a moderate to high SNR. Thus it can be concluded a perfect performance is obtained. In addition, the proposed GAIC scheme attains a better P_d performance than GMDL scheme. However, its P_f performance is worse than GMDL scheme.

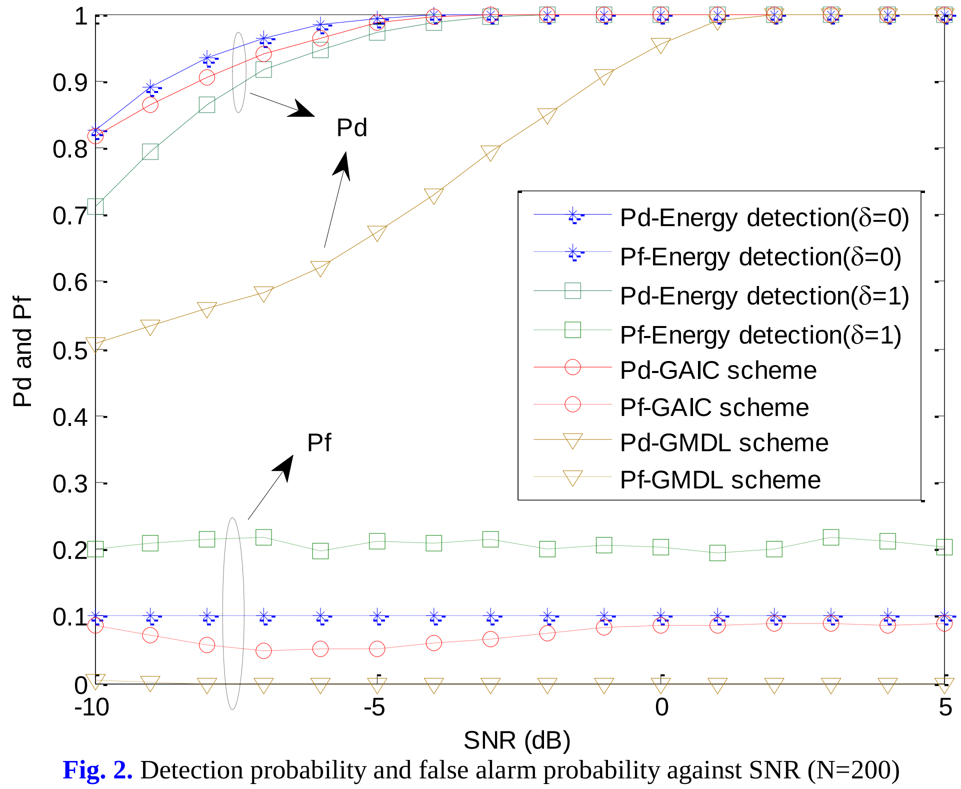

Fig. 2. Detection probability and false alarm probability against SNR (N=200)

4.2 Detection Performance with Different Timing Requirements

For different timing requirements, different number of samples has to be collected at the receiver to satisfy a given quality criteria. Thus, in this section, we show how the number of samples affects the performance of our proposed GAIC/GMDL scheme and energy detection. **Fig. 3** depicts the detection performance, characterized using P_d and P_f, against the number

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of samples at $SNR = -10\,dB$. The figure suggests that when N exceeds a certain value, the performance of energy detection with 1 dB noise uncertainty in terms of P_d is not further improved due to SNR wall [9]. It indicates that noise uncertainty cannot be solved by means of increasing the number of samples, whereas the performance of the others is still enhanced or has reached their limits. This finding means that even though the proposed GMDL scheme has a worse P_d performance than energy detection with 1 dB noise uncertainty when the number of samples is low, it will outperform energy detection with 1 dB noise uncertainty as the number of samples increases. Furthermore, P_f of the proposed approach can meet CR system's requirement and a perfect P_f performance can be obtained in GMDL scheme. P_f of energy detection with 1 dB noise uncertainty is much higher than other methods, making it unreliable, especially when the number of samples is large.

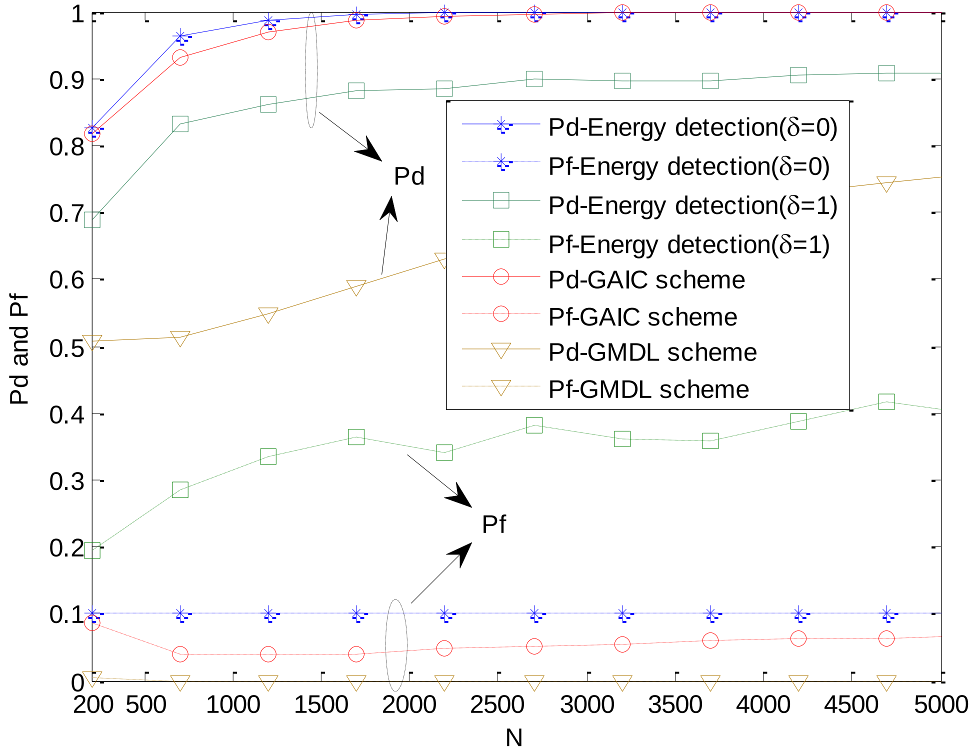

Fig. 3. Detection probability and false alarm probability against the number of samples (SNR=-10 dB)

4.3 Detection Performance with Varying Channel Condition and Strict Quality Requirements

The simulation results shown in this section verify the effectiveness of our proposed GAIC/GMDL algorithm when the number of required samples goes high to satisfy strict quality requirements. To further illustrate the influence of the number of samples more clearly, P_d and P_f against SNR at N=10000 and N=20000 is provided in **Fig. 4** and **Fig. 5**, respectively. It further validates the conclusions drawn in **Fig. 3** that the proposed GMDL scheme will outperform energy detection with 1 dB noise uncertainty in terms of P_d as the number of samples increases. In addition, note that the conclusions obtained in **Fig. 2** can also be applied here.

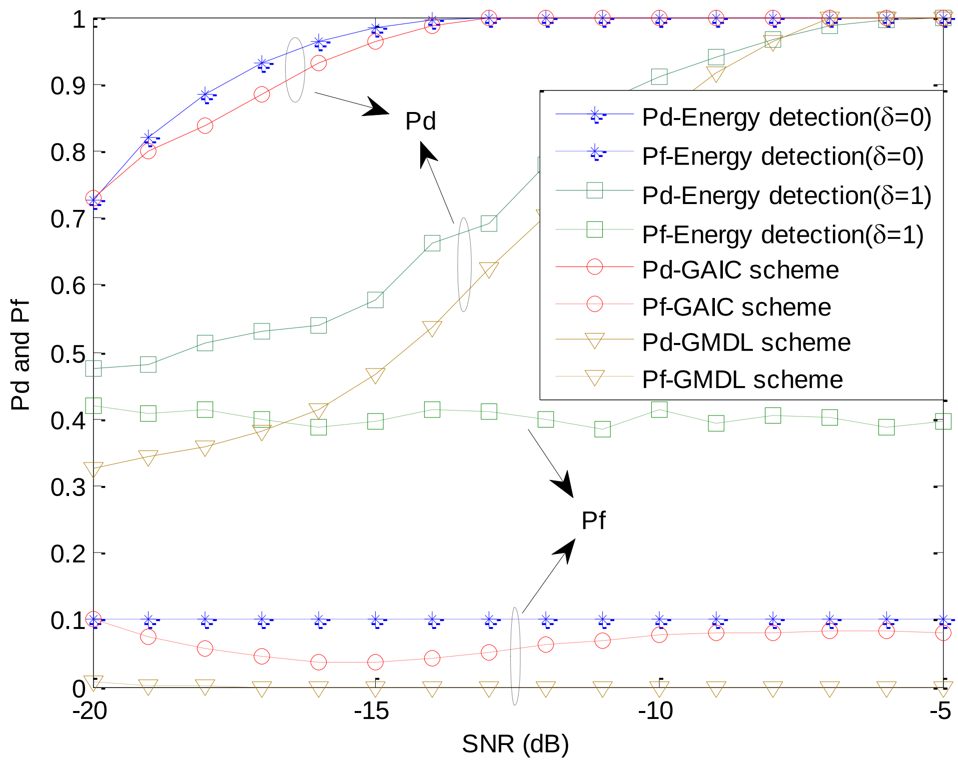

Fig. 4. Detection probability and false alarm probability against SNR (N=10000)

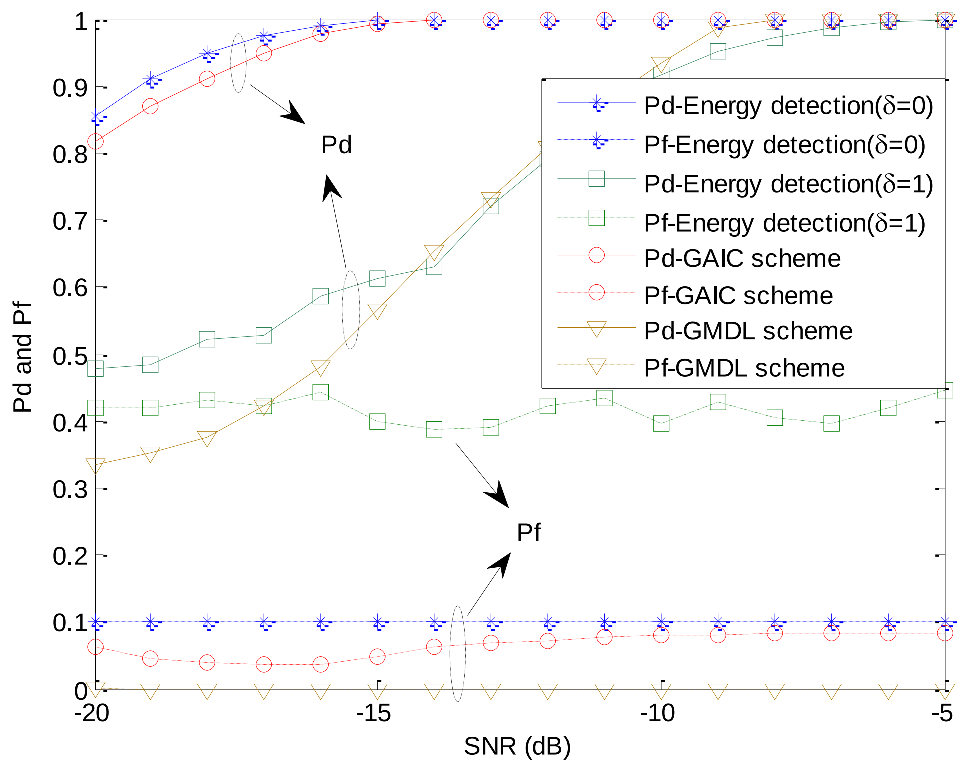

Fig. 5. Detection probability and false alarm probability against SNR (N=20000)

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5. Conclusion

A robust spectrum sensing scheme for blind multiband detection in CR systems is proposed in this paper. To reach the final decisions, the proposed GAIC/GMDL scheme jointly utilizes the information of Gerschgorin radii, signal and noise subspace components together with the likelihood function. The method performs spectrum sensing simultaneously over the total frequency channels rather than a single channel each time. It estimates the number of occupied channels firstly, and then determines the corresponding locations. Furthermore, our scheme needs no prior information about the PU signals, making it appropriate for blind spectrum sensing. In addition, it does not need to set a subjective decision threshold and does not depend on the estimation of the noise power, which is severely deteriorated by the noise uncertainty. Numerical results verify that the proposal is robust to noise uncertainty and outperforms energy detection with noise uncertainty. In general, our proposed scheme is superior to energy detection in the case that there is no knowledge about noise power.

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