Improved Spectrum Sensing Algorithm Combining Energy and Eigenvalues

He Li, Wenjing Zhao, Minglu Jin, and Sang-Jo Yoo

***Abstract*—An improved spectrum sensing algorithm combining energy and eigenvalues is proposed, which employs the energy, maximum eigenvalue and minimum eigenvalue of the sample covariance matrix to construct test statistic. The proposed algorithm includes the MET, MME and EME algorithms as special cases, and it can be seen as a fusion of the test statistics of the MET and EME algorithms. In addition, the false alarm probability and threshold of the proposed method are derived using random matrix theory. The proposed algorithm is a more general algorithm. Simulation results show the effectiveness of the new algorithm.**

***Index Terms*—Cognitive radio, eigenvalue based detection, random matrix theory, spectrum sensing.**

I. Introduction

With the rapid expansion of the wireless broadband and the application of high data rates, the lack of spectrum resources will bring great challenges to future wireless communication networks. A limitation comes from the current fixed spectrum allocation strategy, which leads to the inefficient use of available frequency resources [1]-[4]. A dynamic spectrum sharing technology, namely cognitive radio (CR) technology, can be used to solve the problem of spectrum scarcity [5]. The basic concept of cognitive radio is spectrum reuse or spectrum sharing, which allows cognitive users (secondary users) to communicate through the spectrum licensed to the primary user. For this reason, it is necessary to detect the presence of the primary user, this operation is called as spectrum sensing.

However, intricate real-world scenarios have brought great challenges to spectrum sensing, and also promoted the development of cognitive radio technology. CR technology has been widely concerned by the academic and industry, and a large amount of research focused on designing reliable, accurate, and efficient spectrum sensing algorithms [6]-[8].

The most favorable sensing method is Energy Detection (ED) algorithm [9]-[11], which requires simple hardware implementation and low computational complexity. Moreover, ED does not require priori knowledge about the characteristics of the licensed user's signal. ED method achieves the optimal detection performance for i.i.d signals, while the detection performance is poor for correlated signals. To overcome this shortcoming, Zeng *et al.* proposed maximum eigenvalue detection (MED) method [12]. Since the maximum eigenvalue of the covariance matrix catches the correlations among the signal samples, the proposed method is better than the energy detection for correlated signals.

ED and MED algorithms require known noise power as the premise for detection. However, in the actual system, the noise changes with time leading to the existence of signal-to-noise ratio (SNR) wall phenomenon and the increase of false alarm probability. Therefore, the totally blind detection algorithm came into being, which requires neither signal power information nor noise power information. Zeng and Liang use the ratio of the maximum eigenvalue to the minimum eigenvalue as test statistic (MME) as test statistic. It eliminates the need for the noise-power estimate. Simulations results show that MME improves detection probability for i.i.d signals and correlated signals under noise power uncertainty [13]. There are many spectrum sensing algorithms based on eigenvalues, such as the energy to the minimum eigenvalue (EME) detection, the ratio of the maximum eigenvalue to trace of the sample covariance matrix (MET). The MET method has better detection capacity compared with the MME and EME algorithms [14], [15].

In fact, the maximum and minimum eigenvalues have good applications in various signal detection problems. At low signal-to-noise ratios, these eigenvalue-based blind detection algorithms show good detection performance. The main reason is that the maximum and minimum eigenvalues of sample covariance matrix capture the correlation of the signal and noise characteristics well. An interesting question is whether there is an intrinsic connection between these algorithms? Whether these algorithms can be combined into a more general algorithm to further improve detection performance and take these algorithms as special cases. Motivated by this, we propose a novel fusion spectrum sensing algorithm based on the energy and max-minimum eigenvalues of sample covariance matrix (α-MaxE-En-MinE). The proposed algorithm takes the MET, MME and EME algorithms as its special cases, which has important theoretical significance and valid practical significance.

The rest of the paper is structured as follows. Section II introduces the fundamental signal and system model. Section III reviews some existing detection algorithms and proposes some new detection algorithms based on the maximum eigenvalue, minimum eigenvalue and energy. Some simulation experiments are performed to verify the effectiveness of the proposed algorithms in Section IV. In

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Section V, some conclusions are given.

II. System Model

This paper considers multi-antenna cognitive radio network, which is shown in Fig. 1. Assume that there are P primary users, and each cognitive user is equipped with M receiving antennas to sense the existence of the primary user. The received signal for the mth antenna of the cognitive user is denoted as $r_m(n)$.

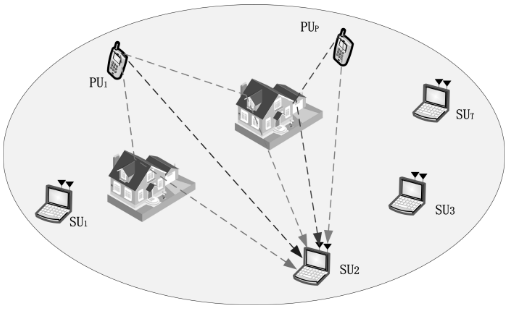

Fig. 1. Spectrum sensing scenario in multi-antenna cognitive radio system.

The spectrum sensing problem is actually a judgment on whether a certain licensed frequency band is available. Assuming that the cognitive user has M receiving antennas, without loss of generality, the sensing problem for the primary user can be transformed into the following binary hypothesis testing problem:

$$\begin{cases} \mathrm{H}_0 : \boldsymbol{r}_m(n) = w_m(n), & m = 1,...,M \\ \mathrm{H}_1 : \boldsymbol{r}_m(n) = \sum_{j=1}^{P}\sum_{i=1}^{C_p} \boldsymbol{h}_{mj}(i) s_j(n-i) + w_m(n) & n = 1,...,N \end{cases} \quad (1)$$

Among them, H_0 indicates that the primary user signal does not exist, and H_1 indicates that the primary user signal exists. $w_m(n) \sim CN(0, \sigma_w^2 \boldsymbol{I})$ is complex additive white noise and follows the 0-mean and σ_w^2 -variance Gaussian distribution, s_j is the jth primary user signal and is independent of noise, h_{mj} is the channel response between the jth primary user and the mth receiving antenna of the cognitive user, C_p is the multi-path channel order.

The received data for the same sampling time can be expressed as the following vector form:

$$\begin{aligned} \boldsymbol{r}(n) &= [r_1(n), r_2(n), ..., r_M(n)]^T \\ \boldsymbol{w}(n) &= [w_1(n), w_2(n), ..., w_M(n)]^T \\ \boldsymbol{h_j}(n) &= [h_{1j}(n), h_{2j}(n), ..., h_{Mj}(n)]^T \\ \boldsymbol{s}(n) &= [s_1(n), ..., s_1(n-C_p), ..., s_p(n), ..., s_P(n-C_p)]^T \end{aligned} \quad (2)$$

The received vector can be represented as $\boldsymbol{r}(n) = \boldsymbol{H}\boldsymbol{s}(n) + \boldsymbol{w}(n)$, where $\boldsymbol{H}$ is the channel response matrix between the primary user and the cognitive user, and $\boldsymbol{H}_j = [\boldsymbol{h}_j(0), ..., \boldsymbol{h}_j(C_p)] \in C^{M \times (C_p+1)}$.

Considering N sampling sequence, the sample covariance matrix of the received signal can be expressed as

$$\boldsymbol{R_r}(N) = \frac{1}{N}\sum_{n=1}^{N} \boldsymbol{r}(n)\boldsymbol{r}^H(n). \quad (3)$$

III. Fusion Detection Method Based on Energy and Eigenvalues

This section firstly reviews several classical spectrum sensing methods, and then proposes a new fusion detection method based on energy and eigenvalues.

A. Related Work

Some typical eigenvalue-based spectrum sensing methods include the MME, EME, MET, and mean-to-square extreme eigenvalue (MSEE) [16] detection methods.This section reviews these typical spectrum sensing detectors and the ED algorithm.

1) Energy detector

Energy Detection is a popular choice for spectrum sensing, and the test statistic is given as follows

$$E_n(N) = \frac{1}{NM}\sum_{n=1}^{N} \left\| \boldsymbol{r}(n) \right\|^2 \quad (4)$$

where ||.|| represents the vector 2-norm. Intuitively, the ED algorithm makes a decision by comparing the energy of the received signal with threshold; if the primary signal exists, then the energy is increased. In fact, the statistic of the ED is an estimation of the received signal variance. The ED algorithm has low computational complexity and does not require prior knowledge of PU signal characteristics. ED is an optimal sensing approach for detecting i.i.d signal, while the detection performance is poor for correlated signals. In addition, ED suffers from severe performance degradation at low SNR.

2) Maximum-minimum eigenvalue (MME) detector

Zeng. at al provides a two-step approach for the case where the rank of the signal subspace is 1 [11]. It firstly derives the General Likelihood Ratio Test (GLRT) detection scheme under the assumption that the noise variance is known, and then employs the minimum eigenvalue of the sample covariance matrix to replace the noise variance. The derived detector calculates the ratio of the maximum eigenvalue to the minimum eigenvalue of the sample covariance matrix, whose test statistic is given by

$$T_{\mathrm{MME}} = \frac{\lambda_{\max}(\boldsymbol{R_r}(N))}{\lambda_{\min}(\boldsymbol{R_r}(N))} \quad (5)$$

MME is an incoherent spectrum detection method, which does not require the prior knowledge of PU and the estimation of noise power. The performance of MME is superior to ED for the case of noise uncertainty. However, the MME has high computational complexity than ED, as it requires to compute the covariance matrix and eigenvalues.

3) Energy-minimum eigenvalue (EME) detector

The test statistic of Energy-Minimum Eigenvalue (EME) Detector is given as follows:

$$T_{\mathrm{EME}} = \frac{\lambda_{\max}(\boldsymbol{R_r}(N))}{E_{\mathrm{n}}} \quad (6)$$

The difference between conventional energy detection and EME is as follows: energy detection compares the signal energy to the noise power, which needs to be estimated in advance, while EME compares the signal energy to the minimum eigenvalue of the sample covariance matrix, which is computed from the received signal only. Both MME and EME only use the received signal samples for detections, and no information on the transmitted signal and channel is needed. Such methods can be called blind detection methods. The major advantage of the proposed methods over energy detection is as follows: energy detection needs the noise power for decision while the MME and EME methods do not need.

4) Maximum eigenvalue-trace (MET) detector

According to Neyman-Pearson criterion, the likelihood ratio detection method is the optimal detection method when the signal and noise information is known. The general signal and noise related information is unknown. At this time, the GLRT method is a common method to solve this kind of problem. The main idea of the GLRT method is to first perform maximum likelihood estimation on unknown parameters, and then use the likelihood ratio detection method to detect. Literature [14] used this idea to estimate the noise power and channel under H_0 and H_1 to obtain the following GLRT method, whose detection statistics are expressed as

$$T_{\text{MET}} = \frac{\lambda_{\max}(\boldsymbol{R_r}(N))}{Tr\left(\boldsymbol{R_r}(N)\right)} \tag{7}$$

where $Tr(Rr)$ is the trace of the sample covariance matrix Rr(N). Simulation experiments show that the MET method has better detection performance under Rayleigh fading channels than MME and other methods.

5) Mean-to-square extreme eigenvalue (MSEE) detector

The test statistic of Mean-to-Square Extreme Eigenvalue (MSEE) Detector is given as follows:

$$T_{\text{MSEE}} = \frac{\lambda_{\max}(\boldsymbol{R_r}(N)) + \lambda_{\max}(\boldsymbol{R_r}(N))}{2\sqrt{\lambda_{\max}(\boldsymbol{R_r}(N))\lambda_{\max}(\boldsymbol{R_r}(N))}} \tag{8}$$

B. Fusion Detection Method Based on Energy and Eigenvalues

The eigenvalues of the sample covariance matrix contains a wealth of information about the received signal, and is an indication of the received signal strength, which can be used to detect the primary user signal. Some spectrum sensing methods using the extreme eigenvalues focuses on the distinction between the maximum and minimum eigenvalues. In essence, the distinction can also be the discrimination between the functions of maximum and minimum eigenvalue. To this end, this paper considers the general combination of the max-minimum eigenvalues and energy, and proposes new spectrum sensing methods. For simplicity, it is called α-MaxE-En-MinE algorithm. The detection statistic of the proposed method is expressed as follows:

$$T_{\alpha-\text{MaxE-En-MinE}} = \left(\frac{\lambda_{\max}(\boldsymbol{R_r}(N))}{En}\right)^{\alpha} \left(\frac{En}{\lambda_{\min}(\boldsymbol{R_r}(N))}\right)^{1-\alpha} \tag{9}$$

where α is a positive number and it is less than or equal to 1. It can be seen from (4) that the proposed method makes use of the energy and max-minimum eigenvalues of the sample covariance matrix. It can be seen from formula (4) that this is the weighted geometric average of two variables. The first variable is the ratio of the maximum eigenvalue to energy, which has never been considered before and is denoted as the MEE detection method. The second variable is the detection statistic of the EME algorithm. Since $En=Tr(Rr)/M$, the detection statistic of the proposed method can be further expressed as

$$\begin{aligned} T_{\alpha-\text{MaxE-En-MinE}} &= T_{\text{MEE}}^{\alpha} T_{\text{EME}}^{1-\alpha} \\ &= \left(M \cdot T_{\text{MET}}\right)^{\alpha} T_{\text{EME}}^{1-\alpha} \\ &= M^{\alpha}\left(T_{\text{MET}}^{\alpha} T_{\text{EME}}^{1-\alpha}\right) \end{aligned} \tag{10}$$

This means that the new detection statistic is the weighted geometric average of the statistics of the MEE algorithm and EME algorithm. It can also be regarded as the weighted geometric average of statistics of the MET algorithm and EME algorithm. This is because the MEE algorithm and the MET algorithm are actually equivalent. In the following, we do not distinguish the MEE algorithm and the MET algorithm, and simply use the "MET" expression.

According to (10), it can be known that the proposed method is a generalization of some existing eigenvalue based detection methods. When α=1, 0.5 and 0, the proposed method is equivalent to the MET method, MME method and EME method, respectively.

The detailed steps of the α-MaxE-En-MinE algorithm are summarized as follows:

Step 1. Compute the sample covariance matrix of the received signal as given in (3).

Step 2. Calculate the maximum eigenvalue and minimum eigenvalue of sample covariance matrix, and denote them as $\lambda_{\max}$ and $\lambda_{\min}$, respectively.

Step 3. Compute the test statistic of the proposed algorithm given in formula (10).

Step 4. Make a decision by comparing test statistic with threshold: if the test statistic is greater than the threshold, then the primary user presents; otherwise, the primary user is absent.

IV. Threshold Settings

The algorithm performance is closely related to not only test statistic but also decision threshold setting. In general, the decision threshold is determined by false alarm probability. To do this, the probability density distribution of test statistic is essential to obtain the false alarm probability. Under the framework of random matrix theory, the false alarm probability and thresholds of several well-known benchmark methods, such as MET and MME, are acquired using the Tracy-Widom (TW) distribution. In similar vein, the false alarm probability of the α-MaxE-En-MinE algorithm can be discussed.

Under H_0, The matrix $\boldsymbol{R_r}(N)$ can be viewed as a Wishart matrix according to random matrix theory. The distribution of maximum eigenvalue of Wishart matrix approximately follows the TW distribution, which is reviewed in Theorem 1 [17], [18].

Theorem 1. For complex noise, let $\mathbf{A}(N)=\frac{N}{\sigma_w^2}\mathbf{R}_w(N)$, $\lambda_{max}(\mathbf{A}(N))$ is the maximum eigenvalue of matrix $\mathbf{A}(N)$. If $0<\lim_{N\to\infty}(M/N)<1$, then $\frac{\lambda_{max}(\mathbf{A}(N))-\mu}{v}$ converges to the Tracy-Widom distribution of order 2 with probability one, where $\mu=(\sqrt{N}+\sqrt{M})^2$ and $v=(\sqrt{N}+\sqrt{M})(\frac{1}{\sqrt{N}}+\frac{1}{\sqrt{M}})^{1/3}$ are the mean and variance of $\mathbf{A}(N)$, respectively.

Theorem 1 describes the asymptotic distribution of the maximum eigenvalue of sample covariance matrix, which provides the foundation for theoretical analysis. Using the result, the detection probability, false alarm probability and threshold of the a-MaxE-En-MinE algorithm are analyzed as follows.

$$\begin{aligned}P_{fa}&=P(T_{\alpha-\text{MaxE-En-MinE}}>\gamma|H_0)\\&=P(\lambda_{\max}^{\alpha}(\boldsymbol{R}_r)>\gamma En^{2\alpha-1}\lambda_{\min}^{1-\alpha})\end{aligned}\tag{11}$$

Under H_0, the energy of the received signal satisfies $En=\frac{1}{ML}\sum_{i=1}^{M}\lambda_1(\boldsymbol{R}_r)=\frac{\sigma_w^2}{L}$, and the minimum eigenvalue is approximately equivalent to $\lambda_{\min}\approx\frac{\sigma_w^2}{N}\left(\sqrt{N}-\sqrt{ML}\right)^2$.

Let $\boldsymbol{A}(\text{N})=\frac{N}{\sigma_w^2}\boldsymbol{R}_n(\text{N})$, then the false alarm probability of the α-MaxE-En-MinE algorithm is expressed as follows:

$$\begin{aligned}P_{fa}&=P\left(\left(\frac{\sigma_w^2}{N}\right)^{\alpha}\lambda_{\max}^{\alpha}(\boldsymbol{A}(\text{N}))>\gamma(\frac{\sigma_w^2}{L})^{2\alpha-1}\left(\frac{\sigma_w^2}{N}\left(\sqrt{N}-\sqrt{ML}\right)^2\right)^{1-\alpha}\right)\\&=P\left(\lambda_{\max}^{\alpha}(\boldsymbol{A}(\text{N}))>\gamma\left(\frac{N}{L}\right)^{2\alpha-1}\left(\sqrt{N}-\sqrt{ML}\right)^{2(1-\alpha)}\right)\\&=P\left(\lambda_{\max}(\boldsymbol{A}(\text{N}))>\gamma^{\frac{1}{\alpha}}\left(\frac{N}{L}\right)^{\frac{2\alpha-1}{\alpha}}\left(\sqrt{N}-\sqrt{ML}\right)^{\frac{2(1-\alpha)}{\alpha}}\right)\end{aligned}\tag{12}$$

When the number of samples N is sufficiently large, $\frac{\lambda_{\max}(\boldsymbol{A}(\text{N}))-\mu}{v}$ follows the TW distribution of order 2. Then

$$\begin{aligned}P_{fa}&=P\left(\frac{\lambda_{\max}(\boldsymbol{A}(\text{N}))-\mu}{v}>\frac{\gamma^{\frac{1}{\alpha}}\left(\frac{N}{L}\right)^{\frac{2\alpha-1}{\alpha}}\left(\sqrt{N}-\sqrt{ML}\right)^{\frac{2(1-\alpha)}{\alpha}}-\mu}{v}\right)\\&\approx1-F_{TW}\left(\frac{\gamma^{\frac{1}{\alpha}}\left(\frac{N}{L}\right)^{\frac{2\alpha-1}{\alpha}}\left(\sqrt{N}-\sqrt{ML}\right)^{\frac{2(1-\alpha)}{\alpha}}-\mu}{v}\right)\end{aligned}\tag{13}$$

where

$$\mu=(\sqrt{N-1}+\sqrt{ML})^2,$$
$$v=(\sqrt{N-1}+\sqrt{ML})(\frac{1}{\sqrt{N-1}}+\frac{1}{\sqrt{ML}})^{\frac{1}{3}}.$$

And then the threshold is obtained employing the relationship between false alarm probability and threshold.

$$\gamma=\frac{\left(F_{TW}^{-1}(1-P_{fa})v+\mu\right)^{\alpha}}{\left(\sqrt{N}-\sqrt{ML}\right)^{2(1-\alpha)}}\left(\frac{L}{N}\right)^{2\alpha-1}\tag{14}$$

where F_{TW}^{-1} is the inverse function of F_{TW}. It is noted that the threshold given in (14) includes the thresholds of MET and MME as special cases.

The detection probability of the α-MaxE-En-MinE algorithm is defined as

$$\begin{aligned}P_d&=P(T_{\alpha-\text{MaxE-En-MinE}}>\gamma|H_1)\\&=P(\lambda_{\max}(\boldsymbol{R}_r)>\gamma^{\frac{1}{\alpha}}En^{\frac{2\alpha-1}{\alpha}}\lambda_{\min}^{\frac{1-\alpha}{\alpha}})\end{aligned}\tag{15}$$

Under H_1, the covariance matrix of the received signal is approximately expressed as $\boldsymbol{R}_r(\text{N})\approx\boldsymbol{H}\boldsymbol{R}_s\boldsymbol{H}+\boldsymbol{R}_w(\text{N})$. The eigenvalues $\lambda_1(\boldsymbol{R}_r(\text{N}))=\eta_i+\lambda_1(\boldsymbol{R}_w(\text{N}))$, where $\eta_i, i\in\{1,...,\text{M}\}$ is the eigenvalues of matrix $\boldsymbol{H}\boldsymbol{R}_s\boldsymbol{H}$ and meets $\eta_1\geq\eta_2\geq...\geq\eta_M$. The energy of received data is $E_N\approx\frac{Tr(\boldsymbol{R}_y(\text{N}))}{ML}=\frac{Tr(\boldsymbol{H}\boldsymbol{R}_s\boldsymbol{H}^H)}{ML}+\frac{Tr(\boldsymbol{R}_w(\text{N}))}{ML}$.

The detection probability is given by (16).

V. Simulations

This section demonstrates the effectiveness of the proposed a-MaxE-En-MinE algorithm through some simulation experiments. In each experiment, it is assumed that primary user independently transmits the BPSK signal, the cognitive user has 4 receiving antennas, and the number of sampling points is 1000. In addition, this paper considers the Rayleigh fading channel. The false alarm probability is set to 0.01, and it is realized through 10,000 Monte Carlo simulation experiments under each SNR. To verify the effectiveness of the proposed method, the MET, MSEE and EME algorithms are taken into consideration.

In the first experiment, it is assumed that there is only one primary user. Fig. 2 shows the detection probability of the α-MaxE-En-MinE algorithm with different α, and the above mentioned algorithms for different SNRs. Here, α ranges from 0.1 to 1 with an interval of 0.1. As shown in the enlarged figure of Fig. 1, the detection performance of the α-MaxE-En-MinE algorithm is increased with the increase of α. It is worth pointing out that the α-MaxE-En-MinE algorithm achieves the optimal performance for α=1. When α is equal to 1, the α-MaxE-En-MinE algorithm becomes the MET algorithm. The simulation result is consistent with the literature [19], i.e., the MET algorithm has the optimal detection performance when there is only one primary user. What's more, the fusion method achieves performance improvement over the MSEE and EME algorithms for $\alpha<1$.

$$
\begin{aligned}
P_d &= P\left(\lambda_{\max}(\boldsymbol{R}_y) > \gamma^{\frac{1}{\alpha}}\left(\frac{Tr(\boldsymbol{H}\boldsymbol{R}_s\boldsymbol{H}^H)}{ML}+\frac{Tr(\boldsymbol{R}_w(\mathrm{N}))}{ML}\right)^{\frac{2\alpha-1}{\alpha}}\lambda_{\min}^{\frac{1-\alpha}{\alpha}}\right)\\
&\approx P\left(\lambda_{\max}(\boldsymbol{A}(\mathrm{N})) > \frac{N}{\sigma_w^2}\left(\gamma^{\frac{1}{\alpha}}\left(\frac{Tr(\boldsymbol{H}\boldsymbol{R}_s\boldsymbol{H}^H)}{ML}+\frac{Tr(\boldsymbol{R}_w(\mathrm{N}))}{ML}\right)^{\frac{2\alpha-1}{\alpha}}\left(\eta_M+\sigma_w^2\right)^{\frac{1-\alpha}{\alpha}}-\eta_1\right)\right)\\
&=1-F_{TW}\left(\frac{\frac{N}{\sigma_w^2}\gamma^{\frac{1}{\alpha}}\left(\frac{Tr(\boldsymbol{H}\boldsymbol{R}_s\boldsymbol{H}^H)}{ML}+\frac{Tr(\boldsymbol{R}_w(\mathrm{N}))}{ML}\right)^{\frac{2\alpha-1}{\alpha}}\left(\eta_M+\sigma_w^2\right)^{\frac{1-\alpha}{\alpha}}-\frac{N}{\sigma_w^2}\eta_1-\mu}{\nu}\right)
\end{aligned}
\quad (16)
$$

In the second experiment, we assume that there are 3 primary users. Fig. 3 gives the comparison results of the proposed algorithm and other algorithms based on eigenvalues. As observed from Fig. 3, we can obtain that the detection performance of the α-MaxE-En-MinE algorithm is decreased with the increase of α. The α-MaxE-En-MinE algorithm is equivalent to the MET, and MME algorithms for α=1, and α=0.5, respectively. The results indicate that the fusion method is superior to the individual algorithm.

At the end, we consider the influence of the number of samples on the detection performance of the proposed method. Fig. 4 plots the detection probability of the α-MaxE-En-MinE algorithm versus SNR under the condition that N=1000, 2000 and 10000. Simulation results show that the detection performance of the α-MaxE-En-MinE algorithm is improved with the number of samples and is superior to the MME, MSEE and MET algorithms.

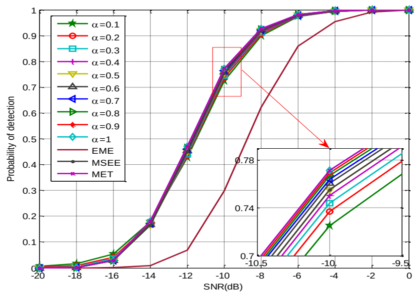

Fig. 2. Probability of detection versus SNRs for one primary user.

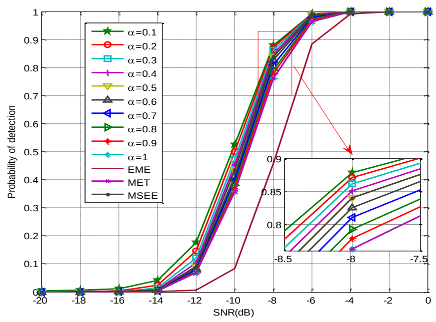

Fig. 3. Probability of detection versus SNRs for three primary users.

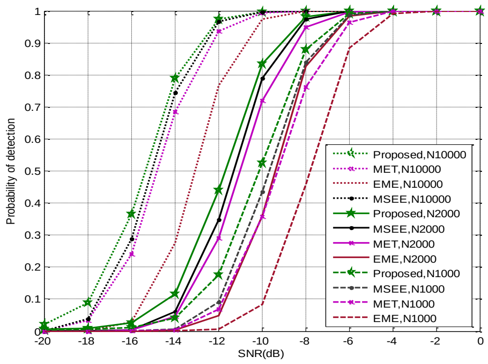

Fig. 4. Probability of detection versus SNRs for different samples.

VI. CONCLUSIONS

In order to better realize spectrum reuse, a new spectrum sensing algorithm based on energy and max-minimum eigenvalues is proposed in this paper. The proposed α-MaxE-En-MinE algorithm is a generalized fusion form of MET and EME algorithms, which maintains the advantages of the MET and EME algorithms. Simulation experiments show that the α-MaxE-En-MinE algorithm has better detection performance than the MET, MME, EME and MSEE algorithms for multiple primary users. Based on the fusion ideas in this paper, many other fusion algorithms can be considered, which has a positive significance for the research on spectrum sensing algorithms.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

H. Li, W. Zhao, and M. Jin conducted conceptualization, methodology, software, validation, experimental data collection, and writing-original draft preparation; S.Yoo conducted writing-review, validation and funding acquisition.

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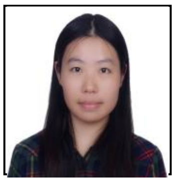

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