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Enhanced Detection Algorithms Based on Eigenvalues and Energy in Random Matrix Theory Paradigm

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ABSTRACT This paper considers the problem of spectrum sensing in multi-antenna cognitive radio networks. Energy detection (ED) method for spectrum sensing does not require any information of the source signal and channel, as well as it is suitable for detecting independent identically distributed signals. Since covariance matrix catches the signal correlations well, the maximum eigenvalue detection (MED) method is more competitive than the ED method for correlated signals. Under the framework of random matrix theory, this paper firstly proposes two enhanced detection algorithms based on the maximum eigenvalue and energy of the signal to achieve performance improvement while preserving the advantages of the two algorithms. The proposed algorithms are a generalization of the ED and MED methods. To render the proposed algorithms more practical, we propose two other new blind spectrum sensing algorithms based on the maximum likelihood estimate of unknown noise variance. Using random matrix theory, the theoretical analysis on detection probability, false alarm probability and threshold are given. Finally, simulation results show the effectiveness and robustness of the proposed algorithms.

INDEX TERMS Cognitive radio, spectrum sensing, random matrix theory.

I. INTRODUCTION

With the rapid development of mobile internet and Internet of Things, the fifth generation (5G) communications system will face new requirements and challenges in wider-coverage, massive-capacity, massive-connectivity and low-latency [1]. The main limitation in meeting these requirements comes from the low utilization of available spectrum resources caused by spectrum fragmentation and the current fixed allocation policy, and thus it necessitates a new communication paradigm to exploit the available wireless spectrum opportunistically. One of the promising solutions to address the problem of spectrum scarcity is enhancing the utilization of available frequency bands with dynamic spectrum sharing (DSS) mechanisms, which is also widely known as cognitive radio (CR) technology [2]–[4]. CR aims to dynamically enhance spectrum utilization through opportunistic spectrum access or spectrum sharing based on interference avoidance [5].

The accurate detection process for primary user (PU) presence is a key functional component of CR, which has attracted wide attention over recent years. A great deal of research has focused on designing accurate and efficient spectrum sensing methods. Various detection methods have different requirements for implementation. The most favorable sensing method is energy detection (ED) algorithm, which requires simple hardware implementation and low computational complexity [6]. Moreover, the ED method does not require knowledge about the characteristics of the licensed user signal. The ED method achieves optimal detection performance for independent identically distributed signals, while its detection performance is poor for correlated signals. In addition to the ED algorithm, some typical algorithms were proposed with different implementation requirements,

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such as matched filter detector, cyclostationary feature detector [7].

What's more, some spectrum sensing algorithms were designed using the eigenvalues of the received signal covariance matrix. They achieve superior performance and robustness because the eigenvalues capture the signal correlations well. These algorithms mostly consider the statistical distribution of the eigenvalues by exploiting the recent results from random matrix theory (RMT). For simplicity, they are collectively called eigenvalue-based detectors (EBD), which rely on the utilization of RMT and different eigenvalue properties of the sample covariance matrix in decision-making process [8]. These EBD techniques can be categorized into the maximum eigenvalue detector (MED) [9]–[14], the maximum eigenvalue to trace (MET) (also called as scaled largest eigenvalue detector) [15]–[20], and the maximum-minimum eigenvalue detector (MME) (also called standard condition number detector) [12], [14], [21], [22]. The EBD is appropriate for practical scenarios because it does not require any prior information of the PU signal. The EBD outperforms than the ED algorithm especially in the presence of noise power uncertainty [14]. In addition, exploiting the properties of the eigenvalues of random Wishart matrices, several detectors based on standard condition number were designed [12], [14], [23], [24], such as asymptotic, semi-asymptotic, and ratio based techniques. More specifically, the Marcenko-Pastur law is used to test a binary hypothesis under the presence of white noise [12]; [14] provided the semi-asymptotic maximum-minimum eigenvalues and energy-minimum eigenvalue algorithms from the consideration of the combination of the Marcenko-Pastur law and Tracy-Widom (TW) distribution; Tracy-Widom Curtiss distribution is exploited to propose ratio based technique [23].

In addition, some combinational algorithms were provided. For example, a combined two-stage detector with the complexity that lies in between the two individual complexities was proposed to achieve better sensing accuracy than the two individual detectors [25]. Ejaz et al proposed a two-stage local spectrum sensing approach. In the first stage, each secondary user (SU) performs existing spectrum sensing algorithms, i.e., energy detection, matched filter detection, and cyclostationary detection. In the second stage, the fuzzy logic that combined the output of each algorithm is used to deduce the presence or absence of a PU [26]. The main motivation for giving a multistage detector is to make use of the advantages of each detector.

Motivated by this, in this paper, a kind of combinational method of energy and maximum eigenvalue of the signal is proposed to take the advantages of the two algorithms and achieves detection performance improvement. In contrast to what has been done in multistage spectrum sensing with fusion, this paper contributes by addressing new fusion methods that have not been studied before to the best of the authors' knowledge. The new fusion methods rely on test statistics, which are different from the well-known data fusion and decision fusion methods. In the proposed methods, two fusion test statistics are given; one is the weighted arithmetic mean of maximum eigenvalue and energy, the another is the weighted geometric mean of maximum eigenvalue and energy. The proposed methods are a generalization of the ED and MED methods, which take the ED and MED algorithms as special cases. However, just as the ED and MED algorithms, the proposed algorithms also require known noise variance as the premise for detection. In practical scenario, the noise variance is unknown and noise changes with time will lead to the existence of the signal-to-noise ratio (SNR) wall phenomenon and the increase of false alarm probability. Thus it is desirable to design a more robust detector whose threshold is independent on noise variance. To this end, some algorithms are proposed in the open literatures including the MME algorithm [14] and energy with LogDet of received samples covariance matrix algorithm [27]. In addition, some previous work considered the problem of noise variance estimation from the framework of maximum likelihood (ML) estimate [11], [15], [19], [28]. The generalized likelihood ratio (GLR) detector is derived under the assumption that the noise variance is unknown [11], [15], [19]. In a similar vein, this paper considers two new test statistics using the ML estimate of unknown noise variance to overcome the noise uncertainty problem. In summary, the contributions of this paper are as follows:

- This paper proposes two new semi-blind spectrum sensing algorithms based on the weighted arithmetic mean of maximum eigenvalue and energy (WAM-MEE) and the weighted geometric mean of maximum eigenvalue and energy (WGM-MEE). Under the framework of random matrix theory, the theoretical analysis on detection probability, false alarm probability and thresholds are given. Simulation results show the effectiveness of the proposed algorithms.
- To render the sensing algorithms more practical, this paper proposes two other new totally blind spectrum sensing algorithms based on the ML estimate of unknown noise variance; one is the ratio of the WAM-MEE to the mean of the smallest $M - 1$ eigenvalues (WAM-MEE-Ev); another is the ratio of the WGM-MEE to the mean of the smallest $M - 1$ eigenvalues (WGM- MEE-Ev). The WAM-MEE-Ev and WGM-MEE-Ev algorithms take the GLR detector as special case. The proposed algorithms do not require the priori knowledge of noise variance, therefore, the WAM-MEE-Ev and WGM-MEE-Ev detectors are more versatile and robust to noise uncertainty than the WAM-MEE and WGM-MEE detectors. The probability of false alarm, decision thresholds, and detection probability are also derived by using the RMT. Simulation results show the WGM-MEE-Ev method performs better than the GLR detector.

The rest of this paper is structured as follows. In Section II, the system model and some existing detection algorithms are introduced. Section III proposes several new detection algorithms based on the maximum eigenvalue and energy.

Using the random matrix theory, the related theoretical analysis of the proposed algorithms is provided in Section IV. In Section V, some simulation experiments are performed to verify the effectiveness of the proposed algorithms. Some conclusions are given in Section VI.

II. SYSTEM MODEL AND TYPICAL SENSING ALGORITHMS

In this section, the system model for multi-antenna scenario is introduced, and then some existing detection algorithms are reviewed.

A. SYSTEM MODEL

Fig. 1 shows a typical multi-antenna scenario for cognitive radio network in which spectrum sensing is carried out by a SU.

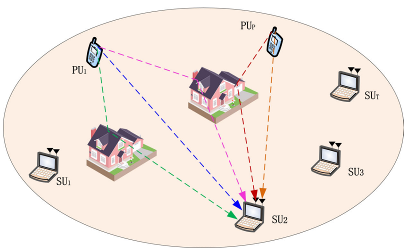

FIGURE 1. Typical spectrum sensing scenario for multi-antenna cognitive radio network.

In this scenario, the SU with multiple antennas periodically senses whether the PU is transmitting signal or not. If the PU is not transmitting signal, then the SU starts to communicate on this frequency band; otherwise it stops communicating or jumps to another vacant frequency band as long as the PU reuses this frequency band. Assume that there are P primary users amd the SU is equipped with M receiving antennas. The received signal at ith receiving antenna is denoted as $y_i(n)$. Without loss of generality, the spectrum sensing can be formalized as the following binary hypothesis testing problem,

$$\begin{aligned} H_0 &: y_i(n) = \eta_i(n), \quad n = 0, 1, \cdots, N-1 \\ H_1 &: y_i(n) = \sum_{j=1}^{P} \sum_{k=0}^{C_{ij}} h_{ij} s_j(n-k) + \eta_i(n), \end{aligned} \tag{1}$$

where n represents the time index of received signal, N is the number of samples, $\eta_i(n) \sim CN(0, \sigma_\eta^2)$ is the additive noise followed complex circular Gaussian distribution with zero mean and σ_η^2-variance, and $s_j(n)$ is the jth PU signal. h_{ij} is the channel response between the jth PU and ith receiving antenna, C_{ij} is the multi-path channel order.

Stacking the samples at the same time, the receiving vector of antenna array is expressed as follows

$$\begin{aligned} Y(n) &= [y_1(n), y_2(n), \cdots, y_M(n)]^T, \\ h_j(n) &= [h_{1j}(n), h_{2j}(n), \cdots, h_{Mj}(n)]^T, \\ \eta(n) &= [\eta_1(n), \eta_2(n), \cdots, \eta_M(n)]^T. \end{aligned} \tag{2}$$

Under H_1, the received signal can be rewritten in vector form

$$Y(n) = \sum_{j=1}^{P} \sum_{k=0}^{C_j} h_j s_j(n-k) + \eta(n), \tag{3}$$

where $C_j = \max_i(C_{ij})$.

For simplicity, let

$$\begin{aligned} \hat{s}(n) = [&s_1(n), s_1(n-1), \ldots, s_1(n-C_1), \ldots, \\ &s_P(n), s_P(n-1), \ldots, s_P(n-C_P)]^T, \end{aligned} \tag{4}$$

and

$$\hat{H} = [h_1(0), \ldots, h_1(C_1), \ldots, h_P(0), \ldots, h_P(C_P)], \tag{5}$$

where $\hat{H}$ is a $M \times (C+P)$ matrix, $C = \sum_{j=1}^{P} C_j$.

Then the received signal is expressed as follows

$$Y(n) = \hat{H}\hat{s}(n) + \eta(n). \tag{6}$$

The sample covariance matrix is defined as follows

$$R_y(N) = \frac{1}{N} \sum_{n=0}^{N-1} Y(n) Y^H(n). \tag{7}$$

When there is no signal (H_0), the entries of Y follow complex Gaussian distribution with zero mean and σ_η^2-variance, then the sample covariance matrix $R_y(N)$ of the received data is a Wishart matrix according to random matrix theory. Under H_0, the sample covariance matrix follows Wishart distribution with N degrees of freedom and a statistical covariance matrix $\Sigma = \frac{1}{N}\sigma_\eta^2 I_M$, which is denoted as $CW_M(N, \frac{1}{N}\sigma_\eta^2 I_M)$. Compared with the null hypothesis, the presence of a PU can lead to changes in the covariance structure of the received signal. What's more, the sample covariance matrix of the received signal can catch the correlations among the signal samples well. Fully exploiting such changes to distinguish signal component from background noise is central to the construction of a powerful detector for spectrum sensing.

Under H_0, the maximum eigenvalue of Wishart matrix approximately follows the TW distribution, which is given in Theorem 1 [29], [30].

Theorem 1: For complex noise, let $A(N) = \frac{N}{\sigma_\eta^2}\hat{R}_\eta(N)$, $\lambda_{max}(A(N))$ be the maximum eigenvalue of $A(N)$. If $0 < \lim_{N\to\infty} (M/N) < 1$, then $\frac{\lambda_{max}(A(N))-\mu}{\nu}$ converges to the Tracy-Widom distribution of order 2 with probability one, where $\mu = (\sqrt{N-1}+\sqrt{M})^2$ and $\nu = (\sqrt{N-1}+\sqrt{M})(\frac{1}{\sqrt{N-1}}+\frac{1}{\sqrt{M}})^{1/3}$ are the mean and scale parameter of $A(N)$, respectively.

Let F_{TW} be the cumulative distribution function (CDF) of the Tracy-Widom distribution of order 2. There is no closed form expression for F_{TW}, which can be calculated by lookup table.

The EBD techniques mostly consider the statistics of maximum eigenvalue of the received signal covariance matrix using the results from Theorem 1. In this paper, we also analyze and derive the false alarm probability, decision thresholds and detection probability of various detection algorithms based on the TW distribution given by Theorem 1.

B. TYPICAL SENSING ALGORITHMS

Many spectrum sensing methods are proposed to the problem of detecting spectrum 'hole' for cognitive radio networks. However, the implementation of these detection mechanisms needs to meet different conditions and requirements. This section reviews several typical spectrum sensing detectors, including the ED, MED and GLR detectors.

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

$$T_{ED} = \frac{1}{NM} \sum_{n=1}^{N} \|Y(n)\|^2, \tag{8}$$

  where $\|\cdot\|^2$ 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. If there is no PU signal, then $T_{ED} = \sigma_\eta^2$; otherwise, $T_{ED} > \sigma_\eta^2$. 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.
  The false alarm probability, threshold and detection probability of the ED method are given as follows [6]

$$P_{fa} = Q(\frac{\gamma_{ED} - \sigma_\eta^2}{\sigma_\eta^2/\sqrt{MN/2}}), \tag{9}$$

$$\gamma_{ED} = \frac{Q^{-1}(P_{fa})\sigma_\eta^2}{\sqrt{MN/2}} + \sigma_\eta^2, \tag{10}$$

$$P_d = Q(\frac{\gamma_{ED} - (\sigma_s^2 + \sigma_\eta^2)}{(\sigma_s^2 + \sigma_\eta^2)/\sqrt{MN/2}}), \tag{11}$$

  where σ_s^2 represents signal variance, and $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp(-t^2/2)dt$.
- Maximum Eigenvalue Detector
  The detection method based on the maximum eigenvalue is proposed to overcome above shortcomings of the ED method. The test statistic of the MED method is expressed as follows

$$T_{MED} = \lambda_{\max}(R_y(N)). \tag{12}$$

  Compared with the ED method, the MED method achieves better detection performance for correlated signal. The false alarm probability, threshold and detection probability are considered in the RMT paradigm [9]. The false alarm probability of the MED method is obtained using Theorem 1,

$$P_{fa} = 1 - F_{TW}\left(\frac{\gamma_{MED}\frac{N}{\sigma_\eta^2} - \mu}{v}\right), \tag{13}$$

  where μ and v are given in Theorem 1. The threshold is derived from (13),

$$\gamma_{MED} = \frac{F_{TW}^{-1}\left(1 - P_{fa}\right)v + \mu}{N}\sigma_\eta^2, \tag{14}$$

  where F_{TW}^{-1} is the inverse function of the F_{TW}.
  The ED and MED algorithms all require known noise power as the premise for detection.
- Generalized Likelihood Ratio(GLR) Detector
  In practical scenario, the noise power is unknown and the noise changes with time will lead to the existence of the SNR wall phenomenon and the increase of false alarm probability. Thus it is desirable to design a more robust detector whose threshold is independent on noise variance. Some previous work considered the problem of noise variance estimation from the framework of ML estimate [11], [15], [19], [28]. Let $\lambda_1, \lambda_2, \ldots, \lambda_M$ denote the eigenvalues of received signal matrix with descend order. The noise variance estimation is the mean of the $(M-1)$ smallest eigenvalues and is expressed as

$$\hat{\sigma}_\eta = \frac{1}{M-1}\sum_{i=2}^{M}\lambda_i. \tag{15}$$

  The GLR is given by [11]

$$T_{GLR} = \frac{\lambda_1}{\frac{1}{M-1}\sum_{i=2}^{M}\lambda_i}. \tag{16}$$

  Unlike the ED and MED algorithms, the GLR detector requires neither noise information, nor transmission signal and channel information. The GLR detector is robust to the noise uncertainty problem. Such method is called blind detection method. The related false alarm probability and threshold are listed as follows [11],

$$P_{fa} \approx 1 - F_{TW}\left(\frac{\gamma_{GLR}N - \mu}{v}\right), \tag{17}$$

$$\gamma_{GLR} = \frac{F_{TW}^{-1}\left(1 - P_{fa}\right)v + \mu}{N}. \tag{18}$$

III. ALGORITHM DESIGN

The spectrum sensing methods introduced in the previous section have their own advantages and disadvantages. Fusion is a commonly used method to enhance performance, and the known methods include data fusion and decision fusion. In contrast to these two fusion method, this paper considers another fusion method based on test statistics of different algorithms. Given the simplicity and validity of the ED and MED algorithms, the fusion of statistics based on energy and maximum eigenvalue is considered to take the advantages of the ED and MED methods. Several new detection algorithms combining energy and maximum eigenvalue are proposed, which achieve better detection performance for both i.i.d signals and correlated signals.

A. WEIGHTED ARITHMETIC MEAN OF MAXIMUM EIGENVALUE AND ENERGY DETECTOR

The commonly used data fusion method is the weighted sum of data, in a similar vein, we firstly consider the weighted average of the MED statistic in (8) and ED statistic in (12), which is expressed as bellow

$$\begin{aligned} T_{WAM-MEE} &= \alpha T_{MED} + (1-\alpha) T_{ED} \\ &= \alpha \lambda_{\max}(R_y(N)) + (1-\alpha) E_N, \end{aligned} \tag{19}$$

where $\lambda_{\max}(R_y(N))$ is the maximum eigenvalue of sample covariance matrix, E_N represents the energy of the received signal, α is a positive constant and $\alpha \in (0, 1]$. For simplicity, the proposed algorithm based on the weighted arithmetic mean of maximum eigenvalue and energy is denoted as WAM-MEE. As seen from formula (19), the proposed WAM-MEE detector is a generalization of the ED and MED methods, and it takes the ED and MED as its special cases. It is noted that in addition to the weighted arithmetic mean, there is other mean such as weighted geometric mean. Thus this paper also considers the weighted geometric mean of maximum eigenvalue and energy as test statistic for spectrum sensing in the following subsection.

B. WEIGHTED GEOMETRIC MEAN OF MAXIMUM EIGENVALUE AND ENERGY DETECTOR

The test statistic is based on the weighted geometric mean of the statistics of the MED and ED, i.e., the weighted geometric mean of maximum eigenvalue and energy (WGM-MEE) is expressed as follows

$$\begin{aligned} T_{WGM-MEE} &= T_{MED}^{\alpha} T_{ED}^{1-\alpha} \\ &= \lambda_{\max}^{\alpha}(R_y(N)) E_N^{1-\alpha}. \end{aligned} \tag{20}$$

For simplicity, the proposed algorithm based on the weighted geometric mean of maximum eigenvalue and energy is denoted as WGM-MEE. As seen from formula (20), the proposed WGM-MEE detector is also a generalization of the ED and MED methods, and it also takes the ED and MED as its special cases. As ED and MED methods, the WAM-MEE and WGM-MEE algorithms also have the noise uncertainty problem, i.e., the thresholds of WAM-MEE and WGM-MEE depend on the noise variance, which is discussed in the next subsection.

C. THE WAM-MEE WITH THE ESTIMATION OF NOISE VARIANCE DETECTOR

This subsection considers two new test statistics using the ML estimate of unknown noise variance given in (15) to overcome the noise uncertainty problem. The first new blind spectrum sensing method can be obtained by dividing the test statistic of the WAM-MEE with the mean of the $(M-1)$ smallest eigenvalues.

$$\begin{aligned} T_{WAM-MEE-Ev} &= \frac{T_{WAM-MEE}}{\hat{\sigma}_{\eta}^2} \\ &= \frac{\alpha \lambda_{\max}(R_y(N)) + (1-\alpha) E_N}{\frac{1}{M-1} \sum_{i=2}^{M} \lambda_i}, \end{aligned} \tag{21}$$

where λ_i is the eigenvalue of sample covariance matrix, α is a positive constant and $\alpha \in (0, 1]$. For simplicity, the proposed method based on (21) is denoted as WAM-MEE-Ev, where Ev stands for estimated noise variance. It is noted that formula (21) can be rewritten as follows

$$\begin{aligned} T_{WAM-MEE-Ev} &= \alpha \frac{\lambda_{\max}(R_y(N))}{\frac{1}{M-1} \sum_{i=2}^{M} \lambda_i} + (1-\alpha) \frac{E_N}{\frac{1}{M-1} \sum_{i=2}^{M} \lambda_i} \\ &= \alpha T_{GLR} + (1-\alpha) T_{EEv}. \end{aligned} \tag{22}$$

The first term in (22) is α times the test statistic of the GLR detector. The second term in (22) is $1-\alpha$ times a test statistic of T_{EEv}. T_{EEv} has not been considered in the open literatures, we call it energy with the estimated noise variance (EEv) detector. Thus both GLR and EEv detectors are special cases of the WAM-MEE-Ev method.

D. THE WGM-MEE WITH THE ESTIMATION OF NOISE VARIANCE DETECTOR

In similar way to the WAM-MEE-Ev detector, the fourth test statistic is obtained by dividing the test statistic of the WGM-MEE detector by the mean of the $M-1$ smallest eigenvalues, which is given as follows

$$T_{WGM-MEE-Ev} = \frac{\lambda_{\max}^{\alpha}(R_y(N)) E_N^{1-\alpha}}{\frac{1}{M-1} \sum_{i=2}^{M} \lambda_i}. \tag{23}$$

For simplicity, this algorithm is denoted as WGM-MEE-Ev. The formula (23) can be rewritten as follows

$$\begin{aligned} T_{WGM-MEE-Ev} &= \left(\frac{\lambda_{\max}(R_y(N))}{\frac{1}{M-1} \sum_{i=2}^{M} \lambda_i} \right)^{\alpha} \left(\frac{E_N}{\frac{1}{M-1} \sum_{i=2}^{M} \lambda_i} \right)^{1-\alpha} \\ &= T_{GLR}^{\alpha} T_{EEv}^{1-\alpha}. \end{aligned} \tag{24}$$

Thus the statistic of the WGM-MEE-Ev detector is the geometric mean of the statistics of the GLR and EEv detectors.

IV. PERFORMANCE ANALYSIS

Random matrix theory, working as a sharp tool, has widely been used in many disciplines including signal processing and wireless communications. In particular, many spectrum sensing algorithms have been proposed and analyzed based on RMT paradigm. The proposed algorithms are closely related to the eigenvalues of the covariance matrix of the received signal. Using the recent results from the RMT, we give the theoretical analysis of the false alarm probability, thresholds and detection probability of the proposed methods.

As shown in Appendix, the false alarm probability and detection probability of the WAM-MEE method are firstly derived using the theorem 1. The false alarm probability is expressed as follows:

$$P_{fa} = 1 - F_{TW}\left(\frac{\frac{\gamma_1}{\alpha}\cdot\frac{N}{\sigma_\eta^2} - \frac{(1-\alpha)}{\alpha}N - \mu}{\nu}\right), \tag{25}$$

where $\mu = (\sqrt{N-1}+\sqrt{ML})^2$ and $\nu = (\sqrt{N-1}+\sqrt{ML})(\frac{1}{\sqrt{N-1}}+\frac{1}{\sqrt{ML}})^{\frac{1}{3}}$.

The analytic expression of threshold γ_1 can be further derived from (25),

$$\gamma_1 = \frac{\alpha\left(F_{TW}^{-1}(1-P_{fa})\nu+\mu\right)\sigma_\eta^2}{N} + (1-\alpha)\,\sigma_\eta^2, \tag{26}$$

where F_{TW}^{-1} is the inverse distribution of Tracy-Widom distribution of order 2.

As observed from (25) and (26), for $\alpha = 1$, we can get the theoretical expressions of the false alarm probability and threshold of the WAM-MEE detector coincide with that of the MED detector.

In addition, the detection probability is given by

$$P_d = 1 - F_{TW}\left(\frac{\frac{N}{\sigma_\eta^2}\left(\frac{\gamma_1-(1-\alpha)\frac{Tr(R_y(N))}{M}}{\alpha}-\rho_1\right)-\mu}{\nu}\right), \tag{27}$$

where ρ_1 is the maximum eigenvalue of matrix $\hat{H}R_s\hat{H}^H$.

The derivations of detection probability and false alarm probability of the WGM-MEE detector are similar to the WAM-MEE detector. The final results are summarized as follows

$$P_{fa} = 1 - F_{TW}\left(\frac{\gamma_2^{\frac{1}{\alpha}}\frac{N^{\frac{1-\alpha}{\alpha}}}{\sigma_\eta^{\frac{2}{\alpha}}} - \mu}{\nu}\right). \tag{28}$$

The threshold is obtained

$$\gamma_2 = \frac{\left(F_{TW}^{-1}(1-P_{fa})\nu+\mu\right)^{\alpha}\sigma_\eta^2}{N^{\alpha}}. \tag{29}$$

In addition, the detection probability is derived

$$P_d = 1 - F_{TW}\left(\frac{\frac{N}{\sigma_\eta^2}\left(\frac{\gamma_2^{\frac{1}{\alpha}}}{\left(\frac{Tr(R_y(N))}{M}\right)^{\frac{1-\alpha}{\alpha}}}-\rho_1\right)-\mu}{\nu}\right). \tag{30}$$

As observed from the (26) and (29), we can get that the thresholds of the WAM-MEE and WGM-MEE detectors are dependent on the the noise variance, which further indicates that the WAM-MEE and WGM-MEE detectors have the noise uncertainty problem.

In what follows, the false alarm probability and threshold of the WAM-MEE-Ev detector are given in similar way to above two methods,

$$P_{fa} = 1 - F_{TW}\left(\frac{(\gamma_3-(1-\alpha))\,N-\mu}{\nu}\right), \tag{31}$$

$$\gamma_3 = \frac{\left(F_{TW}^{-1}(1-P_{fa})\nu+\mu\right)}{N} + (1-\alpha)\,. \tag{32}$$

Under H_1, the noise variance estimation is given by the averaged summation of eigenvalues except the largest one, which is equivalent to the difference of the trace of covariance matrix and the maximum eigenvalue.

$$\hat{\sigma}_\eta = \frac{1}{M-1}(Tr(R_y(N)) - \lambda_{\max}(R_y(N))). \tag{33}$$

Thus the detection probability is derived using the RMT,

$$\begin{aligned} P_d &= \Pr\left(\frac{\alpha\lambda_{\max}(R_y(N))+(1-\alpha)E_N}{\frac{1}{M-1}\sum_{i=2}^{M}\lambda_i} > \gamma_3\,|H_1\right) \\ &= \Pr\left(\frac{\alpha\lambda_{\max}(R_y(N))+(1-\alpha)E_N}{\frac{1}{M-1}(Tr(R_y(N))-\lambda_{\max}(R_y(N)))} > \gamma_3\right) \\ &= \Pr\left(\lambda_{\max}(R_y(N)) > \frac{\left(\frac{\gamma_3}{M-1}-\frac{1-\alpha}{M}\right)}{\alpha+\frac{\gamma_3}{M-1}}Tr(R_y(N)\right), \end{aligned} \tag{34}$$

substitute (33) into (34), then the detection probability is obtained by Theorem 1,

$$\begin{aligned} P_d &= \Pr\left(\lambda_{\max}(R_\eta) > \frac{\left(\frac{\gamma_3}{M-1}-\frac{1-\alpha}{M}\right)}{\alpha+\frac{\gamma_3}{M-1}}Tr(R_y(N)-\rho_1\right) \\ &\approx 1 - F_{TW}\left(\frac{\frac{\left(\frac{\gamma_3}{M-1}-\frac{1-\alpha}{M}\right)}{\alpha+\frac{\gamma_3}{M-1}}Tr(R_y(N)-\rho_1-\mu}{\nu}\right). \end{aligned} \tag{35}$$

The false alarm probability, threshold and detection probability of the WGM-MEE-Ev detector are obtained in a similar way to the WAM-MEE-Ev detector. The details are as follows

$$P_{fa} = 1 - F_{TW}\left(\frac{\gamma_4^{\frac{1}{\alpha}}N-\mu}{\nu}\right), \tag{36}$$

$$\gamma_4 = \frac{\left(F_{TW}^{-1}(1-P_{fa})\nu+\mu\right)^{\alpha}}{N^{\alpha}}, \tag{37}$$

$$P_d = 1 - F_{TW}\left(\frac{\dfrac{\gamma_4^{\frac{1}{\alpha}}\left(1-\frac{1+SNR}{NSNR}\sigma_w^2\right)^{\frac{1}{\alpha}}}{\left(\frac{Tr(R_y(N))}{M}\right)^{\frac{1-\alpha}{\alpha}}} - \rho_1 - \mu}{\nu}\right). \quad (38)$$

V. SIMULATION AND DISCUSSION

In order to verify the performance of the proposed algorithms, this paper considers the scenario with multiple antenna and multiple primary users. The ED algorithm shows good detection performance for weakly correlated signals, while the MED algorithm achieves good detection performance for strongly correlated signals. For comparison, this paper focuses on the detection of weakly correlated signals and strongly correlated signals. Assume that the PU signal is modeled as correlated Gaussian random vector, whose statistical covariance matrix is exponential correlation model and given in the form $\Sigma(i,j) = \rho^{|i-j|}$, and the correlation coefficient ρ is used to control the degree of correlation. This paper takes into account two extreme cases where the correlation coefficient is set to 0.1 and 0.9, respectively. A frequency non-selective fading channel is considered, and each component of channel obeys i.i.d complex circular Gaussian distribution with zero mean and variance of 1, the additive noise also follows the i.i.d Gaussian distribution with zero mean and 1-variance. Assume that there are $P = 3$ primary users, one SU with $M = 4$ antenna. The false alarm probability is set to 0.01, and the number of Monte Carlo simulation is 2000. The theoretical analysis of the optimal α that corresponding to the superior performance is intractable owing to the complicated detection probability, thus the detection performance of various algorithms with different α is analysed by performing some simulation experiments. α is set to (0, 1] with an interval of 0.1.

A. DETECTION PERFORMANCE OF THE WAM-MEE AND WGM-MEE DETECTORS

For comparison, the ED and MED algorithms are considered in this subsection. Fig. 2 shows the detection probability and false alarm probability of the WAM-MEE, ED and MED algorithms for weakly correlated signals. As depicted in Fig. 2, simulation results show that the detection probability of the proposed algorithm decreases with the increase of the α, as well as the false alarm probability of the proposed algorithm decreases with the increase of the α. As observed from Fig. 2, the false alarm probability of the WAM-MEE algorithm does not meet the false alarm probability requirement of 0.01 when $\alpha \leq 0.4$. The best detection performance is achieved at $\alpha = 0.5$, in this case, the algorithm is exactly equivalent to test statistic based on the average of the maximum eigenvalue and energy of the received signal. It is also noted that the ED algorithm has better detection performance than the MED algorithm when PU transmits weakly correlated signals. The proposed algorithm with $\alpha = 0.5, 0.6, 0.7$ obtain higher detection probability than the ED algorithm, and the WAM-MEE algorithm has almost same performance as the ED algorithm for $\alpha = 0.8$, while the WAM-MEE algorithm has inferior performance than the ED algorithm for $\alpha = 0.9$. However, the proposed algorithm achieves better detection performance than the MED algorithm for $\alpha \geq 0.5$.

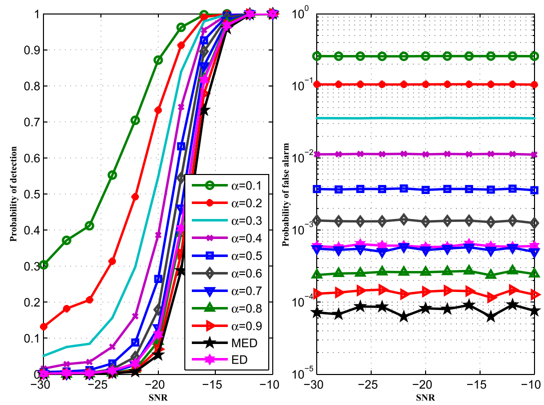

FIGURE 2. Detection performance of the WAM-MEE algorithm with different α, ED and MED for weakly correlated signals ($\alpha = 0.1$).

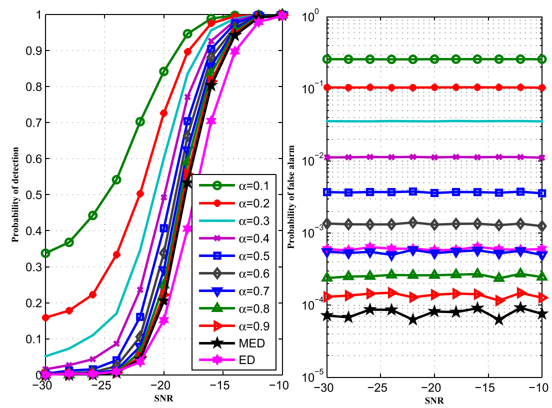

FIGURE 3. Detection performance of the WAM-MEE algorithm with different α, ED and MED for strongly correlated signals ($\alpha = 0.9$).

Fig. 3 shows the comparison results for another scenario where the PU transmits strongly correlated signals ($\rho = 0.9$). The detection performance of the MED algorithm is better than that of the ED algorithm. In this case, the WAM-MEE algorithm has better detection performance than the MED and ED algorithms, and the WAM-MEE algorithm achieves the best detection performance for $\alpha = 0.5$. It is worth pointing out that the combination of the energy and maximum eigenvalue is not a compromise in performance, but a performance improvement.

Fig. 4 and Fig. 5 plot the curves of the detection probability versus SNR of the WGM-MEE algorithm for weakly correlated and strongly correlated signals. As observed from Fig. 4 and Fig. 5, the best detection performance of the WGM-MEE algorithm is obtained in the case of $\alpha = 0.5$ under the given false alarm probability. What's more, simulation results indicate that the WGM-MEE algorithm achieve detection performance improvement over both the ED and MED methods for the case of weakly correlated and strongly correlated signals.

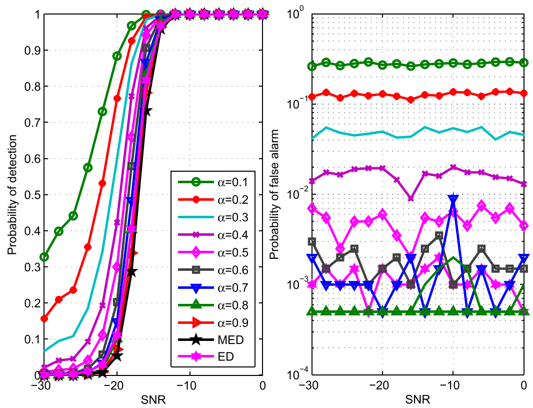

FIGURE 4. Detection performance of the WGM-MEE algorithm with different α, ED and MED for weakly correlated signals ($\alpha = 0.1$).

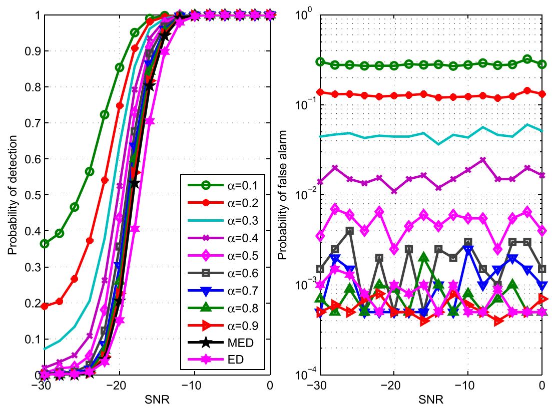

FIGURE 5. Detection performance of the WGM-MEE algorithm with different α, ED and MED for strongly correlated signals ($\alpha = 0.9$).

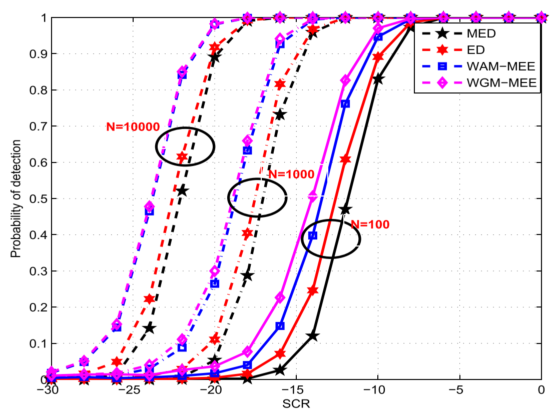

FIGURE 6. Detection performance of the WAM-MEE, WGM-MEE, ED and MED algorithms under different number of samples for weakly correlated signals ($\alpha = 0.1$).

As shown in Section IV, the decision thresholds of all the algorithms rely on the number of the samples. In what follows, the influence of the number of samples N on the detection performance of the algorithm is discussed. For different number of samples, Fig. 6 and Fig. 7 show the detection performance of the proposed WAM-MEE and WGM-MEE algorithms with $\alpha = 0.5$, ED and MED algorithm for weakly correlated signals and strongly correlated signals, respectively. All algorithms have better detection performance with

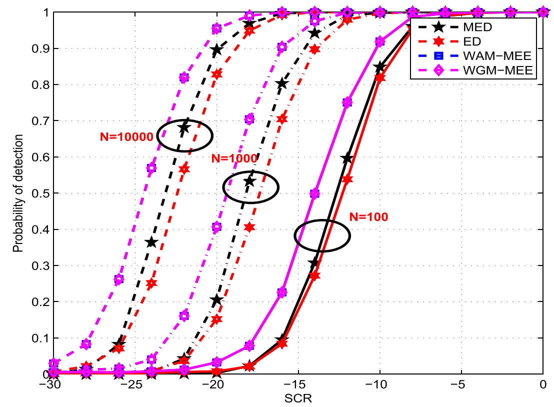

FIGURE 7. Detection performance of the WAM-MEE, WGM-MEE, ED and MED algorithms under different number of samples for strongly correlated signals ($\alpha = 0.9$).

the increase of N, and the proposed algorithm has superior performance than the ED and MED algorithms for all the cases. For weakly correlated signals, the ED algorithm is better than the MED algorithm, while the MED algorithm is superior to the ED algorithm for strongly correlated signals. In addition, the performance gap between the WAM-MEE and WGM-MEE algorithms is narrowed with the increase of N. Especially for highly correlated signals, the detection performance of these two methods is almost overlapped.

B. DETECTION PERFORMANCE OF THE WAM-MEE-EV AND WGM-MEE-EV DETECTORS

In addition to the above mentioned GLR detector, the algorithm using the ratio of maximum eigenvalue to the minimum eigenvalue is a typical algorithm to overcome the noise uncertainty problem. For comparison, the GLR and MME detectors are considered in the following simulation experiments.

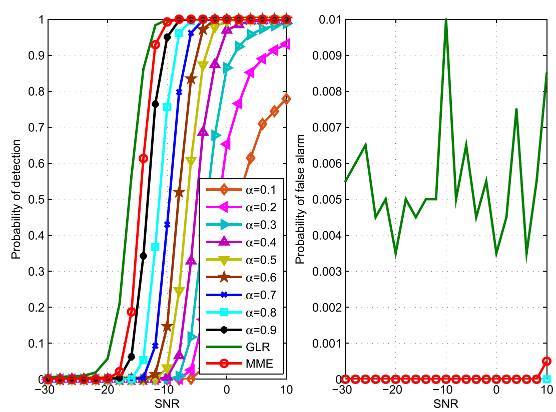

FIGURE 8. Detection performance of the WAM-MEE-Ev algorithm with different α, MME and GLR for weakly correlated signals ($\alpha = 0.1$).

Fig. 8 and Fig. 9 show the detection probability and false alarm probability of the WAM-MEE-Ev, GLR, and MME algorithms for weakly correlated signals and highly correlated signals, respectively. Simulation results indicate that the actual false alarm probability of all the algorithms satisfies

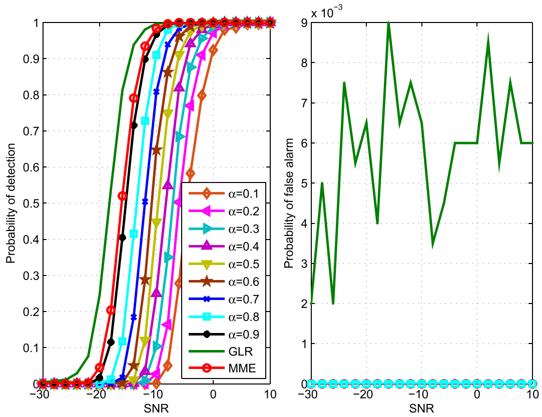

FIGURE 9. Detection performance of the WAM-MEE-Ev algorithm with different α, MME and GLR for strongly correlated signals ($\alpha = 0.9$).

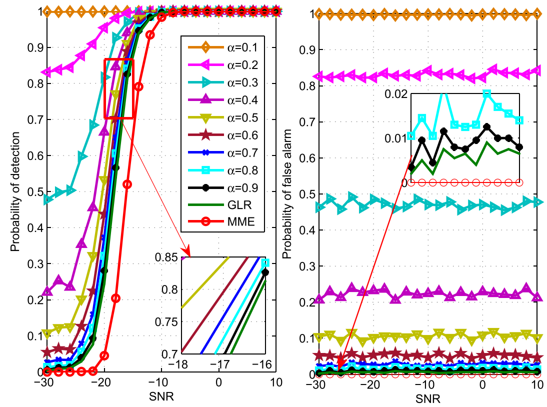

FIGURE 11. Detection performance of the WGM-MEE-Ev algorithm with different α, MME and GLR for highly correlated signals ($\alpha = 0.9$).

the preset false alarm probability. In addition, the results also show that the detection probability of the WAM-MEE-Ev algorithm is improved with the increase of α. It is noticed that the best detection performance of the WAM-MEE-Ev detector is achieved at $\alpha = 1$, in this case, the algorithm is just equivalent to the GLR detector. The detection performance of the WAM-MEE-Ev detector is inferior to that of the GLR and MME algorithms for $\alpha \leq 0.9$.

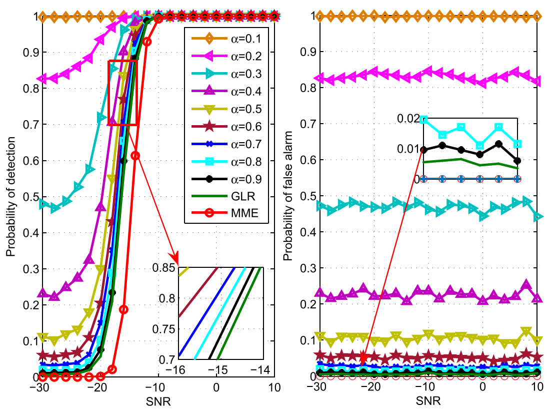

FIGURE 10. Detection performance of the WGM-MEE-Ev algorithm with different α, MME and GLR for weakly correlated signals ($\alpha = 0.1$).

In the following, we compare the detection performance of the WGM-MEE-Ev, MME and GLR detectors for weakly correlated signals and strongly correlated signals, which are shown in Fig. 10 and Fig. 11, respectively. The zoom in Fig. 10 and Fig. 11 indicate that the actual false alarm probability of the WGM-MEE-Ev almost meets the preset false alarm probability in the case of $\alpha \geq 0.9$. The detection performance of the WGM-MEE-Ev algorithm is slightly better than the GLR detector for $\alpha = 0.9$, and it obviously outperforms than the MME detector.

Fig. 12 and Fig. 13 make performance comparison among the WAM-MEE-Ev, WGM-MEE-Ev, GLR and MME methods under different number of samples for weakly correlated signals and strongly correlated signals. Detection performance of all the methods is improved with the number

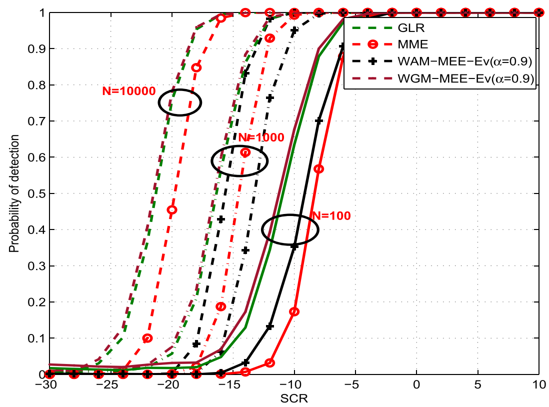

FIGURE 12. Detection performance of the WAM-MEE-Ev, WGM-MEE-Ev, GLR and MME methods under different number of samples for weakly correlated signals ($\alpha = 0.1$).

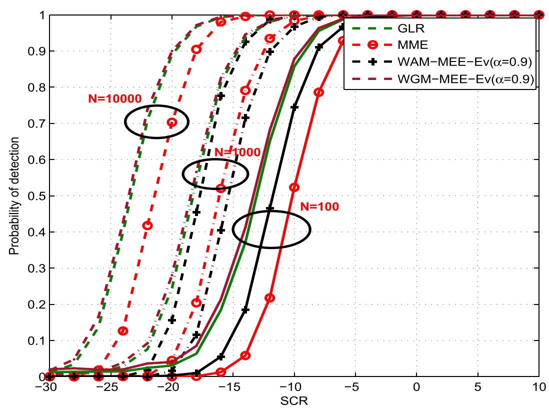

FIGURE 13. Detection performance of the WAM-MEE-Ev, WGM-MEE-Ev, GLR and MME methods under different number of samples for strongly correlated signals ($\alpha = 0.9$).

of samples. The WGM-MEE-Ev method achieves the performance improvement over the WAM-MEE-Ev, GLR and MME methods under different cases of sample number.

To further evaluate the detection performance of the proposed methods, we compare the Receiver Operating Characteristic (ROC) curves of the WAM-MEE($\alpha = 0.5$),

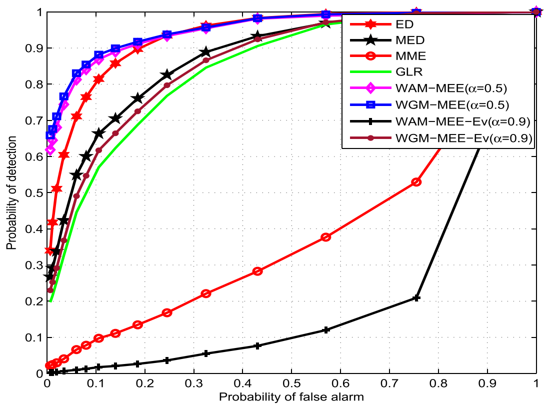

FIGURE 14. **ROC curves of the WAM-MEE, WGM-MEE, WAM-MEE-Ev, WGM-MEE-Ev, ED, MED, GLR and MME methods for weakly correlated signals ($\alpha = 0.1$).**

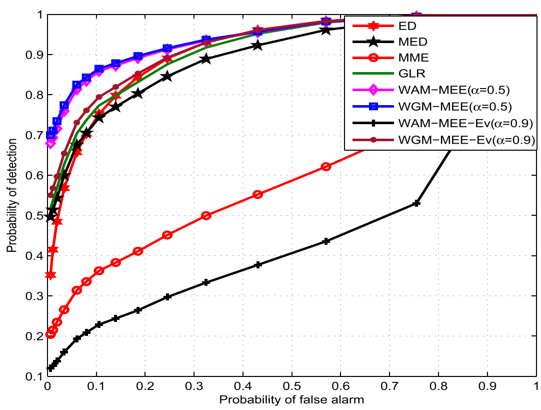

FIGURE 15. **ROC curves of the WAM-MEE, WGM-MEE, WAM-MEE-Ev, WGM-MEE-Ev, ED, MED, GLR and MME methods for strongly correlated signals ($\alpha = 0.9$).**

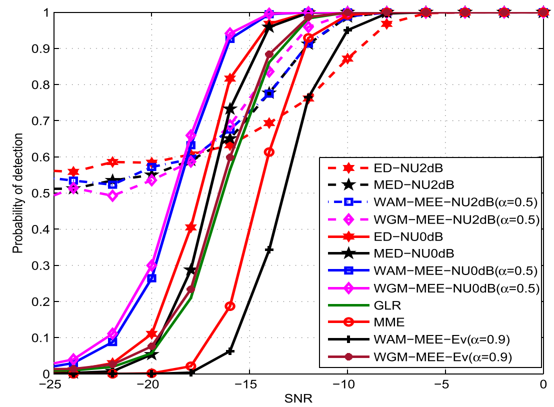

FIGURE 16. **Detection performance comparisons among the WAM-MEE, WGM-MEE, ED, MED, GLR, MME, WAM-MEE-Ev and WGM-MEE-Ev under noise uncertainty with 2dB and weakly correlated signals with $\alpha = 0.1$.**

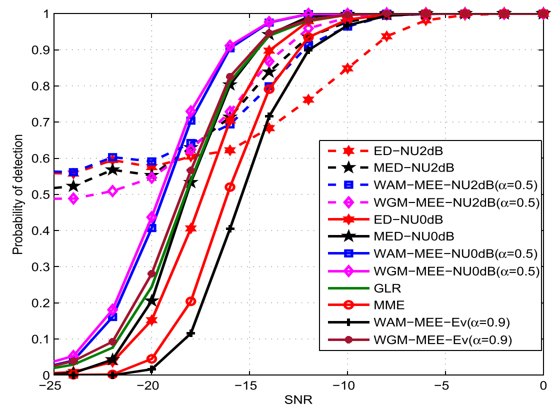

FIGURE 17. **Detection performance comparisons among the WAM-MEE, WGM-MEE, ED, MED, GLR, MME, WAM-MEE-Ev and WGM-MEE-Ev under noise uncertainty with 2dB and highly correlated signals with $\alpha = 0.9$.**

WGM-MEE($\alpha = 0.5$), WAM-MEE-Ev($\alpha = 0.9$), WGM-MEE-Ev($\alpha = 0.9$), ED, MED, GLR and MME methods for the given SNR of -18dB. Here, the WAM-MEE($\alpha = 0.5$) and WGM-MEE($\alpha = 0.5$) mean α is set to 0.5 that representing the best WAM-MEE and WGM-MEE algorithms for different α, so are the WAM-MEE-Ev($\alpha = 0.9$) and WGM-MEE-Ev($\alpha = 0.9$) methods. Fig. 14 and Fig. 15 show the results for weakly correlated signals and strongly correlated signals, respectively. As observed from these two figures, we can obtain that the WAM-MEE and WGM-MEE methods outperform than the above mentioned methods for different false alarm probability; the WGM-MEE-Ev method achieve performance improvement over the GLR and MME methods.

The WAM-MEE, WGM-MEE, ED and MED algorithms all require known noise power as the premise for detection. However, in the actual system, the noise changes with time will lead to the existence of the SNR wall phenomenon and the increase of false alarm probability. Thus, in order to investigate the influence of noise uncertainty on algorithm performance, we discuss the sensitivity of algorithm performance to noise uncertainty through simulation experiments, which are shown in Fig. 16 and Fig. 17. The noise uncertainty bound (in dB) is defined as $B = \sup\left\{10\log_{10}\beta\right\}$, where β is called the noise uncertainty factor, and it is assumed that β is evenly distributed in an interval $[-B, B]$. In practice, the noise uncertainty bound of receiving device is normally 1 to 2 dB [31], and this paper considers the case of 2 dB. For simplicity, "NUxdB" denotes that the noise uncertainty bound is x-dB. It can be seen from simulation results that the ED, MED, WAM-MEE, and WGM-MEE algorithms have noise uncertainty problem. In comparison, the WAM-MEE and WGM-MEE algorithms have less sensitivity to noise uncertainty than the ED algorithm. While the WAM-MEE-Ev and WGM-MEE-Ev algorithms overcome the noise uncertainty problem. What's more, the WGM-MEE-Ev algorithm outperforms than the GLR detector, and it provides 2dB gain than the MME algorithm. Especially for highly correlated signal, the detection performance of the WGM-MEE-Ev algorithm is almost same as that of the MED-NU0dB algorithm.

VI. CONCLUSION

This paper studies the spectrum sensing algorithms based on the test statistics fusion of the ED and MED algorithms in RMT paradigm. The proposed algorithms take the advantages of the two algorithms and achieve detection performance improvement. The proposed methods are a generalization of the ED and MED methods, the effective combinations obviously improve detection performance of the original algorithms. The highly correlated signals and weakly correlated signals are considered in simulation experiments, and simulation results verify the effectiveness of the proposed algorithms. Just like the ED and MED algorithms, the proposed algorithms also have noise uncertainty problem, while the proposed algorithms have less sensitivity to noise uncertainty than the ED algorithm. To further overcome noise uncertainty problem, the WAM-MEE-Ev and WGM-MEE-Ev detectors are proposed using the ML estimate of noise variance. Simulation results indicate the WGM-MEE-Ev detector is more robust and versatile than the GLR and MME algorithms. The methods in this paper have universality and can be applied to the combination of other algorithms for spectrum sensing.

APPENDIX

The false alarm probability of the WAM-MEE detector is derived using theorem 1. Without loss of generality, the false alarm probability is defined as follows

$$P_{fa} = P_r\left(T_{WAM-MEE} > \gamma_1 \mid H_0\right) \tag{39}$$

where $T_{WAM-MEE}$ is the test statistic of the WAM-MEE algorithm, and γ_1 is the decision threshold.

Substitute the test statistic of WAM-MEE in (19) into (39), the false alarm probability is expressed as follows

$$\begin{aligned} P_{fa} &= P_r(\alpha\lambda_{\max} + (1-\alpha)E_N > \gamma_1) \\ &= P_r\left(\alpha\lambda_{\max} > \gamma_1 - (1-\alpha)E_N\right) \\ &= P_r\left(\lambda_{\max} > \frac{\gamma_1 - (1-\alpha)E_N}{\alpha}\right). \end{aligned} \tag{40}$$

Under the null hypothesis, the energy of the received signal approximately satisfies the following relationship,

$$T_N = \frac{Tr(R_y)}{M} \approx \sigma_\eta^2. \tag{41}$$

The false alarm probability is converted into

$$P_{fa} = P_r\left(\lambda_{\max} > \frac{\gamma_1 - (1-\alpha)\sigma_\eta^2}{\alpha}\right). \tag{42}$$

Since $A(N) = \frac{N}{\sigma_\eta^2}R_\eta(N)$, then

$$\begin{aligned} P_{fa} &= P_r\left(\frac{\sigma_\eta^2}{N}\lambda_{\max}(A(N)) > \frac{\gamma_1 - (1-\alpha)\sigma_\eta^2}{\alpha}\right) \\ &= P_r\left(\lambda_{\max}(A(N)) > \frac{\gamma_1}{\alpha}\cdot\frac{N}{\sigma_\eta^2} - \frac{(1-\alpha)}{\alpha}N\right). \end{aligned} \tag{43}$$

As seen from theorem 1, $\frac{\lambda_{\max}(A(N))-\mu}{\nu}$ follows the Tracy-Widom distribution of order 2 when the number of samples N is sufficiently large. The formula (43) is transformed into the following form:

$$P_{fa} = 1 - F_{TW}\left(\frac{\frac{\gamma_1}{\alpha}\cdot\frac{N}{\sigma_\eta^2} - \frac{(1-\alpha)}{\alpha}N - \mu}{\nu}\right). \tag{44}$$

In what follows, we give the analytic expression of detection probability. In general, the detection probability is defined in the form:

$$\begin{aligned} P_d &= P_r(\alpha\lambda_{\max} + (1-\alpha)E_N > \gamma_1) \\ &= P_r\left(\lambda_{\max} > \frac{\gamma_1 - (1-\alpha)E_N}{\alpha}\right). \end{aligned} \tag{45}$$

Under H_1, when the number of samples N is very large, the sample covariance matrix can be approximated as follows:

$$\hat{R}_y(N) \approx \hat{H}R_s\hat{H}^H + R_\eta(N). \tag{46}$$

Then the eigenvalues of $\hat{R}_y(N)$ approximately satisfy

$$\lambda_i(\hat{R}_y(N)) \approx \rho_i + \lambda_i(R_\eta(N)), \tag{47}$$

where $\rho_i, i \in \{1,\ldots,M\}$ are the eigenvalues of matrix $\hat{H}R_s\hat{H}^H$ and meet $\rho_1 \geq \rho_2 \geq \ldots \geq \rho_M$. The detection probability is approximately obtained using Theorem 1,

$$\begin{aligned} P_d &\approx P_r\left(\lambda_{\max}(R_\eta) > \frac{\gamma_1 - (1-\alpha)E_N}{\alpha} - \rho_1\right) \\ &= 1 - F_{TW}\left(\frac{\frac{N}{\sigma_\eta^2}\left(\frac{\gamma_1 - (1-\alpha)\frac{Tr(R_y(N))}{M}}{\alpha} - \rho_1\right) - \mu}{\nu}\right). \end{aligned} \tag{48}$$

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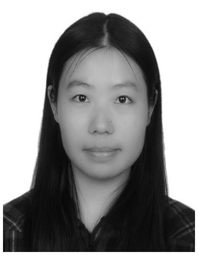

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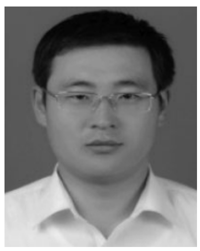

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