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Research Article

On the Eigenvalue Based Detection for Multiantenna Cognitive Radio System

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Eigenvalue based spectrum sensing can make detection by catching correlation features in space and time domains, which can not only reduce the effect of noise uncertainty, but also achieve high detection probability. Hence, the eigenvalue based detection is always a hot topic in spectrum sensing area. However, most existing algorithms only consider part of eigenvalues rather than all the eigenvalues, which does not make full use of correlation of eigenvalues. Motivated by this, this paper focuses on multiantenna system and makes all the eigenvalues weighted for detection. Through the analysis of system model, we transfer the eigenvalue weighting issue to an optimal problem and derive the theoretical expression of detection threshold and probability of false alarm and obtain the close form expression of optimal solution. Finally, we propose new weighting schemes to give promotions of the detection performance. Simulations verify the efficiency of the proposed algorithms.

1. Introduction

The rapid development of wireless services leads to the scarcity of the public radio spectrum becoming more and more serious. Traditionally, licensed spectrum is allocated over relatively long time periods and is intended to be used only by legitimate users. Cognitive radio (CR) technology was proposed to handle the contradiction between the shortage of spectrum resource and the underutilization of licensed spectrum [1, 2]. Spectrum sensing which is a fundamental task of CR is aimed at obtaining the awareness of licensed spectrum usage and existence of primary users (PUs) in a specific geographical location [3–7]. The main function of spectrum sensing is to frequently explore the spectrum holes for the secondary users (SUs) by detecting the presence of primary users so that the SUs can share the licensed spectrum. Therefore, spectrum sensing becomes critical in cognitive radio system.

There have been many discussions and proposed solutions for spectrum sensing [8]. Of these methods, likelihood ratio test (LRT) [9], cyclostationary detection (CSD) [10, 11], and matched filtering (MF) detection [12, 13] can achieve optimal performance while requiring both source signal and noise power information, which is not available in practice. Hence, semiblind methods such as energy detection (ED) [9, 14] and maximum eigenvalue detection (MED) [15] are proposed. Among these, ED is the most commonly chosen scheme for study and implementation due to its relatively low complexity and satisfactory performance under low signal-to-noise ratio (SNR) environment. However, ED heavily relies on the accuracy of the knowledge of noise power which is generally changing over time. This so-called noise uncertainty problem [16] can significantly degrade the performance of ED algorithm.

To overcome these shortcomings, blind detection algorithms which require no information on source signal or noise power have been intensively studied recently [17–21]. The classical blind detection algorithms are the eigenvalue based methods. For example, maximum-minimum eigenvalue (MME) detection [22], arithmetic to geometric mean (AGM) detection [23], and signal-subspace eigenvalues (SSE) method [23] can overcome the shortcoming of ED and achieve outstanding performance. On the other hand, eigenvalue based methods have also been studied in new scenarios, such as cooperative adaptive versions [24] and Multiple Primary Transmit Power (MPTP) scenario [25].

However, most algorithms only consider part of eigenvalues, such as maximum, minimum, and mean value, which does not make full use of all the eigenvalues to make detection. Motivated by this, we focus on the problem of eigenvalue weighting in multiantenna system and analyze the related problems. By analyzing the model of eigenvalue weighting, we transfer the weighting problem to an optimal problem. Using the latest random matrix theory (RMT) [26, 27], we derive the close form expression of probability of detection and probability of false alarm and obtain the optimal solution. Finally, we propose new weighting schemes to give promotions of the detection performance. Simulations verify the efficiency of the proposed algorithms. The main contributions of this paper include the following:

(i) Different from the traditional eigenvalue based detection, we consider making detection by utilizing all of the eigenvalues in the multiantenna system. By transferring the weighting problem to an optimal problem, we analyze and derive an energy based maximum ratio combination (EN-MRC) method.

(ii) Considering the case of correlated signals is common in applications, we use the idea of MRC weighting in EN-MRC method to design an eigenvalue based MRC (EIG-MRC) scheme: signal eigenvalue weighting (SEW) based detection, which needs the a priori information of signals' covariance matrix and noise power.

(iii) To make the detection more practical, we use the maximum likelihood estimation (MLE) approach to design a method of signal eigenvalue approximation weighting (SEAW) based detection, in which only the noise power is needed.

The rest of the paper is organized as follows. Section 2 explains the system model. The eigenvalue weighting based detection is studied in Section 3. Section 4 presents simulation results and conclusion is presented in Section 5. Some notations used in the paper are listed as follows: superscripts T and H stand for transpose and Hermitian transpose (transpose-conjugate), respectively.

2. System Model

Figure 1 illustrates a classical multiantenna spectrum sensing scenario with D randomly distributed primary users (PU in figure) and P randomly distributed secondary users (SU in figure). Once PUs begin to communicate, the surrounding SUs can receive the PU signals and then capture the samples to operate the spectrum sensing.

According to Figure 1, the SUs are equipped with M receiving antennas and there are D PU signals arriving in the antenna array. In this case, the sensing problem in multiantenna cognitive radio system can be written as

$$\begin{aligned} H_0 &: x_i(k) = n_i(k) \\ H_1 &: x_i(k) = \sum_{j=1}^{D} h_{ij} s_j(k) + n_i(k), \end{aligned} \tag{1}$$

where $i = 1, 2, \ldots, M$ represents the ith receiving antenna and $k = 0, 1, \ldots, N-1$ is the kth sample. $x_i(k)$ is the sample of the ith receiving antenna. h_{ij} is the channel gain between the jth PU signal $s_j(k)$ and the ith receiving antenna. $n_i(k)$ is the additive white Gaussian noise (AWGN) with 0 mean, σ_n^2 variance.

Stacking the samples at the same time we can get the following receiving vector of antenna array:

$$\begin{aligned} \mathbf{x}(k) &= [x_1(k), x_2(k), \ldots, x_M(k)]^T, \\ \mathbf{s}(k) &= [s_1(k), s_2(k), \ldots, s_D(k)]^T, \\ \mathbf{n}(k) &= [n_1(k), n_2(k), \ldots, n_M(k)]^T. \end{aligned} \tag{2}$$

Hence, formula (1) can be rewritten as the matrix form:

$$\begin{aligned} H_0 &: \mathbf{X} = \mathbf{N}, \\ H_1 &: \mathbf{X} = \mathbf{HS} + \mathbf{N}, \end{aligned} \tag{3}$$

where $\mathbf{X} = [\mathbf{x}(0), \mathbf{x}(1), \ldots, \mathbf{x}(N-1)]^T$ and $\mathbf{N} = [\mathbf{n}(0), \mathbf{n}(1), \ldots, \mathbf{n}(N-1)]^T$ are the antenna receiving matrix and noise matrix, respectively. $\mathbf{H} \in \mathbb{C}^{M \times D}$ is the channel gain matrix of the signal matrix $\mathbf{S} = [\mathbf{s}(0), \mathbf{s}(1), \ldots, \mathbf{s}(N-1)]^T$.

3. Eigenvalue Weighting Based Detection

3.1. Fundamental of Eigenvalue Weighting Based Detection. Based on (3), the corresponding covariance matrix can be written as

$$\begin{aligned} \mathbf{R_X} &= E(\mathbf{XX}^H), \\ \mathbf{R_S} &= E(\mathbf{SS}^H), \\ \mathbf{R_N} &= E(\mathbf{NN}^H). \end{aligned} \tag{4}$$

Hence, we can rewrite $\mathbf{R_X}$ as

$$\mathbf{R_X} = \mathbf{HR_SH}^H + \mathbf{R_N}. \tag{5}$$

Let $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_M$ and $\rho_1 \geq \rho_2 \geq \cdots \geq \rho_D$ represent the eigenvalues of $\mathbf{R_X}$ and $\mathbf{HR_SH}^H$, respectively. Obviously, when PUs are present, we can get $\lambda_i = \rho_i + \sigma_n^2$; when PUs are absent, that is, $\mathbf{R_X} = \mathbf{R_N}$, we can have $\lambda_1 = \lambda_2 = \cdots = \lambda_M = \sigma_n^2$.

Based on the analysis above, we can make detection by weighting the eigenvalues. Considering the number of samples is finite in reality we can get the following test statistic:

$$T = \sum_{i=1}^{M} w_i \lambda_i (\mathbf{R_X}(N)), \tag{6}$$

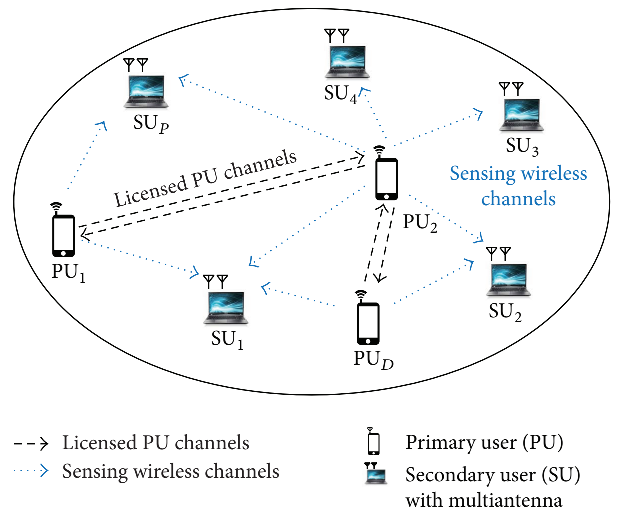

Figure 1: Scenario of spectrum sensing for multiantenna cognitive radio system.

where $\lambda(\cdot)$ is the eigenvalues and w_i is the weighting coefficient. $\mathbf{R_X}(N) = (1/N)\mathbf{XX}^H$ is the samples covariance matrix. Obviously, if $T > \gamma$ (γ is the test threshold), then PUs are present; otherwise, PUs are absent.

Finally, we summarize the general eigenvalue weighting algorithm steps as follows.

Eigenvalue Weighting Based Spectrum Sensing Algorithm for Multiantenna Cognitive Radio System

Step 1 (compute the sample covariance matrix of the received signal). Since the number of samples is finite, we can only use the sample covariance matrix $\mathbf{R_X}(N) = (1/N)\mathbf{XX}^H$.

Step 2 (obtain the eigenvalues of sample covariance matrix). Make eigenvalue decomposition (EVD) of $\mathbf{R_X}(N)$, obtain M eigenvalues, and sort them in a descending order: $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_M$.

Step 3 (calculate the test statistic of the eigenvalue weighting). Let all the eigenvalues be weighted by w_i and compute the sum of them. Thus, we can obtain the test statistic in (6).

Step 4 (decision). If $T > \gamma$, then signal exists ("yes" decision); otherwise, signal does not exist ("no" decision), where γ is a threshold.

3.2. Theoretical Analysis of Eigenvalue Weighting Based Detection. Note that how to select weights w_i is of great importance, which can affect the performance of the algorithm directly. Based on the Neyman-Pearson rule, we can express the weighting selection problem as the following optimal problem [28, 29]:

$$\begin{aligned} \max_{\mathbf{w}} \quad & P_d = \int_r^{\infty} f_{T|H_1}(x;\mathbf{w})\,dx \\ \text{s.t.} \quad & P_{fa} = \int_r^{\infty} f_{T|H_0}(x;\mathbf{w})\,dx, \end{aligned} \tag{7}$$

where $\mathbf{w} = [w_1, w_2, \ldots, w_M]^T$ is the weighting coefficient vector; P_d and P_{fa} represent the probability of detection and the probability of false alarm. $f_{T|H_1}(\cdot)$ and $f_{T|H_0}(\cdot)$ are the probability density function of test statistic under H_1 and H_0, respectively.

Based on (6), we find that it is possible to analyze the distribution of the test statistic whereas the joint probability density function is rather complex, whose close form expression is not available. However, we can transfer the problem of eigenvalue weighting of the matrix to a problem of the trace of a new matrix and the analysis of distribution of the trace is a simple problem. The detailed analysis is showed in the following.

Let $\mathbf{Y} = \mathbf{GX} \in \mathbb{C}^{M\times N}$ and $\mathbf{G} = \operatorname{diag}[g_1, g_2, \ldots, g_M] = \operatorname{diag}[\sqrt{w_1}, \sqrt{w_2}, \ldots, \sqrt{w_M}]^T$. Hence,

$$\mathbf{W_Y} = \mathbf{YY}^H = \mathbf{GW_XG}^H, \tag{8}$$

where $\mathbf{W_X} = \mathbf{XX}^H$. When the number of samples N tends to infinite, the $\mathbf{W_X}$ tends to a diagonal matrix and we can get the following:

$$\operatorname{EVD}(\mathbf{W_Y}) = \operatorname{EVD}\left(\mathbf{GW_XG}^H\right) \approx \mathbf{G}\operatorname{EVD}(\mathbf{W_X})\,\mathbf{G}^H, \tag{9}$$

where EVD$(\cdot)$ represents the diagonal matrix of eigenvalues and the equality holds when the number of samples N tends to infinite. Hence, if we make eigenvalue weighting of $\mathbf{W_X}$ by $\mathbf{w} = [w_1, w_2, \ldots, w_M]^T$ and calculate the sum of the eigenvalues after weighting, then it is equivalent to compute the trace of $\mathbf{W_Y}$. Since $\mathbf{W_X} = N\mathbf{R_X}(N)$, we can rewrite (6) as the following:

$$\begin{aligned} T &= \sum_{i=1}^{M} w_i \lambda_i(\mathbf{R_X}(N)) \approx \sum_{i=1}^{M} \lambda_i(\mathbf{R_Y}(N)) \\ &= \operatorname{Trace}(\mathbf{R_Y}(N)) = \operatorname{Trace}\left(\mathbf{GR_X}(N)\,\mathbf{G}^H\right) \\ &= \frac{1}{N}\sum_{i=1}^{M}\sum_{k=0}^{N-1} w_i \left|r_{\mathbf{X}i}(k)\right|^2, \end{aligned} \tag{10}$$

where $r_{\mathbf{X}i}(k)$ is the ith row, $(k+1)$th element of $\mathbf{R_X}(N)$. Let $a_i = \sum_{k=0}^{N-1} |r_{\mathbf{X}i}(k)|^2$ and thus the test statistic T can be written as

$$T' = NT = \sum_{i=1}^{M} w_i a_i. \tag{11}$$

For simplification, we assume the noise variance $\sigma_n^2 = 1$. When the number of samples is large enough we can get the following expression based on central limit theorem (CRT):

$$a_i \sim \begin{cases} \mathcal{N}\left(N\sum_{i=1}^{M} w_i, 2N\sum_{i=1}^{M} w_i^2\right), & H_0 \\ \mathcal{N}\left(N\sum_{i=1}^{M} w_i(1+r_i), 2N\sum_{i=1}^{M} w_i^2(1+2r_i)\right), & H_1, \end{cases} \tag{12}$$

where $r_i = E|\sum_{j=1}^{D} h_{ij}s_j(k)|^2$ is the power of the PU signals. Therefore, we can obtain the expressions of P_{fa} and P_d, respectively:

$$P_{fa} = P\left\{T' > \gamma \mid H_0\right\} = Q\left(\frac{\gamma - N\sum_{i=1}^{M} w_i}{\sqrt{2N\sum_{i=1}^{M} w_i^2}}\right), \quad (13)$$

$$\begin{aligned} P_d &= P\left\{T' > \gamma \mid H_1\right\} \\ &= Q\left(\frac{\gamma - N\sum_{i=1}^{M} w_i\left(1 + r_i\right)}{\sqrt{2N\sum_{i=1}^{M} w_i^2\left(1 + 2r_i\right)}}\right), \end{aligned} \quad (14)$$

where $Q(x) = \int_x^{+\infty}(1/\sqrt{2\pi})e^{-t^2/2}dt$. Hence, based on (13) and (14), we can finally get the expression as

$$P_d = Q\left(\frac{Q^{-1}\left(P_{fa}\right) - \sqrt{(N/2)\sum_{i=1}^{M}\alpha_i r_i}}{\sqrt{\sum_{i=1}^{M}\alpha_i^2\left(1 + 2r_i\right)}}\right), \quad (15)$$

where $\alpha_i = w_i/\sqrt{\sum_{i=1}^{M} w_i^2}$ and $\sum_{i=1}^{M}\alpha_i^2 = 1$. Since the SNR of spectrum sensing is rather low (−20 dB), which leads to $r_i \ll 1$, we can get $\sum_{i=1}^{M}\alpha_i^2(1 + 2r_i) \approx 1$. Hence, (15) can be approximated as

$$P_d \approx Q\left(Q^{-1}\left(P_{fa}\right) - \sqrt{\frac{N}{2}\sum_{i=1}^{M}\alpha_i r_i}\right). \quad (16)$$

Therefore, problem (7) can be rewritten as

$$\begin{aligned} \max_{\alpha} \quad & \sum_{i=1}^{M}\alpha_i r_i \\ \text{s.t.} \quad & \sum_{i=1}^{M}\alpha_i^2 = 1. \end{aligned} \quad (17)$$

Note that this problem can be solved by Lagrangian multiplier method and the solution is written as

$$\alpha_i^* = \frac{r_i}{\sqrt{\sum_{i=1}^{M} r_i^2}}. \quad (18)$$

Let $\sum_{i=1}^{M} w_i^2 = 1$ and we can finally get the weighting coefficient:

$$w_i^* = \alpha_i^*, \quad 1 \le i \le M. \quad (19)$$

Note that this weighting scheme is exactly identical to the maximal ratio combination (MRC) weighting scheme in [28, 29] and we call it energy based MRC (EN-MRC) detection. Hence, by studying the idea of MRC weighting scheme, we apply this idea into eigenvalue weighting and finally develop a kind of energy based MRC algorithm. The test statistic can be written as

$$T_{\text{EN-MRC}} = \sum_{i=1}^{M}\frac{r_i}{\sqrt{\sum_{i=1}^{M} r_i^2}}\lambda_i, \quad (20)$$

where $r_i = E|\sum_{j=1}^{D} h_{ij}s_j(k)|^2$ is the power of the PU signals.

3.3. Eigenvalue Weighting Based Detection. Note that the transformation from eigenvalue to energy in (9) is approximately equivalent and the equality holds when N tends to infinite. Hence, the corresponding analysis should be more accurate when the number of samples tends to be very large. On the other hand, the analysis under this case is based on the assumption that the received signals are independent and identically distributed (i.i.d.) for each other, which is not very accurate for the case of highly correlated signals. For example, as for (12), the distribution of a_i under H_1 is considered as a linear combination of Gaussian variables with $(1 + r_i)$-variance, which is based on the assumption that the received signals under H_1 are i.i.d. for each other. However, this assumption is only available under a cooperative spectrum sensing model whose samples are collected from different sensing nodes. Hence, the weighting coefficient in (20) is not an appropriate weighting scheme especially for the case of highly correlated signals and thus it needs to be improved for better catching the signals' correlation.

Motivated by this, we try to analyze the weighting coefficients from the aspect of eigenvalue directly. Since $r_i = E|h_{ij}s_j(k)|^2$ is the power of the PU signals and $E[|h_{ij}|^2] = 1$, we can then replace the power of the PU signals r_i in (20) with the eigenvalues of signal covariance matrix $\rho_i = [\text{EVD}(\mathbf{H}\mathbf{R}_\mathbf{S}\mathbf{H}^H)]_i$.

In this case, the test statistic can further capture the correlation among signals and may achieve better performance especially when there are highly correlated PU signals. Hence, we propose a signal eigenvalue weighting (SEW) based detection and the test statistic is given as

$$T_{\text{SEW}} = \sum_{i=1}^{M}\frac{\rho_i}{\sqrt{\sum_{i=1}^{M}\rho_i^2}}\lambda_i, \quad (21)$$

where λ_i and ρ_i are the eigenvalues of sample and signals' covariance matrix, respectively. Although the SEW based detection may perform better performance, it is not available in practice as it needs the a priori information of the channel, signal, and noise. Hence, we try to use the maximum likelihood estimation (MLE) of these parameters to design semiblind detection, in which only noise power is needed. Hence, we will analyze and derive the MLE of eigenvalues of the PU signals' covariance matrix in the following.

According to the analysis in [23], the MLE of signals' covariance matrix $\mathbf{R}_\mathbf{s}$ can be expressed as

$$\begin{aligned} \widehat{\mathbf{R}}_\mathbf{s} = \mathbf{U}_\mathbf{x}\text{Diag}\Big(&\left(\lambda_1 - \sigma_n^2\right)^+, \left(\lambda_2 - \sigma_n^2\right)^+, \ldots, \\ &\left(\lambda_M - \sigma_n^2\right)^+\Big)\mathbf{U}_\mathbf{x}^H, \end{aligned} \quad (22)$$

where $\mathbf{U}_\mathbf{x}$ is the eigenvector of sample covariance $\mathbf{R}_\mathbf{x}(N)$ and $(x)^+ = \max(0, x)$ represents the maximum between x and 0. Hence, the MLE of eigenvalues of PU signals' covariance matrix can be written as

$$\widehat{\rho}_i = \left(\lambda_i - \sigma_n^2\right)^+. \quad (23)$$

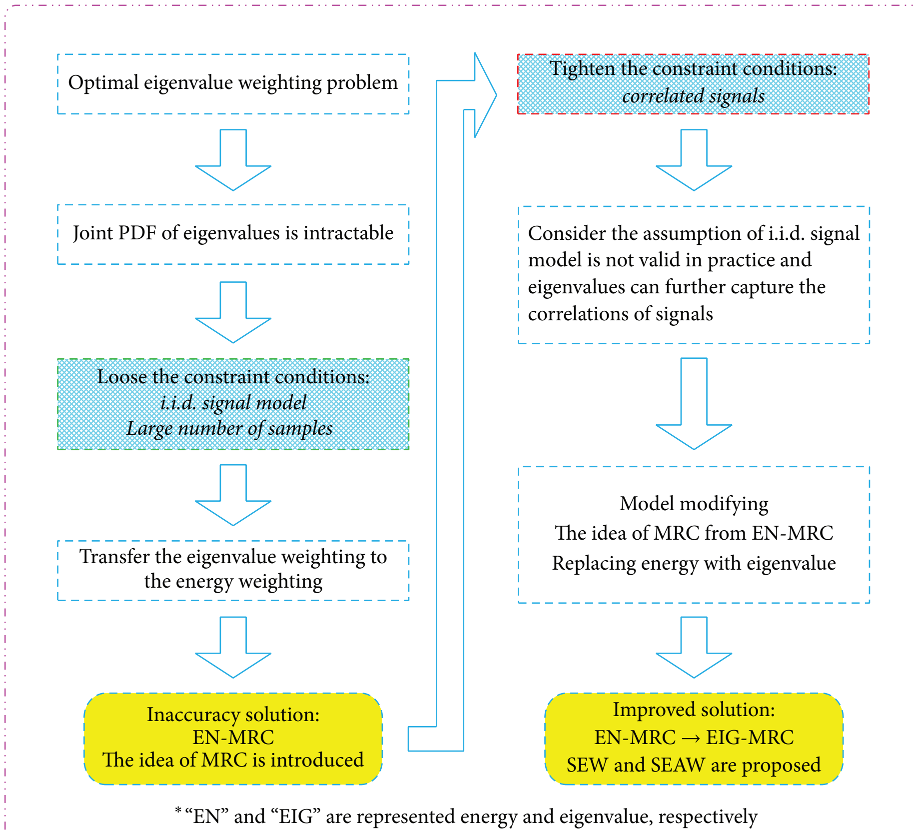

FIGURE 2: Illustration of how to obtain the eigenvalue weighting schemes.

Substituting the MLE of signal eigenvalue into (21) we can obtain the test statistic of signal eigenvalue approximation weighting (SEAW) based detection as

$$T_{\text{SEAW}} = \sum_{i=1}^{M} \frac{\left(\lambda_i - \sigma_n^2\right)^+}{\sqrt{\sum_{j=1}^{M}\left(\left(\lambda_j - \sigma_n^2\right)^+\right)^2}} \lambda_i. \tag{24}$$

As a summary, we propose three weighting schemes: one is traditional MRC based detection (i.e., EN-MRC) and the other two are improvement eigenvalue weighting schemes, that is, SEW based detection and SEAW based detection. For the convenience of comparison, we summarize these three methods in Table 1.

Remark. Since eigenvalue weighting problem can not be solved directly, we first loose the constraint conditions and assume that the PU signals follow the i.i.d. model and the number of samples is very large. In this case, we can obtain an inaccuracy solution: EN-MRC. Based on the MRC weighting scheme, we then tighten the constraint conditions and modify the assumption to make it satisfy the requirements of the practical system, that is, correlated signal model. Considering the eigenvalues can further capture the correlations of signals, we finally replace the energies with eigenvalues and design the eigenvalue based MRC (EIG-MRC) schemes: SEW and SEAW based detection. The corresponding illustration is shown in Figure 2.

4. Simulations and Discussions

This section provides some simulation results for multi-antenna cognitive radio systems in the MATLAB environment. Since this paper focuses the eigenvalue weighting schemes for spectrum sensing, we will compare the proposed EN-MRC, SEW, and SEAW based detection with eigenvalue based methods, including MED, MME, and AGM detection. We assume there is 1 PU or 2 PUs transmitting signal over the Nakagami-m ($m = 1$) channel in presence of AWGN. The SUs are equipped with 4-element antenna array. The stopping criterion set is at 10 000 iterations and the P_{fa} is set as 0.1 (this has been specified as the maximum allowable P_{fa} by the WRAN 802.22 working group).

The simulation results of detection performance in terms of number of samples $N = 100$ with 1 PU and 2 PUs are presented in Figures 3 and 4, respectively. It is shown that when compared with eigenvalue based methods, such as MED, MME, and AGM, the proposed SEW and SEAW based detection perform much higher probability of detection with different SNRs, while the EN-MRC performs a relatively lower detection probability when compared with MED, MME, and AGM detection. It is because algorithms SEW and SEAW are regarded as "EIG-MRC" weighting scheme and MED and

Table 1: Promotion schemes of eigenvalue weighting based spectrum sensing algorithm.

Algorithm	Test statistic	Priori conditions
Energy based maximum ratio combination (EN-MRC)	$T_{\text{EN-MRC}} = \sum_{i=1}^{M} \frac{r_i}{\sqrt{\sum_{i=1}^{M} r_i^2}} \lambda_i$, where λ_i and r_i are the eigenvalues of sample and the power of the PU signals, respectively.	PU signals' energy and noise power
Signal eigenvalue weighting (SEW) based detection	$T_{\text{SEW}} = \sum_{i=1}^{M} \frac{\rho_i}{\sqrt{\sum_{i=1}^{M} \rho_i^2}} \lambda_i$, where λ_i and ρ_i are the eigenvalues of sample and PU signals' covariance matrix, respectively.	Eigenvalues of PU signals' covariance matrix and noise power
Signal eigenvalue approximation weighting (SEAW) based detection	$T_{\text{SEAW}} = \sum_{i=1}^{M} \frac{(\lambda_i - \sigma_n^2)^+}{\sqrt{\sum_{j=1}^{M} ((\lambda_j - \sigma_n^2)^+)^2}} \lambda_i$, where λ_i is the eigenvalues of sample covariance matrix; σ_n^2 is the noise power at receiver.	Noise power at receiver

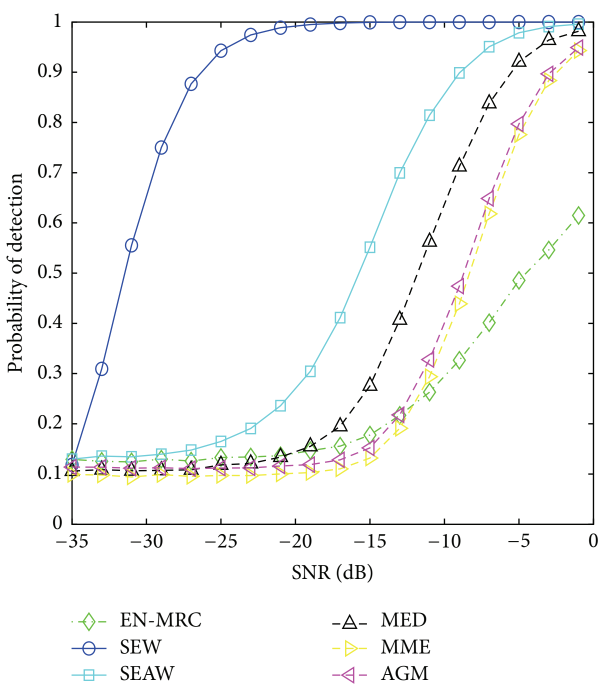

Figure 3: Detection performance under $N = 100$ with 1 PU.

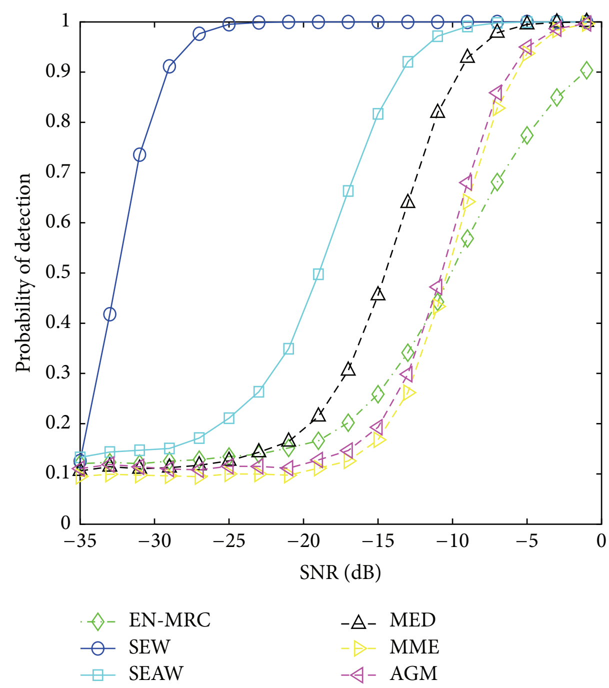

Figure 4: Detection performance under $N = 100$ with 2 PUs.

AGM belong to the selection combination (SC) and equal gain combination (EGC) weighting schemes for eigenvalues, respectively. As for EN-MRC, it is the energy based weighting coefficients, which can not fully capture the correlations. In addition, the MME is just a kind of partial eigenvalue based nonweighting detection and thus it has limited detection performance. However, since low SNR approximation has been adopted to derive the EN-MRC scheme, the EN-MRC is able to achieve a relatively higher detection probability. For example, the EN-MRC is slightly better than MME and AGM when the SNR is ranging from −35 dB to −13 dB. On the other hand, when the SNR increases, the probability of detection of EN-MRC drops a little and presents a slightly worse performance (since the number of eigenvalues for the simulation is very small, the advantages of making detection by using all the eigenvalues or the energies are not obvious, which means the AGM or EN-MRC may not achieve a better performance than MME). When comparing Figure 3 with Figure 4, we can find that the performance increases with the increasing number of PUs, such as a nearly 30% detection probability improvement in terms of −15 dB.

Similarly, Figures 5 and 6 present the simulation results of probability of detection in terms of number of samples $N = 1000$ with 1 PU and 2 PUs. Again, the proposed SEW and SEAW methods achieve a higher detection performance and the EN-MRC outperforms MME and AGM under low SNRs. Hence, the simulation results can further verify that it is just

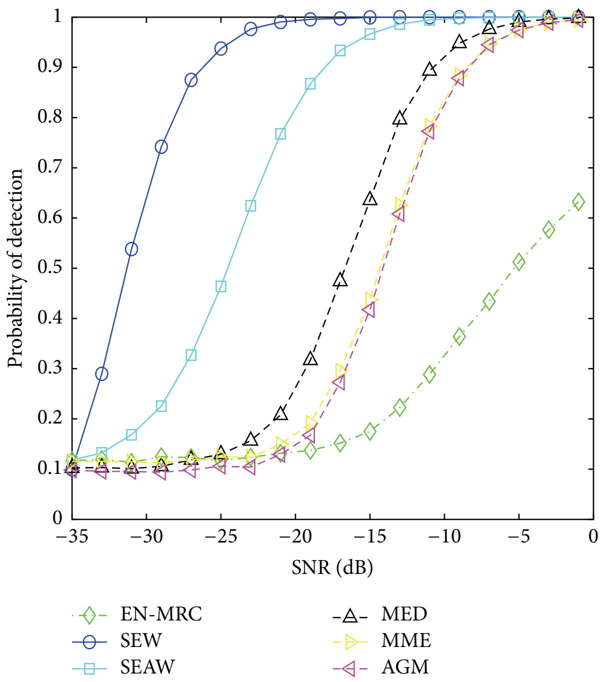

Figure 5: Detection performance under $N = 1000$ with 1 PU.

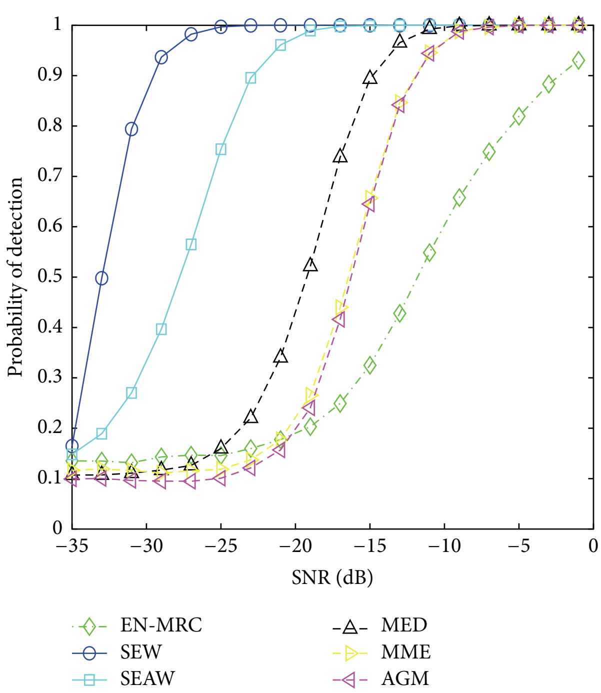

Figure 6: Detection performance under $N = 1000$ with 2 PUs.

the replacement of energy with eigenvalue that leads to the high improvements in terms of detection probability.

In addition, as for the three new methods, we can find that SEW performs the best among these proposed methods, EN-MRC performs the worst, and the performance of SEAW is between these two methods. For example, the probability of detection of SEAW with 2 PUs (i.e., SEAW in Figure 3) is 0.5 in terms of SNR = −15 dB, which is in the middle of P_d of SEW (i.e., 1) and P_d of EN-MRC (i.e., 0.2).

According to Figures 3–6, a more interesting phenomenon can be found; that is, the SEAW's performance shifts from the lower P_d area (close to EN-MRC) to a higher P_d area (close to SEW) with the increasing of number of samples and number of PUs, which is like a kind of lower and upper bounds of the performance of SEAW. If we consider the performance-complexity tradeoff, the proposed SEAW can be selected as an alternative for its low complexity and relatively better performance. Hence, the SEAW may be more suitable for the application in reality.

5. Conclusion

This paper focuses on the problem of the eigenvalue weighting based spectrum sensing in multiantenna cognitive radio system. Through the analysis of system model, we transfer the eigenvalue weighting issue to the energy based weighting problem and derive the theoretical expression of detection threshold and probability of false alarm and finally obtain the close form expression. Considering the case of correlated signals is common in applications, we then design the signal eigenvalue based detection methods and they can achieve more higher detection probability. Simulation results verify the efficiency of the proposed algorithms.

Competing Interests

The authors declare that they have no competing interests.

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