

Optimal Cooperative Sensing for Sensors Equipped with Multiple Antennas

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Abstract—This paper considers multi-sensor multi-antenna spectrum sensing. First, it is assumed that all users are able to send their raw data to the fusion center. In this case the global optimal solution is the likelihood ratio test (LRT) using all the raw data. A simple closed-form expression for the LRT is found. Although LRT is optimal, it is hardly useful in practice due to its reliance on the knowledge of primary user's channels and noise powers of all users. Thus a method using the estimated channels and noise powers is proposed, which is called generalized LRT (GLRT). Secondly, the optimal fusion scheme (OFS) is found if each user computes its test statistic based on an eigenvalue based detection and sends the test statistic to the fusion center. Both GLRT and OFS need the SNR information of all users. To make the detections more practical, two totally blind detections, namely, approximated OFS and approximated GLRT, are proposed. Simulations are provided to support the results.

I. INTRODUCTION

Cognitive radio is now in its second decade. After more than ten years of research, some milestones have been accomplished, but many challenges remain to be overcome. As a fundamental technology for cognitive radio, spectrum sensing has attracted tremendous researches in the past decade [1, 2]. As we know, spectrum sensing for cognitive radio has many special challenges such as very low signal-to-noise ratio (SNR) requirement, propagation channel uncertainty, noise uncertainty, delay uncertainty, and interference uncertainty. Thus most of the known methods do not work well in cognitive radio environment [1–3]. In some cognitive radio applications, it is hardly possible for a single sensor to meet the sensing requirement. Cooperation of multiple sensors thus becomes a must choice. As a result, in recent years there have been many researches in cooperative sensing [4–12].

In this paper, we consider spectrum sensing for a cognitive radio network with multiple distributed users where each user has multiple antennas. First, we assume that all users are able to send their raw data to the fusion center. Based on the Neyman-Pearson theorem, the global optimal sensing is the likelihood ratio test (LRT) using all the raw data. We thus derive a simple closed-form LRT. Unfortunately, it is difficult to use the LRT in practice due to its reliance on the perfect knowledge of primary user's channels and noise powers of all users. Hence, we then derive a method using the estimated channels and noise powers, which is called generalized LRT (GLRT). Secondly, we assume that each user processed its data first and then sends it to the fusion center. Since the eigenvalue based detections (EBDs) [13–20] are known to be effective at single sensor, we assume that each user calculates a test

statistic based on EBD. We find the optimal fusion scheme (OFS) for this situation. Both GLRT and OFS need the SNR information of all users. To make the detections more practical, we propose two totally blind detections, namely, approximated OFS and approximated GLRT.

II. SYSTEM MODEL

Suppose that a cognitive radio network has $M \geq 1$ secondary users, which share the same spectrum (one or multiple bands) with a primary user. Each secondary user is equipped with J antennas. The cognitive radio network needs to sense the primary signals before transmitting. At a sensing period, all the secondary users sense the primary signals cooperatively. We assume that there is a fusion center. At a sensing period, sensor i receives a signal $\mathbf{x}_i(n)$ as

$$\mathcal{H}_0 : \mathbf{x}_i(n) = \boldsymbol{\eta}_i(n)$$

$$\mathcal{H}_1 : \mathbf{x}_i(n) = \mathbf{h}_i s_i(n) + \boldsymbol{\eta}_i(n), \quad i = 1, \dots, M, \quad (1)$$

where $\boldsymbol{\eta}_i(n)$ is a $J \times 1$ noise vector at sensor i , $s_i(n)$ is the received source signal at sensor i and \mathbf{h}_i is the channel vector. Note that $s_i(n)$ is the transmitted primary signal after going through the fading channel with time delay. To simplify notations, we absorb the channel amplitude into $s_i(n)$ to normalize the channel vector, that is, $\|\mathbf{h}_i\|^2 = 1$.

To simplify notations, we stack the signals from M sensors into vectors:

$$\mathbf{x}(n) = [\mathbf{x}_1^T(n) \quad \dots \quad \mathbf{x}_M^T(n)]^T \quad (2)$$

$$\mathbf{s}(n) = [s_1(n) \quad \dots \quad s_M(n)]^T \quad (3)$$

$$\boldsymbol{\eta}(n) = [\boldsymbol{\eta}_1^T(n) \quad \dots \quad \boldsymbol{\eta}_M^T(n)]^T. \quad (4)$$

The hypothesis testing based on N signal samples is then equivalent to

$$\mathcal{H}_0 : \mathbf{x}(n) = \boldsymbol{\eta}(n)$$

$$\mathcal{H}_1 : \mathbf{x}(n) = \mathbf{H}\mathbf{s}(n) + \boldsymbol{\eta}(n), \quad n = 0, \dots, N-1, \quad (5)$$

where \mathbf{H} is a $JM \times M$ matrix: $\mathbf{H} = \text{diag}(\mathbf{h}_1, \dots, \mathbf{h}_M)$.

Spectrum sensing is to choose one of the two hypotheses (\mathcal{H}_0 or \mathcal{H}_1) based on the received signal.

III. LIKELIHOOD RATIO TEST

We know that the optimal sensing is the likelihood ratio test (LRT). Thus the optimal cooperative sensing is the LRT based on the raw data from all sensors:

$$T_{LRT} = \frac{p(\mathbf{x}|\mathcal{H}_1)}{p(\mathbf{x}|\mathcal{H}_0)} \quad (6)$$

where $p(\cdot)$ denotes the probability density function (PDF), and the vector \mathbf{x} represents the aggregation of $\mathbf{x}(n)$, $n = 0, 1, \dots, N-1$.

However, it is not practical to use the LRT directly as it needs the exact distribution of \mathbf{x} and the raw data from all sensors. We need to simplify the test and make it applicable. It is very hard to express the joint distribution $p(\mathbf{x})$ if the signal samples are correlated in time. Here we assume that the signal samples are independent in time: $E(s_i(n)s_i(m)) = 0$, for $n \neq m$. Based on the assumption, $p(\mathbf{x})$ can be decoupled as

$$p(\mathbf{x}|\mathcal{H}_1) = \prod_{n=0}^{N-1} p(\mathbf{x}(n)|\mathcal{H}_1), p(\mathbf{x}|\mathcal{H}_0) = \prod_{n=0}^{N-1} p(\mathbf{x}(n)|\mathcal{H}_0) \quad (7)$$

We further assume that the noise and signal samples have Gaussian distributions, i.e., $\boldsymbol{\eta}(n) \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_\eta)$ and $\mathbf{s}(n) \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_s)$, where $\mathbf{R}_s = E(\mathbf{s}(n)\mathbf{s}^\dagger(n))$, $\mathbf{R}_\eta = E(\boldsymbol{\eta}(n)\boldsymbol{\eta}^\dagger(n))$. Taking logarithm and ignoring constants, we can express the LRT equivalently as

$$T_{LRT} = \frac{1}{N} \sum_{n=0}^{N-1} \mathbf{x}^\dagger(n) \mathbf{R}_\eta^{-1} \mathbf{H} \mathbf{R}_s \mathbf{H}^\dagger (\mathbf{H} \mathbf{R}_s \mathbf{H}^\dagger + \mathbf{R}_\eta)^{-1} \mathbf{x}(n). \quad (8)$$

It is still hard to implement the test above as channel and noise power are required. Furthermore, it uses the cross-correlations among the signals from different sensors, which means that the fusion center needs the raw data from all sensors. The reporting of the raw data is very expensive for practical applications.

In some applications, the sensors are distributed at different locations and far away from each other. Thus the primary signal will most likely arrive at different sensors at different times. For example, in the IEEE 802.22 standard the cell size is typically with radius 30km. In such a cell, the distance differences of different sensors to the primary user could be as large as several kilo-meters. If we sense a TV band with 6MHz bandwidth, delay of one data sample is approximately equals to 50m distance (assume Nyquist rate sampling). Thus the relative time delays can be as large as 20 samples or more. If the delays are different, the signals at different sensors will be independent in space.

The noises at different sensors are independent in space. If our target is to sense at very low SNR, the received signal at a sensor will be dominated by noise. Thus in general we can assume that the whole signals (primary signals plus noises) are approximately independent in space at low SNR: $E(s_i(n)s_j(n)) = 0$, for $i \neq j$.

Based on the assumptions we have

$$\mathbf{R}_\eta = \text{diag}(\sigma_{\eta,1}^2 \mathbf{I}, \dots, \sigma_{\eta,M}^2 \mathbf{I}) \quad (9)$$

$$\mathbf{R}_s = \text{diag}(\sigma_{s,1}^2, \dots, \sigma_{s,M}^2) \quad (10)$$

where $\sigma_{\eta,i}^2 = E(|\eta_i(n)|^2)$, \mathbf{I} is a $J \times J$ identity matrix and $\sigma_{s,i}^2 = E(|s_i(n)|^2)$. After some mathematical derivations we

can express the LRT equivalently as

$$\begin{aligned} T_{LRT} &= \frac{1}{N} \sum_{n=0}^{N-1} \sum_{i=1}^M \frac{\gamma_i}{1 + \gamma_i} \mathbf{x}_i^\dagger(n) \mathbf{h}_i \mathbf{h}_i^\dagger \mathbf{x}_i(n) / \sigma_{\eta,i}^2 \\ &= \sum_{i=1}^M \frac{\gamma_i}{1 + \gamma_i} \mathbf{h}_i \hat{\mathbf{R}}_{x,i} \mathbf{h}_i^\dagger / \sigma_{\eta,i}^2 \end{aligned} \quad (11)$$

where $\hat{\mathbf{R}}_{x,i}$ is the sample covariance matrix for sensor i :

$$\hat{\mathbf{R}}_{x,i} = \frac{1}{N} \sum_{n=0}^{N-1} \mathbf{x}_i(n) \mathbf{x}_i^\dagger(n) \quad (12)$$

and $\gamma_i = \sigma_{s,i}^2 / \sigma_{\eta,i}^2$.

Although it is optimal, LRT is hardly useful in practice as it needs the priori information of the channel, signal and noise power. In the following, we will try to estimate them from the received signal. A LRT test with estimated parameters is usually called a generalized likelihood ratio test (GLRT).

Let $\mathbf{R}_{x,i} = E(\mathbf{x}_i(n) \mathbf{x}_i^\dagger(n))$ be the statistical covariance matrix of the received signal at sensor i . Then

$$\mathcal{H}_1 : \mathbf{R}_{x,i} = \sigma_{s,i}^2 \mathbf{h}_i \mathbf{h}_i^\dagger + \sigma_{\eta,i}^2 \mathbf{I} \quad (13)$$

$$\mathcal{H}_0 : \mathbf{R}_{x,i} = \sigma_{\eta,i}^2 \mathbf{I} \quad (14)$$

At both \mathcal{H}_1 and \mathcal{H}_0 , \mathbf{h}_i is an eigenvector corresponding to the largest eigenvalue of $\mathbf{R}_{x,i}$. The sample covariance matrix $\hat{\mathbf{R}}_{x,i}$ is the maximum likelihood (ML) estimation of $\mathbf{R}_{x,i}$. Hence, the eigenvector corresponding to the largest eigenvalue of $\hat{\mathbf{R}}_{x,i}$ can be used as an estimation for \mathbf{h}_i . Let \mathbf{g}_i be such an eigenvector with $\|\mathbf{g}_i\|^2 = 1$. There are a few ways to estimate the noise power. Let $\lambda_{i,m}$ be the eigenvalues of $\hat{\mathbf{R}}_{x,i}$, $\lambda_{i,1} \geq \lambda_{i,2} \geq \dots \geq \lambda_{i,J}$. One estimation is the $J-1$ smallest eigenvalues of the sample covariance matrix, that is,

$$\hat{\sigma}_{\eta,i}^2 = \frac{1}{J-1} \sum_{m=2}^J \lambda_{i,m}. \quad (15)$$

We can also use the average signal power to be an estimation (it is the ML estimation at \mathcal{H}_0), that is,

$$\hat{\sigma}_{\eta,i}^2 = \frac{1}{NJ} \sum_{n=0}^{N-1} |\mathbf{x}_i(n)|^2. \quad (16)$$

Replacing \mathbf{h}_i and $\sigma_{\eta,i}^2$ by \mathbf{g}_i and $\hat{\sigma}_{\eta,i}^2$, respectively, we have the GLRT with the test statistic being

$$T_{GLRT} = \sum_{i=1}^M \frac{\gamma_i}{1 + \gamma_i} \mathbf{g}_i \hat{\mathbf{R}}_{x,i} \mathbf{g}_i^\dagger / \hat{\sigma}_{\eta,i}^2 = \sum_{i=1}^M \frac{\gamma_i}{1 + \gamma_i} \frac{\lambda_{i,1}}{\hat{\sigma}_{\eta,i}^2}. \quad (17)$$

The SNR at sensor i is:

$$\rho_i = E(\|\mathbf{h}_i s_i(n)\|^2) / E(\|\boldsymbol{\eta}_i\|^2) = \gamma_i / J. \quad (18)$$

Hence we have

$$T_{GLRT} = \sum_{i=1}^M \frac{J \rho_i}{1 + J \rho_i} \frac{\lambda_{i,1}}{\hat{\sigma}_{\eta,i}^2}. \quad (19)$$

¹At \mathcal{H}_1 , the eigenvector corresponding to the largest eigenvalue of $\mathbf{R}_{x,i}$ is unique up to a scalar, while at \mathcal{H}_0 , there are infinite such eigenvectors including \mathbf{h}_i .

The only unknown left is ρ_i or γ_i , which is related to the signal and noise power.

IV. OPTIMAL FUSION SCHEME

It is shown in [14, 15, 18] that the eigenvalue based detections (EBDs) are good methods for a single sensor. Hence we assume that each sensor uses an EBD and sends its test statistic to a fusion center. The fusion center then makes a final decision.

Let T_i be the test statistic at sensor i . As we mentioned above, T_i are approximately independent if the sensors are distributed. In the following, we assume that they are independent.

In general the test statistic of the optimal fusion scheme (OFS) is

$$T_{OFS} = \frac{\prod_{i=1}^M p(T_i|\mathcal{H}_1)}{\prod_{i=1}^M p(T_i|\mathcal{H}_0)}. \quad (20)$$

So far, there are no closed-form expressions for the PDF of T_i for $J > 2$ in literature. So we start from the special case of $J = 2$, which is the most useful case in practice. At this case, the maximum to minimum eigenvalue (MME) and the maximum eigenvalue to trace (MET) are equivalent [14, 15]. Hence we consider the MME at each sensor, that is, $T_i = \lambda_{i,1}/\lambda_{i,J}$. The PDF of T_i is as follows [19].

For real signal and real noise,

$$p(T_i|\mathcal{H}_0) = \frac{1}{4}N(T_i - 1)e^{-N(T_i-1)^2/8}, \quad T_i \geq 1 \quad (21)$$

$$p(T_i|\mathcal{H}_1) = \frac{\alpha_i\sqrt{N}}{2\sqrt{2\pi}}e^{-N(\alpha_i T_i - 1)^2/8} \quad (22)$$

where $\alpha_i = \sigma_{\eta,i}^2/\mu_{i,1}$ with $\mu_{i,1}$ being the maximum eigenvalue of the statistical covariance matrix $\mathbf{R}_{x,i}$.

Similarly, for complex signal and complex noise,

$$p(T_i|\mathcal{H}_0) = \frac{1}{2\sqrt{\pi}}N^{3/2}(T_i - 1)^2e^{-N(T_i-1)^2/4}, \quad T_i \geq 1 \quad (23)$$

$$p(T_i|\mathcal{H}_1) = \frac{\alpha_i\sqrt{N}}{2\sqrt{\pi}}e^{-N(\alpha_i T_i - 1)^2/4}. \quad (24)$$

First, we look at real signal and noise case. Inserting the PDF expressions into (20) we obtain

$$T_{OFS} = \frac{\prod_{i=1}^M \frac{\alpha_i\sqrt{N}}{2\sqrt{2\pi}}e^{-N(\alpha_i T_i - 1)^2/8}}{\prod_{i=1}^M \frac{1}{4}N(T_i - 1)e^{-N(T_i-1)^2/8}}. \quad (25)$$

Taking logarithm and discarding some constants we get an equivalent test statistic as

$$T_{OFS} = \frac{1}{8} \sum_{i=1}^M ((T_i - 1)^2 - (\alpha_i T_i - 1)^2) - \sum_{i=1}^M \log(T_i - 1). \quad (26)$$

For complex signal and noise case. We have

$$T_{OFS} = \frac{\prod_{i=1}^M \frac{\alpha_i\sqrt{N}}{2\sqrt{\pi}}e^{-N(\alpha_i T_i - 1)^2/4}}{\prod_{i=1}^M \frac{1}{2\sqrt{\pi}}N^{3/2}(T_i - 1)^2e^{-N(T_i-1)^2/4}}. \quad (27)$$

Taking logarithm and discarding some constants we get the same statistic as (26). Hence (26) is the optimal fusion scheme for both real and complex input cases.

Obviously the scheme can be used for any J , although we have not proved that it is optimal for $J > 2$.

Please note that the optimal fusion scheme needs α_i . It is easy to verify that α_i is related to ρ_i :

$$\alpha_i = \frac{\sigma_{\eta,i}^2}{\mu_{i,1}} = \frac{\sigma_{\eta,i}^2}{\sigma_{s,i}^2 + \sigma_{\eta,i}^2} = \frac{1}{1 + \gamma_i} = \frac{1}{1 + J\rho_i}. \quad (28)$$

V. PRACTICAL SUB-OPTIMAL METHODS

Our purpose is to estimate the unknown terms $\gamma_i/(1 + \gamma_i)$ or α_i . At \mathcal{H}_1 ,

$$\frac{\gamma_i}{1 + \gamma_i} = \frac{\sigma_{s,i}^2}{\sigma_{s,i}^2 + \sigma_{\eta,i}^2} = \frac{\mu_{i,1} - \sigma_{\eta,i}^2}{\mu_{i,1}} = 1 - \frac{\sigma_{\eta,i}^2}{\mu_{i,1}}. \quad (29)$$

Thus, for large N , it can be approximated by $\frac{\gamma_i}{1 + \gamma_i} = 1 - \frac{\lambda_{i,J}}{\lambda_{i,1}}$. Inserting this into (17) we obtain

$$T_{GLRT} \approx \sum_{i=1}^M \left(1 - \frac{\lambda_{i,J}}{\lambda_{i,1}}\right) \frac{\lambda_{i,1}}{\lambda_{i,J}} = \sum_{i=1}^M \frac{\lambda_{i,1}}{\lambda_{i,J}} - M. \quad (30)$$

Obviously it is equivalent to the equal gain combined (EGC) MME (EGC-MME), that is, the MME detection is used at each sensor and their statistics are then added together:

$$T_{EGC} = \sum_{i=1}^M \frac{\lambda_{i,1}}{\lambda_{i,J}}. \quad (31)$$

This may not be a good method as the estimation is only valid at \mathcal{H}_1 . At \mathcal{H}_0 , $\frac{\gamma_i}{1 + \gamma_i}$ definitely cannot be estimated from the eigenvalues of the covariance matrix as the covariance matrix is not related to the primary signal at all. If our target is to obtain a reliable detection at SNR level $\hat{\rho}$, a more reasonable estimation is therefore

$$\frac{\gamma_i}{1 + \gamma_i} = \max\left(1 - \frac{\lambda_{i,J}}{\lambda_{i,1}}, \frac{J\hat{\rho}}{1 + J\hat{\rho}}\right). \quad (32)$$

We call this method approximated GLRT (AGLRT), which has the test statistic:

$$T_{AGLRT} = \sum_{i=1}^M \max\left(1 - \frac{\lambda_{i,J}}{\lambda_{i,1}}, \frac{J\hat{\rho}}{1 + J\hat{\rho}}\right) \frac{\lambda_{i,1}}{\lambda_{i,J}}. \quad (33)$$

If the SNRs at different sensors have large differences, a natural way is to choose the largest of all test statistics as the test statistic of the fusion center. We call this largest MME (LMME) detection. The test statistic is

$$T_{LMME} = \max_{1 \leq i \leq M} \frac{\lambda_{i,1}}{\lambda_{i,J}}. \quad (34)$$

Note that this is different from the method that uses the test statistic from a known sensor with the largest test statistic. The largest test statistic may not always be at the same sensor due to the dynamic changes of wireless channels. The method is equivalent to the ‘‘OR decision rule’’ [4, 9] when each sensor uses the MME detection.

We can also simplify the OFS by estimating ρ_i . For large N , the sample covariance matrix $\hat{\mathbf{R}}_{x,i}$ approaches to the statistical covariance matrix $\mathbf{R}_{x,i}$. Thus we have $\alpha_i T_i \approx 1$ at low SNR case. Hence we have an approximated OFS (AOFS) as

$$T_{AOFS} = \frac{1}{8} \sum_{i=1}^M (T_i - 1)^2 - \sum_{i=1}^M \log(T_i - 1). \quad (35)$$

The beauty of (35) is that it is a totally blind detection: do not require any information of the signal and noise.

VI. COMPARISONS

Let us first look at the required information of the methods.

- 1) LRT: each sensor needs to send its channel information, sample covariance matrix, SNR and noise power to the fusion center.
- 2) GLRT and OFS: each sensor needs to send its eigenvalues of the sample covariance matrix and SNR to the fusion center.
- 3) AGLRT, AOFS, EGC-MME and LMME: each sensor only needs to send its eigenvalues of the sample covariance matrix to the fusion center.

Obviously, LRT needs the most amount of information, especially the channel and noise power that are hard to obtain in practice. Hence in the following we will no longer address this method. Both GLRT and OFS need the SNR of each sensor. AGLRT, AOFS, EGC-MME and LMME do not need any priori information (the sample covariance matrix is calculated online). They are totally blind detections.

To theoretically compare the detection performances of these methods, we first need to find the closed-form theoretical distributions of the test statistics. While it is relatively easy to obtain the distributions of GLRT and EGC-MME by using similar random matrix theory approaches as done in [15, 19], it is very tough to find the closed-form distributions for the rest of the methods. So for detection performance comparison, we will use simulation results in the next section.

VII. SIMULATIONS

We consider the case of one primary signal. The channels to each sensors are flat-fading and the channel coefficients are unknown but fixed in one sensing slot. The propagation delays of the primary signal to the sensors are random numbers in $\{0, 1, \dots, M-1\}$. We consider the case of $M = 10$.

The relative performances of the methods are obviously affected by the distribution of the SNRs among the sensors. It is hard to have a general model for the distribution as it is related to the locations of sensors and also the surrounding environments. Here we use a simple model: the average SNR of all sensors is $\bar{\gamma} = \frac{1}{M} \sum_{i=1}^M \gamma_i$ and the SNR of user i is $\beta^{i-1} \gamma_{min}$ ($i = 1, \dots, M$), where γ_{min} is the minimum SNR among those of all sensors. β is called the SNR gap among the users. For given average SNR $\bar{\gamma}$ and SNR gap β , we can generate the SNRs of sensors, though the match of the SNRs to the sensors can be random. Note that the difference between the maximum SNR and minimum SNR is $(M-1)10 \log_{10}(\beta)$

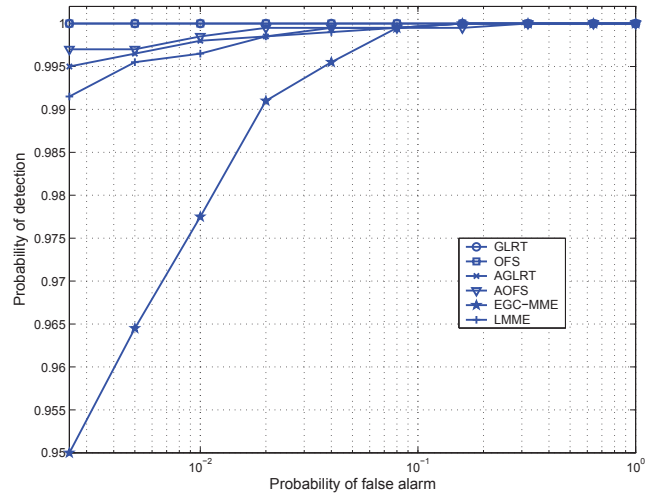


Fig. 1. The ROC curve: $J = 2$, $N = 16000$, $\bar{\gamma} = -20\text{dB}$ and $\beta = 2\text{dB}$

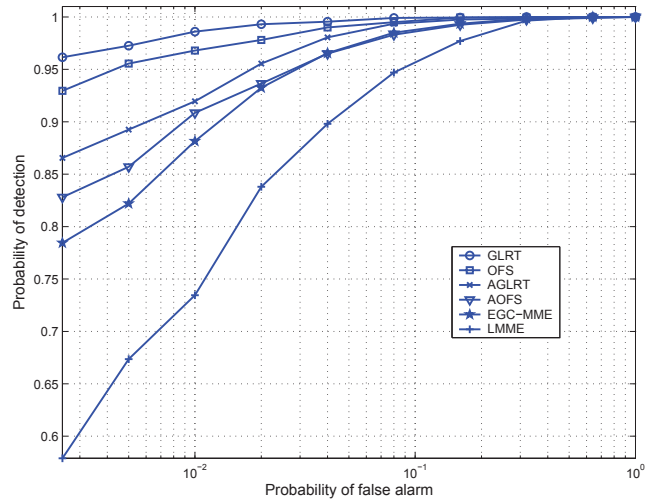


Fig. 2. The ROC curve: $J = 2$, $N = 16000$, $\bar{\gamma} = -20\text{dB}$ and $\beta = 1\text{dB}$

dB. For AGLRT, we choose $\hat{\gamma} = \bar{\gamma}$. All simulation results are obtained from 10,000 Monte-Carlo tests.

We consider three different situations: (1) high variations of SNRs among sensors; (2) moderate variations of SNRs among sensors; (3) low variations of SNRs among sensors. The SNR gaps at these three situations are $\beta = 2\text{dB}$, $\beta = 1\text{dB}$ and $\beta = 0.5\text{dB}$, respectively. For any of the situations, we choose $N = 16,000$ and $\bar{\gamma} = -20\text{dB}$.

The Receiver Operating Characteristics (ROC) curves at situation (1), (2) and (3) are shown in Figures 1, 2 and 3, respectively. At situation (1), GLRT and OFS have similar performances and are better than the other methods. Among the totally blind methods, AOFS is the best followed by LMME, AGLRT and EGC-MME. At situation (2), GLRT is better than OFS. Both of them are still better than the other methods. For the totally blind methods, the best is AGLRT followed by AOFS, EGC-MME and LMME. At situation (3), GLRT is still the best. OFS is now even worse than the

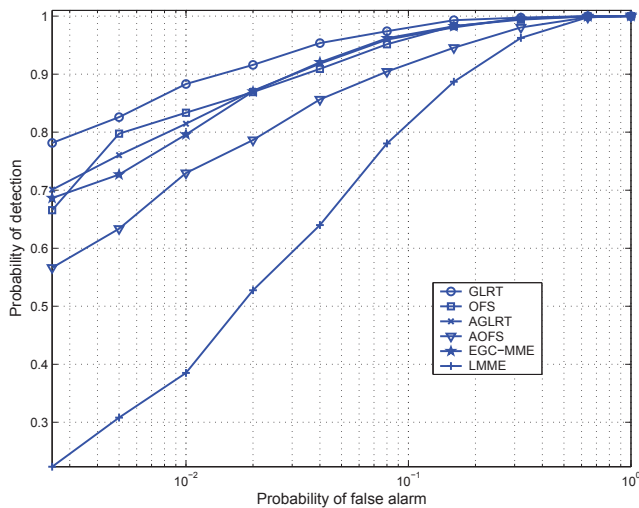


Fig. 3. The ROC curve: $J = 2$, $N = 16000$, $\bar{\gamma} = -20\text{dB}$ and $\beta = 0.5\text{dB}$

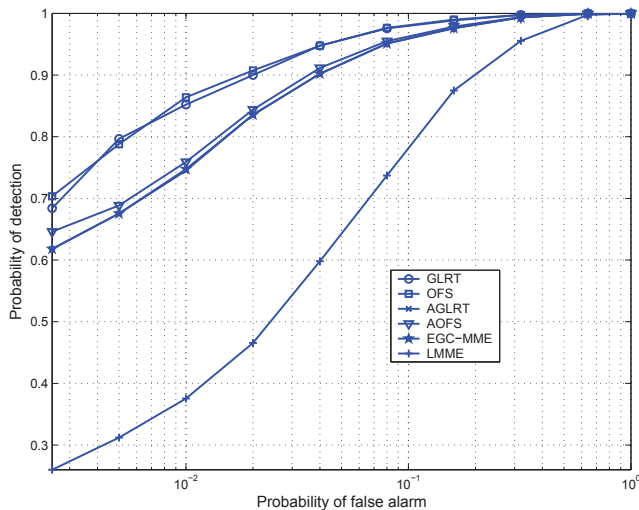


Fig. 4. The ROC curve: $J = 4$, $N = 2000$, $\bar{\gamma} = -18\text{dB}$ and $\beta = 0.5\text{dB}$

AGLRT and EGC-MME. LMME is much worse than the other methods.

All the simulations results above are for $J = 2$. Here we give an example for $J > 2$. At $J = 4$, $N = 2000$, $\bar{\gamma} = -18\text{dB}$, and $\beta = 0.5\text{dB}$, Figures 4 shows the results.

In summary, GLRT and OFS are usually better than the other methods, but both of them need priori information of the SNRs at all sensors. Among the totally blind methods, if the variations of SNRs are high, AOFS, AGLRT and LMME are good choice, while if the variations of SNRs are low, AOFS, EGC-MME and AGLRT are better. To cater for different situations, we recommend to choose AOFS or AGLRT in practice.

VIII. CONCLUSIONS

A simple closed-form expression has been found for the multi-sensor multi-antenna LRT, which is the global optimal solution. Unfortunately, it is difficult to use the LRT in practice

due to its reliance on the knowledge of primary user's channels and noise powers at all sensors. Hence several sup-optimal methods have been proposed. Although their performances vary at different situations, simulations have shown that AOFS and AGLRT generally perform well at all situations. Thus both of them are the recommended candidates in practical applications.

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