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EEF Criterion Based User Selection for Cooperative Spectrum Sensing in Cognitive Radio Network

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***Abstract*—Spectrum sensing is a fundamental technique of cognitive radio (CR) system to detect the presence of primary user (PU) transmissions in the licensed spectrum. This paper investigates secondary user (SU) selection based cooperative spectrum sensing under exponentially embedded family (EEF) criterion. With an aim to estimate the optimal number of cooperative users who are better fitting for participating in cooperative sensing, we propose AIC, MDL, and EEF criteria to select the potential users among all cooperative users in the CR network. Based on the estimated user number, the global test statistic (GTS) is generated, and finally the fusion center (FC) makes the global decision on the presence/absence of the PU signal. Analysis and simulations verify that the proposed user selection based cooperative sensing schemes can significantly improve the spectrum sensing performance.**

***Keywords*—exponentially embedded family, user number estimation, user selection, cooperative spectrum sensing, cognitive radio network.**

I. Introduction

Cognitive radio (CR) technology has been motivated for solving the problem of licensed spectrum under-utilization[1]. Key features of a CR transceiver include the radio environment awareness and spectrum intelligence. CR exploits the underutilized licensed spectrum and access it in an opportunistic manner by means of identifying the licensed spectrum status prior to secondary transmission. The SUs frequently perform spectrum sensing to detect the presence of the PUs, in order not to cause interference to the active PUs. Spectrum sensing is a fundamental and agile technique to detect the PU transmissions. There are a variety of spectrum sensing techniques that can be applied at an individual CR user or multiple CR nodes in a collaborative manner: energy detection (ED), matched filtering (MF) based methods, cyclostationary detection and so forth[2]. Depending on no *a priori* knowledge of the PU signal, ED is widely used for its simplicity and low cost in implementation. However, ED is vulnerable to noise power uncertainty problem and suffers from unsatisfactory sensing performance.

To overcome the shortcomings of ED, various cooperative spectrum sensing methods have been proposed to ameliorate the global sensing performance with the help of multiple SUs reporting their individual spectrum observations to the fusion center (FC) in the CR network. Among the existing methods, eigenvalues based sensing strategies were proposed [3] and serve effectively without requiring readily available *a priori* knowledge. The maximum eigenvalue detection (MED) method extracts the maximum eigenvalue, as the GTS for final decision, of the sample covariance matrix calculated from a limited number of received signal samples [4]. Maximum to minimum eigenvalue (MME) method generates the GTS as the ratio of the maximum eigenvalue to the minimum eigenvalue [5]. Energy with minimum eigenvalue (EME) algorithm compares the received signal energy to the minimum eigenvalue of the sample covariance matrix, which is computed from the received signal samples only[5]. The MED, MME and EME algorithms only depend on the received signal samples for detection, and no information on the transmitted signal and channel is demanded.

It is worth noting that the optimally combined energy detection (OCED) and blindly combined energy detection (BCED) were proposed [6]. They are intrinsically identical to the MED approach with different implementation requirements. OCED relies on the ideal covariance matrix of the received PU signal, and adopts the maximum eigenvector to combine the sample vectors in generating GTS. Therefore, OCED substantially outperform ED, at the price of obtaining PU signal covariance, which is usually infeasible in practice. On the contrary, BCED does not require any information (totally blind) and estimates the eigenvector by using the received signal samples only. Owing to the blind processing manner, BCED is only capable of approaching the sensing performance of ED.

Within the framework of the abovementioned cooperative sensing algorithms, taking into account the different signal propagation distances and environments between the PU transmitter and the individual SU detectors, we propose to divide all the SUs in two groups. One group contains the SUs with strong received PU signal components and the other group is made up of the SUs receiving very weak PU signal only. The philosophy of grouping the users (or viewed as user selection) is that if we can strengthen the former group's effects in sensing and ignore the latter group at all, we may achieve better sensing performance.

Intuitively, a straightforward way to distinguish the SUs in different groups is to first estimate the number of SUs in each group and then separate them by comparing their spectrum observations. The estimation of the number of SUs in the group with strong signal strength is addressed as a main contribution of this paper. We investigate optimal SU number estimation strategies under the criteria of AIC, MDL, and EEF, respectively. After the SUs are selected out and tagged in the desired group, we can generate the GTS with the conventional cooperative sensing methods.

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Analysis and simulation verified that the proposed user selection based cooperative spectrum sensing schemes yield improved sensing performance.

The rest of this paper is organized as follows. Section II describes the system model. From Section III to IV, we develop different user selection schemes under different criteria. In section V, practical implementations of the proposed schemes are given. Simulations and discussions are given in section VI. Section VII concludes the paper.

Notations: boldface capital and small letters are used to denote matrices and vectors, respectively; superscript $(\cdot)^T$ and $(\cdot)^H$ stand for transpose and Hermite transpose, respectively; $E[\cdot]$ represents the expectation operation; $\mathrm{diag}(\cdot)$, $\mathrm{Tr}(\cdot)$ and $\|\cdot\|$ refer to a diagonal matrix, the trace of a matrix, and the Euclidean norm, respectively. Moreover, I_m is an identity matrix of order *m*.

II. System Model

A. *Received Signal and Statistical Properties*

Suppose multiple cooperative SUs are deployed in the CR network, where each SU is equipped with a single antenna. For the FC, the spectrum observations are collected based on a set of *N* discrete-time received signal sample vectors $x[n], n = 0, 1, \cdots, N-1$. The *i*-th component of $x[n]$, denoted as $x_i[n], i = 0, 1, \cdots, M-1$, is the spectrum data of the *i*-th SU at time index *n*, where *M* is the number of cooperative SUs. For convenience, an aggregate observation matrix at the FC is defined as:

$$X = [x[0], x[1], \cdots, x[n] \cdots, x[N-1]] \quad (1)$$

The hypothesis test of spectrum sensing is hence given below:

$$H_0 : x[n] = \eta[n]; \quad (2)$$

$$H_1 : x[n] = s[n] + \eta[n]; \quad (3)$$

where $\eta[n]$ is the additive noise sample vector at the FC, among which the entries are independent and identically distributed (iid) circularly symmetric complex Gaussian (CSCG) variables with zero mean and covariance matrix:

$$R_\eta = E\left\{\eta[n]\eta^H[n]\right\} = \sigma^2 I_M, \quad (4)$$

and $s[n]$ is the received primary signal to be detected with covariance matrix:

$$R_s = E\left\{s[n]s^H[n]\right\}. \quad (5)$$

As for the covariance matrix of the received signal $x[n]$, it is:

$$\begin{aligned} R_x &= E\left\{x[n]x^H[n]\right\} \\ &= E\left\{s[n]s^H[n]\right\} + E\left\{\eta[n]\eta^H[n]\right\} \\ &= R_s + R_\eta . \end{aligned} \quad (6)$$

In practice, based on a limited number of received signal samples, the covariance matrix of $x[n]$ is estimated as:

$$\hat{R}_x = \frac{1}{N}\sum_{n=0}^{N-1} x[n]x^H[n]; \quad (7)$$

where $\hat{R}_x$ is feasible to perform an eigen-decomposition as $\hat{R}_x = U_x \Lambda_x U_x^H$ with U_x being the unitary eigenvector matrix and Λ_x the diagonal eigenvalue matrix, respectively.

Furthermore, it is worth noting that $\hat{R}_x$ can be used to generate the test statistic. Under hypotheses H_0, we have $R_s = 0$. Thus, when the primary signal is not present the sample covariance matrix of the received signal will be $\hat{R}_x = R_\eta = \sigma^2 I_M$.

B. *Global Test Statistics Generation of Existing Algorithms*

The eigenvalue based detectors are salient methods for cooperative spectrum sensing. It is usually assumed that each cooperative SU sends its test statistic to the FC and then the FC makes a final decision based on the fused GTS.

In [6], optimally combined energy detection (OCED) and its blind version (BCED) employ ED after combining the received signal samples in space and time, based on the principle of maximizing the SNR. Optimal combining needs information of the PU source signal and channel, which is usually unknown in practice. Blind combing does not demand any *a priori* information of the source signal and channel and estimates R_x using the received signal samples only. The GTS of OCED and BCED are respectively:

$$T_{OCED}(N) = \frac{1}{N}\sum_{n=0}^{N-1} \|z(n)\|^2; \quad (8)$$

$$T_{BCED}(N) = \frac{1}{N}\sum_{n=0}^{N-1} \|\hat{z}(n)\|^2; \quad (9)$$

where $z(n) = \beta x(n)$, $\hat{z}(n) = \hat{\beta} x(n)$ with β the eigenvector of R_x corresponding to its maximum eigenvalue λ_{max}, and $\hat{\beta}$ the eigenvector of $\hat{R}_x$ corresponding to its maximum eigenvalue $\hat{\lambda}_{max}$.

III. User Selection Based Cooperative Sensing

A. *Estimation of the Number of SUs in Sensing*

Usually, it is assumed that all the *M* SUs participate in reporting spectrum observations to the FC and the FC fuses all the data from them into the GTS, for which OCED, and BCED are good examples.

In practice, the SUs deployed at different physical locations within the CR network are undergoing different channel effects and, consequently, the eigenvalues are distributed as $\lambda_{1;x} \geq \lambda_{2;x} \geq \cdots \geq \lambda_{K;x} \gg \lambda_{K+1;x} \geq \cdots \geq \lambda_{M;x}$, where the first *K* eigenvalues are much greater than the rest (*M*−*K*) eigenvalues. In this sense, the SUs corresponding to the first *K* eigenvalues among all cooperative users may contribute much more than the others. The actual environment of each SU varies in general, and hence results in different eigenvalues of the sample covariance matrix R_s

where the eigenvalues stand for the power of the pure PU signal received at different SUs. With an aim to improve the cooperative sensing performance, we need to determine dimension of the PU signal receiving space where only some SUs receive sufficiently strong PU signals. By distinguishing the SUs in good channel condition, we can easily mitigate the aggregated noise effects resulted by the SUs containing very week PU signal components in their received signals.

Potential methods of estimating the number of SUs, who are receiving strong PU signals, are Akaike Information Criterion (AIC) and Minimum Description Length (MDL). As the basic information theory criterion (ITC) widely used for source number estimation [7], we propose to use AIC and MDL for estimating the number of potential SUs in cooperative sensing. The cost functions of AIC and MDL have the following form [8]:

$$Y_{AIC} = -2N\log\left\{\frac{\prod_{i=K+1}^{M} l_i}{\left(\frac{1}{M-K}\sum_{i=K+1}^{M} l_i\right)^{(M-K)}}\right\} + 2K(2M-K); \tag{10}$$

$$Y_{MDL} = -2N\log\left\{\frac{\prod_{i=K+1}^{M} l_i}{\left(\frac{1}{M-K}\sum_{i=K+1}^{M} l_i\right)^{(M-K)}}\right\} + K(2M-K)\log N; \tag{11}$$

where l_i denotes the i-th decreasing ordered eigenvalues of the sampled covariance matrix R_x $(l_1 > l_2 > \cdots > l_K > l_{K+1} \cdots > l_M)$. The estimated number of SUs receiving strong PU signals is determined by choosing the minimum of (10) or (11), which are given respectively as:

$$\hat{K}_{AIC} = \underset{K=0,1,\cdots,M-1}{\arg\min}\ Y_{AIC}(K) \tag{12}$$

$$\hat{K}_{MDL} = \underset{K=0,1,\cdots,M-1}{\arg\min}\ Y_{MDL}(K) \tag{13}$$

However, owing to the fact that AIC and MDL do not satisfy the consistency estimates, and are greatly affected by the SNR and N, AIC and MDL based estimation methods fail to guarantee satisfactory precision in low SNR scenarios and therefore only yield poor cooperative sensing performance eventually. In order to improve the estimation performance, we consider the criterion of exponentially embedded families (EEF) to replace AIC and MDL in estimation. The EEF function is expressed as [9]:

$$Y_{EEF}(K) = \left\{L_K(x) - \varphi_K\left[\log\left(\frac{L_K(x)}{\varphi_K}\right) + 1\right]\right\} \cdot u\left(\frac{L_K(x)}{\varphi_K} - 1\right), \tag{14}$$

where $u(\cdot)$ represents the unit step function, the penalty term $\varphi_K = K(2M-K) + 1 \approx K(2M-K)$ represents the adaptive parameter, and $L_K(x)$ is the likelihood ratio function defined as:

$$L_K(x) \triangleq 2\log\frac{f(x|\hat{R}_K)}{f(x|\hat{R}_0)}, \tag{15}$$

where $\hat{R}_0$ is the sample covariance matrix under reference model (K=0) and $f(x|\hat{R}_K) = f(x[1], x[2], \cdots, x[N]|\hat{R}_K)$ is the maximum likelihood estimation (MLE) of a Gaussian probability density function with N samples.

According to the theory of matrix decomposition, we have

$$\hat{R}_K = \sum_{i=1}^{K}(\hat{\lambda}_i - \sigma^2)\vartheta_i\vartheta_i^H + \sigma^2 I_M \tag{16}$$

where $\hat{\lambda}_1 > \hat{\lambda}_2 > \cdots > \hat{\lambda}_K$ are eigenvalues of the covariance matrix $\hat{R}_K$ and $\vartheta_1, \vartheta_2, \cdots, \vartheta_K$ are corresponding eigenvectors. The MLE of the eigenvalues and eigenvectors of $\hat{R}_K$ can be denoted as:

$$\hat{\lambda}_i = l_i; \quad i = 1, 2, \cdots, K \tag{17}$$

$$\vartheta_i = u_i; \quad i = 1, 2, \cdots, K \tag{18}$$

where the eigenvalues are $l_1 > l_2 > \cdots > l_K > l_{K+1} > \cdots > l_M$ with corresponding eigenvectors $u_1, u_2, \cdots, u_M$. If $\hat{R}_K$ in (16) is used in (15), the function of EEF is changed as:

$$\begin{aligned} Y_{EEF}(K) = \Big\{ & -2N(\alpha+\beta-\gamma) - K(2M-K) \\ & \cdot \log\left(\frac{-2N(\alpha+\beta-\gamma)}{K(2M-K)} + 1\right)\Big\} \\ & \cdot u\left(\frac{-2N(\alpha+\beta-\gamma)}{K(2M-K)} - 1\right) \end{aligned} \tag{19}$$

where the parameters are,

$$\alpha = \log\left(\prod_{i=1}^{K} l_i\right); \tag{20}$$

$$\beta = (M-K)\log\left(\frac{1}{M-K}\sum_{i=K+1}^{M} l_i\right); \tag{21}$$

$$\gamma = M\log\left(\frac{Tr(\hat{R}_0)}{M}\right). \tag{22}$$

The EEF criterion based estimation can be further improved by employing Gerschgorin unitary transformation in data processing [10]. The expression of GEEF estimation algorithm is:

$$\begin{aligned} Y_{GEEF}(K) = \Big\{ & -2N(\alpha'+\beta'-\gamma') - K^2 \\ & \cdot \log\left(\frac{-2N(\alpha'+\beta'-\gamma')}{K^2}\right) + 1\Big\} \\ & \cdot u\left(\frac{-2N(\alpha'+\beta'-\gamma')}{K^2} - 1\right); \end{aligned} \tag{23}$$

where the parameters are

$$\alpha' = \log\left(\prod_{i=1}^{K} l_i^0\right); \tag{24}$$

$$\beta' = (M-K-1)\log\left(\frac{1}{M-K-1}\sum_{i=K+1}^{M-1} l_i^0\right); \tag{25}$$

$$\gamma' = (M-1)\log\left(\frac{\mathrm{Tr}(\hat{Z}_{11}^K)}{M-1}\right). \tag{26}$$

where $l_i^0 (i = 1, 2, \cdots, M-1)$ is the *i*-th eigenvalue of the matrix $\hat{R}_K$, $\hat{Z}_{11}^K = \mathrm{diag}[\hat{l}_1; \hat{l}_2; \cdots; \hat{l}_K; \hat{\sigma}_n^2; \cdots; \hat{\sigma}_n^2]$. As for $\hat{l}_i$, it is the MLE of l_i^0, $\hat{l}_i = l_i^0 (i = 1, 2, \cdots, K)$,

$$\hat{l}_{K+1} = \hat{l}_{K+2} = \cdots = \hat{l}_{M-1} = \hat{\sigma}_n^2 = \frac{1}{M-K-1}\sum_{i=K+1}^{M-1} l_i^0.$$

Taking into account the EEF computational complexity which is mostly determined by the eigenvalue decomposition of the covariance matrix, we propose to use the received signal power (SP), instead of the eigenvalues, in EFF and come up with the SPEEF to reduce the complexity. We assume that the local power of the *i*-th individual SU is obtained with *N* samplers, and hence computation of the signal power $\theta_i = \sum_{n=0}^{N-1} |x_i[n]|^2$ would be very cost efficient and fast. With submission of θ_i in (16), the SPEEF function is:

$$\begin{aligned}\Upsilon_{SPEEF}(K) = \Bigg[\Big[-2N(\alpha'' + \beta'' - \gamma'') - K(2M-K)\Big] \\ \cdot \log\left(\frac{-2N(\alpha'' + \beta'' - \gamma'')}{K(2M-K)} + 1\right) \\ \cdot u\left(\frac{-2N(\alpha'' + \beta'' - \gamma'')}{K(2M-K)} - 1\right)\Bigg]\end{aligned} \tag{27}$$

with

$$\alpha'' = \log\left(\prod_{i=1}^{K} \theta_i\right); \tag{28}$$

$$\beta'' = (M-K)\log\left(\frac{1}{M-K}\sum_{i=K+1}^{M} \theta_i\right); \tag{29}$$

$$\gamma'' = M\log\left(\frac{\mathrm{Tr}(\hat{R}_0)}{M}\right). \tag{30}$$

The various algorithms estimating the number of the potential SUs can be obtained as follows:

$$\hat{K}_{EEF} = \mathop{\arg\max}_{K=0,1,\cdots,M-1} \Upsilon_{EEF}(K); \tag{31}$$

$$\hat{K}_{GEEF} = \mathop{\arg\max}_{K=0,1,\cdots,M-1} \Upsilon_{GEEF}(K); \tag{32}$$

$$\hat{K}_{SPEEF} = \mathop{\arg\max}_{K=0,1,\cdots,\min(M,N)-1} \Upsilon_{SPEEF}(K). \tag{33}$$

B. Global Test Statistics of the Selected Users

The ideal covariance matrix of the PU signal R_x is usually unknown whereas the sample covariance matrix $\hat{R}_x$ under the condition of limited samples is the only data we can utilize. After the number of SUs is estimated, the spectrum observations need to be fused into GTS at the FC. Firstly, we compute the received signal sample autocorrelation matrix $\hat{R}_x$ with the set of eigenvalues $\lambda = \{\lambda_1, \lambda_2, \cdots, \lambda_M\}$. Assuming $\hat{R}_x$ with the set of eigenvalues λ, we request a descending order of the eigenvalues to obtain the ensemble $\hat{\lambda} = \{\hat{\lambda}_{j_1}, \hat{\lambda}_{j_2}, \cdots, \hat{\lambda}_{j_M}\}$. The number $\{j_1, j_2, \cdots, j_M\}$ is a permutation of the original SU indices $\{1, 2, \ldots, M\}$. With an estimated $\hat{K}$ in previous stage, we need to extract the $\hat{K}$ maximum eigenvalues corresponding to the SUs receiving strong PU signals. The process is completed by selecting the SU indices to form the index ensemble $\hat{\Omega}$:

$$\begin{aligned}\Lambda = \max_{\hat{K}}\{\lambda\} = \max_{\hat{K}}\{\hat{\lambda}\} = \{\hat{\lambda}_{j_1}, \hat{\lambda}_{j_2}, \cdots, \hat{\lambda}_{j_{\hat{K}}}\} \\ \Rightarrow \hat{\Omega} = \{j_1, j_2, \cdots, j_{\hat{K}}\}\end{aligned} \tag{34}$$

In order to combine the spectrum data from the selected SUs and generate the GTS, we form two vectors of μ and $\hat{\nu}$ which select the SUs that will contribute in GTS. μ and $\hat{\nu}$ can be set according to the elements of $\hat{\Omega}$:

$$\mu(i) = \begin{cases} 1; & i \in \hat{\Omega} \\ 0; & \text{else} \end{cases} \tag{35}$$

In [6], OCED and BCED schemes were proposed based on different implementation conditions. Assuming R_x is ideally known, OCED uses the optimal combining matrix $B = \mathrm{diag}(\beta_1)$, where β_1 is the eigenvector corresponding to the maximum eigenvalue of R_x. BCED does not require any information (totally blind) and estimate the eigenvector $\hat{\beta}_1$ only based on the received signal samples. Both of OCED and BCED actually only consider the SU with the maximum received PU signal power and hence treat the maximum eigenvalue as the GTS. In previous stage, we have estimated that there are actually $\hat{K}$ SUs that may contribute more in generating the GTS, therefore, we stack the optimal combining matrices from all SUs and obtain the matrices as $\phi = \left[B_1^T; B_2^T; \cdots; B_M^T\right]^T$ and $\hat{\phi} = \left[\hat{B}_1^T; \hat{B}_2^T; \cdots; \hat{B}_M^T\right]^T$;, where $B_m = \mathrm{diag}(\beta_m)$ and $\hat{B}_m = \mathrm{diag}(\hat{\beta}_m)$ with β_m being the eigenvector of R_x corresponding to λ_m and $\hat{\beta}_m$ the eigenvector of $\hat{R}_x$ corresponding to $\hat{\lambda}_m$.

Subsequently, using the selecting vectors μ and $\hat{\nu}$, we can develop the GTS of optimal user selection combined energy (OUSCE) and blind user selection combined energy (BCUSE) detection algorithms as:

$$T_{OUSCE}(N) = \frac{1}{N}\sum_{n=1}^{N}\|\hat{y}(n)\|^2; \quad (36)$$

$$T_{BUSCE}(N) = \frac{1}{N}\sum_{n=1}^{N}\|\tilde{y}(n)\|^2; \quad (37)$$

where

$$\hat{y}(n) = \frac{1}{\hat{K}}\hat{V}^H x(n) = \frac{1}{\hat{K}}\sum_{i=1}^{\hat{K}} V_i x(n); \quad (38)$$

$$\tilde{y}(n) = \frac{1}{\hat{K}}\tilde{V}^H x(n) = \frac{1}{\hat{K}}\sum_{i=1}^{\hat{K}} \tilde{V}_i x(n): \quad (39)$$

To make the final global decision in cooperative sensing, the GTS in (36) is compared with its threshold which is predefined by the desired false alarm probability before the sensing operation begins.

IV. Simulation and Analyses

In order to verify the performance of the proposed cooperative sensing algorithms, we carried out Monte Carlo computer simulations in Matlab, setting $M = 12$, $K = 6$, and the desired false-alarm probability 0.1. Each simulation runs over 5000 loops. According to different conditions of equation (38) and (39), performance evaluation of EEF, GEEF, and SPEEF based USCE cooperative sensing algorithms can be divided into two classes, namely the OUSCE class under the ideal condition of already known covariance matrix R_s and the BUSCE class under practical condition that no *a priori* information is available. The spectrum sensing performance is usually measured in terms of detection probability and falsealarm probability.

We set the number of samples $N = 1000$ and the SNR range as [-18dB,-4dB]. Fig.1 represents the detection probability of EEF, GEEF and SPEEF based OUSCE algorithms along with BCED, OCED and ED algorithms. In Fig.1, we notice that EEF, GEEF and SPEEF based OUSCE cooperative algorithms yield higher detection probability than the traditional OCED algorithm. Furthermore, SPEEF obtains similar performance with EEF and GEEF, based on lower complexity. Fig.2 depicts the detection probability of EEF, GEEF and SPEEF based BUSCE algorithms along with BCED, OCED and ED algorithms. According to Fig.2, it is easy to find that detection performance of EEF, GEEF and SPEEF based BUSCE algorithms, which require no *a priori* information, have obvious performance improvement in comparison with the original BCED algorithm, and is approaching the ED algorithm for which the noise power is already known.

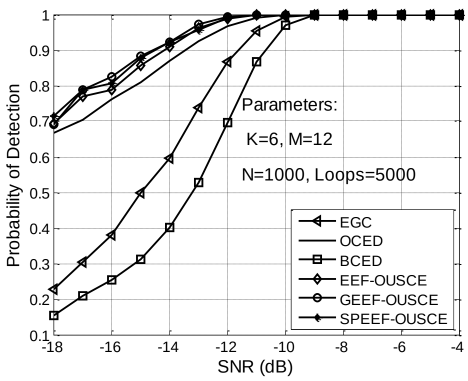

Fig. 1. Detection probability of OUSCE and other algorithms.

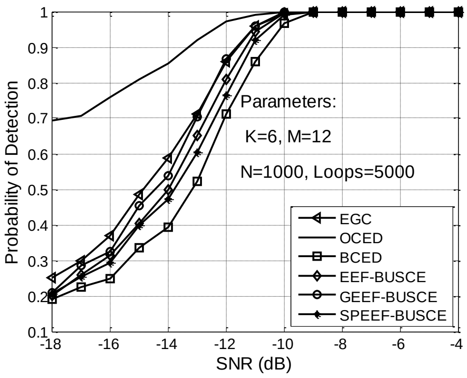

Fig. 2. Detection probability of BUSCE and other algorithms.

V. Conclusion

In this paper, user selection based cooperative sensing algorithms are proposed. Based on the criteria of EEF, GEEF and SPEEF algorithms are developed, to estimate the optimal number of users for generating GTS, and then compared with the conventional cooperative sensing methods, namely the OCED and BCED algorithms. Simulation results show that without any *a prior* information, the user selection based BUSCE schemes have better performance than the original BCED method and approach the ED performance. As for being compared with the OCED method, the proposed OUSCE schemes also outperform among them. Therefore, the proposed EEF criterion based user selection schemes can be effectively applied in practice as an easy-to-implement scheme.

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