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An Optimal Soft Fusion Scheme for Cooperative Spectrum Sensing in Cognitive Radio Network

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***Abstract*—This paper proposes an optimal soft fusion scheme for cooperative spectrum sensing in cognitive radio (CR) network. Multiple cooperative secondary users (SUs) simply serve as relay nodes in the network to provide space diversity for spectrum sensing. An optimal soft fusion scheme of the relayed sensing observations is derived in Neyman-Pearson framework, on the basis of maximizing the deflection coefficient of the global test statistic at the fusion center. However, the proposed fusion scheme requires instantaneous measurements of the received PU signal strengths in SUs with high accuracy, which are extremely difficult to obtain in an energy detection based spectrum sensing scenario. An iterative algorithm is therefore proposed to perform the estimation of the received PU signal strengths. Simulation results illustrate that the proposed optimal soft fusion scheme can significantly improve the spectrum sensing performance and the estimate algorithm can effectively approach the ideal performance of the proposed optimal fusion scheme.**

***Index Terms*—Energy detection, soft fusion, cooperative spectrum sensing, cognitive radio network.**

I. Introduction

In recent years, cognitive radio (CR) has emerged as a promising paradigm for exploiting the spectrum opportunity, which is restricted by the current rigid spectrum allocation scheme, to solve the spectrum scarcity problem of nowadays [1] [2]. Since CRs are inherently lower priority or secondary users (SU), who opportunistically access the temporarily unused licensed spectrum exclusively allocated to primary users (PU), the fundamental requirement for them is to avoid interference to the potential PUs in the vicinity. Hence, in order to reduce the interference generated to the PU to a minimum and utilize the spectrum opportunities with satisfactory efficiency, a SU is practically required to be equipped with superior capability of distinguishing between the presence of PU signals and the spectrum holes.

Among various options for reliably identifying the status of the licensed spectrum [3], spectrum sensing incurs a very low infrastructure cost and is backward compatible with the legacy primary systems. In order to detect the PU signal with unknown location, structure and strength, energy detection exhibits the advantage in implementation simplicity and serves as the optimal spectrum sensing scheme when the detector only knows the power of the received signal. Therefore, it is most commonly used for spectrum sensing. However, energy detection performance is vulnerable to the destructive channel effects, such as multipath fading/shadowing and noise power fluctuating, which result in the hidden terminal problem [4] [5] and ambiguity in detector threshold setting [6], respectively.

These drawbacks imply the necessity for user cooperation in CR networks, where multiple SUs collaborate to perform spectrum sensing, to make compensation for the degraded sensing performance of a single SU [7] [8] [9]. Cooperation among SUs is usually coordinated by a fusion center through either hard decision or soft data fusion strategies. In the case of hard decision fusion schemes, each cooperative SU first senses the spectrum, draws decision on its own spectrum observation independently, and then report the single decision bit to the fusion center; whereas in soft data combination schemes, after the fusion center collects the real values of sensing data from all of the cooperative SUs, it softly fuses them via some algorithms, e.g. optimal combination [10], MRC, and EGC [11] etc., and finally reaches a global decision. It has been demonstrated in [10] that soft data fusion schemes, even with the simple EGC, exhibit significant improvement over the conventional decision fusion schemes, since in the soft data fusion procedure, theoretically infinite virtual bits are used for representing the raw observations of each SU.

In this paper, we investigate a cooperative spectrum sensing scenario, in which each cooperative SU in the network only serves as a simple relay node to provide space diversity for the fusion center to obtain the global decision. The cooperative SUs first sense the spectrum independently and relay their observations to the fusion center. Soft fusion of raw measurements of received signal energies from multiple cooperative SUs is then performed at the fusion center. To facilitate the analyses, we approximate the test statistics in spectrum sensing as Gaussian random variables and develop an optimal soft fusion scheme in the Neyman-Pearson framework. The proposed fusion scheme is optimal in the sense that the deflection coefficient of the global test statistic is maximized by our derived fusion weights.

The rest of this paper is organized as follows. We begin in Section II with the system model by describing the scheme of spectrum observation data relaying in the CR network. In Section III, an optimal weight setting strategy for fusing the observation data is developed and we also propose an iterative estimate algorithm for implementing the fusion weights. Simulations are carried out and analyzed in Section IV. Conclusions are finally drawn in Section V.

Some notations are used as follows: boldface capital and small letters are used to denote matrices and vectors, respectively; superscript $(.)^T$ stands for transpose; $E[.]$ stands for expectation operation; and $\| \, . \, \|_2$ denotes the Euclidean norm.

II. System Model

A. Spectrum Sensing Observation Relaying

We consider K SUs are dispersed over a certain geographical area by some distributing algorithms. The K SUs in the network only simply serve as relay nodes to provide the space diversity for obtaining the global decision. The cooperative spectrum sensing procedure is divided into two phases: *i*) the K SUs independently sense the spectrum, but they neither immediately measure the received signal energy, nor make individual decisions; *ii*) the spectrum observations are relayed to the fusion center, which measures the received signal energies, fuses the raw data into a global test statistic and finally makes the global decision. It is assumed that the individual sensing observations are relayed to the fusion center in an orthogonal manner that the fusion center can easily discern the K observations captured at different SUs in the CR network.

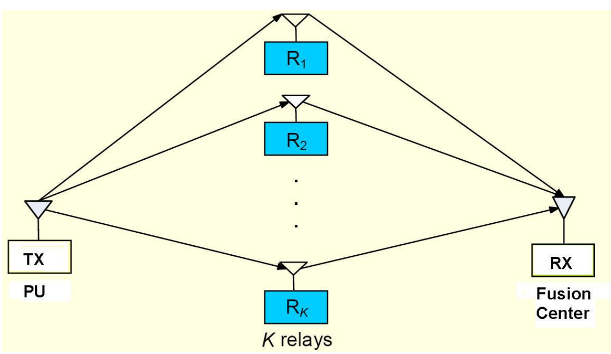

Fig. 1. Relay scheme implemented with K cooperative SUs.

Figure 1 depicts the cooperative sensing scenario investigated in this paper. In the first, the signal received at the i-th SU (relay R_i) is

$$x_i(t) = \begin{cases} n_i(t), & H_0, \ 0 \le t \le T_S \\ \sqrt{E_{PU}} h_i s(t) + n_i(t), & H_1, \ i = 1, 2, \cdots, K \end{cases} \quad (1)$$

where $s(t)$ is the transmitted PU signal at the PU transmitter with amplitude $\sqrt{E_{PU}}$(hereinafter we assume $E[s^2(t)] = 1$), and h_i is the channel gain between the PU and R_i, which accommodates the effects of channel shadowing, channel loss and fading, etc. $n_i(t)$ is the complex additive white Gaussian noise with zero mean and variance σ_i^2, and we assume $n_i(t)$ and $s(t)$ are mutually independent. H_0 and H_1 are the hypotheses of the PU signal being absent and present, respectively. T_S is the effective sensing interval.

After sensing the spectrum, each relay will simply acts in an amplify-and-forward (AAF) manner in the second phase, and the signal received by the fusion center from R_i is

$$\begin{aligned} z_i(t) &= \sqrt{E_i} \bar{h}_i x_i(t) + n_{FC}(t) \\ &= \begin{cases} \sqrt{E_i} \bar{h}_i n_i(t) + n_{FC}(t), & H_0 \\ \sqrt{E_{PU} E_i} h_i \bar{h}_i s(t) + \tilde{n}_{FC,i}(t). & H_1 \end{cases} \end{aligned} \quad (2)$$

where E_i is the transmit power of R_i, $\bar{h}_i$ is the channel gain between the fusion center and R_i, and $n_{FC}(t)$ is the noise at the fusion center with zero mean and variance σ_{FC}^2 (again, we assume that *i*) $n_{FC}(t)$ is independent with both $n_i(t)$ and $s(t)$; *ii*) $n_{FC}(t)$ is the same for each of the relays in the network). Consequently, the equivalent noise variance of $\tilde{n}_{FC,i}(t)$ is

$$\tilde{\sigma}_{FC,i}^2 = E_i |\bar{h}_i|^2 \sigma_i^2 + \sigma_{FC}^2, \quad i = 1, 2, \cdots, K. \quad (3)$$

We can now write the received signals at the fusion center as

$$\mathbf{Z}(t) = \begin{cases} \mathbf{\Pi}_0 \times \mathbf{n}(t) + n_{FC}(t)\mathbf{1}, & H_0 \\ \mathbf{\Pi}_1 \times s(t)\mathbf{1} + \tilde{\mathbf{n}}_{FC}(t). & H_1 \end{cases} \quad (4)$$

where signals $\mathbf{Z}(t) = [z_1(t), z_2(t), \cdots, z_K(t)]^T$ are received by the fusion center, $\mathbf{n}(t) = [n_1(t), n_2(t), \cdots, n_K(t)]^T$ are the noise components at the K relays, $\tilde{\mathbf{n}}_{FC}(t) = [\tilde{n}_{FC,1}(t), \tilde{n}_{FC,2}(t), \cdots, \tilde{n}_{FC,K}(t)]^T$ are the combined K noise components at the fusion center, and $\mathbf{1}$ is the column vector of all ones. $\mathbf{\Pi}_0$ and $\mathbf{\Pi}_1$ are diagonal matrices with $\boldsymbol{\pi}_0 = [\sqrt{E_1}\bar{h}_1, \sqrt{E_2}\bar{h}_2, \cdots, \sqrt{E_K}\bar{h}_K]^T$ and $\boldsymbol{\pi}_1 = [\sqrt{E_{PU}E_1}h_1\bar{h}_1, \sqrt{E_{PU}E_2}h_2\bar{h}_2, \cdots, \sqrt{E_{PU}E_K}h_K\bar{h}_K]^T$ on their diagonals, respectively.

B. Energy Measuring and Fusing at the Fusion Center

The soft fusion process is carried out at the fusion center. The fusion center first measures the received signal energies from the K relays,

$$\mathbf{Z} = \int_0^{T_S} |\mathbf{Z}(t)|^2 dt = \begin{cases} \mathbf{Z}_0, & H_0 \\ \mathbf{Z}_1, & H_1 \end{cases} \quad (5)$$

where $\mathbf{Z}_0 = [z_{0,1}, z_{0,2}, \cdots, z_{0,K}]^T$ and $\mathbf{Z}_1 = [z_{1,1}, z_{1,2}, \cdots, z_{1,K}]^T$ are the test statistics captured within sensing interval T_S and frequency bandwidth W.

The captured PU signal energies in test statistics $\mathbf{Z}_1$ can be represented by the sum of $2T_SW$ virtual samples [12]

$$\begin{aligned} \theta_i &= \frac{1}{2W} \sum\nolimits_{n=1}^{2T_SW} |z_{1,i,n}|^2 \\ &= \gamma_i N_{0,i} W T_S = E_{PU} E_i |h_i|^2 |\bar{h}_i|^2 T_S, \end{aligned} \quad (6)$$

where $z_{1,i,n}$ is the sample of the relayed signal $z_i(t)$ at time instant n under hypothesis H_1, $N_{0,i}$ is the equivalent one-sided noise power spectral density corresponding to the i-th relayed signal, and $\gamma_i = \varepsilon_i/(N_{0,i}WT_S)$ is the PU signal-to-noise ratio (SNR) of the i-th relayed signal. According to (4), we can summarize the noise power densities as,

$$N_{0,i} = \left(E_i |\bar{h}_i|^2 \sigma_i^2 + \sigma_{FC}^2\right)/W, \quad i = 1, 2, \cdots, K. \quad (7)$$

When T_SW is asymptotically large (e.g., larger than 100) [13], we can approximate the test statistics $\mathbf{Z}$ as normal distributed variables, according to the central limit theorem (CLT), with means and variances

$$\begin{cases} \mu_{0,i} = E[z_{0,i}] = N_{0,i} T_S W, \\ \delta_{0,i}^2 = Var[z_{0,i}] = N_{0,i}^2 T_S W. \end{cases} \quad H_0 \tag{8}$$

$$\begin{cases} \mu_{1,i} = E[z_{1,i}] = N_{0,i} T_S W + \theta_i, \\ \delta_{1,i}^2 = Var[z_{1,i}] = N_{0,i}^2 T_S W + 2N_{0,i}\theta_i. \end{cases} \quad H_1 \tag{9}$$

Based on $\mathbf{Z}$, by allocating different weight coefficients to them and combining them all, the fusion center fuses the K observations into a global statistic Z_c,

$$Z_c = \sum_{i=1}^{K} \omega_i Z_i = \boldsymbol{\omega}^T \mathbf{Z}, \tag{10}$$

where $\boldsymbol{\omega} = [\omega_1, \omega_2, \cdots, \omega_K]^T$ is the weighting coefficients satisfying $\|\boldsymbol{\omega}\|_2^2 = 1,\ \omega_i \geq 0$. The combining weight for the signal from a particular SU represents its contribution to the global decision. Consequently, the global test statistics Z_c has its means given by

$$\bar{Z}_c = E[Z_c] = \begin{cases} \boldsymbol{\omega}^T \mathbf{u}_0, & H_0 \\ \boldsymbol{\omega}^T \mathbf{u}_1, & H_1 \end{cases} \tag{11}$$

where $\mathbf{u}_0 = [u_{0,1}, u_{0,2}, \cdots, u_{0,K}]^T$ and $\mathbf{u}_1 = [u_{1,1}, u_{1,2}, \cdots, u_{1,K}]^T$.

Regarding the variances of Z_c, we obtain

$$Var[Z_c] = \begin{cases} \sum_{i=1}^{K} \delta_{0,i}^2 {\omega_i}^2 = \boldsymbol{\omega}^T \boldsymbol{\Sigma}_0 \boldsymbol{\omega}, & H_0 \\ \sum_{i=1}^{K} \delta_{1,i}^2 {\omega_i}^2 = \boldsymbol{\omega}^T \boldsymbol{\Sigma}_1 \boldsymbol{\omega}, & H_1 \end{cases} \tag{12}$$

where $\boldsymbol{\Sigma}_0$ and $\boldsymbol{\Sigma}_1$ are diagonal matrices with $\boldsymbol{\delta}_0^2 = [\delta_{0,1}^2, \delta_{0,2}^2, \cdots, \delta_{0,K}^2]^T$ and $\boldsymbol{\delta}_1^2 = [\delta_{1,1}^2, \delta_{1,2}^2, \cdots, \delta_{1,K}^2]^T$ on the diagonals, respectively.

Given a global threshold λ at the fusion center, the probabilities of false alarm and detection in cooperative spectrum sensing are

$$P_{FA} = Q\left(\frac{\lambda - \mathbf{u}_0^T \boldsymbol{\omega}}{\sqrt{\boldsymbol{\omega}^T \boldsymbol{\Sigma}_0 \boldsymbol{\omega}}}\right), \quad P_D = Q\left(\frac{\lambda - \mathbf{u}_1^T \boldsymbol{\omega}}{\sqrt{\boldsymbol{\omega}^T \boldsymbol{\Sigma}_1 \boldsymbol{\omega}}}\right), \tag{13}$$

where $Q(x) = \int_x^{+\infty} \exp(-t^2/2) dt / \sqrt{2\pi}$.

III. Proposed Optimal Soft Fusion Scheme

A. Weight Optimization in Neyman-Pearson Criteria

For a cooperative spectrum sensing algorithm, the main metric of sensing performance is either the maximization of the detection probability for a target false alarm probability or minimization of the false alarm probability for a target detection probability. Setting the threshold λ for a desired probability of false alarm $P_{FA,DES}$, we obtain the probability of detection with the Neyman-Pearson criteria,

$$P_D = Q\left(\frac{Q^{-1}(P_{FA,DES})\sqrt{\boldsymbol{\omega}^T \boldsymbol{\Sigma}_0 \boldsymbol{\omega}} + \mathbf{u}_0^T \boldsymbol{\omega} - \mathbf{u}_1^T \boldsymbol{\omega}}{\sqrt{\boldsymbol{\omega}^T \boldsymbol{\Sigma}_1 \boldsymbol{\omega}}}\right). \tag{14}$$

where $Q^{-1}(.)$ is the inverse function of $Q(.)$.

From (12) and (13) it is clear that the weight vector $\boldsymbol{\omega}$ plays an important role in determining the PDFs of the global test statistic Z_c under both hypotheses. To measure the effect of the PDF on the detection performance, we introduce the deflection coefficient (DC) [14]

$$d_{DC}^2(\boldsymbol{\omega}) = \frac{(E[Z_c|H_1] - E[Z_c|H_0])^2}{Var(Z_c|H_0)} = \frac{\left(\boldsymbol{\Theta}^T \boldsymbol{\omega}\right)^2}{\boldsymbol{\omega}^T \boldsymbol{\Sigma}_0 \boldsymbol{\omega}}. \tag{15}$$

where

$$\begin{aligned} \boldsymbol{\Theta} &= [\theta_1, \theta_2, \cdots, \theta_K]^T \\ &= \left[E_{PU} E_1 |h_1|^2 |\bar{h}_1|^2 T_S, \cdots, E_{PU} E_K |h_K|^2 |\bar{h}_K|^2 T_S\right]^T. \end{aligned}$$

The deflection coefficient in (15) provides a good measure of the detection performance, since it characterizes the variance-normalized distance between the centers of two conditional PDFs of Z_c. Therefore, the optimal weight vector $\boldsymbol{\omega}_{opt,DC}$ is defined as the one that maximizes the distance $d_{DC}^2(\boldsymbol{\omega})$

$$\boldsymbol{\omega}_{opt,DC} = \underset{\boldsymbol{\omega}}{\operatorname{argmax}}\, d_{DC}^2(\boldsymbol{\omega}). \tag{16}$$

By solving the equation $\partial d_{DC}^2(\boldsymbol{\omega}) / \partial \boldsymbol{\omega} = 0$, we obtain

$$\boldsymbol{\omega}_{opt,DC}^* = \frac{\boldsymbol{\omega}^T \boldsymbol{\Sigma}_0 \boldsymbol{\omega}}{\boldsymbol{\omega}^T \boldsymbol{\Theta}} \boldsymbol{\Sigma}_0^{-1} \boldsymbol{\Theta} = \beta_{DC} \boldsymbol{\Sigma}_0^{-1} \boldsymbol{\Theta}, \tag{17}$$

where β_{DC} is a scaling factor determined by $\boldsymbol{\omega}$, but it does not affect the detection performance in (14). By setting β_{DC} to 1 and normalizing each weighting coefficient, we obtain the optimal weighting vector

$$\boldsymbol{\omega}_{opt,DC} = \boldsymbol{\omega}_{opt,DC}^* / \left\|\boldsymbol{\omega}_{opt,DC}^*\right\|_2. \tag{18}$$

The detection performance is then given by

$$P_D = Q\left(\frac{Q^{-1}(P_{FA\_DES})\sqrt{\boldsymbol{\Theta}^T \boldsymbol{\Sigma}_0^{-1} \boldsymbol{\Theta}} - \boldsymbol{\Theta}^T \boldsymbol{\Sigma}_0^{-1} \boldsymbol{\Theta}}{\sqrt{\boldsymbol{\Theta}^T \boldsymbol{\Sigma}_0^{-2} \Sigma_1 \boldsymbol{\Theta}}}\right), \tag{19}$$

For a given $P_{FA,DES}$, P_D is maximized in the sense that the distance between the two PDFs of Z_c under hypotheses H_0 and H_1 is enlarged to the most by $\boldsymbol{\omega}_{opt,DC}$. The detection performance P_D in (14) is actually a probability conditioned on the vector $\boldsymbol{\Theta}$, which is a random variable vector determined by channel gains h_i and $\bar{h}_i$. The statistically averaged P_D is

$$\bar{P}_D = \int_{\boldsymbol{\Omega}_+^K} P_D(\mathbf{X}) p_{\boldsymbol{\Theta}}(\mathbf{X}) d\mathbf{X}, \tag{20}$$

where $p_{\boldsymbol{\Theta}}(.)$ is the joint PDF of the K-variable vector $\boldsymbol{\Theta}$ and $\boldsymbol{\Omega}_+^K$ is the K dimensional positive vector space.

B. Implementation of the Proposed Optimal Fusion Scheme

The optimal weighting vector in (18) is mainly determined by the signal energy quantities $E_{PU}|h_i|^2$, under the assumption that the channel gains $\bar{h}_i$, the relay power E_i, and the noise variances σ_i^2 and σ_{FC}^2 are readily available for the fusion center before the sensing operation begins. These assumptions are justified by the fact that each SU can perform noise power

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estimation between the consecutive sensing intervals, and the channel gains $\bar{h}_i$ between the SUs and the fusion center can also be obtained accurately due to some pilot-aided channel estimations performed at the fusion center. Additionally, we assume the channel coherence time of $\bar{h}_i$ is much larger than the channel estimation period, such that the fusion center could adaptively estimate the channel gains from the SUs with small overhead. Moreover, we also assume that the noise power levels are constant over a sufficiently long period of time, which means only negligible noise power fluctuations exist and thus barely affect the global threshold setting.

With the above assumptions, the only parameters we need to identify for setting the weight vector are the signal energy quantities $\{E_{PU}|h_i|^2\}$. To obtain PU signal energies hidden in the raw sensing data of the cooperative SUs, a simple yet effective method is employed hereafter, introducing records about PU's behaviors, where the current sensing data $\mathbf{Z}$ is categorized and stored in a *Presence* or *Absence* matrix for future reference, according to the current global decision. In other words, if it is decided that the current data $\mathbf{Z}$ contains the PU signal energy, it will be stored in an K-by-L *Presence* matrix $\mathbf{Z}^{(P)}$ in a first-in-first-out (FIFO) manner; otherwise it is stored in an K-by-L *Absence* matrix $\mathbf{Z}^{(A)}$. The estimates of $E_{PU}|h_i|^2$ for the current statistic $Z_{c,n}$ are calculated via simple arithmetic averaging operations

$$\begin{aligned}\tilde{E}_{PU}\left|\tilde{h}_{i,n}\right|^2 &= \frac{1}{E_i\left|\bar{h}_{i,n-1}\right|T_S}\frac{1}{L}\sum_{m=n-L}^{n-1}|Z_{i,m}^{(P)} - Z_{i,m}^{(A)}| \\ &= \frac{L-1}{L}\Delta_{i,n-1}^{(P)} + \frac{1}{E_i\left|\bar{h}_{i,n-1}\right|T_S}\frac{1}{L}\left|Z_{i,n-1}^{(P)} - Z_{i,n-1}^{(A)}\right|,\end{aligned} \tag{21}$$

where n is the time index of the current sensing data, L is the reference matrix depth, and $\Delta_{i,j}^{(P)}$ is the estimate of $E_{PU}|h_i|^2$ at instant j. An implicit assumption behind (21) are that the channels between the PU and the K SUs are slowly varying, which means the matrix depth L should be set sufficiently shorter than the channel varying interval.

IV. Simulations and Discussions

In this section, the proposed optimal cooperative spectrum sensing scheme is evaluated via simulations. The basic parameters are fixed and set as T_S = 1ms, W = 1MHz, K = 10 and L = 16. Each simulation consisted of 10^5 iterations. The channel gains between K SUs and the target PU are generated according to a complex normal distribution, which suggests that the PU signal is undergoing independent and identically distributed (i.i.d) Rayleigh fading, before reaching the K SUs. In simulation, we suppose that the variances $\{\delta_{0,i}^2\}$ are distributed around an average level δ^2, with a deviation d, which is normally distributed as $N(0, D\delta^2)$. D indicates the location difference factor in the cognitive radio network area.

For simplicity, we assume that the PU signal power E_{PU} and the channel gains $\{h_i\}$ had constant values for each sensing interval T_S, provided that T_S was sufficiently small. This assumption is reasonable and can be encountered in a realistic scenario, where the variation of the dynamic radio environment is reflected in the channel gains' variation over a relatively large time-scale.

Figure 2 shows the receiver operating characteristics (ROC) of the proposed cooperative sensing schemes. As expected and shown, given the same number of cooperative SUs, the theoretical optimal weight vector $\boldsymbol{\omega}_{opt,DC}$ outperforms the estimation implemented weight vector $\tilde{\boldsymbol{\omega}}_{opt,DC}$, with non-trivial differences. This performance degradation is resulted by the absence of *a priori* knowledge of PU signal in the fusion center and the challenging task of extracting the PU signal energy from the background noise in a low SNR environment. However, this performance deterioration can be sufficiently compensated for by increasing in the number of cooperative SUs and obtaining an optimal L which is adaptively adjusted according to the channel variation speed. Compared to the MRC and EGC schemes, the proposed optimal fusion scheme improves the cooperative spectrum sensing performance significantly. As we can see in Fig.2, the performance of MRC scheme approaches that of the proposed optimal soft fusion scheme, when the SNR is increasing from -18 dB to -15 dB and the deviation D of noise variances is decreased from 40% to 20%. When SNR is -15 dB and D is only 20%, the performance of estimated $\tilde{\boldsymbol{\omega}}_{opt,DC}$ is almost the same with that of the theoretical weights $\boldsymbol{\omega}_{MRC}$.

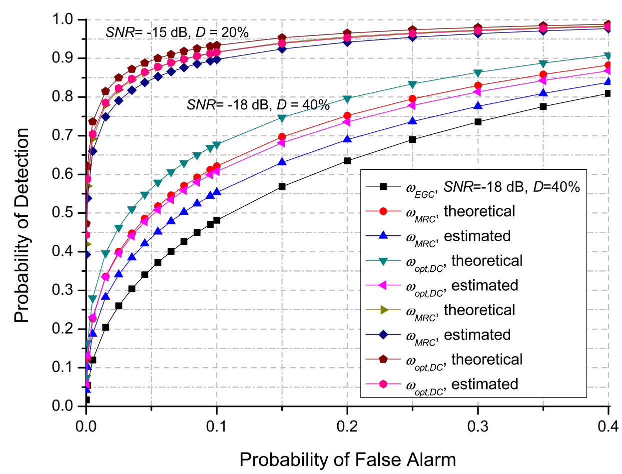

Fig. 2. ROC performance of the proposed optimal fusion scheme.

V. Conclusions

In this paper, an optimal soft fusion strategy based cooperative spectrum sensing scheme in a CR network is investigated and analyzed, consisting of allocation of optimal weights to spectrum observations collected from multiple cooperative SUs. An iterative weight setting scheme is also proposed to practically estimate the PU signal energies, to obtain the optimal weight vector. As illustrated by our analysis and simulations, the proposed optimal soft fusion scheme yields significant improvements in spectrum sensing.

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