Analysis and Optimization of Cooperative Spectrum Sensing with Noisy Decision Transmission

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Abstract

Cooperative spectrum sensing (CSS) with decision fusion is considered as a key technology for tackling the challenges caused by fading/shadowing effects and noise uncertainty in spectrum sensing in cognitive radio. However, most existing solutions assume an error-free decision transmission, which is obviously not the case in realistic scenarios. This paper extends the general decision-fusion-based CSS scheme by considering the fading/shadowing effects and noise corruption in the common control channels. With this more practical model, the fusion centre first estimates the local decisions using a binary minimum error probability detector, and then combines them to get the final result. Theoretical analysis and simulation of this CSS scheme are performed over typical channels, which suggest some performance deterioration compared with the pure case that assumes an error-free decision transmission. Furthermore, the fusion strategy optimization in the proposed cooperation model is also investigated using the Bayesian criteria. The numerical results show that the total error rate of noisy CSS is higher than that of the pure case, and the optimal values of fusion parameter in the counting rule under both cases decrease as the local detection threshold increases.

Keywords: Cognitive radio, cooperative spectrum sensing, energy detection, decision fusion, minimum error probability criteria, Bayesian criteria

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1. Introduction

Cognitive radio (CR) is widely considered as the next big thing in wireless communication because of its promising paradigm for solving the increasingly severe spectrum scarcity problem [1][2]. In an opportunistic manner, secondary (unauthorized) users (SU) in a cognitive radio network (CRN) can dynamically exploit the precious white or grey spectrum holes [3], which are underutilized by the current primary (authorized) users (PU) in multiple dimensions of time, space, code, and so on [4]. Under a hierarchical dynamic access model [5], this kind of spectrum sharing is only allowed when interference is not introduced to the PUs, which entails periodic or continuous spectrum identification by SUs. Direct spectrum sensing has received more attention than the other candidates for spectrum identification, such as database or beacons, owing to the relatively low infrastructure cost and compatibility with the existing legacy primary systems [6].

As the fundamental issue of CRN, spectrum sensing generally means to detect quickly and reliably the presence of the primary signals [7]. Among various possibilities, energy detection (ED) [8][9] is the optimal sensing algorithm and has been widely applied thanks to its relatively low complexity and lack of requirements for prior knowledge of the network. However, ED performance is very susceptible to multipath fading/shadowing and noise uncertainty, which necessitates cooperative spectrum sensing (CSS) among different SUs in the MAC layer of CRN [10][11][12]. Recently, numerous ED-based CSS schemes that take advantage of spatial diversity in centralized or decentralized scenarios have been proposed in the literature. On the basis of the fusion methods in cooperation, the existing schemes can be categorized mainly into data fusion [13][14][15][16]and decision fusion [12][13][17][18][19]. With regard to the former, typical algorithms, such as maximal ratio combination [13], equal gain combination [13], deflection-criteria based combination [14], and optimal weigh-setting combination [15][16], have been investigated. With regard to the latter, CSS with OR-rule decision fusion has been demonstrated to improve the detection performance, relax the local sensitivity requirements, and increase the agility and efficiency of the secondary access [12]. Furthermore, the optimization of CSS with the *K out of N rule* (also called the counting rule) has been discussed [18][19]. Many researchers have also proposed some softened decision fusion schemes that require sharing more information on the reliability and accuracy of different SUs [13][20]. For example, two bits are used to represent each local decision, and then all the decisions are summed up with different weights at the base station [13]. More details about these two categories of fusion-based CSS schemes can be found in the literature [1]. Some other related studies on spectrum sensing include sensing scheduling [21][22], sensing security[23][24], relay-based CSS schemes[25][26][27], and consensus- based CSS schemes[24][28].

In employing decision fusion instead of data fusion, obvious performance degradation occurs because of the information loss during the combination. However, in practice, decision fusion may still be the better choice because of its significantly lower communication overhead and narrower bandwidth in the common control channels. These characteristics coincide well with the tenet of CRN: high spectrum efficiency.

Most CSS schemes with decision fusion in published papers assume an error-free decision transmission. However, such assumption may result in misleading performance interpretations because decision transmission is hardly perfect in realistic scenarios [29]. In this paper, we extend this pure cooperation model by acknowledging the fading/shadowing effects and noise corruption in the common control channels, which are collectively called as noisy CSS. Using numerical and simulation results, we analyze the local performance of energy detection over several typical channels. Moreover, we extend the CSS scheme based on energy detection and the *K out of N rule* by considering the fading/shadowing/ correlated shadowing effects and noise corruption not only in the sensing channels but also in the control channels [12][17][29]. Using the proposed model, we verify if performance deterioration occurs by comparing the extended CSS scheme and the pure case with ideal decision transmission. Finally, we investigate further the optimal fusion strategy in the proposed scheme. We recognize that the optimal value of K in the counting rule depends primarily on the channel characteristics and the detection threshold in local sensing.

The rest of this paper is organized as follows. In Section 2, the system model that considers an imperfect decision transmission is developed. In Section 3, the performance of local sensing, pure CSS, and noisy CSS over different channels are analyzed and simulated. In Section 4, the optimization problem is investigated. In Section 5, the conclusions are drawn.

2. System Model

In the present study, the system setup is a CRN composed of N SUs and a fusion centre (FC), as shown in **Fig. 1**. We assume that each SU performs spectrum sensing simultaneously by detecting the primary signal in the sensing channel. Local binary decisions are sent through the control channels to the FC for combination. The primary signal and decision signals may be faded and noise corrupted during transmission, respectively, due to the imperfections of the communication mediums.

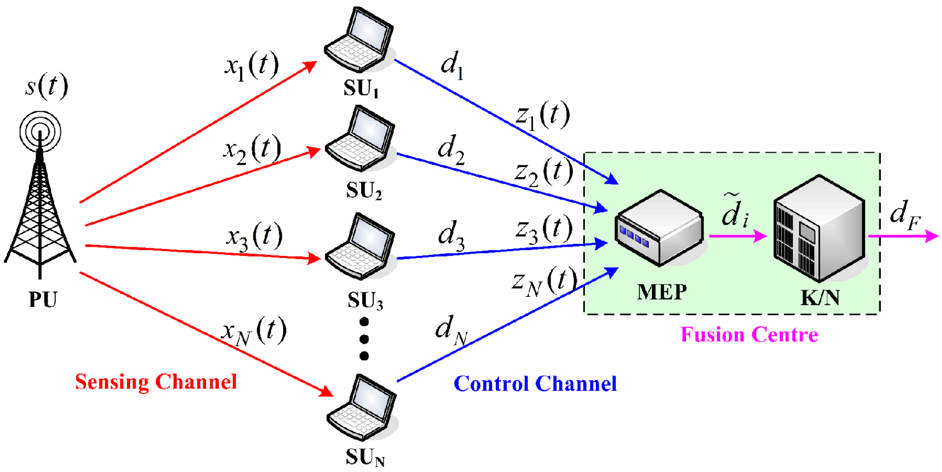


Fig. 1. System setup

2.1 Local Spectrum Sensing

We choose energy detectors for local sensing without obscuring the analysis by employing more sophisticated sensing algorithms, since our goal is to characterize the performance gains achieved by cooperation. **Fig. 2** illustrates the block diagram of an energy detector [8][9], where $x_i(t)$, λ_{si}, d_i, and δ_{si}^2 denote the observed signal, the detection threshold, the local binary decision ('0'/'1'), and the average noise power at SU_i ($i \in [1, N]$), respectively.

According to the detection theory developed by Urkowitz[8], the detection process can be formulated as a binary hypothesis testing problem:

$$Y_i = \frac{1}{\delta_{si}^2}\sum_{n=1}^{2m} x_i^2(n) = \begin{cases} \frac{1}{\delta_{si}^2}\sum_{n=1}^{2m} w_{s_i}^2(n), & H_0 \\ \frac{1}{\delta_{si}^2}\sum_{n=1}^{2m}\left(h_{si}(n)s(n)+w_{si}(n)\right)^2, & H_1 \end{cases} \tag{1}$$

where m is the time-bandwidth product, $m=TW$, T is the observation time, W is the sensing channel bandwidth, $s(n)$ is the sampled primary signal, and Y_i, $h_{si}(n)$, and $w_{si}(n)$ represent the normalized test statistic, the sampled amplitude gain, and the sampled additive white Gaussian noise at SU_i, respectively.

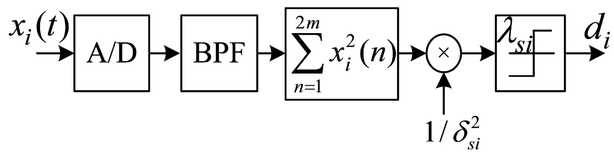


Fig. 2. Block diagram of the i-th energy detector

Y_i has been derived as having a central and a non-central chi-square distributions under H_0 and H_1, respectively [8][9]:

$$Y_i \sim \begin{cases} \chi_{2m}^2, & H_0 \\ \chi_{2m}^2\left(2m\gamma_{si}\right), & H_1 \end{cases} \tag{2}$$

where γ_{si} is the local sensing SNR with the definition

$$\gamma_{si} = \frac{P_{si}}{\delta_{si}^2} = \frac{\frac{1}{2m}\sum_{n=1}^{2m}\left|h_{si}(n)\mathrm{s}(n)\right|^2}{N_{0i}W} \tag{3}$$

N_{0i} denotes the one-sided noise power spectral density, and P_{si} is the received primary signal power. The following generic probabilistic model is typically used in characterizing the local sensing performance:

$$P_{ij} = \Pr\left\{d_i = H_i \mid H_j\right\}, \quad i,j \in \{0,1\}$$

In particular, we use $P_{di} = P_{11}$ and $P_{fi} = P_{10}$ to denote the probabilities of detection and false alarm at SU_i, respectively.

2.2 Decision Transmission

The control channels and the sensing channels are always assumed to have similar characteristics. Thus, the decision transmission model is

$$z_i(t) = h_{ci}(t)Ad_i + w_{ci}(t) \tag{4}$$

where A, $z_i(t)$, $h_{ci}(t)$, and $w_{ci}(t)$ represent the amplification factor, the received signal, the channel gain, and the additive white Gaussian noise with zero mean in the i-th control channel, respectively. Hence, the SNR of the i-th control channel is

$$\gamma_{ci} = \frac{\frac{1}{T_1}\int_0^{T_1} |h_{ci}(t)|^2 A^2 dt}{\delta_{ci}^2} \tag{5}$$

where δ_{ci}^2 is the average noise power.

2.3 Decision Fusion

To realize the spatial diversity, the fusion centre has to accomplish the following tasks [29]:

(1) Estimate the initial local decisions from the received signals, which might have been faded and noise corrupted in the control channels.

(2) Fuse the estimated decisions with the proper combination rules.

For the first step, we use a detector based on the minimum error probability (MEP) criteria [30]. The recovery of the decisions can also be modeled as a binary signal detection problem:

$$z_i(t) = \begin{cases} w_{ci}(t), & D_{io} \\ h_{ci}(t)A + w_{ci}(t), & D_{i1} \end{cases} \tag{6}$$

where D_{io} and D_{i1} denote the initial i-th decision '0' and '1', respectively. The costs of right estimations are always considered to be zero and that of error estimations equal to one, i.e., $c_{00} = c_{11} = 0$, $c_{01} = c_{10} = 1$, $c_{00} = c_{11} = 0$, and $c_{01} = c_{10} = 1$. Thus, the classical Bayesian average risk is reduced to the average error probability

$$\overline{R}_i = P_{ie} = P(D_{i0})P(say\ D_{i1} \mid D_{i0}) + P(D_{i1})P(say\ D_{i0} \mid D_{i1}) \tag{7}$$

where $P(D_{i0})$ and $P(D_{i1})$ are the probabilities of D_{io} and D_{i1}, respectively. Then,

$$P(D_{i0}) = P\{d_i = 0\} = P_{01}P_{H_1} + P_{00}P_{H_0} = (1 - P_{di})P_{H_1} + (1 - P_{fi})P_{H_0} \tag{8}$$

$$P(D_{i1}) = P\{d_i = 1\} = P_{11}P_{H_1} + P_{10}P_{H_0} = P_{di}P_{H_1} + P_{fi}P_{H_0} \tag{9}$$

where P_{H_1} and P_{H_0} denote the probabilities of the presence and the absence of the primary user, respectively. Hence, the MEP-rule based detection can be represented as [30]

$$\Lambda(z_i) = \frac{f(z \mid D_{i1})}{f(z \mid D_{i0})} \mathop{\gtrless}_{D_{i0}}^{D_{i1}} \frac{P(D_{i0})}{P(D_{i1})} = \Lambda_{i0} \tag{10}$$

In the AWGN control channels, the detection process has been derived [30], which can be simplified as

$$\widetilde{d}_i = \begin{cases} 0, & if\ z_i < \lambda_{ci} \\ 1, & if\ z_i \geq \lambda_{ci} \end{cases} \tag{11}$$

where $\lambda_{ci} = \frac{A}{2} + \frac{\delta_{ci}^2 \ln \Lambda_{i0}}{A}$ is the threshold of the MEP detector, and $\widetilde{d}_i$ is the estimate of the i^{th} local decision. The MEP detector requires the knowledge of $P(D_{i0})$ and $P(D_{i1})$ that may be unknown at FC. Therefore, we use the approximation method similar to that given in the literature [29]. With the application of the Strong Law of Large Numbers,

$$\lim_{N\to\infty} \overline{Z} = \lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N} z_i = AP(D_{i1}) \tag{12}$$

An unbiased estimate of $P(D_{i1})$ is $\tilde{P}(D_{i1})=\frac{\overline{Z}}{A}$ because N is finite in practice. Then, $\tilde{P}(D_{i0})=1-\frac{\overline{Z}}{A}$. Thus, λ_{ci} can be approximated as

$$\tilde{\lambda}_{ci}=\frac{A}{2}+\frac{\delta_{ci}^2}{A}\ln\frac{1-\tilde{P}(D_{i1})}{\tilde{P}(D_{i1})}=\frac{A}{2}+\frac{\delta_{ci}^2}{A}\ln\frac{A-\overline{Z}}{\overline{Z}}=\frac{A}{2}+\frac{A}{\gamma_{ci}}\ln\frac{A-\overline{Z}}{\overline{Z}} \tag{13}$$

After the estimation of all the binary decisions $\tilde{d}_1,\tilde{d}_2\cdots\tilde{d}_N$, FC continues to combine them to obtain the final decision d_F for the current sensing period, and then broadcast it to all the cooperative SUs. For simplicity, we choose the *K out of N rule* for the decision combination:

$$d_F=\begin{cases}0, & \sum_{i=1}^{N}\tilde{d}_i<K\\ 1, & \sum_{i=1}^{N}\tilde{d}_i\geq K\end{cases} \tag{14}$$

which means that $d_F=1$ if K or more estimated local decisions are equal to 1. In special cases, the fusion rule is reduced to the OR rule, the AND rule, and the MAJ rule when K is equal to 1, N, and $\lceil N/2\rceil$, respectively.

3. Performance Analysis and Simulation

3.1 Local Sensing Performance

Over the AWGN sensing channels, $h_{si}(n)$ is deterministic. Thus, the probabilities of detection, false alarm, and miss detection at SU_i may be written as [9]

$$P_{di}=P\{Y_i>\lambda_i\,|\,H_1\}=Q_m\left(\sqrt{2m\gamma_{si}},\sqrt{\lambda_i}\right) \tag{15}$$

$$P_{fi}=P\{Y_i>\lambda_i\,|\,H_0\}=1-\Gamma\left(\lambda_i/2,m\right) \tag{16}$$

$$P_{mi}=1-P_{di} \tag{17}$$

respectively, where $Q_m(\cdot,\cdot)$ and $\Gamma(\cdot,\cdot)$ represent the Marcum Q-function and the incomplete gamma function, respectively, with the definitions [31]

$$Q_m(a,b)=\int_b^\infty\frac{x^m}{a^{m-1}}\exp\left(-\frac{x^2+a^2}{2}\right)I_{m-1}(ax)\,dx\,, \tag{18}$$

$$\Gamma(x,a)=\frac{1}{\Gamma(a)}\int_0^x e^{-t}t^{a-1}dt\,, \tag{19}$$

where $\Gamma(a)$ is the gamma function $\Gamma(a)=\int_0^\infty e^{-t}t^{a-1}dt$.

The local performance can be extended to account for different channel effects, such as fading/shadowing [9]. As expected, P_f remains constant under any channel because it is considered when the primary signal is absent, and is thus independent of the sensing SNR. When the sensing channel gain varies due to fading/shadowing, the average probability of detection can be derived by averaging P_{di} in (15) over the probability density function (PDF) of γ_{si} [9],

$$\overline{P}_{di} = \int_{\gamma_{si}} Q_m\left(\sqrt{2mx}, \sqrt{\lambda_i}\right) f_{\gamma_{si}}(x)\,dx \tag{20}$$

In general, the SNR of a practical channel can be statistically represented via the combination of three terms [17]:

$$SNR_{dB} = \overline{SNR}_{dB} + Shadow_{dB} + Fading_{dB} \tag{21}$$

where the three terms in dB on the right denote the mean SNR, the shadowing (also called large scale fading) effects, and the small scale fading effects, respectively. The characteristics of several typical channels often used in wireless communication are summarized as follows:

Log-normal shadowing channel: After attenuation by the obstacles in the propagation path, the empirical measurements suggest that the variation of the received power follows a normal distribution when represented in dB. Thus, the PDF of the linear SNR γ (as opposed to dB) is [17]

$$f_\gamma(x) = \frac{10}{\ln(10)\sigma_{dB}} \frac{1}{\sqrt{2\pi}x} \exp\left(-\frac{\left(10\log(x) - 10\log(\overline{\gamma})\right)^2}{2\sigma_{dB}^2}\right) \tag{22}$$

where σ_{dB} is the dB-spread of the shadowing effects, and $\overline{\gamma}$ is the average SNR.

Rayleigh channel: The signal amplitude in this kind of channel follows a Rayleigh distribution, and γ follows an exponential PDF [9]:

$$f_\gamma(x) = \frac{1}{\overline{\gamma}} \exp\left(-\frac{x}{\overline{\gamma}}\right) \tag{23}$$

Nakagami channel: In this channel, the signal amplitude follows a Nakagami distribution. Then, γ follows a gamma PDF [9]:

$$f_\gamma(x) = \frac{1}{\Gamma(g)} \left(\frac{g}{\overline{\gamma}}\right)^g x^{g-1} \exp\left(-\frac{g}{\overline{\gamma}}x\right) \tag{24}$$

where g is the Nakagami parameter, and the channel is reduced to either AWGN when $g = \infty$, or Rayleigh when $g = 1$.

Suzuki channel: This channel is a mixture of Rayleigh and Shadowing effects, and γ follows a Suzuki distribution [17]:

$$f_\gamma(x) = \int_0^\infty \frac{1}{t^2} \frac{10}{\ln(10)} \frac{1}{\sqrt{2\pi\sigma_{dB}}} \exp\left(-\frac{x}{t} - \frac{\left(10\log(t) - 10\log(\overline{\gamma})\right)}{2\sigma_{dB}^2}\right) dt \tag{25}$$

Closed expressions and numerical results of the performance in some of the above channels have been given in the literature [9][12][17]. To validate the analysis above, we perform a simulation study on the local sensing. First, we choose a BPSK signal as the primary signal. After its transmission in the fading/shadowing channels listed above, an energy detector is used to sense its presence via Monte Carlo simulation with 100,000 trials. The simulation parameters are given as follows: $m = 5$, $\overline{\gamma}_s = 5dB$, $\sigma_{dB} = 6dB$, and $g = 3$. **Fig. 3** shows the complementary receiver operating characteristic (CROC) curves (plot of P_m vs P_f) over these channels. The corresponding theoretical results calculated by numerical integration methods in (20) are also given for comparison. The simulation results clearly coincide well with that in theory. The detection over the AWGN channel outperforms other cases most of the time. In contrast, the Suzuki channel provides the worst-case scenario among all of the listed channels. Further simulations are also performed with some primary signals that are more complicated, such as a mixed signal. The results are very similar with that in **Fig. 3**, which verifies that the energy detector solely depends on signal power, rather than on signal forms or any other prior knowledge.

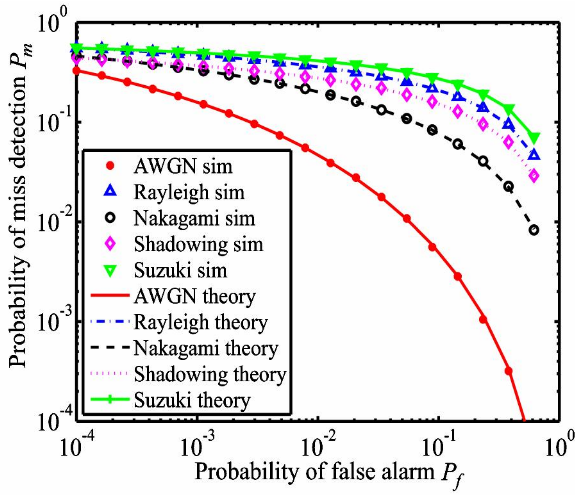


Fig. 3. Complementary receiver operating characteristic (CROC) curves of local energy detection over typical channels

3.2 Collective Sensing Performance of CSS

For simplicity, the relative distances between any two SUs are assumed to be smaller than their distances to the PU. Thus, we first consider that all N SUs experience independent and identically distributed channel effects, with the same $\bar{\gamma}_s$ in all sensing channels and the same $\bar{\gamma}_c$ in all control channels. Spatially correlated shadowing is discussed later.

For the AWGN scenario, the primary signal and the local decisions are assumed to be only corrupted by noise without any fading or shadowing, $w_s \sim N(0,\delta_s^2)$ and $w_c \sim N(0,\delta_c^2)$. Intuitively, the equivalent local performance at FC after decision estimation may deteriorate to some extent. For SU_i, the equivalent local probabilities of false alarm and detection can be derived as follows:

$$\begin{aligned}\widetilde{P}_{fi} &= P\{\widetilde{d}_i = 1 \mid H_0\} \\ &= P\{\widetilde{d}_i = 1 \mid d_i = 1\}P\{d_i = 1 \mid H_0\} + P\{\widetilde{d}_i = 1 \mid d_i = 0\}P\{d_i = 0 \mid H_0\} \\ &= P\{z_i > \lambda_{ci} \mid D_{i1}\}P_{fi} + P\{z_i > \lambda_{ci} \mid D_{i0}\}\left(1 - P_{fi}\right) \\ &= P\{w_{ci} > \lambda_{ci} - A\}P_{fi} + P\{w_{ci} > \lambda_{ci}\}\left(1 - P_{fi}\right) \\ &= Q\left(\frac{\lambda_{ci} - A}{\delta_{ci}}\right)P_{fi} + Q\left(\frac{\lambda_{ci}}{\delta_{ci}}\right)\left(1 - P_{fi}\right)\end{aligned} \tag{26}$$

$$\widetilde{P}_{di} = P\{\widetilde{d}_i = 1 \mid H_1\} = Q\left(\frac{\lambda_{ci} - A}{\delta_{ci}}\right)P_{di} + Q\left(\frac{\lambda_{ci}}{\delta_{ci}}\right)\left(1 - P_{di}\right) \tag{27}$$

where $Q(x)=\frac{1}{\sqrt{2\pi}}\int_x^{\infty}\exp\left(-t^2/2\right)\,dt$.

After fusion by the *K out of N rule*, the collective probabilities of false alarm, detection, and miss detection are

$$\widetilde{Q}_f=\sum_{n=K}^{N}\binom{N}{n}\widetilde{P}_{fi}^{\,n}\left(1-\widetilde{P}_{fi}\right)^{N-n}=1-B_F\left(K-1,N,\widetilde{P}_{fi}\right) \tag{28}$$

$$\widetilde{Q}_d=\sum_{n=K}^{N}\binom{N}{n}\widetilde{P}_{di}^{\,n}\left(1-\widetilde{P}_{di}\right)^{N-n}=1-B_F\left(K-1,N,\widetilde{P}_{di}\right) \tag{29}$$

$$\widetilde{Q}_m=B_F\left(K-1,N,\widetilde{P}_{di}\right) \tag{30}$$

respectively, because the noise statistics of all SUs are the same. In (30), $B_F\left(m,M,p\right)=\binom{M}{m}p^m\left(1-p\right)^{M-m}$ is the Binomial cumulative distribution function [31].

Furthermore, we can also obtain the average performance in fading/shadowing scenarios with variational γ_s and γ_c by integrating (28)–(30) with the PDFs of γ_s and γ_c :

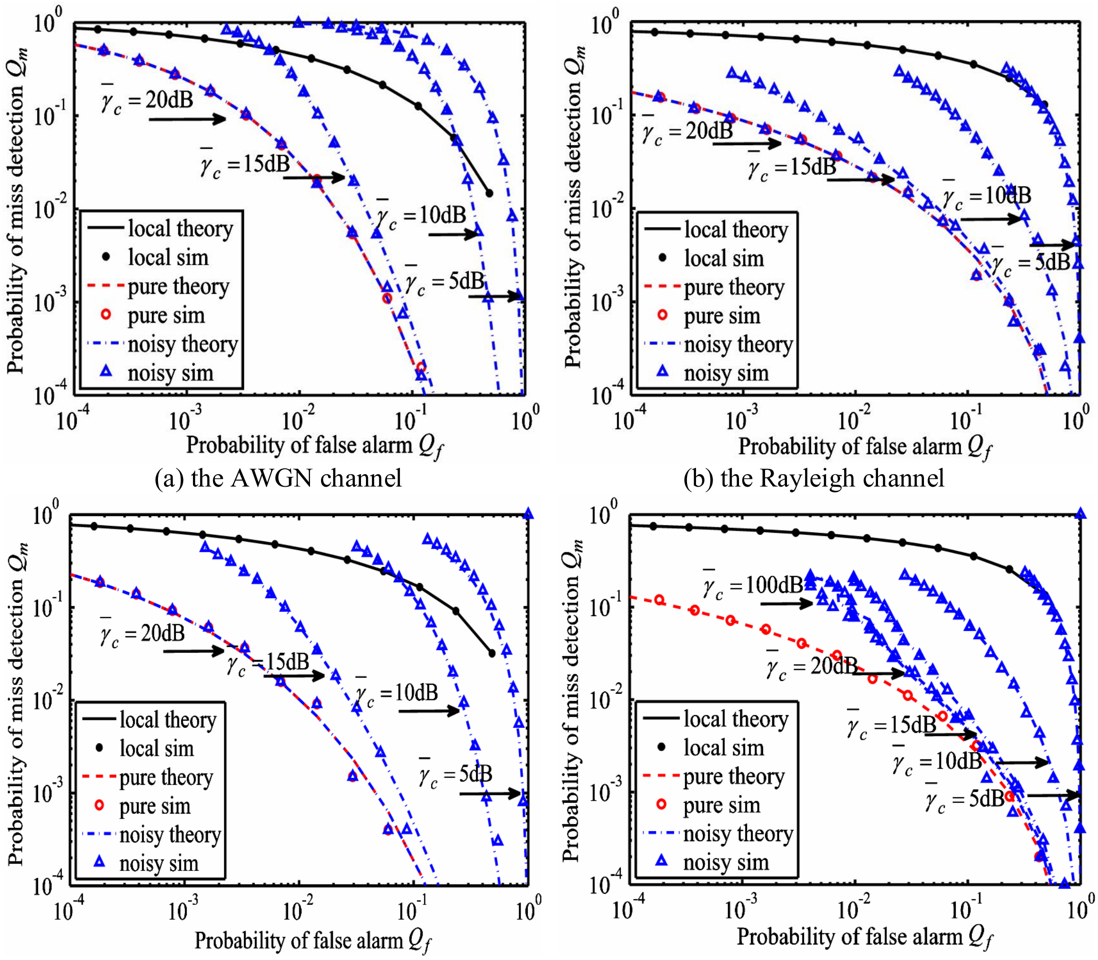
$$\widetilde{Q}_{f,avg}=\int_{\gamma_c}\int_{\gamma_s}\widetilde{Q}_f f_{\gamma_s}(x)f_{\gamma_c}(y)dxdy \tag{31}$$

$$\widetilde{Q}_{d,avg}=\int_{\gamma_c}\int_{\gamma_s}\widetilde{Q}_d f_{\gamma_s}(x)f_{\gamma_c}(y)dxdy \tag{32}$$

$$\widetilde{Q}_{m,avg}=1-\widetilde{Q}_{d,avg} \tag{33}$$

The CROC curves of CSS with noisy decisions over several typical channels for various $\overline{\gamma}_c$ are plotted in **Fig. 4-(a)–(d)**. These plots are obtained by numerical computation and are also verified with Monte Carlo simulation according to Section 2 with 100,000 trials. The simulation process is performed with a BPSK primary signal and 10 SUs ($N=10$), and setting other parameters as $m=10$, $\overline{\gamma}_s=0dB$, $\sigma_{dB}=2dB$, and $K=1$ (the OR rule). For comparison, the corresponding simulated and theoretical performance of local sensing and pure CSS (i.e., the CSS scheme without any fading or noise corruption in the control channels [12]) are also shown. Thus, in all below figures, we use 'noisy', 'local,' and 'pure' as shorthand representations of the three schemes, and also, we use Q_f and Q_m to denote their general probabilities of false alarm and miss detection, respectively.

As expected, CSS can effectively counteract the deleterious impacts of fading/shadowing in sensing channels because the decision fusion can result in a higher chance of having a user with its sensing SNR well above the average. However, there is a performance drop in the noisy CSS compared with that in the pure case. This drop is due to the transmission error of the local decisions caused by fading/shadowing effects and noise corruption in the common control channels. The collective performance of noisy CSS is even worse than the local performance when $\overline{\gamma}_c$ is lower than some value, for example 10dB over AWGN channel, and 5dB over Rayleigh channel. This implies no necessity for cooperation under such condition. Moreover, the performance of noisy CSS improves as $\overline{\gamma}_c$ increases. It is almost equivalent to that of the pure case when $\overline{\gamma}_c$ is higher than 20dB over all listed channels, except for the Suzuki channel where there is always a gap between the two cases even when $\overline{\gamma}_c$ is very high [**Fig. 4-(d)**].



(a) the AWGN channel (b) the Rayleigh channel

(c) the Shadowing channel (d) the Suzuki channel

Fig. 4. Complementary receiver operating characteristic (CROC) curves of CSS with noisy decisions for various average control SNRs over different channels

3.3 Spatially Correlated Shadowing Effects

The analysis and simulations above are based on the condition that all SUs experience independent channel effects. This is safely assumed for scenarios with only multipath fading like Rayleigh and Nakagami [32]. However, in practice, there is usually a degree of spatial correlation associated with the log-normal shadowing, which will degrade the performance of CSS intuitively because similar shadowing effects of different SUs may partly counter the collaboration gain [12][32]. To examine the impact of correlated shadowing, we employ an exponential correlation model given in the literature [32]:

$$R_{ij} = \exp\left(-\alpha b_{ij}\right) \tag{34}$$

where R_{ij} and b_{ij} ($i, j \in [1, N]$) denote the correlation factor and distance between the SU_i and SU_j, respectively; and α is an environment-dependent parameter, with $\alpha \approx 0.1204$ in urban areas and $\alpha \approx 0.002$ in suburban areas[32]. The random variable (RV) for shadowing without correlation in the i-th sensing or control channel can be represented as

$$Shadow_{i,\mathrm{dB}} = \sigma_{\mathrm{dB}} X_i \tag{35}$$

where X_i is an RV with standard Gaussian distribution. If the correlation is considered, the RV becomes

$$\begin{aligned} Shadow_{i,\mathrm{dB}} &= \sqrt{R_{i1}}\sigma_{\mathrm{dB}}X_1 + \sqrt{R_{i2}}\sigma_{\mathrm{dB}}X_2 + \cdots \sqrt{R_{ii}}\sigma_{\mathrm{dB}}X_i + \cdots + \sqrt{R_{iN}}\sigma_{\mathrm{dB}}X_N \\ &= \sum_{j=1}^{N}\sqrt{R_{ij}}\sigma_{\mathrm{dB}}X_j = \sum_{j=1}^{N}\sqrt{C_{ij}}X_j \end{aligned} \tag{36}$$

where C_{ij} denotes the element of the covariance matrix,

$$C_{ij} = Cov\left(Shadow_{i,\mathrm{dB}}, Shadow_{j,\mathrm{dB}}\right) = R_{ij}\sigma_{\mathrm{dB}}^2 \tag{37}$$

The correlated shadowing effect is obviously closely bound up with the topology of the CRN. In the following simulation, we consider a centralized case where 10 SUs are uniformly distributed around a circle with FC as the centre and r as the radius. **Fig. 5** shows the CROC curves of CSS with correlated shadowing over the Suzuki channels for various values of r. Both the pure and noisy cooperation cases are considered with the parameters set as $m=10$, $\overline{\gamma}_s = 0\text{dB}$, $\overline{\gamma}_c = 20\text{dB}$, $\sigma_{\mathrm{dB}} = 2\text{dB}$, $\alpha \approx 0.002$, $N=10$, and $K=1$ (the OR rule). The spatial correlation degrades the performance of CSS under both the noisy and pure models for all values of r. Furthermore, this effect becomes significant when the users are dispersed over a smaller circle, which suggests that cooperation over a large distance is more feasible than a dense case confined to a small area.

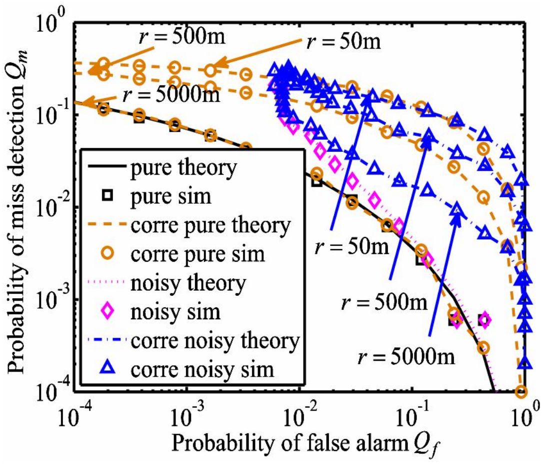


Fig. 5. Complementary receiver operating characteristic (CROC) curves of the CSS with correlated shadowing over the Suzuki channels for various values of r

4. Optimization of the Cooperative Spectrum Sensing

In this section, we investigate the optimal K in the counting rule used for the decision fusion at FC. Under the Bayesian criteria, we aim at minimizing the total error rate Θ denoted by

$$\underset{1\le K\le N}{Min} \quad \Theta = W_f Q_f + W_m Q_m \tag{38}$$

where W_f is the cost of false alarm, and $W_m = 1 - W_f$ corresponds to the miss detection cost.

Both the pure and noisy CSS are studied using the general numerical search method according to (28)–(33) and (38), and their optimal fusion strategies (i.e., optimal values of K)

can be obtained. Given $m=10$, $\overline{\gamma}_s=0dB$, $\overline{\gamma}_c=10dB$, $\sigma_{dB}=2dB$, $N=10$, $W_f=0.2$, and $W_m=0.8$, **Figs. 6-(a)–(d)** show the error rate curves as the function of the local sensing threshold λ_{si} for several typical values of K ($K=1,5,10,K_{opt}$) over the AWGN, Rayleigh, Shadowing, and Suzuki channels, respectively. The optimal fusion strategy compares quite favorably with the non-optimal cases over these channels. As expected, there is always a higher error rate in the noisy CSS because the fading/shadowing effects or noise corruption during decision transmission, aside from the local detection algorithms limitation, may also lead to error decisions at FC. **Fig. 7** shows the exact optimal values of K for different λ_{si} over the AWGN and Suzuki channels. Although the detailed values of K_{opt} for specified λ_{si} under different scenarios are clearly not the same, their variation trends coincide well with each other, that is, as the detection threshold increases, the optimal value decreases.

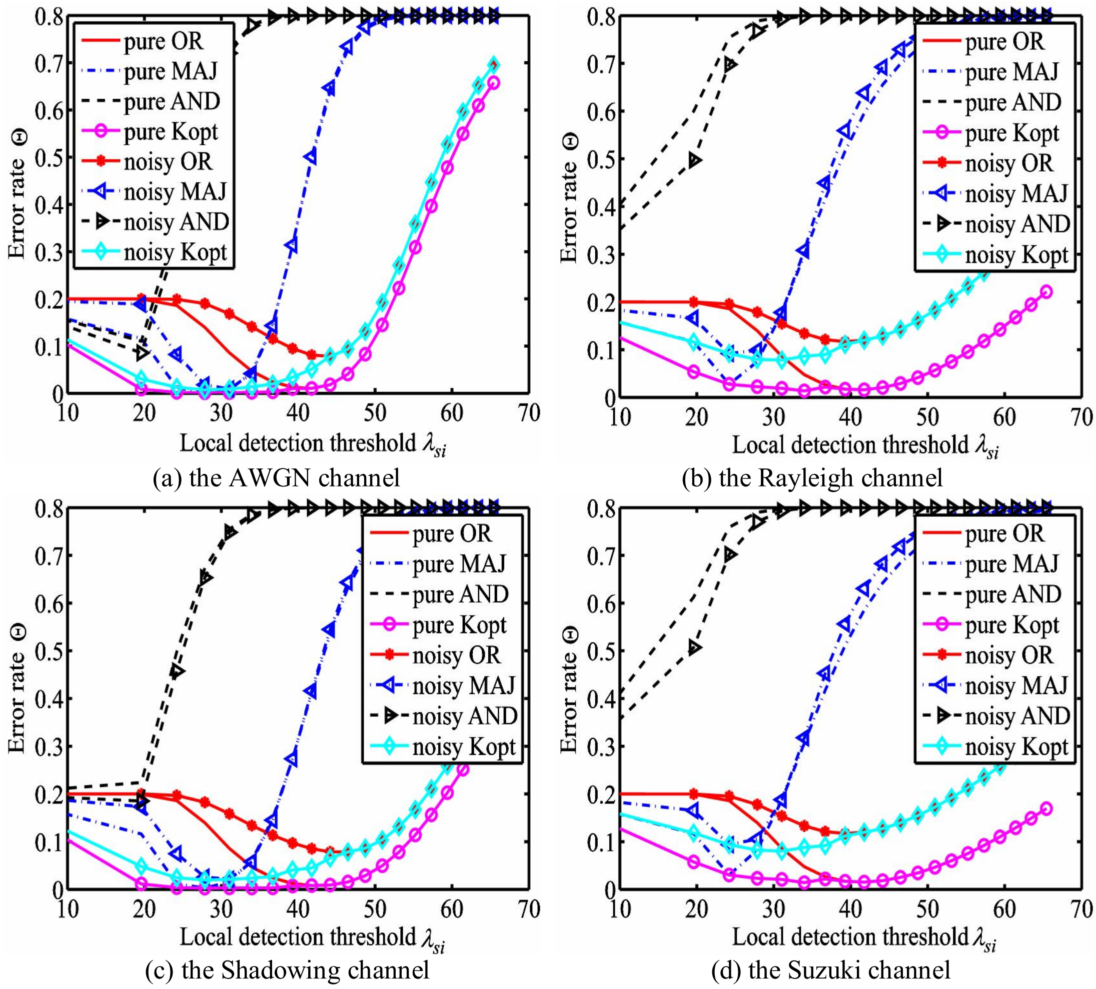


Fig. 6. Comparison of the total error rate in the noisy and pure CSS for different K over different channels

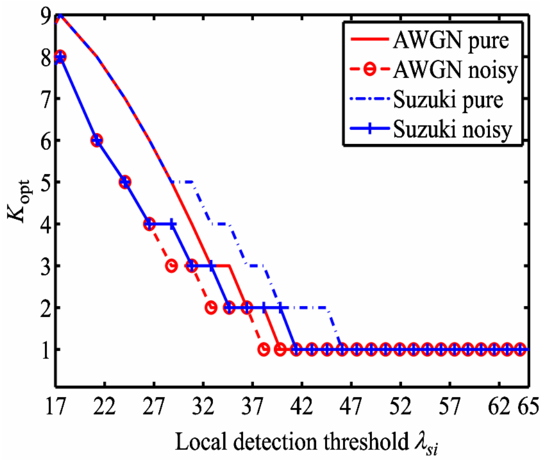


Fig. 7. Optimal fusion strategy (versus local detection threshold) of CSS over the AWGN and Suzuki channels

5. Conclusion and Future Work

In this paper, we have investigated the CSS scheme based on energy detection and the *K out of N rule* under an extended system model that considers an imperfect decision transmission in the control channels. Before the final combination, the fusion centre estimates the initial decisions utilizing an MEP binary detector because the received decisions may fade and be noise corrupted during transmission. As demonstrated by both the numerical and simulation results over several typical channels, the performance gains of CSS relative to the local sensing under the proposed model have some degradation compared with that in the ideal case that assumes an error-free decision transmission. The performance gains are even insignificant if the average SNR in the control channel is very low. Moreover, we have also investigated the optimization problem under this practical model to minimize the total error rate. The results suggest a decreased variation trend in the optimal value of K with the increasing local threshold.

Although we have studied the effect of imperfect control channels on the performance of the traditional K/N-rule-based CSS, more studies must be conducted to develop efficient CSS schemes in such an environment [33]. For example, designing a joint local decision recovery and final decision fusion scheme is a helpful tool. In addition, characterizing the performance of CSS schemes under different spatial distributions of cooperative users and different correlation models of shadowing effects is of great importance. Other interesting issues for future research include extending the uncertainty models of the control channels by error probability, which can generally accommodate any distorting effects, and also, developing some online algorithms [34] for maximizing the throughput of CRN when the sensing outcome is not always reliable.

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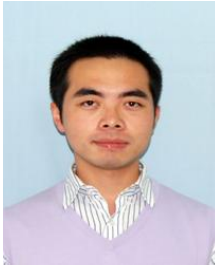

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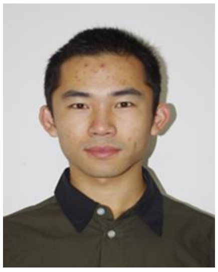

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