# Collaborative spectrum sensing by combining energy and Cyclostationarity-based Detection schemes

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**Abstract:** In this paper, the problem of spectrum sensing in cognitive radio communication networks is considered. This paper proposes a robust decision fusion scheme that can perform well when interference caused by other sources is present. Specifically, the proposed detection scheme is based on fusing the local decisions from energy detectors and cyclostationarity-based detectors. The proposed fusion scheme is different from other power spectrum-sensing technology developed so far in that other fusion technologies are based on fusing the local decisions from the same type of detectors instead of the different types of detectors as considered here. The proposed scheme was compared with schemes fusing the same type of detectors, and the results show that the proposed scheme is more robust against possible interference.

**Keywords:** spectrum sensing; energy detection; cyclostationary detection; cognitive radio; decision fusion; distributed detection; robust; interference.

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## 1 Introduction

Access to the radio spectrum is currently granted exclusively to individual telecom operators. However, it is shown that not all the spectrum is used for all the available time through investigations of spectrum utilisation. Indeed, it is shown that 15–85% of the allocated spectrum is idle in some locations or some times of the day (Sadeghi and Azmi, 2008; Cabric et al., 2004). Hence, it is clear that the radio spectrum is not utilised in an efficient way (Sridhara et al., 2008). The problem above calls for the design of the dynamic spectrum access or cognitive radios (Mitora and Maquire, 1999; FCC, 2003; Zhang and Zheng, 2010; El-Hajj et al., 2011; Habachi and hayel, 2012; Lopez-Benitez and Casadevall, 2012), which makes the use of unused spectrum by sensing the spectrum hole and renders the utilisation of radio spectrum more efficient (Yucek and Arslan, 2009). Similar ideas to the dynamic spectrum access can be also found in Hwang et al. (2010) and Du et al. (2009). In cognitive radio networks, Primary Users (PUs) or licensed users can use a specific part of the spectrum with higher priority, and Secondary Users (SUs), who have lower priority, exploit this spectrum in a way so that they do not cause interference to PUs. Therefore, SUs need to have the ability of spectrum sensing to check whether the spectrum is used by PUs.

Therefore, the dynamic spectrum access has been proposed to solve these current spectrum inefficiency problems. Dynamic spectrum access techniques allow cognitive radio networks to operate in the best available channel. In CR networks, there are two kinds of users. One is the primary (licensed or legal) users, the other is the CR or SUs. The basic idea of CR networks is to share the rare spectrum. This means that secondary users are allowed to access the licensed spectrum.

The most common techniques of spectrum sensing for cognitive radios in the literature are Energy Detection (ED) (Urkowitz, 1967; Digham et al., 2007) and Cyclostationarity-based Detection (CD) (Ye et al., 2007; Gardner, 1988; Dandawat and Giannakis, 1994). ED and CD both have their advantage and drawback in spectrum sensing. ED has the advantage of low computational complexity and without the need of the prior knowledge of the modulation types employed by primary users. However, the performance of ED could degrade significantly in an interference-limited environment. As opposed to ED, CD requires the knowledge of the modulation type or data rate and hence has the advantage of being robust against the interference caused by other sources. However, CD has higher computational complexity as compared with ED. According to the statement above, the motivation was to design a robust spectrum-sensing detector against unknown interference and the detector should also perform well when no interference is present. The goal is achieved in this work by fusing the decisions from both ED and CD. Specifically, the decision fusion technique developed in the area of distributed detection (Varshney, 1997) is applied to the problem to combine the decisions from ED and CD. In Ganesan and Li (2007a, 2007b), the decision fusion approach is also utilised to combine the decisions made by different SUs. The problem is different from Ganesan and Li (2007a, 2007b) in that local decisions are fused from different types of detectors to achieve the goal of robustness. It is worth mentioning that the proposed decision fusion scheme employed at the fusion centre does not pay for more computational amount because the fusion centre simply employs the distributed detection technique to fuse the local decisions from SUs. The increasing computational complexity due to the use of CD is only at the SU, which is commonly assumed to have the hardware or software built for CD. The simulation results obtained from the conducted example show that the proposed scheme is more robust against all possible interference when compared with the conventional fusion scheme, which combines the local decision with the same type of detectors.

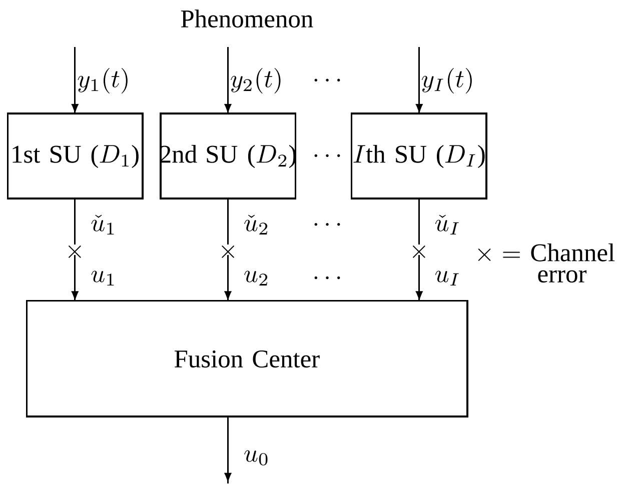
The organisation of the paper is as follows. Section 2 introduces the considered system model. Both ED and CD techniques for power spectrum sensing are also briefly introduced in the section. Section 3 proposes the distributed detection scheme, combining the local decisions with both ED and CD. Performance evaluation of the proposed scheme is provided in Section 4. Section 5 concludes this paper.

## 2 System model and spectrum-sensing methods

### 2.1 Network operation

As depicted in Figure 1, $I$ SUs denoted as $D_i$, $i = 1, \ldots, I$, and a fusion centre are used to detect whether or not the PU is using its spectrum in a collaborative manner. In this paper, hypothesis $H_0$ represents that PU is not present. On the other hand, alternative $H_1$ represents that PU is active. The *a* *priori* probabilities of $H_0$ and $H_1$ are denoted by $\pi_0$ and $\pi_1$, respectively. When performing spectrum sensing, each $D_i$ observes the phenomenon and takes its own observation, $y_i(t)$, $i = 1, \ldots, I$. In this paper, it is assumed that the observations are conditionally independent given $H_0$ or $H_1$. Each detector makes a local decision $\check{u}_i$ in favour of either the presence or absence of PU based on its own observations $y_i(t)$. In this paper, $\check{u}_i = 0$ is made if the $i$th SU decides the absence of PU, and $\check{u}_i = 1$ is made, otherwise. After each SU makes its decision locally, it sends its binary decision to the fusion centre. Due to channel transmission errors, the fusion centre receives $u_i$, where $u_i$ may or may not equal $\check{u}_i$. In addition, an assumption is made that a communication error event, i.e., $[u_i \neq \check{u}_i]$ is independent across SUs. The probability $\Pr[u_i \neq \check{u}_i]$ is denoted by $\epsilon_i$. Hereafter, $\epsilon_i = \epsilon$ is set for each $i$. After receiving $u_i$, $i = 1, \ldots, I$, the fusion centre then combines them to produce a final decision $u_0$. In this work, $u_0 = 0$ is made if the fusion centre decides the absence of PU, and $u_0 = 1$ is made, otherwise. The aim is to develop a decision fusion scheme to combine the local decisions made by different types of detectors such that the collaborative spectrum sensing is robust against the unknown interference.

**Figure 1** System model for collaborative power spectrum sensing




## 2.2 Energy Detection at a single SU

When performing power spectrum sensing, the detector at the $i$th SU will decide whether or not the PUs are present based on the received signals $y_i(t)$. Let $y_i[k]$ be the sample of received signal $y_i(t)$, $k = 0, \ldots, N-1$, and $N$ is the number of samples. The binary-hypopaper-testing problem can be formulated as

$$\begin{aligned} &H_0 : y_i[k] = n_i[k]; \\ &H_1 : y_i[k] = x[k] + n_i[k], \end{aligned} \tag{1}$$

where $x[k]$ is the transmitted signal from the PUs with its variance equalling $\sigma_x^2$, and the noise $n_i[k]$ is an additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_n^2$.

The decision statistic for energy detection in the discrete-time model is then the sum of the squares of samples, which is expressed as

$$\mathcal{T}_i = \sum_{k=0}^{N-1} (y_i[k])^2. \tag{2}$$

The distribution of $\mathcal{T}_i$ conditioned on $H_0$ and $H_1$ is given by

$$\mathcal{T}_i \sim \begin{cases} \chi_N^2 & H_0 \\ \chi_N^2(2\gamma) & H_1 \end{cases}, \tag{3}$$

where $\gamma$ denotes the received signal SNR. In addition, $\chi_N^2$ and $\chi_N^2(2\gamma)$ are central and non-central chi-square with a non-centrality parameter of $2\gamma$, respectively, and both are with $N$ degrees of freedom. The ED scheme compares the statistic $\mathcal{T}_i$ with a given threshold $\Gamma_e$, and the decision is then made in accordance with

$$\begin{aligned} &\mathcal{T}_i > \Gamma_e \text{ decide PU signal present;} \\ &\mathcal{T}_i < \Gamma_e \text{ decide PU signal absent.} \end{aligned} \tag{4}$$

If the number of samples, $N$, is large enough, the distribution of statistic $\mathcal{T}_i$ converges to Gaussian distributions under both hypotheses $H_1$ and $H_0$ in accordance with the central limit theorem Cabric et al. (2006a), and are given by

$$\begin{aligned} &\mathcal{T}_i \sim \mathcal{N}(N\sigma_n^2, 2N\sigma_n^4) \text{ under } H_0 \\ &\mathcal{T}_i \sim \mathcal{N}(N(\sigma_n^2 + \sigma_x^2), 2N(\sigma_n^2 + \sigma_x^2)^2) \text{ under } H_1. \end{aligned} \tag{5}$$

Accordingly, the probabilities of false alarm and detection resulted from the decision rule in equation (4) are, respectively, given by

$$P_f = Q\left(\frac{\Gamma_e - N\sigma_n^2}{\sqrt{2N\sigma_n^4}}\right), \tag{6}$$

and

$$P_d = Q\left(\frac{\Gamma_e - N(\sigma_n^2 + \sigma_x^2)}{\sqrt{2N(\sigma_n^2 + \sigma_x^2)^2}}\right). \tag{7}$$

## 2.3 Cyclostationarity-based Detection at a single SU

It is known that the modulated signals are generally coupled with sine wave carriers, pulse trains, etc., which results in built-in periodic property for the modulated signals. Therefore, a modulated signal $y_i(t)$ can be characterised as cyclostationary. Specifically, let $y_i(t)$ be a zero-mean random process with values in $\mathbb{R}$, then $y_i(t)$ is said to be cyclostationary if

$$c_{y_i y_i}(t, \tau) = E\left[y_i(t) y_i(t+\tau)\right] = c_{y_i y_i}(t + T_d, \tau), \tag{8}$$

where $T_d$ is the cyclic period. When using a Fourier series to represent $c_{y_iy_i}(t,\tau)$ with respect to time $t$, we have

$$c_{y_iy_i}(t,\tau) = c_{y_iy_i}(\tau) + \sum_{\alpha\in\psi} C_{y_iy_i}(\alpha,\tau)\mathrm{e}^{j2\pi\alpha t}, \tag{9}$$

where $C_{y_iy_i}(\alpha,\tau)$ is named the cyclic covariance function and is given by

$$C_{y_iy_i}(\alpha,\tau) = \lim_{Z\to\infty}\frac{1}{Z}\int_{-Z/2}^{Z/2} c_{y_iy_i}(t,\tau)\mathrm{e}^{j2\pi\alpha t}, \tag{10}$$

where $\alpha$ is said to be the cyclic frequency and $\psi$ is the total set of cyclic frequencies. Note that if the random process $y_i(t)$ is stationary, then the statistical properties of $y_i(t)$ is independent of time, and equation (9) reduces to

$$c_{y_iy_i}(t,\tau) = c_{y_iy_i}(\tau).$$

Due to the cyclostationary property, $c_{y_iy_i}(t,\tau)e^{j2\pi\alpha t} = E[y_i(t)y_i^*(t-\tau)e^{j2\pi\alpha t}]$ is non-zero for certain values of $\alpha\in\psi$. On the other hand, for a signal which does not exhibit cyclostationarity, for example, white Gaussian noise, it will go to zero for all $\alpha\neq 0$. Let us define $\bar{c}_{y_iy_i}(t,\tau) = c_{y_iy_i}(t,\tau) - c_{y_iy_i}(\tau)$. Then based on the discussion above and the definition of hypotheses, CD is to perform the following hypotheses testing problem:

$$\begin{aligned} &H_0 : \bar{c}_{y_iy_i}(t,\tau) = 0;\\ &H_1 : \bar{c}_{y_iy_i}(t,\tau) \neq 0. \end{aligned} \tag{11}$$

Using the sampled version of $y_i(t)$ and the same number of samples as ED, equation (8) can be expressed as

$$\hat{c}^{(S)}_{y_iy_i}(k,\tau) = \frac{1}{S}\sum_{s=0}^{S-1} y_i[k+sq]y_i[k+sq+\tau], \quad k\in[0,q-1], \tag{12}$$

where $q = N/S$ is an integer. The estimator given in equation (12) is the appropriate estimator of $c_{y_iy_i}(t,\tau)$ for cyclostationary signals with cyclo-period equalling $q$ or one from the integer fraction of $q$ (Ghozzia et al., 2006) (see also Dandawat and Giannakis (1994)), i.e., the cyclic frequencies set $\psi$ is $\{\frac{m}{q}\}_{m\in N,\frac{m}{q}<1}$.

Given a fixed $\tau$, the estimator in equation (12) can be used to construct the following row vector:

$$\hat{c}^{(S)}_{y_iy_i} \triangleq [\hat{c}^{(S)}_{y_iy_i}(0,\tau),\ldots,\hat{c}^{(S)}_{y_iy_i}(q-1,\tau)].$$

Subtracting the vector $\hat{c}^{(S)}_{y_iy_i}$ by its mean $\bar{c}_{y_iy_i}(n,\tau)$, we can obtain the row vector $\hat{\bar{c}}^{(S)}_{y_iy_i}$. The covariance matrix $\hat{\Sigma}$ is then calculated in accordance with

$$\begin{aligned}\hat{\Sigma}\{\hat{c}^{(S)}_{y_iy_i}(k,\tau),\hat{c}^{(S)}_{y_iy_i}(j,\gamma)\} &= \hat{\Sigma}\{z^{k,\tau}(s), z^{j,\gamma}(s)\}\\ &= \frac{1}{S}\sum_{s=0}^{S-1} z^{k,\tau}(s)z^{j,\gamma}(s),\end{aligned} \tag{13}$$

where $z^{k,\tau}(s) = y_i\left[k+\frac{sN}{S}\right]y_i\left[k+\frac{sN}{S}+\tau\right]$.

To test the hypothesis given in equation (11), we then compute the value of the test statistic $\ell_i = S\hat{\bar{c}}^{(S)}_{y_iy_i}\hat{\Sigma}\hat{\bar{c}}^{(S)T}_{y_iy_i}$, where $T$ denotes the operation of matrix transpose. In Dandawat and Giannakis (1994) and Ghozzia et al. (2006), it is shown that, under $H_0$, $\ell_i$ converges in distribution to $\chi^2_q$, where $\chi^2_q$ is chi-square distribution with $q$ degrees of freedom. Hence, the chi-square test (Cramer, 1999) is used for the CD to perform the binary-hypothesis-testing problem, and makes the decision in accordance with

$$\begin{aligned} &\ell_i > \Gamma_c \text{ decide PU signal present;}\\ &\ell_i < \Gamma_c \text{ decide PU signal absent,}\end{aligned} \tag{14}$$

where the threshold $\Gamma_c$ is chosen to satisfy a given false alarm rate, i.e.,

$$P_F = \Pr(\breve{u}_i = 1|H_0) = \Pr(\ell_i > \Gamma_c|H_0) \leq q_f.$$

It is worth mentioning that when the chi-square test is employed, the probability of detection, i.e., $\Pr(\breve{u}_i = 1|H_1)$, approaches 1 when $q\to\infty$ (see Cramer (1999)). This implies that the CD has almost zero probability of making a wrong decision when PUs are using the spectrum.

## 3 Collaborative detection using both EDs and CDs

The works in Yucek and Arslan (2009) and Cabric et al. (2006b) state that CD performs worse than ED when the noise is stationary. However, CD is more robust against possible interference (Lin and Chen, 2008). If ED is employed at $i$th SU, the received signal at $i$th SU is given in equation (1). When the number of samples, $N$, is large enough,[1] the statistic given in equation (2) under $H_0$ and $H_1$ can be approximated as a Gaussian random variable in equation (5). In this case, we can employ the optimal detector, i.e., the Likelihood Ratio Test (LRT), for ED and is given by

$$\Lambda(\mathcal{T}_i) = \frac{\Pr(\mathcal{T}_i|H_1)}{\Pr(\mathcal{T}_i|H_0)} \underset{\breve{u}_i=0}{\overset{\breve{u}_i=1}{\gtrless}} \frac{\pi_0}{\pi_1} = \eta. \tag{15}$$

If CD is employed at $i$th SU, then the chi-square test given in equation (14) is used to make decisions $\breve{u}_i$. It is worthy to note that the LRT test cannot be employed for the considered CD since the distribution of the statistic $\ell_i$ given $H_1$ is difficult to obtain. After the decisions $\breve{u}_i$, $i = 1,\ldots,I$ are locally made, the fusion centre then receives the decisions, $u_i$, $i=1,\ldots,I$. Since the binary symmetric channel is assumed between each SU and the fusion centre, the received local detection performance can be expressed as

$$\Pr(u_i|H_j) = \sum_{\breve{u}_i=0}^{1}\Pr(u_i|\breve{u}_i)\Pr(\breve{u}_i|H_j), \quad j=0,1. \tag{16}$$

Based on the received local detection performance given above, we propose to adopt the Chair-Varshney fusion rule (see Varshney, 1997) at the fusion centre to make a final decision, which is given by

$$\Lambda(\{u_i\}_{i=1}^{I}) = \frac{\Pr(u_1, u_2, \ldots, u_I|H_1)}{\Pr(u_1, u_2, \ldots, u_I|H_0)} \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \frac{\pi_0}{1-\pi_0}. \quad (17)$$

Since the observations at local decision detectors are assumed to be conditionally independent, given each hypothesis and each SU makes its decision based on its own observations, we have

$$\Pr(\breve{u}_1, \breve{u}_2, \ldots, \breve{u}_I|H_j) = \prod_{i=1}^{I} \Pr(\breve{u}_i|H_j), j = 0, 1. \quad (18)$$

Using the assumption that the communication error is independent across SUs and equation (18), the fusion rule equation (17) can be rewritten as

$$\prod_{i=1}^{I} \frac{\Pr(u_i|H_1)}{\Pr(u_i|H_0)} \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \frac{\pi_0}{1-\pi_0} = \eta_0', \quad (19)$$

where the threshold of the LRT at the fusion centre has been defined as $\eta_0'$. Let $\mathcal{I}_E$ be the index set of the local decisions made by EDs and $\mathcal{I}_c$ be the index set of the local decisions made by CDs, then the fusion rule can be rewritten as

$$L(\{u_i\}_{i=1}^{I}) = \sum_{i\in\mathcal{I}_E} \log \frac{\Pr(u_i|H_1)}{\Pr(u_i|H_0)} + \sum_{i\in\mathcal{I}_C} \log \frac{\Pr(u_i|H_1)}{\Pr(u_i|H_0)} \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \eta_0, \quad (20)$$

where $\eta_0 = \log \eta_0'$.

When the system is in the interference-free situations and hence the signal model is given in equation (1), the local detectors and the fusion rule given above will result in the probability of final decision error given by

$$P_e = \sum_{u_i, i=1,\ldots,I} P\left(L(\{u_i\}_{i=1}^{I}) > \eta_0|H_0\right)\pi_0 + P\left(L(\{u_i\}_{i=1}^{I}) < \eta_0|H_1\right)(1-\pi_0). \quad (21)$$

However, when the system is in the presence of the interference caused by other transmission sources, the signal model is no more given in equation (1) and hence the error probability is no more given in equation (21). In the next section, the proposed collaborative detection scheme is shown to be more robust against the interference from other transmission sources.

## 4 Simulation results

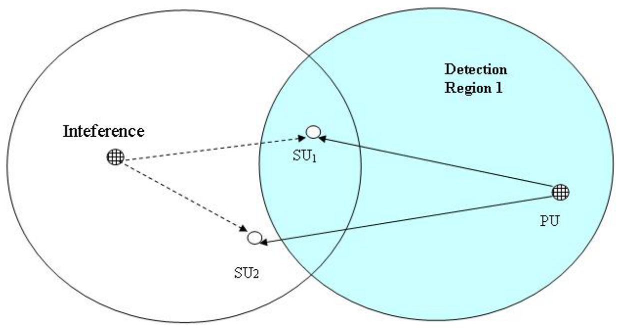
Consider a possible scenario of power spectrum sensing as shown in Figure 2, where each SU may sometimes locate at the area in the presence of the interference source.

Based on the scenario considered above and let $y_{1i}(t)$ and $y_{2i}(t)$ be the transmitted signals of PU and the interference source, respectively, the received signal at $i$th SU is given by

$$y_i[k] = \begin{cases} by_{2i}[k] + n_i[k] & H_0 \\ y_{1i}[k] + by_{2i}[k] + n_i[k] & H_1 \end{cases}, \quad (22)$$

where $b \in \{1, 0\}$ is a Bernoulli random variable with the parameter $p$, and $p$ represents the probability of the event that $i$th SU moves to the region overlapped with the area of the interference source. In other words, $p$ is the probability of the event that the interference occurs at each individual SU when the SU detects whether PU is using its spectrum.

**Figure 2** Spectrum-sensing scenario in cognitive radio network in the presence of interference (see online version for colours)




In this evaluation, the probability $p$ is assumed to be unknown to the SUs. Hence, when performing power spectrum sensing to make a decision in favour of $H_0$ or $H_1$, each SU calculates its decision statistic (either ED or CD) using the signal generated from the model given in equation (22), but compares it with the threshold (either ED or CD) designed by assuming the signal model in equation (1).

In this evaluation, it is assumed that one ED and one CD are used to perform the spectrum sensing. In addition, the number of samples $N = 4000$ is set for both ED and CD. When CD is employed at the SU, $\tau = 0$ and $S = 500$ ($q = N/S = 8$) are set. The PU is assumed to be modulated by using a Binary Phase Shift Keying (BPSK) signal with a carrier frequency $f_{c1} = 1/4$ and the amplitude of signal $A_1 = 4$. The interference source is assumed to be modulated by using a BPSK signal with a carrier frequency $f_{c2} = 3/11$ and the amplitude of signal $A_2 = 3$. In addition, the noise $n_i[k]$ is assumed to be an AWGN with zero mean and variance equalling 64. The probabilities of false alarm of both ED and CD are set to be 0.02. Moreover, the crossover probability $\epsilon = 0.01$ is set for all simulations.

Figures 3–5 show the performance comparison of the scheme combining ED and ED, the scheme combining ED and CD, and the scheme combining CD and CD for $\pi_0 = 0.3$, 0.5, and 0.8, respectively. In Figure 3, the scheme combining ED and CD performs the best and the scheme combining CD and CD performs the worst when $p$ is small. When $p$ becomes larger, the scheme combining CD and CD performs the best and even outperforms the scheme combining ED and CD. The phenomenon occurs because the figure is simulated when $\pi_0$ is small (or $\pi_1$ is large) and, therefore, fusing the local decisions from both CDs, each of which has almost zero probability of miss detection when $H_1$ is true, achieves the best performance. However, when $H_0$ is true, CD is not necessarily the best detector, i.e., the detector with the smallest false alarm probability. As can be seen in Figure 4, the performance of the scheme combining CD and CD loses too much as compared with the scheme combining ED and CD when both hypotheses are equally likely. The reason is that, in this scenario, $\pi_0$ becomes larger and hence the probability of the event that CD is the best detector decreases, which in turn causes the scheme combining ED and CD to outperform the scheme combining CD and CD. The result shown in Figure 5 again confirms the justification and conclusions drawn from the results illustrated in Figures 3 and 4. Overall, as illustrated in Figures 3–5, the scheme combining ED and CD has the best performance over the others in most ranges of the value of $p$. It only performs worse than the scheme combining ED and ED at the range of small value of $p$. However, the scheme combining ED and ED performs very badly when the value of $p$ is large. Our simulation results demonstrate that the decision fusion using the local decisions from ED and CD has the best robustness against the interference caused by other sources.

**Figure 3** Performance comparison of the scheme combining ED and ED, the scheme combining ED and CD, and the scheme combining CD and CD when $p$ is unknown to the fusion centre. $\pi_0 = 0.3$ is set in this figure

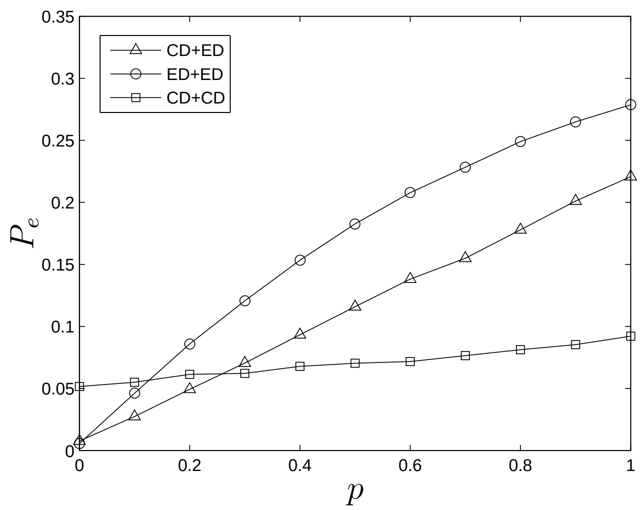



**Figure 4** Performance comparison of the scheme combining ED and ED, the scheme combining ED and CD, and the scheme combining CD and CD when $p$ is unknown to the fusion centre. $\pi_0 = 0.5$ is set in this figure

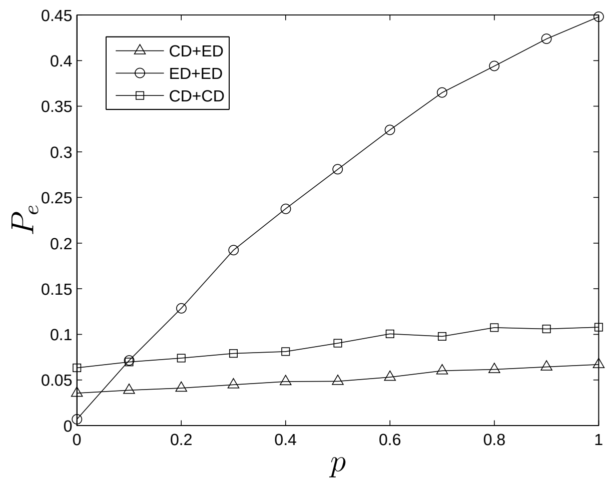
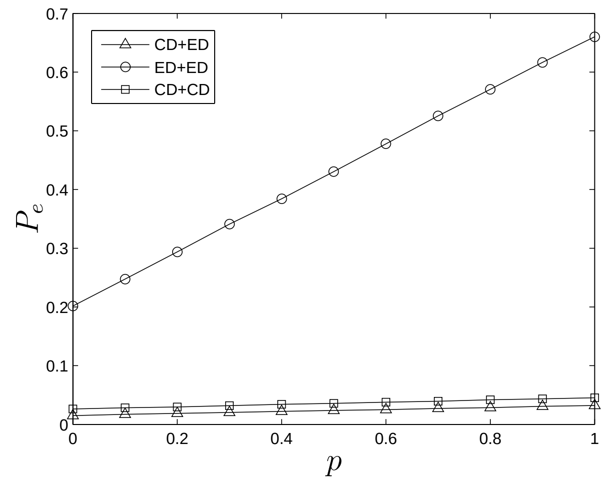



**Figure 5** Performance comparison of the scheme combining ED and ED, the scheme combining ED and CD and the scheme combining CD and CD when $p$ is unknown to the fusion centre. $\pi_0 = 0.8$ is set in this figure




## 5 Conclusions

In this paper, a robust distributed detection scheme has been proposed for power spectrum sensing in cognitive radio networks. This work is motivated by the fact that ED outperforms CD when the stationary noise is considered and no interference is present, but CD is more robust against the interference caused by other sources. To take the advantages of both ED and CD, the proposed scheme employs the decision fusion techniques to combine the local decisions from both EDs and CDs. The obtained simulation results show that the proposed scheme is more robust as compared with the conventional fusion scheme, which combines the local decision from the same type of detectors.

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## Note

[1] The number of samples $N$ used for CD is usually large, and hence, it can be assumed that $N$ is large enough for ED in this work, because the fusion centre is to fuse the decisions made by both ED and CD using the same number of samples.