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# Performance Analysis of Centralized Cooperative Spectrum Sensing Technique for Cognitive Radio Networks

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## ABSTRACT

Cognitive radio network is a new communication paradigm to address spectrum under utilization and scarcity problems by sharing the spectrum holes (unused licensed frequency bands) opportunistically. Spectrum sensing which determines spectrum holes by detecting the presence of licensed user, also known as primary user, on the associated spectrum, is a primary function of the cognitive radio. The performance of spectrum sensing greatly influences the overall performance of cognitive radio network. In this study, we have analyzed the performance of cooperative spectrum technique by employing wavelet transform to denoise the primary user signal to improve SNR value received at the cognitive radio, the secondary user. This improves the accuracy of the sensing algorithm as reflected in the simulation results presented here. The performance has been analyzed for AWGN and rayleigh fading channel models under different SNR conditions and for varying number of cooperating users for both without and with wavelet transform. Simulation results show significant improvement in the spectrum sensing performance.

**Key words:** Cognitive radio, cooperative spectrum sensing, energy detection, wavelet denoising

## INTRODUCTION

**Motivations for cognitive radio:** Recent studies show that most of the assigned spectrum is underutilized; spectrum measurement taken in New York City has shown that the maximum total spectrum occupancy is only 13.1% from 30 MHz to 3 GHz (Letaief and Zhang, 2009).

All of the frequency bands are exclusively allocated to specific services and no spectrum available for future wireless applications. Hence, the increasing number of higher data rate wireless applications will lead to spectrum scarcity. Cognitive Radio (CR) technology can solve spectrum scarcity and spectrum underutilization problems by identifying unused licensed frequency bands and using them opportunistically without harmful interference to the licensed users.

The Federal Communications Commission (FCC) has passed the proposal on spectrum reuse, allowing unlicensed operation in the bands of licensed users to motivate the research on CR technology.

**Spectrum sensing:** In cognitive radio, spectrum sensing is done to locate unused spectrum segments and optimally use these segments without harmful interference to the licensed users, also known as Primary Users (PU). The best way to detect the availability of some portions of the spectrum is to detect the PU that is receiving data within the range of a CR.

The various spectrum sensing methods proposed in literature are: Energy detector based sensing, waveform based sensing, cyclostationary based sensing, matched filter based sensing, radio identification based sensing, multitaper spectrum estimation and wavelet transform estimation based sensing.

Among the existing spectrum sensing algorithms for CR, energy detection has been widely applied since it is simple in terms of computation, less complex to implement and it does not require any prior knowledge of the licensed user's signal (Liang *et al*., 2008).

## ENERGY DETECTION BASED SPECTRUM SENSING

The spectrum sensing for primary signal detection can be formulated as a binary hypothesis-testing problem (Eq. 1):

$$\begin{aligned} y(t) &= n(t),\ \text{H0: Primary user is absent} \\ y(t) &= h(t)\bullet x(t) + n(t),\ \text{H1: Primary user is in operation} \end{aligned} \tag{1}$$

where, y(t) represents received signal at CR, x(t) represents transmitted signal by PU, h(t) is the channel gain of the sensing channel between the PU and the CR, n(t) is the zero-mean Additive White Gaussian Noise (AWGN).

The energy detection method is optimal for detecting any unknown zero-mean constellation signal (Ghasemi and Sousa, 2005). In energy detection approach, the radio frequency energy in the channels or the Received Signal Strength Indicator (RSSI) is measured in a fixed bandwidth W over an observation time window to determine whether the channel is occupied or not. The received energy is compared with a prefixed threshold. The decision is made based on the above hypothesis-testing (Pandharipande and Linnartz, 2007).

The sensing performance is measured in terms of probability of detection $P_d$ or the probability of missed detection $P_m$ and probability of false alarm.

Probability of detection ($P_d$) is defined under hypothesis H1 as the probability of correctly detecting the presence of the primary signal.

Probability of false alarm ($P_f$) is defined under hypothesis H0 as the probability of falsely declaring the presence of primary signal (Eq. 2-3):

$$P_d = P\{\text{decision} = H1\,|H1\} = P\{Y>\lambda|H1\} \tag{2}$$

$$P_f = P\{\text{decision} = H1\,|H0\} = P\{Y>\lambda|H0\} \tag{3}$$

From the primary user perspective, higher the probability of detection better will be the primary user protection. From the secondary user perspective, lower the probability of false alarm better will be the opportunity for unlicensed access.

We assume that the sensing channel is time-invariant during the sensing process. The energy collected at the ith CR in the frequency domain is denoted by $E_i$ which serves as a decision statistic and has the following distribution (Letaief and Zhang, 2009) (Eq. 4):

$$E_i \approx \begin{cases} X_{2u}^2 & H_0 \\ X_{2u}^2(2\gamma_i) & H_1 \end{cases} \tag{4}$$

where, $X_{2u}^2$ denotes a central chi-square distribution with 2u degrees of freedom and $X_{2u}^2$ $(2\gamma_i)$ denotes a non central chi-square distribution with u degrees of freedom and a non-centrality parameter $2\gamma_i$, respectively. The instantaneous Signal-to-Noise Ratio (SNR) of the received signal at the ith cognitive radio is $\gamma_i$ and u = TW is the time-bandwidth product.

For the ith cognitive radio with the energy detector, the average probability of false alarm, the average probability of detection and the average probability of missed detection over AWGN channel are given, respectively by Urkowitz (1967) (Eq. 5-9):

$$P_{f,i} = \text{prob}\left\{E_i > \lambda_i / H_0\right\} \tag{5}$$

$$P_{f,i} = \frac{\Gamma\left(u, \frac{\lambda i}{2}\right)}{\Gamma(u)} \tag{6}$$

$$P_{d,i} = \text{prob}\left\{E_i > \lambda_i / H_1\right\} \tag{7}$$

$$P_{d,i} = Q_u\left(\sqrt{2\gamma_i}, \sqrt{\lambda_i}\right) \tag{8}$$

$$P_{m,i} = 1 - P_{d,i} \tag{9}$$

where, $Q_u(a, b)$ is generalized Marcum function $\gamma(a)$ and $\gamma(a,b)$ are complete and incomplete gamma functions, respectively, $\gamma$ is the instantaneous SNR and follows exponential distribution with the mean value $\bar{\Upsilon}$, $\lambda$ is the prefixed threshold, u is the time bandwidth product of the energy detector.

If signal amplitude follows a Rayleigh distribution, then the SNR $\gamma$ follows an exponential PDF given by Eq. 10:

$$f(r) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right), \ \gamma \geq 0 \tag{10}$$

The expression for probability of detection $P_{dray}$ is given by Letaief and Zhang (2009) (Eq. 11):

$$P_{dray} = e^{-\frac{\lambda}{2}} \sum_{n=0}^{u-2} \frac{1}{n!}\left(\frac{\lambda}{2}\right)^n + \left(\frac{1+\bar{\Upsilon}}{\bar{\Upsilon}}\right)^{u-1}\left[e - \left(\frac{\lambda}{2(1+\bar{\Upsilon})}\right) - e^{-\frac{\lambda}{2}} \sum_{n=0}^{u-2} \frac{1}{n!}\left(\frac{\lambda\bar{\Upsilon}}{2(1+\bar{\Upsilon})}\right)^n\right] \tag{11}$$

## SPECTRUM SENSING WITH WAVELET DENOISING

**Wavelet transform:** Wavelet transform is widely used in denoising signal processing applications. The Continuous Wavelet Transform (CWT) is provided by Eq. 12, where y(t) is the signal to be analyzed, $\psi(t)$ is the mother wavelet or the basis function (Rioul and Vetterli, 1991) (Eq. 12):

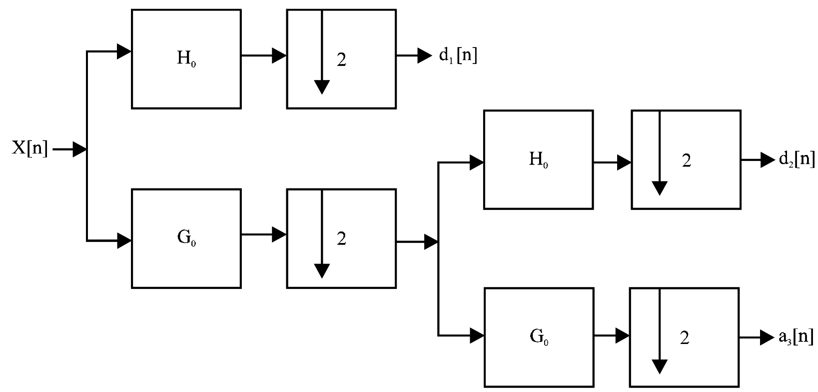


Fig. 1: 1D two-level discrete wavelet decomposition tree

$$Y_{WT}(a,b) = \frac{1}{\sqrt{|a|}} \int y(t) \bullet \Psi^* \left( \frac{t-b}{a} \right) dt \tag{12}$$

The Discrete Wavelet Transform (DWT) is a sampled version of the CWT. The DWT is computed by successive low pass and high pass filterings of the discrete time-domain signal as shown in Fig. 1. The signal is denoted as X[n], where, n is an integer. The low pass filter is denoted by $G_0$ while the high pass filter is denoted by $H_0$. At each level, the high pass filter produces detail information d[n] while the low pass filter associated with scaling function produces coarse approximations a[n].

**Spectrum sensing with 1-D wavelet denoising:** A CR node has to detect M consecutive sampling points in the band of a licensed user each time (Eq. 13):

$$\begin{aligned} Y[i] &= N[i], H0 \\ Y[i] &= h \times X[i] + N[i], H1 \end{aligned} \tag{13}$$

where, Y [i], X[i] and N[i] are the signal received at CR, signal transmitted by PU and the noise of the i-th sampling point respectively and 'h' is the channel gain.

The objective of energy sensing is to decide whether H0 or H1 is true by sensing the energy of the signal Y which is given by M:

$$E = \sum_{i=1}^{M} |Y[i]|^2$$

As energy sensing requires very short detection period, the channel gain and primary user's signal are supposed to have few changes during each detection period. So, the system model in Eq. 13 can be simplified (Wang *et al.*, 2010) as:

$$Y[i] = \begin{cases} N[i] & H_0 \\ x + N[i] & H_1 \end{cases} \tag{14}$$

Wavelet denoising is useful mainly based on the “concentrating” ability of wavelet transform. The signal always has its energy concentrated in a small number of wavelet dimensions and the noise spreads its energy over a large number of coefficients. Equation 14 can be written in wavelet transform domain as (Rioul and Vetterli, 1991) (Eq. 15):

$$[a_y, d_y] = WY = W(X+N) = WX+WN \tag{15}$$

where, W denote a left invertible wavelet transformation matrix of the Discrete Wavelet Transform (DWT), X equals [x, x,..., x] or a M length zero vector. Since X has few changes, the detail information of WX is nearly zero. So, the detail information $d_y$ only contains the detail information of noise in the wavelet transformation domain. After removing this detail information, the desired signal can be retrieved by the inverse wavelet transform without any loss of the original signal X; while the noise energy is significantly lowered. Higher SNR yields better sensing performance.

The procedure of spectrum sensing with 1-D wavelet denoising (Wang *et al*., 2010) is summarized as follows:

- Calculate the discrete wavelet transform coefficients of signal Y = [y1, y2,..., yM] and get the detail information $d_y$ and coarse approximation $a_y$
- Set the detail information vector $d_y = 0$, calculate the inverse wavelet transform with coarse approximation $a_y$ and new detail information $d_y$ and get the new signal Y'
- Calculate the energy of the new signal Y'
- Compare energy with the threshold value and make a decision on the presence or absence of PU

## COOPERATIVE SPECTRUM SENSING

One of the most challenging issues of spectrum sensing is the hidden terminal problem which happens when the cognitive radio is shadowed or in deep fade. To address this issue, multiple cognitive radios can be coordinated to perform spectrum sensing. Several recent works have shown that cooperative spectrum sensing as shown in Fig. 2 can greatly increase the probability of detection in fading channels (Letaief and Zhang, 2009).

Cooperative spectrum sensing can be classified into centralized, distributed and relay-assisted, based on how cooperating CR users share the sensing data in the network (Akyildiz *et al*., 2011). These three types are illustrated in Fig. 3.

**Centralized cooperative spectrum sensing:** In centralized cooperative sensing, a central entity called Fusion Center (FC) controls the three-step process of cooperative sensing. First, the FC selects a channel or a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. Second, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs and informs the decision back to cooperating CR users. As shown in Fig. 3a, CR0 is the FC and CR1-CR5 are cooperating CR users performing local sensing and reporting the results back to CR0. For local sensing, all CR users are tuned to the selected licensed channel or frequency

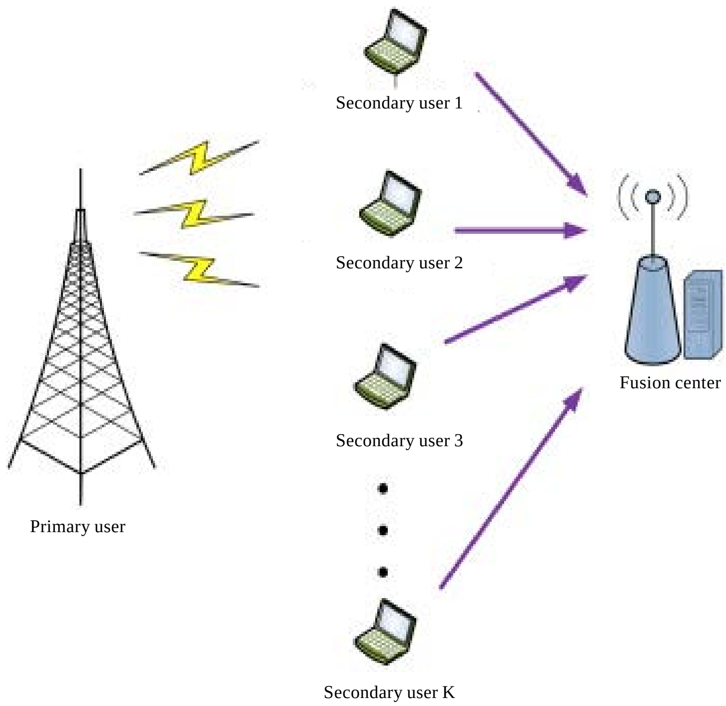


Fig. 2: Structure of cooperative spectrum sensing

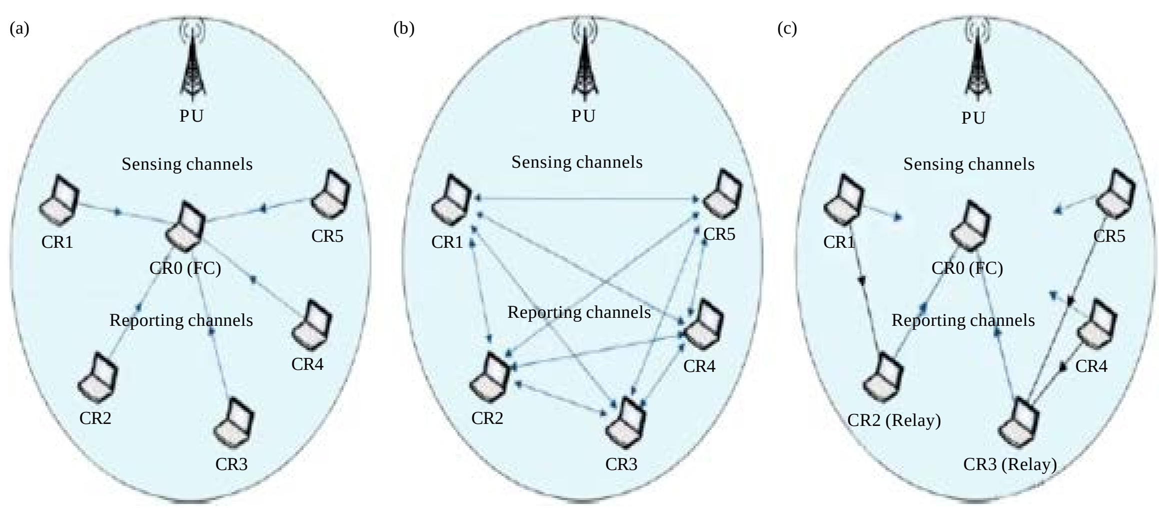


Fig. 3(a-c): Classification of cooperative spectrum sensing, (a) Centralized, (b) Distributed and (c) Relay-assisted

band where a wireless point-to-point link between the PU transmitter and each cooperating CR user, known as sensing channel, is used for observing the primary signal. For data reporting, all CR users are tuned to a control channel called a reporting channel.

**Distributed cooperative spectrum sensing:** Distributed cooperative sensing does not rely on a FC for making the cooperative decision. In this case, CR users communicate among themselves and converge to a unified decision on the presence or absence of PUs by iterations. Figure 3b illustrates the cooperation in the distributed manner. After local sensing, CR1-CR5 share the local sensing results with other users within their transmission range. Based on a distributed algorithm, each CR user sends its own sensing data to other users, combines its data with the received sensing data and decides whether or not the PU is present by using a local criterion. If the criterion is not satisfied, CR users send their combined results to other users again and repeat this process until the algorithm is converged and a decision is reached. In this manner, this distributed scheme may take several iterations to reach the unanimous cooperative decision.

**Relay-assisted cooperative spectrum sensing:** Since both sensing channel and report channel are not perfect, a CR user observing a weak sensing channel and a strong report channel and a CR user with a strong sensing channel and a weak report channel, for example, can complement and cooperate with each other to improve the performance of cooperative sensing. In Fig. 3c, CR1, CR4 and CR5, who observe strong PU signals, may suffer from a weak report channel. CR2 and CR3, who have a strong report channel, can serve as relays to assist in forwarding the sensing results from CR1, CR4 and CR5 to the FC. In this case, the report channels from CR2 and CR3 to the FC can also be called relay channels. Note that although Fig. 3c shows a centralized structure, the relay-assisted cooperative sensing can exist in distributed scheme also. In fact, when the sensing results need to be forwarded by multiple hops to reach the intended receive node, all the intermediate hops are relays. Thus, if both centralized and distributed structures are one-hop cooperative sensing, the relay-assisted structure can be considered as multi-hop cooperative sensing.

In this study, we have used centralized cooperative sensing technique.

## DATA FUSION

In cooperative sensing, data fusion is a process of combining local sensing data for hypothesis testing. Depending on the control channel bandwidth requirement, reported sensing results may be of different forms, types and sizes. In general, the sensing results reported to the FC or shared with neighboring users can be combined in three different ways in descending order of demanding control channel bandwidth:

- **Soft combining:** CR users can transmit the entire local sensing samples or the complete local test statistics for soft decision
- **Quantized soft combining:** CR users can quantize the local sensing results and send only the quantized data for soft combining to alleviate control channel communication overhead
- **Hard combining:** CR users make a local decision and transmit the one-bit decision for hard combining. Hence, using soft combining at the FC can achieve the best detection performance among all three at the cost of control channel overhead while the quantized soft combining and hard combining require much less control channel bandwidth with possibly degraded performance due to the loss of information from quantization (Akyildiz *et al*., 2011)

**Hard combining and decision fusions:** When binary local decisions are reported to the FC, it is convenient to use linear fusion rules to make a final decision about the presence of PU. The commonly used fusion rules are AND, OR and majority rules.

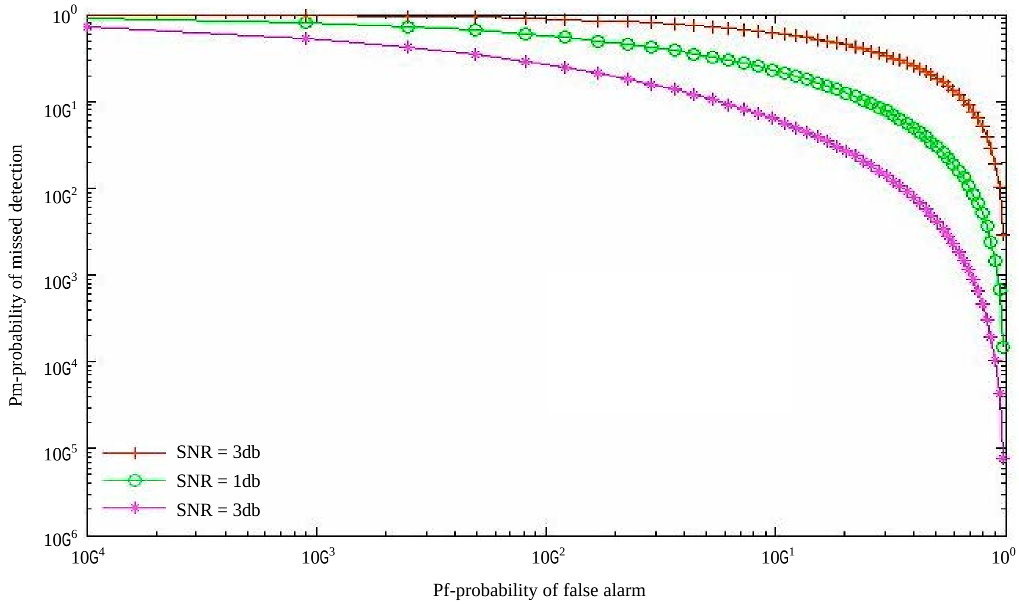


Fig. 4: Sensing performance with different SNR values over AWGN channel

In this study, we have used OR fusion rules because given a targeted probability of false alarm $P_f$, the individual secondary users' threshold can be easily derived and the sensing performance can be evaluated. In OR fusion rule, when at least one out of k secondary users detect the PU, the final decision at the FC declares as PU is present. The overall probabilities of false alarm Qf and missed detection Qm are therefore, respectively:

$$Qf = 1 - \prod_{i=1}^{k} 1 - (P_{f,i}) \tag{16}$$

$$Qm = \prod_{i=1}^{k} 1 - (P_{d,i})$$

## SIMULATION RESULTS AND ANALYSIS

Numerical simulations were carried out for a centralized cooperative spectrum sensing with OR fusion rule for the following cases:

**Case 1:** We plotted the Complementary Receiver Operating Characteristics (CROC) curves, $P_m$ vs. $P_f$ for different SNR values to prove the improvement in performance when SNR increases. The probability of missed detection, $P_m$, decreases with increase in SNR as shown in Fig. 4. The simulation scenario for this case is tabulated in Table 1

**Case 2:** CROC curves have been plotted without and with wavelet denoising technique. Graphs in Fig. 5 show reduction in $P_m$ with wavelet denoising because of improvement in the SNR. The parameters considered for this case are indicated in Table 2

**Case 3:** CROC curves have been plotted with different cooperative users for both without and with wavelet denoising. The scenario for this case is highlighted in Table 3. The plots in Fig. 6 show reduction in $P_m$ for increased number of cooperative users with wavelet denoising technique

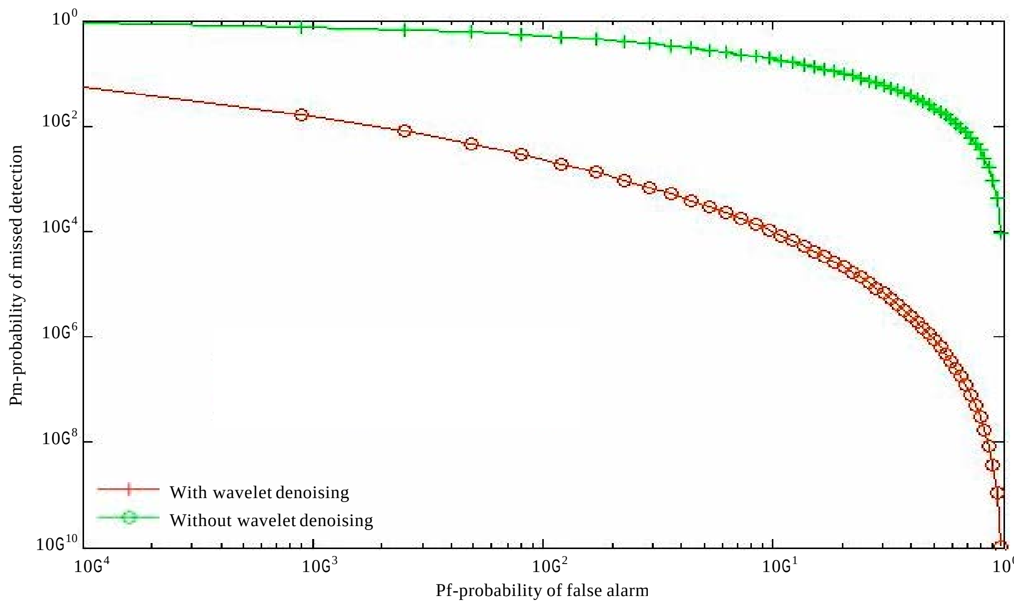


Fig. 5: Sensing performance without and with wavelet denoising over rayleigh fading channel

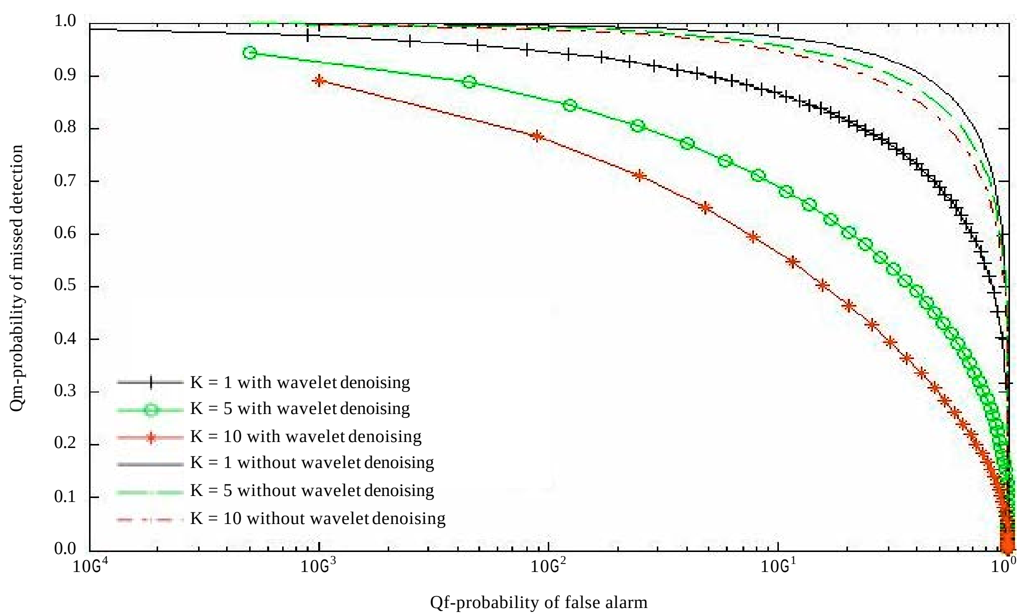


Fig. 6: Cooperative sensing performance for different numbers of secondary users (K) without and with wavelet denoising over rayleigh fading channel

Table 1: Simulation parameters for case 1

| Parameters | Value |
|---|---|
| Time bandwidth product (u) | 5 |
| SNR (dB) | -3, 1, 3 |
| No. of cooperating users (K) | 1 |
| Sensing channel model | AWGN |

Table 2: Simulation parameters for case 2

| Parameters | Value |
|---|---|
| Time bandwidth product (u) | 5 |
| SNR (db) | 4 |
| No. of cooperating users (K) | 1 |
| Sensing channel model | Rayleigh fading |

Table 3: Simulation parameters for case 3

| Parameters | Value |
|---|---|
| Time bandwidth product (u) | 5 |
| No. of cooperating users (K) | 1, 5, 10 |
| SNR (db) | 4 |
| Sensing channel model | Rayleigh fading |

## CONCLUSION

In this study, we have analyzed the performance of a cooperative spectrum sensing technique over AWGN and rayleigh fading channel models by employing 1D wavelet transform to increase the accuracy of spectrum sensing algorithm. Simulations were carried out under different SNR conditions and with varying numbers of cooperative users for both without and with wavelet denoising technique. Simulation results show improvement in performance in terms of reduction in the probability of missed detection in all the cases.

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