

Performance Evaluation and Comparison of Different Transmitter Detection Techniques for Application in Cognitive Radio

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Abstract Wireless communications and the utilization of the radio frequency spectrum have witnessed a tremendous boom during the past few decades. The current static frequency allocation schemes are unable to accommodate the requirements of an increasing number of higher data rate devices. Cognitive radio (CR) with effective primary user detection has become a candidate for more efficient spectrum utilization systems based on opportunistic spectrum sharing. In this work, performance of energy, replica correlation, and cooperative detector have been evaluated and compared by various performance metrics. To evaluate the performance of the detection techniques MATLAB software has been used for simulation. From the simulated results the replica correlation detector is better than energy detector under both additive white Gaussian noise (AWGN) and Rayleigh fading channels. The cooperative detection helps to reduce the fading effect of single node detection. It has outperformed the performance of single user energy and replica correlation detector. Noise introduced considerable amount of degradation in the detection performance of energy and replica correlation detector and the cooperative detection helps to reduce the effect of noise uncertainty factor in the detection performance of CR.

Keywords Cognitive radio, Hypothesis test, and spectrum detector

1. Introduction

Communication is broadly classified, as wired and wireless. It is commonly believed that there is a scarcity of spectrum availability for wireless and hence need to be economically. This misconception arises due to the intense competition for use of spectra at some selected band of frequencies. At some other frequencies there is very little usage of spectrum. This seems totally in contradiction to the concern of spectrum shortage. In fact we have abundant spectrum and the spectrum shortage is in an artificial one due to the regulatory and licensing process. In general, the spectrum usage is inconsistent with different regulatory agencies. For example, the frequency chart of the Federal Communication Commission (FCC) in the United States indicates that there are multiple allocations over all of the frequency bands [1], [2]. This discrepancy between these agencies allocations and actual usage forces to look for a new approach to spectrum licensing. What is clearly needed is an opportunistic usage of this licensed spectrum. An approach, which can meet these goals, is to develop a radio that is able to reliably sense the spectral environment over a wide

bandwidth, detect the presence or absence of primary users and use the spectrum only if communication does not interfere with any primary user. These radios are lower priority secondary users, which exploit cognitive radio (CR) techniques, to ensure non-interfering co-existence with the primary users.

Various researchers have studied on detection mechanisms. Determination of threshold level for minimizing spectrum-sensing error in energy detection techniques has been investigated [3], [4]. On collaborative detection of TV, E. Visotsky, et al, has studied transmission in support of dynamic spectrum sharing [5]. Since one of the main requirements of CR systems is the ability to reliably detect the presence of the primary transmissions, it needs special attention and further investigations. Therefore, this work principally focuses on reducing interference between primary and secondary (cognitive) users by comparing the performance of various spectrum detection techniques under both AWGN and Rayleigh fading channel. Considering different metrics that should be considered in the real time communication system model, this work concentrates on the evaluation and comparison of the performance of the different detection techniques.

2. Theoretical Background

Spectrum sensing is based on a well known technique

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called signal detection. In a nutshell, signal detection can be described as a method for identifying the presence of a signal in a noisy environment. Analytically, signal detection can be reduced to a simple identification problem, formalized as a hypothesis test [7], [24], [25] which can be described as shown in Fig.4.1.

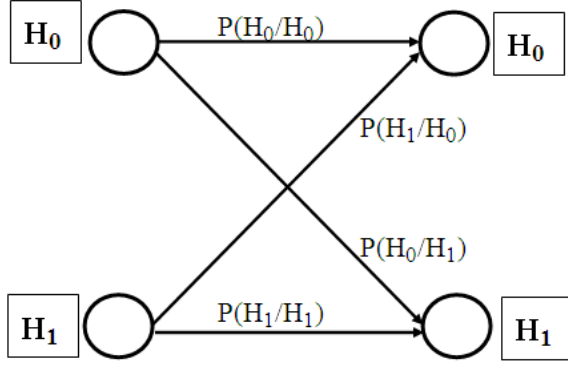


Figure 1. Hypothesis test and possible outcomes with their corresponding probabilities

Spectrum sensing can be viewed as a binary hypothesis testing problem in which hypothesis H_0 indicates that the primary user (PU) is inactive whereas hypothesis H_1 indicates that a PU is active. If we denote the signal received at a secondary user (SU) by $R(t)$, it can be written as [10], [12]

$$R(t) = \begin{cases} n(t) & : H_0 \\ hs(t) + n(t) & : H_1 \end{cases} \quad (1)$$

where $n(t)$ is the noise introduced by AWGN, h is the amplitude gain of the channel, $s(t)$ is the primary users (PU's) transmitted signal, H_0 is noise-only hypothesis and H_1 is the signal plus noise hypothesis. That means H_0 and H_1 are the sensed states for absence and presence of signal, respectively. Then, as seen in Fig.1, we can define four possible cases for the detected signal:

- Case1: declaring H_0 when H_0 is true ($H_0|H_0$);
- Case2: declaring H_1 when H_1 is true ($H_1|H_1$);
- Case3: declaring H_0 when H_1 is true ($H_0|H_1$);
- Case4: declaring H_1 when H_0 is true ($H_1|H_0$).

The performance of spectrum sensing can be characterized by the probability of false alarm.

($P_f = P(H_1|H_0)$), probability of miss detection and the probability of detection ($P_d = P(H_1|H_1)$).

The term P_f is the probability that a secondary user decides the primary user is active when the PU is actually inactive. It reflects the level of missed access opportunity for the SU. The term P_d is the probability that a SU decides that the PU is active when the PU is actually active. The probability of miss detection ($P_m = 1 - P_d$) indicates the level of interference introduced to the PU (Primary users) by a SU (secondary users). Typically, P_m is restricted to be below an acceptable level to protect the PU. Among the above cases, case 2 is

known as a correct detection, whereas cases 3 and 4 are known as a missed detection and a false alarm, respectively. Clearly, the aim of the signal detector is to achieve correct detection all of the time, but this can never be perfectly achieved in practice because of the statistical nature of the problem. Therefore, signal detectors are designed to operate within prescribed minimum error levels. Missed detections are the biggest issue for spectrum sensing, as it means possibly interfering with the primary system. Nevertheless, it is desirable to keep the false alarm rate as low as possible for spectrum sensing, so that the system can exploit all possible transmission opportunities.

2.1. The Energy Detector Algorithm

Energy detection is the most common way of spectrum detection because of its low computational and implementation complexities [6]. The decision is made by comparing the decision statistics, which corresponds to energy collected in the observation time, to an appropriate threshold [7-9]. This threshold (λ) is traditionally selected from the statistics of the noise in such a way as to satisfy the false alarm rate specification of the detector based on constant false alarm rate (CFAR) principle.

The energy detector relies completely on the variance of the noise, which is taken as a fixed value. This is generally not true in practice, where the noise floor varies and we have considered the effect of noise uncertainty as will be discussed in the next section.

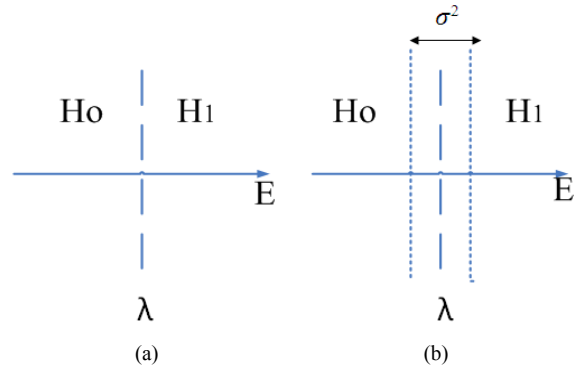


Figure 2. Ideal (a) and actual (b) energy detection schemes

Essentially this means that the energy detector will generate errors during those variations (especially when the signal to noise ratio is very low) where we see an area of uncertainty surrounding the threshold, σ^2 , as shown in Fig. 2(b). This is in contrast with the case portrayed in Fig 2(a) in which perfect noise knowledge is considered.

2.1.1. System Model of Energy Detection under Awgn Channel

The system model for energy detection that is used to identify the presence or absence of primary signal is shown in Fig 3. In order to measure the energy of the received signal, the output signal of band pass filter with bandwidth W , (used to limit the noise power and to normalize the noise variance),

is squared and integrated over the observation interval T . Finally, the output of the summation (integration for continuous signal) is compared with a threshold, λ , to decide whether a licensed user is present or not [10].

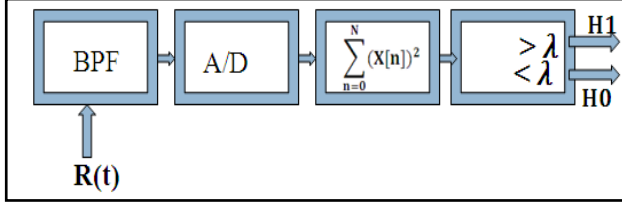


Figure 3. Block diagram of energy detector system model

We took the threshold value for the cost of probability of false alarm of less than or equal to 10% and different values of noise variance ranging from 0.5 to 1.

The energy detector decides between two hypotheses H_1 , which corresponds to signal plus noise, and H_0 (null hypothesis), which is the noise-only hypothesis [11]. The hypothesis model for transmitter detection is as expressed in Eqn. 1.

The decision statistics Y for zero mean Gaussian distributed noise only (H_0) follows the central chi-square distribution with $2TW$ degrees of freedom (where TW is the time-bandwidth product). On the other hand, H_1 follows a non-central chi-squared distribution with $2TW$ degrees of freedom and non-centrality parameters 2γ (where γ is the mean SNR in the linear scale). Thus, the observation decision statistics ($Y = \sum_{n=0}^N (X[n])^2$, where $x[n]$ is the output signal of the A/D) and is given as [10, 12-14]

$$Y = \begin{cases} \chi^2_{2TW} & H_0 \\ \chi^2_{2TW}(2\gamma) & H_1 \end{cases} \quad (2)$$

where χ^2_{2TW} is the central Chi-square distribution with $2TW$ degrees of freedom and 2γ is the non-centrality parameter. The Probability density function (PDF) of test statistic Y of (2) can then be expressed as [10], [12], [12], [15]

$$f_y(y) = \begin{cases} \frac{1}{2^{TW} \Gamma(TW)} y^{TW-1} e^{-\frac{y}{2}}, & H_0 \\ \frac{1}{2} \left(\frac{y}{2\gamma} \right)^{\frac{TW-1}{2}} e^{-\frac{2\gamma+y}{2}} I_{TW-1}(\sqrt{2\gamma y}), & H_1 \end{cases} \quad (3)$$

where $\Gamma(\cdot)$ is gamma function and $I_x(\cdot)$ is the x^{th} -order modified Bessel functions of the first kind. The probability of detection (P_d) and false alarm (P_f) are respectively given as [16]-[19].

$$P_d = P_r(Y > \lambda | H_1) = Q_{(N=TW)}(\sqrt{2\gamma}, \sqrt{\lambda}) \quad (4)$$

$$P_f = P_r(Y > \lambda | H_0) = \frac{\Gamma(TW \frac{\lambda}{2})}{\Gamma(TW)} \quad (5)$$

where $Q_{(N=TW)}(\cdot, \cdot)$ is the generalized Marcum Q-function.

With sufficiently large values of observation (N), the distribution of the test statistic can be approximated as Gaussian distribution (using central limit theorem) and the statistic is given by [10]

$$Y \approx \begin{cases} \mathcal{N}(\mu_0, \sigma_0^2) & H_0 \\ \mathcal{N}(\mu_1, \sigma_1^2) & H_1 \end{cases} \quad (6)$$

where $\mathcal{N}(\mu, \sigma^2)$ is the Gaussian distribution with mean μ and variance σ^2 . The mean and variance for both hypotheses H_0 and H_1 are given respectively as:

$$(\mu_0 = N\sigma_n^2; \sigma_0^2 = 2N\sigma_n^4) \text{ and}$$

$$(\mu_1 = N(\sigma_s^2 + \sigma_n^2), \sigma_1^2 = 2N(\sigma_s^2 + \sigma_n^2)^2).$$

With these substitutions P_d and P_f for sufficiently large value of N can be expressed as [9], [10]

$$P_d = Q\left(\frac{\lambda - N(\sigma_n^2 + \sigma_s^2)}{\sqrt{2N(\sigma_n^2 + \sigma_s^2)^2}}\right) = Q\left(\frac{\lambda - N(1+\gamma)\sigma_n^2}{\sqrt{2N(1+2\gamma)\sigma_n^4}}\right) \quad (7)$$

$$P_f = Q\left(\frac{\lambda - N\sigma_n^2}{\sqrt{2N\sigma_n^4}}\right) \quad (8)$$

where $Q(\cdot)$ is the complementary error function.

2.1.2. Noise Uncertainty Model of Energy Detector under Awgn Channel

Although it is generally assumed for simplicity that the variance of the receiver noise is known, in reality noise variance is not exactly known of any system inspite of the system calibration a priori. There are several factors that contribute for the existence of noise uncertainty. For example, thermal noise due to change in temperature, change in amplifier gain due to change in temperature, calibration error etc. As noise uncertainty in the receiver is unavoidable, it is very important to analyse its effect on the detection performance.

Let us model the noise process $w[n]$ to have any distribution W from a set of possible distributions, w . This set is called the noise uncertainty set. Although the actual noise variance might vary over distributions set w , let us assume that there is a single nominal noise variance σ_n^2 associated with the noise uncertainty set w . As energy detector evaluates the detection performance based on the incoming signal, the distributional uncertainty of noise can be summarized in a single interval $\sigma_w^2 \epsilon[(\frac{1}{\rho})\sigma_n^2, \rho\sigma_n^2]$, where σ_n^2 is the nominal noise power and $\rho > 1$ is the parameter that quantifies the size of the noise uncertainty.

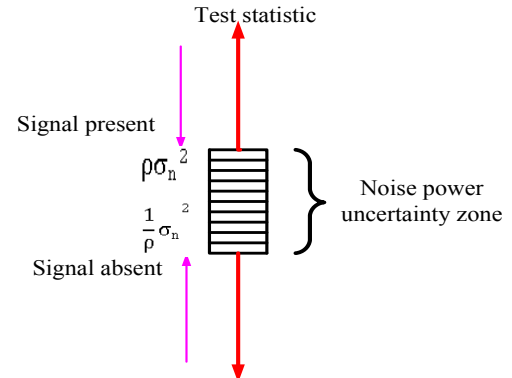


Figure 4. Noise uncertainty regions

To understand the noise uncertainty for the detector, the shaded area in Fig. 4 represents the uncertainty in the noise power. By including the noise uncertainty factor, probability of false alarm, threshold and probability of detection can be written as [9-10]

$$P_f = Q\left(\frac{\lambda - N\rho\sigma_n^2}{\sqrt{2N\rho^2\sigma_n^4}}\right), P_d = Q\left(\frac{\lambda - N\left(\frac{1}{\rho}\sigma_n^2 + \sigma_s^2\right)}{\sqrt{2N\left(\frac{1}{\rho}\sigma_n^2 + \sigma_s^2\right)^2}}\right) \quad (9)$$

where

$$\lambda = \sqrt{N\rho^2\sigma_n^4}Q^{-1}(P_{fa}) + N\rho\sigma_n^2 \quad (10)$$

2.1.3. Energy Detection under Rayleigh Fading Channel

Radio wave propagation through wireless channels is a complicated phenomenon characterized by various effects, such as multipath and shadowing. A precise mathematical description of this phenomenon is either unknown or too complex for manageable communications systems analyses. However, considerable efforts have been devoted to the statistical modeling and characterization of these different effects. When fading affects systems, the received carrier amplitude is modulated by the fading amplitude α , where α is a random variable (RV) with mean-square value $\Omega = \alpha^2$ and probability density function (PDF), $p_\alpha(\alpha)$, which is dependent on the nature of the radio propagation environment. After passing through the fading channel, the signal is perturbed at the receiver by AWGN, which is typically assumed to be statistically independent of the fading amplitude α , and which is characterized by a one-sided power spectral density, N_0 (W/Hz). Equivalently, the received instantaneous signal power is modulated by α^2 . We define the instantaneous SNR per symbol by $\gamma = \alpha^2 E_s / N_0$ and the average SNR per symbol by $\bar{\gamma} = \Omega E_s / N_0$, where E_s is the energy per symbol. Our performance evaluation of digital communications over fading channels will generally be a function of the average SNR per symbol $\bar{\gamma}$. In addition, the PDF of γ is obtained by introducing a change of variables in the expression for the fading PDF, $p_\alpha(\alpha)$ of α , yielding [9]

$$p_\gamma(\gamma) = f_\gamma(\gamma) = \frac{p_\alpha(\sqrt{\Omega\gamma/\bar{\gamma}})}{2\sqrt{\gamma\bar{\gamma}/\Omega}} \quad (11)$$

Multipath fading (without direct line of sight) is relatively fast and is, therefore, responsible for the short signal variations. It is frequently modeled by Rayleigh distribution and the channel fading amplitude is distributed according to [9]

$$p_\alpha(\alpha) = \frac{2\alpha}{\Omega} \exp\left(-\frac{\alpha^2}{\Omega}\right), \alpha \geq 0. \quad (12)$$

If the signal amplitude follows Rayleigh distribution, then the instantaneous SNR per symbol of the channel, γ , follows an exponential pdf given by [10], [13-15]

$$p_\gamma(\gamma) = f_\gamma(\gamma) = \frac{1}{\bar{\gamma}} \exp\left(-\frac{\gamma}{\bar{\gamma}}\right) \quad (13)$$

From (2), the energy of the signal for both the H_0 and H_1 cases, under the assumption that h is Rayleigh distributed is given by [9], [10]

$$Y = \begin{cases} \chi^2_{2(N+1)} & : H_0 \\ e_{2(\gamma^2+1)} + \chi^2_{2N} & : H_1 \end{cases} \quad (14)$$

where $e_{2(\gamma^2+1)}$ is the exponential distribution with parameter $\alpha = 2(\gamma^2 + 1)$ with probability density function $f(x, \alpha) = \alpha e^{-\alpha x}$. Under the hypothesis H_0 , the statistics are the same as for the AWGN channel case (P_f is independent of the SNR). However, H_1 behaves differently and has P_d given by [11], [14], [17], [18]

$$P_d = \int_0^\infty Q_{(N+1)}(\sqrt{2\gamma}, \sqrt{\lambda}) f_\gamma(x) dx \quad (15)$$

Substituting (13) into (15) the closed form of P_d becomes [10]

$$P_d = e^{-\frac{\lambda}{2}} \sum_{n=0}^{N-2} \frac{1}{n!} \left(\frac{\lambda}{2}\right)^n + \left(\frac{1+\bar{\gamma}}{\bar{\gamma}}\right)^{N-1} * \left(e^{-\frac{\lambda}{2(1+\bar{\gamma})}} - e^{-\frac{\lambda}{2} \sum_{n=0}^{N-2} \frac{1}{n!} \left(\frac{\lambda+\bar{\gamma}}{2(1+\bar{\gamma})}\right)^n}\right) \quad (16)$$

2.2. Replica Correlation Detector (RCD) Algorithm

2.2.1. RCD under Awgn Channel

A replica-correlation detector is performed based on the correlation between the received signal $X(t)$ and the replica known primary signal $s(t)$ (signal transmitted by the licensed transmitter). The block diagram of system model is shown in Fig.5.

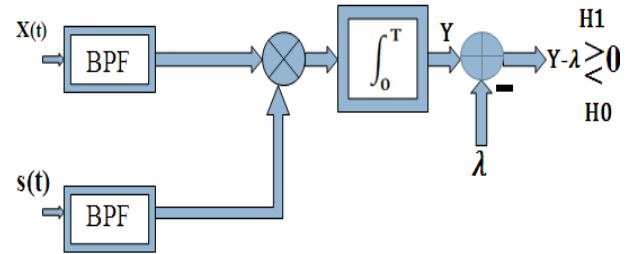


Figure 5. Block diagram of replica correlation detector system for continuous time case

The hypothesis model for transmitter detection can be defined as

$$x(t) = \begin{cases} n(t) & : H_0 \\ s(t) + n(t) & : H_1 \end{cases} \quad (17)$$

A decision value of replica-correlation detector for the presence of both continuous and discrete signal is given, respectively, as:

$$Y = \text{Re}\left\{\int_0^T x(t) S^*(t) dt\right\} > \lambda \quad (18)$$

$$Y = \text{Re}\left\{\sum_{n=0}^{N-1} x[n] S^*[n]\right\} > \lambda \quad (19)$$

From the assumption that noise is independent of signal, the received signals or samples can be considered as independent. As the result, $x(t)s(t)$ or $x[n]s[n]$ is a sequence of independent identically distributed (i.i.d) random variables with zero mean and variance of $\sigma_n^2 \sigma_s^2$ for hypothesis H_0 , and mean of σ_s^2 and variance of

$\sigma_s^2(1 + \sigma_n^2 + \sigma_s^2)$ for hypothesis H_1 . Using central limit theorem to the decision static of the replica correlation detector Y for large sample index value N , the distribution of the test statistic can be approximated as Gaussian and statistically expressed as [9], [10]

$$Y \sim \begin{cases} \mathcal{N}(0, N\sigma_n^2\sigma_s^2) & : H_0 \\ \mathcal{N}(N\sigma_s^2, N\sigma_s^2(1 + \sigma_n^2 + \sigma_s^2)) & : H_1 \end{cases} \quad (20)$$

Then the two probabilities are expressed as

$$P_d = Q\left(\frac{\lambda - N\sigma_s^2}{\sqrt{N\sigma_s^2(1 + \sigma_n^2 + \sigma_s^2)}}\right) \quad (21)$$

and

$$P_f = Q\left(\frac{\lambda}{\sqrt{N\sigma_n^2\sigma_s^2}}\right) \quad (22)$$

By applying the concept described on noise uncertainty of energy detector we can know the effect of noise uncertainty on the performance of replica correlation detector. The fading effect for replica correlation detection also analyzed by the procedure we have followed for energy detection.

2.3. Cooperative Detector Algorithm

Among many other challenges one of the most important challenge for the implementation of CR network is the hidden node problem, when a CR is shadowed or in a deep fade [20], [21]. Cooperative systems such as wireless sensor networks exploit the benefits of spatial diversity that geographically dispersed sensors provide. In the case of cooperative detection multiple CR's can collaborate with each other in order to make a global decision about the existence of the PU as shown in the scenario of Fig.6. Therefore cooperative detection refers to spectrum sensing methods where information from multiple secondary users is incorporated for primary user detection.

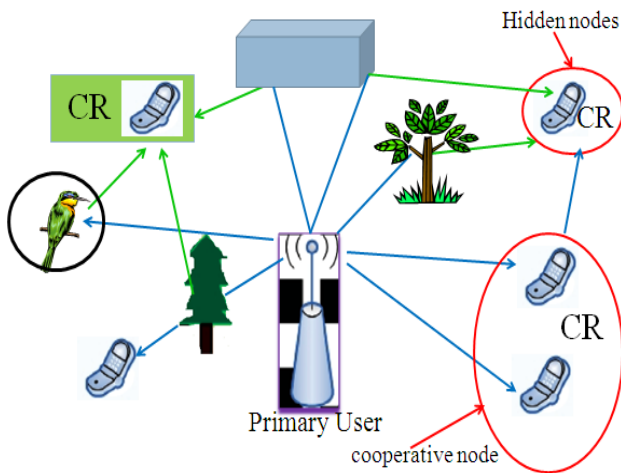


Figure 6. Scenario of cooperative signal detection for cognitive radio

Cooperative detection can be implemented either in a centralized or distributed manner [22]. In centralized systems, the local sensors (CR's) take local measurement to detect the primary user and forward their decision to a central processor that performs the final decision to accept or reject

the hypothesis based on the decision reports. Contrary to centralized systems, in decentralized systems, cognitive nodes share sensing information among each other but they make their own decisions as to which part of the spectrum they can use. Hence there is no need a backbone infrastructure for the case of distributed detection. These two systems are shown in Fig.7.

In Cooperative spectrum detection (CSD), every SU performs its own spectrum sensing measurements and can also make a local decision on whether the PU is present or absent. All of the SUs forward their soft (local measurement) or hard (1-bit) decision to a common receiver, often called fusion center or a band manager. Fusion center may be centralized or distributed.

In hard decision combining, fusion center collects binary decisions from the individual SUs, identifies the available spectrum and then broadcasts this information to the other SUs. There are many ways to combine or fuse hard decisions based on counting rules. We have used OR (If one of the decisions is "1," the final decision is "1.") and AND (If and only if all decisions are "1," the final decision is "1") fusion rule. In AND all CRs should declare H_1 in order to make a global decision that PU is present while in OR rule, fusion center declares H_1 if any of the received decision is H_1 .

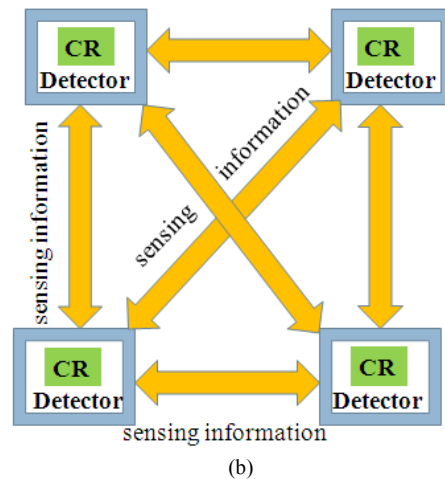
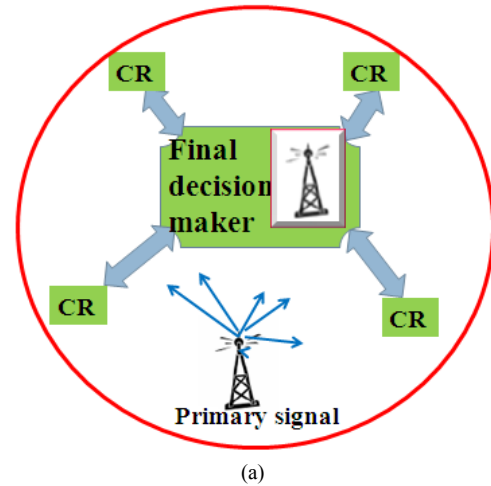


Figure 7. Fusion center of cooperative detection (a) centralized (b) distributed

Then the average P_d and P_f for the k-out-of- ($n=N_s$) rule are related to their single-user counterparts by [24]

$$Q_d = P_{dt} = 1 - \sum_{i=k}^{N_s} \binom{N_s}{i} P_d^i (1 - P_d)^{N_s-i} \quad (23)$$

$$Q_f = P_{ft} = 1 - \sum_{i=k}^{N_s} \binom{N_s}{i} P_f^i (1 - P_f)^{N_s-i} \quad (24)$$

where, P_d^i and P_f^i are the P_d and P_f for user i , respectively; $N_s = n$ is number of secondary users. $k=1$ and N_s for OR and AND rule, respectively.

Since we are compared the performance of energy, replica correlation and cooperative detection, we have implemented both energy detection based cooperative detection (all nodes under cooperation use energy detection) and replica correlation detection based cooperative detection (all nodes under cooperation use replica correlation detection). In this section we found a mathematical expression for energy detection based cooperative detection when all secondary cognitive users use energy detection. The system model for our implementation is shown in Fig.8.

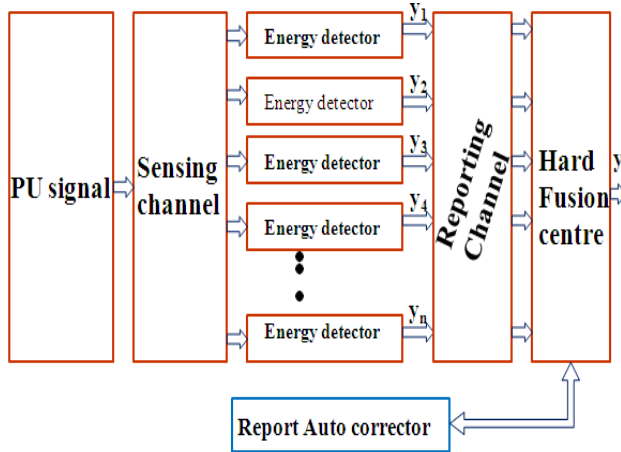


Figure 8. System model for energy detector based cooperative detector algorithm

For the system each SU uses energy detector algorithm to make local decision. The sensing (reporting) information from each energy detector are passed through reporting channel to the fusion center. At fusion center hard decision fusion is used because of lower communication overhead over the reporting channels. If the server of hard fusion center receives a local decision '0' due to imperfect reporting channel, it has a pre-knowledge that only detection '1' result is reported so it auto-corrects the reported error using report autocorrector block. By assuming equal P_d and P_f for each secondary nodes, Q_d and Q_f of OR-rule fusion centre under AWGN channel are expressed as [23]

$$Q_d = 1 - \left(1 - Q \left(\frac{\lambda - N(\sigma_n^2 + \sigma_s^2)}{\sqrt{2N(\sigma_n^2 + \sigma_s^2)}} \right) \right)^{N_s}$$

and

$$Q_f = 1 - \left(1 - Q \left(\frac{\lambda - N\sigma_n^2}{\sqrt{2N\sigma_n^4}} \right) \right)^{N_s} \quad (25)$$

Whenever noise uncertainty factor is considered the corresponding probabilities are obtained in the same manner as before and similar procedures could be used when each cognitive radio of energy detector for cooperative detection is under fading channel.

When the secondary users performing their detection operation in a collaborative way, each secondary users can use replica correlation detection. That means the secondary user detector is performed on the correlation between the received signal and the replica known signal. Then multiple receivers process their observed data independently and send their decisions to a specific user, which then makes a final decision or each receivers can decide by the combination of its decision result and the information it got from other receiver. The system model for the replica correlation based cooperative detector is similar with the energy based cooperative detector except replica correlation detector replaces its local detector of energy detector. Thus the performance parameters for replica correlation based cooperative detection under AWGN could be derived in the same way as energy detector. But since our target for cooperative detection is under fading channel, Q_d is expressed as [23]

$$Q_d = 1 - \left(1 - \int_0^\infty Q \left(\frac{\lambda - N\sigma_s^2}{\sqrt{N\sigma_s^2(1 + \sigma_n^2 + \sigma_s^2)}} \right) \frac{1}{\gamma} \exp \left(-\frac{x}{\gamma} \right) dx \right)^{N_s} \quad (26)$$

3. Simulation Results and Discussion

In this section some results of the work are presented. All simulations are carried out under the consideration of required P_d of 90%, P_f of 10% and P_m of 10% within the bandwidth of 6 MHz. All the performance evaluations are carried out for the simulation parameters shown in appendix Table 1.

Simulation results for the performance evaluation of energy and replica correlation detector algorithm under AWGN and Rayleigh fading channels are presented. Figure 8 and Fig. 9 are carried out to show P_d and P_m of both energy and replica correlation detector algorithm under AWGN for SNR=5dB. As can be seen from the results, replica correlation detector got better performance. This is because the known signal is correlated with the received signal at the receiver in the case of replica correlation detector.

Figure 10 shows the simulation result of receiver ROC of energy and replica correlation detector under Rayleigh fading channel for SNR of 2dB. As one can see from the result, the performance of the detectors at acceptable $P_f = 0.1$ is low. Especially energy detector is highly affected by the Rayleigh fading channel. In general, in an environment with Rayleigh fading single node detection are not sufficiently reliable for dynamic spectrum utilization.

That means the sensing performance in Rayleigh fading channel is significantly lower compared to the AWGN channel.

Next, simulation results for energy and replica correlation based cooperative detection algorithm are presented. This is shown in Figs. 11 and 12 and it is carried out for SNR value of -10dB for energy based cooperative detector algorithm under Rayleigh fading channel. The number of secondary nodes used for cooperation are $N_s=n=2, 3, 4$ and 10. The probability of false alarm is shown in Fig. 13.

The simulation was done by using both AND and OR - rule fusion scheme. The cooperative detector delivers better performance even at low SNR level and the OR rule fusion scheme delivers better performance. Fig.14 shows P_d versus threshold for replica correlation based cooperative detector ($N_s=2$) under Rayleigh fading channel for the SNR level of -10 dB.

Classical detection theory suggests that degradation in probability of detection or receiver operating characteristics can be countered by increasing the sensing time. But it is possible to achieve better performance using cooperative detection without increasing the sensing time and this concept is verified by results of Fig.15 and Fig 16. The simulations of Fig.15 and 16 are carried out for acceptable probability of false alarm, which is 10%, signal to noise ratio of -10dB and number of secondary nodes used for collaboration are two ($N_s=n=2$) for both energy and replica correlation based cooperative detector algorithms.

The performance depicting CROC are simulated and shown in Fig. 17 for all types of detectors.

From this result one observes that, at $P_f = 0.1$, the P_m of

double nodes replica correlation based cooperative detector is lower than double nodes energy detector based cooperative detector. This shows that the replica correlation based cooperative detection gives better performance. This is because getting minimum probability of miss detection results better probability of detection.

In simulating the previous results it was assumed that the additive noise is white and Gaussian with zero mean and with known variance. However, the noise term is an aggregation of various sources. Furthermore, it was assumed that the receiver precisely knows the noise variance, so that the threshold can be set accordingly.

However, this is not realizable as noise could vary over time. Therefore, to show this effect the noise uncertainty factor was considered and the simulation results for the detection techniques with the consideration of noise uncertainty are shown below. As one can see from Fig. 18, the CROC for both energy and replica correlation detector gives some additional P_m at specific P_f for the detector without the consideration of noise uncertainty factor. Fig. 19 shows the effect of noise uncertainty on the performance of detectors. For $\text{Rho} = 0\text{dB}$, the result corresponds to the case without noise uncertainty consideration. But as the value of noise uncertainty factor increases, the performance degrades. It can be seen clearly from the results that cooperative detection improves the performance of single node detection.

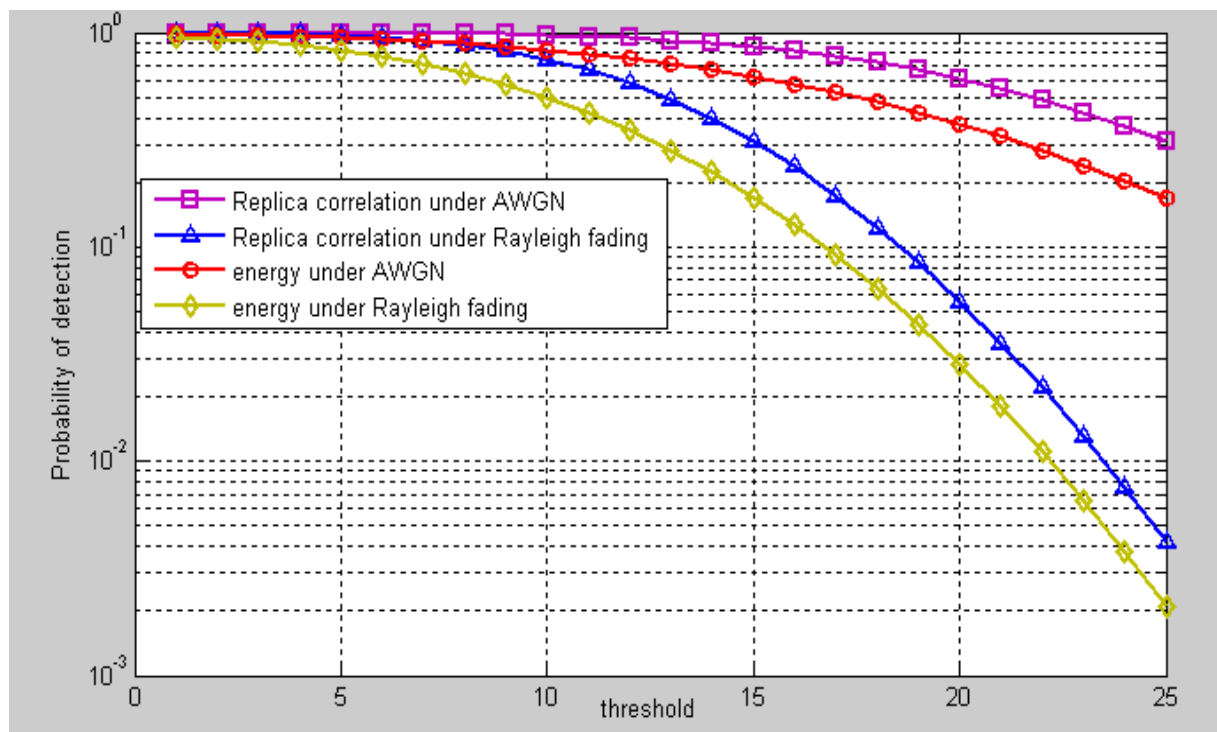


Figure 8. Performance of energy and replica correlation detector using P_d under both AWGN and Rayleigh fading channel (SNR=5dB)

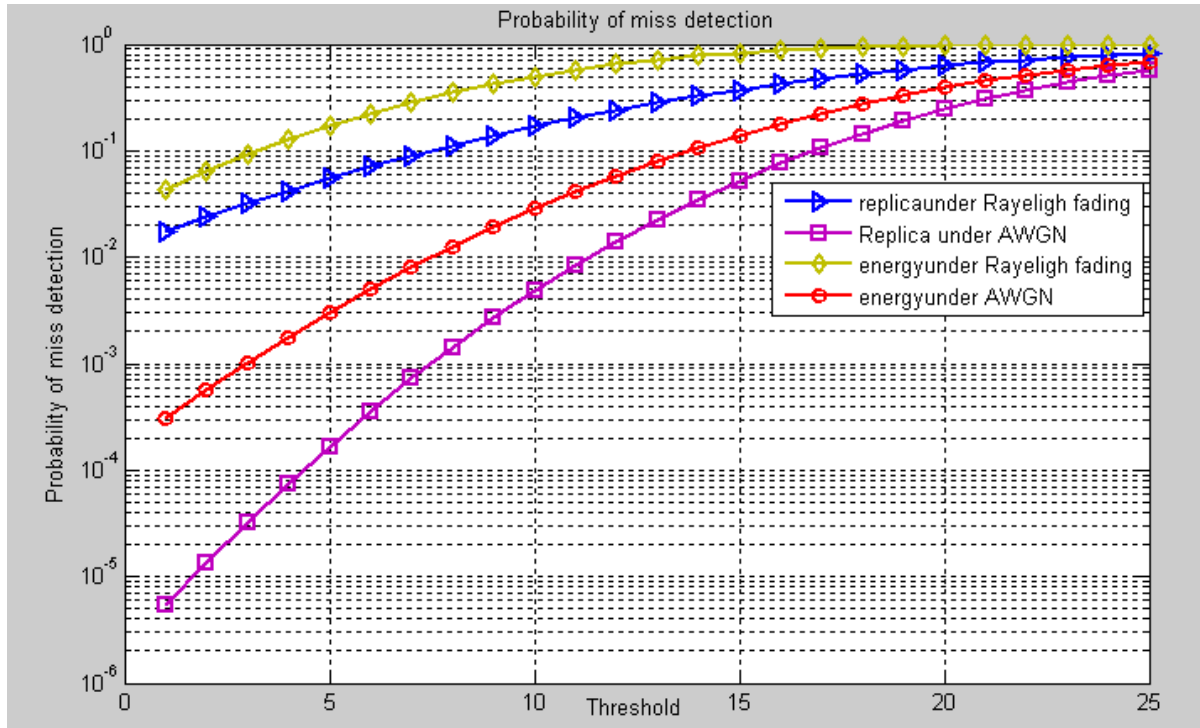


Figure 9. Performance of energy and replica correlation detector using probability of miss detection under both AWGN and Rayleigh fading channel (SNR=5dB)

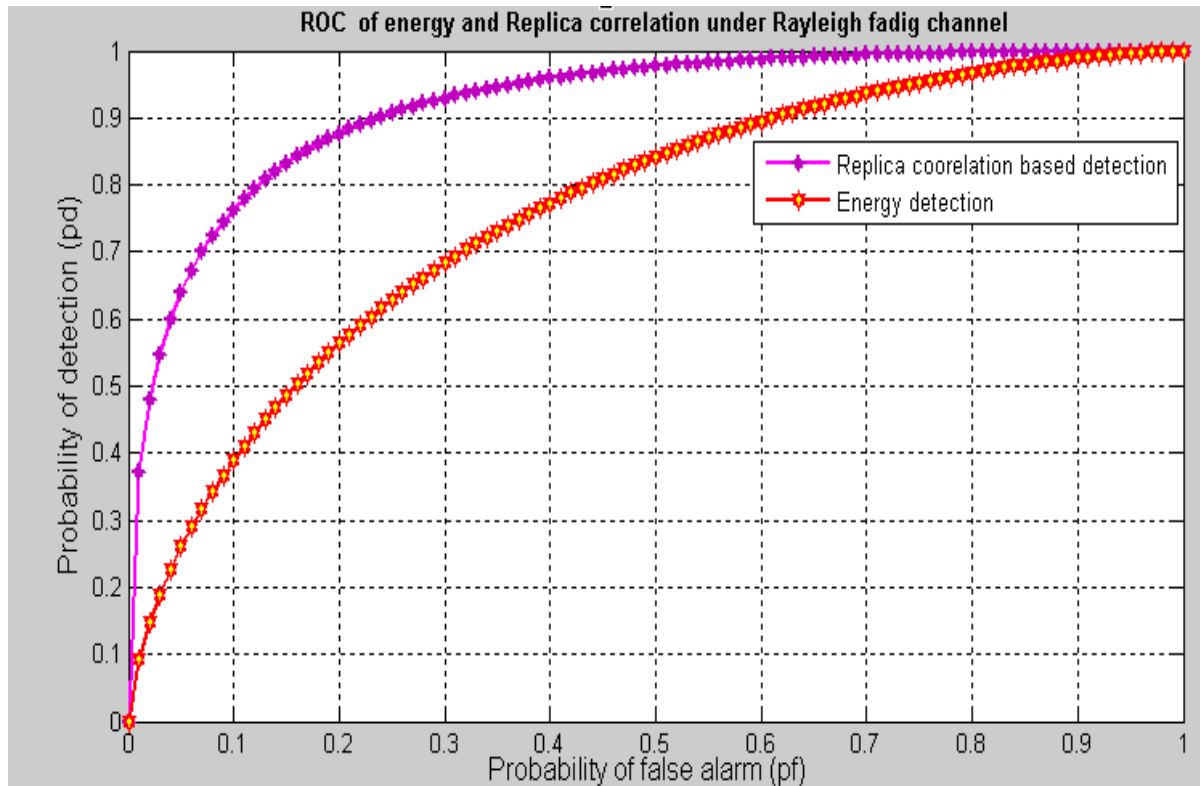


Figure 10. ROC of single node energy and replica correlation based detection under Rayleigh fading channel for SNR=2dB

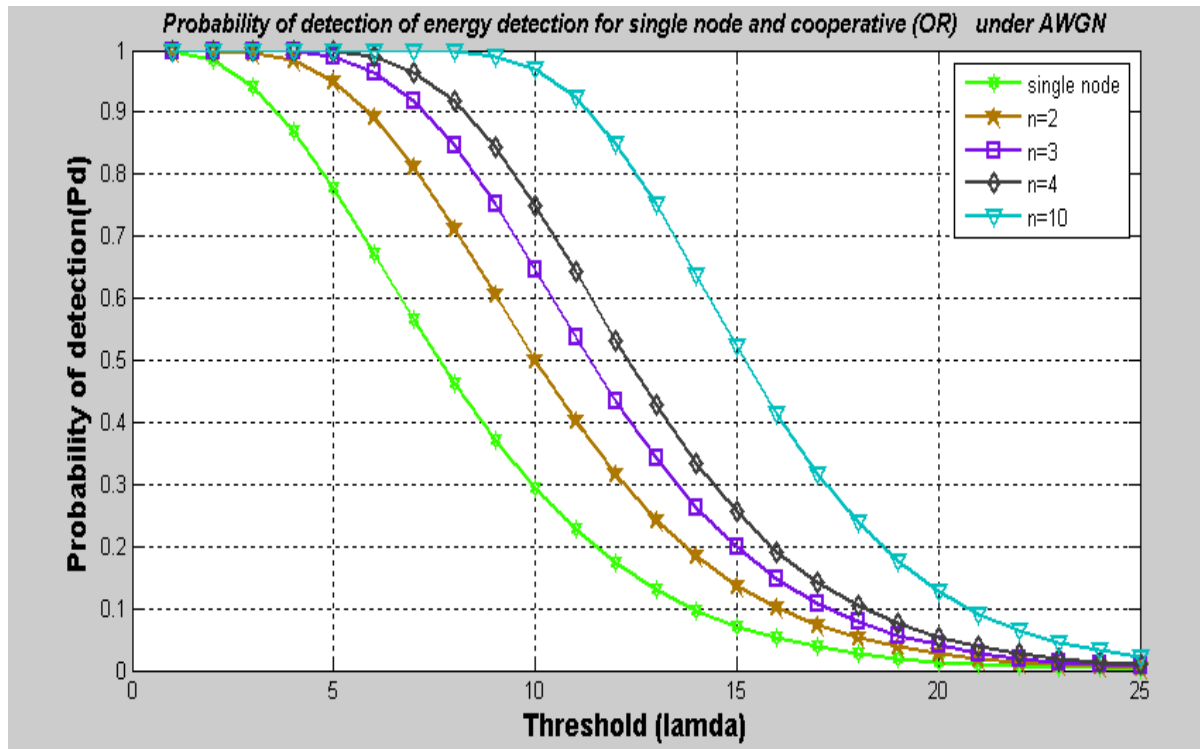


Figure 11. Performance of energy and its cooperative detection for different number of secondary users (nodes) using "OR" rule fusion scheme

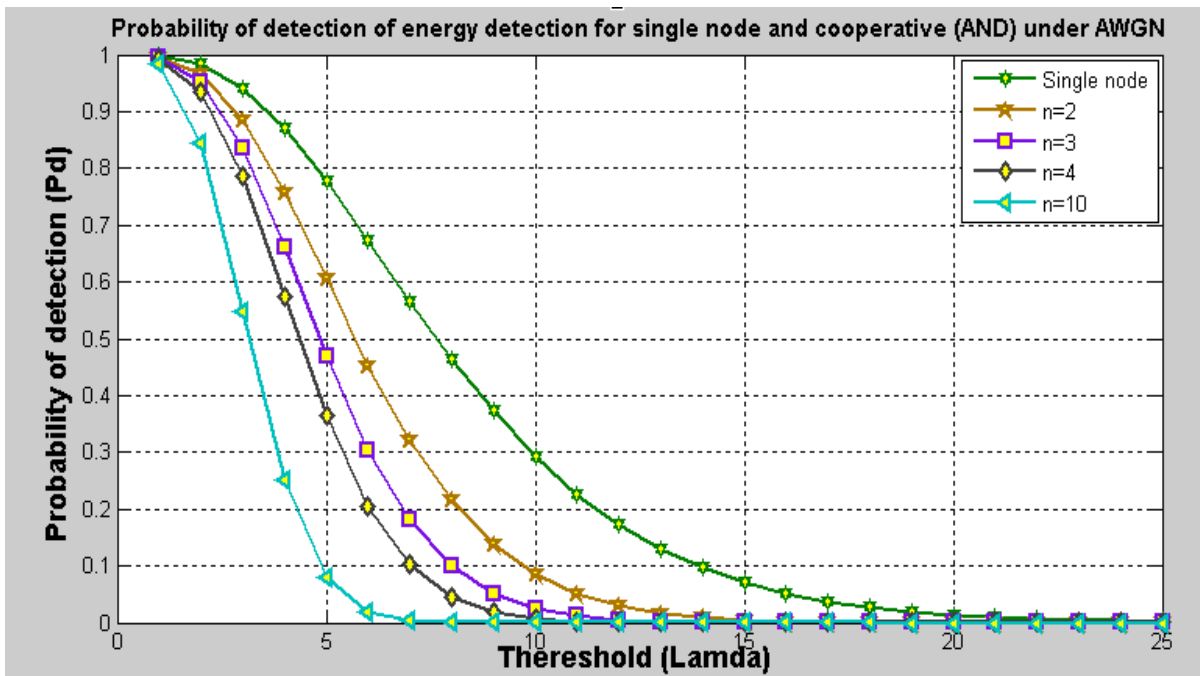


Figure 12. Performances of energy and its cooperative detection for different number of secondary users ($N_s=n=1, 2, 3, 4$ and 10) using "AND" rule fusion scheme

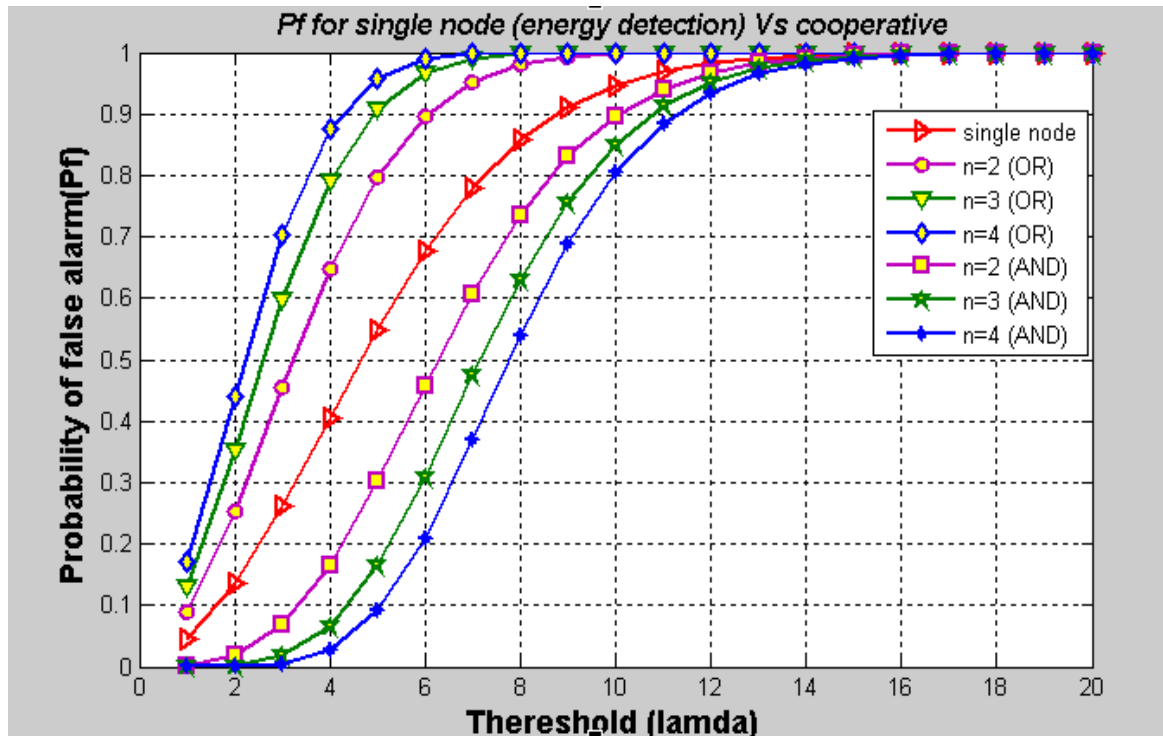


Figure 13. Performance of energy and its cooperative detection for different secondary users for both "OR" and "AND" rule fusion scheme

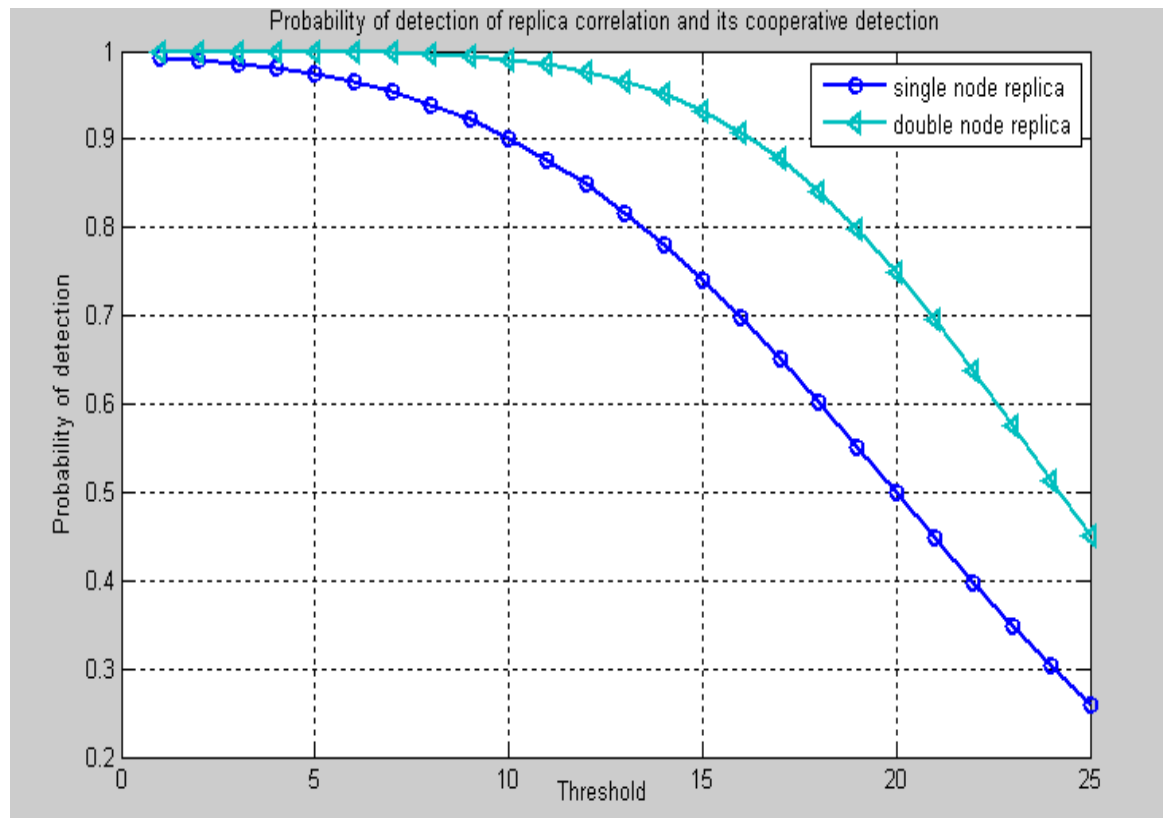


Figure 14. Pd of replica correlation and its cooperative under fading channel (SNR=-10dB)

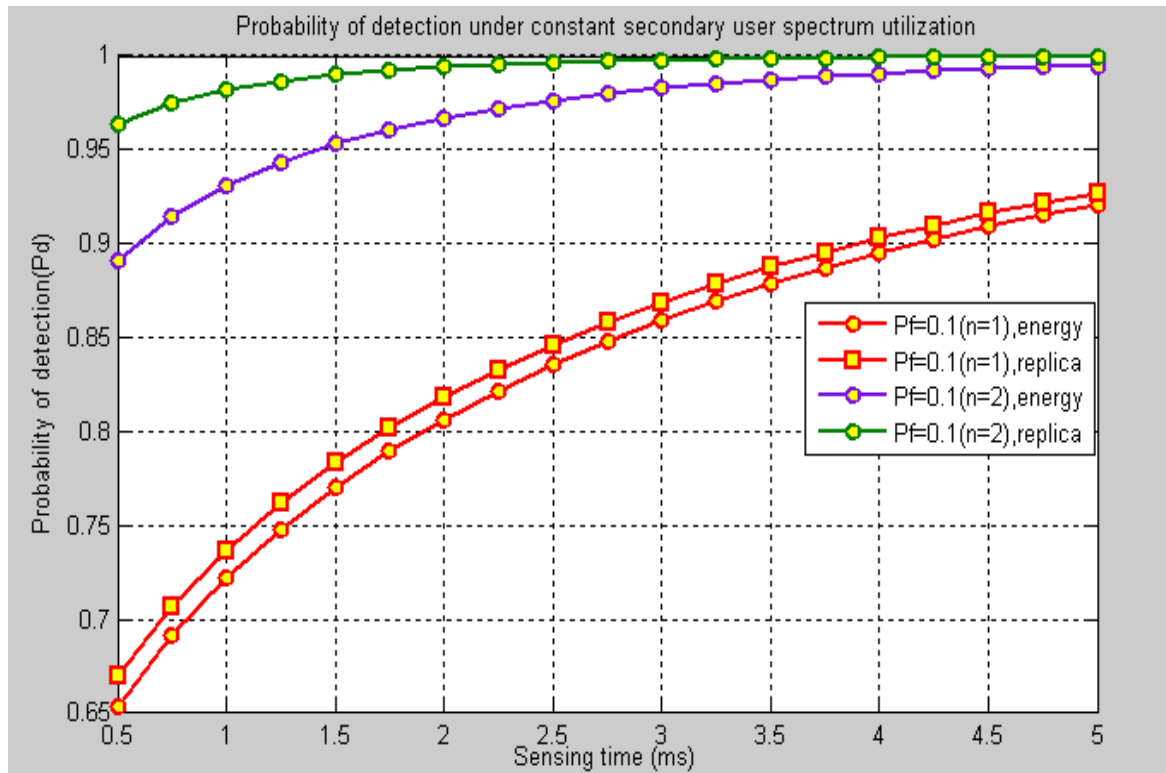


Figure 15. Plot of probability of detection versus sensing time for the three detector algorithms ("OR" rule fusion scheme, $N_s=2$)

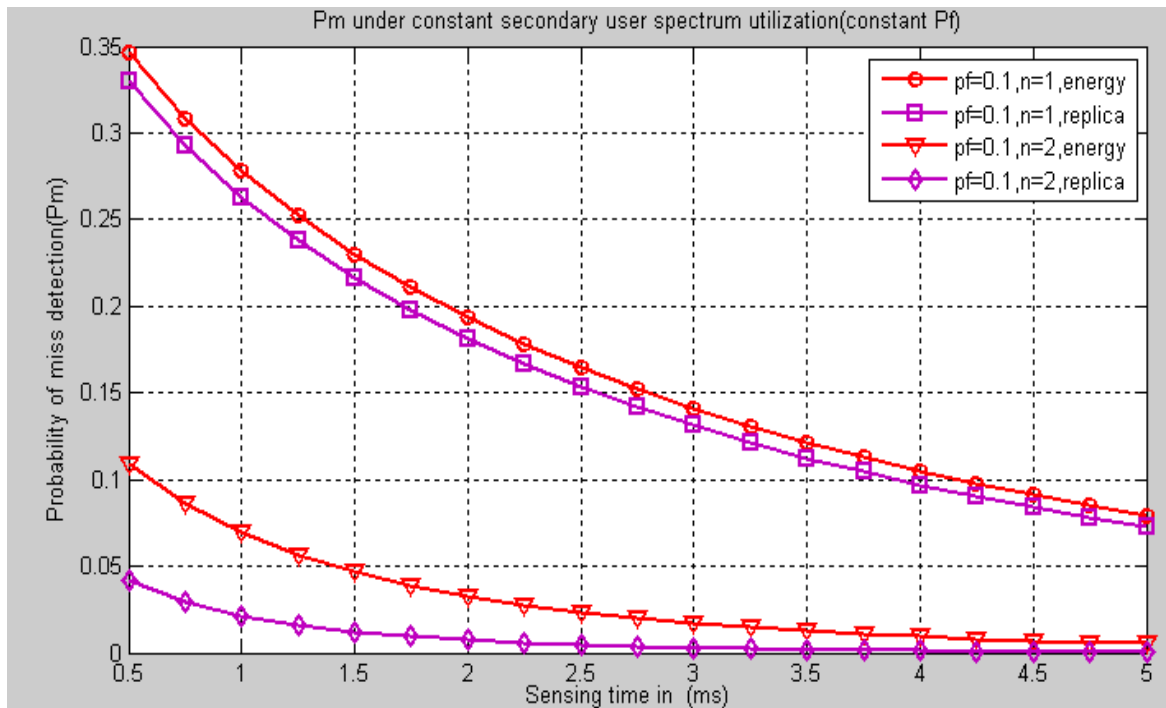


Figure 16. Plot of probability of miss detection versus sensing time for the three detector algorithms ("OR" rule fusion scheme, $N_s=2$)

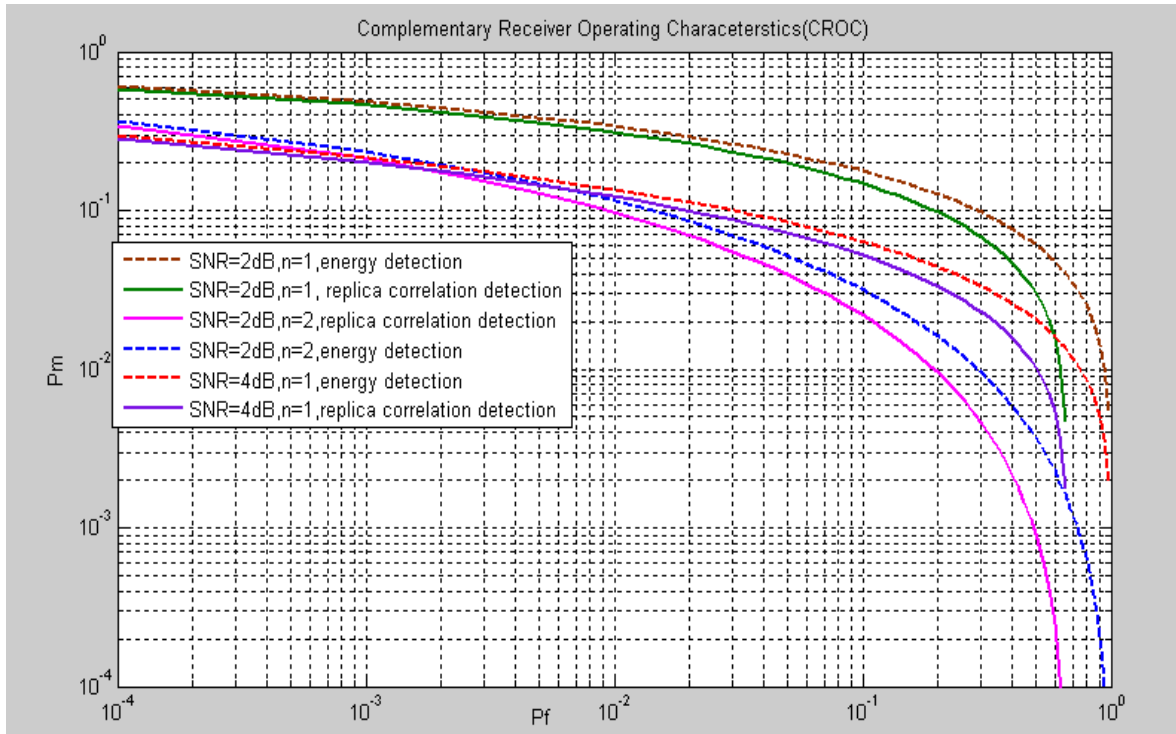


Figure 17. Complementary ROC performance comparison detector algorithms ($N_s=n=1, 2$ and $SNR=2dB$ and $4dB$)

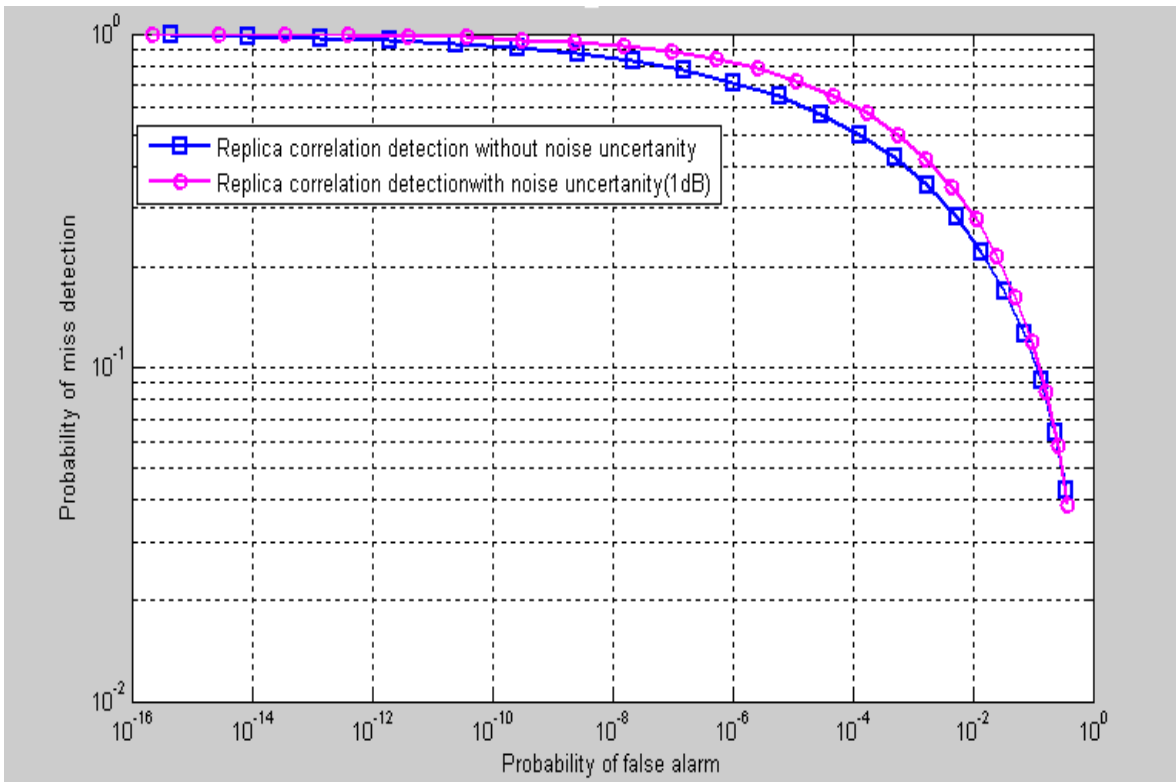


Figure 18. Plot of complementary receiver operating characteristics energy detector under consideration of noise uncertainty factor ($Rho=1dB$)

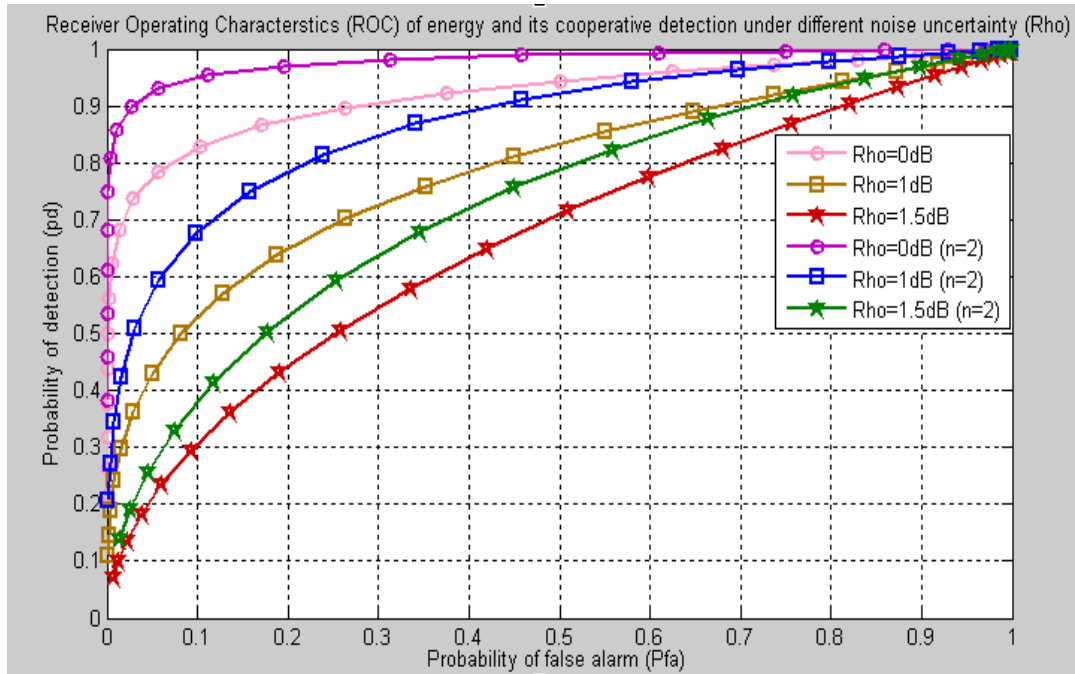


Figure 19. ROC of energy detector and its cooperative detector with noise uncertainty factor

4. Conclusions

Based on the obtained results the following conclusions are drawn from this work. Energy detector drops its performance for lower SNR value and this performance are shown by P_d , P_m and ROC. But to reduce the chance of interference with the primary users, an increase in probability of detection is needed and this is performed by increasing number of samples, increasing sensing time and by incorporating more secondary users, where replica correlation detector needs a sensing time lower than energy detector. Rayleigh fading degrades the performance of single node energy and replica correlation detector so that cooperative detection is the best option for spectrum detection in faded environments by introducing additional communications overhead of decision fusion. To introduce considerable amount of degradation in the detection performance of energy and replica correlation, noise uncertainty has been considered and the cooperative detection helps to reduce the effect of noise uncertainty factor in the overall detection performance of cognitive radio. Moreover, it was shown that the OR rule outperforms the AND rule in lower detection threshold.

Appendix

Table 1. Simulation Parameters Used for Spectrum Detector Performance Evaluation

No.	Simulation parameters	Types and value	Remark
1	Interference signal	AWGN	No other interfering signal (assumption)
2	Bandwidth (W)	6MHz	
3	Modulation	BPSK	
4	Channel	AWGN and Rayleigh	
5	Noise variance (σ_n^2)	Variable (0.5 to 1)	Known and approximate
6	Noise uncertainty (ρ)	Varies from 0 to 5dB	
7	Number of observations (N)	Variable (10-100)	
8	Number of secondary nodes ($N_s=n$)	1-10	
9	Probability of detection	$\geq 90\%$	Required for detection performance comparisons
10	Probability of false alarm	$\leq 10\%$	Required for detection performance comparisons
11	Probability of miss detection	$< 10\%$	Required for detection performance comparisons

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