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Adaptive Techniques to Detect White Spaces Using Spectrum Sensing In Cognitive Radio

Ms. T. Anupama,
Department of ECE, UCEK,JNTUK JNTUK,
Conn
Kakinada, India,
thota.anupa@gmail.com

K.Jhansi Rani,
Department.ofECE, UCEK, JNTUK
Kakinada,India,
jhansikaka@gmail.com

Abstract- Spectrum sensing is one of the key technologies to realize dynamic spectrum access in cognitive radio systems. Cognitive radios have been proposed as a possible solution to improve spectrum utilization by enabling opportunistic spectrum sharing. The main requirement for allowing CR's to use proper exploitation of white spaces in the radio spectrum requires fast, robust, and accurate methods for their detection. Spectrum sensing allows cognitive users to autonomously identify unused portions of the radio spectrum. In this work, energy detection technique is considered for spectrum sensing and uses the cost-function that depends upon a single parameter which gives the aggregate information about the present or absent of licensed users. The process of threshold selection for energy detection is addressed by the constant false alarm method and selection is carried out considering present conditions of noise levels. In this paper, simulation results shown that if we dynamically adjust the detection threshold based on noise level present during the detection process. The detection of white spaces will be higher at lower sampling time as compared with probability of detection and false alarm rate.

Keywords:Cognitive radio, spectrum sensing, energy detection, spectrum utilization, threshold selection.

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I. INTRODUCTION

In our modern technology, wireless products and wireless communication are the most convince way to communicate in our people's life, and this makes motivated us to deal with unused spectrum in radio frequency bands. In radio frequency spectrum, some users which have been licensed are highly congested they are known as primary users(PU) while the other users which are largely unoccupied the spectrum band at most of the time are unlicensed users and they are also known as secondary users(SU'S). Cognitive radio is the intelligent radio device which can improve the spectrum utilization efficiently and detect the available portions in a spectrum or white spaces in an opportunistic manner [2]. In this, spectrum sensing is the existing technology to deal with unlicensed bands and it mainly trade-off between the probability of false alarm rate and detection. In cognitive radio scenario, energy detection technique is used to identify the vacant spaces in the spectrum band and detect the primary user signal continuously to protect or not to occur any interface in the radio frequency band. In energy detection technique spectrum sensing is autonomously allows cognitive or secondary users to identify unused spectrum bands without having the priorknowledge about the signal present in a frequency band while compared to other adaptive techniques. The performance of spectrum sensing greatly depends on threshold setting. mostly conventional spectrum sensing methods adopts fixed detection threshold to distinguish primary user signal from the noise.so that the signal will fluctuates due to the noise power and in energy detection technique the signal in the system highly depends on environmental conditions. Therefore, there is a more chances of getting high missed detection and false alarm probability. To minimize this problem some authors derived the optimal threshold technique algorithm by considering a cost-function depends upon a single weighted node in an adaptive cooperative scheme to improve deflection coefficient. So, that probability of false alarm rate and missed detection improves as compared to the fixed conventional one. Therefore, our proposal method can improve the deflection coefficient by assuming the weighted strategies in a test statistic manner. In adaptive threshold technique to overcome the noise variance we can consider the estimation of errors to determine the detection threshold. In this work, we propose the algorithm for selecting optimal threshold that minimizes probability of detection error in a cooperative sensing scheme.so that we can improve the performance of spectrum efficiency [6]. And in this work, we present preliminary results on the evaluation of energy detection performance, when the constant false alarm rate method is considered for detection threshold selection. Therefore, our aim of work is to identify the optimal detection threshold considering weighted parameter, noise variance, and interference in cognitive systems. The rest of the paper is organized as follows: section 2 can splits in 2 parts 2.1 defines the system model of PU spectrum sensing based on energy detection. In section 2.2, we implement the new cost function based on new energy detection proposals. And in section 3, we determine the proposed method new detection threshold to reduce the error for high spectrum utilization and to improve the probability of detection. And in section 3 shows that desired simulation and analysis and in section 4 results of proposed method are shown. Finally, conclusion and future work are presented in section 5.

II (a)System model:

The system is composed by considering the single primary user and single secondary user. SU's with the energy detection technique is used to detect the presence or absence of PU's over the interval of time T, under the hypothesis of Ho & H1.

$H_0: x(n) = w(n)$ $\quad (no\ PU\ signal)$ $H_1: x(n) = h(n)s(n) + w(n)$ $(PU\ signal\ is\ present)$- (1)

Where Y(n) is the received signal at corresponding samples. HO & H1 are the hypothesis for PU signal present or absent respectively. S(n) is the primary user signal. h(n) is the channel gain and w(n) represents the AWGN and is assumed to be independently and identically distributed with zero mean and variance.

In cognitive radio, the traffic pattern of primary user is changes, i.e., both the hypothesis H0 & H1 holds at certain interval of time to observe the detection process.

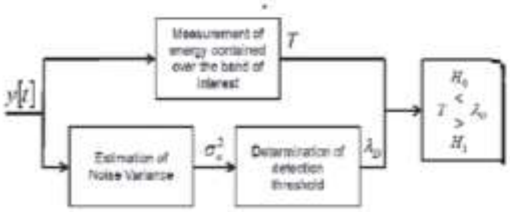

Fig1: Block diagram of energy detection process

Energy detector provides energy estimates corresponding to that hypothesis. The energy estimates can be assumed as Ym , the statistical test for energy detection is,

$y_k = \sum_{n=1}^{N} |x(n+kN)|^2$ -(2)

Where N is the no. of samples.

k-consists of discrete time index associated with o/p energy estimator. Based on primary signal presence or absence, the decision statistics can change per the chi-squared distribution with the same degree of freedom. If N is large enough, number of samples used for detection can make use of central limit theorem to approximate the distribution of test static mean and variance as Gaussian function [3]. And it can be expressed as,

$$E[y_k] = N\sigma_n^2 \quad \text{if } H_0 \text{ Holds} \qquad -(3)$$
$$= [N + \eta_k]\sigma_n^2 \quad \text{if } H_1 \text{ Holds}$$

Where η_k is N times SNR at the SU node is defined as,

$$\eta_k = \frac{|h_k|^2}{\sigma_n^2} \sum_{n=0}^{N-1} |s(n+kN|^2 \quad - (4)$$

The detection is based on both hypothesis and error in the signal. there are two types of errors arise in detection process by sensing the primary user signal, one is probability of false alarm rate (Pf) where the ho is absent and another type of error is probability of missed detection (Pm) where h1 is absent. We can also observe the performance by complementing the missed detection i.e., probability of detection and from the likelihood test statistics we can define P_f and P_d as,

$P_f = Pr(y_k > \gamma|H_0)$-(5)

$P_d = \Pr(y_k > \gamma|H_1)$ $-(6)$

From the above equations, it has seen clearly that, both P_f & P_d closely depend on threshold value γ .similarly under the hypothesis of Ho &H1 the threshold of probability of detection and probability of false alarm rate based on the constant false alarm probability.

Threshold setting algorithm:

The performance of spectrum sensing greatly depends on setting of a detection threshold. for example, an experimental threshold is set to measure the noise power. For better detection probability, we have to reduce the probability of false and missed detection. To get this some authors can introduce a weighting factor in an optimal threshold algorithm to minimize the trade-off between detection and false alarm probability. This threshold algorithm is proposes based on energy estimates on a single node or weighted cooperative node in spectrum sensing to improve the deflection coefficient.

If the energy estimates were as close to their average value as possible then there may be an improvement of the detection performance i.e., the variances of the energy estimates were as small as possible. In this context, one could conceive the following single node-based cost-function that helps us motivate our proposals:

$J(\omega) = E[(d_k - \omega y_k)^2]$ - (7)

where d_k is the desired signal at instant k, ideally equal to E $[y_k]$, y_k is the corresponding energy estimate, and ωis a node-dependent control parameter. Here we employ ωy_k to perform SS, where the parameter ω can be computed using standard adaptive algorithms that search for the minimum of either the cost-function J(ω) or a deterministic approximation of it. On closely observing, we see that ωy_k is a product of scalars and the resulting ωwill bear memory corresponding to previous energy estimates due to its adaptive nature. In addition, it is worth noting that minimizing the above equation is a convex optimization problem under two hypotheses (H_0 and H_1), thus implying that there exists one optimal solution for each hypothesis, which means that the detection task employing ωis a well-posed problem [8]. Consequently, if the energy detector can provide several energy estimates of the same hypothesis during various consecutive timeslots k, the control parameter ωcan filter out possible abrupt variations present in current signal y_k. Therefore, using ωas the detection parameter instead of the raw estimates y_k or the product ωy_k since it is less sensitive to random fluctuations of the measurements which do not arise from actual changes of hypothesis, and it also allows us to perform some modifications in the cost-function to improve the test statistic.

ISSN: 2454-4248
151 – 156

II(b) Determining Detection Threshold:

The deflection coefficient, which is a meaningful figure of merit, is employed for evaluating different detection tests. It is given as,

$$\delta^2 = \frac{(E[T]_{H1} - E[T]_{H0})^2}{Var\,[T]_{H0}} \qquad -(8)$$

Where T is a given test statistic. On introducing the Gaussian assumptions, the maximization of deflection leads to similar behaviour as the likelihood ratio receiver. From above equation, if one could modify the test statistic by increasing the distance between the means or reducing the variance of the test, then one could improve the detection process. The detection test based on ωcan be considerably improved by choosing adequately the inputs and the desired signal. For that purpose, we following cost-function:

$$\tilde{J}(\omega_i) = E[(\tilde{d}_k - \omega\tilde{u}_k)^2 \qquad -(9)$$

Where $\tilde{u}_k = |y_k - \gamma|$, $\tilde{d}_k = d_k - \gamma$, and γ is the threshold over the test statistic y_k for a predefined P_f, i.e.,

$$\gamma = E[y_k]_{H_0} + Q^{-1}(P_f) Var[y_k]_{H_1} \qquad -(10)$$

In conventional EDtechniques in which energy estimates are directly used in thedetection process, δ^2 is same for all predefined P_f. This method modifies thestatistics of the test as a function of $P_f$due to the inclusion ofγ. Thus, the deflectioncoefficient, and ultimately the detection performance itself, willchange according to the desired P_f. Therefore, to perform SS the following cost-function is used in this adaptive model,

$$\tilde{J}(\omega_i) = E[(\tilde{d}_k - \omega\tilde{u}_k)^2] \qquad -(11)$$

- In this context, a reasonable approximation can be obtained through an LMS-like solution, as follows

$$\omega_{k+1} = \omega_k + \mu\, \varepsilon_{m,k}\tilde{u}_k \qquad -(12)$$

- where $\mu$is the step-size and the output-error coefficient $\varepsilon_k$is computed as,

$$\varepsilon_k = \tilde{d}_k + \omega_k\tilde{u}_k \qquad -(13)$$

- As a result, the use of above expressions allows us to sense in an adaptive way through the following detection test:

$$\omega_k \underset{H_0}{\overset{H_1}{\gtrless}} \tilde{\gamma} \qquad -(14)$$

where $\tilde{\gamma}$is the new detection threshold.

The probability of false alarm P_f, which is defined as the probability of detecting $H_1$when H_0 holds, can be expressed *as*,

$$P_f = \left(\frac{\tilde{\gamma} - E[\omega_k]_{H0}}{\sqrt{Var\,[\omega_k]_{H0}}} \right) -(15)$$

we can obtain a $\tilde{\gamma}$ for a predefined P_f, as follows:

$$\tilde{\gamma} = E[\omega_k]_{H_0} + Q^{-1}(P_f)\sqrt{Var[\omega_k]_{H_0}} \qquad -(16)$$

Desired graphs:

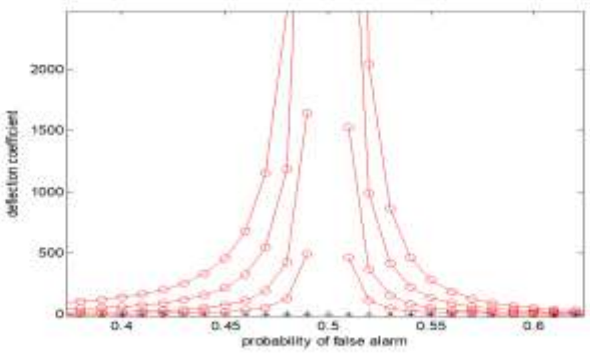

Fig1: deflection coefficient versus P_f

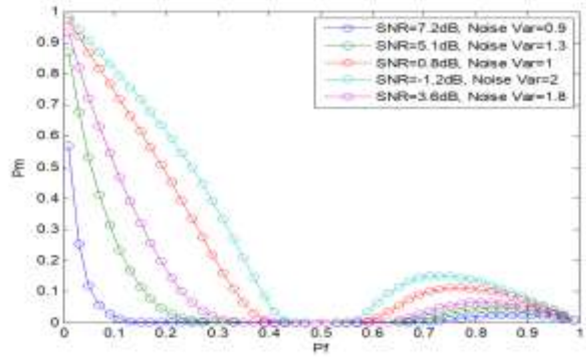

Fig2: Pm versus P_f

Fig 1 illustrates, large values of deflection coefficient leads to make the signal difference between two hypotheses and performs better detection. By observing the equation (8),we can say that by increasing the distance between the mean or reducing the variance of the test static we can improve the detection process [10]. hence in fig 2: we can observe that around pf=0.5 deflection coefficient is tends to infinity due to the unstable behaviour of pm in this region. The performance of the proposed algorithm can be improved through the weighted strategies. And this can be seen in fig2, that which represents the probability of missed detection versus probability of false alarm to improve the detection probability. but at pf=0.5 we can observe a smoothness behaviour or less values of samples due to the detection process in both transient and steady state because of high SNR and low sampling rate. To overcome this problem, we are introducing a new threshold to minimize the error probability as it increases the detection performances.

III. Proposed method

To get a better trade-off between the probability of detection and probability of false alarm rate we must minimize the error probability decision based on the primary user spectrum utilization α and threshold value range of *(0<* α*<1).*

$$min(P_e(\gamma)) = min\{(1-\alpha)P_f + \alpha(1-P_d)\} \qquad -(17)$$

Where $(1-P_d)$denotes the probability of missed detection that indicates PUs being absent while present. $\alpha(1-P_d)$denotes the error decision probability with spectrum

ISSN: 2454-4248
151 – 156

utilization α for PUs being present. $(1-\alpha)P_f$ is the probability of error decision for PUs being absent. Therefore, our aim is to find an adaptive threshold to minimize the total probability of error decision as much as possible.

$$P_e(\gamma) = (1-\alpha)P_f + \alpha(1-P_d) \qquad \text{-(18)}$$

By substituting the equations (5) & (6) into (8). We get,

Probability of error, $P_e(\gamma) = (1-\alpha)P_f + \alpha(1-P_d)$

$$=(1-\alpha)Q\left(\frac{\gamma-\sigma_n^2}{\sigma_n^2/\sqrt{N/2}}\right) + \alpha\left[1-Q\left(\frac{\gamma-(\sigma_n^2+\sigma_s^2)}{(\sigma_n^2+\sigma_s^2)/\sqrt{N/2}}\right)\right]$$

$$=\frac{1-\alpha}{\sqrt{\pi}}\int_{\frac{a}{\sqrt{2}}}^{\infty} e^{-z^2}\,dz - \frac{\alpha}{\sqrt{\pi}}\int_{\frac{b}{\sqrt{2}}}^{\infty} e^{-z^2}\,dz + \alpha \qquad \text{-(19)}$$

Where $a = \frac{(\gamma-\sigma_n^2)}{\sigma_n^2}.\sqrt{N/2}$ and b= $\frac{\gamma-(\sigma_n^2+\sigma_s^2)}{\sigma_n^2+\sigma_s^2}.\sqrt{N/2}$. On considering that the spectrum utilization factor α specified, then the probability of error decision $P_e(\gamma)$ becomes a function which changes with the changing threshold γ. Then, let $\frac{\partial P_e(\gamma)}{\partial\gamma} = 0$,

$$\frac{(2\sigma_n^2+2\sigma_s^2)\gamma^2}{2\sigma_n^2(\sigma_n^2+\sigma_s^2)} - \gamma - \frac{2\sigma_n^2(\sigma_n^2+\sigma_s^2)}{\sigma_n^2 N} \ln\frac{(1-\alpha)(\sigma_n^2+\sigma_s^2)}{\alpha\sigma_n^2} = 0 \quad \text{-(20)}$$

Therefore, as the detection threshold is real and positive optimal adaptive threshold can minimize the error decision probability. on substituting the SNR=σ_s^2/σ_n^2.By substituting this SNR value in above equations we get the desired threshold solutions as,

$$\gamma_1 = \frac{1+\sqrt{1+\frac{4(2\sigma_n^2+\sigma_s^2)}{N\sigma_s^2}.\ln\left(\frac{(1-\alpha)(\sigma_s^2+\sigma_n^2)}{\alpha\sigma_n^2}\right)}}{(2\sigma_n^2+\sigma_s^2)/\sigma_n^2(\sigma_n^2+\sigma_s^2)}, \qquad \text{-(11)}$$

$$\gamma_2 = \frac{1-\sqrt{1+\frac{4(2\sigma_n^2+\sigma_s^2)}{N\sigma_s^2}.\ln\left(\frac{(1-\alpha)(\sigma_s^2+\sigma_n^2)}{\alpha\sigma_n^2}\right)}}{(2\sigma_n^2+\sigma_s^2)/\sigma_n^2(\sigma_n^2+\sigma_s^2)} \qquad \text{-(12)}$$

Therefore, we observe the new threshold based on the primary utilization in the frequency band is and it changes as per α,

$$\gamma^* = \sigma_n^2.\frac{1+\sqrt{1+\frac{4}{N}.\left(1+\frac{2}{SNR}\right).\ln\left(\frac{(1-\alpha)}{\alpha}.(1+SNR)\right)}}{(2+SNR)/(1+SNR)} \text{-(13)}$$

III(b)simulation results and analysis:

The spectrum utilization can with low and high percentage exhibits a symmetric property centred at the 50% utilization. above equation (13) can also can changes based on N when it reaches to positive infinity values. mainly spectrum utilization does not affect the threshold value as it only based on SNR's and samples. And the observed graphs for the new determined threshold based on primary user spectrum utilization are shown below,

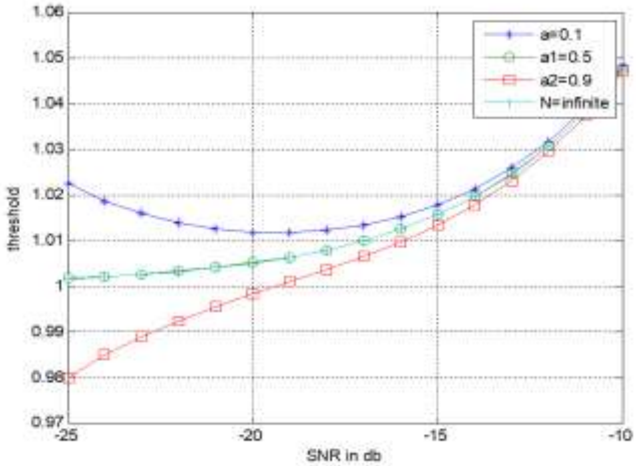

Fig3: threshold versus SNR

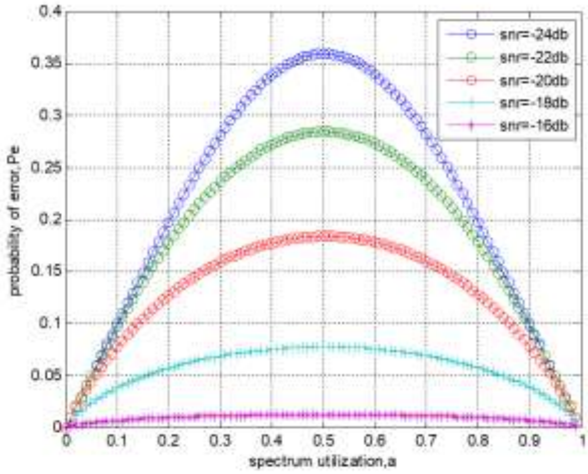

Fig4: spectrum utilization versus P_e

Fig. 3. The red square line for sample points *N* is overlapped with the blue star line for the 50% spectrum utilization. This is because $(1-\alpha)/\alpha$ is equal to 1 when α = 50%. The spectrum utilization has no effect on the setting of the adaptive threshold, which is only determined by the sample points and SNR.

In fig4 different range of SNR's can vary accordingly to probability of error detection at samples N = 65537. The spectrum utilization is ranges from 0 to 1 with nose variance=1.

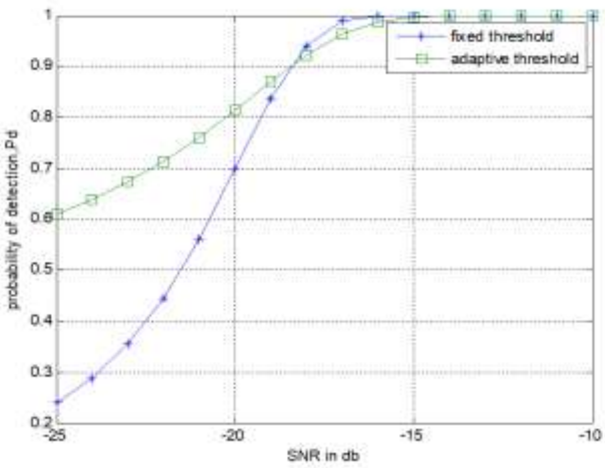

Fig4: SNR verses P_d

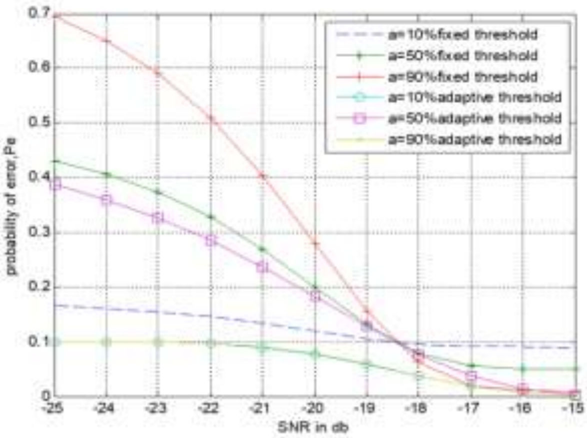

Fig5: SNR versus P_e

In fig 5 we can illustrate that as the SNR varies from -25db to -10db probability of detection changes and this canbe observed both in fixed threshold setup and variable threshold setup. And this proposed energy detection technique achieves the better detection probability at lower SNR values as compared to the conventional fixed one [15]. based on this the spectrum utilization of primary user can vary from 10% to 90%. From fig 4, we can observe the probability of error (Pe)can be vary according to different SNR's in both conventional fixed one and setting threshold and the higher decision error probability is achieved at α =50%.

IV.Results and analysis:

The highest Pe indicates the lowest total spectrum utilization ratio for both primary and secondary users. Probability of error at adaptive threshold at low spectrum utilization at 10% is same at high spectrum utilization 90%. By observing the error probability at different SNR'S, it shows the symmetric property and justify the above threshold equation. From fig 7 we can illustrate that probability of detection versus probability of false alarm in both conventional fixed and new adaptive detection threshold as the error probability decreases false and missed detection is also decreases and therefore the detection probability increases. And by observing this our proposed new detection threshold based on the spectrum utilization in energy detection technique is improved the detection probability at low values of pm and at pf=0.5.

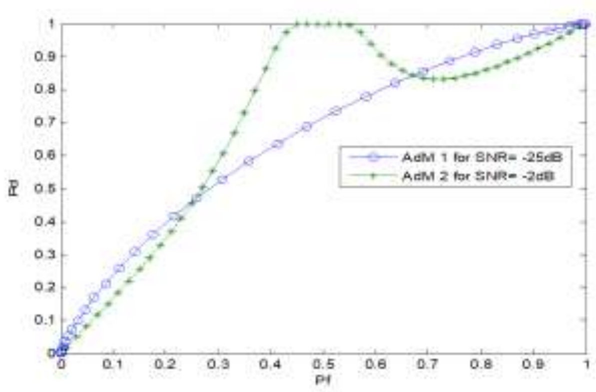

Fig 7: P_d versus P_f

V.Conclusion:

By taking a new weighted factor or cost function that determines the new statistics based on adaptive parameter is formulated.The adaptive algorithm employs pre-processed information based on the energy estimates and noise variances. It is efficient in detecting the white spaces in the available radio spectrum. But at lower values of missed detection probability the deflection coefficient tends to infinity at pf=0.5. therefore, the energy detection technique cannot produce any information or less amount of information in that range due to having high SNR and lower level of samples. Our results shown that by reducing the error probability we can improve detection process by depending the primary spectrum utilization factor. It can be concluded that when designing the CR systems, the PUs spectrum utilization should be taken for better detection probability of PU.

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ISSN: 2454-4248
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