International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 10 (2015) pp. 27121-27128

http://www.ripublication.com

# The Performance Analysis of Optimal Adaptive Threshold Control In Cognitive Radio Networks

**V.Arthi[1], N.Nagarajan[2], S.Praveen Chakkravarthy[3]**
*[1]Sri Krishna College of Technology, Coimbatore, Tamilnadu, India*
*[2,3] Coimbatore Institute of Engineering & Technology, Coimbatore, Tamilnadu, India.*
*Email:[1]arthi.psv@gmail.com,[2]swekalnag@gmail.com,[3]too.spc@gmail.com*

## Abstract

Spectrum sensing is the key process in cognitive radio networks. Secondary users should detect correctly whether the primary user is present or not in the particular spectrum within a minimum detection period. Inaccurate detection may cause interference to the primary user. Among many spectrum sensing techniques energy detection is commonly used, because of its low implementation complexity. In low SNR regime the performance of energy detection declines due to noise uncertainty. In this paper we propose a new energy detection method, by considering in low SNR. An adaptive threshold method is also discussed to combat noise uncertainty. Simulation results show that the proposed method increases the probability of detection and hence reduces the miss detection probability.

**Key words**: Cognitive Radio, Energy Detection, Noise uncertainty, adaptive threshold, Signal to noise ratio.

## Introduction

A dynamic spectrum access technique provides better spectral efficiency and frequency spectrum access based on cognitive radio networks. Using cognitive radio networks, unlicensed user(secondary user) can share the spectrum of licensed user(licensed user), when it is free. Spectrum sensing is a key function of cognitive radio networks, which identifies the unused spectrum [1].Spectrum sensing uses three detection techniques to detect the primary user: Matched filter detection, energy detection and feature detection. If the receiver knows only the power of the signal, then the best detector is energy detector[2]. Matched filter can be used ,when the receiver knows the signal[3].Signal detection in very low SNR region is discussed in [4].In this paper we discusses about energy detection method.

Cognitive radio must be able to detect the weak primary signals in order to avoid interference with the primary user [5].While detecting the primary user, noise has to be considered. In real scenario the noise may not be uniform thus noise uncertainty arises. In the presence of noise uncertainty [6],they derives a fundamental bound on detection performance in low SNR, assuming noise as white noise. For every detector, we can fix a SNR, below which detection is not possible in the presence of noise uncertainty. Traditional spectrum sensing schemes use fixed threshold which are sensitive to noise uncertainty. In [7] proposes dynamic threshold energy detection algorithm to combat noise uncertainty. Threshold is calculated using CFAR, which provides constant probability of false alarm rate even in high SNR environment.

In [8] explains, the SINR at secondary user receiver changes in real time scenario, hence adjust the threshold in cognitive radio system accordingly to the SINR. It increases the secondary users' average rate by using an optimal policy function to increase the threshold linearly with the function of SINR. Histogram based method is proposed to calculate the threshold of energy detection in noise varying real environment [9]In [10] an estimated noise variance is used to determine the threshold. They proposed a method to analyze the statistical performance of energy detection and explain how they affect the performance of spectrum sensing. In [11] they describe, noise uncertainty comprises of device noise uncertainty and environmental interference uncertainty and also concludes environmental interference is the main cause of uncertainty. They proposed proposed a power differentiation scheme, that differentiates the target primary signal from environmental interference and device noise to increase the sensing performance.

In this paper we propose a new threshold level by considering noise uncertainty in low SNR regime. The rest of the paper follows as, Section II discusses the detection model and threshold calculation without noise uncertainty. Section III describes the effect of noise uncertainty. Adaptive optimal threshold to combat noise uncertainty is discussed in section IV. Section V discusses the simulation results and section VI concludes the paper.

## Detection Model

In energy detection, secondary user senses the presence of primary user to occupy the spectrum if it is free. Only the power of the primary user signal is known, with that calculate the energy of the signal and compare it with the predefined threshold $\lambda$. Detector gives the output based on hypothesis test. If the energy of the received signal is greater than the threshold $\lambda$, exists $H_1$, indicates the presence of primary user hence secondary user cannot access the channel. Otherwise, exists $H_0$, indicates primary user absent, then secondary user can access the channel. The performance of energy detector is characterized by the following metrics; $p_d$ probability of detection indicates that the primary user is present when the hypothesis is $H_1$.$p_f$ probability of false alarm indicates that the primary user is present when the hypothesis is $H_0$.i.e actually primary user is not present. This probability must be as low as possible to increase the spectrum utilization.

Input signal to the cognitive radio terminal is BPSK modulated (n) is the primary user signal and it is assumed to be (iid) random process of zero mean and variance

$\sigma_x^2$.w(n) is assumed to be AWGN of variance $\sigma_n^2$.y(n) is the received signal at the secondary user. Then the hypothesis is given as

$$y(n) = \begin{cases} w(n), & H_0 \quad Signal\ absent \\ x(n) + w(n), & H_1 \quad Signal\ Present \end{cases} \tag{1}$$

Where n=0,1,…..N; N-number of samples.
The energy of the received signal is calculated as

$$D = \sum_{k=1}^{N} |Y[k]|^2 \gtrless_{H_0}^{H_1} \lambda \tag{2}$$

λ being the threshold value, the hypothesis can be written as

D>λ :$H_1$ PU present

D< λ :$H_0$ PU absent

For large N, i.e for large detection period, D can be approximated as Gaussian distribution

$$D \sim \begin{cases} Normal(\mu_0,\ {\sigma_0}^2) & H_0 \\ Normal(\mu_1,\ {\sigma_1}^2) & H_1 \end{cases} \tag{3}$$

Where σ and μ is defined as

$$\begin{cases} \mu_0 = N{\sigma_n}^2 & H_0 \\ \mu_1 = N{\sigma_n}^2(\gamma + 1) & H_1 \end{cases} \tag{4}$$

$$\begin{cases} {\sigma_0}^2 = 2N{\sigma_n}^4 & H_0 \\ {\sigma_1}^2 = 2N{\sigma_n}^4(\gamma + 1)^2 & H_1 \end{cases} \tag{5}$$

Where γ is the average power signal to noise ratio(SNR).

$P_m$ probability of misdetection is another metric ,it depicts, secondary user indicates primary user is not present but actually it is present .It causes interference to the primary user, it should be kept minimal. An optimal threshold should be chosen between $P_m$ and $P_f$ .

$P_d$ , $P_f$ and $P_m$ are given as

$$P_d = Prob\{D > \lambda | H_1\}; \quad P_d = \frac{1}{2} erfc\left[\frac{\lambda - \mu_1}{\sqrt{2}\,\sigma_1}\right] \tag{6}$$

$$P_f = Prob\{D > \lambda | H_0\}; \quad P_f = \frac{1}{2} erfc\left[\frac{\lambda - \mu_0}{\sqrt{2}\,\sigma_0}\right] \tag{7}$$

Where erfc is the complementary error function.

$$P_m = 1 - P_d \tag{8}$$

The prior information about the probabilities of primary user presence and absence are given by $PH_1$ and $PH_0$.Then probability of error is given as

$$P_e = PH_0 P_f + PH_1\, P_m \tag{9}$$

Detection performance depends on probability of sensing error. Probability of false alarm should be minimum , it allows more spectral access. To reduce interference to the primary user, lower $P_m$ is desired. An optimal threshold between $P_m$ and $P_f$ should be chosen to minimize error probability. An optimal threshold is chosen to minimize the error probability under spectrum sensing constraint is represented as

$$\lambda^{opt} = \arg min_{\lambda}(PH_0Pf + PH_1Pm) \tag{10}$$

Under the sensing constraint and assuming the spectrum occupancy as 0.5 the closed form expression of optimal threshold is given by

$$\lambda^{opt} = \frac{-B+\sqrt{B^2-AC}}{A} \tag{11}$$

Where $A = \sigma_1^2 - \sigma_0^2$ ;$B = \sigma_0^2\mu_1 - \sigma_1^2\mu_0$;$C = \sigma_1^2\mu_0^2 - \sigma_0^2\mu_1 - 2\sigma_1^2\sigma_0^2 \ln\left(\frac{\sigma_1}{\sigma_0}\right)$

Minimum number of samples required to satisfy the sensing constraint is given by

$$N_{min} = 2[erfc^{-1}(2Pf^*) - (1+\gamma)erfc^{-1}(2Pd^*)]^2\gamma^{-2} \tag{12}$$

Where $P_f^*$ and $P_d^*$ are the sensing constraints

## Noise Uncertainty

In real environment noise power may not be constant, it fluctuates over time and location due to interference from weak signals and thermal noise.Thus noise uncertainty may arise.The determined optimal threshold is proportional to noise power $\sigma_n^2$, hence the performance of previous method degrades in noise uncertainty environment.

Noise uncertainty is modeled as

$\sigma^2 \in (\sigma_{min}^2, \sigma_{max}^2,)$

$\sigma_{min}^2 = \sigma_n^2/\rho$ :lower bound of noise uncertainty

$\sigma_{max}^2 = \sigma_n^2\rho$ :upper bound of noise uncertainty

where ρ is the noise uncertainty factor

The decision statistic under noise uncertainty is defined as

$$D \sim \begin{cases} Normal(N\rho\sigma_n^2, \quad 2N\rho^2\sigma_n^4) & H_0 \\ Normal\left(N\sigma_n^2\left(\frac{1}{\rho}+\gamma\right), 2N\sigma_n^4\left(\frac{1}{\rho}+\gamma\right)^2\right) & H_1 \end{cases} \tag{13}$$

With the above factor probability of detection and probability of false alarm can be written as

$$P_d = \frac{1}{2} erfc\left[\frac{\lambda - N\sigma_n^2\left(\frac{1}{\rho}+\gamma\right)}{\sqrt{4N}\sigma_n^2\left(\frac{1}{\rho}+\gamma\right)}\right] \tag{14}$$

$$P_f = \frac{1}{2} erfc\left[\frac{\lambda - N\rho\sigma_n^2}{\sqrt{4N}\rho\,\sigma_n^2}\right] \tag{15}$$

$P_m = 1 - P_d$

The optimal threshold can be calculated using equation (11) by substituting the parameters in equation (13). Minimum number of samples required to satisfy the sensing constraint($P_d^*, P_f^*$) is given by

$$N_{min} = \left( \frac{2\left[\rho erfc^{-1}(2Pf^{*}) - \left(\frac{1}{\rho}+\gamma\right) erfc^{-1}(2Pd^{*})\right]^{2}}{\left[\gamma - \left(\rho - \frac{1}{\rho}\right)\right]} \right) \tag{16}$$

When γ reduces to ρ-1/ρ then N turns to infinity (i.e) this is the minimum SNR bound below that number of samples required to detect the signal is infinity.It is practically not achievable.Thus the minimum SNR bound,below which signal cannot be detected is given as $SNR_{bound}$= ρ-1/ρ.

## Adaptive Optimal Threshold Method

To combat noise uncertainty the optimal threshold can be adjusted as

$\lambda^{*} \in (\lambda/\rho^{*}, \rho^{*}\lambda)$ where $\rho^{*}$ is the dynamic threshold factor and it should be greater than or equal to 1 to indicate the dynamic factor( $\rho^{*}$ >=1).By considering the noise uncertainty and adaptive threshold factor the detection and false alarm probabilities are given as

$$P_d = \min_{\lambda^{*} \in \left(\frac{\lambda}{\rho^{*}}, \rho^{*}\lambda\right)} \min_{\sigma^2 \in \left(\frac{\sigma_n^2}{\rho}, \rho\sigma_n^2\right)} \frac{1}{2} erfc\left[\frac{\lambda^{*} - \mu_1}{\sqrt{2}\sigma_1}\right]$$

$$P_d = \frac{1}{2} erfc\left[\frac{\frac{\lambda}{\rho^{*}} - \mu_1}{\sqrt{2}\sigma_1}\right] \tag{17}$$

$$P_f = \max_{\lambda^{*} \in \left(\frac{\lambda}{\rho^{*}}, \rho^{*}\lambda\right)} \max_{\sigma^2 \in \left(\frac{\sigma_n^2}{\rho}, \rho\sigma_n^2\right)} \frac{1}{2} erfc\left[\frac{\lambda^{*} - \mu_0}{\sqrt{2}\sigma_0}\right]$$

$$P_f = \frac{1}{2} erfc\left[\frac{\rho^{*}\lambda - \mu_0}{\sqrt{2}\sigma_0}\right] \tag{18}$$

The modified parameters for threshold calculation A, Band C are give as

$$A = \rho^{*2}\sigma_1^2 - \left(\frac{1}{\rho^{*2}}\right)\sigma_0^2; \; B = \left(\frac{1}{\rho^{*}}\right)\sigma_0^2\mu_1 - \rho^{*}\sigma_1^2\mu_0 \; ;$$

$$C = \sigma_1^2\mu_0^2 - \sigma_0^2\mu_1^2 - 2\sigma_1^2\sigma_0^2 \ln\left(\rho^{*2}\sigma_1/\sigma_0\right)$$

Again the adaptive threshold can be calculated using the equation (11) with the above parameters. Minimum number of samples required to satisfy the sensing constraint ($P_d$*,$P_f$*) is given by

$$N_{min} = \frac{2\left[\left(\frac{\rho}{\rho^{*}}\right) erfc^{-1}(2Pf^{*}) - \rho^{*}\left(\frac{1}{\rho}+\gamma\right) erfc^{-1}(2Pd^{*})\right]^{2}}{\rho^{*2}\left[\gamma - \left(\frac{\rho}{\rho^{*2}} - \frac{1}{\rho}\right)\right]^{2}} \tag{19}$$

SNR bound is defined as $SNR_{bound} = \frac{\rho}{\rho^{*2}} - \frac{1}{\rho}$

## Simulation Results

Simulation results show performance of the proposed method by comparing the probability of error with different SNR range and with the number of samples.

Fig 1 shows the effect of number of samples in the probability of error. It is observed, for increasing N the probability of error reduces for given low SNR. For more number of samples the probability of sensing error is reduced and it is kept constant even at very low SNR.

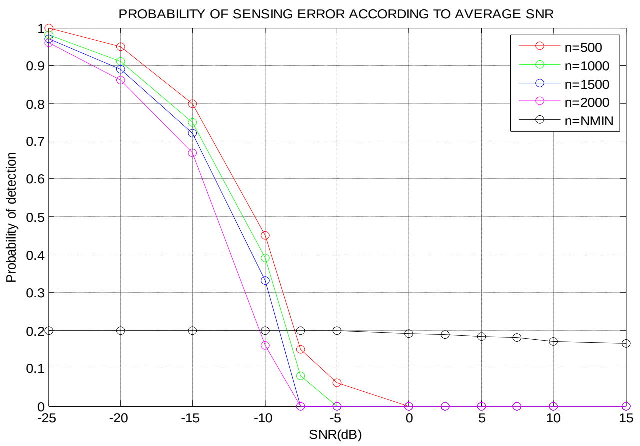


**Figure 1:** Probability of sensing error with number of samples

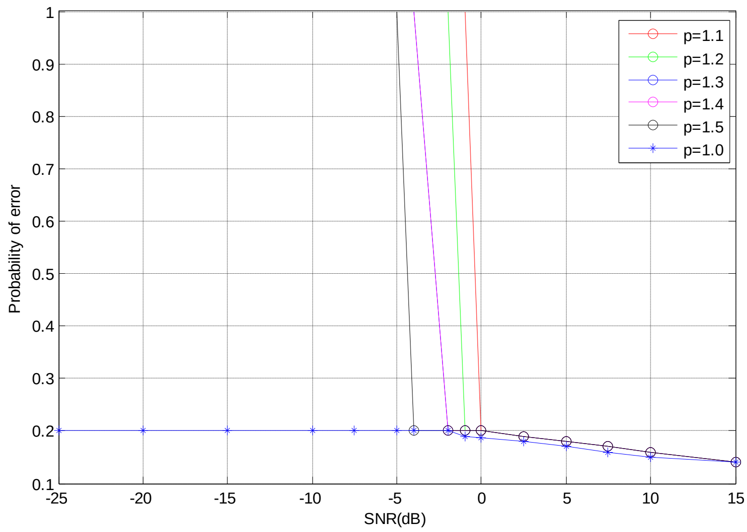


**Figure 2:** Probability of error with noise uncertainty

Fig 2 shows the effect of noise uncertainty in the probability of error. When the noise uncertainty factor increases the probability of error increases and SNR bound also gets increased.

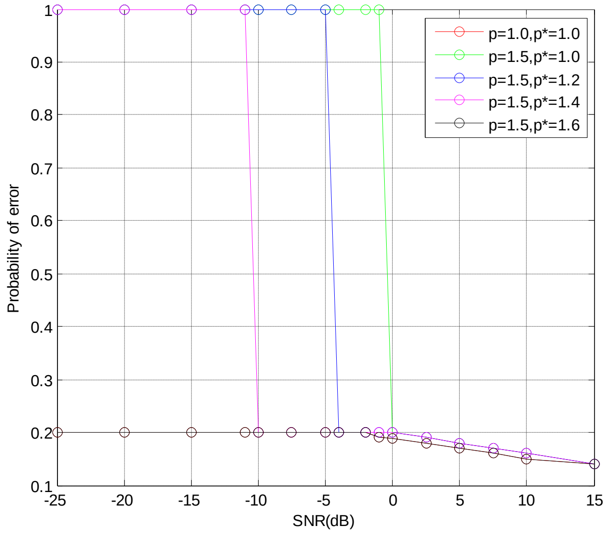


**Figure 3:** Probability of Error With Noise Uncertainty and Dynamic Threshold

Fig 3 explains the probability of sensing error for different SNR values with noise uncertainty factor ρ and adaptive threshold factor ρ*.When the adaptive threshold factor increases the performance of sensing error increases and the adaptive threshold factor is greater than the noise uncertainty factor, probability of error reduces greatly even at very low SNR.

## Conclusion

In this paper we proposed an optimal threshold determination method and its performance in noise uncertainty is discussed. An adaptive optimal threshold scheme is proposed to combat the noise uncertainty and to minimize the sensing error. The minimum required samples under low SNR regime are also discussed. Simulation results show that the proposed method reduces the detection error even in low SNR condition.

## References


[1] D. Cabric, *et al*, 2004.., "Implementation issues in spectrum sensing for cognitive radios," *Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers*, vol. 1, pp. 772-776

[2] Kyungtae Kim et.al,2010, “Energy Detection Based Spectrum Sensing for Cognitive Radio: An Experimental Study”, *IEEE globecom proceedings*.

[3] Xiang Ling et al,2012.,”Adaptive Threshold Control for Energy Detection Based Spectrum Sensing in Cognitive Radios”, *IEEE Wireless communications letters*, vol 1,pp.448- 451

[4] R. Tandra and A. Sahai,2005, "Fundamental limits on detection in low SNR under noise uncertainty," in *International Conference on Wireless Networks, Communications and Mobile Computing,* pp. 464-469.
[5] Haykin S, 2005, 'Cognitive radio: Brain powered wireless communications', IEEE J. sel. Areas communications, vol 23,pp.201-220.
[6] T. Yucek and H. Arslan, 2009., "A survey of spectrum sensing algorithms for cognitive radio applications," *Communications Surveys &Tutorials, IEEE,* vol. 11, pp. 116-130
[7] W. Haijun*, et al*, 2010., "Cooperative Spectrum Sensing in Cognitive Radio under Noise Uncertainty," *IEEE 71st Vehicular Technology Conference (VTC '10-Spring),,* pp. 1-5
[8] W. Jinbo*, et al*, 2009., "The Performance Merit of Dynamic Threshold Energy Detection Algorithm in Cognitive Radio Systems," *1st International Conference on Information Science and Engineering(ICISE),* pp. 692-695.
[9] Zhuan Ye et al,2008., "Energy Detection using Estimated Noise Variance for Spectrum Sensing in Cognitive Radio Networks", *WCNC proceedings*, pp-711716.
[10] Bingxuan Z et al,2012, "A Blind Power Differentiation Scheme for Energy Detection- based Spectrum Sensing" *ICON*,pp.320-325.
[11] Z. Qiwei*, et al*,2008.,"An efficient multi-resolution spectrum sensing method for cognitive radio," *Third International Conference on Communications and Networking in China, ,* pp. 1226-1229