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Improvement of Energy Detection Based Spectrum Sensing in Cognitive Radio Network Using Adaptive Threshold

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Abstract: *There is a huge demand for spectrum, but in conventional system radio spectrum is inefficiently used. To overcome this problem and improve spectrum utilization, cognitive radio concept has been proposed. Cognitive radio (CR) is the greatest mechanism for use spectrum efficiently. The main objective of CR is to use scarce and limited natural resources efficiently without any interference to the primary users. One of most challenging issues in cognitive radio systems is spectrum sensing concepts. There are various spectrum sensing techniques like matched filter detection, energy detection, cyclostationary detection, covariance detection and wavelet detection. Out of these techniques energy detection has got the most attention by the researchers due to its simplicity and low computational requirements. In this study we explain the Energy detection spectrum sensing method that still used in cognitive radio. Energy detection scheme has taken for spectrum sensing because it doesn't require any prior information of the primary user (PU) signal, but the performance of energy detection scheme degrades at low signal to noise ratio (SNR) region. Since the performance of energy detection scheme highly depends on noise. In this paper, we have proposed an adaptive threshold for energy detection scheme to improve the detection performance at low SNR region. Our proposed adaptive threshold is a function of the detection threshold and SNR of the primary user received at the sensing node. Simulation results will show that the detection performance of our proposed scheme is much better than the fixed threshold based energy detector at low SNR region.*

Keywords: *Cognitive Radio, Spectrum sensing, Energy detection, Detection threshold, Adaptive threshold.*

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I. Introduction

Now-A-Days The Demand Of The Wireless Spectrum Resources Increases Exponentially Because Of The Rapid Growth Of Wireless Technologies. Due To The Fixed Spectrum Allocation Policy, The Problem Of Spectrum Scarcity Arises. Federal Communications Commission (FCC) Elicit That These Fixed Allocated Bands Are Most Of The Time And At Different Locations Are Unutilized By The Primary Users (PU's) [1]. To Solve The Problem Of Spectrum Scarcity And To Increase Spectrum Utilization Cognitive Radio (CR) Has Been Proposed. CR Is The Key Technology, Initially Proposed By J. Mitola [2] In 1999 To Use The Underutilized Portion Of The Licensed Band By Sus Opportunistically. CR Is A Smart And Intelligent Radio That Can Change Its Transmission Parameters According To Its Environment In Which It Operates. To Perfectly Utilize The Spectrum Cognitive Radio Has To Sense The Spectrum To Find Whether A PU Is Active Or Not. So Spectrum Sensing Is A Very Important Process To Discover The Spectrum Holes. There Are Three Main Techniques Of Spectrum Sensing: Matched Filter Detection, Energy Detection, And Cyclostationary Feature Detection. In Match Filter Detection Takes Short Time To Achieve Detection Result But It Requires Complete Knowledge Of PU Signaling Features. It's Optimal Method Of Detection PU When Transmitted Signal Is Known. Cyclostationary Offers Good Performance Of Detection Of PU's But It Takes A Long Time To Complete Sensing And Also Need Knowledge Of The PU Cyclic Frequencies. But In Energy Detection Method Is Very Attractive And Suitable Method For Its Easy Implementation And Low Computational Complexity. There Is No Need Any Priori Information Of PU's Signal. . In Energy Detection, A Well Selected Threshold Will Significantly Improve The Performance Of Energy Detection. In [3], Hyun-Ho Choi Proposed Threshold As An Adaptive In Nature According To The Effect Of Transmission Power Of The Secondary User (SU). Sensing Threshold Only Depended On The Statistical Property Of Received Signal Authors Explain In [4]. Using The Lagrange Multipliers Method Author Achieves The Optimal Single Threshold In [5]. In [6], An Algorithm Based On Double-Threshold Is Presented, Which Is Different From Traditional Single-Threshold Design, And Makes Considerable Improvement Of Detection Performance. In [6] Requires Another Time Of Spectrum Sensing Until Getting The Result. In [7], The Author Sets A Maximum Sensing Numbers. If The Number Of Spectrum Sensing Times Exceeds The Maximum Limit, SU Will Turn To Sense Other Spectrum. In [8], Threshold Changes According To Signal To Interference Plus Noise Ratio (SINR) Received At The SU

Receiver End With The Aim To Maximize The Average Throughput Of The SU. Authors In [9] And [10] Have Proposed The Precaution Is Better Than The Cure (PBC) Approach To Enhance The Throughput Of SU.

In Order To Cope With This Challenge, In This Paper We Present A Novel An Adaptive Threshold Based Energy Delectation Method To Improve The Performance Of Spectrum Sensing For CR At Low SNR Region. Simulation Results Show That Our Proposed System Given Better Result Than The Fixed Threshold System. The Remainder Of The Paper Is Organized As Follows: System Model Is Presented In Section II. The Proposed Adaptive Threshold Detection Mechanism Is Introduced And Analyzed In Section III. Simulation Results And Analysis Are Shown In Section IV And Finally Our Conclusions Are Drawn In Section V.

II. System Model

A. General Model

The flow chart of conventional energy detector as follows:

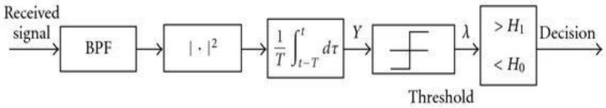


Figure 1 Conventional Energy Detector

The received signal through the band-pass filter and ADC (Analog Digital Converter) is squared and summed, and then compared with the energy detection threshold. If it is greater than the threshold, then the primary user (PU) is judged to be presented, and the SUs cannot use the channel. Otherwise, the PU is judged as absence, and the SUs can use the channel for data transmission.

The general model for spectrum sensing is binary hypothesis can be defined as

$$y(n) = \begin{cases} H_0 : & u(n) \\ H_1 : & h * s(n) + u(n) \end{cases} \quad \text{.........(1)}$$

Where y(n) is the signal received by the cognitive user, s(n) is the received PU with mean zero and variance σ_s^2, u(n) is the Additive White Gaussian Noise (AWGN) with mean zero and variance σ_u^2, and h is the amplitude gain of the channel. In eq.(1), H_0 is the null hypothesis, which states that there is no licensed user signal in the analyzed spectrum band. H_1 is the alternative hypothesis, which indicates that there exists a primary user signal.

B. Energy Detection

Let τ be the available sensing time and N the number of samples (N is the maximum integer not greater than τf_s, and for notation simplicity, we assume $N = \tau f_s$). The test statistic for energy detector is given by

$$\mathrm{T(y)} = \frac{1}{\mathrm{N}} \sum_{\mathrm{n}=1}^{\mathrm{N}} |\mathrm{y(n)}|^2 \dots\dots\dots\dots\dots\dots (2)$$

Under hypothesis H_0, the test static $T(y)$ is a random variable whose probability density function (PDF), $p_0(x)$ is a Chi square distribution with $2N$ degrees of freedom for complex valued case, and with N degrees of freedom for real-valued case.

If we choose the detection threshold as, the probability of false alarm given by

$$P_f(\epsilon, \tau) = P_r(T(y) > \epsilon | H_0) = \int_{\epsilon}^{\infty} p_0(x) dx \dots\dots\dots\dots (3)$$

Using central limit theorem (CLT), we have the following proposition.

Proposition 1: For a large N, the PDF of $T(y)$ under hypothesis H_0 can be approximated by a Gaussian distribution with mean $\mu_0 = \sigma_u^2$ and variance

$$\sigma_0^2 = \frac{1}{N} [E|u(n)|^4 - \sigma_u^4] \dots\dots\dots\dots\dots (4)$$

Further,

1. If u(n) is real-valued Gaussian variable, then $E|u(n)|^4 = 3\sigma_u^4$, thus $\sigma_0^2 = \frac{2}{N}\sigma_u^4$.
2. If u(n) is CSCG , then $E|u(n)|^4 = 2\sigma_u^4$, thus $\sigma_0^2 = \frac{1}{N}\sigma_u^4$.

Next, we focus on the CSCG noise case for which the probability of false alarm is given by

$$P_f(\epsilon, \tau) = Q\left(\left(\frac{\epsilon}{\sigma_u^2} - 1\right)\sqrt{\tau f_s}\right) \dots\dots\dots\dots\dots. (5),$$

Where Q(·) is the complementary distribution function of the standard Gaussian, i.e.,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{t^2}{2}\right) dt \ldots\ldots\ldots\ldots(6)$$

Under hypothesis H_1, denote $p_1(x)$ as the PDF of the test static $T(y)$. For a chosen threshold, the probability of detection is given by

$$P_d(\epsilon,\tau) = P_r(T(y) > \epsilon | H_1) = \int_{\epsilon}^{\infty} p_1(x)dx \ldots\ldots\ldots(7)$$

Proposition 2: For a large N, the PDF of $T(y)$ under hypothesis H_1 can be approximated by a Gaussian distribution with mean $\mu_1 = (\gamma + 1)\,\sigma_u^2$ and variance

$$\sigma_1^2 = \frac{1}{N}\left[E|s(n)|^4 + E|u(n)|^4 - (\sigma_s^2 - \sigma_u^2)^2\right] \ldots\ldots(8),$$

If $s(n)$ and $u(n)$ are both circularly symmetric and complex valued, and

$$\sigma_1^2 = \frac{1}{N}\left[E|s(n)|^4 + E|u(n)|^4 - (\sigma_s^2 - \sigma_u^2)^2 + 2\sigma_s^2\sigma_u^2\right] \ldots\ldots(9)$$

If s(n) and u(n) are both real-valued. Furthermore,

1. If s(n) is complex PSK modulated and u(n) is CSCG, then $\sigma_1^2 = \frac{1}{N}(2\gamma + 1)\sigma_u^4$
2. If s(n) is BPSK modulated and u(n) is real-valued Gaussian, then $\sigma_1^2 = \frac{2}{N}(2\gamma + 1)\sigma_u^4$
3. If s(n) and u(n) are both CSCG, $E|s(n)|^4 = 2\sigma_u^4$ and $E|u(n)|^4 = 2\sigma_u^4$, then $\sigma_1^2 = \frac{1}{N}(\gamma + 1)^2\,\sigma_u^4$
4. If s(n) and u(n) are both real-valued Gaussian, , $E|s(n)|^4 = 3\sigma_u^4$ and $E|u(n)|^4 = 3\sigma_u^4$, then $\sigma_1^2 = \frac{2}{N}(\gamma + 1)^2\,\sigma_u^4$

We focus on the complex-valued PSK signal and CSCG noise case. Based on the PDF of the test static, the probability of detection can be approximated by

$$P_d(\epsilon,\tau) = Q\left(\left(\frac{\epsilon}{\sigma_u^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma+1}}\right) \ldots\ldots\ldots(10).$$

For a target probability of detection $\overline{P_d}$, the detection threshold can be determined by

$$\left(\frac{\epsilon}{\sigma_u^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma+1}}) = Q^{-1}(\overline{P_d}) \ldots\ldots\ldots\ldots(11).$$

From equ.(5), on the other hand, this threshold is related to the probability of false alarm as follows:

$$Q^{-1}(\overline{P_f}) = \left(\frac{\epsilon}{\sigma_u^2} - 1\right)\sqrt{\tau f_s} \ldots\ldots\ldots\ldots\ldots\ldots(12),$$

Therefore, for a target probability of detection $\overline{P_d}$, the probability of false alarm is related to the target detection probability as follows:

$$P_f = Q\left(\sqrt{2\gamma+1}\,Q^{-1}(\overline{P_d}) + \sqrt{\tau f_s}\gamma\right) \ldots\ldots\ldots(13)$$

On the other hand, for a target probability of false alarm, $\overline{P_f}$, the probability of detection is given by

$$P_d = Q\left(\frac{1}{\sqrt{2\gamma+1}}\left(Q^{-1}(\overline{P_f}) - \sqrt{\tau f_s}\gamma\right)\right) \ldots\ldots(14)$$

Finally, for a given pair of target probabilities ($\overline{P_d}$, $\overline{P_f}$) the number of required samples to achieve these targets can be determined from (11) and (12) by cancelling out the threshold variable

The minimum number of samples is given by

$$N_{min} = \frac{1}{\gamma^2}\left[Q^{-1}(\overline{P_f}) - Q^{-1}(\overline{P_d})\sqrt{2\gamma+1}\right]^2 \ldots\ldots(15)$$

C. Single Threshold Detection Model

In single threshold based energy detection scheme energy of the received signal is compared with single detection threshold [11]. When energy of the received signal is greater than the detection threshold ((T(y) >ε), it represents the presence of PU depicted as H_1 and vice versa.

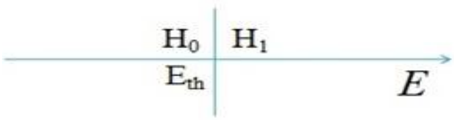


Figure.2 Single threshold model [11]

As shown in above figure, Where, E denotes the received energy, E_{th} means the threshold. If E is less than E_{th} , it is concluded that the primary use is absent, depicted as H_0 . Otherwise, the primary is presented, depicted as H_1. When N is large enough probability of detection (P_d), false alarm probability (P_f), missed detection probability (P_m) and collision probability (P_c) can be given as respectively [11],

$$P_d = Q\left(\frac{\varepsilon - (\sigma_s^2 + \sigma_u^2)}{\frac{\sigma_s^2 + \sigma_u^2}{\sqrt{(N/2)}}}\right) \ldots .(16)$$

$$P_f = Q\left(\frac{\varepsilon - \sigma_u^2}{\frac{\sigma_u^2}{\sqrt{(N/2)}}}\right) \ldots \ldots \ldots .(17)$$

$$P_m = 1 - P_d \ldots \ldots \ldots \ldots \ldots \ldots \ldots .(18)$$

$$P_c = P_m \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots (19)$$

From equ. (12) we get for single fixed threshold (let $N=\tau f_s$):

$$\varepsilon=(Q^{-1}(P_f)/\sqrt{N})+1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots(20)$$

D. Double Threshold Detection Model

As shown in figure double-threshold detection is based on the single-threshold detection by adding another threshold, usually represented as E_{thl} and E_{th2} . If E > E_{th2}, it is concluded that the PU occupies the channel. If E < E_{thl} , the decision is that the channel is available. If E_{thl}< E <E_{th2}, spectrum sensing is executed once more [11].

Figure.3 Double threshold model [11]

For maximize P_d where given P_f then from Neyman Pearson theorem we get,

$$\frac{P(x;H1)}{P(x;H2)} > \varepsilon \ldots\ldots\ldots(21)$$

Where P(x; H_1) and P(x ; H_2) are the probability density function (pdf) of received signal under hypothesis and respectively.

Then,

$$\frac{\frac{1}{\{2\pi(\sigma_s^2+\sigma_u^2)\}^{\frac{N}{2}}} \exp\left[-\frac{1}{2(\sigma_s^2+\sigma_u^2)} \sum_{n=1}^{N} y^2(n)\right]}{\frac{1}{\{2\pi(\sigma_u^2)\}^{N/2}} \exp\left[-\frac{1}{2\sigma_u^2} \sum_{n=1}^{N} y^2(n)\right]} > \varepsilon$$

Or,

$$\frac{\{2\pi(\sigma_u^2)\}^{N/2}}{\{2\pi(\sigma_s^2+\sigma_u^2)\}^{\frac{N}{2}}} \exp\left[-\frac{1}{2(\sigma_s^2+\sigma_u^2)} \sum_{n=1}^{N} y^2(n) + \frac{1}{2\sigma_u^2} \sum_{n=1}^{N} y^2(n)\right] > \varepsilon$$

Or, Taking natural logarithm (ln) in both side,

$$\frac{1}{2}\left[\frac{1}{\sigma_u^2} - \frac{1}{(\sigma_s^2+\sigma_u^2)}\right] \sum_{n=1}^{N} y^2(n) > \ln(\varepsilon) + \frac{N}{2} \ln\left(\frac{\sigma_s^2+\sigma_u^2}{\sigma_u^2}\right)$$

$$\text{Or,} \frac{1}{N} \sum_{n=1}^{N} y^2(n) > \frac{\frac{2}{N}\ln(\varepsilon) + \ln\left(\frac{\sigma_s^2+\sigma_u^2}{\sigma_u^2}\right)}{\left[\frac{1}{\sigma_u^2} - \frac{1}{(\sigma_s^2+\sigma_u^2)}\right]} \ldots\ldots\ldots\ldots.. (22$$

$$\text{Or,} T(y) > \varepsilon' \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (23)$$

Where, $\varepsilon' = \frac{\frac{2}{N}\ln(\varepsilon)+\ln(1+\gamma)}{\left[\frac{1}{\sigma_u^2} - \frac{1}{(\sigma_s^2+\sigma_u^2)}\right]} = \frac{\frac{2}{N}\ln(\varepsilon)+\ln(1+\gamma)}{\left[\frac{\sigma_s^2}{\sigma_u^2(\sigma_s^2+\sigma_u^2)}\right]} = \frac{\frac{2}{N}\ln(\varepsilon)+\ln(1+\gamma)}{\left[\frac{\gamma}{\sigma_u^2(1+\gamma)}\right]}$

and (SNR) $\gamma = \frac{\sigma_s^2}{\sigma_u^2}$

For double threshold we can write:

$$\varepsilon_{th1} = m\varepsilon' \ldots\ldots\ldots\ldots\ldots\ldots (24)$$
$$\varepsilon_{th2} = n\varepsilon' \ldots\ldots\ldots\ldots\ldots\ldots (25)$$

Where m and n are constant values.

III. Proposed Adaptive Threshold Detection Model

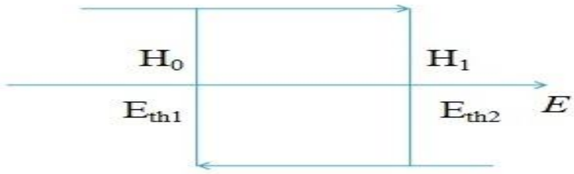
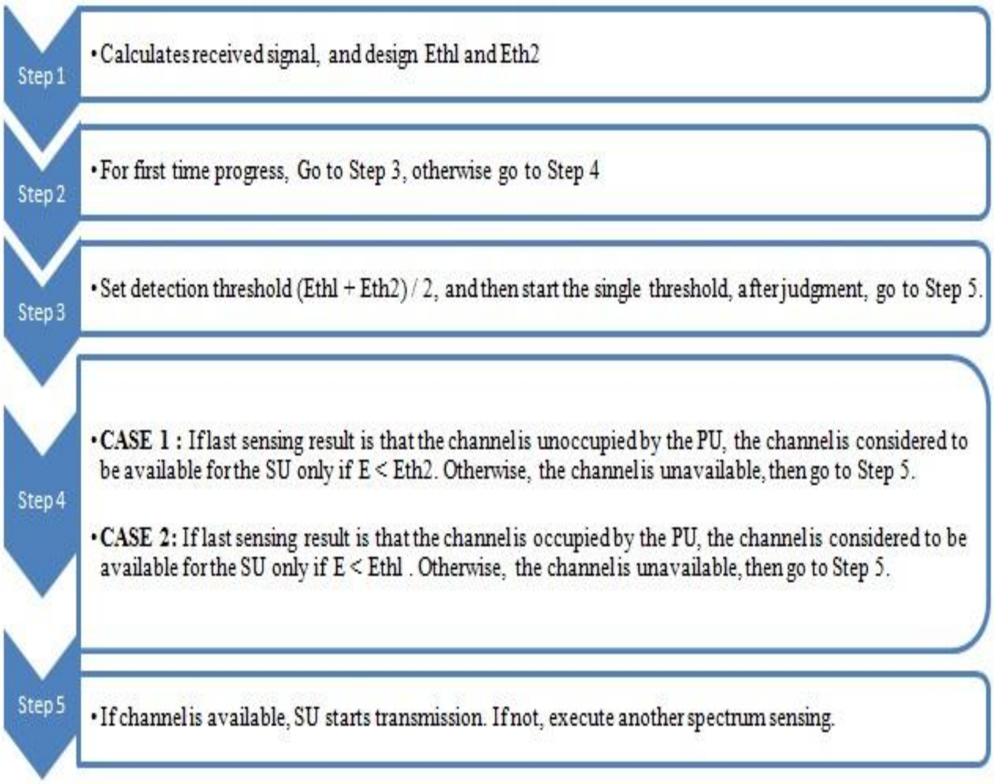


Figure.4 Adaptive threshold model

As shown in above figure proposed adaptive works as follows:



Given figure 5 show the flowchart of above steps:

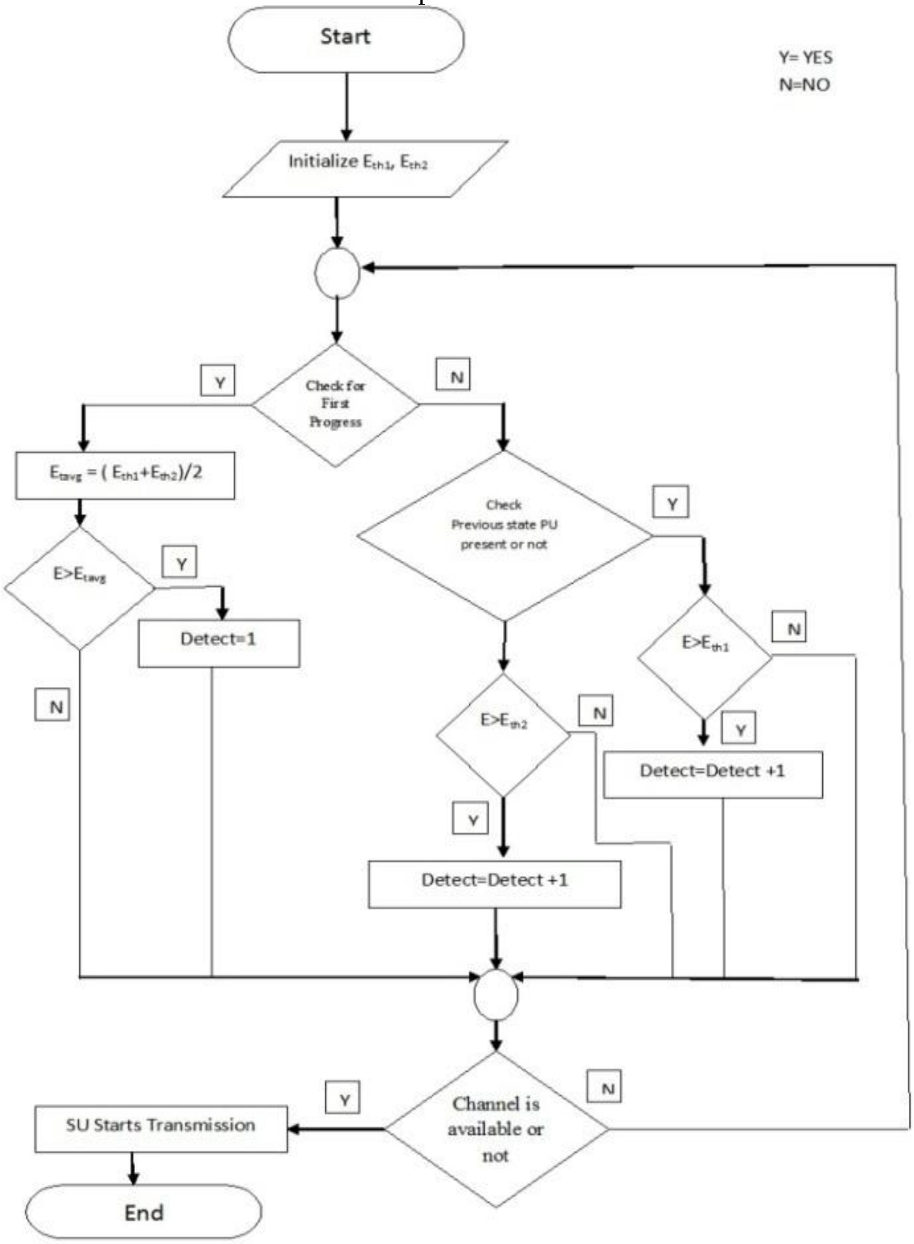


Figure.5 Flowchart of adaptive threshold model

IV. Simulation Result And Analysis

The emphasis is to analyze the sensing performance of the CR under the proposed adaptive threshold based energy detection scheme, simulation results are shown in this section to compare the our proposed approach with the traditional fixed threshold based energy detection scheme. For simulation, we have taken 1000 samples and probability of false alarm is fixed at 0.01. We assume m = 1 and n= 25.

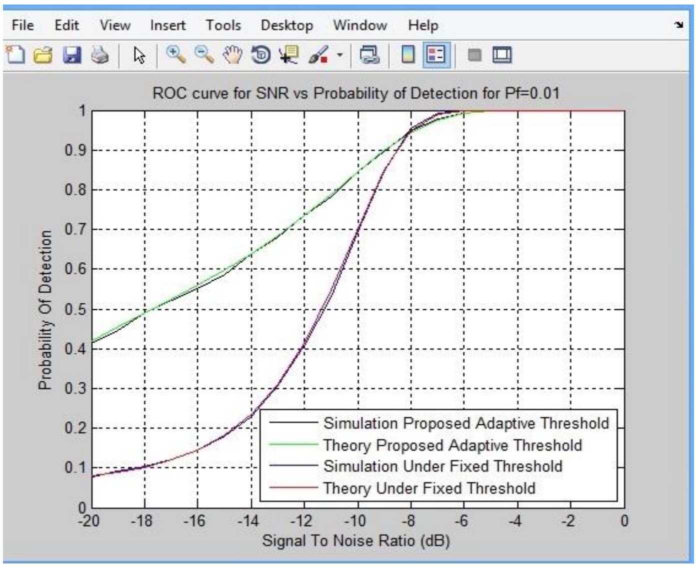


Figure.6 SNR vs Probability of Detection (P_d) for P_f = 0.01

From figure 6 it can be easily observed that the probability of detection for both simulated and theoretical cases with adaptive threshold is much better than fixed threshold under low SNR values.
For miss detection we know:
P_m=1-P_d

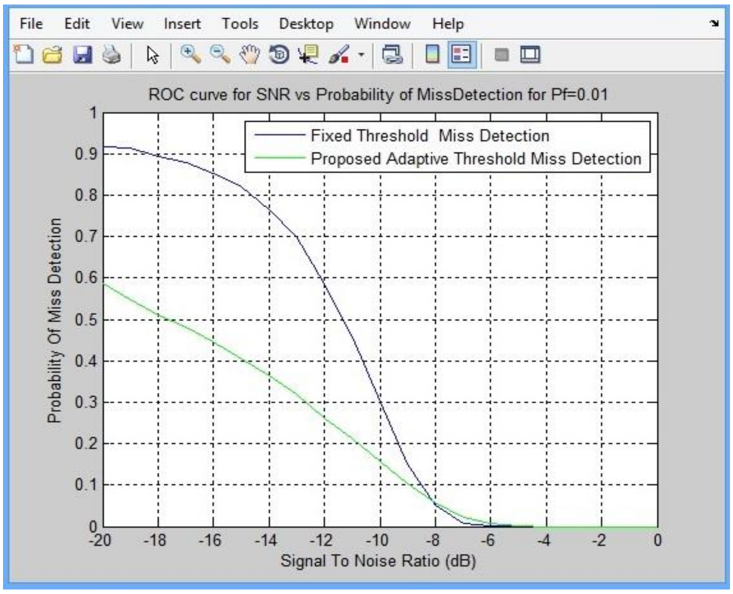


Figure.7 SNR vs Probability of Miss Detection (Pm) for Pf = 0.01

From figure 7, it can be easily observed that the probability of miss detection with proposed adaptive threshold is much lower than fixed threshold under low SNR values.
Again we can write, Total Error Rate = Probability of miss detection + Probability of False alarm = P_m+ P_f

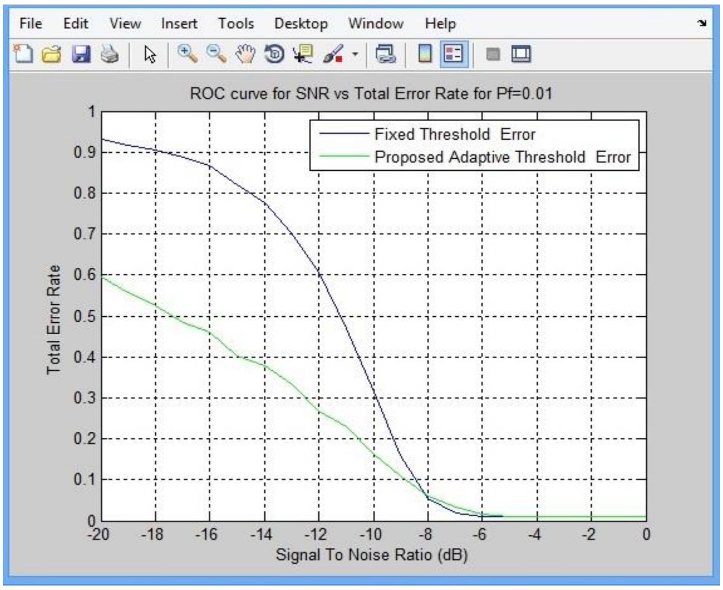


Figure.8 SNR vs Total Error Rate for $P_f = 0.01$

From figure.8 it is clear that the total error rate with proposed adaptive threshold is much lower than fixed threshold.

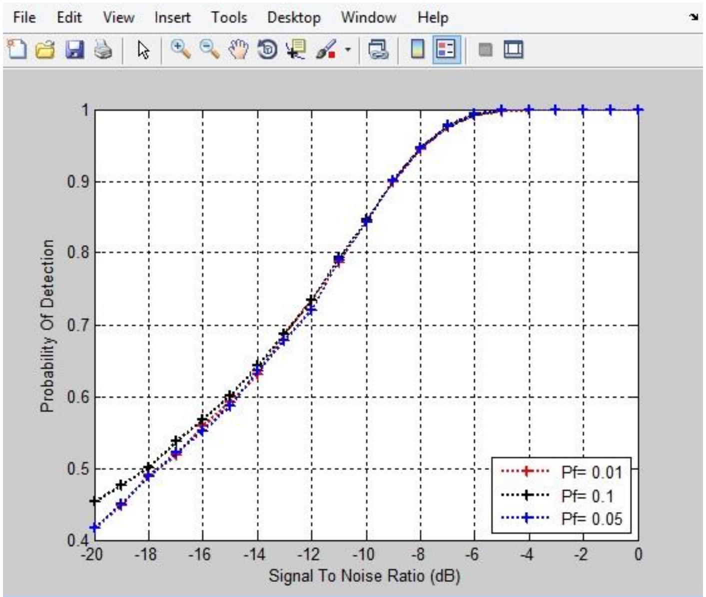


Figure.9 SNR vs Probability of Detection (P_d) for $P_f = 0.01$, 0.1 and 0.05

Figure.9 shows the graphs are drawn between probability of detection and SNR under various probability of false alarm. It can be easily observed that for low SNR region probability of detection increases with increase in the probability of false alarm and for higher SNR graphs are converged.

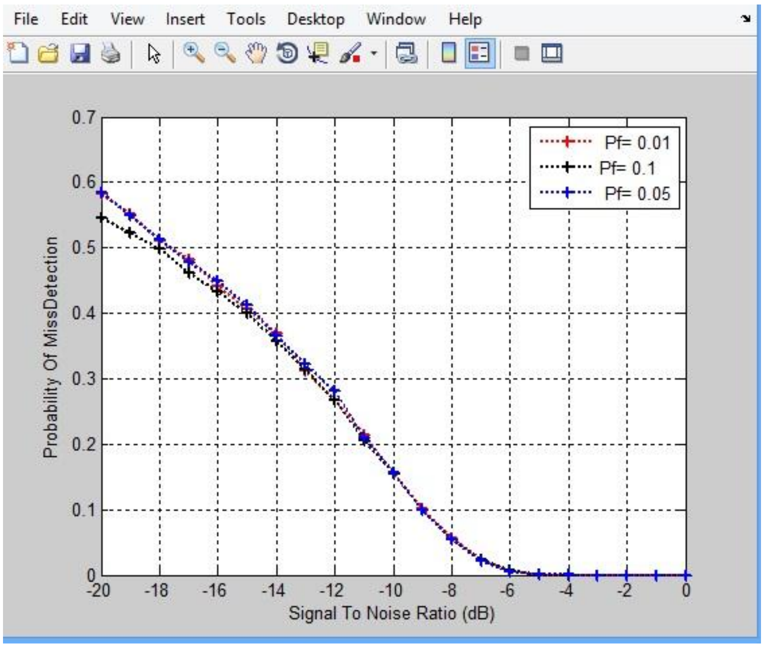


Figure.10 SNR vs Probability of Miss Detection (P_m) for P_f = 0.01, 0.1 and 0.05

Figure.10 shows the graphs are drawn between probability of miss detection and SNR under various probability of false alarm. It can be easily observed that for low SNR region probability of miss detection decreases with increase in the probability of false alarm and for higher SNR graphs are converged.

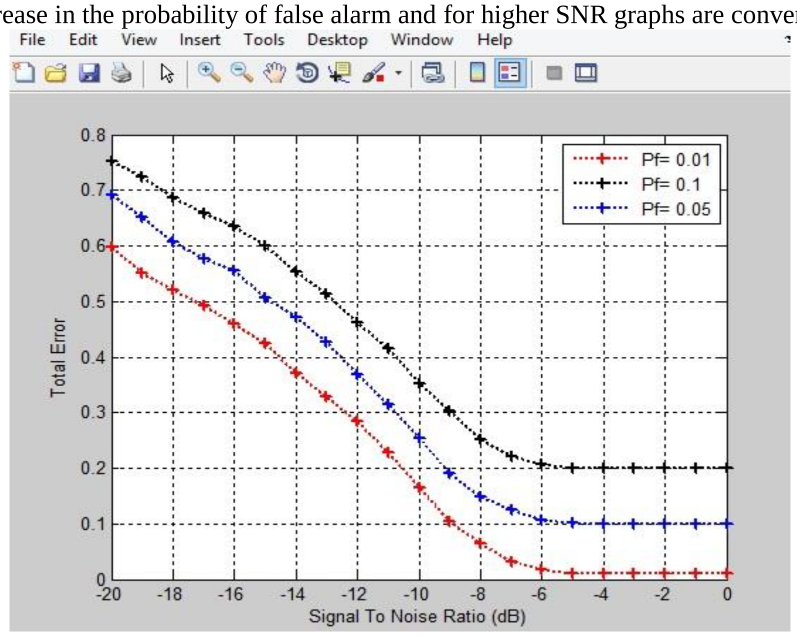


Figure.11 SNR vs Total Error for P_f = 0.01, 0.1 and 0.05

V. Conclusion

This paper proposed adaptive threshold detection model of energy detection based spectrum sensing. Through maximized the probability of detection with respect to a false alarm rate constraint in order to find the detector thresholds for each stage. Derivation and simulation results show that our proposed adaptive threshold can effectively enhanced the detecting probability and the utilization of spectrum holes at low SNR region.

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References

[1] FCC, "Spectrum Policy Task Force Report," *In Proceedings Of The Federal Communications Commission (FCC)*, Washington DC, USA, Nov. 2002.

[2] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE Personal Communications Magazine*, August 1999, pp. 13-18.

[3] Hyun-Ho Choi, K. Jang and Y. Cheong, "Adaptive sensing threshold control based on transmission power in cognitive radio systems," *IEEE 3rd International Conference on Cognitive Radio Oriented Wireless Networks and Communication*, pp. 1-6, May 2008.

[4] Gorcin A., Qaraqe K.A., Celebi H., Arslan H .. An adaptive threshold method for spectrum sensing in multi-channel cognitive radio networks. IEEE International Conference on Telecommunications (lCT), 2010 .

[5] Joshi,D.R.,Popescu,D.C.,Dobre,O.A . Dynamic threshold adaptation for spectrum sensing in cognitive radio systems. Radio and Wireless Symposium (RWS), 2010 IEEE. 2010, Page(s): 468 - 47l.

[6] Jinbo WU,Tao Luo,Guangxin Yue. An Energy Detection Algorithm Based on Doublethreshold in CR Systems. IEEE International Conference on Information Science and Engineering (lCISE). 2009.

[7] Bangsheng Zong, ling Hu, Tiecheng Song, Adaptive spectrum sensing scheme with punishing mechanism in cognitive radio networks. IEEE International Conference on Communication Technology (lCCT). 2010, Page(s): 1160 - 1163.

[8] X. Ling, B. Wu, H. Wen, Pin-Han Ho, Z. Bao and L. Pan, "Adaptive threshold control for energy detection based spectrum sensing in cognitive radios," *IEEE Wireless Communications Letters*, Vol. 1, No. 5, pp. 4481- 451, Oct. 2012.

[9] Gaurav Verma and O.P. Sahu, "Throughput Enhancement to the Cognitive Radio Networks under the Precaution is Better than the Cure (PBC) Approach*", IEEE International Conference on Signal Processing and Communication Engineering Systems (SPACES),* pp. 492-496, KL University, Vaddeswaram, India, Jan. 2015.

[10] Gaurav Verma and O.P. Sahu, "Throughput Enhancement to the Cognitive Radio Networks Under the Precaution Based Cooperation of the Primary Users", *IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES)*,pp. 1-5, NIT Calicut, Kerala, India, Jan. 2015.

[11] Jinbo WU, Tao Luo, Guangxin Yue. An Energy Detection Algorithm Based on Double threshold in CR Systems. IEEE International Conference on Information Science and Engineering (lCISE). 2009.

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