TEST Engineering & Management

May – June 2020
ISSN: 0193-4120 Page No. 323 - 327

Energy Detector for Spectrum Sensing in TVWS Based Cognitive Radio Networks

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Article Info
Volume 83
Page Number: 323 - 327
Publication Issue:
May - June 2020

Article History
***Article Received**: 11August 2019*
***Revised**: 18November 2019*
***Accepted**: 23January 2020*
***Publication**:07May2020*

Abstract:
In this paper we have implemented energy detector for spectrum sensing in cognitive radio networks. Based on the noise variance how the detection performance is varying has been observed.To deal with this a technique called BLIND is proposed in this paper. For implementation of this technique we used MATLAB and simulation results have been shown which helps in proper usage of cognitive radio networks.

Keywords: *Detection probability (Pd), False alarm probability (Pf), Signal to Noise Ratio (SNR), Energy detection, Spectrum sensing, Received Signal(R(s)), Transmitted Signal (T(s)), Primary User Signal P1, Secondary User Signal S1.*

I. INTRODUCTION

The technology behind cognitive radio networks was suggested as an intelligent solution for the enhancement of accessing radio spectrum and to resolve its scarcity problem.The systems used for this technology senses the unused parts of the spectrum and allows secondary users to access it. There are so many sensing techniques have been proposed but among them ENERGY DETECTION based sensing is the best one.

The energy detection estimates the power of the N samples obtained by comparing the average FFT square in those N samples to the threshold. If this energy meets this threshold then primary users considered as absents. Another wise considered absent primary user signal.This technique is easy because we need not need to know about previous primary user signal. The effectiveness of this technique depends heavily, however, on random noise. It's much easier than the matched filter and automotive sensing technology.Thus, energy detection efficiency with a state threshold is reduced. This means that prior noise power know-how or accurate the detection output must be increased in its level.

The performance of this technique depends on how many times the tests has been done and the level of sensing.The performance can be increased by taking a greater number of samples, but it will reflect for a certain range of SNR values only. If the number of samples is more than the sensing time will be more.For example,in broadband sensing, the number of samples cannot be increased if the researcher demands that compressive sensing can be used in order to minimize sample count. By adjusting the dynamic limit to the noise level of the R(s)will enhance the detection efficiency.

The remaining paper is structured according to the structure of this journal. The second section addresses both the mathematical model and solution using MATLAB code. The third section describes the findings and addresses them. Ultimately, in the conclusion paragraph the findings and future research are drawn.

Now the threshold energy is to be calculated. For that there are two methods using noise estimation and without using noise estimation. The formulas for those are:

II. Methodology

A. Mathematical Model

The first and most important step is identification of spectrum i.e., the state in which the spectrum present.

$$\mathfrak{H}_0: R(s) = T(s) \quad (1)$$

$$\mathfrak{H}_1: R(s) = T(s) + Noise \quad (2)$$

(1) Represents P1 is notpresent and
(2) Represents P1 is present

By doing the square of Fast Fourier Transform (FFT) we can get the energy of N-samples and it was averaged as follows

$$\sum_{n=1}^{N} |R(s)|^2 \quad (3)$$

The sensing decision is then compared to ED to:

E < TD : P1 is absent
E > TD : P1 is present

Where E is Energy of N samples and TD is sensing threshold.

Through Pd and Pf the detection performance can be estimated. The right decision number will relate Pd. And Pf means that the total number of tests where primary user is wrongly identified. These are the following probabilities:

$$Pd = Probability\ (E > TD : \mathfrak{H}_1) \quad (4)$$

$$Pf = Probability\ (E > TD : \mathfrak{H}_0) \quad (5)$$

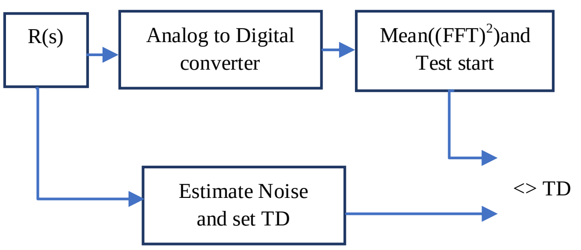
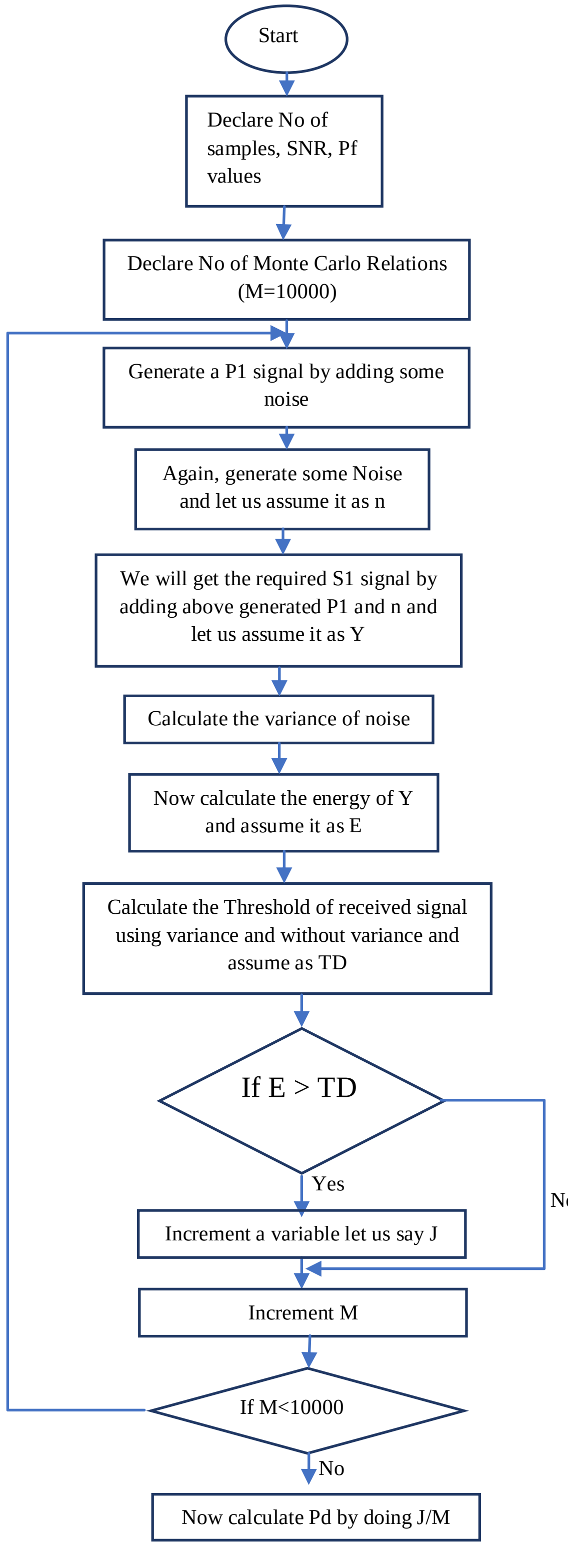


Fig 1. Energy Detection

$$TD = e * \left(1+\frac{Q(P_{fa})}{\sqrt{\frac{N}{2}}}\right)$$ - using noise estimation

$$TD = 1+\frac{Q^{-1}(P_{fa})}{\sqrt{N}}$$ - With out using noise estimation

III. Algorithm Implementation



To assess the model's efficiency, we implemented the model in MATLAB. Fig 2. Represents the scenario how the code is going to be designed. As we did not separate the transmitter and receiver, we combinedly implemented both in the single code.

IV. Results

Using the above proposed model several experiments have been done to evaluate the performance for the model. The efficiency of this model is based on threshold, so both the thresholds were implemented at various Pf and SNR and N values.

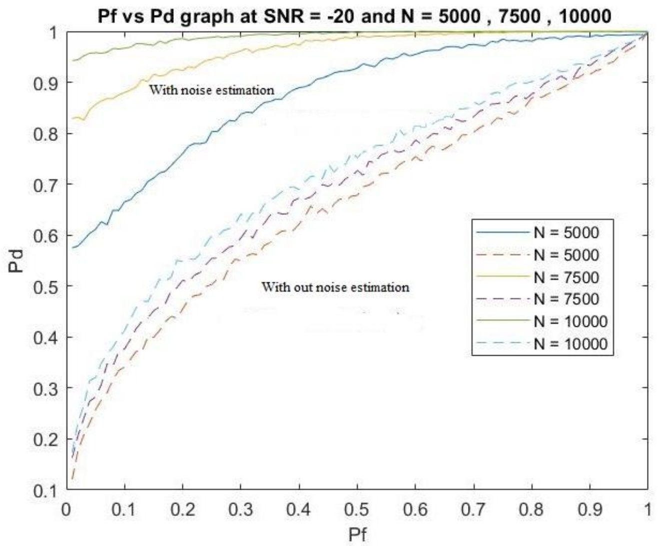


Fig3. Pd vs Pfplot at SNR -20dB and different N values

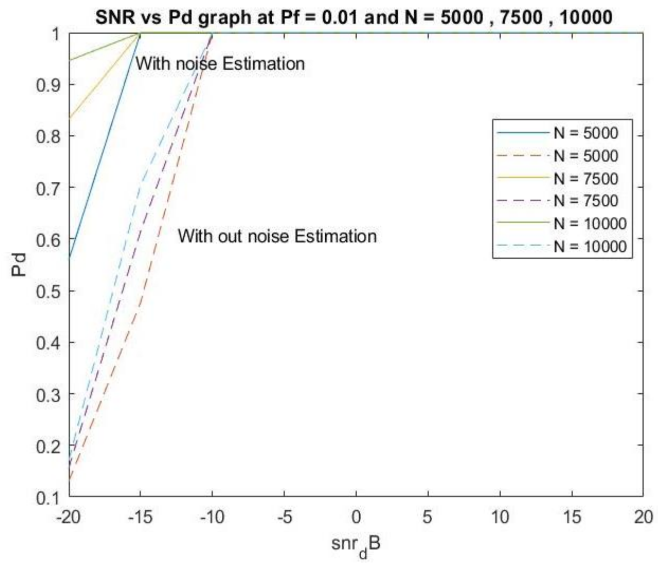


Fig 4. Pd vs SNR plot at Pf 1% and different N values

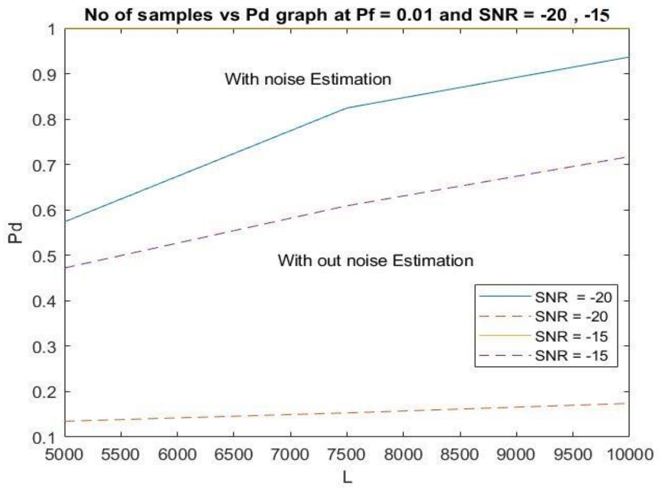


Fig 5. Pd vs N plot at Pf 1% and different SNR values

V. Conclusion

At the onset, the results on probability of detection using energy detector are obtained. Fig3 shows the receiver operating characteristics (ROC) which indicate he considerable loss of primary bandwidth opportunity, if we use a smaller number of samples at mentioned -20dB SNR.

By setting $P_{fa} = 0.01$, 1% and counting the received signal SNR at maintained lower limits i.e., -20dB. The results in Fig4 shows that there is 90% probability of detection of presence of primary in this setting requires at least 10000 samples with noise estimation. However over by taking 10000 samples probability of detection is considerably low at given setting without noise estimation. In other way using at least 5000 samples primary signal presence can be correctly detected at -15dB for 1% P_{fa} .

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