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EVALUATION OF ENERGY DETECTION BASED SPECTRUM SENSING IN COGNITIVE RADIO NETWORKS

Patan Babjan and V. Rajendran
Department of Electronics and Communication Engineering VELS Institute of Science, Technology and Advanced Studies, Chennai, India
E-Mail: pbabjan408@gmail.com

ABSTRACT

Spectrum sensing is the process of identifying the free (unused) spectrum of the main user without making any interference or upsetting the rights of licence users. This procedure takes place without creating any interference and without disturbing the rights of licence users. It means identifying gaps in the spectrum that are not being utilised. The most effective method for locating gaps in spectrum use is to search for key users. The development of an energy detector and a detector based on cyclostationarity for an OFDM-based cognitive radio system, as well as the implementation of these detectors and an evaluation of their performance, are the primary focuses of this project. The idea behind cognitive radio is to make the most of the underutilized spectral resources by utilising unused spectrums in an opportunistic way. This is accomplished via the notion of cognitive radio. Main users of the spectrum are typically incumbent licensees, while secondary users of the spectrum are users who wish to make opportunistic use of the spectrum when main users are not actively using it. This is an example of a cognitive radio system. The cognitive radios are required to do spectrum sensing to determine whether or not the spectrum is accessible. Both the energy detector and the cyclostationary detector are derived, then we implement them, and then we assess them. Plotting the Receiver Operating Characteristics (ROC) in clean and noisy situations allows us to assess the performance of the detectors.

Keywords: wireless communication, cognitive radio, energy detection, cyclostationarity, spectrum.

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INTRODUCTION

Users are now engaged in a wide range of wireless access system services. Only a few innovative systems are made possible by employing frequencies other than the broadband-friendly 800-6000 MHz spectrum. Cellular communications and wireless technologies, as well as spectrum bands the Ultrahigh High Frequency (UHF) and Very High Frequency (VHF) bands. The frequency spectrum in wireless communication (WC) is as follows: as pricey as gold. Wireless service providers must invest a significant amount of money. For the privilege of paying to use the frequency spectrum for communication. Since WC has grown over this time, several new systems have often been used in the same region. Every system user may be seen here. Has a high data rate demand due to certain types of Quality of Service (QoS) Services. High bandwidth demand is hence a must. The number of subscribers grows as well, which causes frequency to become saturated. After 10 years, most spectrum bands that are suitable for Mobile communication technologies may be fully functional and novel. A solution is necessary. Using the is one of the potential outcomes is The "Cognitive Radio" method. A capable technology called Cognitive Radio (CR) has produced an alternate strategy to improve Electromagnetic (EM) use regularly.

Cognitive users are allowed to use the licensed band under CR. over dynamic frequency assigned when the Primary Users (PUs) are in an inactive state to progress the frequency usage and therefore it prevents frequency insufficiency. For this, there is a need for vital smart Spectrum Sensing (SS) systems that can sense the existence of frequency holes and assign the band to secondary users without creating any interference to primary users. The spectrum holes (unused spectrum) are represented in Figure-1.

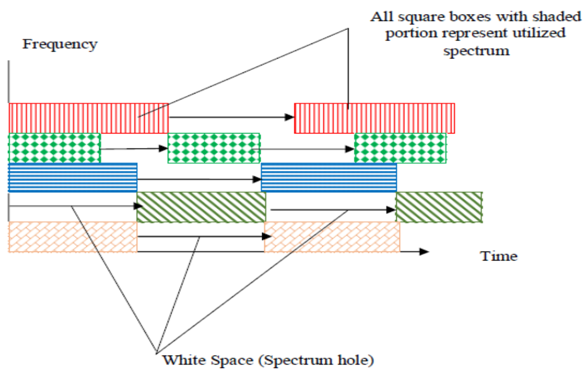

Figure-1. Illustration of spectrum holes.

This study examines the MATLAB model and Energy Detection (ED) technique for identifying main users.

The energy detector is a kind of semi-blind sensing that does not need any prior knowledge of the signal to identify the existence of PUs. It's straightforward to create and use, but it performs best in low-noise environments with a high Signal-to-Noise Ratio (SNR). Although energy detectors function poorly in low signal-to-noise ratio (SNR) environments, this presents an opportunity for novel sensing techniques to be adopted; in other words, these systems manage to go around the issue

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by providing a perfect presentation even in low SNR scenarios.

The spectrum assignment technique used by modern wireless networks is static, according to research by [1]. However, between 15% and 85% of the available spectrum is very seldom used, and its geographical use varies greatly across time and space. To get around spectrum scarcity and insufficiency, it's important to think of new ways of communicating that make use of the available wireless bandwidth. The goals of DSA and CR Network are to provide for the aforementioned wants. New features and research obstacles associated with CRNs are described in length. Open research questions are also sketched out, as is the impact of these functions on the presentation.

DSA is a promising approach for addressing the pressing issue of the current wireless communications spectrum limitation. Its goal is to recycle weakly engaged frequency bands without significantly impacting the original licensed user. In this case, the testing ground is the time domain implementation of this concept. Here, we provide an empirically grounded numerical model. [2] Investigate this concept and reveal how it might be used to create access methods.

Issues with the proposed wideband signal path are shown by [3] research. His proposed design for a low-noise amplifier not only eliminates input capacitance via inductive performance in negative feedback but also shortens the time required for spectrum detection. He suggests using RF-assisted SS to boost Pd.

In their comprehensive assessment of the techniques used to ensure compatibility in the IEEE 802 family of wireless networks [4]. In MATLAB/Simulink, an example system has been set up to carry out CR.

[5] Looked at how adjusting the threshold level in conjunction with Energy Detection may improve spectrum sensing performance. Improving spectrum efficiency requires lowering the threshold level of sensing error, which decreases the collision probability and increases the amount of unused spectrum. The utilisation level of the available spectrum must be met when determining the threshold level to provide the necessary safety level for a main user.

An immoral detector should ensure a decrease in Pfa and an increase in Pd. In [6] suggests Pfa, which requires less spectrum consumption. Uncertainty in noise may persist in a real-time setting owing to noise variability. Decision making in Energy Detection might be impacted by NU.

Therefore, a suitable detection technique relies on a threshold to overcome the expected noise uncertainties [7].

The threshold, which is designed in a fully known noisy information situation, determines how precisely the choice may be made. The licenced user signal identification in uncertainty and poor SNR environment is investigated by [8]. They provide a mathematical model for noise uncertainty and fading, and they define the SNR wall below which detector signal sensing fails. The system model uses the collected signal information to set the SNR boundaries. [9] developed a tweaked Energy Detection technique to improve performance.

Energy Detection sensing techniques are provided by [10] about the covariance matrix of the secondary users' Eigen standard received signals. Two sensing algorithms are described. The first approach is based on the ratio of average to minimum Eigen value, whereas the second algorithm is based on the maximum to minimum Eigen value. Pd and Pfa are calculated using Random Matrix Theory.

The fundamental requirement of CR was discussed by [11] who argued that it was to prevent encroachment on the primary users. The major consumers benefit from CR's SS since it demonstrates the decrease of interference. The main limitations serve to detect the signal of a licenced user in a low signal-to-noise ratio (SNR) environment. The strategies to examine these restrictions by looking at various signal processing techniques are outlined.

By dynamically adjusting the threshold value relative to the linear growth function of instantaneous SINR, [12] established the Energy Detection technique. To determine the threshold, we first formulate the linear policy function that allows a higher threshold under high signal-to-noise ratio (SNR) situations.

To calculate the standard deviation of the principal user signal, [13] show the sensitivity of consecutive tests. By using a sequential version of the energy detector to project the variance of the main signal using an iterative hybrid Bayesian approach, we may increase throughput by a factor of 2–6 compared to a test using a fixed sample size.

The standard detector's squaring method was replaced with positive operation, which [14] investigated in their complete energy detector. It is indicated that the uniform distribution offers the best performance among the distributions used in deriving the expression for the SNR wall.

For spectrum sensing in CRNs, [15] proposed a selection-based approach. Energy Detection and the covariance full rate detecting technique come together to form this method. Energy Detection and covariance technique comparisons are performed for several input data. In contrast to other methods, the performance of the choice created method is less affected by the structure of the input data and theoretical analysis.

[16] Evaluated the collision probability between the CR user and main user and the likelihood of frequency band inaccessible to the CR user as part of their analysis of spectrum sensing utilising Energy Detection. By increasing the number of detection thresholds, it is possible to reduce the likelihood of collisions between unlicensed and licenced users and to prevent interference by secondary users on licenced ones.

SS is used to identify the free frequency band in CRNs. An adaptive double threshold Energy Detection method is suggested for spectrum sensing to boost detection performance and decrease sensing failure issues. [17] Provide results showing that the suggested adaptive system outperforms CED by 12.8% at -8 dB SNR in terms of Pd.

An Energy Detection method taking into account two threshold levels was presented by [18]. The normal energy supplied by the licenced user and the NU power is used to establish the threshold values. The results show that compared to the standard detection approach, performance is enhanced.

The performance of several detectors in CRNs was analysed, and the system's resistance to noise power uncertainty was studied, [19]. It is time to compare the energy detectors to the LR test detectors. When compared to traditional Energy Detection, the suggested detection systems are more resistant to noise uncertainties and changes.

The challenge of modifying the best sensing time while taking into account many aspects, such as spectrum handoff and the dynamical state of PUs, was highlighted by [20]. In this way, the multichannel CR network's output is optimised. The framework of a rather intuitive Markov decision process is used to analyse the situation.

To improve the display of global detection, [21] suggested using an energy statistic weighting method at the CSS CR network coordinator. A weighted energy combining scheme is employed to improve detection performance.

[22] suggested a two-stage SS process. Sensing is carried out first using Energy Detection, and then, for enhanced detection, cyclostationary detection is used. However, this approach requires more time for sensing and is computationally intensive.

As explained by [23], the NU decreases reliability during spectrum sensing because of SNR barriers. Each tertiary user is advised to use double threshold detectors for LS as part of a proposed adaptive algorithmic CSS. Since the NU is not the same for each secondary user, the suggested approach achieves higher performance than CSS using either an individual threshold or two fixed thresholds.

When the noise fluctuations are greater, it is difficult to control the single threshold with the noise changes; nonetheless, using a single threshold does help with the sensing error problem. The secondary user's consistency in making decisions is based only on this one criterion. Changes in the ambient noise level close to the judgment threshold might introduce errors. The precision of detection is limited to the area under study.

In Energy Detection, a double threshold approach can yield good results in low signal-to-noise ratio (SNR) regions but fails to deal with the confused area problem or the uncertain region (i.e., when the received energy falls between the two thresholds, the spectrum sensing process is repeated, increasing the sensing cycle, and consequently degrading detection performance).

Energy Detection's adaptive double threshold approach improves spectrum sensing in CR networks in NU environments by allowing for high detection probabilities even at low signal-to-noise ratios and by resolving issues in the confused area region.

The purpose of this study is to illustrate the formidable difficulties inherent to SS in CRNs. As said before, the primary difficulty in the study effort is that the suggested RAT determination approach to eliminate spectrum sensing error, decrease Pmd, and increase frequency band utilisation without increasing frequency sensing cycles in two adaptive thresholds is not feasible. The number of accidental interactions between the main user and the cognitive user is decreased using the Energy Detection approach and a detector based on cyclostationarity in NU settings.

2. SYSTEM MODEL

Users are separated into two distinct groups inside the cognitive radio network: primary users (PUs) and secondary users (SUs). The discovery of PUs' signals in spectrum sensing may be seen as binary testing of the hypothesis that they exist. Issue with the hypotheses H0 and H1, both of which are defined as [24].

$$\begin{cases} H_o : PUs\ do\ not\ exist \\ H_1 : PUs\ exist \end{cases} \tag{1}$$

At the beginning of the sensing phase, when an SU is beginning to feel the spectrum, it will require a specific number of N of signal samples before it can decide whether or not a PU is present. The assumption is made that the SU receiver has more than one isotropic antenna, with M being more than 1. The signal ri(n) received at the ith antenna may be represented as:

$$r_i(n) = h_i * s(n) + \eta_{ci}(n) \tag{2}$$

In this paper, it is assumed that the phase shift of hi is known to SU, and we will evaluate the performance of the proposed method for both the nonfading channel and IID Rayleigh fading channel. +us, the output $y_i(n)$ of the i^{th} antenna can be modeled as:

$$y_i(n) = \frac{h_i^*}{h_i} r_i\,(n) = \begin{cases} \eta_i(n);\ H_o, \\ h_i * s(n) + \eta_i(n); H_1, \end{cases} \tag{3}$$

Where |hi| is the norm of the channel coefficient hi, si(n) is the PU signal sampled by antenna i, and ηi(n)~N(0, σ^2η) [22]. In the nonfading channel, |hi| can be simply set as 1, while in a Rayleigh fading channel, |hi| obeys Rayleigh distribution.

Note that how to get an estimate of the channel coefficient is beyond the scope of the paper, but it is useful to deal with this issue and analyse the effect of imperfect channel estimation in the future. +e performance of a spectrum-sensing algorithm can usually be evaluated by two probabilities PD and PFA. PFA is the probability of a false alarm that H1 is assumed when H0 is true, while PD denotes the probability of detection that H1 is accepted when H1 is true. +ey are defined as:

$$P_f = P_r\{(y(n){:}\,H_1)\ /H_o\}$$
$$P_d = P_r\{(y(n){:}\,H_1)\ /H_1\} \tag{4}$$

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3. PROPOSED METHODOLOGY

The detection of spectrum is the primary focus of this study since it is the most important ability of CR that determines the availability of spectrum gaps in the band for distribution to secondary users. The information about the authorised frequency band is kept at its most basic level to facilitate access to the frequency gaps while maintaining complete discretion about the licenced user. In spectrum detection, CR is used to identify the vicinity of licenced users inside an authorised frequency band and to utilise that specific frequency band, when it is permitted to increase the frequency proficiency. This is done so that licenced users may expand their frequency proficiency. When a primary user reaches a certain spectrum band, a secondary user should immediately cease using that frequency band to avoid producing interference for the prime user. This will allow the secondary user to keep a safe distance from the interference that might be caused by the primary user. The following are the two kinds of spectrum holes known as SH:

Temporal SH: It appears that the unlicensed user can utilize the band when no primary user is broadcasting during a certain period. Spatial

SH: It appears that the unlicensed user can utilize the spectrum outside the area when the licensed user broadcast is within the area.

There are many existing Spectrum Sensing algorithms emphases on local observations of the CR based on licensed user-transmitted signals. Various Spectrum Sensing schemes have been developed to find out the occurrence or non-occurrence of the primary user. Spectrum sensing, also known as the spectrum detection method, is the primary responsibility of the cognitive cycle and the primary obstacle for the CRs to overcome. In spectrum sensing, the investigation of the spectrum and the discovery of unused bands and their subsequent sharing, all while avoiding PU's occupation of the spectrum. The term "action of a radio measuring signal feature" is one way to describe what it is. As illustrated in Figure-2, a wide variety of spectrum detection methods may be used to increase the likelihood of a successful detection.

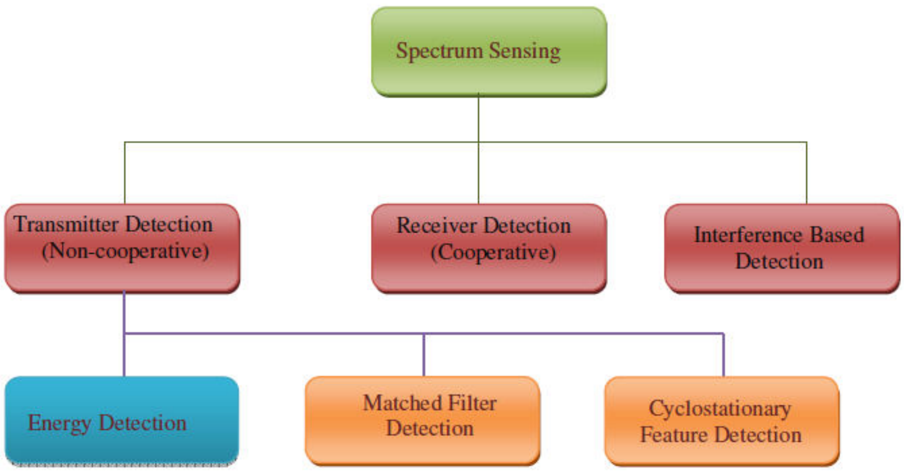

Figure-2. Spectrum detection techniques.

3.1 Energy Detection

The Energy Detection technique is the one that is used for this study endeavor. The energy detector is also known as a radiometry or periodogram detector, and it is the detector that is used the most commonly in SS. It is the detector that has the least amount of computing complexity, the simplest analytical model, and the least amount of difficulty in achieving its hardware and software goals. It is not essential to have any prior information on the principal user signal. This detector does not function very well when the noise strength cannot be determined with absolute certainty. The energy detector yield is a statistic that is used during testing, and it is calculated as the signal that was received with the entire amount of energy. This signal may be analysed in either the time domain or the frequency domain. To achieve optimal performance, it is necessary to have a strong signal power, a prolonged detection time, and a low noise power.

The ED method performs the hypothesis testing according to equ 5.

$$T_{\mathrm{ED}} = \sum_{i=1}^{M}\{ \sum_{n=0}^{N-1}(|y_i(n)|^2 \underset{H_0}{\overset{H_1}{<}}\} \quad (5)$$

ED($_{\mathrm{Pf,\,ED}}$) can be written as equ 6 and 7

$$P_{f,\mathrm{ED}} = \frac{\Gamma(\mathrm{MN}/2, \lambda_{\mathrm{ED}}/2\sigma_\eta^2)}{\Gamma(\mathrm{MN}/2)}, \quad (6)$$

$$P_{f,\mathrm{ED}} = Q\left(\frac{\lambda_{\mathrm{ED}} - \mathrm{MN}\sigma_\eta^2}{\sigma_\eta^2\sqrt{2\mathrm{MN}}}\right),$$
$$P_{d,\mathrm{ED}} = Q\left(\frac{\lambda_{\mathrm{ED}} - \mathrm{MN}\sigma_\eta^2 \times (1+\mathrm{SNR})}{\sigma_\eta^2\sqrt{2\mathrm{MN}(1+\mathrm{SNR})}}\right), \quad (7)$$

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where Q(•) is the Q function and SNR is the signal-to-noise ratio, defined as

$$\mathrm{SNR} = \frac{P_s}{\sigma_\eta^2} = \frac{\sum_{i=1}^{M}\{\sum_{n=0}^{N-1}(|s_i(n)|^2)\}}{\mathrm{MN}\sigma_\eta^2}, \tag{8}$$

The Energy Detection block is seen in Figure 3; a Band Pass Filter (BPF) selects the required bandwidth from the input signal band. After that, the signal is squared and integrated across the period that was being observed. The energy detector yield is what's known as a test statistic, and it's compared to a decision threshold to find the band's availability. The threshold may be selected to minimise judgment error, with the precise noise level and the signal strength from the licenced user both being known. The mistake in noise variance is referred to as noise uncertainty (NU), and it is the cause of performance loss.

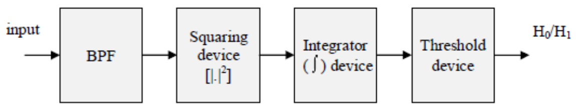

Figure-3. Representation of energy detector block diagram.

3.2 Cyclostationary Feature Detection

This technique can differentiate between modulated signals and noise effectively. The feature detector takes advantage of the fact that the primary modulated signals have spectral correlations with cyclostationary due to the built-in idleness of signal periodicity (for example, carriers of sine wave, trains of pulse, and cyclic prefixes), whereas the noise is a broad-sense stationary signal that does not have any correlations at all. Evaluation of a spectral correlation function is the way to go about accomplishing this project.

A diagram of the cylostationary apparatus may be seen in Figure-4. A cyclic frequency, denoted by f-, is possessed by the correlation function. After this, the autocorrelation of the signal, denoted by R (f), is reached, and the mean of the signal is computed. The technique for feature detection is then carried out based on the values that were collected.

As a result, these feature detectors have a robust relationship to NU despite their increased processing complexity and extended observation intervals. In addition to this, the main users must have the concept of the cyclic frequencies, although the secondary users may or may not need this. program flow chart is shown in Figure-5.

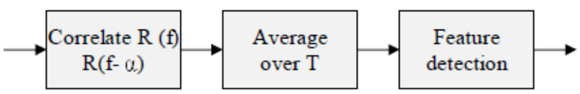

Figure-4. Block drawing of cyclostationary detector.

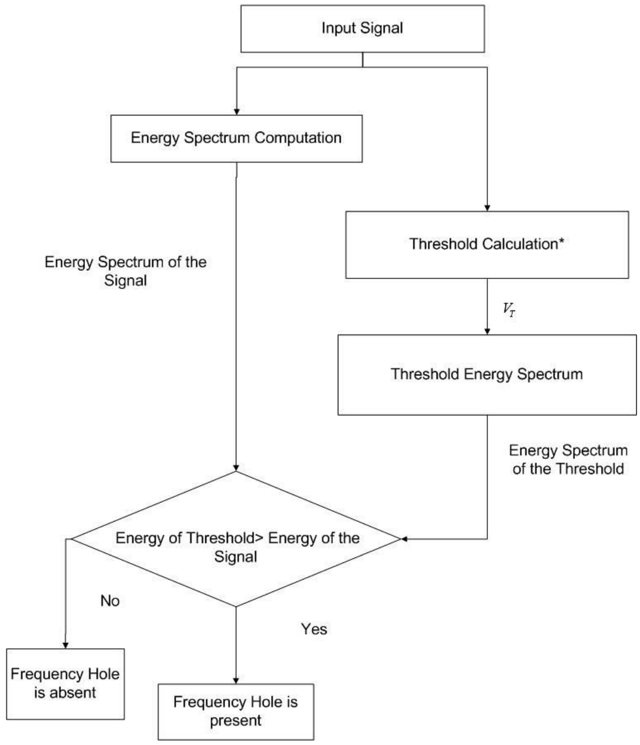

Figure-5. Flow chart for program.

3.3 Adaptive Threshold Optimization Model

The high precision selection of the threshold expression is crucial to the detection performance of the energy detector in cognitive radio systems; without it, the detection performance would suffer. When creating models for spectrum sensing, one of the goals is to ensure that noise and key user signals can be properly differentiated from one another.

In general, developed models are evaluated based on criteria such as their accuracy and the percentage of true positives they produce. On the other hand, the real performance may be evaluated by using estimations that were made artificially in reverse and applying them to the measurements. To enhance the spectrum sensing performance of cognitive radio networks, this section presents a novel threshold expression model that is based on an online learning algorithm.

Spectrum sensing is based on a specified binary hypothesis testing issue, which is dependent on the threshold expression. This is the essential essence of spectrum sensing. Figure-5 provides a visual representation of this correlation. This illustrates the distribution that would be predicted for a difference between the two groups given the hypotheses H0 (true negative) and H1 (true positive) respectively. It is obvious that if we raise the rate of type I errors, also known as false positives or false alarms, we would see a reduction in the rate of type II errors, also known as false negatives or missed detections, and vice versa. Alterations to the degree of correctness of both the H0 and H1 hypotheses result in modifications to the overall error probability. As a result, there is a very fine line to walk in terms of

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striking a balance between the risk of not detecting anything and the risk of making a false detection.

As can be seen in Figure-6, the classification of the data into positive and negative categories yields two distinct classes, which can then be used to examine and maintain the equilibrium between the two. The critical thresholds are as follows:

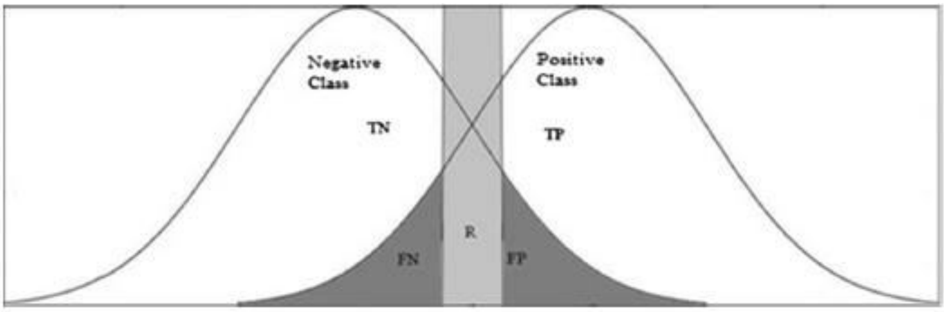

Figure-6. Statistical distribution curves related to classes.

Decided for these classes, resulting in the existence of a limbo. Then, with the assistance of an algorithm for online learning, the procedures that need to be done to acquire the most suitable threshold in the grey region.

4. SIMULATION RESULTS

To assess the effectiveness of the suggested strategy, simulated results are provided below. For each experiment, there are 1000 trials. It is assumed that the PU signal is a BPSK signal with a central frequency of 20 MHz, a data transmission rate of 20 kbps, a sampling frequency of 200 ksps, and a Gaussian noise variance of 2 = 1. The effectiveness of the suggested approach (ED-BS) and the ED method will be contrasted. Table 1 lists the default and modification settings.

Table-1. Default and modification parameters.

Default Parameters		Modification Parameters
Nd	32	64
Nc	8	16
SNR	10	100
SNR_low	10	30
NUM_Statistics	1000	10000

4.1 Energy Detector

From the plot Figure-7, we can easily observe that the theoretical Pd and calculated Pd increases with the SNR value. We can also verify that Pfa is under 0.05. Figure-7a represents the detector performance with 1000 statistics and Figure-7b represents the detector performance with 100000 statistics. We can observe that by increasing the amount of test statistics, the detector performs at its best.

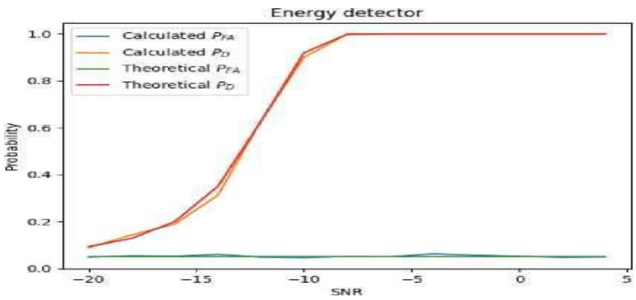

Figure-7 (a). For 1000 records.

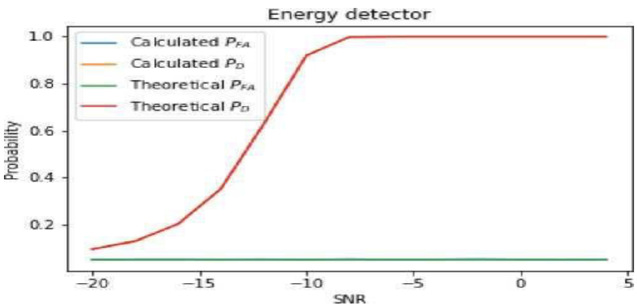

Figure-7(b). For 100000 records.

From the plot Figure-8, we can observe a clear drop in theoretical Pd and calculated Pd compared to the previous case when we have noisy estimates. However, the performance drop is negligible for higher values of SNR - owing to the smaller noise component. Figure-8a represents the detector performance with 1000 statistics and Figure-8b represents the detector performance with 100000 statistics. We can observe that by increasing the amount of test statistics, the detector performs at its best.

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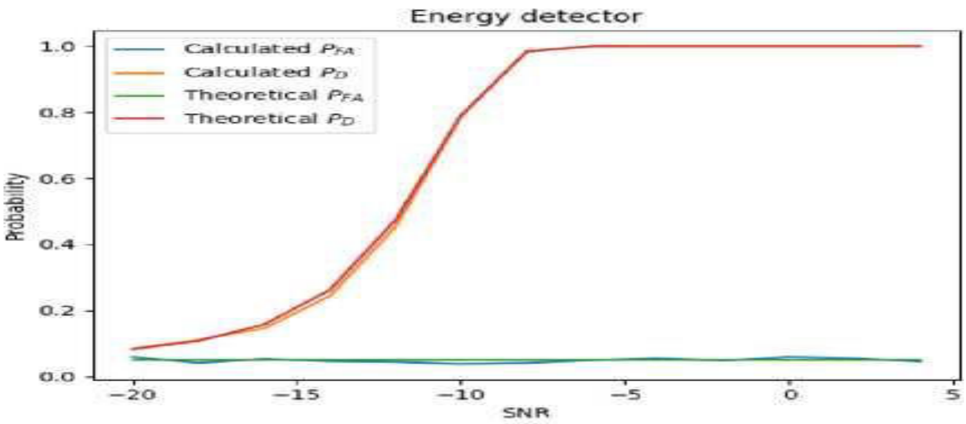
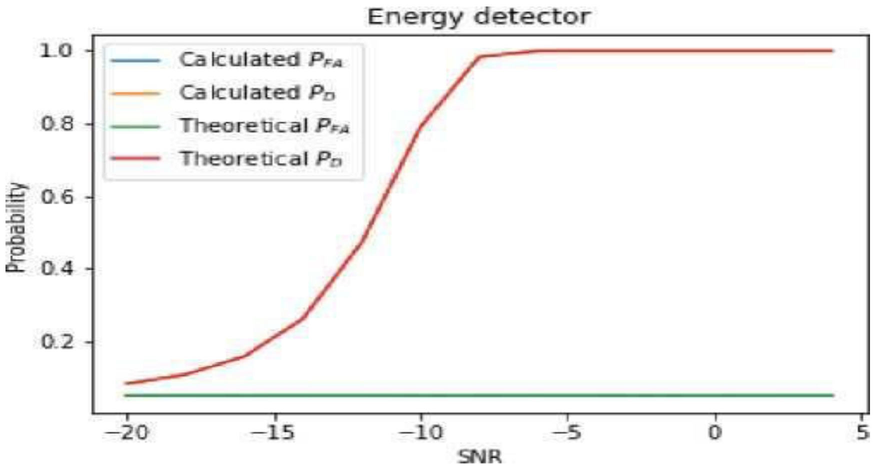


(a) For 1000 records



(b) For 100000 records

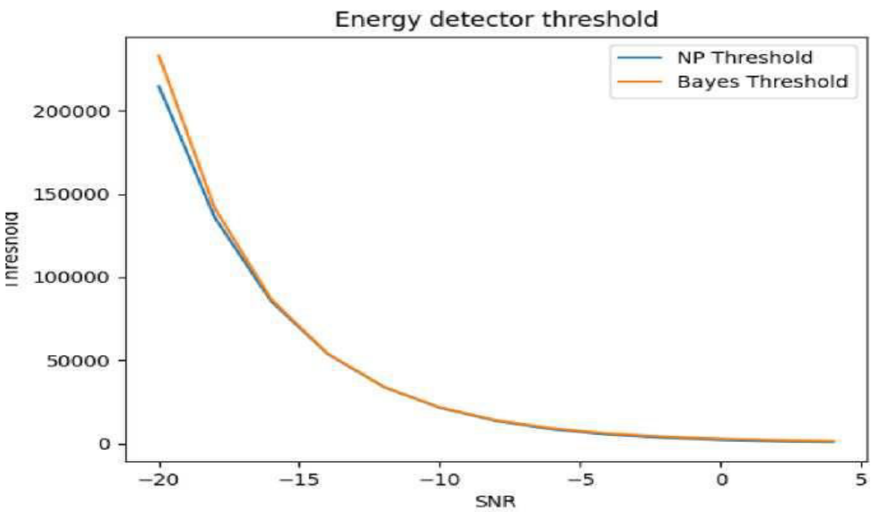


Figure 3: Threshold

4.2 Cyclostationary Detector

Subpart - A

From the plots Figure-9 and Figure-10, we can verify that the means and variances match with the same of that of the complex Gaussian distribution we derived. Figure (9) represents the detector performance with 1000 statistics and Figure-10 represents the detector performance with 100000 statistics. We can observe that by increasing the amount of test statistics, the detector performs at its best.

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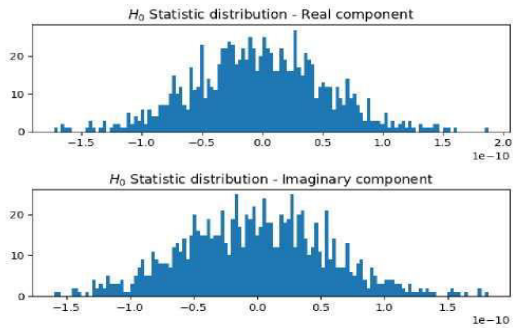
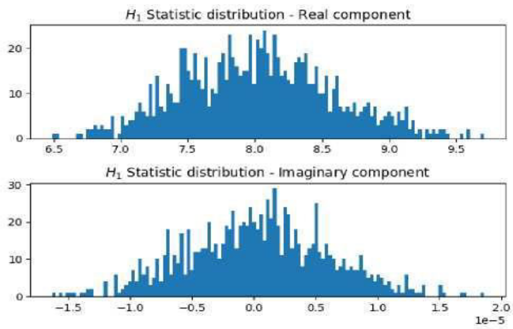
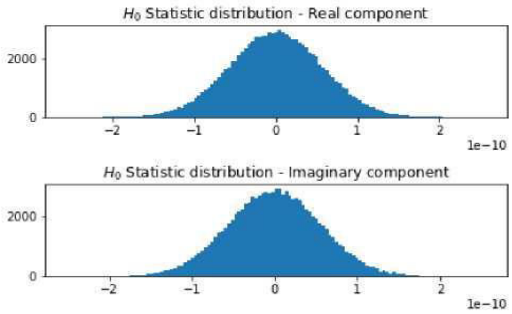


a) Hypothesis H0

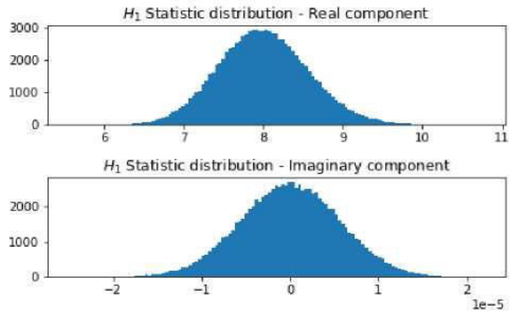


(b) Hypothesis Hi

Figure-9. Distribution for 1000 Statistics.



a) Hypothesis H0

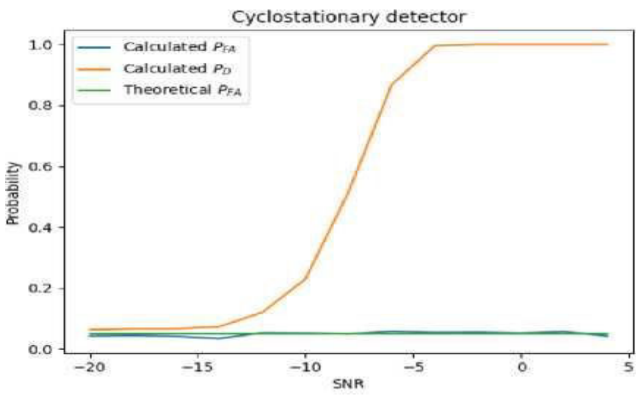


(b) Hypothesis Hi

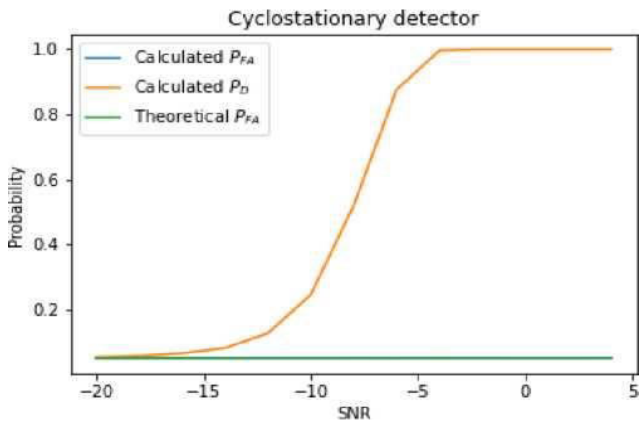
Figure-10. Distribution for 100000 Statistics.

Subpart – B

From the plot Figure-11, we can easily observe that the calculated Pd increases with the SNR value. We can also verify that Pfa is under 0.05. Figure (11a) represents the detector performance with 1000 statistics and Figure-11b represents the detector performance with 100000 statistics. We can see that with an increased number of test statistics, we get the ideal detector performance.



(a) For 1000 records



b) For 100000 records

Figure-11. Probability VS SNR.

Subpart – C

From the plot Figure-12, we can observe a clear drop in calculated Pd compared to the previous case. However, the performance drop is negligible for higher values of SNR - owing to the smaller noise component. We can also observe that the drop in performance for the cyclostationary detector is lesser compared to the same case with the energy detector and hence it is less prone to noisy estimates. Figure-12a represents the detector performance with 1000 statistics and Figure-12b represents the detector performance with 100000 statistics. We can observe that by increasing the amount of test statistics, the detector performs at its best.

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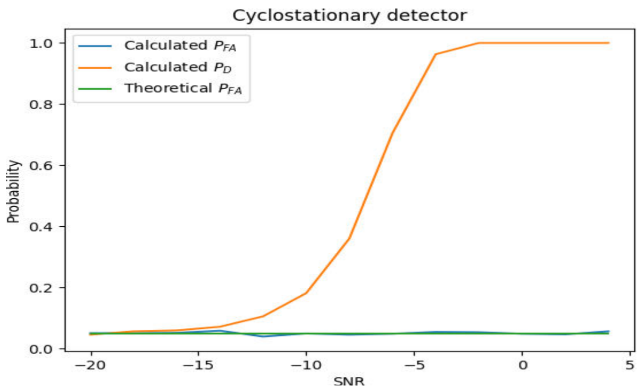
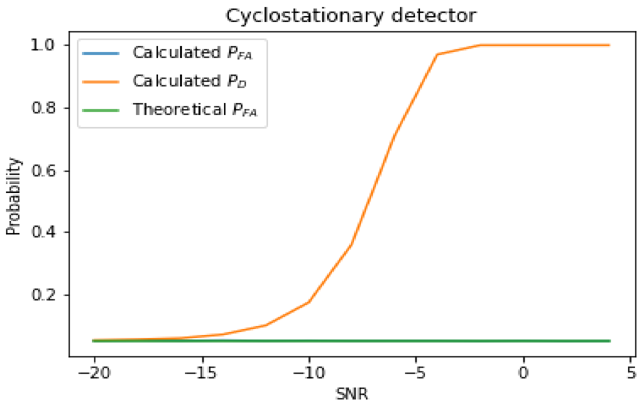


(a) FOR 1000 RECORDS



FOR 10000 RECORDS

Figure-12. Probability VS SNR.

5. CONCLUSIONS

A novel approach to spectrum sensing is presented in this research. The suggested technique relies on ED, however unlike traditional ED calculations; it does not need an estimate of the noise variance.

The threshold used in this technique does not need the unlike ED, we have some idea of the noise variance, therefore we may use noise variance uncertainty is reduced greatly. The performance of the proposed system is evaluated by checking its accuracy, network latency, and beam selection. Finally, Using The RoC Curve, We Can Find the Spectrum Is Available Or Not. Third-Party Spectrum Is Used or Not. Here There Is The Roc Curve Is Increasing Finally Conclude That Third Party Is Not Used This Spectrum.

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