Advancement of Non-coherent Spectrum Sensing Technique in Cognitive Radio Networks - A Simulation-Based Analysis

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Abstract. This article provides a concise overview of commonly employed Spectrum Sensing methods in Cognitive Radio (CR). In practical situations where the receiver lacks access to information about the Primary User (PU) signal, the Energy-based detection approach proves to be more appropriate for Spectrum Sensing in CR. The article also explores the advancements made in the Non-coherent (Energy detection) spectrum sensing approach. Additionally, the effectiveness of spectrum sensing heavily relies on selecting the appropriate threshold. Consequently, the article presents a simulation-based analysis of the Static threshold and Adaptive double threshold algorithm, including their limitations. To enhance detection performance, the article proposes the Modified threshold as an alternative to the Static threshold and Adaptive double threshold algorithm. The performance of the Modified threshold is validated using a MATLAB simulator with a QPSK modulated Orthogonal Frequency Division Multiplexing (OFDM) signal. The results demonstrate that the Modified Threshold outperforms the Static and Adaptive double threshold algorithms, particularly at low Signal to Noise Ratio (SNR) levels.

Keywords: Cognitive Radio · Non-cooperative Spectrum Sensing · Detection Probability · Threshold

1 Introduction

The transition from using only voice communication to incorporating multimedia applications has created a need for higher data rates, resulting in a significant demand for radio spectrum resources. However, the allocation of these resources often lacks efficiency, leading to some parts of the spectrum being heavily used while others remain unused or rarely utilized, as shown in Fig. 1. Research studies indicate that approximately 70% of the total spectrum is not fully utilized [1]. This inefficient distribution of spectrum can result in service disruptions. The scarcity of available spectrum is a critical concern in network research that requires attention. To address this issue, CR technology has emerged as a promising solution by allowing opportunistic access to underutilized spectrum. In CR,

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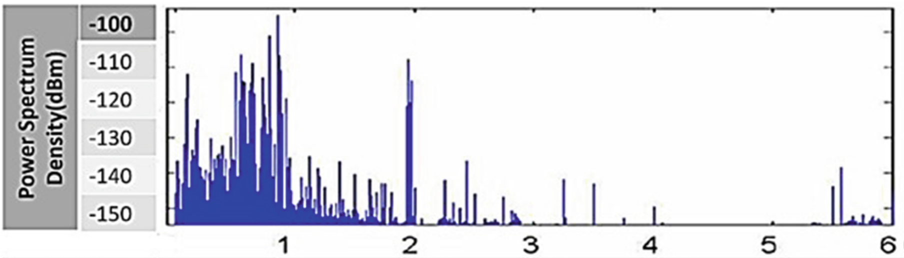
secondary users (SUs) can utilize the spectrum band opportunistically without causing interference to the PUs. CR techniques enable efficient utilization and opportunistic sharing of the spectrum.

CR empowers users to (1) Assess the accessibility of various spectrum segments and identify the existence of authorized users while operating within a licensed frequency range, (2) Select the optimal available channel, (3) Facilitate collaborative access to this channel among multiple users, and (4) Exit the channel when a registered user is identified.



Freq.(GHz)	0-1	1-2	2-3	3-4	4-5	5-6
Utilization(%)	54.4	35.1	7.6	0.25	0.128	4.6

Fig. 1. Spectrum Utilization.

In order to function efficiently within a dynamic spectrum environment, CR networks rely on spectrum-aware operations, which encompass a CR cycle [3]. After identifying the optimal channel, the network protocol needs to adapt to the available spectrum. Consequently, functionalities must be in place to facilitate this transition in the network protocols. The cognitive cycle comprises several key functions as illustrated in Fig 2.

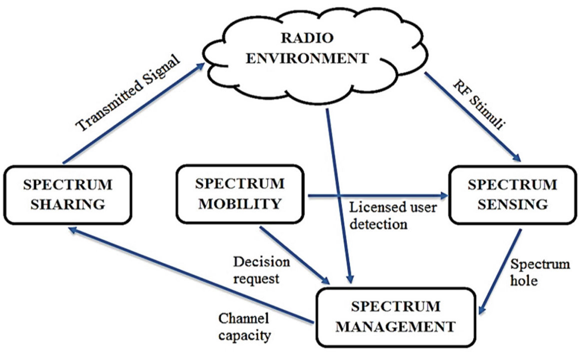


Fig. 2. CR Cycle.

Spectrum sensing (SS) serves as the fundamental module for CR by allowing SUs to detect the existence or non-existence of signals in the frequency bands. A reliable and effective SS approach is essential to prevent interference with PUs in cases where a spectrum band is already in use. Conversely, if the band is unused and the CR system fails to detect its availability, it results in under-utilization of the available radio spectrum. Therefore, Spectrum Sensing holds utmost importance in the entire CR network, ensuring optimal use of the resources.

Research indicates that the effectiveness of SS methods are compromised due to various factors such as multi-path fading, shadowing, and receiver uncertainty. In the subsequent module, SUs make decisions based on their observations. However, due to the uncertainty inherent in the detected measurements, these decisions can be incorrect or delayed, leading to sub-optimal spectrum allocation. Consequently, uncertainty propagation impacts all the processes related to radio spectrum, resulting in a degradation of CR performance. One significant source of uncertainty is NU, which relies heavily on the proper selection of threshold values. Therefore, it is crucial to address this uncertainty issue in CR by employing appropriate threshold and ensuring accurate and timely SS to enhance detection efficiency. There are situations where the PU receiver may be located beyond the radius of the PU transmitter. This scenario can result in false detection or a failure to find the availability of unused radio spectrum. It is important to acknowledge that it is generally challenging for SUs to distinguish PUs. Hence, in most cases, all received signals, including both PU and SU transmissions, are treated as a single combined signal, denoted as w(t). The SU signal, r(t), can be mathematically represented [5].

$$r(t) = \begin{cases} g\{t\} \rightarrow H_0 \\ w\{t\} + g\{t\} \rightarrow H_1 \end{cases} \tag{1}$$

The noise taken as AWGN and is represented by g(t) in the given equation. The hypotheses H_0 and H_1 correspond to the non-existence and existence of PU, respectively. Therefore, the objective of SS is to make a decision between H_0 and H_1 based on the received signal r(t). The performance of the detection process is evaluated using the Probabilities of Detection (Pd), False-Alarm Probability (Pf), and Miss-Detection Probability (Pm).

The articles' sections are outlined as follows: An overview of Non-cooperative Spectrum sensing techniques, accompanied by a literature survey is found in Sect. 2. Section 3 introduces the proposal for the Modified threshold. In Sect. 4, the simulations for the Static threshold, Adaptive double threshold, and Modified threshold are presented. The paper concludes in Sect. 5.

2 Non-cooperative Spectrum Sensing Techniques and Related Works

In the last few decades, several techniques for SS have emerged and been introduced. In this study, we have categorized these approaches into cooperative and non-cooperative SS techniques, as illustrated in Fig. 3. In the Non-cooperative approach, a single SU is self-sufficient in detecting and making decisions regarding spectrum utilization. On the other hand, in the cooperative approach, multiple SUs collaborate to collectively make decisions and detect vacant spectrum bands. In the context of cooperative, multiple users work together to make collective decisions, necessitating the sharing of information. However, this approach can pose challenges for resource-limited networks due to additional tasks like channel sharing and pilot channel implementation, as well as increased overhead traffic resulting from information sharing. Despite these challenges, Cooperative approaches offer more accurate sensing performance, especially in the presence of factors like NU, fading, and shadowing. On the other hand, Non-cooperative SS techniques can be categorized into Energy Detection (ED), Matched filter-based detection (MFD), Cyclostationary feature-based detection (CSFD), and more. Table 1 presents the available and commonly used Non-cooperative spectrum sensing techniques [2–4,7,8].

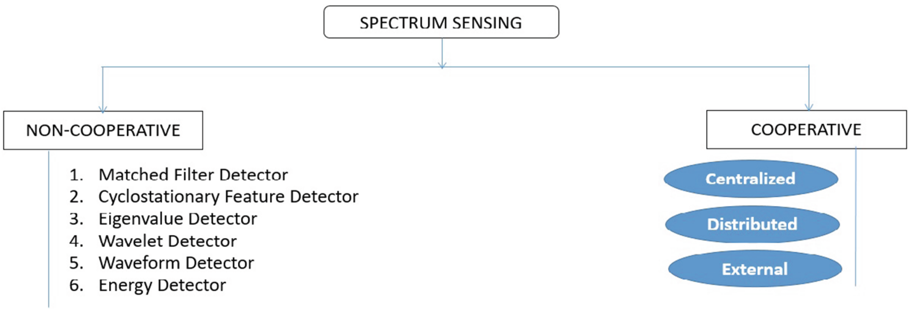


Fig. 3. SS Techniques.

It is important to highlight that ED is an appealing approach because it does not necessitate any prior knowledge about the PU. At a same time, its detection accuracy is considerably lower compared to other techniques. On the other hand, Wavelet-based and CSFD offer higher accuracy but come with the trade-off of increased complexity, longer sensing time, and higher cost. This can result in a high cost per efficiency ratio. ED stands out in terms of computational complexity, requiring minimal energy compared to other listed approaches.

The literature survey reveals that despite extensive research, CR still faces challenges in various aspects. These challenges includes:

a) Detection accuracy, which is often compromised by factors such as: (1) Hidden Primary User Problem, (2) Channel Uncertainty, (3) Noise Uncertainty (NU), and (4) Spread Spectrum Users that result in very low SNR for users. b) Lack of knowledge about primary user transmission patterns/parameters. c) Determining the optimal sensing duration and frequency. d) Ensuring self-coexistence, i.e., the ability of CR devices to coexist and operate without caus-

Table 1. Comparison Between Non-Cooperative Spectrum Sensing Techniques.

Approach	Narrowband/ Wideband	*Direct /Indirect*	Prior Signal Information	Accuracy	Computational Complexity	Sensing Time	Cost	Energy Efficiency
Energy Detector	Both	Direct/In direct	No	Very Poor	Very Very Low	Very Very Less	Very Very Low	Very Very Low
Matched Filter Detector	Narrowband	Direct	Yes	Very Good	Very Low	Very Less	Very Low	Medium
Waveform Detector	Narrowband	Direct	Yes	Poor	Medium	Medium	Low	Very Low
Eigen value Detector	Narrowband	Indirect	Yes	Very Poor	Low	Less	Medium	Low
Wavelet Detector	Wideband	Indirect	Yes	Medium	Very High	Very Large	Very High	Very High
Cyclostationary Feature Detector	Narrowband	Indirect	Yes	Good	High	Large	High	High

ing interference to each other. e) Addressing security concerns related to CR networks.

In conclusion, these challenges highlight the need for continued research and development to enhance the performance and efficiency of CR. Among the various spectrum sensing methods, ED stands out as an attractive option due to its simplicity and cost-effectiveness, which appeals to many researchers. However, ED is not without its limitations, including the following issues:

- Resilience against NU
- Selection of optimal design parameters such as threshold and observation window length to achieve better detection accuracy
- Performance degradation at lower SNR values Inefficiency in detecting spread spectrum signals.

Addressing these challenges is crucial for improving the reliability and effectiveness of ED in CR systems. To address the challenges associated with ED, researchers have proposed various advancements. In a study by the authors [9], they mathematically analyze the trade-off between sensing duration and throughput in CR using the ED. Additionally, the authors state the minimum number of samples required. In their study [10], the authors propose a method that utilizes ST approach. Additionally, the SS used is coherent and hence demonstrates better results compared to ED. Building upon this work, in [11], the authors further develop the method by considering eigenvalues in two ways to determine the presence or absence of the PU signal which is a coherent detector for PU signal detection. In [12], the authors discuss various non-cooperative SS approaches and their advantages and disadvantages. ED, CSFD, and MFD are specifically presented for CR ad-hoc networks in [13]. An ED algorithm based on a Double Threshold (DT) is also demonstrated in [14] to increase detection efficiency and mitigate potential miss-detections. The study [15] focuses on Adaptive Threshold for ED. The author presents simulation results for higher SNR values. A comparative analysis between single and dynamic thresholds is carried out in [16], where the dynamic threshold is determined by measuring the noise level. The outcome indicates the dynamic threshold improves detection accuracy compared to the ST. In the study [17], the detection of multiple PU signals for spectrum sensing is explored. The research focuses on investigating variations in NU levels, which commonly range from 0.5 dB to 1 dB in practical SS scenarios. In [18], authors propose an adaptive threshold method for ED-based SS. Simulation results clarify that this approach achieves good throughput for SUs with higher SNR. In [19], the efficacy of the ED approach in the presence of NU is investigated using a double threshold. Simulations are carried out within the Digital TV licensed band. The findings demonstrate that the double threshold surpasses the performance of the ST method when NU is present.

In [5], the authors explore OFDM-based SS. The study compares the performance of ED and Wavelet-based detection. The results reveal that the Wavelet-based detection approach outperforms the ED with an identical environment. In [20], the authors analyze the performance of ED-based CR systems in both AWGN and Rayleigh fading channels. They observe a performance improvement of 1.3 times in the AWGN channel and 0.5 times in the Rayleigh channel. Another study [21] introduces the concept of random sampling in ED and evaluates its performance with ROC analysis. In [22], the authors compare ED, Auto correlation-based detection, and MFD techniques with a dynamic threshold using a QPSK-modulated signal. The dynamic threshold outperforms the ST. A comprehensive analysis of different detection approaches, including ED, MFD, CSFD, and Wavelet-based detection, is presented in [7]. The results indicate that the Wavelet-based detection approach outperforms all other methods. [23] highlights the advantages and disadvantages of various sensing approaches. The efficiency of ED-based CR systems is assessed in [24] by proposing an intelligent threshold selection method based on the Constant Detection Rate (CDR) principle. The authors provide mathematical expressions for Pd with Constant False Alarm Rate (CFAR) as well as for CDR. In [6], the authors discuss both Non-cooperative and Cooperative approaches for CR, highlighting their advantages and limitations along with the associated challenges. They also introduce a hybrid spectrum sensing approach that combines MFD and ED. The implementation of the double threshold algorithm to enhance the detection performance with ED is presented in [25]. The authors demonstrate that the DT algorithm outperforms the conventional approach, resulting in improved detection efficiency. Enhancement in ED using adaptive threshold is presented in [26]. For detection, The authors have obtained the adaptive threshold ($\varGamma a$) by averaging the double thresholds i.e.,

$$\varGamma a = \frac{UpperThreshold + LowerThreshold}{2} \tag{2}$$

The efficacy of the adaptive threshold is improved compared to the ST. The issue of the confused state region is addressed by the Markov model proposed in [26]. The author also considers the impact of NU. [27] introduce an enhanced

ED approach that demonstrates favorable performance even at low SNR values. A survey-based evaluation of various spectrum sensing approaches is presented in [28]. The authors assess these approaches in terms of detection accuracy, complexity, robustness, NU resilience, power consumption, requirement of PU signal, cost, sensing time, and reliability. In [29], a new adaptive threshold-based ED approach is introduced. This method aims to enhance the detection performance in scenarios where the NU is present. In a recent study [1], the Golden section search algorithm is presented to increase the efficiency of ED. The algorithm employs thresholds defined as follows:

$$\Gamma_{lower} = 0.9 * \frac{Q^{-1}(Pf) + 1}{\sqrt{N}} \tag{3}$$

and

$$\Gamma_{upper} = 1.1 * \frac{Q^{-1}(Pf) + 1}{\sqrt{N}} \tag{4}$$

Performance evaluation is conducted in [3] to assess the effectiveness of CDR in AWGN and Rayleigh channels. The study focuses on the analysis of detection performance using ED, MFD, and CSFD. Additionally, the authors investigate the performance of both ST and adaptive double threshold approaches in the context of a Rayleigh fading channel. The evaluation is performed using an OFDM signal.

From the above literature studies, it is evident that parametric approaches are not practical due to the unknown nature of the actual spectrum status. Cooperative spectrum sensing approaches suffer from drawbacks such as energy inefficiency, longer sensing time, and high cost per detection efficiency. It is acknowledged that a balance needs to be struck between energy efficiency and spectral efficiency, Also, the relationship between the sensing capability and the attainable throughput for SUs. Despite extensive research in the past decade, none of the SS approaches provide fail-safe performance in diverse environments, particularly regarding the accuracy of PU detection and the trade-off between Pd and Pf. Furthermore, the discussed SS methods fail to fully satisfy the requirements for good detection accuracy, low cost, short sensing time, and low power consumption. Some methods show promising detection performance but come with drawbacks such as high processing time, high power requirements, reliance on prior knowledge of PU at the receiver side, and the need for proper threshold setting. The detection accuracy of these methods heavily relies on the selection of the threshold.

3 Proposal for Modified Threshold (MT)

The ED approach involves matching the Average Energy (AE) of the signal received with a (Γ) to determine whether the PU signal is exist or not [3]. If the AE exceeds the (Γ), it indicates the existence of the PU signal; otherwise, it is considered non-existence. ST ((Γ)) value is given as Eq. (6) [3]. This proposal is also available in our pre-print [30] and [31].

$$\Gamma = \frac{Q^{-1}(Pf)+1}{\sqrt{N}} \tag{5}$$

where Q is represented as marcum Q function. To improve the performance in the presence of NU, an adaptive double threshold approach is introduced in [27], utilizing a Markov model. The Upper Threshold (UT) and Lower Threshold (LT) values are calculated using Eq. (8) and Eq. (9) [27], respectively.

$$UT = (\frac{2}{N}(Q^{-1}(Pf)+1)) * NU \tag{6}$$

and

$$LT = (\frac{2}{N}(Q^{-1}(Pf)+1)) * \frac{1}{NU} \tag{7}$$

As the NU level increases from 0.5 dB to 1 dB, the difference amongst the thresholds is also increases, aiming to reduce the likelihood of missed detections. Consequently, the ED employing the adaptive double threshold demonstrates improved performance, especially in low SNR scenarios. However, the use of a double threshold can result in increased detection time, which may be inconsistent with the requirements of efficient spectrum sensing.

Inspired by the aforementioned, this research suggests obtaining a static threshold parameter through the adaptive double threshold method. This is achieved by calculating the sum, difference, mean, and median values of the UT and LT.

$$\lambda_a = UT + LT \tag{8}$$

$$\lambda_s = UT - LT \tag{9}$$

$$\lambda_{mean} = mean(UT\&LT) \tag{10}$$

$$\lambda_{median} = median(UT\&LT) \tag{11}$$

The threshold values derived from mean, median, and subtraction techniques are consistently lower than the UT, leading to improved detection performance. Figure 4 illustrates the variation in the derived threshold for a range of Pf, considering a NU = 1 dB. The results demonstrate the mean, median, and subtraction of the UT and LT. The subtraction result in lower threshold values, which intuitively contribute to better detection performance. Additionally, during simulation, we observed that the judiciously derived value of λ_s, which is the modified threshold parameter, is the lowest among all the derived thresholds. Therefore, this study suggests utilizing λ_s as a modified threshold. To investigate the influence of NU on λ_s, another simulation is conducted as shown in Fig. 5 which illustrates the variations in the threshold for a range of Pf. It is observed that as NU increases, the value of λ_s tends to approach the ST. It is important to note that the value of λ_s is always lesser than or equal to the ST. Therefore, utilizing λ_s as a threshold parameter ensures the protection of performance when employing ED for a worst scenario. To highlight the advantages of the MT, the performance of the detector using the MT is correlated with that using the ST and the adaptive DT. The subsequent section provides a detailed explanation of the simulation for clarity.

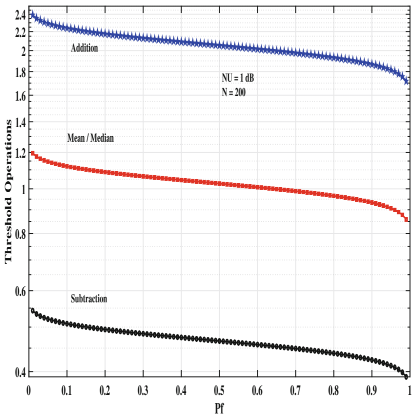


Fig. 4. Threshold against Pf.

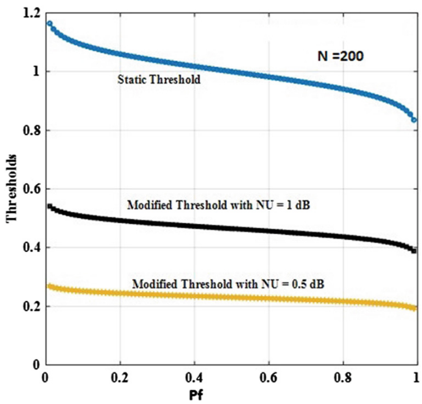


Fig. 5. Efficiency of MT with respect to ST.

4 Simulations

The AE of the signal is balanced with a threshold value set in the detector. For simulation purposes, we consider the system model depicted in Fig. 6. In this model, a QPSK-modulated OFDM signal is transmitted over a Rayleigh fading channel. The FFT size is set to 2048, and as per 3gpp specification, we have taken 200 samples for analysis. The selection of the ST relies on the N and the Pf. To assess the impact of N and Pf on the ST, we present the simulation results in Fig. 7 and Fig. 8.

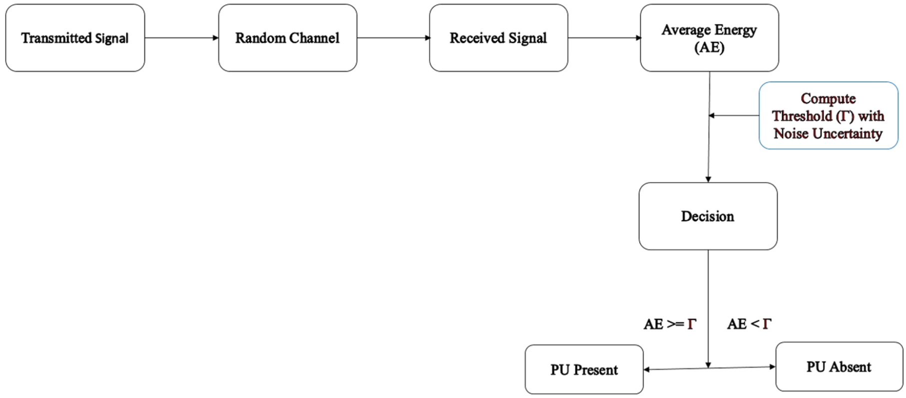


Fig. 6. General System Model.

The purpose of the simulation is to examine the influence of the Pf on the ST. It is observed that as Pf decreases, the ST also decreases. However, from the perspective of the SU, a lower Pf is desired to achieve higher throughput. Therefore, we maintain Pf at a value of 0.1 and vary the N to observe its impact on the ST, as illustrated in Fig. 8.

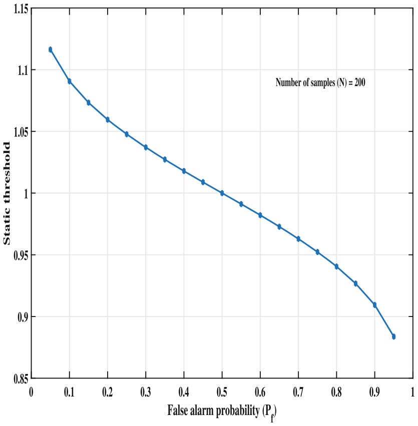


Fig. 7. Effect of Pf on ST.

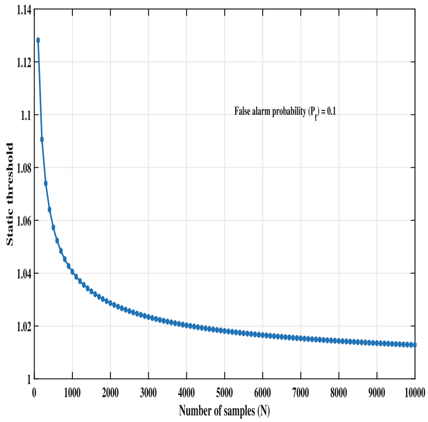


Fig. 8. Effect of N on ST.

As the N increases, the decision threshold decreases, leading to a more complex detector. Additionally, it is crucial to carefully select the values of N and the Pf to achieve an optimal threshold for effective detection performance. Furthermore, we have investigated the influence of the ST on a QPSK-modulated OFDM system. The system is configured with N = 200 and Pf = 0.1. We plot the AE on the y-axis, while varying the SNR in dB on the x-axis as shown in Fig. 9. The existence of the PU is declared if the AE is equal to or greater than

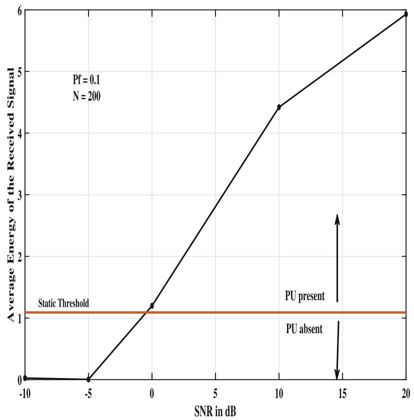


Fig. 9. Impact of SNR in dB on AE.

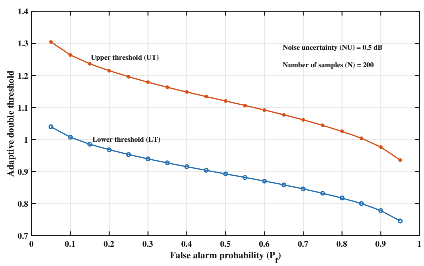


Fig. 10. Impact of Pf on Adaptive Double Threshold.

1.091 dB, otherwise, non-existence. The ST demonstrates reliable PU detection without considering the impact of NU. To address the issue of NU, an adaptive double threshold algorithm was proposed [27]. To evaluate the effectiveness of the adaptive DT, we conducted simulations using NU values of 0.5 dB and 1 dB, with N set to 200. The Pf values were varied on the x-axis, while the upper and lower thresholds were observed and plotted on the y-axis as per Fig. 11. By examining Fig. 10 and Fig. 11, it is observed that as NU increases from 0.5 dB to 1 dB, the gap between the LT and UT also widens. This indicates that the concept behind the adaptive double threshold is to expand or increase the difference between the thresholds in order to account for any false detections caused by NU. Furthermore, we plot to assess the influence of the parameter N on the adaptive double threshold. In these simulations, we set Pf to 0.1 and NU to 0.5 dB and 1 dB, and varied the value of N. Figure 12 and Fig. 13 demonstrate that as the NU increases, the difference between the UT and LT also increases. However, this can result in unnecessary delays and increased complexity, as the decision matrix needs to be reevaluated when the observed value falls between the UT and LT. To evaluate the detection efficiency of SS with the adaptive double threshold, we conducted simulations where we varied the SNR in dB on the x-axis and observed the AE. Figure 14 illustrates that the difference between the UT and LT increases in order to mitigate the risk of miss-detection caused by increasing NU. It is evident from the figure that if the AE exceeds the UT, the detector declares the PU as present. Conversely, if the AE falls below the LT, the detector declares the PU as absent. However, when the decision falls between the UT and LT, no decision is made, and the algorithm repeats the cycle until a decision is reached.

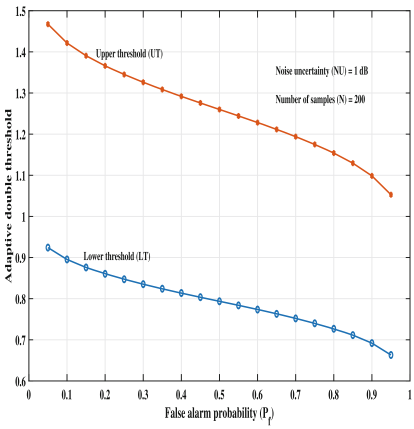


Fig. 11. Impact of Pf on Adaptive Double Threshold.

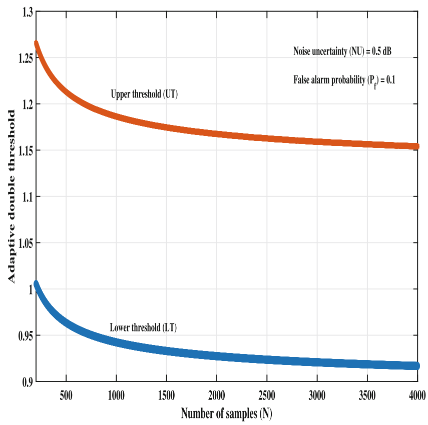


Fig. 12. Impact of N on an Adaptive Double Threshold.

This highlights the need for an MT that can account for NU. Nevertheless, it should be noted that increasing the threshold difference also leads to increased

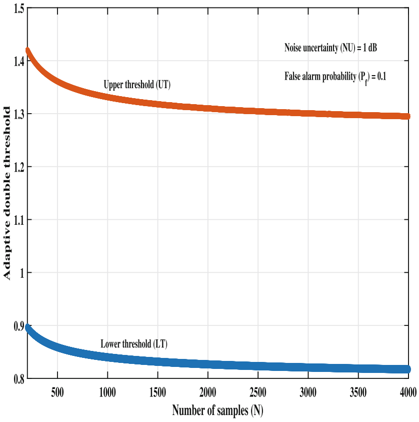


Fig. 13. Impact of N on an Adaptive Double Threshold.

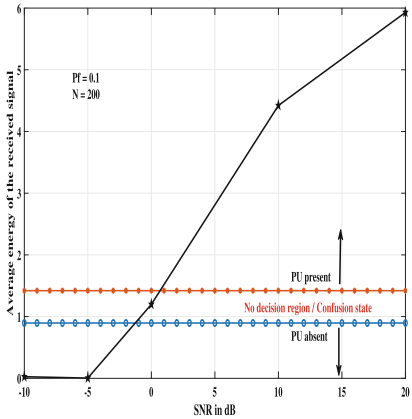


Fig. 14. Impact of SNR in dB on AE.

algorithm complexity. Consequently, further results are developed to validate the usefulness of the MT. Under the same simulation parameters, it is evident that the proposed MT exhibits a lower value compared to the ST and Adaptive double threshold. Furthermore, the issue of the ST not accounting for the impact of NU is effectively addressed in the proposed MT. The decision made by the MT is accurate, leading to an improvement in detection efficiency, which was lacking in the adaptive double threshold approach. Figure 15 and Fig. 16 indicate that the detection efficiency can be significantly enhanced with the MT in comparison to the ST and Adaptive double threshold. Additionally, as NU increases, the performance of the MT also improves. In this simulation, we adopted a NU value of 1 dB, as suggested in the literature [17]. The MT not only reduces the Pm but also reduces computational complexity, making it a promising choice for improving SS performance.

The success of the proposed approach has been verified by examining its impact on the AE of the received QPSK modulated OFDM signal, as depicted in Fig. 17. The analytical expression of Pd over a Rayleigh fading channel is taken from [9].

We apply the proposal (MT) to the above and obtained the results. It is observed that the MT outperforms the ST and Adaptive DT which results in better detection efficiency for the MT-based detector.

The simulation result is also developed to observe the impact of SNR on the Pd. We take Pf as 0.1, NU as 1 dB, and run for 10e3 monte-carlo simulations. We observe that all approaches i.e. with ST, MT, and Adaptive double threshold showed a rising trend for Pd with the increase in SNR as observed from Fig. 18. Moreover, the MT outperforms the ST and the Adaptive double threshold approach. We see around 41.27 % and 26.38 % relative improvement at SNR=0 dB in the performance with MT as compared to that of the Adaptive

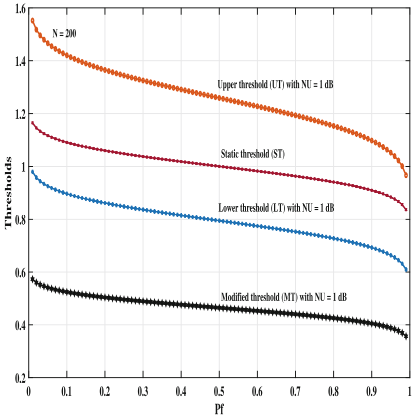


Fig. 15. MT Efficiency against Pf.

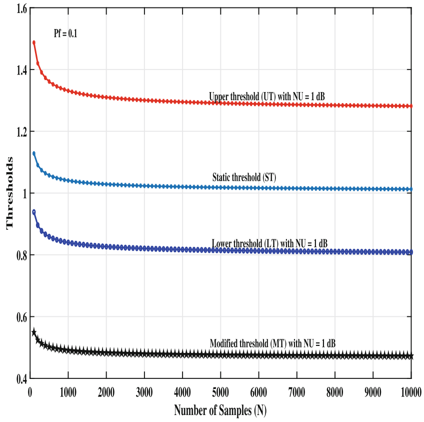


Fig. 16. Efficiency of MT against N.

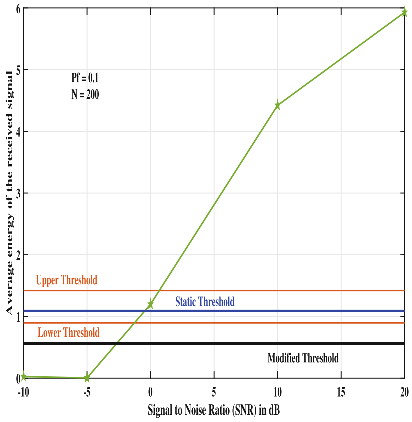


Fig. 17. Impact of SNR in dB on AE.

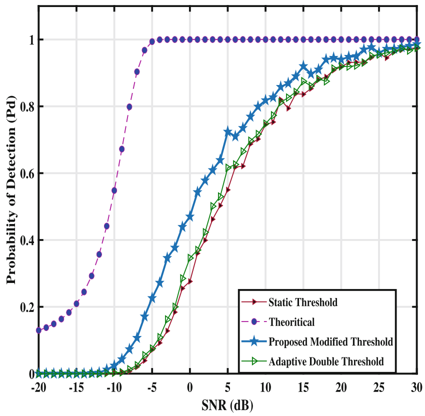


Fig. 18. Impact of SNR in dB on Pd.

double threshold and the ST respectively. The decision of PU is also judged by the ROC. The higher the area, the better the detector efficiency. Hence, to check the efficiency of the MT, we simulated ROC taking SNR=0 dB and NU as 1 dB. From Fig. 19, We observe around 23.77 % and 35.55 % relative improvement at Pf = 0.1 with an MT-based detector compared to ST and the Adaptive double threshold algorithm.

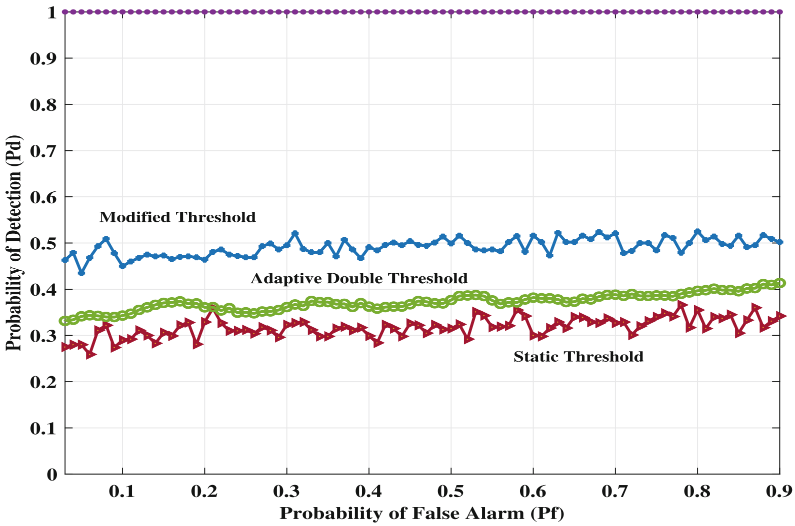


Fig. 19. Efficiency of MT on ROC.

5 Conclusion

The simulation outcomes indicate that the MT (Modified Threshold) outperforms both the ST and Adaptive DT methods in terms of false alarm probability (Pf), missed detection probability (Pm), Number of Samples (N), and SNR. The proposed MT approach demonstrates effective management of Noise uncertainty (NU) and achieves precise and efficient detection, especially at lower SNR levels. The proposed method's validity is confirmed by employing a Rayleigh fading channel to transmit a QPSK modulated OFDM signal. Importantly, the MT does not have any adverse effects on the inherent behavior of the detector.

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