ENHANCED SIGNAL ENERGY DETECTION TECHNIQUE FOR LOW SNR SPECTRUM SENSING IN COGNITIVE RADIO – HYBRID APPROACH

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ABSTRACT

Identification of Primary User (PU) signals in the context of Cognitive Radio (CR) networks essentially calls for an efficient spectrum sensing methodology. Even though the mainstream Energy Detection technique has several severe drawbacks, specifically at low SNR environments that impair effective detection of PU signals, this article presents a novel hybrid methodology consisting of the ESED technique. The integration of wavelet denoising with adaptive thresholding effectively mitigates the shortcomings of traditional ED. Simulation results are presented and clearly show that ESED technique offers high detection accuracy with moderate computational complexity. It is a more favourable approach to resource-limited CR devices that enhance the reliability of spectrum sensing in low SNR conditions. This new method has outstanding performance. In particular, for probability of detection (Pd) equal to 1 at an SNR of -10 dB, it achieved a detection probability (Pd) of 0.8 at an SNR of -20 dB. High detection probabilities under low SNR circumstances cannot be attained with the use of the traditional method as observed from comparisons. Consequently, this method effectively identifies Primary Users (PUs) and optimizes spectrum utilization, thereby enhancing spectrum management, reducing interference, and ensuring the efficient allocation of resources.

KEYWORDS

Spectrum sensing, Cognitive Radio, Energy Detection, Wavelet denoising, Adaptive Thresholding

1. INTRODUCTION

Cognitive radio (CR) technology is an advanced dynamic spectrum acquisition solution that significantly facilitates spectrum utilization efficiency [1]. The basic objective of a CR network is to detect unused spectrum and use it efficiently without interfering with the communication of primary users (PUs). The objective of spectrum sensing techniques is to detect PU usage in order to enable secondary users to access vacant bands when the PU is inactive [2]. The most widely used technique in the domain of spectrum sensing is ED; it has been more favoured since it is easier and computationally easy. In measurement of signal strength in ED, the presence or absence of PU is revealed, thus making the technique simpler as well as cost- effective [3]. However, one of its main limitations is the degraded performance in low mean-to-noise (SNR) conditions, where the detection probability and reliability of the ED method decrease significantly in low SNR environments, high noise makes it difficult for ED to see PU signals, potentially increasing false alarms and missed detections [5]. Recent research and advanced techniques, like wavelet demolition and adaptive thresholds, suggest that ED performance can be enhanced by reducing noise and optimizing the detection thresholds; therefore, the reliability, performance of CR networks have improved, and the efficiency has increased. The rest of the paper is divided as follows: Section 2 discusses relevant work done so far and challenges, Section

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3 enlists proposed solutions, Section 4 describes and discusses the simulation results, followed with implementation and deployment challenges in section 5 and the conclusions are drawn in Section 6. The above is represented in the block diagram given below.

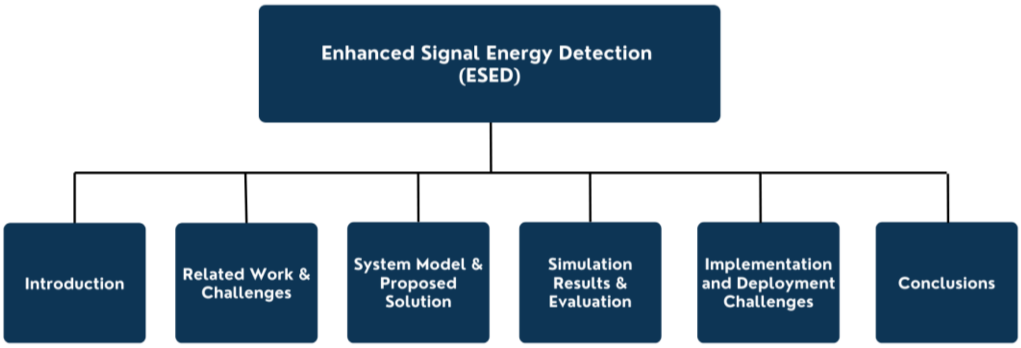

Figure 1 Enhanced Signal Energy Detection (ESED)

2. RELATED WORK AND CHALLENGES

Challenges and Limitations in Threshold settings and Energy Detection: A series of innovative spectrum sensing techniques on threshold settings and energy detection are outlined in various research papers. Firstly, [9] introduces energy detection (ED) method that surpasses classical approaches by incorporating multiple antennas without estimating noise variance, catering to Gaussian and Rayleigh fading channels. This will simplify the system but degrade the performance when noise conditions vary, it cannot address more complex channels, multiple antennas, will increase hardware cost, complexity and power consumption cannot perform well when distinguishing between different types of signals. Optimal threshold selection in dynamic environment is challenging and it will not provide dynamic selection of optimize threshold, apart from Gaussian and Raleigh fading, real world testing is needed in various cognitive radio environment. Although the proposed method performs well at low SNR levels, the reliability of detection at low SNR in more challenging and dynamic environment is limited. Building upon this, [10] proposes a two-stage sensing scheme integrating energy detection and Renyi entropy-based detection, demonstrating superior performance metrics such as probability of detection and false alarm probability over single-stage methods. This two stage method introduces computational complexity, latency and it involves more complex calculations so it's computationally expensive particularly in real-time. Although authors addressed the noise uncertainty problem, but still performance at low SNR is challenging. In real-world scenario, low power devices face difficulty in implementing this solution. Performance observed in AWGN channel may not accurate in other wireless real-time environment involves shadowing, multipath fading and interference. It has limited adaptability to more advanced methods.

Machine Learning and Online Threshold Optimisation: In [11], the focus shifts to enhancing energy detector accuracy through machine learning models, showcasing maximal accuracy under diverse channel conditions. Authors reported in this paper, that complex tree algorithm achieved better performance across all channel conditions. Using machine learning technique, system can differentiate between PU and SU very easily and manage interference more efficiently and this will help cognitive radio taking accurate decisions. Adaptive learning capability will be increased with ML and makes the system robust and can handle different noisy environments. By applying ML, system improves accuracy without increasing processing time. It is demonstrated that machine learning algorithms enhance the accuracy in spectrum sensing. Authors tested their solution in AWGN channel only, need to be tested in other channel conditions. It is completely rely on labelled data set for training, obtaining high quality data set is challenging and inadequate data set leads to degrading of performance. Integration of ML introduces additional complexity, so devices with sufficient power and memory are needed to handle ML models and low power devices may not support. Addressing spectrum sensing accuracy in cognitive networks, [12] presents an optimum threshold expression derived from an online algorithm, refining detection probabilities. Authors showed that spectrum sensing accuracy is enhanced with their proposed online learning algorithm especially at low SNR values. By continuously learning historical detection data, it dynamically adjusts the decision threshold, results in taking more accurate decisions regarding presence or absence of primary user. This algorithm reduces decision errors, including false alarm and missed alarm probabilities, which leads to more efficient spectrum utilization. This algorithm has been tested not only on AWGN also in more complex environments, such as Rayleigh, Nakagami-m, Rician, and Weibull channels. Because of this versatility and effectiveness, this algorithm could be used in real world wireless communications. Complexity of this algorithm and optimization process may add computational overhead, this makes less suitable for devices with limited computational power. Author focused more on threshold optimization only and ignored other aspects such as channel estimation and noise uncertainty etc. Because of real-time adaption of thresholds could introduce delays, it will negatively impact detection speed.

Local vs Global Thresholding and Enhanced Energy Detection in Cognitive Radio: Comparative analysis between local and global thresholding techniques in [13] highlights the superiority of global adaptive methods for signal detection in Cognitive Radio (CR). Authors' study validates practicality of proposed method. Authors proved that, GTT performs better than LTT in signal detection particularly of detection. LTT suffer from low detection probability and under dynamic and unpredicted conditions, GTT are more suitable for cognitive radio systems. Number of algorithms tested based on LTT and GTT classes are limited so broader methods can provide comprehensive understanding of strengths and weaknesses of various adaptive threshold techniques. This paper suggests more on improving GTTs and dismisses the improvement of LTTs, as for specific scenarios LTTs might perform better than GTTs. That's the reason it may not generalize to all cognitive radio cases. Furthermore, [14] introduces a novel approach to boost energy detection performance, particularly in scenarios with low signal-to-noise ratios and probabilities of false alarm. This paper showed that, this technique could result in better discrimination between signal and noise. This technique performs better than traditional methods. It is demonstrated only for 0.5 SNR and need to be tested on various SNR values to make it generalize. Author's assumption here, limited to Gaussian distribution of signal and noise power and may not work on other environments. Lack of real world testing as it is not accounted here. Computational complexity compared to traditional system is not available, it leads to limited usage on devices and real world applications. In this paper focus is given on improving detection probability for low probability of false alarm only, not taken into account energy efficiency and detection time. Even though this paper suggested that potential generalization of method at any SNR values but not shown how it is to be achieved.

Fast two step energy detection and work on narrowband and wideband techniques: Leveraging advanced algorithms, [15] introduces the Fast Two-Step Energy Detection (FED) algorithm, enhancing conventional energy detection through improved sampling processes. Authors claimed that reducing samples, enhance detection speed, lower computational costs, fast decision making and make method more efficient in real-time spectrum sensing. Adaptive sampling approach that selects sampling from N-point to 2N-point, further improves spectrum sensing process. Optimisation of detection thresholds, this algorithm maximizes the detection probability and keeping false alarm probability constant. Trade-off between faster detection speeds at the expense of less accuracy loss is not acceptable at live environments. This algorithm works well at high SNR regions and in low SNR regions performance is very poor. Demonstrated optimized threshold mechanism but double threshold will add complexity and become challenge for devices with limited processing or memory elements. Beyond algorithmic advancements, [16] offers a comprehensive review of narrowband and wideband spectrum sensing techniques, providing valuable insights for future research directions. Authors offered advances in spectrum sensing techniques, explored clear classification of narrow band and wide band spectrum sensing, discussed latest enabling technologies, addressed spectrum access issues and real world application of cognitive radio. Also this paper provides valuable future directions, lacks practical implementation details, focuses on narrow and wide band without much discussion on hybrid techniques. Moreover, [17] proposes spectrum sensing based on autocorrelation, comparing received signal characteristics to determine signal presence. Proposed method can be more robust compared to traditional methods. Used flexibility in experimental setup by adjusting noise and SNR levels. Experiment need to be done on various environments not just Gaussian. In comparison with traditional methods, this method proved better. Relying on software and needs adaption to different hardware or platforms.

Innovative adaptive techniques for Cognitive Radio Applications: Adaptive techniques take centre stage in [18], where an algorithm based on the Enhanced Energy Detection approach dynamically assesses primary user presence. This algorithm minimizes decision error probability, reduces the computational complexity and maintains high accuracy. This algorithm’s adaptive nature and minimal overhead makes it suitable for real time dynamic spectrum access scenarios. Additionally, [19] presents an adaptive threshold detection model, contributing to enhanced spectrum sensing accuracy. This paper addressed inefficiency in spectrum usage problem and showed that, performance is better even at low SNR levels. No new previous knowledge is required, which makes sensing process simple and more flexible. Focuses on only one spectrum sensing method and need other methods should also be studied. It is noise dependent making it less robust. Real world testing, implementation challenges and no any comparative analysis are not addressed. Understanding spectrum occupancy is vital, as showcased in [20], which conducts a detailed study to identify underutilized bands for cognitive radio applications. This paper demonstrates practical availability of unused spectrum bands and underutilized frequency bands are identified, Long term spectrum measurement approach and application of cognitive radio are prime focus of this paper. Demonstrated results for specific region may not be suitable other regions, focused on small frequency bands, leaving out higher bands. Work is based on historical data and not provided real-time data which is essential for dynamic spectrum access in cognitive radio. Absence of technical implementation and focus only on energy detection method makes difficult for generalization. Utilizing advanced learning techniques, [21] introduces a spectrum sensing algorithm based on self-supervised contrast learning, offering promising avenues for spectrum sensing refinement. Improved sensing performance with less labelled datasets is demonstrated. This algorithm works well at high SNRs and not shown at low SNRs, limited focus on real time adaption for spectrum usage. Notably, [22] presents an adaptive threshold method devoid of noise variance or SNR requirements, demonstrating superior performance in minimizing false alarms and missed detections. Detection performance is improved by dynamically adjusting the threshold based on first and second order statistics of recorded signals. Elimination of noise variance or SNR reduces the complexity of detection process. This proposed method works for both narrow band and wide band spectrum sensing on cognitive radios. This approach lowers the false alarm detection probability and missed detection probability. Drawback in this approach is uniform SNR, which is not possible as SNR varies across different frequency bands. Detection performance will be affected if inaccuracy occurs in first and second order statistics of signals. Method not shown, how it handles the noisy environment.

Optimising Spectrum Sensing in Statistical Threshold Settings, Dynamic Noise Adaption and Multi Antenna Techniques: Statistical insights inform threshold settings in [23], enabling the attainment of target detection probabilities. Detection performance is improved and false alarm is reduced through the use of prior statistical information. It is effective in high SNR conditions. Advantage of this method is to set threshold based on specific performance goals, more suitable for high SNR environments. This algorithm performs well at large sample size. Presents generalized form of threshold setting applicable to general cases. Since this method relies on statistical information and inaccurate information can lead to incorrect threshold settings. This algorithm cannot work on low SNR and high interference areas. Another drawback of this algorithm is it is dependent on high sample sizes and performance will degrade with low sample size. Setting thresholds for more than two states (idle, active and intermediate states), introduces added complexity. Dynamic adaptations to noise levels for constant false alarm rates are explored in [24], emphasizing the role of sensing duration in detection probability. This proposed method improves utilization underused frequency bands, interference is avoided, simple energy detection technique is used. Constant false alarm rate (CFAR) method used here allows dynamic adjustment of threshold according to noise levels, which leads to better detection performance. This dynamically adapting threshold will improve probability of detection, especially in moderate SNR scenarios. Despite dynamic threshold adaption, noise uncertainty is a major challenging issue. This method does not differentiate between types of signals. There is complexity in threshold settings, algorithm performs better at high SNR and gain performance is degraded with low SNR environment. Study focused on QPSK scheme and need to be tested on other modulation schemes to make it generalized. Furthermore, [25] advocates for dynamic threshold selection based on measured noise power during detection, reducing false alarms and improving detection probabilities. Author presented without any prior information of primary user, dynamic threshold selection based on noise level, improved detection performance, decreases false alarm probability improves overall system efficiency. Authors measured the noise level using blind technique in real time on sample covariance matrix eigenvalues. Solution is tested on real world systems like GNU Radio Software. Drawbacks of this techniques are, performance is low at low SNRs, even with dynamic threshold, algorithm could not distinguish between signal and noise, noise uncertainty remains a challenging issue, dynamic threshold selection based on noise adds computational complexity to the system, blind noise measurement technique for measuring noise based on covariance eigenvalue matrix may introduce errors in certain condition, leads to degrade detection performance. Paper [26] demonstrates the efficacy of threshold calculation without noise variance using multiple antennas, outperforming traditional energy detection methods. Proposed energy detection method is widely used due to its low implementation complexity, estimation of noise variance is eliminated, which makes detection process more robust and accurate, improved performance at low SNRs, where detection probability close to 1 at -15db SNR. This method works well not only in Gaussian channels also in Rayleigh fading channels. Performs better on two or more than two antennas but failed to perform on single antenna. Multiple antennas will add complexity to processing method. Real time testing is needed to validate method's effectiveness.

Bisection Method for Optimum Threshold and Adaptive model for Enhanced Efficiency: The bisection method proposed in [27] offers a robust approach to detect optimum energy levels, particularly in fuzzy regions between high and low thresholds. No any prior information of primary user's signal characteristics is required, algorithm detects optimal threshold, improves detection probability compared to traditional methods, threshold optimization in fuzzy region, reduces collision between primary and secondary regions. Stochastic features of noise are taken into account makes system more robust. This scheme increases probability of detection, especially when SNR is low and uncertain. This algorithm reduces communication traffic, channel bandwidth and energy consumption leading to efficient resource utilization. Slight increase of probability of false alarm may incorrectly identify the system as occupied. Use of bisection method for determining the optimal threshold adds complexity to the system, performance is dependent on stochastic noise model and inaccurate noise characteristics model leads to performance degradation. Spectrum sensing using adaptive threshold proposed in [28], demonstrated that over all spectrum efficiency is enhanced by this system, no prior information about primary user is required, this adaptive threshold model improves detection performance even at low SNR levels, by dynamically adjusting threshold based on noisy environment. This algorithm not only increase probability of detection also reduces false alarm probability. It is sensitive to noise and cannot differentiate between noise and primary user at very low SNRs. Introduction of adaptive threshold model always increase detection performance but adds a layer of computational complexity. To validate the results, further testing in real world environment is needed. Together, these advancements contribute significantly to the evolution of spectrum sensing techniques, addressing challenges and enhancing performance across various scenarios.

Low SNR Energy Detection, Two stage Models, and Genetic Algorithm: In [29], authors proposed, new approach in energy detection at low SNR, demonstrated better sensing performance. In this solution, spectrum utilization is improved, maintains the balance between false alarm probability and detection probability, throughput is increased, performs better at low SNRs. Authors did not address the noise certainty, complexity is very high compared to traditional methods, focus is on single band spectrum sensing and not accounted the multiband spectrum sensing. If channel conditions change rapidly, optimized threshold may need recalibration, which is challenging in real-time environments. Two stage model shown in [30], enhances the sensing performance of CR systems in low SNR conditions. Its main benefit is that optimum sensing time and maximum throughput is achieved by maintaining high detection probability and low false alarm rate, which also improves spectrum efficiency. Interval-dependent de-noising and adaptive thresholding are used to reduce noise, which provides better accuracy than traditional ED methods. Some drawbacks include the need for higher computational complexity and real-time tuning, and further research is also needed in fading channels. Spectrum sensing in cognitive radio using genetic algorithm is proposed in [31], where fitness values are used to identify white spaces to accommodate SUs, authors demonstrated that their proposed method works faster and more accurate. Spectrum is used efficiently, and false alarms and missed detections are minimized. The disadvantages of this system include its reliance on parameter adjustment, computational complexity, difficulties with real-world application and risk of overhead in processing fitness values. Further study is needed to address and minimize these constraints.

3. SYSTEM MODEL AND PROPOSED SOLUTION

In the Proposed Enhanced Signal Energy Detection (ESED) technique we overcome the issues of traditional Energy Detection (ED), especially when SNR is low. In this technique we achieve accurate detection of Primary User (PU) signals in CR networks by using Wavelet Denoising and Adaptive Thresholding. Wavelet denoising removes noise without distorting the main features of the signal, and adaptive thresholding dynamically adjusts the threshold to account for the variability of background noise, improving detection accuracy and false alarms.

The ESED procedure, as demonstrated in the block diagram in Figure 2 below is divided into the following essential steps: Wavelet Denoising using the Daubechies wavelet db3 is done to effectively remove noise from the signal. Adaptive Thresholding takes place where an estimate of the noise power is used to determine the threshold hence an adaptive approach is produced in the signal processing procedure. The next step is the Energy Verification, in which the energy of the denoised signal is calculated, an important aspect of achieving proper detection. Finally, the Detection step concludes with the comparison of the derived energy against the adaptive threshold to establish the existence of a signal, explained in proposed algorithm in next section and discussed in detail in the subsequent sections.

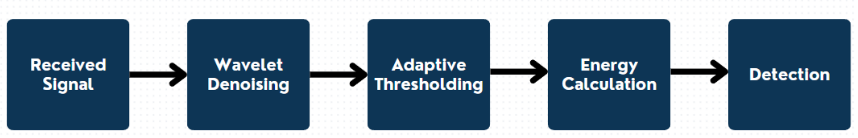

Figure 2 Proposed Functional Block Diagram

3.1. Proposed Algorithm

1. Begin

// Step 1: Received Signal
2. Sample the received signal:
x[n] ← Sample(x(t)), a judgment associated with n from 1 to N

// Step 2: Wavelet Denoising
3. Generating the Wavelet Transform:
X ← WaveletTransform(x[n])

4. Apply Thresholding to remove noise:
T wavelet ← CalculateThreshold(X)
X_thresholded ← ApplyThreshold(X, T_wavelet)

5. Denoised signal reconstruction takes place here:
x_denoised[n] ← InverseWaveletTransform(X_thresholded)

// Step 3: Adaptive Thresholding
6. Get Adaptive Threshold:
T_adaptive ← ComputeAdaptiveThreshold(x_denoised)

// Step 4: Energy Calculation
7. Calculate Energy of the denoised signal:
E ← 0
For all n=1 to N
E←E+|x_denoised[n]|^2
End For

// Step 5: Detection
8. If E>T_adaptive Then
DetectionResult ← "Signal Detected"
Else
DetectionResult ← "No Signal"
End If

// Output Result
9. Output DetectionResult

10. End

3.2. Received Signal

In spectrum sensing received signal is presented as a combination of the transmitted signal and noise and can be written as follows:

$$y(t) = x(t) + n(t) \tag{1}$$

Where:
• y(t) is the received signal at time t
• x(t) is the signal sent by the primary user
• n(t) is the Additive white Gaussian noise (AWGN)

The received signal is sampled in time and a discrete set of samples is produced as follows:

$$y[n] = x[n] + n[n], \quad \text{for } n=1,2,...,N \tag{2}$$

Where N is the total number of samples. The objective here is to determine whether x(t) is present in y(t) or not.

3.3. Wavelet Denoising

The impact of noise on the received signals is considerably lessened using Wavelet Denoising's effect as the received signals are analyzed in terms of different frequency components and the sections which are power dominant are separated. In this case, having chosen the Daubechies wavelet (db3 for instance), the level of the received signal is decomposed by the ESED method enabling reduction of noise while preserving the core feature of the signal from distortion to a great extent. It's the transient nature of the signal that is preserved, which is the reason it is preferable to use Daubechies wavelet for encapsulating the weak signals as received in spectrums sensing that are non-stationary [5, 7].

Formula: Wavelet Coefficients and Thresholding

The received signal r(t) is decomposed into approximation and detail coefficient C_D across multiple levels. Thresholding is then applied to coefficients:

$$\widetilde{C_D} = \begin{cases} 0 & if|C_D| < T \\ C_D - T.sign(C_D) & if|C_D| \geq T \end{cases} \tag{3}$$

where T is the threshold derived from the noise level in the signal, estimated using a noise power model.

3.4. Adaptive Thresholding

Adaptive Thresholding is achieved by estimating the amount of noise present in the real-time system and accordingly modifies the threshold. Unlike classical methods that involve a fixed threshold, adaptive thresholding estimates the threshold noise power σ^2 through the application of the median absolute deviation (MAD) technique on the detail coefficients [9].

Adaptive threshold λ is calculated as shown below:

$$\lambda = \sigma\sqrt{2\ln(N)} \tag{4}$$

where, N is the sample size and σ is the noise standard deviation, which is calculated as:

$$\sigma = \frac{\text{median}(|C_D|)}{0.6745} \tag{5}$$

In this approach the threshold level is adjusted according to the noise floor, which provides robust detection even in the case of varying noise [6].

3.5. Energy Calculation

After denoising, the signal's energy determines if a PU signal is there or not. This energy E sensing interval T denoised signal in T in which $S_d(t)$ is estimated as:

$$E = \frac{1}{N}\sum_{n=1}^{N} |S_d(n)|^2 \tag{6}$$

Here N is the total number of samples obtained during the sensing time. To ensure the effective estimation of PU signals, it provides reliable power estimate [3].

3.6. Detection Comparison

This step will compare the adaptive threshold with the estimated energy. In case the energy exceeds the threshold, it can detect PU:

$$Decision = \begin{cases} PU\ Detected & if\ E > \lambda \\ No\ PU\ Detected & if\ E \leq \lambda \end{cases} \tag{7}$$

Such an adaptive comparison enhances the accuracy of detection especially when noise is fluctuating, thereby making ESED a reliable solution to CR networks [1, 2].

4. Simulation Results and Evaluation

A series of simulations has been conducted. The initial simulation focuses on the detection of PU, while the subsequent simulation assesses the probability of detection and the probability of false alarm at low signal-to-noise ratio (SNR) values. Ultimately, the proposed model has been evaluated against a traditional model. Each aspect has been thoroughly discussed in this document.

4.1. Simulations Part – I: PU's Detection

In this implementation, parameters used are presented in following table1.

Table 1

Parameters set as follows
PU signal: BPSK modulated
Noise: AWGN
SNR: -30 dB to 0 dB
Threshold: adaptive

Figure 3 shows the collected noise signal; it clearly discriminates properties of the signal and accompanying noise. Such preliminary evaluation gives a fundamental ground for subsequent processing instructions, which are necessary factors in enhancing signal quality and detection effectiveness.

Figure 4 represents a denoising wavelet approach which effectively removes noise using the db3 Daubech wavelet without compromising on important features of the signal. This denoising process is much needed and reduces the effect of noise with regard to SNR, necessary for detailed measurements.

Then, the adaptive thresholding scheme follows and produces Figure 5. As observed in Figure 5, those adaptive threshold values calculated are marked in it, since they are adaptively changing according to noise power estimation. Meanwhile, the proposed system shapes a threshold based on the nature of noise, thereby enhancing the accuracy of detection of the PU signal in this way.

Figure 6 presents the computation procedure of energy. It clearly shows the approach taken to calculate the energy of the filtered signal. This step is crucial as energy proves to be a measure of the power of the signal, hence enabling a reasonable comparison with the adaptive threshold.

In Figure 7, the calculated energy is compared against the adaptive threshold, which gives whether the PU signal is available or not. This comparison in simple words is based on the valid detection in cognitive radio systems. In this figure '1' indicates that the PU signal is available and '0' indicate that the PU signal is absent.

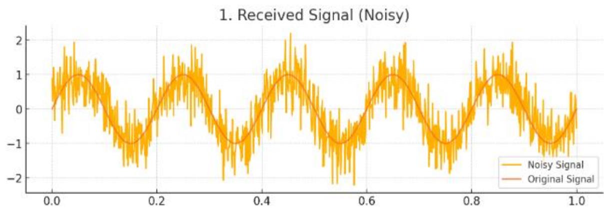

Figure 3 Received Signal with Noise

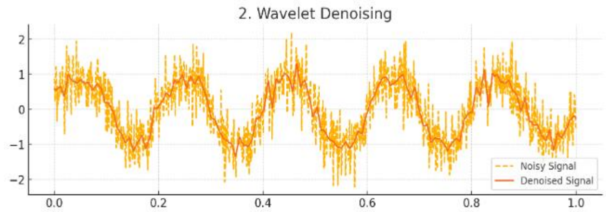

Figure 4 Wavelet Denoising

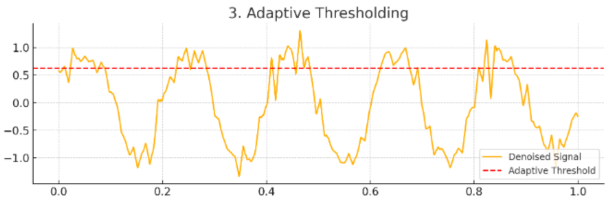

Figure 5 Adaptive Thresholding

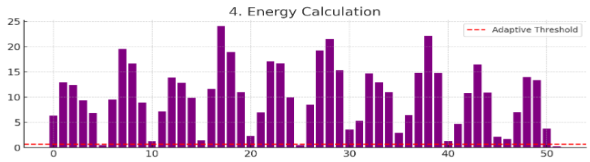

Figure 6 Energy Calculation

Figure 7 PU Detection

4.2. Simulations Part – II: *Pd* and *Pf* measurements

The figure 8 shows the relationship between Probability of Detection (Pd) and Signal-to-Noise Ratio (SNR) (dB) at different values of Probability of False Alarm (Pf) using Wavelet Denoising and Adaptive Thresholding techniques. SNR is depicted on the x-axis, where it shows how strong the signal is relative to the noise; Pd, on the y-axis, indicates the probability of correctly detecting a signal. The graph includes several curves corresponding to different values of Pf (0.01, 0.09, 0.1, and 0.2), demonstrating how detection performance is modified for changing false alarm probabilities. For very low SNR values there is a range from -50 dB to -30 dB, the Pd remains rather low, in the range of 0.4-0.6, signifying that signal detection is unreliable in extremely noisy conditions.

For increasing values of SNR, Pd improves drastically, representing better detection capability. At around -10 dB SNR, Pd approaches 1.0, and detection is almost perfect, with all curves trending together. It is inferred that a larger Pf value, say 0.2, gives a slightly better Pd at lower SNRs; a system with a higher false alarm rate is more sensitive to detect weak signals.

Overall, results indicate that Wavelet Denoising and Adaptive Thresholding are very effective, significantly improving the detection performance for low-SNR environments. Analysis of this work can be valuable for the determination of the efficiency of signal detection algorithms in noise conditions, having applications in spectrum sensing for cognitive radio systems.

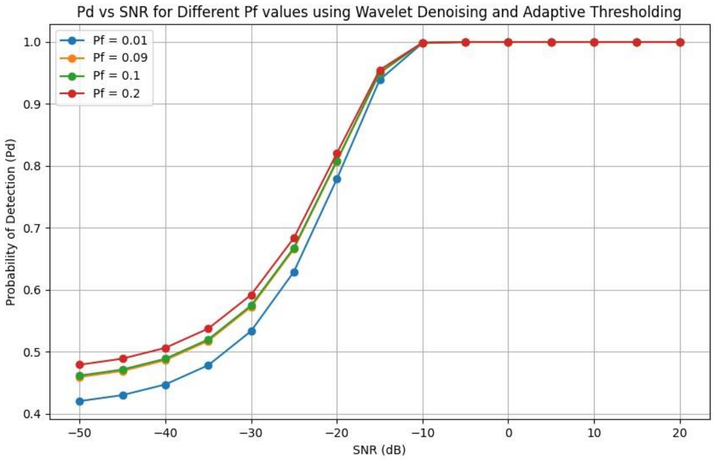

Figure 8 Pd vs SNR at different Pf values

The plot in figure 9, shows the relationship between the possibility of detection (Pd) and false alarm probability (Pf) in a spectrum sensing system. The X-axis represents a false alarm probability (Pf), which indicates the possibility of detecting an indication when someone is present, while no one is present, while the Y-axis detection is the probability (Pd) the one who measures how correct the system detects. A signal. Different coloured curves correspond to different SNR levels (-10 db, -15 db, -20 db and -25 db).

The plot shows that the high SNR leads to better detection performance. The blue curve (SNR = -10 db) is the highest, indicating that in high SNR even increases the possibility of detecting less false alarm speeds quickly. When SNR decreases (eg -15 db, -20 db, -25 db), reducing the right, which means a high false alarm to achieve a given detection option for the system. The opportunity is required. At low SNR levels, such as -20 dB and -25 db, the possibility of detection increases slower, making it difficult to detect weak signals to a high false alarm speed is tolerated. . This is an important challenge in spectrum sensing for cognitive radio systems, where it is important to detect weak signals in the noise environment.

In addition, the possibility of plot detection and trade lid between false alarms is emphasized. A high Pf increases Pds, but at the expense of more false alarms, while a low Pf reduces false alarm, but also reduces the possibility of detection on especially at low SNR levels. This trade -off is important for practical applications, such as spectrum sensing in 5G and beyond, where it is a major challenge to effectively detect weak signs while reducing false alarms.

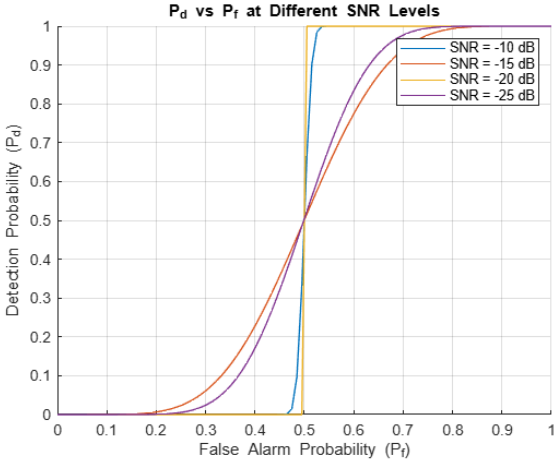

Figure 9 Pd vs Pf at different SNR levels

Probability of detection (Pd) vs probability of false alarm (Pf): Figure 10 in Probability of Detection (Pd) and Probability of False Alarm (Pf) is shown when SNR is -20 dB. This graph demonstrates that at Pf = 0.1, Pd whose value is more than 0.4. This means that if the system tolerates a small number of false alarms (meaning Pf = 0.1), then detection probability Pd is at acceptable level.

This is quite good (above 0.4), even at a low SNR like -20 dB. This indicates that the system can achieve a reasonable detection level even under low signal-to-noise ratio conditions, if few false alarms are allowed. Overall, Figure 10 shows that at an SNR of -20 dB values of Pd and Pf. A balance can be achieved between Pf kept it less (0.1) Pd can be maintained more than 0.4.

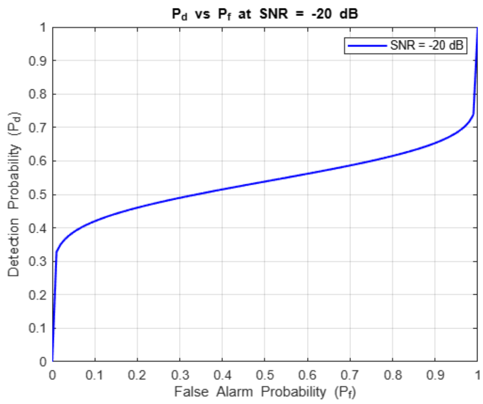

Figure 10 *Pd* vs *Pf* at SNR = -20dB

4.3. Simulations Part – III: Comparison of Wavelet Denoising and Conventional Energy Detection Methods

Simulations in Figure 11 shows the comparison of Wavelet Denoising and Traditional methods in terms of Detection Probability at different SNR levels (Pd) and False Alarm Probability (Pf) measures. This simulation is trying to show how much the proposed wavelet denoising method is better than traditional methods.

Traditional Method (SNR = -10 dB): When SNR for traditional method is -10 dB, then $Pf = 0$, Pd has reached only 0.4. and when Pf there is a gradual increase, so Pd, it also decreased a little but never reached 1 (or maximum detection). Meaning, it is difficult to achieve high detection probability in the traditional method, even if we have a slight obstacle to false alarm.

Wavelet Denoising (SNR = -10 dB): When wavelet denoising method is used and SNR is -10 dB, then Pf reached to 0.5 then Pd, the value of has reached 1. This shows that with the help of wavelet denoising the system achieves maximum detection probability without generating too many false alarms. This means that the wavelet denoising method is more effective than the traditional one, especially when working at low SNR.

Wavelet (SNR = -15 and -25 dB): If SNR is -15 or -25 dB and wavelet denoising is used, when Pf reached to 0.8 then Pd the maximum i.e. 1 is reached. This means that even at low SNR levels the wavelet method achieves high detection probability, which is more accurate compared to the traditional method. In traditional method this maximum detection is never achieved, regardless of SNR and Pf whose values are increasing.

From simulations of Figure 11, we conclude that the wavelet denoising method provides better detection even in low SNR conditions and is more reliable, especially when high Pd and low Pf. This new method is more beneficial than the traditional method because wavelet denoising can maintain maximum detection even in low signal strength.

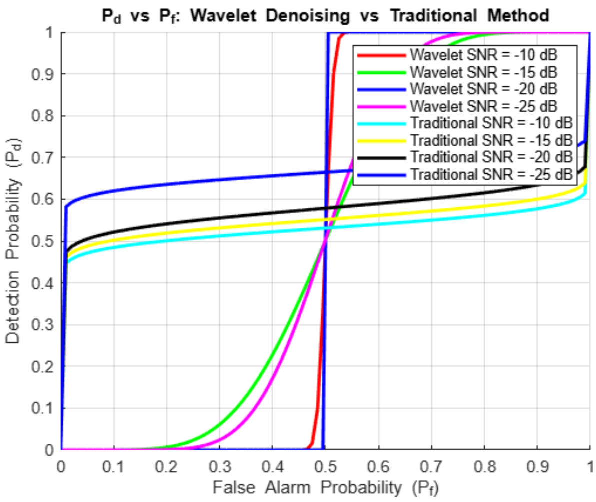

Figure 11 Comparison: Wavelet Denoising vs Traditional

5. Implementation and Deployment Challenges

These need to be addressed before deploying this ESED hybrid model:

Algorithm Complexity: The algorithm is better than existing ones but the wavelet transform and adaptive threshold computation can be computationally expensive. These may not be feasible on resource constrained devices (e.g. IoT devices or low power cognitive radios) due to limited processing power and memory.

Real-time: Almost real time processing under real time constraints and may be low latency as environments may have continuous noise; this can be a problem. Major limitation is that system should adaptively and quickly adjust itself to varying SNR levels without contributing too much of a delay.

Noise Power Estimation Accuracy: For establishing an adaptive threshold, accurate estimation of noise power becomes vital. In fact, the real-world noise conditions usually have to be very different styles. False alarms and misses of detections can be caused due to noise misestimate, thus making the system that much more unreliable.

Hardware Limitations: Wavelet denoising implementation of the adaptive thresholding approach in hardware might possess particular hardware like a DSP or FPGA to deal with estimated computation loads. The extra expense in complication renders the system entirely unusable under practical conditions.

Sensitivity Parameter Tuning: The wavelet denoising and adaptive thresholding methods are susceptible to parameter selection and will require significant testing and tuning efforts to discovered the optimal parameters for varying environments and SNR levels.

Scalability to Multiband Sensing: The scheme proposed is inherently limited to single band based spectrum sensing which is also going to bring in more aerial difficulties especially ranging from the increased computational load to the correct modelling of noise estimation techniques.

Robustness in Non-Stationary Environments: System performance has been evaluated by means of controlled simulations, but in practice the real world environment generates non-stationary noise, interference, and multipath fading. Much concern about how these conditions can be kept robust in the dynamic and uncertain situations has to be resolved.

Energy Consumption: Even this appears economically highly computationally efficient relative to various traditional methods, the energy consumption allowance would still remain high for wavelet denoising and adaptive thresholding to allow operation for continuous times in a battery-operated device, reducing its lifetime.

Integrating with Current Systems: Modifying hardware and software architecture to properly accommodate the proposed hybrid model into the existing cognitive radio design or spectrum sensing system would be a hard interoperability challenge.

Validation in Real Environment: Simulation has shown a lot of potential in system performance, and this validates the importance of assessing the real practical viability. Possible hardware dampness, environmental noise, and interference with other devices may adversely affect practical deployments.

6. CONCLUSIONS

In this research, a hybrid model combining Wavelet denoising and adaptive thresholding techniques is proposed to improve energy detection at low SNR levels. The simulation experiments are organized into three parts. Part I of the proposed solution removes energy from the received signal using Daubechies wavelet (db3), and the threshold is dynamically calculated based on estimated noise power, reducing false alarms and increasing sensitivity to weak signals by ensuring that detection is flexible and adjusts to changes in background noise. The energy of the denoised signal is calculated and compared to the adaptive threshold to determine whether or not PU is present. Part II of the proposed solution exhibits the SNR and *Pd* connection, with highest *Pd* at low SNRs, Pf effect on *Pd* and performance at SNRs of -10 and -20 dB, achieved

Pd = 1 at Pf = 0.5, and achieved *Pd* = 0.8 at *Pf* = 0.5. Simulations show that the system gets increasingly accurate in identifying signals at as low as -10db and -20db as the SNR and chance of false alarm increases. Part III of the proposed part compares the proposed solution to the conventional. At SNR = -10 dB and *Pf* = 0, the conventional technique achieves Pd of 0.4, whereas the new wavelet method achieves *Pd* of 1 at SNR = -15 and -25 dB and *Pf* = 0.8. This *Pd* has not been reached using traditional method. This demonstrates that at low SNR, the chance of detection is higher, while the probability of false alarm is matched with the acceptance level. The computational complexity of this system is modest. Wavelet transform and adaptive threshold calculation may be computationally costly, but they are more efficient than traditional approaches since they require less time and are ideal for real-time processing. This indicates that this system makes efficient use of computing resources while yet delivering great performance. Key aspects mentioned in Implementation and deployment challenges section need to be addressed before deployment to achieve the objectives.

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