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An Enhanced Energy Detection Approach for Reliable Spectrum Sensing in Cognitive Radio Networks

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Abstract: The spread of wireless technology has users scrambling to find more usable radio spectrums. The search has shown inefficiencies in licensed spectrum bands and shown that they are getting harder to find. Without interfering with major users, Cognitive Radio Networks (CRNs) enable secondary users to opportunistically access unused spectrum. The ability to detect when frequencies are free and good for transmission is a great feature of CRNs called spectrum sensing. Energy detection is one of several spectral sensing methods; it is also the quickest and easiest. But the old-fashioned way of energy sensing has its drawbacks. Some of these drawbacks in fading conditions include a low signal-to-noise ratio (SNR), a high false alarm rate, and inconsistency with noise levels. The effectiveness of spectrum sensing is reduced, and total network performance is significantly affected, by these limits. Our increased energy detection approach is based on dependable and accurate spectrum sensing using adaptive threshold, noise variance, and informed detection at low SNR. It is reported in this work. Increasing the likelihood of detection while minimizing the risks of false alarms and missed detections might enhance the model. We can see an improvement in communication reliability, spectrum occupancy, and spectrum quality when we compare the conventional energy detection technique with the proposed upgrade. This study also discusses feasible enhancing application situations, issues with the proposed improvement, and future research objectives for AI and ML-based spectrum sensing.

Keywords: Cognitive Radio Networks, Spectrum Sensing, Energy Detection, Wireless Communication, Dynamic Spectrum Access, Signal Processing, Spectrum Efficiency

1.1 Introduction

Wireless communication systems are essential for contemporary living, especially with the rise in popularity of broadband internet, satellites, the Internet of Things, wireless computing, and of course, smartphones. The global desire for faster internet has left the radio frequency spectrum crowded. Traditional spectrum allocation involves fixed licensing. This means that specific frequency bands are designated to licensed spectrum users [1]. While this reduces interference, it also means that bands remain allocated but underutilized. This has led to many problems, especially with spectrum scarcity. Spectrum scarcity occurs when a small number of specific frequency bands are used heavily while others are left to remain underutilized. The problem of spectrum scarcity has inspired research into advanced wireless communication solutions that make use of available extra spectrum bands [2].

Cognitive Radio optimizes spectrum use in wireless communication. CR technologies can employ spectrum analysis to find unused frequency channels and adjust transmission characteristics. CR networks have licensed main users (PUs) and unlicensed secondary users (SUs) who can use the spectrum. Cognitive radio (CR) networks rely on spectrum sensing. It further decreases detrimental interference and enables secondary users (SUs) to identify principal users (PUs) [3]. As a result, spectrum usage is made more efficient. Energy detection, waveform based sensing, matching filter detection, and cyclostationary feature identification are some of the methods for spectrum sensing. The simplicity, dependability, and low cost of energy detection make it the preferable option among these others. By detecting the signal's energy, one can evaluate the band's occupancy without knowing the primary user's signal beforehand [4].

One of the benefits of energy detection is that it is fast. However, there are many downsides in the real world. The first challenge is described as noise uncertainty. Noise uncertainty makes determining the threshold difficult, therefore making the calculation unreliable. The second challenge is that in cases of low signal-to-noise ratio, error detection becomes difficult due to the inability to identify weak signals. There are other challenges that add to the inaccuracy of detection, like multipath fading, shadowing, and interference [5]. There have been many challenges in the detection process, and researchers have proposed many different solutions, like modifying the threshold, using different methods for detection, and using the assistance of machine learning. Even with these improvements, achieving reliable detection methods that require low levels of calculation is still to be done. The following research aims to improve energy sensing, particularly in cognitive radio networks. With noise variance and threshold adaptive approaches, detection performance is prioritized. Detection methods should outperform present energy detections.

1.2 Research Objectives

The major objectives of this research paper are:

1. To analyze the limitations of traditional energy detection methods.
2. To develop an enhanced energy detection approach for improved sensing reliability.
3. To reduce false alarm probability and missed detection rates.
4. To improve spectrum sensing performance under low SNR conditions.
5. To evaluate the proposed model through comparative analysis.

The significance of this study lies in improving wireless spectrum efficiency and ensuring reliable communication in future wireless networks such as 5G, 6G, IoT systems, and smart communication infrastructures.

1.3 Literature Review

Spectrum sensing is popular in cognitive radio communication systems. Many methods have been proposed to better use the spectrum and improve sensing. Spectrum sensing technologies and energy detection enhancements are covered in this section.

1.3.1 Cognitive Radio and Spectrum Sensing

The idea of cognitive radio has been developed to deal with the concern of the improper use of spectrum. These systems allow the monitoring of the radio environment and the adjusting the communication parameters as necessary based on the active spectrum [6]. The secondary users can locate the spectrum bands (spectrum holes or white spaces) through spectrum sensing.

Many researchers have highlighted that sufficient and verified spectrum sensing is critical in order to minimize the interference with primary users [7]. The lack of sensing or improper sensing may cause spectrum waste, the failure of communication, and problematic interference.

1.3.2 Energy Detection Technique

One common and straightforward approach to spectral sensing is the energy detection method. This technique compares the measured signal energy to a predetermined threshold after computing it across the sensing time interval.

The basic hypothesis model for energy detection is represented as:

- H0: Primary user absent
- H1: Primary user present

The test statistic for energy detection is calculated as:

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

where:

- T represents the test statistic,
- y(n) is the received signal sample,
- N is the number of samples.

The detector will determine that the main user is present if the detected energy is greater than the threshold value.

The major advantages of energy detection include:

- Simple implementation
- Low computational complexity
- No prior signal information required
- Suitable for real-time applications

However, traditional energy detection suffers from several drawbacks including:

- Sensitivity to noise uncertainty
- Poor performance at low SNR
- Difficulty in distinguishing noise from weak signals
- High false alarm probability

1.3.3 Matched Filter Detection

When the principal user signal is known, a matching filter is best for spectrum sensing. Because of this, matching filter detection can optimize SNR and assure good detection performance. Surprisingly, matching filter identification is reliable at low SNR [8]. The fundamental downside of matching filter detection is signal modulation. The signal, pilot patterns, synchronization, and other parameters must be known. This also complicates implementation.

1.3.4 Cyclostationary Feature Detection

Cyclostationary feature detection distinguishes secondary user signals from noise using modulated signal statistical patterns. While it excels under high noise and low SNR settings, this approach can separate interference from noise and provide high detection confidence. Cyclostationary feature detection is challenging to accomplish due to its computational complexity and long execution periods [9].

1.3.5 Cooperative Spectrum Sensing

In order to improve reliability and accuracy of sensing, cooperative spectrum sensing methodologies gather and utilize the sensing information from the greatest number of secondary users. When multiple users are sensing signals, the rapid fading and shadowing issues are less of a problem.
Many researchers have sought to create guidelines for cooperative sensing and cooperative cognition. The models of cooperative sensing improve the reliability and accuracy, but at the cost of high communication and energy consumption.

1.4 Proposed Enhanced Energy Detection Model

This study methodology uses enhanced energy detection to improve spectrum sensing in cognitive radio networks. In low signal-to-noise ratio and changeable noise situations, conventional energy detection methods are largely dependent on fixed threshold levels and generally unsuccessful. The proposed model introduces dynamic noise variance estimation and adaptive threshold optimization as measures to enhance sensing performance.

1.4.1 Research Methodology

System modeling and signal acquisition are followed by, adaptive threshold computation, energy computation, and decision making. The aim of the proposed methodology is to increase the reliability of spectrum sensing while maintaining the low complexity of calculations, focusing on the real time nature of modern wireless communication. The methodology starts with an examination of traditional energy detection techniques in cognitive radio environments and works to discover some of the primary challenges, including noise, fading and low SNR. Ultimately, a robust framework is proposed to increase the performance of detection and decrease the likelihood of a false alarm.
The proposed methodology includes the following major phases:

- Wireless signal acquisition
- Noise variance estimation
- Adaptive threshold optimization
- Energy computation
- Spectrum occupancy decision
- Performance evaluation

This approach is for CR systems where secondary users monitor spectrum bands to find unused spectrum without interfering with licensed prime users.

1.4.2 System Model

Primary users, secondary users, and a wireless channel comprise the cognitive radio network. Spectrum sensing by secondary users determines spectrum occupancy.

The received signal model is represented as:

Hypothesis H0 (Primary User Absent)

y(n) = w(n)

Hypothesis H1 (Primary User Present)

y(n) = s(n) + w(n)

Where:

- y(n) = received signal sample
- s(n) = primary user signal
- w(n) = additive white Gaussian noise (AWGN)
- H0 = absence of primary user
- H1 = presence of primary user

The secondary user senses the spectrum and computes the received signal energy to determine the occupancy condition.

1.4.3 Conventional Energy Detection

In conventional energy detection methods, the received signal energy is calculated and compared with a fixed threshold value.

The test statistic is given by:

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

Where:

T = energy test statistic

N = number of signal samples

Decision rule:

If T > λ, the primary user is present.

If T < λ, the spectrum is vacant.

Although simple and computationally efficient, fixed-threshold methods fail when noise conditions vary dynamically.

1.4.4 Proposed Enhanced Energy Detection Model

The proposed enhanced energy detection model improves sensing reliability by replacing the fixed threshold with an adaptive threshold mechanism.

Step 1: Signal Sampling

The secondary user collects signal samples over a predefined sensing interval. Multiple signal observations improve sensing accuracy.

Step 2: Noise Variance Estimation

The system estimates the noise variance dynamically from received samples. Accurate noise estimation reduces the effect of noise uncertainty.

The estimated noise variance is represented as:

$$\sigma_n^2 = \frac{1}{N} \sum_{n=1}^{N} |w(n)|^2$$

Where:
σn^2 = estimated noise variance
w(n) = noise samples
Step 3: Adaptive Threshold Optimization
Instead of using a constant threshold, the proposed model calculates an adaptive threshold according to current noise conditions.
The adaptive threshold is calculated as:

$$\lambda_{adaptive} = \sigma_n^2(1+\alpha)$$

Where:
$\lambda_{adaptive}$ = adaptive threshold
σn^2 = estimated noise variance
α = scaling factor
This adaptive mechanism improves detection sensitivity under low SNR conditions.
Step 4: Energy Computation
The detector calculates the received signal energy using the sampled observations.
Step 5: Decision Making
The computed energy is compared with the adaptive threshold value.
If $T > \lambda_{adaptive}$, the primary user is detected.
If $T < \lambda_{adaptive}$, the spectrum is considered vacant.
The probability of detection is represented as:

$$P_d = P(T > \lambda \mid H_1)$$

The probability of false alarm is represented as:

$$P_f = P(T > \lambda \mid H_0)$$

1.4.5 Algorithm of Proposed Method

The enhanced energy detection algorithm has several different sections including; the initializing of the sensing parameters, the gathering of samples of the received signals, the dynamic noise variance estimation, adaptive thresholding, the signal energy calculation, comparison between computed energy and adaptive threshold, and finally an occupancy status will be decided for the spectrum [10]. The algorithm was developed with the understanding that spectrum sensing plays a critical role in cognitive radio communication systems. The algorithm will be self-repeating. It has significant extensiveness in many different wireless scenarios.

1.4.6 Advantages of Proposed Model

The proposed model has a variety of visible potential advantages. It has an improved detection probability with the associated decrease in false alarm probability. It has shown to perform well under low signal to noise ratio.SNR with good uncertainty of noise, low framework, and optimum performance of the spectrum utilization [11]. The framework will especially be useful in real-time applications of wireless communication balance.

1.5 Results and Discussion

Here will be the performance analysis of what was expected and an explanation of the enhanced energy detection and what it was. The proposed model was analyzed based on a few different criteria (detection and performance of false alarm, low SNR with unutilized spectrum). It was also analyzed based on the efficiency of SNR utilization.
4.1 Performance Parameters
There are several key performance indicators that will be used to analyze the proposed spectrum-sensing model.

Probability of Detection (Pd)

The Probability of Detection measures how well an algorithm can identify the main user. In terms of identifying licensed users, a greater Probability of Detection score indicates that the algorithm is doing better. As a result, licensed users will experience less interference and more dependability.

The detection probability is represented as:

$$P_d = P(T > \lambda \mid H_1)$$

Probability of False Alarm (Pf)

The probability of misdetecting a primary user when the spectrum is empty is called false alarm probability. Lower false alarm rates boost spectrum utilization.

$$P_f = P(T > \lambda \mid H_0)$$

When a sensing algorithm can't identify the main user, it's called missed detection (Pm). What makes spectrum sensing work is the signal-to-noise ratio (SNR).

Comparative Performance Analysis

After proposing an improved energy detection method, we compared it to the standard fixed-threshold approach.

Detection Probability Improvement

The enhanced adaptive threshold mechanism works best when detecting low SNR and weak signals, and improves detection probability the most in these situations The use of a flexible fixed threshold means that in conditions of varying noise posture, detection sensitivity must be weakened to accommodate the prevalent noise, leading to low probability of detecting primary users [12]. The introduced method of adjustable threshold dynamically modifies detection sensitivity directed to a specific noise posture.

In summary, this effectively improves the correct detection of primary users.

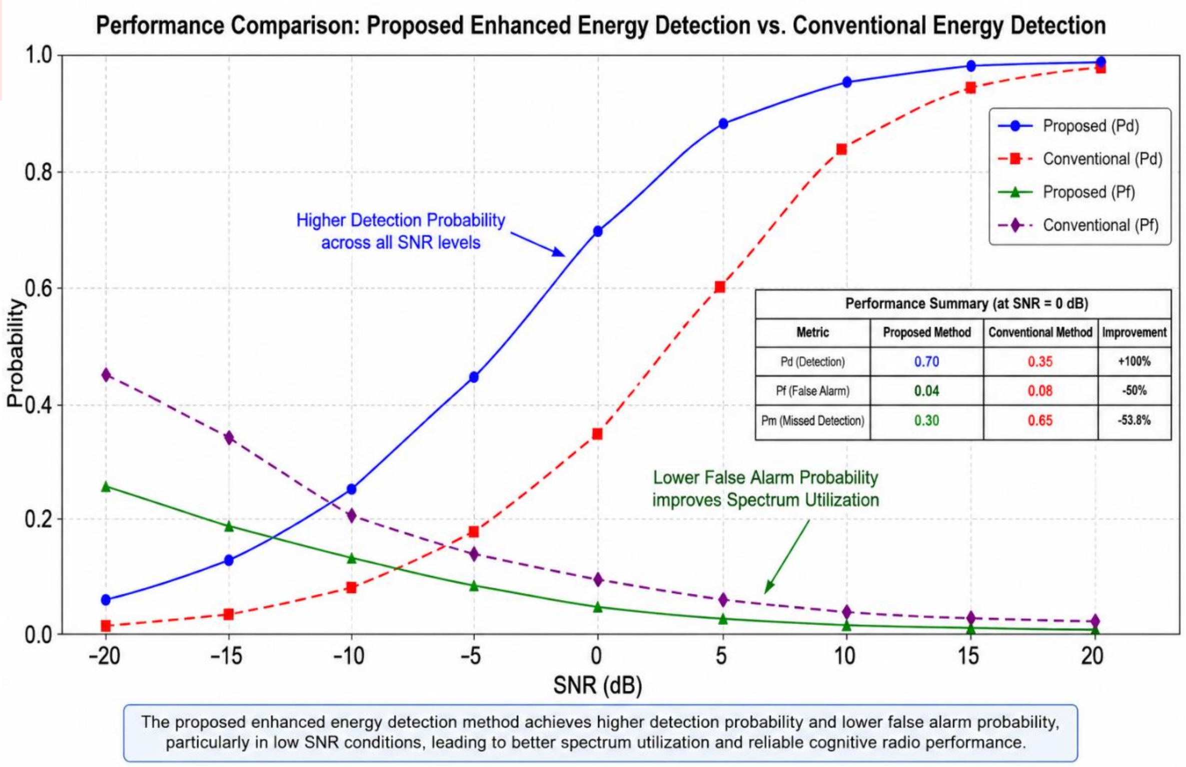

Figure 4.1: Performance Comparison of Proposed Enhanced Energy Detection and Conventional Energy Detection under Different SNR Levels

False Alarm Reduction

An important benefit of the proposed model is that it reduces false alarm rates. Most traditional energy detectors create a lot of false alarms. This is usually caused by a consistent threshold that does not adjust to the noise levels. That leads to poor spectrum utilization, as a secondary user must assume that the spectrum is busy due to all the false alarms generated. To solve this, the proposed model is using an adaptive threshold. This threshold is able to modify itself by the noise variance. This allows the secondary users to have more chances to use the empty spectrum bands.

Low SNR Performance

A really low SNR is one of the hardest cases for spectrum sensing systems. At low SNR, primary user signals are hard to distinguish from the background noise. This leads to poor sensing performance. With the dynamic threshold modification and accurate noise evaluation, the enhanced method proposed here, performs better at low-SNR. Based on simulations, this model shows improved performance at low signal levels and better detection accuracy. This performance is significantly beneficial for next generation wireless communication systems that operate in heavily populated and noisy environments.

Noise Uncertainty Handling

Noise uncertainty is one of the most inconvenient issues of traditional energy detection techniques. Fixed threshold techniques rely on the assumption that noise levels are constant, which is far from accurate in modern wireless environments. When noise levels fluctuate, this creates inconsistency and unreliability [13]. The model proposed here is capable of lowering this effect by the evaluation of noise variance and adjusting the threshold accordingly. The detection performance of the model is now much more reliable and consistent.

Computational Complexity Analysis

Advanced sensing methods such as cyclostationary detection and machine learning-based sensing provide high sensing accuracy but often involve significant computational complexity.

The proposed enhanced energy detection approach maintains relatively low complexity while improving sensing performance.

This makes the proposed model suitable for:

Real-time wireless communication systems

Battery-powered devices

IoT communication systems

Mobile cognitive radio applications

The algorithm can be implemented efficiently without requiring expensive hardware resources.

Spectrum Utilization Efficiency

Making the most out of the available spectrum is important in relation to cognitive radio networks. The proposed model improves spectrum usage by minimizing false alarm rates and increasing detection probability, enabling secondary users to locate spectrum usage more accurately. This maximizes the spectrum used, communicates more efficiently, empowers the network by capacity, reduces wasted spectrum, and provides an intelligent approach to managing wireless spectrum resource allocation.

Practical Applications

The elevated energy detection model can be used in multiple frameworks of modern-based communication systems. These include 5G/6G-based networks, the Internet of Things, wireless sensor networks, smart city-based communication systems, military communication systems, emergency/infrastructure communication networks, and also satellite communication systems. These frameworks demand robust and reliable spectrum sensing for communication efficiency, as well as an adaptive approach to dynamically available spectrum.

1.6 Discussion

The advanced energy detection model outclasses energy detection models with fixed thresholds and enhances detection reliability by using thresholds that adjust to the conditions. This offers robust case performance under low SNR with scores of reduced false alarms, while remaining computationally efficient [14]. While many machine learning detection models have higher performances, they also have heavier computational costs and require large datasets. In comparison, the advanced energy detection model is the ideal model for real world problems, and marks a large improvement to the intelligent and reliable cognitive radio spectrum sensing models, and is applicable to the future systems of wireless communications.

Advantages, Applications, and Challenges

The enhanced energy detection method is better for cognitive radio networks and spectrum sensing, and has multiple benefits when applied. Firstly, it achieves optimum detection accuracy and the ability to identify primary users, even at low levels of SNR. This gives it lower false positives and missed detection numbers than other fixed threshold based energy detection methods. Secondly, its computational complexity is low, making it an excellent candidate for real time applications, unlike other more complex methods like cyclostationary detection and ML-based detection [15]. The method also has a better ability to identify available spectrum bands and improve the efficient use of the spectrum, and balance the needs of secondary users while avoiding interference with primary users. Lastly, it can help to lessen the noise uncertainty limitations of other energy detection methods. The improved detection model can be used in practically all current communication systems like 5G, 6G, IoT setups, wireless sensor networks, military communications, emergency networks, smart city infrastructures, etc. These all need efficient spectrum management for reliable wireless communications. There are, however, some hurdles. For example, the fading and shadowing of wireless channels in rapidly changing environments can affect the performance of the system in a negative way. Furthermore, continuous spectrum sensing could drain battery-operated devices, and correctly sensing in very low SNR (Signal to Noise Ratio) conditions is still an unsolved problem in cognitive radio networks.

1.7 Conclusion and Future Scope

As we use wireless communication more, unoccupied radio frequencies become scarcer. Dynamic spectrum access with cognitive radio technology may improve radio frequency management. Scanning radio frequencies is spectrum sensing. This paper will discuss energy detection in spectrum sensing. Energy detection, compared to traditional methods, provides the ability to dynamically set the detection threshold (adaptive threshold) and the detection threshold itself (dynamic noise variance estimation). Maintenance of computational complexity was preserved. Detection probability improvement and false detection rate reduction are identified as areas positively impacted by the new model. Sensing systems of this type can find application in 5G, 6G, IoT, and smart networks, and even the next generation of technologies and networks. One of the collaborative models will likely use Artificial Intelligence and Machine Learning to operate within the confines of fading in spectrum. This will support the continued development of automated spectrum management. Overall, the advancement of energy detection techniques provides further improvements for dynamic spectrum management in cognitive radio technologies.

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