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EVALUATING THE CHARACTERISTICS OF THE VTSM SPECTRUM SENSING METHOD IN COGNITIVE RADIO NETWORKS

Introduction

The spectrum sensing problem has transformed significantly with the emergence of cognitive radio and opportunistic spectrum access concepts. These developments have added new layers of complexity to the challenges encountered by cognitive radio systems. This paper provides an in-depth survey of spectrum sensing methodologies designed specifically for cognitive radio networks. This research introduces the notion of multi-dimensional spectrum sensing by investigating various facets of the spectrum sensing issue from a cognitive radio standpoint. It underscores the challenges linked to spectrum sensing and evaluates the methods that enable it. Furthermore, the paper explores cooperative sensing concepts and their different forms, discusses external sensing algorithms and alternative methods, and examines the statistical modeling of network traffic to forecast primary user behavior.

Spectrum sensing is a key task in the development of cognitive radio, enabling the identification of usage patterns across dimensions such as time, frequency, space, and angle. This capability is essential for efficiently utilizing available spectrum. However, continuous spectrum sensing is demanding for wireless devices. To address this, we propose a monitoring platform that offers spectrum sensing as a service. This service utilizes geographically distributed spectrum sensors, implemented via software-defined radio (SDR). These sensors perform sensing operations and send the results to a centralized storage and computing platform, which then distributes the data to requesting devices. Although this service cannot eliminate the need for spectrum sensing by wireless terminals, it can significantly improve energy efficiency and extend standby times by instructing mobile devices to conduct sensing only when and where unused radio bands are expected.

One of the most critical components of the cognitive radio concept is the ability to measure, sense, learn, and be aware of parameters related to radio channel characteristics, spectrum availability, power, operating environment, user requirements, applications, available networks, local policies, and other operating restrictions. In cognitive radio terminology, primary users are defined as users with higher priority or legacy rights over a specific part of the spectrum. In contrast, secondary users, who have lower priority, utilize the spectrum in a manner that does not interfere with primary users. Therefore, secondary users need cognitive radio capabilities to reliably sense the spectrum, determine if it is being used by primary users, and adjust radio parameters to exploit the unused spectrum.

This paper focuses on spectrum sensing, the most crucial element in establishing cognitive radio. Spectrum sensing entails gaining awareness of spectrum usage and detecting the presence of primary users within a geographical area. This awareness can be obtained through geolocation and databases, beacons, or local spectrum sensing by cognitive radios. Beacons, for instance, transmit information about spectrum occupancy and other advanced features like channel quality. The emphasis of this paper is on spectrum sensing performed by cognitive radios because of its wider application areas and lower infrastructure requirements. Other sensing methods are also discussed as necessary.

Traditionally, spectrum sensing has been viewed as the measurement of spectral content or radio frequency energy over the spectrum. In cognitive radio, however, this term encompasses a broader scope, involving the acquisition of spectrum usage characteristics across multiple dimensions such as time, space, frequency, and code. It also includes identifying various signal types occupying the spectrum, including their modulation, waveform, bandwidth, and carrier frequency, among other attributes. This comprehensive approach necessitates advanced signal analysis techniques and increased computational complexity.

In summary, this paper explores the complex challenges associated with spectrum sensing in cognitive radio networks. It reviews current methods and introduces new ideas to improve our understanding and implementation of effective spectrum sensing strategies. By analyzing and exploring different approaches in detail, this study aids in the continuous development and optimization of cognitive radio systems, ensuring that the spectrum is utilized efficiently and reliably.

Analysis of recent research and publications

In recent years, we've witnessed notable progress in the realm of spectrum sensing within cognitive radio networks. This surge in advancement is largely propelled by the growing necessity to enhance the efficiency and dependability of spectrum utilization. Researchers have delved into an array of methodologies, each presenting unique advantages and hurdles. This review highlights some of the key methods that have been prominently featured in academic discussions, namely Energy Detector Based Sensing, Waveform-Based Sensing, Cyclostationarity-Based Sensing, and Matched-Filtering.

Energy Detector Based Sensing is one of the most common methods due to its simplicity and ease of implementation. It works by measuring the energy of the received signal and comparing it to a predefined threshold to detect the presence of a primary user. Despite its straightforward approach, this method is highly susceptible to noise and interference, which can lead to false alarms and missed detections [1]. Recent studies have proposed various enhancements, such as adaptive thresholding and cooperative sensing, to improve its robustness and reliability [2].

Waveform-Based Sensing relies on the known patterns of the primary user's signal. By comparing the received signal to these known patterns, this method can accurately detect the presence of primary users [3]. This approach is highly effective when the primary user's signal characteristics are well-known and stable. However, its performance can degrade in the presence of signal variations or when the exact waveform is not known. Recent research has focused on developing more adaptive algorithms that can handle a wider range of signal variations and improve detection accuracy [4].

Cyclostationarity-Based Sensing takes advantage of the cyclostationary properties of the primary user's signal, such as periodicity in the mean and autocorrelation. This method is capable of distinguishing between different types of signals and is less affected by noise compared to energy detection [5]. However, it requires complex signal processing and higher computational resources. Recent advancements have aimed at optimizing the computational efficiency of cyclostationary feature extraction and developing more sophisticated algorithms to enhance detection performance in low signal-to-noise ratio (SNR) environments [6].

Matched-Filtering is considered the optimal detection method when the primary user's signal is known. It works by correlating the received signal with a known template of the primary user's signal, providing the highest detection probability for a given SNR [7]. Despite its optimal performance, matched-filtering requires precise knowledge of the primary user's signal and can be computationally intensive. Recent publications have explored techniques to reduce the computational burden and adapt matched-filtering for scenarios with partial or imperfect knowledge of the primary user's signal [8].

Each of these methods has been extensively studied and improved upon in recent research. For instance, hybrid approaches combining multiple sensing techniques have been proposed to leverage the strengths of each method while mitigating their individual weaknesses [9]. These hybrid methods aim to provide more robust and reliable spectrum sensing by integrating information from different sensing algorithms.

The ongoing research in spectrum sensing methodologies highlights the importance of developing adaptive and efficient techniques to meet the dynamic and diverse requirements of cognitive radio networks. Future work is likely to focus on further enhancing the reliability and efficiency of these methods, exploring new signal processing techniques, and integrating machine learning approaches to improve the overall performance of spectrum sensing in cognitive radio environments [10].

Problem Statement

The rapid expansion of wireless communication technologies has led to an unprecedented demand for spectrum resources. Traditional static spectrum allocation policies have proven inadequate, resulting in significant underutilization of available spectrum bands. This inefficiency has prompted the exploration of dynamic spectrum access solutions, such as cognitive radio networks (CRNs), which allow secondary users to exploit vacant spectrum bands opportunistically [1]. Despite the promise of CRNs, effective spectrum sensing remains a significant challenge.

One of the primary issues in spectrum sensing is the accurate detection of spectrum holes without causing interference to primary users. Traditional methods, including energy detection, waveform-based sensing, cyclostationarity-based sensing, and matched filtering, each have their own set of limitations. Energy detection, for example, is highly susceptible to noise, leading to high false alarm rates, especially in low signal-to-noise ratio (SNR) environments [2, 3]. Waveform-based sensing and matched filtering require prior knowledge of the primary user's signal, which may not always be available or accurate [4, 5].

The variability of wireless environments further complicates spectrum sensing. Factors such as fading, shadowing, and varying interference levels can significantly impact the performance of traditional sensing methods. Cyclostationarity-based sensing, while robust to noise, demands high computational resources and complex signal processing, making it less feasible for real-time applications in dynamic environments [6, 7]. These challenges necessitate the development of more adaptive and efficient spectrum sensing techniques.

Recent advancements have introduced the concept of Variable Threshold Sensing (VTS), which dynamically adjusts the sensing threshold based on the observed noise level. This adaptive approach aims to enhance detection accuracy and reduce false alarm rates, addressing some of the key limitations of traditional methods [8]. However, comprehensive evaluations of VTS under various operational conditions are essential to validate its effectiveness and identify areas for further improvement.

Another critical issue is the integration of spectrum sensing methods into the overall framework of CRNs. Effective spectrum sensing must detect the presence of primary users and provide reliable information to support spectrum management decisions. This includes real-time adaptation to changing network conditions, efficient allocation of spectrum resources, and minimization of interference. The interplay between spectrum sensing and other cognitive radio functions is crucial for the seamless operation of CRNs [9].

Moreover, the increasing complexity of wireless environments, with the proliferation of diverse devices and services, underscores the need for advanced spectrum sensing techniques. Traditional methods may not suffice in scenarios with heterogeneous network conditions and varied user requirements. Therefore, there is a pressing need for innovative solutions that can adapt to these complexities and ensure reliable spectrum access for secondary users [10].

The evaluation of the VTSM spectrum sensing method in different scenarios, including varying SNR conditions, diverse primary user signals, and fluctuating noise environments, is critical. Such evaluations will provide insights into the practical applications of VTS and its potential to enhance the performance of CRNs. By comparing VTS with traditional methods, this research aims to highlight its advantages and limitations, contributing to the ongoing development of more effective spectrum sensing strategies [11].

In conclusion, the development of robust and efficient spectrum sensing methods is vital for the successful deployment of cognitive radio networks. The VTSM spectrum sensing method offers a promising approach, but thorough analysis and optimization are required to ensure its efficacy in real-world applications. This study aims to address these challenges by providing a comprehensive evaluation of VTS, thereby contributing to the broader understanding and advancement of cognitive radio technologies [12].

The purpose of the article

The goal of this article is to examine how the Variable Threshold Sensing (VTS) method performs in cognitive radio networks. Given the ever-changing nature of wireless environments and the need for efficient spectrum use, it's important to look into advanced spectrum sensing techniques that can adjust to different conditions. This study gives a detailed analysis of VTS, highlighting its potential benefits over traditional spectrum sensing methods and its ability to enhance the accuracy and reliability of spectrum detection.

Another important goal of this research is to compare the VTS method with well-known spectrum sensing techniques like energy detection, waveform-based sensing, cyclostationarity-based sensing, and matched filtering. By thoroughly evaluating these methods under various signal-to-noise ratio (SNR) conditions, primary user signal types, and noise environments, this article aims to pinpoint the specific situations where VTS performs better than other methods. This comparative analysis will offer practical insights into the applications of VTS and help steer future research and development in this area.

Lastly, the article aims to contribute to the broader understanding of cognitive radio networks by examining the integration of VTS with other spectrum management strategies. By assessing how VTS can enhance overall spectrum efficiency and reduce interference in CRNs, this study provides a foundation for further innovation and optimization in cognitive radio technologies. Ultimately, the findings of this research will support the ongoing efforts to develop more robust and effective spectrum sensing solutions, ensuring the successful deployment and operation of cognitive radio networks.

Summary of the main material

This section provides a detailed description and mathematical characterization of existing spectrum sensing methods used in cognitive radio networks (CRNs), along with a comparative analysis based on key performance criteria. The methods discussed include Energy Detector Based Sensing, Waveform-Based Sensing, Cyclostationarity-Based Sensing, Matched-Filtering, and Variable Time Segment (VTS) Sensing.

Energy Detector Based Sensing (EDS) is one of the most widely used methods due to its simplicity and low computational requirements. It measures the energy in the received signal and compares it to a predefined threshold to decide the presence of a primary user. The decision statistic for EDS is given by:

$$T = \frac{1}{N}\sum_{n=0}^{N-1}|r[n]|^2, \quad (1)$$

where $r[n]$ is the received signal, and N is the number of samples [13–15].

The detection threshold λ is chosen based on the desired false alarm rate P_{fa}

$$\left(P_{fa} = P(T > \lambda|H_0)\right), \quad (2)$$

where H_0represents the hypothesis that no primary user is present [13–15].

The performance of the detection algorithm can be summarized with two probabilities: probability of detection P_D and probability of false alarm P_{fa}. P_D is the probability of detecting a signal on the considered frequency when it truly is present. Thus, a large detection probability is desired. It can be formulated as [1]:

$$P_D = P(T > \lambda|H_1). \quad (3)$$

To compare the performance across various threshold values, we can use receiver operating characteristic (ROC) curves. This analysis enables us to identify the optimal threshold. Figure 1 illustrates the ROC curves for different SNR values [1].

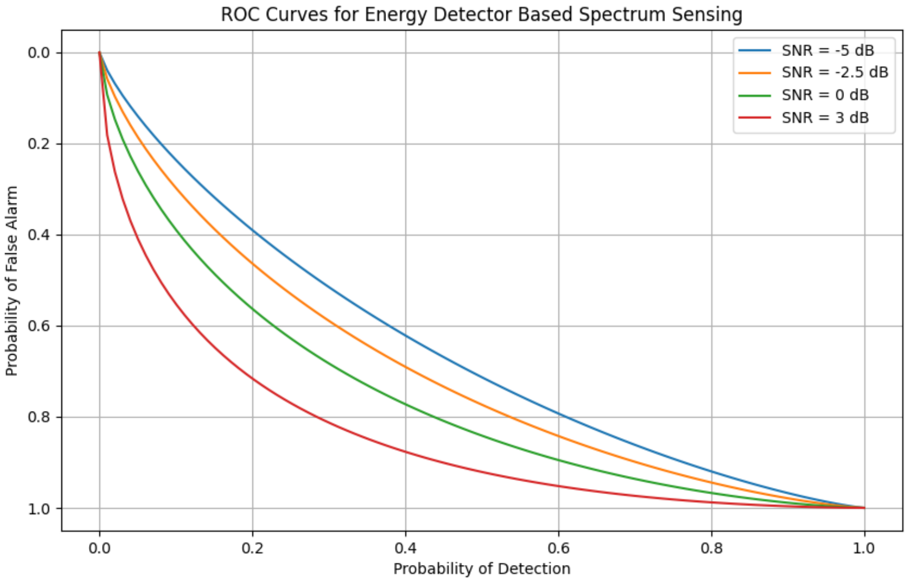

Fig. 1. ROC curves for EDS spectrum sensing under different SNR values

Waveform-Based Sensing (WFB) is applicable to systems with known signal patterns, such as pilot signals or preambles. It involves correlating the received signal with a known reference waveform [1,5]. Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. A preamble is a known sequence transmitted before each burst, and a midamble is transmitted in the middle of a burst or slot. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [16-18]. The decision statistic for Waveform-Based Sensing is given by:

$$T = \left|\sum_{n=0}^{N-1} r[n]s^*[n]\right|, \quad (4)$$

where $r[n]$ is the received signal, and $s[n]$ is the known reference signal [16–18]. In the absence of the primary user, the value becomes [1]:

$$T = \left|\sum_{n=0}^{N-1} w[n]s^*[n]\right|. \quad (5)$$

Similarly, in the presence of a primary user's signal, the sensing metric becomes

$$T = \frac{1}{N}\sum_{n=0}^{N-1}|r[n]|^2 + \left|\sum_{n=0}^{N-1} w[n]s^*[n]\right|. \quad (6)$$

Cyclostationarity-based sensing (CSD) exploits the cyclostationary properties of the received signals, which arise from the periodicity in the signal or its statistics such as mean and autocorrelation. This method differentiates primary user signals from noise by analyzing spectral correlation functions.

Instead of using power spectral density (PSD), the cyclic correlation function is employed to detect signals within a given spectrum. Cyclostationarity-based detection algorithms can distinguish between noise and primary users' signals. Cyclostationary signals have statistical properties that vary periodically with time, unlike noise which is typically wide-sense stationary. This method is particularly robust against noise uncertainty and can distinguish between different types of transmissions.

The cyclic autocorrelation function is defined as:

$$R_y(\tau,\alpha) = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} y(t)y^*(t+\tau)e^{-j2\pi\alpha t}\,dt \quad (7)$$

where *y(t)* is the received signal, τ is the time delay, and α is the cyclic frequency [20–22].

Matched Filtering (MF) is the optimal detection technique when the primary user's signal is known. It maximizes the signal-to-noise ratio (SNR) in the presence of additive stochastic noise. A matched filter is a linear filter used in digital signal processing (DSP) that maximizes the signal-to-noise ratio (SNR) in the presence of stochastic additive noise to enable coherent detection. The probabilities of detection and false alarm are defined as [22, 23]:

$$P_{fa} = Q\left(\frac{\eta}{\sigma_{H_0}}\right), \quad (8)$$

$$P_D = Q\left(\frac{\eta-\mu_{H_1}}{\sigma_{H_1}}\right). \quad (9)$$

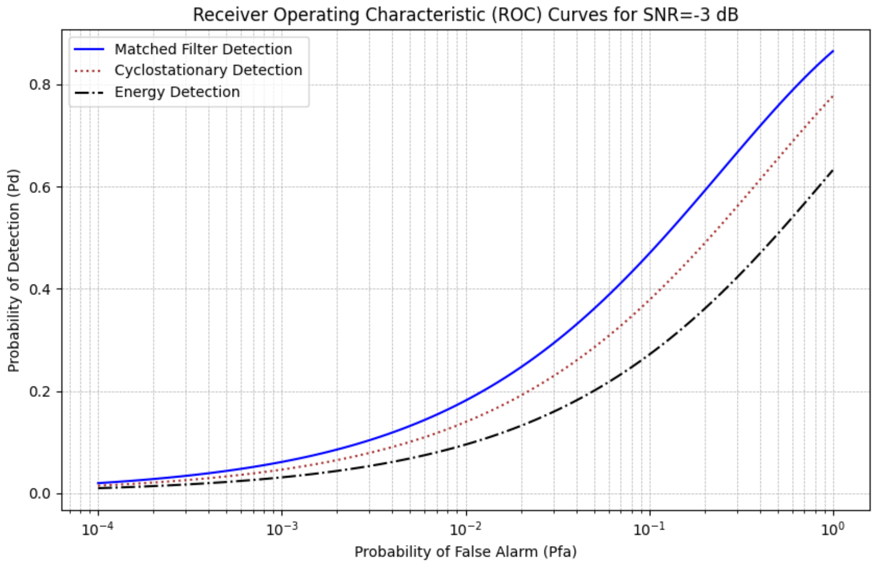

Fig. 2. ROC curves for three detection methods: MF, CSD, and EDS for SNR = -3dB

The Variable Time Segment Monitoring (VTSM) method is used to optimize the detection and analysis of spectral characteristics of signals. This method involves dividing time series into segments of varying lengths, which allows for a more flexible and efficient exploration of the signal's frequency content.

The signal is divided into time segments of varying lengths instead of uniformly distributed time segments. For each segment, the Discrete Fourier Transform (DFT) is computed to obtain the spectral characteristics of each segment. The segments can be adapted to provide a more accurate analysis of specific frequency components of the signal. The spectral characteristics of each segment are analyzed to identify significant frequency components and their changes over time. This process provides more detailed and accurate information about the signal, as each segment is optimally selected to detect specific spectral features.

The key steps in the VTSM method involve initializing by setting the initial segment length and threshold, and estimating initial noise variance. Segmentation and detection involve calculating the energy for each segment, comparing it with the threshold to make a decision, updating segment length based on variance estimate, and adapting the threshold for the next segment.

Consider a received signal *r*(*t*) over a time segment T_k , where *k* denotes the segment index. The signal can be modeled as:

$$r(t) = s(t) + n(t), \quad (10)$$

where *s*(*t*) is the primary user's signal and *n(t)* is the noise component.

The total observation time is divided into variable-length segments T_k. The length of each segment is determined based on the statistical properties of the received signal in the previous segments. The decision to adapt the segment length can be formulated as:

$$T_{k+1} = f\left(T_k, \widehat{\sigma_k^2}\right), \qquad (11)$$

where σ_k^2 is the estimated variance of the received signal in the *k-th* segment.

For each time segment T_k, the energy detector calculates the test statistic as:

$$E_k = \frac{1}{T_k}\int_0^{T_k} |r(t)|^2\, dt. \qquad (12)$$

The performance of the VTS method can be evaluated using the following metrics:

$$P_D = P(E_k > \lambda_k | H_1), \qquad (13)$$

$$P_{fa} = P(E_k > \lambda_k | H_0). \qquad (14)$$

Table 1

Performance Metrics of Spectrum Sensing Methods

Method	Detection Accuracy	False Alarm Rate	Latency	Computational Complexity
EDS	Moderate	High	Low	Low
WFB	High	Low	Moderate	High
CSD	High	Low	High	High
MF	Very High	Very Low	Moderate	Very High
VTSM	High	Low	Moderate	Moderate

The ROC curve for Spectrum Sensing Methods (Fig. 3) shows the trade-off between the detection probability and the false alarm probability.

Each spectrum sensing method analyzed–Energy Detector Based Sensing, Waveform-Based Sensing, Cyclostationarity-Based Sensing, Matched Filtering, and Variable Time Segment Monitoring (VTSM)—offers distinct advantages and limitations.

Energy Detector Based Sensing is characterized by its simplicity and low computational complexity, making it suitable for real-time applications, though its high false alarm rate under low SNR conditions limits its effectiveness (Fig. 3).

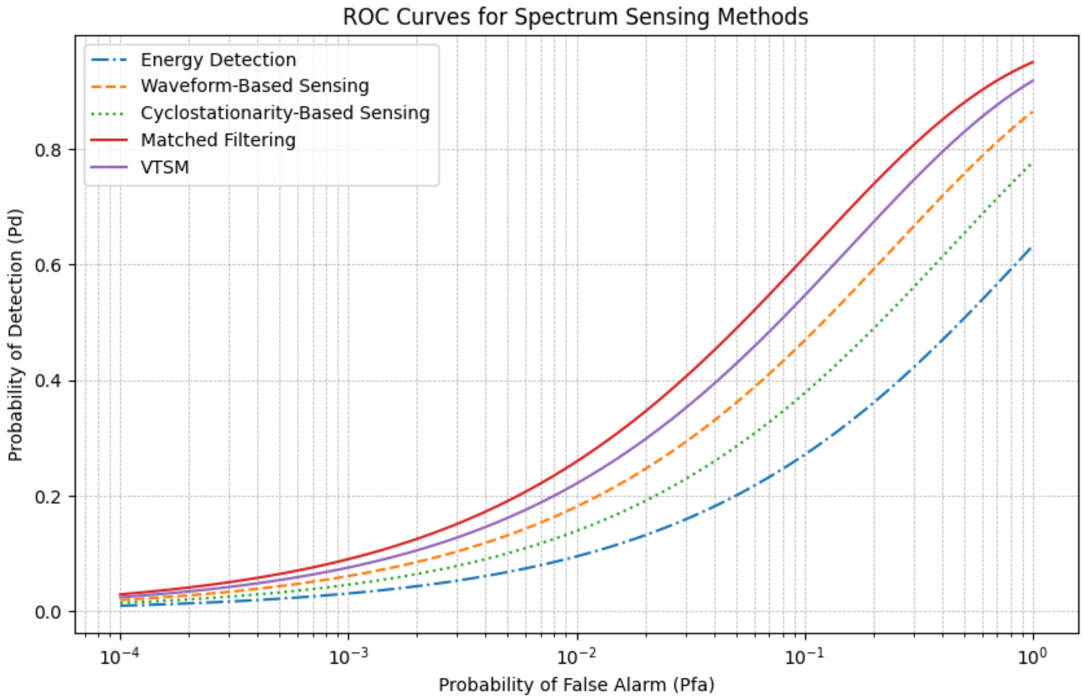

Fig. 3. ROC curves for Spectrum Sensing Methods

Waveform-Based Sensing and Cyclostationarity-Based Sensing provide high detection accuracy and low false alarm rates, but their need for prior knowledge of the signal and high computational demands make them less flexible in dynamic environments.

Matched Filtering, while offering the highest detection accuracy and the lowest false alarm rate, is also the most computationally intensive and is best used when the primary user's signal is well known.

The Variable Time Segment Monitoring (VTSM) method distinguishes itself with a balanced approach that integrates flexibility, accuracy, and moderate computational complexity. By dynamically adjusting the length of time segments according to the observed signal characteristics, VTSM adeptly adapts to changing signal environments, achieving high detection accuracy and low false alarm rates. This adaptability makes VTSM especially suitable for dynamic and complex environments, providing a versatile solution for spectrum sensing.

Conclusions

Spectrum sensing is a critical component of cognitive radio networks, enabling the efficient and dynamic use of available frequency bands. Effective spectrum monitoring ensures that cognitive radios can accurately detect the presence of primary users, minimize interference, and optimize the utilization of the spectrum. The ability to detect and adapt to changing signal environments is paramount for the successful implementation of cognitive radio systems, which aim to address the increasing demand for wireless communication bandwidth.

The choice of spectrum sensing method plays a crucial role in achieving these goals. Each method—Energy Detector Based Sensing, Waveform-Based Sensing, Cyclostationarity-Based Sensing, Matched Filtering, and Variable Time Segment Monitoring (VTSM) – offers distinct advantages and is suited to different scenarios. VTSM, in particular, stands out for its balanced approach, combining flexibility, accuracy, and moderate computational complexity, making it especially suitable for dynamic and complex environments. Ultimately, selecting the most appropriate spectrum sensing method depends on the specific requirements of the application, including accuracy needs, tolerance for false alarms, available computational resources, and the nature of the signal environment. By carefully considering these factors, cognitive radio networks can achieve reliable and efficient spectrum sensing, ensuring optimal performance and resource utilization.

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ОЦІНКА ХАРАКТЕРИСТИК МЕТОДУ МОНІТОРИНГУ СПЕКТРУ VTSM ДЛЯ МЕРЕЖ КОГНІТИВНОГО РАДІО

У статті досліджено проблеми спектрального аналізу у когнітивних радіомережах (CRN), які обумовлені зростаючим попитом на ефективне використання спектру. Проаналізовано альтернативні традиційні методи спектрального моніторингу, зокрема, моніторинг на основі енергетичного детектора, моніторинг на основі форми сигналу, циклостаціонарний моніторинг та узгоджену фільтрацію.

Основна увага в дослідженні приділяється методу змінного моніторингу часових сегментів (VTSM), новому підходу, який оптимізує спектральний моніторинг *шляхом динамічного регулювання часових сегментів, що використовуються для аналізу спектральних характеристик. У статті підкреслюється здатність методу VTSM підвищувати точність виявлення хибних тривог та знижувати їх рівень шляхом адаптації до різних радіо середовищ, що робить метод особливо придатним для складних і динамічних сценаріїв CRN.*

У статті проведено порівняльну оцінку методу VTSM з традиційними методами за ключовими показниками ефективності, такими як точність виявлення, рівень хибних тривог, затримка та обчислювальна складність. Аналіз показує, що хоча традиційні методи мають свої переваги, VTSM пропонує збалансований підхід, поєднуючи гнучкість, точність і помірні обчислювальні вимоги, що *робить його універсальним рішенням. Також метод VTSM відрізняється своєю здатністю динамічно адаптувати довжину часових сегментів на основі характеристик сигналу, що спостерігаються, забезпечуючи високу точність виявлення та низький рівень хибних тривог.*

Отримані результати сприяють більш глибокому розумінню та розвитку когнітивних радіомереж, підтримуючи розробку більш надійних та ефективних рішень для спектрального моніторингу, які є надзвичайно важливими для оптимізації продуктивності мережі та забезпечення надійного зв'язку в умовах великої завантаженості когнітивного радіосередовища. Перспективи подальшого дослідження включають поглиблену оцінку VTSM у реальних умовах експлуатації, а також можливість його інтеграції з іншими методами моніторингу для підвищення загальної ефективності CRN.

Ключові слова: «розумне» радіо, когнітивне радіо, частотний діапазон, моніторинг спектру, спектральна ефективність, циклостаціонарність, узгоджене фільтрування, метод VTSM, енергетичний детектор.

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EVALUATING THE CHARACTERISTICS OF THE VTS SPECTRUM SENSING METHOD IN COGNITIVE RADIO NETWORKS

The article investigates the complexities associated with spectrum analysis in cognitive radio networks (CRNs). It begins by acknowledging the *evolving challenges of spectrum sensing due to the dynamic nature of wireless environments and the increasing demand for efficient spectrum utilization. The study thoroughly examines various traditional spectrum sensing methods, including Energy Detector Based Sensing, Waveform-Based Sensing, Cyclostationarity-Based Sensing, and Matched Filtering.*

The focus of the research is on the Variable Time Segment Monitoring (VTSM) method, a novel approach that optimizes spectrum sensing by dynamically *adjusting the time segments used for analyzing spectral characteristics. The paper highlights the VTSM method's ability to enhance detection accuracy and reduce false alarms by adapting to different signal environments, making it particularly suited for complex and dynamic CRN scenarios.*

Furthermore, the article compares VTSM with traditional methods across key performance metrics such as detection accuracy, false alarm rate, latency, and computational complexity. The analysis reveals that while traditional methods have their strengths, VTSM offers *a balanced approach, combining flexibility, accuracy, and moderate computational demands, thereby providing a versatile solution for modern spectrum sensing challenges. The findings contribute to the broader understanding and advancement of cognitive radio technologies, supporting the development of more robust and efficient spectrum sensing solutions, which are crucial for optimizing network performance and ensuring reliable communication in increasingly congested and complex wireless environments.*

The article concludes by emphasizing the importance of selecting the appropriate spectrum sensing method based on the specific requirements of the CRN application, considering factors such as accuracy, computational resources, and environmental dynamics. The findings contribute to the broader understanding and advancement of cognitive radio technologies, supporting the development of more robust and efficient spectrum sensing solutions.

Keywords: «smart» radio, cognitive radio, frequency range, spectrum monitoring, spectral efficiency, cyclostationarity, matched filtering, VTSM method, energy detector.

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