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Cognitive Radio Networks for Wireless Communications using Spectrum Sensing Technique: A Review

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Abstract

The exponential growth of wireless communication technologies has led to an increasing demand for radio spectrum, resulting in inefficient utilization and severe spectrum scarcity issues. Cognitive Radio Networks (CRNs) have emerged as a promising solution to address this challenge by enabling dynamic spectrum access. CRNs allow unlicensed users, known as secondary users (SUs), to opportunistically utilize the underutilized spectrum allocated to licensed or primary users (PUs) without causing harmful interference. Among the core functions of CRNs, spectrum sensing plays a pivotal role in detecting vacant spectrum bands (spectrum holes) and ensuring seamless and interference-free communication.

This review provides a comprehensive analysis of various spectrum sensing techniques used in CRNs, including energy detection, matched filtering, cyclostationary feature detection, and cooperative sensing. Each technique is examined in terms of its operational principles, advantages, limitations, and applicability under different signal and channel conditions. The paper also discusses key performance metrics such as probability of detection, false alarm rate, and sensing time, which are critical for evaluating sensing accuracy. Furthermore, the review highlights recent advances such as machine learning-based sensing, compressive sensing, and their potential integration with emerging technologies like 5G, 6G, and IoT. The paper concludes by identifying key challenges and proposing future research directions aimed at improving the efficiency, reliability, and adaptability of spectrum sensing in cognitive radio networks.

***Keywords*- Cognitive Radio (CR), Spectrum Sensing (SS), Wireless Communication**

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INTRODUCTION

The rapid proliferation of wireless devices and the continuous emergence of new wireless applications have significantly increased the demand for radio spectrum resources. Traditionally, spectrum allocation is performed using static licensing schemes, where specific frequency bands are assigned to licensed or primary users (PUs) for long periods. While this approach ensures interference-free communication for licensed users, it leads to inefficient spectrum utilization, as many allocated frequency bands remain underutilized or idle in time, space, and frequency dimensions. Studies conducted by regulatory bodies such as the Federal Communications Commission (FCC) have revealed that large portions of the licensed spectrum are often underused, resulting in what is commonly known as spectrum scarcity.

To overcome this inefficiency, Cognitive Radio (CR) technology was introduced as a promising solution. Cognitive radio enables dynamic spectrum access by allowing unlicensed or secondary users (SUs) to opportunistically utilize the underused spectrum without causing interference to primary users. This is achieved through the intelligent sensing and adaptation of the radio environment, making CR an essential component of next-generation wireless communication systems, including 5G, 6G, and the Internet of Things (IoT).

A Cognitive Radio Network (CRN) is a wireless communication framework built on the principles of cognitive radio. CRNs consist of intelligent wireless devices capable of sensing their spectral environment, learning from historical data, and adapting their transmission parameters accordingly. One of the most critical functionalities of CRNs is spectrum sensing, which enables secondary users to identify vacant spectrum bands (also known as white spaces) and utilize them without causing interference to the licensed users. Accurate and reliable spectrum sensing is essential for ensuring the safe coexistence of primary and secondary users and for improving the overall efficiency of spectrum utilization. Various spectrum sensing techniques have been developed and explored in the literature, each with its own strengths and limitations. Commonly used techniques include energy detection, matched filtering, cyclostationary feature detection, and cooperative sensing. Energy detection is the simplest and most widely used method due to its low complexity and no prior knowledge requirement of the primary signal. However, it suffers from low performance in low signal-to-noise ratio (SNR) environments. Matched filtering offers better detection accuracy but requires prior knowledge of the PU’s signal, making it less practical in dynamic scenarios. Cyclostationary detection, which exploits the periodic features of modulated signals, provides high detection performance under low SNR but is computationally intensive. Cooperative sensing improves overall accuracy by allowing multiple users to collaborate and share sensing information, thus mitigating issues like shadowing and multipath fading.

The choice of an appropriate spectrum sensing technique depends on several performance metrics, including probability of detection, false alarm rate, detection time, and energy efficiency. Moreover, challenges such as noise uncertainty, hardware limitations, real-time processing constraints, and security concerns must be addressed to enable practical deployment of CRNs.

With the evolution of wireless communication systems, recent research has increasingly focused on the integration of machine learning (ML) and deep learning (DL) algorithms into spectrum sensing. These intelligent techniques allow CRNs to predict spectrum availability, enhance detection accuracy, and adapt to dynamic environments. Additionally, emerging paradigms such as reconfigurable intelligent surfaces (RIS) and federated learning offer new opportunities to enhance sensing capabilities.

This review aims to provide a comprehensive overview of the various spectrum sensing techniques used in cognitive radio networks. It also explores recent advancements, evaluates the performance of existing methods, and discusses current challenges and future research directions. The goal is to support researchers and practitioners in understanding the state-of-the-art in CRN spectrum sensing and contribute to the development of more efficient and intelligent wireless communication systems.

LITERATURE REVIEW

J. Yao et al. [1], spectrum sensing is a major difficulty for cognitive radio (CR) networks, particularly when spectrum is scarce. Because fluid antenna systems (FASs) may dynamically modify antenna placements for increased channel gain, they can provide an unconventional solution. This letter examines a FAS-driven CR system in which a secondary user (SU) modifies fluid antenna placements to pick up signals from the primary user (PU). Under the limitations of the false alarm likelihood and the SU's received beamforming, our goal is to maximize the detection probability. To solve this issue, we first define the problem to determine its solution and then derive a closed-form expression for the ideal detection threshold. The problem is then broken down into multiple subproblems using an alternate optimization (AO) approach that takes into account both the antenna placements at the SU and the received beamforming. A closed-form solution is used to solve the beamforming subproblem, and sequential convex approximation (SCA) is used to solve the fluid antenna placements. According to simulation results, the suggested approach significantly improves spectrum sensing performance over conventional fixed-position antenna (FPA) techniques.

Y. Xu et al. [2], spectrum sensing is a major difficulty for cognitive radio (CR) networks, particularly when spectrum is scarce. Because fluid antenna systems (FASs) may dynamically modify antenna placements for increased channel gain, they can provide an unconventional solution. This letter examines a FAS-driven CR system in which a secondary user (SU) modifies fluid antenna placements to pick up signals from the primary user (PU). Under the limitations of the false alarm likelihood and the SU's received beamforming, our goal is to maximize the detection probability. To solve this issue, we first define the problem to determine its solution and then derive a closed-form expression for the ideal detection threshold. The problem is then broken down into multiple subproblems using an alternate optimization (AO) approach that takes into account both the antenna placements at the SU and the received beamforming. A closed-form solution is used to solve the beamforming subproblem, and sequential convex approximation (SCA) is used to solve the fluid antenna placements. According to simulation results, the suggested approach significantly improves spectrum sensing performance over conventional fixed-position antenna (FPA) techniques.

M. Wasilewska et al. [3], examines federated learning (FL)-based spectrum sensing (SS) that is secure and dependable in the context of cognitive radio (CR). There is discussion of FL's architectures, methods, and motivation in SS. Threats to these algorithms' security and privacy are reviewed, along with potential defenses against them. Additionally, several illustrated instances are given along with design suggestions for FL-based SS in next CRs.

R. M. Alonso et al. [4], spectrum scarcity can be lessened by using new generation networks, which are based on Cognitive Radio technology and enable dynamic spectrum distribution. Additionally, these networks have the robust capacity to operate dynamically in order to save energy. In this work, we propose a new wireless network optimization algorithm based on a cloud sharing-decision mechanism for cognitive radio networks. Exposure, power consumption, and spectrum usage were the three KPIs that were optimized. The best trade-off between the KPIs is identified for a genuine suburban setting in Ghent, Belgium. Our optimization algorithm for the cloud-based architecture simultaneously decreased the network power consumption by 27.5%, the average worldwide exposure by 34.3%, and the spectrum utilization by 34.5% when compared to a typical Cognitive Radio network design. Our method outperforms the old architecture by 4.8% in terms of network power consumption, 7.3% in terms of spectrum utilization, and 4.3% in terms of global exposure, even for the worst-case optimization (worst result attained by a single KPI).

S. A. Khan et al. [5], spectrum sensing is crucial for cognitive radios to recognize and exploit unutilized frequency channels. Traditional spectrum sensing methods depend on identifying characteristics in signals that are received at particular locations. Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have, however, recently shown promise in enhancing the accuracy and effectiveness of spectrum sensing. By utilizing convolutional neural networks (CNNs), our study presents a novel method for spectrum sensing that greatly improves the accuracy and efficiency of locating underutilized frequency regions. To enable unmatched adaptability to new signals, we train our model using a variety of signal types and noise data, treating spectrum sensing as a classification problem. Our approach exhibits better performance and versatility than conventional approaches like the frequency domain entropy-based and maximum–minimum eigenvalue ratio-based approaches. Specifically, our CNN-based method shows remarkable accuracy, even surpassing previous techniques in the presence of additive white Gaussian noise (AWGN).

Yiru Liu, Bo Ai et al. [6], 5G and 6G mobile communication systems have adopted massive multiple-input multiple-output (MIMO), a lucrative method to significantly increase spectral efficiency. Base stations (BSs) with many antennas can serve numerous users and different cells simultaneously and at the same frequency by utilizing the right downlink precoding algorithms. However, in huge MIMO communication systems, the mutual coupling effect caused by the small antenna array produces deceptive results. In order to overcome the mutual coupling problem, we concentrate on the mutual coupling impact for massive MIMO systems using minimal mean square error (MMSE) precoding, zero-forcing (ZF), regularize ZF (RZF), and maximal ratio transmission (MRT). Furthermore, in order to assess how mutual coupling affects system performance, we create the closed-form expressions of the spectral efficiency (SE). The efficiency of the suggested mutual coupling effect evaluation approach is confirmed

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by simulation findings, which also show how mutual coupling significantly affects the performance of huge MIMO systems.

SPECTRUM SENSING

A major challenge in cognitive radio is that the secondary users need to detect the presence of primary users in a licensed spectrum and quit the frequency band as quickly as possible if the corresponding primary radio emerges in order to avoid interference to primary users. This technique is called spectrum sensing. Spectrum sensing and estimation is the first step to implement Cognitive Radio system [5]. We can categorize spectrum sensing techniques into direct method, which is considered as frequency domain approach, where the estimation is carried out directly from signal and indirect method, which is known as time domain approach, where the estimation is performed using autocorrelation of the signal. Another way of categorizing the spectrum sensing and estimation methods is by making group into model based parametric method and period gram based nonparametric method.

a. Primary transmitter detection: In this case, the detection of primary users is performed based on the received signal at CR users. This approach includes matched filter (MF) based detection, energy-based detection, covariance-based detection, waveform-based detection, cyclostationary based detection, radio identification-based detection and random Hough Transform based detection.

b. Cooperative and collaborative detection: In this approach, the primary signals for spectrum opportunities are detected reliably by interacting or cooperating with other users, and the method can be implemented as either centralized access to spectrum coordinated by a spectrum server or distributed approach implied by the spectrum load smoothing algorithm or external detection.

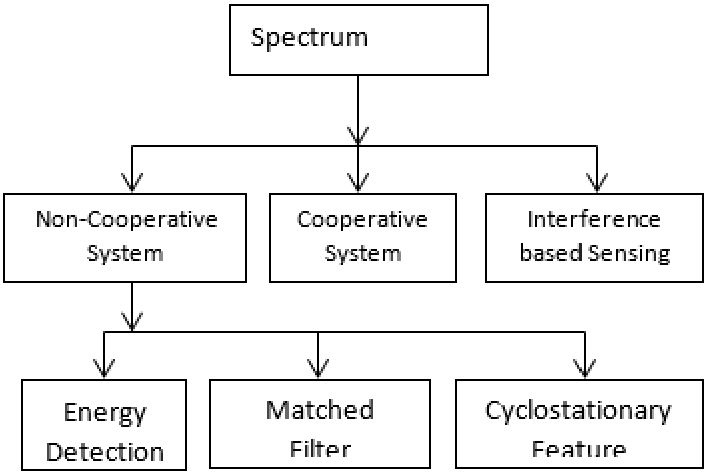

Figure 1: Classification of spectrum sensing techniques

Figure 1 shows the detailed classification of spectrum Sensing techniques. They are broadly classified into three main types, transmitter detection or non-cooperative sensing, cooperative sensing and interference-based sensing. Transmitter detection technique is further classified into energy detection, matched filter detection and cyclostationary feature detection [12].

Non-cooperative Spectrum Sensing

Since it is difficult to sense the status of the primary receiver, so to detect the primary user transmission it is necessary to detect the signals sent by the primary transmitter. This kind of spectrum sensing is also called primary transmitter detection.

Energy Detection

If CR users have no information about the primary signals, then energy detection can be used for spectrum sensing. ED is optimal detector if noise power is known to the CR user [2]. Energy detection is very simple and easy to implement. It is the most popular spectrum sensing technique. In energy detection, the presence of the signal is detected by measuring the signal over an observation time.

Advantages: Simple and fewer complexes than other techniques No prior knowledge of the primary signal required Easy to implement

Disadvantages: High sensing time required to achieve the desired probability of detection Using ED, it is not easy to distinguish Primary Signal from noise signal Detection performance is limited by noise uncertainty Spread spectrum signals cannot be detected by ED.

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Matched Filter

Detection In matched filter detection SNR of the received signal is maximized. The CR user needs to have the prior knowledge of the primary signal transmitted by the primary user. This is the basic requirement for the matched filter detection. Matched filter operation defines a correlation in which unknown signal is convolved with the filter whose impulse response is the mirror and time shifted versions of a reference signal [6].

Advantages: It needs less detection time. When information of the primary user signal is known to the CR user then Matched Filter Detector is optimal detector in stationary Gaussian noise [3].

Disadvantages: It needs priori knowledge of the received signal. High Complexity.

Cyclostationary Feature Detection

The modulated signals are generally cyclostationary in nature and this kind of feature of these signals can be used in this technique to detect the signal. A cyclostationary signals have the statistical properties that vary periodically with time [7]. This periodicity is used to identify the presence or absence of primary users. Due to the periodicity, these cyclostationary signals exhibit the features of periodic statistics and spectral correlation, which is not found in stationary noise [8].

Advantages: Robust to noise uncertainties and better performance in low SNR regions. Capable of distinguishing the CR transmissions from various types of PU signals. No synchronization required Improves the overall CR throughput

Disadvantages: Highly complex method Long sensing time

METHODOLOGY

The circuit will be implementations in MATLAB 2013b software, with the main parameters described below. We generated a random binary signal generate in a serial manner. To analyze a signal in the time domain, we apply IFFT (Inverse Fast Fourier Transform) and convert it from parallel to serial OFDM signal to add a cyclic prefix (CP), which helps avoids interference between OFDM symbols.

This signal is then feed through an Additive White Gaussian Noise (AWGN) channel. At the receiver end, the CP is removed and the signal converted from serial to parallel to get the original, with FFT applied to each symbol for analysis in the frequency domain. After demodulation, the signal is cross correlated with that of a time-shifted local oscillator.

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Finally, the received signal is compared to a threshold value (ʎ) following the SNR or determines whether the signal is absent or present; if the received signal is greater than the threshold value, there will be detection, otherwise not:

S(t) = n(t) H0

S(t) = {h*P(t) + n(t)} H1

where S(t) is the secondary user, P(t) the primary user's transmitted signal, n(t) is AWGN, h the amplitude gain of the channel, H0 = there's no primary user, and H1 = primary user is present.

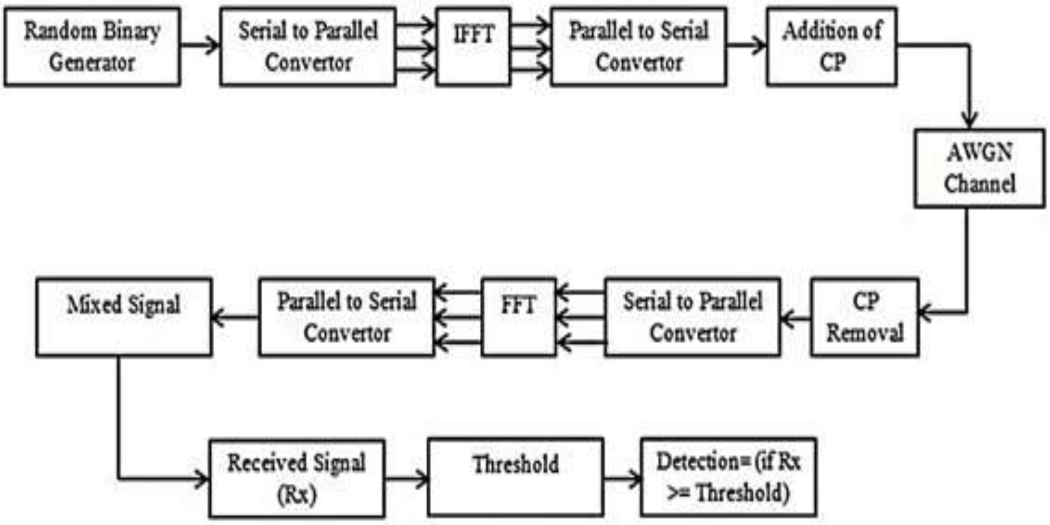

Figure 2: MIMO-OFDM System using Matched Filter Detection Technique

CONCLUSION

Cognitive Radio Networks represent a transformative approach to addressing the increasing demand for wireless spectrum by enabling intelligent and dynamic spectrum access. At the core of this innovation lies spectrum sensing, a fundamental function that allows secondary users to detect unused frequency bands without interfering with primary users. This review has presented an in-depth analysis of various spectrum sensing techniques—such as energy detection, matched filtering, cyclostationary feature detection, and cooperative sensing—highlighting their operational principles, advantages, limitations, and practical applicability.

The study emphasizes the importance of balancing detection accuracy, sensing time, and computational complexity to ensure efficient spectrum utilization. While traditional techniques offer simplicity and ease of implementation, advanced approaches incorporating machine learning and signal processing are gaining attention due to their adaptability and robustness in dynamic environments.

Despite significant progress, challenges such as noise uncertainty, hidden node problems, and real-time implementation continue to affect the performance of spectrum sensing. Future research should focus on intelligent sensing algorithms, energy-efficient hardware solutions, and integration with next-generation wireless technologies like 5G, 6G, and IoT. Furthermore, the use of AI and cooperative strategies promises enhanced sensing accuracy and spectrum utilization.

Overall, the evolution of spectrum sensing techniques will play a critical role in realizing the full potential of cognitive radio networks and ensuring more efficient and reliable wireless communication systems.

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