Review

A Review of Recent Deep Learning Methods in Spectrum Sensing

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Abstract

This paper reviews cognitive radio Spectrum sensing (SS) techniques. With increasing demand for wireless spectrum resources cognitive radio (CR), there is a lack of spectrum resources due to the fixed use policy. The idea of cognitive radio (CR) networks has been the subject of numerous research works as a way of utilizing spectrum resources efficiently. Spectrum sensing (SS) techniques have been proposed, and various effective spectrum utilization methods have been developed. Deep learning techniques have outperformed conventional methods for Spectrum sensing (SS). high demand for wireless communicationsA review and comparison of the merits and drawbacks of each technique are given. A description of the use of deep learning techniques in Spectrum sensing (SS) is given next. Lastly, the challenges of deep learning techniques and potential areas of future research are reviewed.

Keywords: cognitive radio (CR), Spectrum sensing (SS), deep learning (DL), machine learning (ML), and Deep Spectrum Sensing (UDSS).

I. Introduction

By the year 2028, mobile subscribers will grow to 9.2 billion from 8.4 billion in the year 2022, according to recent studies. This ultimately results in a lack of spectrum resources. Advanced management strategies are required to alleviate the spectrum shortage [1]. It has been achievable to enhance the efficiency of spectrum utilization by means of Cognitive Radio (CR) technology. One of its key tasks is Spectrum Sensing (SS) [2]. Spectrum sensing (SS) has shown huge potential with the latest developments in CR and Deep Learning (DL). DL algorithms have been more efficient compared to conventional methods and have been successfully applied to improve Spectrum sensing (SS) in CR networks [3]. Apart from addressing wireless technology identification, particularly for 5G and Internet of Things (IoT) applications, these methods were originally intended for modulation recognition [4]. Wireless communication combined with DL techniques is a significant area of research [3]. Irrespective of the existing progress, to advance

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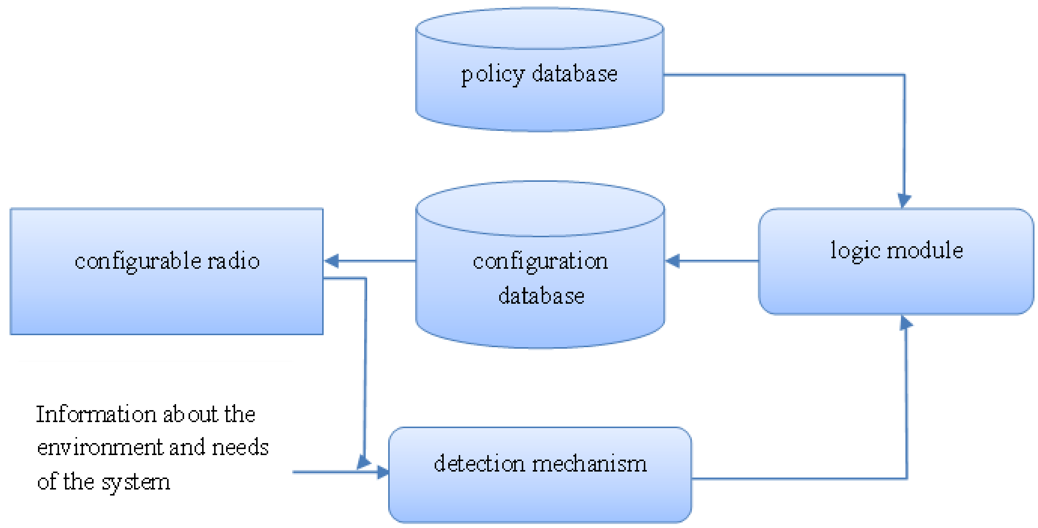

Fig. 1. Figure 1. Main components of the CR network

precision and efficiency under difficult scenarios, some problems still require more research [5]. Individual countries presently manage and allocate spectrum resources. For example, spectrum allocation and management is the responsibility of the Federal Communications Commission in the United States, but China's National Radio Administration. In our nation, the state has the authority to govern the radio frequency spectrum as well as the orbital locations of communication satellites. An overview of recent research activities dedicated to the implementation of deep learning techniques to Spectrum sensing (SS) is the intention of this article.

Figure 1 illustrates the essential components that constitute a cognitive radio system, each playing a pivotal role in its overall functionality and adaptability. The primary component is the reconfigurable radio element, which serves as the foundation of the system's operational capabilities. This component is designed to be highly flexible, enabling adjustments to various parameters, including operating frequency, bandwidth, and multiple other technical specifications. The reconfigurability of the radio component is crucial for efficient spectrum utilization, allowing the system to dynamically adapt to varying communication requirements and environmental conditions. In conjunction with the radio component, the system must incorporate a detection module. This module is integral to the cognitive radio's ability to perceive its operational environment. It is responsible for capturing and processing signals from the radio components, thereby facilitating the identification of available spectrum opportunities. The effectiveness of this detection module is critical, as it directly influences the system's ability to make informed decisions regarding spectrum access and allocation. Another fundamental aspect of the cognitive radio system is the policy database. This database functions as a repository of rules and guidelines that govern the system's operational decisions. It determines the appropriateness of specific actions based on contextual factors, such as current spectrum availability and regulatory constraints. Moreover, the ability to modify and update this database is essential, as it allows the system to remain responsive to changing conditions and user requirements, thereby enhancing its operational efficacy. Additionally, the system must include a logical module that processes input data derived from the detection module and interacts with the policy database. This module is tasked with analyzing the information it receives and determining the optimal configuration for the radio components in real time. It acts as the decision-making hub of the system, ensuring that the actions taken align with the established policies. A crucial feature of the logical module is its capacity for experience-based learning. This capability enables the system to learn from past interactions and outcomes, allowing it to refine its decision-making processes over time. By incorporating machine learning techniques, the logical module can enhance its predictive accuracy and operational performance, adapting to new challenges and optimizing spectrum utilization. Lastly, the configuration database is an essential component that maintains the current settings of the radio components. It ensures that the system operates within the parameters defined by the logical module and facilitates the implementation of any changes to the configuration as required. This

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ongoing maintenance of configuration integrity is vital for the stability and reliability of the cognitive radio system. In summary, the interplay among these components—reconfigurable radio elements, detection modules, policy databases, logical modules with learning capabilities, and configuration databases—forms a cohesive and adaptive cognitive radio system. This architecture enables the system to effectively navigate dynamic communication environments, optimize spectrum usage, and fulfill the diverse needs of users in real-time scenarios.The main role of Spectrum sensing (SS) is carried out by making a decision between detecting two different states of the channel. It is the state where H0 - channel can be empty, usable, and H1 - channel busy. Spectrum sensing (SS) continuously monitors the spectrum of the licensed user (PU) to find available spectrum resources. The decision-making, allocation of the sensed available spectrum, and other operations are carried out only when the channel is in the empty state. This process is crucial for adapting the communication parameters to the surrounding radio environment, and ultimately, it improves the efficiency and use of the available spectrum. Thus, improvement in the accuracy of Spectrum sensing (SS) in its effective utilization. Figure 2 shows the fundamental working principles of the Spectrum sensing (SS) process.

II. Methods

The traditional methods of Spectrum sensing (SS) are as follows: Energy Detection (ED), Matched Filtering Detection (MFD), Cyclostationary Detection (CFD), Eigenvalue-Based Detection (EBD), Covariance-Based Detection (CBD), and Waveform Detection (WD) [9-14]. In the last decade, these methods have been categorized into two general classes: narrowband and wideband sensing methods, each appropriate to different bandwidth requirements [10]. Energy detection is suitable because of its low complexity and low requirement for prior knowledge but is less efficient in distinguishing between signal and noise at low Signal-to-Noise Ratio (SNR). Detection based on identifying signal features using the cyclostationary method, however, enhances resistance to noise by using cyclic autocorrelation analysis but requires more samples and increases the Spectrum sensing (SS) time. Matched filtering detection is based on comparing received samples with stored signal patterns, which enhances performance but requires prior knowledge of signal features in a dynamic environment. Predefining such features in a dynamic environment could be problematic. While energy detection is the most prevalent, matched filtering detection theoretically guarantees high performance in additive white Gaussian noise channels, whereas cyclostationary detection exploits the frequency of modulated signals to enhance detection. SS traditional methods can be categorized as probability-based and feature-based. Theoretically optimal approaches are probability-based but require computation, while feature-based approaches prefer to utilize manually crafted features that require expert experience [9,12,14,15]. Spectrum sensing (SS) methods can also be categorized based on the number of nodes utilized for detection: single-node spectrum sensing and cooperative spectrum sensing [11]. In single-node spectrum sensing, data is gathered and examined from one special device. In cooperative spectrum sensing, several devices gather data about the radio environment for sensing shared spectrum resources. Traditional spectral recognition methods have a number of disadvantages that may limit their effectiveness. Firstly, they exhibit high sensitivity to noise, which can lead to a decrease in recognition accuracy in the presence of interference. In addition, these methods often require data preprocessing, which increases the time and complexity of the work. When processing large amounts of data, traditional algorithms can experience difficulties, especially in real-time conditions. They also have limited adaptability to different types of spectra and changing conditions, which makes them difficult to adjust. In the context of multidimensional data, traditional methods may be ineffective, which limits their use in complex tasks. Finally, to achieve high recognition accuracy, a significant amount of training data is often required, which may not be available in some cases. These shortcomings highlight the need to move towards more modern approaches such as machine learning methods that are more flexible and efficient. In general, traditional methods of determining the spectrum face problems such as a high frequency of false alarms, which leads to an erroneous determination of the activity of primary users in the absence of a signal, that is, the system may mistakenly determine the user's activity when the spectrum is free. They are also sensitive to noise, which reduces accuracy in low SNR conditions, and detection accuracy drops significantly in urban or industrial areas. In addition, in the context of 5G/6G, dynamic environments complicate the adaptation of such methods, as they require prior knowledge of the signal, which is ineffective with uncertainty. In the context of 5G/6G, these problems are increasing: the lack of spectrum due to the growing number of devices, the available spectrum is becoming limited. Static distribution does not adapt to dynamic conditions, fixed distribution schemes lead to unused parts of the spectrum, and traditional methods are ineffective at high load. Coordination between users becomes more complicated: in 5G/6G, the interaction of SU and PU requires complex algorithms, but traditional approaches do not provide adaptability.

As can be seen from the table, traditional methods are inferior in accuracy and noise resistance. For example, ED suffers from a high false positive rate in low SNR environments, while deep learning shows high accuracy even in dynamic environments. This confirms the need to switch to adaptive algorithms for 5G/6G, where the requirements for spectrum and data processing speed are critically high. The majority of the recent studies in this field have utilized deep learning methods for Spectrum sensing (SS) and proposed several techniques. These studies have been demonstrating the superiority of spectrum detection algorithms that are based

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TABLE I
TABLE 1. COMPARATIVE ANALYSIS OF METHODS

method	accuracy	frequency of false alarm	computational costs
ED	Low	High	Low
MFD	Average	Medium	High
CBD	Average	Low	Very high
Deep learning	High	Low	High(adaptive)

on deep learning compared to traditional approaches. Moreover, we will explore the key techniques proposed in these studies and compare their strengths and weaknesses. Table 2 displays modern research using deep learning methods in Spectrum sensing (SS).

TABLE II
TABLE 2. MODERN RESEARCH UTILIZING DEEP LEARNING METHODS IN SPECTRUM SENSING

Research	methods	advantages	limitations
[6]	D3QN	• improved performance • stability • reduction of revaluation	• requires significant computing resources • depends on the availability of sufficient data volume and quality • requires a careful approach to implementation and configuration
[8]	CNN	• the ability to extract complex features • improved performance	• requires significant computing resources • requires preliminary training • requires a large amount of training data
[16]	CNN-RNN	• improved detection • of low false alarm probability (Pf) values • Transfer Learning	• requires a lot of training data • noise sensitivity • requires significant computing resources
[17]	SSDNN	• comparatively high accuracy	• lack of marked-up data
[18]	DetectNet	• no need for additional information • high performance	• dependence on the signal structure • lack of precise performance control
[19]	CNN-LSTM	• combined feature extraction • avoiding information loss	• dependence on data quality • model complexity • the need for a large amount of data
[20]	DCS	• autonomous learning • accounting for correlations • flexibility	• requires a lot of training data • depending on the initial conditions
[22]	UDSS	• data collected in the absence of primary user signals • good performance	• difficulty of setting up

The majority of the recent studies in this field have utilized deep learning methods for Spectrum Sensing and proposed several techniques. These studies have been demonstrating the superiority of spectrum detection algorithms that are based on deep learning compared to traditional approaches. Moreover, we will explore the key techniques proposed in these studies and compare their strengths and weaknesses. Table 2 displays modern research using deep learning methods in Spectrum Sensing.

III. RESULTS

The CNN method uses cascading multi-channel convolutions with residual connections to sense the presence of primary users' spectrum [8]. By using CNN and RNN methods, spatial and temporal features of signals can be extracted, leading to improved signal recognition quality. This method entails data preparation, choosing parts of the signals to train, and fine-tuning the model. The

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method also prevents overfitting [16]. The Dueling Double Deep Q-Network (D3QN) methodology incorporates the double learning system and the double Q-learning methodology that improves the algorithm's performance and stability [6]. Most effective under the multiray fading and other Gaussian interference conditions most effective deep neural network methodology with semisupervision (SSDNN). It was suggested because labeled samples are difficult to obtain under practical radio communication conditions. The methodology learns the characteristics of the signals with few labeled samples and uses unlabeled samples to self-train with high-confidence instances labeled with synthetic labels to increase the volume of data. SSDNN obtained promising results with detection probability over 90% with high SNR and a limited volume of labeled data [17]. The DetectNet approach uses the architecture of convolutional long-term deep neural networks (CLDNN). It does not require knowledge of the source signals or noise density, which makes it suitable for use in cognitive radio communication systems [18]. The CNN-LSTM method is a combination of CNN to isolate spatial and LSTM to isolate temporal features of a signal, which makes it more efficient at processing information from received signals. It has demonstrated higher performance compared to traditional single-node methods, especially in conditions of low signal-to-noise ratio (SNR), with a detection probability of approximately 98.64% during training [19]. The deep cooperative sensing (DCS) method is based on the use of convolutional neural networks (CNNs) to combine the results of individual Spectrum sensing (SS) by several secondary users into a cognitive radio network [20]. The Graph neural network and the GNN reinforcement learning method are aimed at optimizing energy efficiency in distributed collaborative Spectrum sensing (SS) for cognitive radio networks [21]. The Unsupervised Deep Spectrum Sensing (UDSS) method is based on a Variational AutoEncoder (VAE) and deep clustering analysis [22]. Therefore, deep learning methods for Spectrum sensing (SS) achieve significant advantages, including high accuracy and performance in spectrum detection. However, they also present various limitations that must be solved and tackled. Notable limitations include the need for vast computational resources and huge training data. For instance, the CNN-RNN model, via transfer learning, has significantly enhanced spectrum detection in CR with low complexity while evading the limitations of traditional methods. Thus, Spectrum sensing (SS) methods are evolving at a rapid rate, with traditional methods being complemented and increasingly replaced by advanced machine learning and deep learning methods, which enhance detection accuracy as well as operational efficiency in cognitive radio systems. Modeling the behavior of cognitive data networks, particularly in wireless systems, is extremely difficult. Key factors include the number of devices, e.g., IoT devices, the type of applications such as smart environments, and the heterogeneity of transmission technologies. Nonlinearity and complexity of the data traffic with temporal and spatial correlations complicate the analysis and prediction of such networks even further [11]. Deep learning (DL) methods are becoming increasingly popular in spectral sensing (SS), however, the limited availability of large radio frequency datasets has become a key factor that hinders the effective use of DL algorithms in SS. Most of the listed methods require huge amounts of data for model training, validation, and testing. In addition, requirements such as labeling of datasets, computational complexity, and the risks of retrofitting have also become constraints that make it difficult to apply the methods. As a result, the implementation of models in real time involves the use of highly specialized equipment, while the adaptation of algorithms to dynamic situations remains an open question [7].

A. Discussion

Current research indicates that the increasing number of mobile users causes a shortage of radio frequency spectrum. This calls for the evolution of new spectrum management techniques where cognitive radio (CR) techniques are starting to take center stage. Cognitive radio makes it possible for secondary users (SUs) to employ free frequency bands that are unused by primary users (PU). The primary role played by CR is the spectrum definition (SS) process that makes the use of free frequency bands possible in real time. The recent breakthroughs in deep learning (DL) opened new doors to enhancing the efficiency of the Spectrum sensing (SS). The use of algorithms like the convolutional neural networks (CNN) and the recurrent neural networks (RNN) indicates that there are tremendous advantages over the conventional techniques like the use of energy detection (ED) and cyclostationary detection (CFD). The conventional techniques are limited to low efficiency under low SNR conditions and the need to use prior knowledge about the signals. The use of deep learning enhances the precision and the speed of speech recognition because there is the capability to adapt to dynamics. For instance, techniques like Dueling Double Deep Q-Network (D3QN) and Semi-Supervised Deep Neural Network (SSDNN) indicate superior performance with a detection rate of more than 90%, even under noisy conditions. The techniques are free from the need to use knowledge about the signals and are efficient to use both the labeled and the unlabeled data to train. Nevertheless, despite the noticeable progress in deep learning methods, there are problems that require further study and solution. These include the need to improve detection efficiency in difficult conditions such as high signal density and the presence of obstacles. In addition, the reliability and adaptability of algorithms to the changing conditions of the radio frequency spectrum are critical factors for creating reliable and effective cognitive radio communication systems. Thus, the use of deep learning methods

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in spectrum recognition processes is considered as a valid and promising research area that can contribute to more efficient use of limited radio frequency resources in the context of growing demand for wireless services.

IV. Conclusion

Current research confirms that using deep learning techniques to determine the spectrum opens up new possibilities for cognitive radio networks, especially in 5G/6G environments. Traditional methods suffer from a high false alarm rate and an inability to adapt to dynamic environments. In contrast, deep learning demonstrates high detection accuracy and noise tolerance, which is critically important for effective spectrum management in the face of an increasing number of devices and a shortage of frequency resources. The priority areas for modern methods are data processing speed, energy efficiency, and adaptability. However, the successful implementation of such solutions requires a balance between computational complexity and accuracy. As the article highlights, the integration of deep learning into 5G/6G systems will not only improve spectrum allocation, but also provide scalability to support the IoT. Adapting methods to specific scenarios, such as urban environments with high levels of interference or industrial networks with high latency requirements, remains a key factor.

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