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Spectrum Sensing using Machine learning in Wireless Communication: Recent Advances and Challenges

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ABSTRACT

In recent years, the heterogeneous wireless network, which can support high-density and high-rate traffic, has attracted much research interest from both academic and industry sectors. The cooperation between the macro base stations (BSs) and the femto BSs can greatly improve the quality of service (QoS) of the user equipment, as well as the spectrum efficiency and the energy efficiency. The demand for bandwidth-critical applications has stimulated the research community not only to develop new ways of communication, but also to use the existing spectrum efficiently. In this paper, we aim to provide an in-depth survey on the most recent advances in spectrum sensing techniques in cognitive radio network.

Keywords:- Wireless communication, cognitive radio network, Spectrum sensing, Orthogonal frequency-division multiplexing, Quality of service.

INRODUCTION

With the rapid advancement of wireless communication technologies and the advent of the 5G paradigm, spectrum resources have become highly scarce. As per the spectrum occupancy campaign, the overall usage of spectrum band varies from 7% to 34%, which demonstrates significant under-utilization of spectrum resources. Cognitive radio (CR) technology [3] has emerged as a potential solution to trade-off between spectrum availability and its demanding growth. It aims at reusing the temporarily unoccupied frequency bands, known as spectrum holes or white spaces, in an opportunistic manner ensuring that the licensed user does not face any interference. The licensed user in the CR network is referred to as primary user (PU) while the unlicensed user as a secondary user (SU). The underlying principle of CR is to allow the SUs to access the temporarily unoccupied licensed bands in an opportunistic and non-interfering manner [3].

Orthogonal frequency-division multiplexing (OFDM) is one of most important techniques in designing advanced wireless communications systems since it can achieve high spectral efficiency while mitigate fading/interference. Conventional wireless communications focuses on cooperative relationship since they share underlying protocol for all of users. As the fast development of wireless communications, non-cooperative communications are becoming ubiquitous in both civilian and military areas. In the non-cooperative scenarios, signal modulation identification (SMI) techniques are required to recognize different modulations of all of the received signals [2]. Most of existing techniques on modulation identification are based on feature extraction and machine learning classification algorithms. Traditional feature extraction methods are available, such as higher order cumulants (HOC), discrete wavelet transform, adaptive wavelet transform, and mixed parameters. Machine learning based classifiers are designed with k-nearest neighbor (KNN), support vector machine (SVM), decision tree (DT) and naive Bayesian.

Machine learning (ML) based approaches have recently been proposed to provide a new avenue to general spectrum sensing including that for OFDM configuration. Supervised and semi supervised learning algorithms were developed for a unchanged RF environment with fixed SNR, where the eigen values of the received signal covariance matrix are utilized as the features. Given received signal energy and likelihood ratio test statistic with different SNRs, binary classification based artificial neural network (ANN)was adopted In addition to these localized spectrum sensing methods, ML based cooperative spectrum sensing (CSS) methods were also studied in the literature [1].

CR has been introduced as a candidate to perform Dynamic Spectrum Allocation (DSA) by exploiting the free frequency bands that are called "Spectrum Holes" or "white spaces". Being capable to identify its spectral opportunities, CR classifies the users into two categories: licensed, the Primary Users (PUs) and unlicensed, the Secondary Users (SUs). The spectrum sharing between PU and SU is based on the fact that the SU should respect the PU's Quality of Service. Any harmful interference coming from SU to PU transmission is prohibited. Therefore, three paradigms of CR based on the spectrum access can be distinguished according to the possibility of co-existence of SU and PU transmissions in the same channel, the permitted transmit power of SU and the cooperation between SU and PU [7]:

1. Underlay Access: the SU may transmit in parallel with the PU on the same channel. However, the transmitted power should not exceed a certain threshold in order to limit the interference effect of SU on PU bellow a tolerable value.

2. Overlay Access: the SU may transmit simultaneously with the PU on the same channel up to its maximum power, but at the cost of playing a role of relay between two or more PUs. In this case, the SU sends its data while relaying the PUs. This kind of access requires a high level of cooperation between PU and SU that may exposes the PUs privacy and makes it discoverable by SU.

3. Interweave Access: SU is allowed to transmit on the channel only when the PU is absent. The SU can transmit up to its maximum power on the whole bandwidth. This paradigm is also known by classical CR and will be addressed by this paper given its popularity.

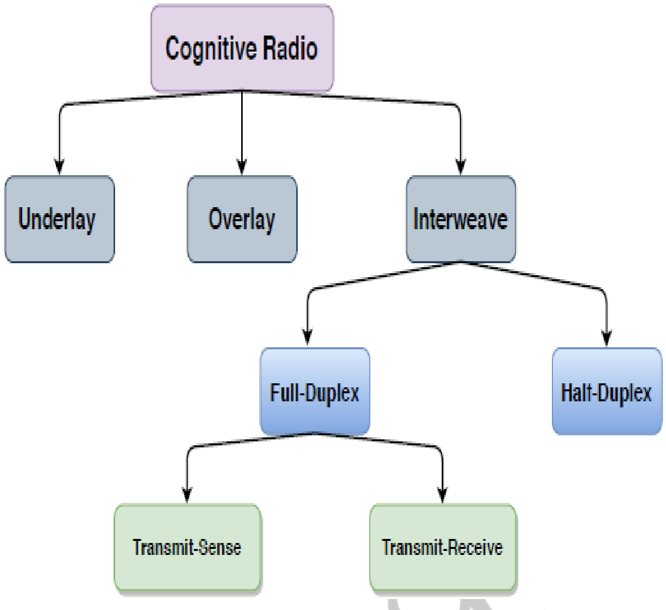

Fig. 1: The access paradigms of CR [7].

Although the main purpose of spectrum sensing is the instantaneous detection of opportunistic white spaces, the sequence of sensing decisions can be utilized to estimate the PU activity statistics and occupancy patterns. PU activity statistics include idle/busy period duration, their minimum duration, mean, higher-order moments and distribution followed by the idle/busy periods. This statistical information can be useful in the CR network to predict the future spectrum occupancy trends, schedule spectrum sensing, selection of appropriate spectrum band and channel of operation for CR system, optimize the system performance and improve the spectral efficiency.

The CR works through a cognition cycle with four functional phases which are sensing, decision, sharing, and mobility. The cognition cycle begins with SS phase through which the available spectrum resources are detected over the selected spectrum band using different SS approaches. Based on the detection results, the decision is made to concurrently share the band, or to cease transmission in that band. Once a CR decides to exploit the band, a proper Medium Access Control (MAC) protocol is employed and power allocation should be considered to satisfy the PU protection. Finally, switching from band to another is performed through the mobility phase. This work initially discusses the main design factors of CR-based IoT systems [6].

II CHALLENGES IN CR

In fact, CR is preferable in a simple and predicable radio environment. With further evolution of cellular communications to the 5G and its beyond, future wireless networks become more complicated and unpredictable than ever before [4]. As a result, CR faces the following challenges. First, with the exponential increase of communication devices (including both mobile devices and small base stations), the wireless networks in the 5G and beyond will be at large-scale with heterogeneous network typologies, which makes it costly for the CR devices to learn a complete and accurate radio environment information. Second, users may have various service demands (e.g., requests for text, audio, or video contents) with different technologies (e.g., 2G to 5G, and WiFi). In brief, the radio traffic models in the 5G and beyond are highly dynamic, which makes it difficult for CR devices to learn and predict. Third, with the visualization and cloudification of wireless networks in the 5G and beyond, multiple-dimensional resources (e.g., time, spectrum, spatial, computing, storage) at different layers (e.g., physical layer, link layer, network layer) need to be coordinated and allocated.

Traditional automatic modulation classification methods can be divided into two categories: likelihood-based methods and feature-based methods. The likelihood-based methods calculate the likelihood function of the received signal and compare it with a certain threshold to make decision. Although the likelihood-based method can minimize the error rate, its computational complexity is high, and it cannot adapt to unknown channel conditions and mismatch between transmitter and receiver (such as clock frequency deviation). The feature-based methods calculate certain features of the received signal, such as mean, standard deviation and kurtosis of the normalized centered amplitude, absolute normalized instantaneous frequency, higher order moments, higher order cumulants, cyclic moments, cyclic cumulants of the received signal. The computational complexity of these methods is relatively low, but the selection of features relies too much on manual analysis. It is very difficult to find features that can adapt to non-ideal conditions and distinguish between multiple modulation types. Therefore, automatic modulation classification is a very challenging task [9].

III RELATED WORK

The ever increasing demand for ubiquitous broadband service and massive connection has led to explosive growth in the requirement for spectrum resource. Cognitive radio, an intelligent wireless technology, opens a potential communication paradigm to achieve more efficient and flexible spectrum use. [1] This paper addresses the spectrum sensing problem in an orthogonal frequency-division multiplexing (OFDM) system based on machine learning. To adapt to signal-to-noise ratio (SNR) variations, they first formulate the sensing problem into a novel SNR-related multi-class classification problem. Then, we train a naive Bayes classifier (NBC), and propose a class-reduction assisted prediction method to reduce spectrum sensing time.

Signal modulation identification (SMI) plays a very important role in orthogonal frequency-division multiplexing (OFDM) systems. Currently, SMI methods are often implemented via feature extraction based on machine learning. However, the traditional methods encounter a bottleneck where the probability of correct classification (PCC) is very limited and hence it is hard to implement in practical OFDM systems due to the fact that traditional methods are difficult to extract feature of the OFDM signals. In order solve these problems [2] They propose a deep learning (DL) based SMI method for Identifying OFDM signals. Specifically, convolutional neural network (CNN) is adopted to train in-phase and quadrature (IQ) samples for OFDM signals. Then we choose dropout layer to prevent overfitting and improve its identification accuracy.

The cognitive radio (CR) network consists of primary users (PUs) and secondary users (SUs). The SUs in the CR network senses the spectrum band to opportunistically access the white space. Exploiting the white spaces helps to improve the spectrum efficiency. [3] In this work, a deep learning aided LSTM-SS scheme was proposed that hat implicitly learns all the important features in the time series spectrum data i.e., it exploits the temporal dependency in the spectrum data. Furthermore, they also compute the PU activity statistics like on and off period duration, duty cycle, and propose a PAS-SS scheme to enhance the sensing performance. The proposed LSTM-SS and PAS-SS schemes are evaluated and validated on empirical data of different wireless technologies captured using two test-bed setups. Results indicate that the proposed LSTM-SS has an improved detection performance and classification accuracy as compared to the ANN-based hybrid sensing scheme, IED, and CED, even under the low SNR regime.

To improve the spectrum efficiency, CR enables unlicensed usage of licensed spectrum resources. It has been regarded as the key enabler for intelligent communications. In this article [4] author will provide an overview on the intelligent communication in the past two decades to illustrate the revolution of its capability from cognition to artificial intelligence (AI). Particularly, this article starts from a comprehensive review of typical spectrum sensing and sharing, followed by the recent achievements on the AI enabled intelligent radio. Moreover, research challenges in the future intelligent communications will be discussed to show a path to the real deployment of intelligent radio. After witnessing the glorious developments of CR in the past 20 years, they try to provide readers a clear picture on how intelligent radio could be further developed to smartly utilize the limited spectrum resources as well as to optimally configure wireless devices in the future communication systems.

Different from classical wireless communication scheme, the modulation parameters in OFDM-IM scheme includes not only the signal constellation, but also the number of active subcarriers. In this paper [5] author extend FB based AMR method for OFDM-IM scheme and proposed a practical DNN based method to recognize parameters in OFDM-IM. The PCC simulations show that our proposed DNN-based method is effective for AMR in OFDM-IM, and has almost 100% the recognition accuracy when SNR is above 6dB.

Cognitive radio (CR)-based Internet of Things (IoT) system is an effective step toward a world of smart technology. Many frameworks have been proposed to build CR-based IoT systems. The CR-based IoT frameworks are the key points on which this survey focuses. Efficient spectrum sensing and sharing are the main functional components of the CR-based IoT. Reviews of recent SS and sharing approaches are presented in this survey. This survey [6] classifies the SS and sharing approaches and discusses the merits and limitations of those approaches. Moreover, this survey discusses the design factors of the CR-based IoT and the criteria by which the proper SS and access approaches are selected. Furthermore, the survey explores the integration of newly emerging technologies with the CR-based IoT systems. Finally, the survey highlights some emerging challenges and concludes with suggesting future research directions and open issues.

Channel Sensing (CS) plays an essential role in a Cognitive Radio (CR) networks to diagnose the available frequency resources. In this paper [7] author aim to provide an in-depth survey on the most recent advances in CS, covering its paradigms in Half-Duplex and Full-Duplex, while detailing the functioning modes in Full-Duplex paradigm. The recent achievements of the applications of CS for CR-based Internet of Things and Wireless Sensors Networks are also presented. Research work towards suitable protocols in addition to the Spectrum Sensing as a Service are discussed. Moreover, the adoption of the learning techniques in CS is surveyed, giving a wide view on their applications and impact on the SS performance. Future research axes and challenging points are highlighted based on the current and emerging techniques in wireless communications.

The specifications of 5G technology are currently being standardized by international regulatory agencies and they hold promise for a wide array of applications ranging from transportation to health. Testing of this standard across a matrix of specifications and applications presents a daunting challenge. To overcome this, a 5G test bed design which is based on reconfigurable components enabled by Software Defined Networks (SDNs) and Software Defined Radios (SDRs) has been presented in this paper [8]. The reconfigurable measurement hardware has been designed such that it can be integrated across all the layers of TCP/IP protocol through an open-source software defined architecture. Programmability is a key feature of this architecture, and this has been addressed by a Software Development Kit (SDK). The SDK contains pre-built IP, a baseline end to end stack implementation, and an application programming interface (API) for accessing different features of the platform.

IV CONCLUSION

With the aim of identifying the status of the licensed spectrum and enabling secondary access, spectrum sensing techniques have been extensively investigated for cognitive radio (CR) in recent years. In order to guarantee that, as little interference is generated to the primary user (PU) as possible, secondary users (SUs) in the cognitive radio network (CRN) can only gain opportunistic access to the licensed frequency band (LFB) when they detect no PU activity over it. In this paper we preview the different techniques for the spectrum sensing and their applications.

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