Research on Key Technology of Full Duplex Cognitive Radio Network

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Abstract. In traditional half duplex cognitive radio networks, secondary users can only sense the spectrum or transmit at a given time. This kind of half duplex network limits the throughput of users, because the user unit can’t transmit data in spectrum sensing. However, with the development of self-interference suppression (SIS) technology, full duplex cognitive radio network allows spectrum sensing and data transmission on a given channel at the same time. Compared with traditional half duplex network, full duplex network improves throughput and reduces conflicts. In order to explore the future development direction of spectrum sensing technology, in the context of full duplex cognitive radio, a comprehensive study of radio network is carried out, including key technologies, current challenges and future research directions.

1. Introduction
The electromagnetic spectrum usually refers to the electromagnetic wave family which is arranged continuously according to the electromagnetic wave frequency. The frequency range is generally 0 ~ 3000GHZ, which is a national rare natural resource. In order to realize the coexistence of various wireless services and avoid the interference between different services. At present, the radio frequency is divided by the radio spectrum management center, which divides different electromagnetic wave bands for different communication services. This kind of static management mode leads to the poor utilization of electromagnetic spectrum, which causes a certain waste in the space domain, time domain and frequency domain. Some measurements show that the utilization rate of electromagnetic spectrum is only 15% ~ 85% due to the traditional static allocation strategy [1].

With the increasing demand of cognitive radio networks, researchers are focusing on the dynamic spectrum sharing [2]. In cognitive radio networks, secondary users (SU) perceive the surrounding wireless environment and opportunistically access the spectrum hole for communication, thus realizing the sharing of dynamic spectrum resources and improving the utilization of electromagnetic spectrum [3-4].

The main technical difficulties of dynamic spectrum sharing lie in the discovery and utilization of spectrum opportunities. As the basis of the latter, the former is the focus of cognitive radio research. The basic way to determine the current slot spectrum state by signal detection is called spectrum sensing.

Traditional cognitive radio networks are half duplex cognitive radio networks (HD-CRN). In HD-CRN, SU divides continuous time slots into two segments, the first segment is used for spectrum sensing, and the second half is used for data transmission. This method limits the throughput of SU and increases the risk of data conflict. However, with the development of SIS technology, full duplex cognitive radio
networks (FD-CRN) allow simultaneous spectrum sensing and transmission over a given channel. Compared with HD-CRN, FD-CRN can improve network throughput and reduce data conflict.

2. Full duplex cognitive radio networks

In HD-CRN, SU uses the method of dividing time slots for spectrum discovery and spectrum opportunity utilization. This method will bring two problems: first, SU sacrifices a long period of time for spectrum sensing, which reduces the communication time and throughput. Second, SU can't sense the spectrum during data transmission. If the authorized user is also called the primary user (PU) to join the network, it will cause conflict and affect the PU communication. Secondly, SU in HD-CRN uses two independent channels to transmit and receive data. This dual channel operation not only requires more spectrum resources than a single channel, but also increases the delay due to the need to detect the spectrum of the two channels separately.

Therefore, people think whether they can complete spectrum detection and data transmission in a frequency band at the same time. This idea is considered impractical for a long time, because receiving and transmitting in the same frequency band at the same time will inevitably lead to the transmission signal looping back to the receiving antenna\cite{5}, resulting in a strong self interference (SI) of nearly 120dB\cite{6}. But in recent years, with the development of SIS technology, full duplex cognitive radio technology has become more and more feasible. Reference \cite{7-9} describes the feasibility of in band full duplex (IBFD) technology in detail, reference \cite{10-12} describes the possibility of integrating full duplex technology into cognitive radio network in detail, and reference \cite{13} proposes a cognitive radio network based on IBFD, which realizes simultaneous data transmission and spectrum sensing. The simulation results show that this solution provides enough self interference cancellation and achieves almost the same spectrum sensing accuracy as half duplex. In reference \cite{14}, the traditional half duplex cognitive radio network protocol is called listen before talk (LBT), and the protocol proposed in full duplex network is called listen and talk (LAT). The performance of cooperative spectrum sensing based on this protocol is studied, and the SU transmit power is optimized with the throughput of cognitive radio network as the optimization objective.

Using FD-CRN solves many problems in HD-CRN, as shown in Figure 1. In FD-CRN, SU can simultaneously detect spectrum and transmit data or receive and transmit data on the same idle channel in a given time period. Compared with HD-CRN, FD-CRN usually only need half of the spectrum resources \cite{15}. SU does not need to interrupt transmission for channel detection, but also reduces channel conflict and minimizes data loss. Therefore, the scheme improves the utilization of spectrum resources and the overall network capacity.

![Figure 1 Full duplex cognitive radio network model](image)

The development of self interference suppression technology stimulates the development of full duplex cognitive radio. However, SI can not be eliminated completely. For full duplex cognitive radio, the influence of residual self-interference (RSI) signal on cognition must also be considered. Reference \cite{16} studies the influence of RSI on FD-CRN, analyzes the influence of near-field spatial RSI on remote
users, and finds that the channel can well fit the fading of RSI. In full duplex cognitive radio, the signals received by cognitive users are described as

$$r(t) = h_s s(t) + h_i x(t) + n(t)$$  \(1\)

Among them, \(r(t)\) for the signals received by cognitive users, \(h_s\) for channel transmission parameters from authorized users to cognitive users, \(s(t)\) for useful signals sent by authorized users, \(h_i\) for self-interference channel transmission parameters, \(x(t)\) for self-interference signals of cognitive users, and \(n(t)\) for noise in channels.

With the development of SIS technology in recent years, in band full duplex communication becomes more and more mature. Cognitive radio technology based on IBFD communication has also developed rapidly. Compared with HD-CRN, FD-CRN have higher utilization of spectrum resources and lower conflict probability of data transmission, which opens up a new direction for the development of cognitive radio in the future.

3. Spectrum sensing

Dynamic spectrum access in full duplex cognitive radio networks mainly focuses on the following two aspects: spectrum opportunity discovery and spectrum opportunity utilization. Among them, spectrum opportunity discovery is to continuously detect the frequency band allocated to PU and detect whether the frequency band is being used by PU. Spectrum sensing is the basic way to determine the current time slot spectrum status by signal detection, which is the core technology of full duplex cognitive radio. The existing research mainly starts from signal detection, cooperative mode, data fusion and so on.

3.1. Signal detection

The early research of spectrum sensing focused on determining whether PU signal exists in current time slot and current frequency band [17]. If it is determined to exist, the current slot cannot be used by SU; if it is determined to be idle, the band can be used by SU. The above problems are usually modeled as a binary hypothesis test problem, which is solved by signal detection technology. Common signal detection technologies include matching filter detection, eigenvalue detection, energy detection, etc.

3.1.1. Matching filter detection

In the case of stationary Gaussian noise, matched filter detection is the best detection[18], which makes the performance of the filter consistent with the characteristics of the signal and maximizes the output signal-to-noise ratio. Matched filter detection belongs to coherent detection, although it can obtain good detection performance, it needs to know the prior information of the authorized user's signal, such as signal bandwidth, modulation mode, pulse waveform and so on. Reference [15] based on the system model of cognitive users using matched filter detection, the closed form solution of false alarm probability and detection probability of the full duplex matched filter is derived.

As far as the current research is concerned, the application of matched filter detection is not very extensive because it needs the prior information of PU. Moreover, in FD-CRN, the existence of RSI increases the uncertainty of the signal, so the research of spectrum sensing based on matched filter detection has not received more attention.

3.1.2. Feature detection

Feature detection refers to the use of some inherent characteristics of the PU signal for analysis, so as to achieve the effect of signal detection. Such as signal cyclostationary characteristics, correlation characteristics, wavelet characteristics, etc.

Cyclostationary feature detection can effectively distinguish between noise and PU signal by using the average value of the PU signal and the intrinsic periodicity of the autocorrelation function [19], and good detection performance can be obtained in the region of low signal-to-noise ratio (SNR). However, since the received signal must satisfy the cyclic stability in a broad sense, and the signal is strictly related
to the noise, a longer observation period is required in practical applications, which results in a large amount of data calculation and a long sensing time. In order to overcome the above shortcomings, reference [20] proposed an algorithm based on cyclic autocorrelation characteristics and Hilbert transform theory. The algorithm can change the cycle frequency and sampling times according to the current electromagnetic environment, reducing the computational complexity. Reference [21] proposed correlation detection of signal period maps, which solved the problem of low SNR but at the cost of requiring a part of PU prior information. Reference [22] proposed a covariance matrix detection, but it needs to have a strong correlation between the sampled signals. In order to solve the problem of correlation, reference [23] proposed a signal envelope spectrum sensing based on Rayleigh multipath fading channel, which turned the correlation requirement of the sampled signal to the signal envelope correlation requirement. Since the envelope of the signal has lower frequency components, it has stronger correlation with the same sampled signal.

In recent years, with the continuous improvement of software and hardware computing capabilities, deep learning has attracted extensive attention in various fields. The combination of deep learning and spectrum sensing opens up a new direction for the development of spectrum sensing, which is also the trend of future development. In reference [24], a modulation recognition pattern based on long-term and short-term memory neural network is proposed, which uses the phase and amplitude information in the training data to train the model without complex eigenvalues. In reference [25], a fully connected artificial neural network is constructed by combining the perception network of signal cyclostationary feature with the feature input layer of neural network. The algorithm does not need to preset the spectrum decision threshold, and effectively reduces the impact of noise fluctuation on the spectrum sensing performance. In reference [26], a deep learning spectrum sensing algorithm based on convolutional neural network is proposed. The algorithm does not need the probability model of signal and noise, nor the PU activity mode model. The algorithm absorbs the existing sensing data and historical sensing data at the same time. Using these data, the intrinsic activity mode of PU can be learned, which is conducive to spectrum detection.

In general, the combination of feature-based detection and deep learning has opened up a new way for the development of spectrum sensing, especially in FD-CRN. Combining the characteristics of SI, the angle and amplitude information of signal are used to distinguish PU signal and noise, which opens up a new direction for the future development of spectrum detection in FD-CRN.

3.1.3. Energy detection
Energy detection is the most widely used spectrum detection algorithm at present [27]. Energy detection algorithm, also known as power based detection algorithm, is uncorrelated detection algorithm. It does not need to know the prior knowledge of user signal. It only needs to measure the total energy of the received signal in the observation space and compare with the preset decision threshold to determine whether there is PU signal. However, its disadvantage is that it is easily affected by noise uncertainty, and its detection performance drops sharply in low SNR environment.

In order to solve the problem of poor detection performance in low SNR environment, scholars have proposed many solutions in recent years. For single user, reference [28] proposes an energy detection algorithm based on fast Fourier transform, which uses window function to retain useful spectrum information. In reference [29], an adaptive single threshold energy detection algorithm based on noise uncertainty is proposed. In reference [30], an energy detection method combining inter frame correlation is proposed. In this method, the correlation statistics parameters are added to analyze the correlation of signals between frames at different times to assist energy detection to determine the existence of PU.

In reference [31], an energy detection algorithm based on double thresholds is proposed. When the multi-user is in the middle of the two thresholds, it is unable to judge, and the detection effect is not ideal. In reference [32], an adaptive dual threshold cooperative spectrum sensing algorithm is proposed. By calculating the signal-to-noise ratio of each node, the weight is obtained, the decision threshold is adjusted, the current decision result is fully connected with the front and back time, and the final decision result is obtained by fusing the decision information of each node. A zero crossing double threshold
cooperative spectrum sensing algorithm is proposed in reference [33]. The influence of the number of cognitive users, the number of sampling points used in calculation, different SNR and decision coefficient on the detection probability is studied. In reference [34], a sequential cooperative spectrum sensing algorithm based on dynamic adaptive double threshold energy detection is proposed. In order to optimize the detection probability, the dynamic adaptive double threshold model of cooperative users is established by sequential method, and the received energy value between the two thresholds is determined by soft decision.

Energy detection algorithm, with its small amount of calculation and simple implementation, has become the most widely used detection algorithm in spectrum sensing. Especially the energy detection algorithm based on double threshold has been widely used in multi-user cooperative spectrum sensing. At present, it is the improvement of double threshold energy detection algorithm. One of the research directions is the adaptive double threshold detection algorithm, especially the combination with deep learning and other machine learning algorithms to improve the traditional energy detection algorithm.

3.2. Collaboration mode
The problems of random noise, fading, shadow and hidden terminal in wireless channel bring severe challenges to single user spectrum sensing technology, and promote the development of multi-user cooperative spectrum sensing (CSS) technology. In cooperative spectrum sensing, spectrum information is exchanged between sensing nodes (SN) [35]. According to the different ways of interaction between SN, CSS is divided into centralized and distributed.

3.2.1. Centralized collaboration
In centralized cooperative spectrum sensing, there is a fusion centre (FC), and each SU acts as a sensing node to upload its sensing data to FC. FC collects all the information and determines whether there is PU in the channel according to a certain data fusion algorithm. Due to the existence of FC, the centralized cooperative spectrum sensing can control the detection nodes globally, which makes it easier to optimize the overall situation and improves the reliability of detection. It is mainly used for centralized access network with base station or central access point, such as cellular mobile network, WLAN, etc.

Reference [36] studies the cooperative spectrum sensing model in cellular networks, which works in full duplex mode and solves the SI problem through a passive propagation SIS technology. Reference [37] proposed a CSS method to resist malicious nodes. In LAT model, this method reduces SI interference, improves detection probability and robustness to bad nodes.

3.2.2. Distributed collaboration
In distributed cooperative spectrum sensing, the sensing nodes fuse the local and adjacent borrow points to make judgment, so this cooperative method is more conducive to the self-organization of the network and has higher flexibility. It is applicable to the distributed network without centre, such as wireless sensor network, wireless multi hop network, etc.

Reference [38] evaluated the throughput of CSS network under LAT protocol and LBT protocol. Compared with LBT protocol, the throughput of LAT protocol is greatly improved. In reference [39], a distributed relay cooperation is proposed, which is beneficial for some hidden nodes to send data. It is analyzed that cognitive radio network has greater throughput in FD-CRN.

CSS is a multi-user cooperative detection, and the detection reliability is higher than that of single user. In FD-CRN, CSS can help users to improve the throughput. However, from the current research point of view, most of the current research assume that the collaborative environment is a narrow and isomorphic spectrum environment, and the research on heterogeneous spectrum environment is less. In the actual heterogeneous spectrum environment, RSI will also interfere with sensing nodes except itself.
3.3. Data fusion
The information of different sensing nodes is fused through the formula, as shown in Figure 2. The data fusion centre uses the fused results for hypothesis testing. According to the types of fusion data, there are mainly hard value fusion [40], soft value fusion [41] and multi bit quantization value fusion [42].

3.3.1. Hard value fusion
Hard value fusion is that the sensing node sends 1-bit sensing result to FC, and FC uses common and, or, K-out-of-N fusion criteria to make decisions. In reference [43], an algorithm is proposed to obtain the optimal sensing time and K value for k-out-of-N fusion rules with the network throughput as the optimization objective. In reference [44], a decision fusion rule based on weight is proposed, in which the local decision results of each sensing node are given weight as the global decision statistics.

At present, there are many methods to discuss the parameter optimization and performance improvement of hard value fusion, but the secure and reliable data fusion under malicious attacks is the focus of future attention.

3.3.2. Soft value fusion
FC receives the complete sensing results of sensing nodes, and uses a variety of fusion algorithms for merging, including equal gain merging algorithm, selection merging algorithm and maximum ratio merging algorithm, which is a kind of linear weighted fusion algorithm [45]. In reference [46], a soft decision cooperative spectrum sensing method based on dynamic threshold is proposed, in which the received signal energy is used to estimate the noise uncertainty factor to dynamically update the global decision threshold.

At present, the algorithm based on soft value fusion mainly uses the means of energy detection, but the research on other detection means is less, and the research on data fusion of different types of detectors is also less.

3.3.3. Quantitative value fusion
The so-called quantization value fusion is compared with soft data fusion. Quantization value fusion does not need to transmit the complete sensing data to FC as soft data fusion, only the perceived results need to be quantified into multiple bits, which reduces the cost of channel resources.

In reference [47], a multi bit quantization CSS method based on NP fusion criterion is proposed, and the lower bound of PU signal detection probability is given. In reference [48], a quantization fusion principle based on confidence level is proposed, and the confidence is obtained by using fuzzy logic function. The optimal quantization threshold is obtained by maximizing the detection probability of the whole set. Reference [49] quantifies the results of energy sensing, analyzes and discusses the problem of data fusion based on quantization in the control channel with errors, compares different data fusion criteria in cooperative spectrum sensing, and compares the quantization parameters and data fusion methods for joint optimization.
At present, CSS based on quantization value fusion mainly uses uniform quantization algorithm to quantify the energy detection results, and further models the optimization objectives such as system throughput and detection probability as the quantization threshold function, and solves the function to obtain the quantization threshold. However, there are few researches on the optimization of fusion decision and the joint optimization of multiple fusion algorithms.

4. Future research focus
From detection based on signal energy to detection based on other features. In FD-CRN, the main research of spectrum detection focuses on energy detection. However, the application of other signal features, such as angle and amplitude information, to spectrum detection in FD-CRN network is not deep enough.

From homogeneous spectrum environment to heterogeneous spectrum environment. In the current CSS research, most of the users are in a relatively small space area, and all users in the area are faced with the same spectrum environment and access opportunities. However, in terms of the current network environment, with the development of Internet of things and cellular mobile network, sensing users in different locations are facing heterogeneous spectrum environment and access opportunities, and the traditional data fusion theory is not applicable.

From ideal spectrum sensing to more secure spectrum sensing. At present, in the research of cooperative spectrum sensing algorithm, all the data considered are ideal data, but there are actually malicious spectrum sensing nodes falsifying local sensing data to mislead the global fusion decision. How to obtain the user diversity gain and improve the security and confidentiality of perception is the focus of future research.

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