Research on Cooperative Spectrum Sensing Algorithm

Yu Gao[1], Xin-Lin Huang[1(✉)], Si-Yue Sun[2], Xiaowei Tang[1], and Yuan Xu[1]

[1] The Department of Information and Communication Engineering, Tongji University, Shanghai 201804, People's Republic of China
{2459461554,962080229,2604952900}@qq.com, xlhuang@tongji.edu.cn

[2] Shanghai Engineering Center for Micro-Satellites, Shanghai, People's Republic of China
sunmissmoon@163.com

Abstract. The rapid development of wireless communication brings us convenience as well as scarcity of radio spectrum resources. Hence, scientists proposed cognitive radio technology to solve this problem. Spectrum sensing is a pivotal technology protecting primary users from interference of secondary users in cognitive radio, and can be achieved by different algorithms which will result in different performances. In this paper an original cooperative broadband spectrum sensing algorithm based on undersampling is proposed to reduce the hardware overhead as well as satisfying the requirement of system performance. The proposed cooperative spectrum sensing algorithm will use undersampling technology in the secondary user in order to save costs and reduce hardware overhead. On this premise, in the process of information transmission, the algorithm have adopted a method which is similar to VOFDM for signal transmission in the channel between secondary users and fusion center, so that the system can overcome the intersymbol interference caused by broadband signal and rebuild the state of primary users in the fusion center. The simulation results shows that the performance of proposed algorithm is similar to the traditional single-node spectrum sensing algorithm and "or" decision algorithm, however, worse than "and" decision algorithm. The performance loss is acceptable considering its effect of reducing hardware overhead.

Keywords: Cognitive radio · Cooperative spectrum sensing · Undersampling · Vector orthogonal frequency-division multiplexing

1 Introduction

With the development of wireless communication, wireless communication network becomes an indispensable part in our society, followed by the popularity of wireless access equipment and the increase of wireless service and applications. It is merited that such a development is limited by the lack of wireless spectrum resources.

Recent years a wireless communication technology named cognitive radio is proposed by Dr. Joseph Mitola to solve the problem mentioned above. Cognitive radio can

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continuously detects the channels, makes a decision of PU's existence, and finally access the idle spectrum opportunistically by using Radio Knowledge Representation Language (RKRL) [1]. In this paper the spectrum sensing part will be researched.

The current spectrum sensing technology is a PU detection technology in receivers, thus according to the number of receivers, it can be divided into single-point spectrum sensing and cooperative spectrum sensing. The computer complexity of single-point spectrum sensing is low, thus it can be easily realized. However, for its limited sensing data, the accuracy of single-point spectrum sensing is worse than that of cooperative spectrum sensing. For these reasons, single-point spectrum sensing is gradually replaced by cooperative spectrum sensing [2, 3].

In real applications, the centralized sensing model (see Fig. 1) is the most common of cooperative spectrum sensing models [4–7]. The network of centralized sensing model consists of many SUs and a fusion center (FC), which can gather SUs' sensing data, make a comprehensive decision and broadcast such spectrum decision to all SUs. Centralized sensing model has high real-time performance, although it requires a powerful computation ability.

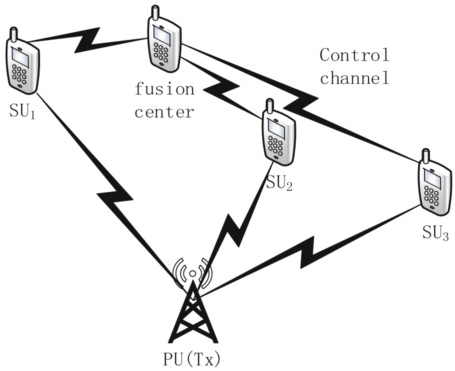

Fig. 1. Centralized sensing model

The current spectrum sensing technology is continuing to mature with the developing requirement of hardware, especially the growing high frequency at which SUs sample the target signal. To reduce the cost of receivers, a cooperative spectrum sensing algorithm based on undersampling is proposed in this paper. As the name implies, an undersampling strategy is used in SUs' receivers, on that premise, a technology similar to vector orthogonal frequency division multiplexing (VOFDM) is applied in fusion stage to restore the primeval signals.

The main contributions of this paper are as followings:

(1) The SUs of the proposed algorithm adopt an undersampling strategy to obtain the sensing data. The time of all the SUs must be synchronized so that the symbols of each time slot can be obtained by a SU.
(2) VOFDM is used in data fusion stage of the proposed algorithm to reduce the transmit distortion of broadband signals.

2 Cooperative Spectrum Sensing

2.1 Cooperative Spectrum Sensing Process

Cooperative spectrum sensing is coordinated by cognitive radio base station (CRBS), and it is assumed that all the SUs involved in cooperative sensing have the same spectrum state so that the decision made by FC is suitable for all these SUs. In real applications, however, the SUs are too decentralized to regard as sharing the same state, thus a clustering cognitive radio network is proposed (see Fig. 2), where the SUs is divided into many clusters according to geographic condition, distance and other factors and each cluster has a cluster head (CH) to control the sensing process. The SUs within a cluster can be consider sharing the same spectrum state, which can not only solve the problem that the spectrum decision of the FC is not consistent with the practical spectrum state of the SUs, but also reduce the energy consumption of multi-hop sensing information transmission to FC.

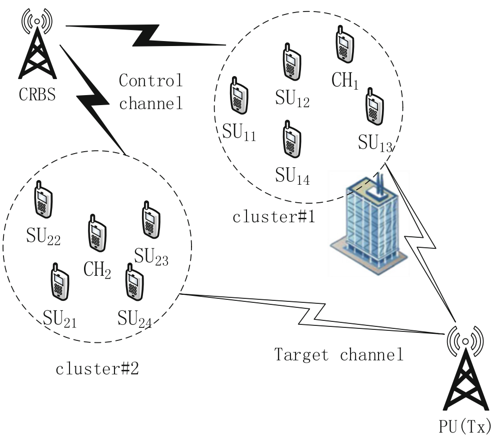

Fig. 2. The clustering cognitive radio network

After observing the target channel in a sensing period, SUs within a cluster will transmit the sensing information to CH. CH will make a locally spectrum decision about current channel state using data fusion algorithm, and broadcast the spectrum decision to SUs within the cluster through control channel. The data fusion algorithms will be discussed next.

2.2 Data Fusion Algorithms

It is mentioned above that the centralized sensing model is the most common of cooperative spectrum sensing models, and in centralized sensing model the FC would make the spectrum decision of PU's state based on SUs' sensing data. Such a decision must be made by using data fusion algorithms. Data fusion algorithms can be divided into three types according to the size of SUs' sensing data and the requirement of control channel bandwidth [8], which are as follows.

Soft combining. If the control channel bandwidth is wide, SUs will send the sensing data completely to FC, such a process is called as soft combining. Equal gain combining, Maximum likelihood ratio combining and selection combining are all belong to soft combining.

Hard combining. Hard combining is a multiple-step decision under a narrow control channel bandwidth, where SUs will make a decision of sensing data respectively and send the 1bit decision results to FC to reduce the channel overhead. The commonly used algorithms, 'and' decision, 'or' decision and 'majority' decision, are all hard combining algorithm. In 'or' decision, the FU will consider PU existing as long as there is one SU decision that the channel is occupied by PU. In 'and' decision, the FU will consider PU existing only if all the SUs decide that the channel is occupied by PU. The 'majority' decision is a compromise of the above two algorithm that the FU will consider PU existing when more than half of the SUs decide that the channel is occupied by PU. All in all, those algorithm can be reduced to 'k out of N' algorithm, where the FU will consider PU existing when more than k SUs of the all N SUs decide that the channel is occupied by PU [9]. The false alarm probability Q_f and the detection probability Q_d of 'k out of N' algorithm can be represented as:

$$Q_f = P\{H_0|H_1\} = \sum_{l=k}^{n} \binom{n}{l} P_f^l \left(1 - P_f\right)^{n-l} \tag{1}$$

$$Q_d = P\{H_1|H_1\} = \sum_{l=k}^{n} \binom{n}{l} P_d^l (1 - P_d)^{n-l} \tag{2}$$

where H_0 stands for the circumstance that PU is turned of and H_1 stand for the circumstance of the target channel is occupied by PU. P_f and P_d are the false alarm probability and the detection probability of a SU. Obviously, when k separately equals to 1, n and n/2, 'k out of N' algorithm would become 'and' decision, 'or' decision and 'majority' decision algorithm.

Softened hard combining. In the practical application of cooperative spectrum sensing network, the reliability of different SUs may be different under the effects of complex conditions. Thus the softened hard combining is proposed, where the SUs send a reliability parameter α (i.e., the weight of each decision result) as well as the 1bit decision results to FC to improve the performance of spectrum sensing decision.

3 Cooperative Spectrum Sensing Algorithm Based on Under-Sampling

According to the Nyquist Sampling Theorem, the sampling frequency of receivers must be greater than or equal to twice of the maximum signal frequency (i.e., $f_s \geq 2f_H$), otherwise, the spectrum aliasing will occur and the original signal will be unable to restore completely. In practical applications, the sampling frequency of receivers may be set as 4 to 10 times of the maximum signal frequency.

However, the higher the sampling frequency is, the more expensive the receivers are. Thus high sampling frequency brings us accuracy as well as huge cost. On the one hand, the low frequency samplers can be used to percept the high frequency signal in spectrum sensing system under the condition of undemanding accuracy requirement, the price of which is just lossy restore. On the other hand, the sample frequency of SUs may be limited by hardware devices. The spectrum aliasing will happen while the target channel bandwidth is wide. Thus the original signal has to be restored under a low sample frequency, which is called undersampling. In this section, a cooperative broadband spectrum sensing algorithm based on undersampling is proposed, and the algorithm is divided into two stages: SUs undersampling and sensing data fusion. The details will be discussed below.

3.1 SUs Undersampling

The first stage of cooperative broadband spectrum sensing algorithm based on undersampling is SUs undersampling. In traditional cognitive radio network, the high frequency sampling is adopted in SUs receivers. Moreover, all the SUs receivers adopt uniform and periodic sampling, i.e., the entire channel signal is gathered in each SU. It is assumed that each SU needs to gather M data in unit time to meet the requirement of perception precision, those data can be represented as:

$$Y_n = (y_{n,0}, y_{n,1}, \ldots, y_{n,M-1}), \qquad n = 0, 1, \ldots, N-1 \tag{3}$$

where Y_n is the sensing data of the nth SU, and N is the number of SUs in a cluster. The initial state of the M data can be represented as,

$$X = (x_0, x_1, \ldots, x_{M-1}) \tag{4}$$

As shown in Eqs. (3) and (4), x_k is the PU state and $y_{n,k}$ is the PU decision state decided by the nth SU. Both of x_k and $y_{n,k}$ can be represented by {0,1}, “0” represents that the channel is idle and “1” represents that the channel is occupied by PU. The final PU decision state y_k will be made by FC according to data fusion algorithm and $y_{n,k}$.

However, in the proposed algorithm, it is assumed that there are N SUs and each of them needs to gather K data in unit time (i.e., $M = NK$) and the Eq. (4) can be rewritten as $X = (x_0, x_1, \ldots, x_{NK-1})$. The sensing data of each SU can be represented as:

$$Y_n = (y_n, y_{N+n}, y_{2N+n} \ldots, y_{(K-1)N+n}), \qquad n = 0, 1, \ldots, N-1 \tag{5}$$

As shown in Eq. (5), the SUs are sampling the target channel alternately (see Fig. 3), and obviously the time synchronism of SUs must be accurate.

From Fig. 3, we can conclude that in the proposed cooperative spectrum sensing algorithm each time slot has only one sensing data instead of N sensing data in traditional cooperative spectrum sensing algorithm. Moreover, the SUs will gather all

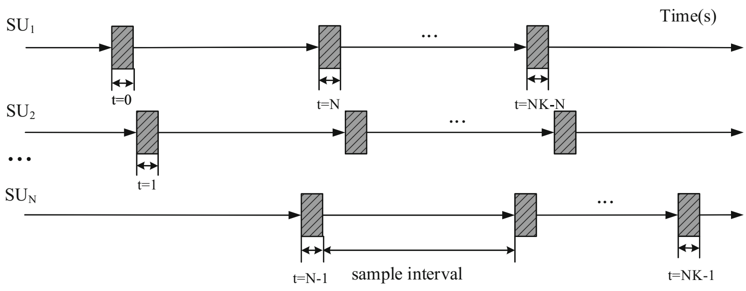

Fig. 3. Sampling process of the proposed algorithm

the K data, modulate these data, and finally send all the decision results simultaneously to the FC. Such a process will be shown in the next subsection.

3.2 Sensing Data Fusion

In the proposed algorithm, the steps of data fusion stage are similar to the multiple-input multiple-output vector orthogonal frequency division multiplexing (MIMO-VOFDM) technology [10], which is shown in Fig. 4.

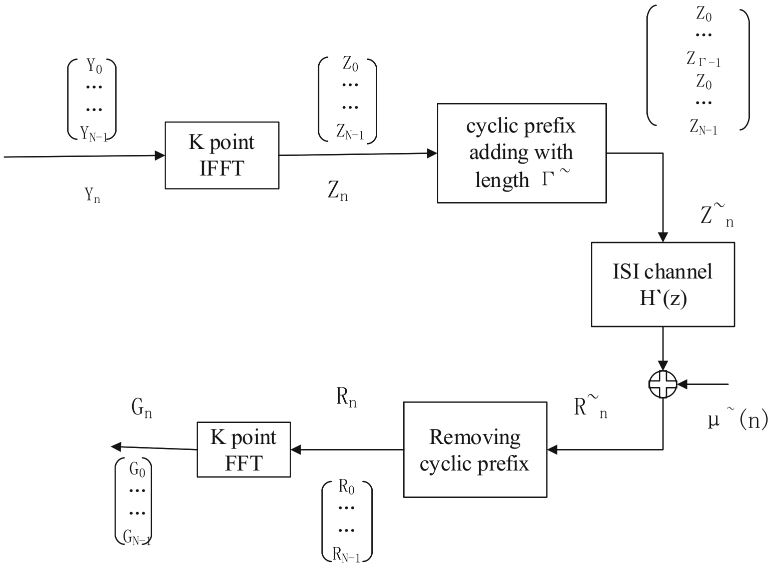

Fig. 4. The data fusion process of the proposed algorithm

In VOFDM, the modulation system of transmitter is inverse fast Fourier transform (IFFT) and the demodulation system of receiver is fast Fourier transform (FFT), such modulate and demodulate way can be used in the proposed algorithm. The transition symbols can be represented as,

$$\begin{pmatrix} y_0 & y_N & \cdots & y_{(K-1)N} \\ y_1 & y_{N+1} & \cdots & y_{(K-1)N+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_{N-1} & y_{2N-1} & \cdots & y_{KN-1} \end{pmatrix} \tag{6}$$

The K elements of the nth line in Eq. (6) is the received symbols of the nth SU, and in the transmitter of each SU, those K symbols are transformed into K new symbols by IFFT. Then the K new symbols will be transmitted in K different subchannels respectively (each subchannel has N symbols in it), just as VOFDM does. The K new symbols $Z(n)$ can be represented as:

$$Z_k(n) = \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} Y_n(k) \exp(\frac{j2\pi nk}{K}) \qquad k = 1, 2, \ldots, K-1 \tag{7}$$

Equation (7) is the formula of IFFT, where $Z_k(n)$ stands for the nth signal of the kth subchannel.

Due to the ISI channel, cyclic prefix must be inserted before Z_k, here we insert the first $\tilde{\Gamma}$ elements of Z_k before Z_k (or we can insert the last $\tilde{\Gamma}$ elements of Z_k before Z_k). The symbols after insertion $\hat{Z}_k$ can be represented as:

$$\hat{Z}_k = (Z_k(0), Z_k(1), \ldots, Z_k(\tilde{\Gamma} - 1), Z_k(0), Z_k(1), \ldots, Z_k(N-1)) \tag{8}$$

where the length of cyclic prefix $\tilde{\Gamma} \geq [L/N]$ for the purpose of removing the ISI, and L is the order of channel transfer function $H(z)$ ($H(z) = \sum_{n=0}^{L} h(n) z^{-n}$).

For simplicity, the channel transfer function is assumed known. According to [10], the transfer function $H(z)$ can be rewritten as:

$$\bar{H}(z) = \begin{bmatrix} h_0(z) & z^{-1}h_{K-1}(z) & \cdots & z^{-1}h_1(z) \\ h_1(z) & h_0(z) & \cdots & z^{-1}h_2(z) \\ \vdots & \vdots & \vdots & \vdots \\ h_{K-2}(z) & h_{K-3}(z) & \cdots & z^{-1}h_{K-1}(z) \\ h_{K-1}(z) & h_{K-2}(z) & \cdots & h_0(z) \end{bmatrix} \tag{9}$$

where $h_k(z)$ is the kth polynomial of $H(z)$, which can be represented as:

$$h_k(z) = \sum_l h(Kl + k) z^{-l}, \qquad k = 0, 1, \ldots, K-1 \tag{10}$$

And the relationship between the transfer information symbol of the kth subchannel $\hat{Z}_k$ and the received signal of the kth subchannel R_k can be formulated as:

$$R_k = \bar{H}_k \hat{Z}_k + \tilde{\xi}_k, \qquad k = 0, 1, \ldots, K-1 \tag{11}$$

where $\bar{H}_k = \bar{H}(z)|_{z=\exp(j2\pi k/N)}$, $k = 0, 1, \ldots, K-1$, and $\tilde{\xi}_k$ is the FFT of the additive noise $\xi(n)$ and therefore has the same statistics as $\xi(n)$.

After passing through the ISI channel, the received signal needs to remove the cyclic prefix. The signal after removing cyclic prefix can be represented as:

$$\hat{R}_k = (R_k(0), R_k(1), \ldots, R_k(N-1)) \qquad k = 0, 1, \ldots, N-1 \tag{12}$$

And finally all of the $\hat{R}_k$ need to be demodulated at the receiver by K point FFT, which can be represented as:

$$G_n(k) = \frac{1}{\sqrt{K}} \sum_{l=0}^{K-1} \hat{R}_l(k) \exp\left(\frac{-j2\pi nl}{K}\right), \qquad n = 0, 1, \ldots, K-1 \tag{13}$$

where G_n is the reduced signal of Y_n, and after a parallel-to-serial transform process, we can get the spectrum decision of PU.

4 Simulation

In this section the feasibility and performance of proposed algorithm will be evaluated through comparing with "and" decision algorithm, "or" decision algorithm and single-point sensing algorithm. Please note that the noise power is assumed 10 mW and the SU number is assumed 5. The sensing data are observed in the durations of sensing period.

The performance of spectrum sensing algorithm can be measured by detection probability and false alarm probability. Three different spectrum sensing cases are considered, and the simulation results are plotted in Figs. 5, 6 and 7. In Fig. 5, the number of SUs is set to 5 and the SNR of received signals are set to 5 dB. In Fig. 6, the number of SUs is set to 5 and the SNR of received signals are set to 0 dB. In Fig. 7, the number of SUs is set to 5 and the SNR of received signals are set to -5 dB. We can draw a conclusion from Figs. 5, 6 and 7 that the performance of the proposed algorithm is almost the same as that of "or" decision algorithm and single-point sensing algorithm, and a little poorer that the performance of "and" decision algorithm. Considering its effect of reducing hardware overhead, such a performance loss is acceptable.

In Fig. 8, the SNR-BER performance curve of the proposed algorithm is plotted. It is shown that the BER is reducing with the increasing of SNR, and when SNR is 5 dB, the BER is $10^{-0.6}$(0.25), which means the proposed algorithm had better be used in high SNR cases.

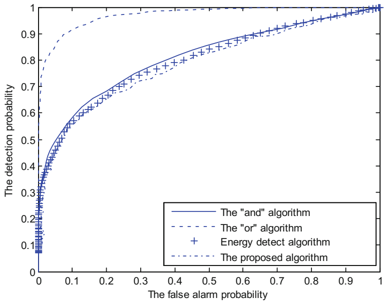

Fig. 5. Spectrum sensing performance comparisons under channel SNRs = 5 dB.

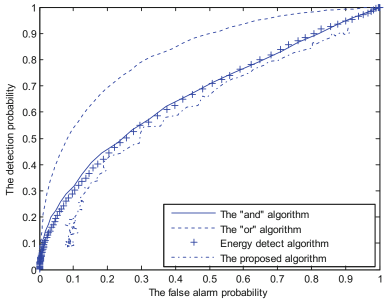

Fig. 6. Spectrum sensing performance comparisons under channel SNRs = 0 dB.

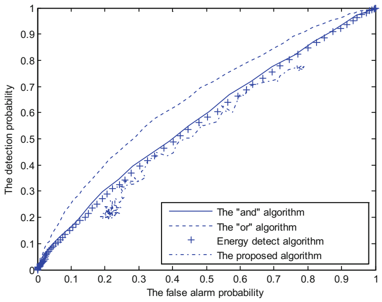

Fig. 7. Spectrum sensing performance comparisons under channel SNRs = −5 dB.

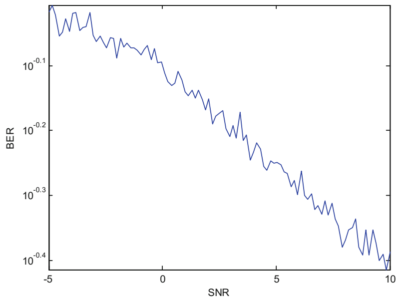

Fig. 8. Performance curve of the proposed algorithm.

5 Conclusion

In this paper, a cooperative spectrum sensing algorithm based on undersampling has been proposed. In the proposed cooperative spectrum sensing network, the undersampling technology is used in SUs to save costs and reduce hardware overhead. Then, the algorithm have adopted a method which is similar to VOFDM for signal transmission in the channel between secondary users and fusion center, so that the system can overcome the intersymbol interference caused by broadband signal and rebuild the state of primary users in the fusion center. Under three different channel SNR cases, the simulation results show that the performance of proposed algorithm is similar to the traditional single-node spectrum sensing and the “or” decision algorithm, however, worse than “and” decision algorithm. The performance loss is acceptable considering its effect of reducing hardware overhead.

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