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Performance of Cyclostationary Features Based Spectrum Sensing Method in A Multiple Antenna Cognitive Radio System

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Abstract— **In this paper, spectrum sensing methods in a multiple antenna cognitive radio (CR) system are discussed. We firstly present a simplified cyclostationary features based detector for single antenna, with relatively low computation complexity compared to traditional cyclostationary feature detection method. In order to achieve better signal detection performance in low SNR regions where the cyclostationary features are overwhelmed by strong noise, we resort to multiple antenna technique. We then propose three signal detection methods for multiple antenna scheme, namely maximum ratio combination method, multiple decision result fusion method and comparison detection method, which are motivated by MIMO techniques and structure characteristic of spectral correlation function estimation. The simulation results show the performance improvement of signal detection obtained by utilizing the three proposed multiple antenna processing methods, in terms of detection probability.**

I. Introduction

Wireless communication technology has enjoyed remarkable development in past few years, leading to the explosion of wireless applications. The dramatic increase in the demand of additional spectrum resource makes the spectrum scarcity become a conspicuous problem. Spectrum is inherently a limited natural resource, hence the access to which is regulated by governments. In traditional spectrum management systems, frequency bands are statically assigned to specific users. With most of the spectrum has been allocated, it is hard to provide vacant bands for new coming users or services. However, according to the recent report published by Spectrum Policy Task Force (SPTF) within Federal Communications Commission (FCC), most of the spectrum are under-utilized for significant periods of time [1]. It indicates that the scarcity of spectrum is mainly due to inefficient spectrum allocation, rather than physical spectrum inadequacy, which limits the potential of spectrum utilization. Therefore, the technology of cognitive radio (CR) was proposed in order to implement efficient spectrum utilization [2], [3].

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CR technology introduces the concept of dynamic spectrum allocation, which allows the unauthorized users (secondary users) to share the spectrum originally assigned to the authorized users (primary users). In CR regulations, primary users have a higher priority than secondary users. Therefore, the share of spectrum resource is based on the premise that secondary users should not cause harmful interference to primary users.

Restrained by these regulations, secondary users have to employ some spectrum sensing methods to identify whether the primary users are present or not, so as to ensure the quality-of-service (QoS) of primary users and exploit the chances of dynamic spectrum sharing for the secondary users. That is to say, spectrum sensing is the fundamental task in CR networks. Several spectrum sensing methods have been proposed so far, e.g. matched filter, energy detector, and cyclostationary feature detection [4]. Matched filter can achieve the best performance, however it requires the secondary users to have a prior knowledge of the signals sent by primary users, which makes it not fit for practical use since plenty of information of various signal classes need to be stored. Energy detector is a relatively simple one, which does not require prior information of signals, and is easy to be implemented. However, an energy detector's performance in low SNR areas is not satisfactory, where the strong noise and interference diminish the implementation simplicity of the detector. Cyclostationary feature detection, which detects the signal by exploiting the cyclostationary feature in signals, provides an alternative way for spectrum sensing. By employing Spectral Correlation Function (SCF) in sensing process, cyclostationary feature detection can obtain a satisfactory sensing result even in low SNR regions, since the cyclostationary features embedded in man-made signals are not so sensitive to noise. But at the same time, in extremely low SNR regions, the cyclostationary features would be overwhelmed by strong noise [5]. In this paper, we in particular focus on seeking for solutions to this problem.

Due to fading and interference of the channel, signals detected by the secondary users could be very weak, hence it is hard to obtain a reliable spectrum sensing result, especially

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in low SNR regions. In order to solve this problem, we resort to the MIMO technology. MIMO is designed to combat channel fading and improve receiver performance through various diversity methods, which illuminates us to apply such technology to spectrum sensing issue, in that the precision of spectrum sensing is influenced by the same factors as well. We first propose a simplified single antenna detector based on the theory of cyclostationary feature detection and spectral correlation function, with relatively lower computation complexity. We then propose three detection methods utilizing the benefit of multiple antennas, which are proved by simulation to have more accurate sensing results than that when only single antenna is present.

The rest of this paper is organized as follows. In Section II, we will describe the theoretical background of original cyclostationary feature detection method for single antenna which based on SCF calculation, and propose a simplified version of such method with lower computation complexity. In Section III, we elaborate three spectrum sensing methods for multiple antenna systems. In Section IV we present the simulation results and finally we conclude the whole paper in Section V.

II. Cyclostationary Feature Analysis

A. Theoretical Background

In general, modulated signals are considered to be cyclostationary random processes since such signals used in communication are coupled with sine wave carriers, hoping sequences, pulse trains or cyclic prefixes which result in built-in periodicity. The underlying cyclostationary features of modulated signals can bring benefits to signal identification and classification, for instance.

A signal $x(t)$ is considered to be cyclostationary in wide sense if its mean and autocorrelation exhibit periodicity as follows:

$$m_x(t + T_0) = m_x(t) \tag{1}$$

$$R_x(t + T_0, u + T_0) = R_x(t, u) \tag{2}$$

where the period of mean and autocorrelation is T_0. If we replace t and u in (2) with $t + \tau/2$ and $t - \tau/2$, i.e. $R_x(t + \tau/2, t - \tau/2)$, we can further express (2) in Fourier series as [6]

$$R_x(t + \tau/2, t - \tau/2) = \sum_{\alpha} R_x^{\alpha}(\tau) e^{j2\pi\alpha t} \tag{3}$$

where $R_x^{\alpha}(\tau)$ denotes the Cyclic Autocorrelation (CA) function and α denotes the cyclic frequency. The CA can be obtained by

$$R_x^{\alpha}(\tau) = \frac{1}{T} \int_{-1/T}^{1/T} R_x(t + \tau/2, t - \tau/2) e^{-j2\pi\alpha t} dt \tag{4}$$

The Fourier transform of the cyclic autocorrelation function is defined as the Cyclic Spectral Density (CSD) function, given by

$$S_x^{\alpha}(f) = \int_{-\infty}^{\infty} R_x^{\alpha}(\tau) e^{-j2\pi f\tau} d\tau \tag{5}$$

This function is also named as Spectral Correlation Function (SCF). SCF can be measured by the normalized correlation between two spectral components of $x(t)$ at frequencies $(f + \alpha/2)$ and $(f - \alpha/2)$ over an interval of length Δt. Thus the ideal measurement of SCF can be express as follows:

$$S_x^{\alpha}(f) = \lim_{T\to\infty} \lim_{\Delta t\to\infty} \int_{-\Delta t/2}^{\Delta t/2} \frac{1}{T} X_T(t, f + \alpha/2) X_T^*(t, f - \alpha/2) dt \tag{6}$$

where finite time Fourier transform of $x(t)$ is defined as

$$X_T(t, f) \triangleq \int_{t-T/2}^{t+T/2} x(u) e^{-j2\pi f u} du \tag{7}$$

It can be seen from (6) that the Power Spectrum Density (PSD) is the special case of spectral correlation function for $\alpha = 0$. SCF provides us a richer domain for detection of cyclostationary signals, while it performs especially well when trying to distinct cyclostationary signals from noise [7]. Noise is stationary process, thus its SCF, i.e. $S_N^{\alpha}(f)$ equals to zero for all $\alpha \neq 0$. Since cyclostationary signals have peaks in certain positions of SCF diagrams, we can benefit a lot from the spectral correlation characteristic of noise mentioned above for deciding whether certain cyclostationary signals are present. However, it requires sufficient high computation complexity for obtaining a reliable SCF estimation, which will result in an unaffordable sensing time so that secondary users may lose spectrum sharing opportunities [7], [8]. In order to reduce the computation complexity of cyclostationary feature detection method and reserve its advantage for signal detection, we propose a simplified estimation method based on cyclostationary feature detection and spectral correlation function.

B. Simplified Cyclostationary Features Based Estimation Method

The ideal SCF estimation includes all the information of frequency domain and cyclic domain, thus results in high computation complexity and long sensing time. However, consider a bandpass modulated signal with lowest frequency b and highest frequency B, the non-zero magnitude regions of its SCF estimation are limited in the four shaded areas as shown in Fig. 1 [8]. Therefore, we can only estimate its SCF in these areas. Moreover, since we can not precisely locate the four supported areas for different signals, while notice that the axis of zero spectral frequency and axis of zero cyclic frequency cross the main parts of the four areas, we will only carry out SCF estimation on these two axes. In other words, we will only calculate the values of $S_x^{\alpha}(0)$ and $S_x^{0}(f)$, where the latter one is actually the power spectrum density. Such simplified estimation method can be supported by [7], [8], the figures in which show that peak values of SCF estimation of different modulated signals mainly occur on the two axes mentioned above, hence the simplified method reserves the main useful information of SCF estimation. By applying this method in spectrum sensing, the computation time is obviously reduced compared to original SCF estimation method.

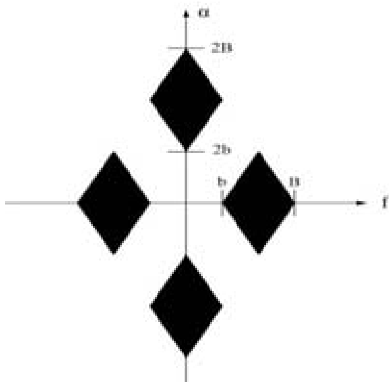

Fig. 1. Support regions of SCF estimation for bandpass signal with lowest frequency b and highest frequency B.

C. Basic Detector For Single Antenna

Traditional SCF estimation results are given by showing figures, one can decide whether the signal is present by observing the peak values on the figures. In order to explain our detection methods mathematically in detection probabilities and false alarm rates, we define our *basic detector* for single antenna in the following.

In this paper, we consider a simple signal model as follows:

$$y(t) = x(t) + n(t) \tag{8}$$

where $n(t)$ denotes additive zero-mean white Gaussian noise (AWGN). First, the threshold of zero spectral frequency axis and zero cyclic frequency axis are calculated respectively when no signal is present, i.e. $y(t) = n(t)$:

$$TH_\alpha = \frac{\max(S_y^\alpha(0))}{(\sum_{\alpha=-N/2}^{N/2-1} S_y^\alpha(0))/N} \tag{9}$$

$$TH_f = \frac{\max(S_y^0(f))}{(\sum_{f=-M/2}^{M/2-1} S_y^0(f))/M} \tag{10}$$

where TH_α and TH_f denote the threshold of zero spectral frequency axis and zero cyclic frequency axis respectively, N and M denote the length of $S_y^\alpha(0)$ and $S_y^0(f)$, respectively. To perform threshold based signal detection in AWGN, we in prior present the following hypotheses:

$$\begin{aligned} \mathcal{H}_0 &: r(t) = n(t) \\ \mathcal{H}_1 &: r(t) = s(t) + n(t). \end{aligned} \tag{11}$$

Let R_α and R_f denote the calculation results of the received signal on zero spectral frequency axis and zero cyclic frequency axis using the same calculation way in (9) and (10), respectively. By employing threshold based signal detection method, we declare a signal is present on zero spectral frequency axis if $R_\alpha > TH_\alpha$, while declare present on zero cyclic frequency axis if $R_f > TH_f$. We employ hard decision on combining the two decision results above for the final signal detection result, which can be concluded as follows

$$\begin{aligned} R_\alpha \le TH_\alpha \text{ and } R_f \le TH_f &: \text{ Declare } \mathcal{H}_0 \\ R_\alpha > TH_\alpha \text{ or } R_f > TH_f &: \text{ Declare } \mathcal{H}_1. \end{aligned} \tag{12}$$

III. Multiple Antenna Signal Detection Method

Compared to energy detector, cyclostationary feature detector still performs well in relatively low SNR regions, say around 0dB, where the energy detector works bad. The reason is that the features of cyclostationary signals in SCF estimation are still clear enough to be detected in such SNR regions. However, if SNR gets lower, the cyclostationary features could be overwhelmed by strong noise, resulting in sensing sensitivity reduction. To overcome such limitation and improve spectrum sensing sensitivity, we resort to MIMO technique, or say multiple antennas. In other words, we extend our proposed basic detection method for single antenna in Section II to multiple antenna scheme. In the rest of this paper, the term *basic detector* is referred to the one we proposed in Section II-C. We will present three different multiple antenna signal detection methods in the following subsections.

A. Maximum Ratio Combination Method

This method is motivated by the maximum ratio combination technique in MIMO systems. Assume $r_i(t)$, $i = 1, 2, ..., M$ denotes the received signals on M antennas respectively, the output $y(t)$, which is also the input of basic detector, is given by

$$y(t) = \sum_{i=1}^{M} r_i(t) \tag{13}$$

Let ρ_i be the SNR on i-th antenna, the input SNR of the detector is the sum of the SNRs on individual antennas,

$$\rho_{MRC} = \sum_{i=1}^{M} \rho_i \tag{14}$$

By processing the combined signal $y(t)$ with basic detector, we can obtain the final signal detection result through the decision of basic detector. Similar to the conclusion in MIMO system that the performance of the receiver will upgrade due to the augment in total SNR by employing maximum ratio combination technique, the sensitivity of the detector will also benefit from this method. The improvement is intuitionistic and will be justified in simulation results.

B. Multiple Decision Result Fusion Method

In this method, we first carry out detection process of basic detector on each antenna of the secondary receiver for the corresponding received signal, then we obtain M decision results for M antennas. The secondary receiver decides $\mathcal{H}_1$ if any of the M decision results are $\mathcal{H}_1$, while decides $\mathcal{H}_0$ if all of the M decision results are $\mathcal{H}_0$. This fusion rule is known as the OR-rule or 1-out-of-n rule [9].

C. Comparison Detection Method

The SCF estimation of received signals can actually be treated as sum of two parts: the modulated signal part (if present) and noise part. By applying same calculation algorithm on all antennas, the modulated signal parts of SCF estimation should be identical in all the estimation results, while the noise parts may vary. In other words, the location of peak values of the modulated signal part will remain the same, while that of the noise part is random. Although the influence caused by AWGN on received signals may vary on different antennas, the location of peak values of SCF estimation results on different antennas should be the same or fluctuate in a small range if modulated signals are present, especially when SNR is moderate. We also consider the problem that the location of peak values may change due to the influence of noise, however the interference of noise is small and will not change the peak value location or change it only in a very small range in the regions where SNR is not especially low. Such structure characteristic of SCF estimation motivates us to propose a novel signal detection method specifically designed for multiple antenna systems.

The method can be illustrated as follows:

1) Randomly select one from the total M antennas as the standard antenna, then process the received signal on which with basic detector.

2) Search for the location of peak value of the estimation results on the axis of zero spectral frequency and axis of zero cyclic frequency respectively, named $L^{\alpha}_{standard}$ and $L^{f}_{standard}$ accordingly.

3) Select regions that are respectively centered at $L^{\alpha}_{standard}$ and $L^{f}_{standard}$, which we term as *confidence region* α and *confidence region* f.

4) Process the received signals on the rest $M-1$ antennas with basic detector, where we obtain L^{α}_{i} and L^{f}_{i}, $i = 1, 2, ...M-1$ for each antenna.

5) By applying the 1-out-of-n fusion rule, if any of the $M-1$ L^{α}_{i} fall into the *confidence region* α, we set $\theta_{\alpha} = 1$; while we set $\theta_f = 1$ when any of the $M-1$ L^{f}_{i} fall into the *confidence region* f; otherwise we set $\theta_{\alpha} = 0$ and $\theta_f = 0$.

6) The final signal detection result can be obtained by

$$\begin{aligned} \theta_{\alpha} = 0 \text{ and } \theta_f = 0 : \ \text{Declare } \mathcal{H}_0 \\ \theta_{\alpha} = 1 \text{ or } \theta_f = 1 : \ \text{Declare } \mathcal{H}_1. \end{aligned} \tag{15}$$

In this method we compare the estimation results on multiple antennas to make the final decision, hence we name it *Comparison Detection Method*.

The sensitivity and accuracy of this detection method are controlled by the selection of the width of confidence region. A too large region will result in high false alarm rate especially in low SNR regions, while a too small region will make the method be easily interfered by noise, accomplished with the reduction in sensitivity. Therefore, when in practical use, one can firstly obtain a histogram which shows the relationship between the statistical false alarm rate and the width of confidence region. Then for a given false alarm rate, one can search the histogram for the corresponding confidence region width. The advantage of comparison detection method lies that it doesn't require the setting of threshold, which is difficult to choose an appropriate one. Furthermore, the sensitivity is controllable by adjusting the parameter of the confidence region.

IV. Simulation Result

In our simulation, we illustrate the detection performance improvement brought by multiple antenna processing methods comparing to single antenna processing method, through probability of detection at given SNRs, on the premise of a prespecified false alarm rate. The false alarm rate in the simulation can be obtain by estimating the histogram of the detection results of each method in Section III when the input signal is noise [10]. We use BPSK signals for detection test in our simulation. We compare the three methods proposed in Section III respectively as SNR varies from -14dB to 0dB, under the cases of single antenna, two antennas and four antennas.

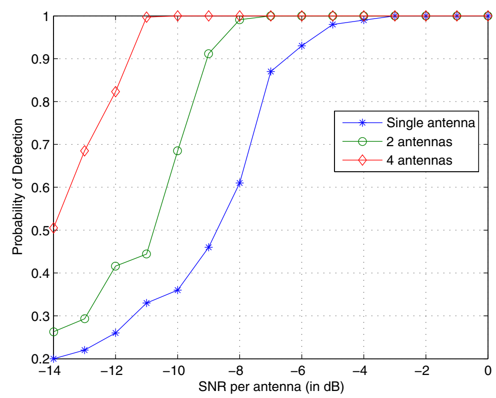

Fig. 2. Detection performance of Maximum Ratio Combination Method with 10% false alarm rate

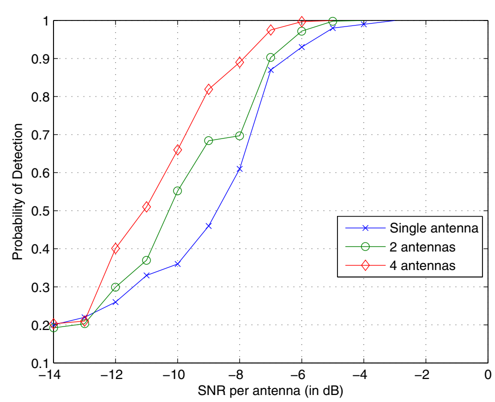

Fig. 3. Detection performance of Multiple Decision Result Fusion Method with 10% false alarm rate

Figure 2 illustrates the achieved detection probability of maximum ratio combination method with varying SNR under the cases of different antenna numbers, at a false alarm rate of 10%. It shows that the performance improvement is evident, and the detection probability rises along with the increment of antenna numbers. Figure 3 presents the performance of multiple decision result fusion method at a false alarm rate of 10%. The detection accuracy also rises as the antenna numbers increases.

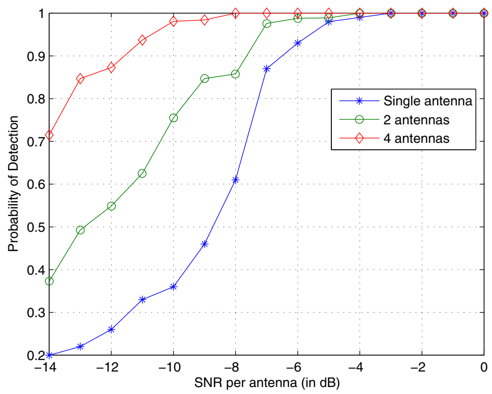

Fig. 4. Detection performance of Comparison Detection Method with 15% false alarm rate

Figure 4 shows the comparison between the comparison detection method and the single antenna case which employs the basic detector in Section II-C, at a false alarm rate of 15%. For the *confidence region* mentioned in this method, here we choose the region width as 5% of the total data length of the calculation result on zero spectral frequency axis and zero cyclic frequency axis. It can be seen from the figure that the performance of the comparison detection method gets better as the number of antennas increases from 2 to 4. We show as well that the performance of the comparison detection method which are specifically designed for multiple antennas also exceeds that of the single antenna scheme employs the basic detector in Section II-C.

TABLE I

Detection probability of three multiple antenna detection methods under different false alarm rate, at SNR=-10dB with 2 antennas

False Alarm Rate	10%	15%	20%
Maximum Ratio Combination Method	0.689	0.847	0.98
Multiple Decision Result Fusion Method	0.552	0.58	0.62
Comparison Detection Method	0.69	0.732	0.755

TABLE II

Detection probability of three multiple antenna detection methods under different false alarm rate, at SNR=-10dB with 4 antennas

False Alarm Rate	10%	15%	20%
Maximum Ratio Combination Method	1	1	1
Multiple Decision Result Fusion Method	0.651	0.678	0.74
Comparison Detection Method	0.951	0.981	1

Table I and table II show the comparison between the three methods proposed in Section III in the case of 2 antennas and 4 antennas respectively, in terms of detection probability under false alarm rate of 10%, 15% and 20% when SNR=-10dB. It can be seen from these two tables that maximum ratio combination method performs the best, comparison detection method ranks second, and multiple decision result fusion method performs the worst. However it can also be found from figure 2 and figure 4 that in lower SNR regions, say under -12dB, comparison detection method works better than maximum ratio combination method. Our explanation for such results is that the SNR value on each antennas increases synchronously in our simulation, thus the input SNR of the basic detector in maximum ratio combination method increases much faster than that of comparison detection method, especially when SNR is relatively high, say over -12dB. As a result, in relatively low SNR regions, comparison detection method performs the best, while maximum ratio combination method performs the best in relatively high SNR regions.

V. Conclusions

In this paper we consider the feasibility of employing multiple antennas in order to achieve better performance in cyclostationary features based spectrum sensing methods. To overcome the computation complexity of traditional cyclostationary feature detection method, we proposed a simplified cyclostationary features based detector as the fundament of the latter multiple antenna sensing methods. We then propose three sensing methods which are motivated by MIMO technique and cyclic spectrum characteristics, exploiting the potential of applying multiple antennas for better spectrum sensing performance. The simulation results show that: 1) the detection performance of the three multiple antenna sensing methods are better than the single antenna sensing method, while the improvement is much more evident as the antenna amount increases; 2) comparison detection method performs the best in relatively low SNR regions, while maximum ratio combination method performs the best in relatively high SNR regions.

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