# Cyclostationary Detection Based Spectrum Sensing for Cognitive Radio Networks

Yang Liu[1], Zhangdui Zhong[1], Gongpu Wang[2], and Dan Hu[3]
[1]State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China
[2]School of Computer and Information Technology, Beijing Jiaotong University, Beijing, China
[3]State Grid Information and Telecommunication Branch (Anhui Province), Hefei, China
Email: {1111011, zhdzhong}@bjtu.edu.cn; gpwang@bjtu.edu.cn; sghudan@sina.com

***Abstract*—**In this paper, cyclostationary detection Based spectrum sensing is considered for cognitive radio networks. We first summarize the existing first-order and second-order cyclostationary detection algorithms, which can be considered as a brief tutorial on detection theory of the cyclostationary signals. Based on this, we propose a cooperative spectrum sensing method for a cognitive radio networks with multiple terminals and one fusion center. It is shown that the proposed method have reliable performance even in low signal-to-noise ratio (SNR) region. It is also found that the increasing number of secondary users (SUs) can result in improved detection performance, especially at low SNR. Simulation results are then provided to corroborate the proposed studies.

***Index Terms*—**Cognitive radio, cooperative spectrum sensing, cyclostationary detection.

## I. Introduction

The past two decades witness a rapid proliferation of wireless network technologies. Nowadays, with the popularity of intelligent terminals, there are increasing demands for high data rate wireless access and services, which requires higher spectrum utilization efficiency as well as more spectrum [1]. Cognitive radio (CR) [2] is proposed as a promising technology to improve spectrum utilization efficiency and solve the spectrum scarcity issue. In a CR network, the unlicensed users, also referred to as cognitive users or secondary users (SUs), can communicate with each other over the licensed bands when the primary users (PUs) are absent or the interference to the PUs are below a certain threshold.

Typically, a cognitive transmission process could be divided into two phase as Fig. 1 shows: spectrum sensing phase and data transmission phase. In the spectrum sensing phase, SUs attempt to find a spectrum hole, which is the frequency band assigned to PUs but is not being used at a particular time and geographic location [3]. In the data transmission phase, SUs transmit data through the detected spectrum hole. Therefore, accurate spectrum sensing is the basis of data transmission.

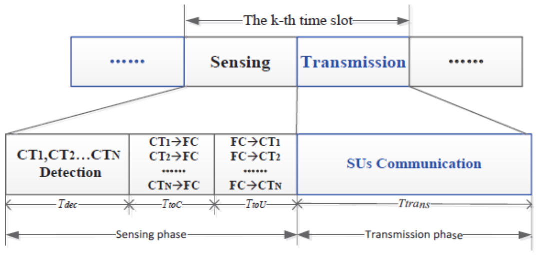


Fig. 1. The n-th transmission time slot of cognitive networks.

The existing spectrum sensing techniques are usually divided into energy detection, matched filter and cyclostationary detection [4]. Among them, energy detection based sensing methods are the most widely used approach due to its low computational and implementation. However, most of the existing studies on energy detection methods are subject to the statistical characteristics of the PUs' signals and noises and its performance may be deteriorated seriously in low signal-to-noise ratio (SNR) region [5]. Matched-filtering can be considered as the optimal method for detection of primary users when the transmitted signal is known [6], while it is short for the requirements of perfect knowledge from the PUs' signal features to demodulate the received signals, which make the sensing unit of the SU impractically large to adopt all signal types [7]. As a spectrum sensing scheme in cognitive radio, cyclostationary detection is especially appealing because it is capable of differentiating the primary signal from the interference and noise. Due to its noise rejection property, cyclostationary detection works even in very low SNR region, where the traditional signal detection method, such as the energy detector, fails. Reference [8] gives the basic methods to detect the presence of cyclostationarity and [9] apply this methods in the spectrum sensing. However, their algorithm would become complicated when the SU have no knowledge of the cyclic frequency of the PU's signals.

To further improve the accuracy of detection, cooperative sensing is employed. In next generation communication systems, cooperative communication is not only a promising technology to improve the cognitive transmission of CR networks [10], but also a convenient way to perform cooperative sensing, and cooperative spectrum sensing could combat shadowing, fading and time-varying natures of wireless channels [11].

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In this paper, we utilize cyclostationary detection to perform the cooperative spectrum sensing. The basic ideas of first-order and second-order cyclostationary detection are summarized. Based on this, the spectrum sensing algorithm is proposed, which is adopted to a more general situation where the SUs do not know the distribution of PU's signal and noise. The simulation results shows that the cyclostationarity based detection could improve the sensing accuracy, especially in the low SNR region.

The remainder of this paper is organized as follows. Section II describes the system and builds up the theoretical model. In section III, we conclude the existing first-order and seconder-order cyclostationary detection algorithms and propose our detection methods for cooperative spectrum sensing. Section IV verifies our proposed theoretical studies though simulation results and Section V concludes the paper.

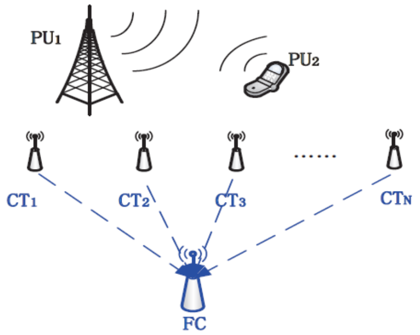


Fig. 2. System model: joint existence of a primary network and a cognitive network

## II. System Model

Consider a joint existence of the primary network and a secondary network as Fig. 2 shows. Primary network, including $PU_1$ and $PU_2$, is communicating over certain licensed bands. Without loss of generality, we only consider the case $PU_1$ transmits data to $PU_2$ due to the symmetry of primary users. The secondary network is a traditional wireless communication network, including N SUs and one fusion center (FC).

The SUs work in a periodical slotted structure that is shown in Fig. 1. Each period is divided into two phase: sensing phase and transmission phase. $T_{dec}$, $T_{toR}$, $T_I$ and $T_{II}$ denotes the time each part of process takes. At the beginning of each period, the SUs sense the bands simultaneously. Assuming each SU can receive PU's signal from the same symbol and the total number of received symbols is N. Then $CT_1$, $CT_2$,⋯, $CT_N$ sent their sensing data to FC, and FC combines the sensing data to determine the primary users' state. For simplicity, we assume the sensing data sent form $CT_1$, $CT_2$,⋯, $CT_N$ to

FC is free of error. If FC determine any spectrum hole, it will broadcast the information to SUs and then the *SUs* utilize the spectrum hole to transmit their information in the transmission phase. In this paper, we mainly focus on the sensing phase.

In the sensing phase, the i-th user's received discrete-time signal is

$$x_i(t) = \gamma_i s(t) + n_i(t), \quad i = 1, 2, \cdots, N, \tag{1}$$

where $s(t)$ is the PU's zero mean signal, $\gamma_i$ denotes the channel gain from the PU to the $i$-th SU and $n_i(t)$ is the received noise with zero mean at $i$-th SU. Specially, the probability distribution of PU's signal and noise are not limited to certain distribution in this paper.

Then the SUs send the received symbols to the FC and FC link them sequentially to form a new time series

$$y(t) = [x_1(t), x_2(t), \cdots, x_N(t)] \tag{2}$$

which will be used for the final detection of the presence of cyclostationarity.

## III. Cyclostationary Detection Algorithms

In this section, we give a brief introduction of first-order and second-order periodicity to lay the groundwork for our proposed algorithm. Next a cyclostationary detection based spectrum sensing algorithm is proposed to solve the detection problem suggested in Section II.

### A. First-order Periodicity

Define

$$x(t) = s(t) + n(t) \tag{3}$$

where $n(t)$ is a zero-mean Gaussian noise and $s(t)$ is a deterministic complex sinusoidal signal

$$s(t) = Ae^{j(2\pi f_0 t + \theta)} \tag{4}$$

Noting that the parameters $A$, $f_0$ and $\theta$ in the singal $s(t)$ are constant, the mean value of the signal $x(t)$ can be expressed as

$$M_x(t) = E\{x(t)\} = Ae^{j(2\pi f_0 t + \theta)} \tag{5}$$

Clearly, $M_x(t)$ is a function of time $t$. Thus the value $A$ cannot be obtained from direct average of $x(t)$.

However, if the value of $f_0$ is known, then we can sample the signal $x(t)$ with period $T_0 = 1/f_0$ to estimate the mean value $x(t)$. That is, the sampling time series are $\cdots, t-2T_0, t-T_0, t, t+T_0, t+2T_0, \cdots$. And $M_x(t)$ can be written as

$$M_x(t) = \lim_{N\to\infty} \frac{1}{2N+1} \sum_{n=-N}^{N} x(t+nT_0) \tag{6}$$

It can be readily checked that $M_x(t)$ is periodical function with period $T_0$. Noting that Fourier Theory shows that any periodic function can be decomposed into the sum of a (possibly infinite) set of simple oscillating functions, namely sines, cosines or complex exponentials. Therefore, define $\alpha = m/T_0$ and we can express $M_x(t)$ as

$$M_x(t) = \sum_{m=-\infty}^{\infty} M_x^{\alpha} e^{j2\pi\alpha t} \tag{7}$$

where the Fourier coefficient $M_x^{\alpha}$ is

$$M_x^\alpha = \frac{1}{T_0}\int_{-T_0/2}^{T_0/2} M_x(t)e^{-j2\pi\alpha t}\mathrm{d}t \tag{8}$$

Define $T=(2N+1)T_0$ and substituting (6) into (8) will produce

$$\begin{aligned}
M_x^\alpha &= \frac{1}{T_0}\int_{-T_0/2}^{T_0/2}\lim_{N\to\infty}\frac{1}{2N+1}\sum_{n=-N}^{N} x(t+nT_0)e^{-j2\pi\alpha t}\mathrm{d}t \\
&= \lim_{N\to\infty}\frac{1}{(2N+1)T_0}\int_{-T_0/2}^{T_0/2}\sum_{n=-N}^{N} x(t+nT_0)e^{-j2\pi\alpha t}\mathrm{d}t \\
&= \lim_{N\to\infty}\frac{1}{(2N+1)T_0}\sum_{n=-N}^{N}\int_{-T_0/2}^{T_0/2} x(t+nT_0)e^{-j2\pi\alpha t}\mathrm{d}t \\
&= \lim_{N\to\infty}\frac{1}{T}\sum_{n=-N}^{N}\int_{-\frac{T_0}{2}+nT_0}^{\frac{T_0}{2}+nT_0} x(u)e^{-j2\pi\alpha(u-nT_0)}\mathrm{d}u \\
&= \lim_{N\to\infty}\frac{1}{T}\sum_{n=-N}^{N}\int_{-\frac{T_0}{2}+nT_0}^{\frac{T_0}{2}+nT_0} x(u)e^{-j2\pi\alpha u}\mathrm{d}u \\
&= \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} x(t)e^{-j2\pi\alpha t}\mathrm{d}t,
\end{aligned} \tag{9}$$

where $e^{j2\pi\alpha nT_0}=1$ is utilized in the above derivation process.

Clearly,

$$M_x^\alpha = \begin{cases} Ae^{j\theta} & \alpha = f_0 \\ 0 & \alpha \neq f_0 \end{cases} \tag{10}$$

Thus if we can find an nonzero $\alpha$ which make $M_x^\alpha$ not zero as well, $x(t)$ is first-order cyclostationary and one of its cyclic frequency is $\alpha$.

### B. *Second-order Periodicity*

Suppose $a(t)$ is a zero-mean real low-pass random signal and define

$$u(t) = a(t)\cos(2\pi f_0 t) \tag{11}$$

It can be readily checked that

$$E\{u(t)\} = E\{a(t)\cos(2\pi f_0 t)\} = 0 \tag{12}$$

Therefore, there exists no first-order cyclostationaity in the signal $u(t)$. To exploit the cyclostationaity hidden in the signal $u(t)$, let us define $v(t)=u^2(t)$ and then we can find

$$v(t) = a^2(t)\cos^2(2\pi f_0 t) = \frac{1}{2}a^2(t)(1+\cos(4\pi f_0 t)). \tag{13}$$

Suppose $b(t)=a^2(t)$ and the Fourier transform of $b(t)$ is $S_b(f)$. Thus we can obtain the Fourier transform of $v(t)$ as

$$S_v(f) = \frac{1}{2}\left[S_b(f) + \frac{1}{2}S_b(f+2f_0) + \frac{1}{2}S_b(f-2f_0)\right] \tag{14}$$

Furthermore, if the signal $a(t)$ is random binary bits $+1$ or $-1$, then we can find $b(t)=1$ and

$$v(t) = \frac{1}{2} + \frac{1}{2}\cos(4\pi f_0 t) \tag{15}$$

Clearly, $v(t)$ is first-order cyclostationary signal and accordingly $u(t)$ is second-order cyclostationary signal.

### C. *Spectrum Sensing Algorithm*

Consider the fused time series $y(t)$, which is a zero-mean non-stationary complex signal. The correlation function of $y(t)$ is defined as

$$R_y(t;\tau) = E\{y(t)y^*(t-\tau)\} \tag{16}$$

Noting that $E\{y(t)y^*(t)\}$ is a special case for $R_y(t;\tau)$ when $\tau=0$.

If $R_y(t;\tau)$ is a periodical function of time $t$ with period $T_0$, then it can be decomposed into the sum of a set of complex exponentials

$$R_y(t;\tau) = \sum_{m=-\infty}^{\infty} R_y^\alpha(\tau)e^{j2\pi\frac{m}{T_0}t} = \sum_{m=-\infty}^{\infty} R_y^\alpha(\tau)e^{j2\pi\alpha t} \tag{17}$$

where $\alpha=\frac{m}{T_0}$ and $R_y^\alpha(\tau)$ is the Fourier co-efficiencies and

$$R_y^\alpha(\tau) = \frac{1}{T_0}\int_{-T_0/2}^{T_0/2} R_y(t;\tau)e^{-j2\pi\alpha t}\mathrm{d}t \tag{18}$$

Noting that $R_y(t;\tau)$ can be written as

$$R_y(t;\tau) = \lim_{N\to\infty}\frac{1}{2N+1}\sum_{n=-N}^{N} y(t+nT_0)y^*(t+nT_0-\tau), \tag{19}$$

substitute (19) into (18) will give

$$\begin{aligned}
R_y^\alpha(\tau) &= \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T_0}{2}}^{\frac{T_0}{2}}\sum_{n=-N}^{N} y(t+nT_0)y^*(t+nT_0-\tau)e^{-j2\pi\alpha t}\mathrm{d}t \\
&= \lim_{T\to\infty}\frac{1}{T}\sum_{n=-N}^{N}\int_{-\frac{T_0}{2}}^{\frac{T_0}{2}} y(t+nT_0)y^*(t+nT_0-\tau)e^{-j2\pi\alpha t}\mathrm{d}t \\
&= \lim_{T\to\infty}\frac{1}{T}\sum_{n=-N}^{N}\int_{-\frac{T_0}{2}+nT_0}^{\frac{T_0}{2}+nT_0} y(u)y^*(u-\tau)e^{-j2\pi\alpha(u-nT_0)}\mathrm{d}u \\
&= \lim_{T\to\infty}\frac{1}{T}\sum_{n=-N}^{N}\int_{-\frac{T_0}{2}+nT_0}^{\frac{T_0}{2}+nT_0} y(u)y^*(u-\tau)e^{-j2\pi\alpha u}\mathrm{d}u \\
&= \lim_{T\to\infty}\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} y(t)y^*(t-\tau)e^{-j2\pi\alpha t}\mathrm{d}t
\end{aligned} \tag{20}$$

Define $y(t)y^*(t-\tau)=g(t,\tau)$ and the function $g(t,\tau)$ can also be expressed as

$$g(t,\tau) = y(t+\frac{\tau}{2})y^*(t-\frac{\tau}{2}) \tag{21}$$

It is shown in (20) that the value of $R_y^\alpha(\tau)$ denotes the Fourier coefficient of the time function $g(t,\tau)$ at the frequency $\alpha$. Those frequencies $\alpha$ that satisfies $R_y^\alpha(\tau)\neq 0$ are referred to as cyclic frequencies of the signal $y(t)$. Noting that cyclic frequencies include zero cyclic frequency ($\alpha=0$) and non-zero cyclic frequencies; and that the zero cyclic frequency corresponds to the stationary part of the signal $y(t)$ whereas the non-zero cyclic frequencies describe the cyclostationarity of the signal $y(t)$.

Then we consider the property of $y(t)$. The time varying covariance of it is given as $c_{2y}(t;\tau)=E\{y(t)y(t+\tau)\}$, which can be expanded by Fourier series (FS) with respect to time $t$ as

$$c_{2y}(t;\tau) = \sum_{\alpha\in\Lambda} C_{2y}(\alpha;\tau)e^{j\alpha t} \tag{22}$$

where the Fourier coefficient $C_{2y}(\alpha;\tau)$ is called the cyclic covariance at cyclic frequency $\alpha$ and

$$C_{2y}(\alpha;\tau) = \lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1} c_{2y}(t;\tau)e^{-j\alpha t} \tag{23}$$

$$\Lambda \triangleq \{\alpha | 0 \le \alpha < \pi, C_{2y}(\alpha;\tau) \neq 0\} \tag{24}$$

Therefore, we can obtain the estimation of $C_{2y}(\alpha;\tau)$ as

$$\hat{C}_{2y}(\alpha;\tau) \triangleq \frac{1}{T}\sum_{t=0}^{T-1} y(t)y(t+\tau)e^{-j\alpha t} = C_{2y}(\alpha;\tau) + \epsilon_{2y}^{(T)}(\alpha;\tau) \tag{25}$$

which includes the real value part $C_{2y}(\alpha;\tau)$ and the estimation error $\epsilon_{2y}^{(T)}(\alpha;\tau)$.

Let $\tau_2, \tau_2, \cdots, \tau_M$ be a fixed set of time delay shift, $T$ is the detection time for each SU, i.e. $\alpha = \frac{1}{T}$. The matrix form of $\hat{C}_{2y}(\alpha;\tau)$ with respect to the delay shift $\tau_m$ is given as

$$\begin{aligned}\hat{\mathbf{c}}_{2y}^{(T)} \triangleq \Big[&\Re\{\hat{C}_{2y}^{(T)}(\alpha;\tau_1)\}, \cdots, \Re\{\hat{C}_{2y}^{(T)}(\alpha;\tau_M)\} \\ &\Im\{\hat{C}_{2y}^{(T)}(\alpha;\tau_1)\}, \cdots, \Im\{\hat{C}_{2y}^{(T)}(\alpha;\tau_M)\}\Big]\end{aligned} \tag{26}$$

Accordingly, the real value of $\hat{\mathbf{c}}_{2y}^{(T)}$ and the error of it can be written as

$$\begin{aligned}\mathbf{c}_{2y}^{(T)} \triangleq \Big[&\Re\{C_{2y}^{(T)}(\alpha;\tau_1)\}, \cdots, \Re\{C_{2y}^{(T)}(\alpha;\tau_M)\} \\ &\Im\{C_{2y}^{(T)}(\alpha;\tau_1)\}, \cdots, \Im\{C_{2y}^{(T)}(\alpha;\tau_M)\}\Big]\end{aligned} \tag{27}$$

$$\begin{aligned}\epsilon_{2y}^{(T)} \triangleq \Big[&\Re\{\epsilon_{2y}^{(T)}(\alpha;\tau_1)\}, \cdots, \Re\{\epsilon_{2y}^{(T)}(\alpha;\tau_M)\} \\ &\Im\{\epsilon_{2y}^{(T)}(\alpha;\tau_1)\}, \cdots, \Im\{\epsilon_{2y}^{(T)}(\alpha;\tau_M)\}\Big]\end{aligned} \tag{28}$$

Then we have

$$\hat{\mathbf{c}}_{2y}^{(T)} = \mathbf{c}_{2y}^{(T)} + \epsilon_{2y}^{(T)} \tag{29}$$

with (25) and the problem of spectrum sensing could be transformed to checking whether $\alpha$ is a cyclic frequency or not, which could be formulated as (30) shows.

$$H_0: \ \forall\{\tau_m\}_{m=1}^{M}, \ \Lambda = \varnothing \text{ and } \hat{\mathbf{c}}_{2\mathrm{y}}^{(\mathrm{T})} = \epsilon_{2\mathrm{y}}^{(\mathrm{T})};$$

$$H_1: \ \forall\{\tau_m\}_{m=1}^{M}, \ \exists\alpha \in \Lambda \text{ satisfies } \hat{\mathbf{c}}_{2\mathrm{y}}^{(\mathrm{T})} = \mathbf{c}_{2\mathrm{y}}^{(\mathrm{T})} + \epsilon_{2\mathrm{y}}^{(\mathrm{T})} \tag{30}$$

When the PU do not occupy the spectrum, i.e. $H_0$ holds, $y(t)$is formed by N noise series, while when $H_1$ holds, $y(t)$ is formed by the same PU's signals added with uncertain noises. And this problem is solved in [8] by a Neyman-Pearson theorem.

## IV. Simulation Results

In this section, we give the simulation results corresponding to the theoretical analysis in Section III.

Fig. 3 shows the detection results of first-order cyclostationarity. Here we set $x(t)$ =6 $\cos(2\pi f_0 t) + n(t)$. The first figure gives waveform of the pure signal and the signal with noise. Then the second figure shows the calculation of $M_x^\alpha$ with different $\alpha$. We can find that the real part of $M_x^\alpha$ achieve an obvious nonzero value at the cyclic frequency point, while for other values of $M_x^\alpha$ is approximating to zero. From this method we could obtain the cyclic frequency of an first-order cyclostationary signal.

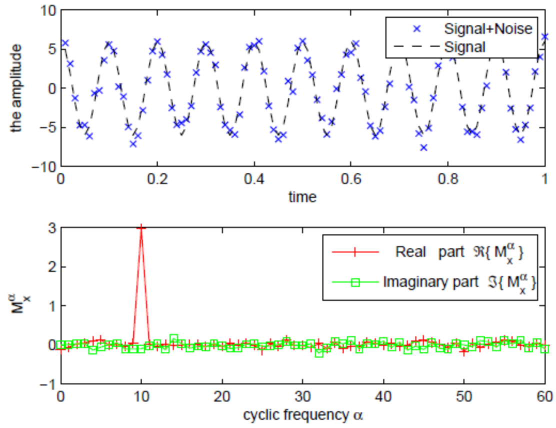


Fig. 3. Detection of the first-order cyclostationarity.

Fig. 4 consider the second-order cyclostationarity situation. Here we set $x(t) = A(t)\cos(2\pi f_0 t) + n(t)$.

The original signal and its noise version is plotted in the first figure. $M_x^\alpha$ of $x(t)$ is also calculated in the second figure. However it can be hardly found any regulation in this figure due to the reason that $E\{x(t)\} = E\{A(t)\}\cos(2\pi f_0 t) + 0 = 0$ . Thus, we calculate $y(t) = x^2(t)$ in order to find out hidden cyclo-stationarity of $x(t)$. The third figure gives the results of $M_y^\alpha$ with different $\alpha$. Similarly, we could find the cyclic frequency at the nonzero point of $M_y^\alpha$'s real part.

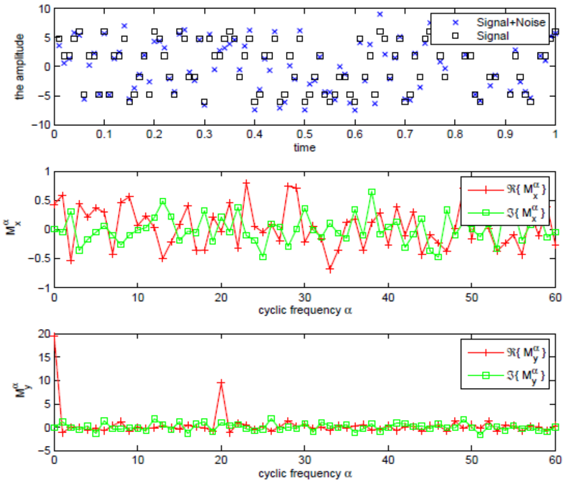


Fig. 4. Detection of the second-order cyclostationarity.

Fig. 5 shows the performance of our proposed algorithm. We fix $s(t)$ to be a zero mean time series with duration $T$, and $y(t)$ is defined as Section III. Thus the cyclic frequency is $\frac{m}{T}, m = 1, 2, \cdots$. It is shown that when $\alpha$ is the integer multiplies of the cyclic frequency, the absolute value of $R_y^\alpha$ is much larger than the other case. Generally, $T$ could be set previously by the controller of the SU networks. Therefore we can detect the presence of cyclostationarity through calculating the absolute value of $R_y^\alpha$ where $\alpha = \frac{m}{T}, m = 1, 2, \cdots, T$.

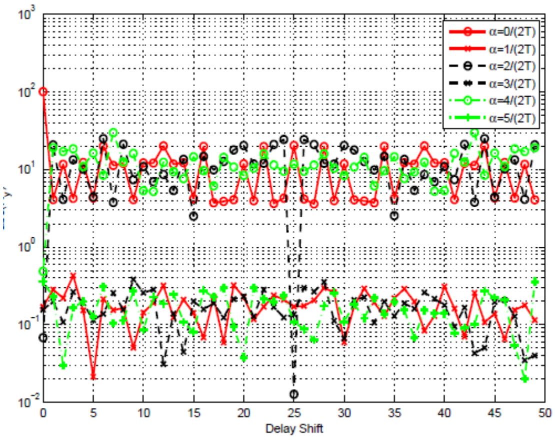


Fig. 5. Spectrum sensing results with different $\alpha$.

Finally, the performance of the proposed detection algorithm is shown in Fig. 6. We can find that the cyclostationarity based detection methods perform well even in some negative SNRs region, where the traditional energy detector can hardly work, which is an improvement of the previous study [12]. In addition, Fig. 6 also shows that the increasing of SUs' number could improve the performance in low SNR region, while in high SNR region that could only provide limited gain.

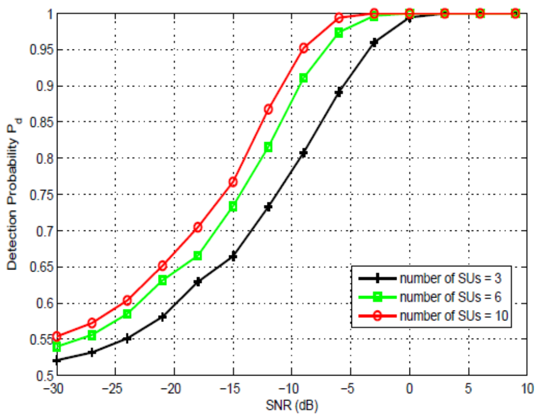


Fig. 6. The detection probability of the spectrum sensing algorithm versus SNR with different numbers of SUs..

## V. Conclusion

Cyclostationary detection Based spectrum sensing was considered for cognitive radio networks in this paper. The existing first-order and second-order cyclostationary detection algorithms were concluded and a cooperative spectrum sensing method was proposed to detect the spectrum hole. It was shown that the proposed method have reliable performance even in low SNR region. It was also found that the increasing number of SUs can improve detection performance especially in low SNR region.

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**Yang Liu** received B.E. degree from School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, China, in 2011. Currently, he is working toward the Ph.D. degree in State Key Laboratory of Rail Traffic Control and Safety & School of Electronic and Information Engineering, Beijing Jiaotong University. His current research interests are in the field of detection theory and spectrum sensing for cognitive radio networks.

**Zhangdui Zhong** is a professor and advisor of Ph. D. candidates in Beijing Jiaotong University, Beijing, China. He is now a director of School of Computer and Information Technology and a Chief Scientist of State Key Laboratory of Rail Traffic Control and Safety in Beijing Jiaotong University. He is also a director of the Innovative Research Team of Ministry of Education, and a Chief Scientist of Ministry of Railways in China. He is an executive council member of Radio Association of China, and a deputy director of Radio Association of Beijing. His interests are wireless communications for railways, control theory and techniques for railways, and GSM-R system. His research has been widely used in the railway engineering, such as Qinghai-Xizang railway, Datong-Qinhuangdao Heavy Haul railway, and many high-speed railway lines of China.

He has authored/co-authored 7 books, 5 invention patents, and over 200 scientific research papers in his research area. He received MaoYiSheng Scientific Award of China, ZhanTianYou Railway Honorary Award of China, and Top 10 Science/Technology Achievements Award of Chinese Universities.

**Gongpu Wang** received the B.Eng. degree in communication engineering from Anhui University, Hefei, Anhui, China, in 2001, the M.Sc. degree from Beijing University of Posts and Telecommunications, Beijing, China, in 2004. From 2004 to 2007, he was an assistant professor in Beijing University of Posts and Telecommunications. He received Ph.D. degree from University of Alberta, Edmonton, Canada, in 2011. Currently, he is an associate professor in School of Computer and Information Technology, Beijing Jiaotong University, China. His research interests include wireless communication theory and signal processing technologies..

**Dan Hu** received the B.Eng. degree in communication engineering from Anhui University, Hefei, Anhui, China, in 2001, and the M.Sc. degree from Beijing University of Posts and Telecommunications, Beijing, China, in 2006. Currently, he is an engineer in State Grid Information and Telecommunication Branch (Anhui Province), Hefei, China. His research interests include communication theory and signal processing technologies.er-cased.