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RESEARCH ARTICLE

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An improved cooperative spectrum detection algorithm for cognitive radio

Abstract The ability to detect the primary user's signal is one of the main performances for cognitive radio networks. Based on the multi-different-cyclic-frequency characteristics of the cyclostationary primary user's signal and the cooperation detection advantage of the multi-secondary-user, the paper presents the weighted cooperative spectrum detection algorithm based on cyclostationarity in detail. The core of the algorithm is to detect the primary user's signal by the secondary users' cooperation detection to the multi-different-cyclic-frequency, and to make a final decision according to the fusion data of the independent secondary users' detection results. Meanwhile, in order to improve the detection performance, the paper proposes a method to optimize the weight on basis of the deflection coefficient criterion. The result of simulation shows that the proposed algorithm has better performance even in low signal-to-noise ratio (SNR).

Keywords cyclostationary detection, deflection coefficient, weight optimization, cooperative detection

1 Introduction

With the development of wireless communication traffic, the contradiction between the large spectrum requirements of the secondary users (SUs) and the underutilized spectrum static assigned to the primary users (PUs) is increasingly serious. Based on its capability of detecting the unused frequency-band from the authorized spectrum, cognitive radio is considered as the most effective technique to improve the spectrum utilization. To access the authorized band, the secondary users should continuously monitor authorized spectrum in wireless environment. Meanwhile, the secondary users should exit the occupied channel when the primary users reusing the band in order to avoid the interference to the primary users [1]. Thus, spectrum detection is considered as one of the key technologies of cognitive communication.

The classical spectrum detection methods are mainly power spectrum estimation, energy detection, and cyclostationarity sensing [2]. In the case of low signal-to-noise ratio (SNR), power spectrum estimation cannot make a reliable estimation. It is easy to achieve energy detection, but its performance could be influenced by the uncertainty of the noise power, and its detection performance will decline sharply when the signal drowns in the noise. In addition, the power spectrum estimation and energy detection cannot distinguish among the modulation signal, noise, or interference. The cyclostationarity detection can distinguish the coexistence signals with cyclostationary properties at different cycle frequencies. It also has better detection performance in the low SNR cases.

In wireless communication networks, there is usually much information about the primary user's signal statistics and structural characteristics, such as the modulation method, channel coding type, symbol rate, pilot signal, etc. In application, advantage of these features can be taken to design cyclostationarity detector to detect low SNR signal [3]. In this paper, the signal's symbol rate of the primary users is adapted to design cyclostationary detector because it is the digital modulation signal cyclostationary property. The symbol rate will be estimated according to Refs. [4,5] even if it is unknown.

Cooperative detection algorithms have been well studied in Refs. [6–10], and the spectrum sensing by cyclic frequency characteristics has also been widely adapted in cognitive domains [8–11]. Reference [8] presented the cooperative detection algorithm with multiple secondary

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users at a single cycle frequency. Comparing to the traditional cyclostationary, it reduced the computational complexity of sensing algorithm, but it did not use the abundant information of communication signal at different cycle frequencies, such as the modulation method, channel coding type, symbol rate, pilot signal, etc. Therefore, the detection performance is influenced for only a single cycle frequency and not making full use of the primary users' signal cyclostationary properties. To improve the signal detection performance further, Refs. [9,10] proposed the detection algorithm with a single secondary user at multiple cyclic frequencies, but it does not apply the spatial diversity gain produced by multi-user cooperative detection. The two algorithms mentioned above just use some simple data fusion methods, such as equal gain combining (EGC) to fuse data. Therefore, the two algorithms are only the sub-optimum algorithms.

Based on the classical cycle autocorrelation estimator and its gradual characteristics [10], the improved algorithm is proposed in the paper, which uses multi-user to realize weighed cooperative detection with multiple different cycle frequencies (MDCF-WCD). This algorithm takes full advantage of spatial diversity gain produced by cooperation detection and the cyclostationary properties of the primary users' signals. Meanwhile, in order to further improve the detection performance, a deflection coefficient (DC)-based weight optimization method is presented to fuse data in the paper. Compared with the above two methods, simulation results show that the algorithm proposed in this paper further improves the signal detection performance.

2 Cyclostationarity property review

Many of the signals are regarded as a cyclostationary random process in wireless communication systems and radar systems. The statistical characteristic of the cyclostationary process is a random process. For example, its mean and autocorrelation function is the function changing cyclical over time. The primary user's signal could be detected in the case of lower SNR if the primary user's signal shows cyclostationary property.

If the mean and autocorrelation function of $x(t)$ is the function changing cyclical over time T_0, $x(t)$ is called second-order cyclostationary process. As the periodic autocorrelation function, it can be represented with its Fourier series:

$$R_{xx^*}(t+\tau,t-\tau)=\sum_{\alpha\in A}R_{xx^*}(\tau)\mathrm{e}^{\mathrm{j}2\pi\alpha t}, \tag{1}$$

where $R_{xx^*}(t+\tau,t-\tau)$ is complex autocorrelation function, $A=\left\{\alpha=\dfrac{m}{T_0}\right\}$, m is an integer. $R_{xx^*}(\tau)$ is Fourier coefficient which depends on delay τ.

$$R_{xx^*}(\alpha,\tau)\triangleq\frac{1}{T_0}\int_{-T_0/2}^{T_0/2}R_{xx^*}(t+\tau,t-\tau)\mathrm{e}^{-\mathrm{j}2\pi\alpha t}\mathrm{d}t. \tag{2}$$

In general, these Fourier series are called cycle autocorrelation function. α is called cycle frequency. More generally, if a random process $x(t)$ meets $R_{xx^*}(\alpha,\tau)\neq 0$ and $\alpha\neq 0$, the random process $x(t)$ can be considered as cyclostationary at the cycle frequency α.

3 MDCF-WCD algorithm

3.1 Gradual estimator of cyclic covariance

For finite-length sequence $x(t)$, the consistent estimation of $R_{xx^*}(\alpha,\tau)$ can be represented as

$$\begin{aligned}\hat{R}_{xx^*}(\alpha,\tau)&\triangleq\frac{1}{M}\sum_{t=1}^{M}x(t)x^*(t+\tau)\mathrm{e}^{-\mathrm{j}2\pi\alpha t}\\&=R_{xx^*}(\alpha,\tau)+\varepsilon_{xx^*}(\alpha,\tau),\end{aligned} \tag{3}$$

where $\varepsilon_{xx^*}(\alpha,\tau)$ is estimation error, and $\varepsilon_{xx^*}(\alpha,\tau)\to 0$ while $M\to\infty$.

Due to the limited length of the data in application, $\hat{R}_{xx^*}(\alpha,\tau)$ is not equal to zero even if α is not a cycle frequency. Thus, for a given α ($\alpha\neq 0$), whether α is a cycle frequency cannot be determined by $\hat{R}_{xx^*}(\alpha,\tau)$ directly.

The vector $\hat{r}_{xx^*}(\alpha)$ is constructed by the second-order statistics $\hat{R}_{xx^*}(\alpha,\tau)$:

$$\begin{aligned}\hat{r}_{xx^*}(\alpha)\triangleq\big[&\mathrm{Re}\{\hat{R}_{xx^*}(\alpha,\tau_1)\},\dots,\mathrm{Re}\{\hat{R}_{xx^*}(\alpha,\tau_N)\},\\&\mathrm{Im}\{\hat{R}_{xx^*}(\alpha,\tau_1)\},\dots,\mathrm{Im}\{\hat{R}_{xx^*}(\alpha,\tau_N)\}\big]_{1\times 2N},\end{aligned} \tag{4}$$

where $\hat{r}_{xx^*}(\alpha)$ is a $1\times 2N$ vector, containing the real part and imaginary part estimated in cyclic autocorrelation function.

The covariance matrix of $\hat{r}_{xx^*}(\alpha)$ is obtained by referring Ref. [10]:

$$\hat{\Sigma}_{xx^*}(\alpha)=\begin{bmatrix}\mathrm{Re}\left\{\dfrac{Q+Q^*}{2}\right\}, & \mathrm{Im}\left\{\dfrac{Q-Q^*}{2}\right\}\\ \mathrm{Im}\left\{\dfrac{Q+Q^*}{2}\right\}, & \mathrm{Re}\left\{\dfrac{Q^*-Q}{2}\right\}\end{bmatrix}_{2N\times 2N}. \tag{5}$$

Inputting the (m,n)th element of complex covariance matrix, Q and Q^* can be calculated as following:

$$\begin{aligned}Q(m,n)&=S_{f_{\tau_m}f_{\tau_n}}(2\alpha,\alpha),\\Q^*(m,n)&=S^*_{f_{\tau_m}f_{\tau_n}}(0,-\alpha),\end{aligned} \tag{6}$$

where $S_{f_{\tau_m}f_{\tau_n}}(\alpha,\omega)$ and $S^*_{f_{\tau_m}f_{\tau_n}}(\alpha,\omega)$ are the non-complex conjugation and complex conjugation of cyclic spectrum, which can be estimated by the smooth frequency domain of the cyclic periodogram.

$$\hat{S}_{f_{\tau_m}f_{\tau_n}}(2\alpha,\alpha) = \frac{1}{ML}\sum_{S=-(L-1)/2}^{(L-1)/2} C(s) \cdot F_{\tau_n}\left(\alpha - \frac{2\pi s}{M}\right)F_{\tau_m}\left(\alpha + \frac{2\pi s}{M}\right), \quad (7)$$

$$\hat{S}^*_{f_{\tau_m}f_{\tau_n}}(0,-\alpha) = \frac{1}{ML}\sum_{S=-(L-1)/2}^{(L-1)/2} C(s) \cdot F^*_{\tau_n}\left(\alpha + \frac{2\pi s}{M}\right)F_{\tau_m}\left(\alpha + \frac{2\pi s}{M}\right), \quad (8)$$

where $F_\tau(\omega) = \sum_{t=1}^{M} x(t)x^*(t+\tau)\mathrm{e}^{-\mathrm{j}\omega t}$, C is the normalized window function with odd length L.

The hypothesis test model is constructed to determine whether $x(t)$ has cyclostationary property as following, namely, the existence of nonzero cycle frequency of $x(t)$ [6]:

$$\begin{aligned} H_0 &: \forall\{\tau_n\}_{n=1}^N \Rightarrow \hat{r}_{xx^*}(\alpha) = \hat{\varepsilon}_{xx^*}(\alpha), \quad \alpha \notin A, \\ H_1 &: \{\tau_n\}_{n=1}^N \Rightarrow \hat{r}_{xx^*}(\alpha) = \hat{r}_{xx^*}(\alpha) + \hat{\varepsilon}_{xx^*}(\alpha), \quad \alpha \in A, \end{aligned} \quad (9)$$

where $\hat{\varepsilon}_{xx^*}(\alpha)$ is the estimation error and it follows the gradual normal distribution. $\lim_{M\to\infty}\sqrt{M}\hat{\varepsilon}_{xx^*}(\alpha) \xrightarrow{D} N\left(0,\hat{\Sigma}_{xx^*}(\alpha)\right)$ [11], D means convergence. Therefore, the generalized likelihood ratio can be obtained by the gradual normal distribution of $\hat{r}_{xx^*}(\alpha)$.

$$\xi = \frac{f(\hat{r}_{xx^*}(\alpha)|H_1)}{f(\hat{r}_{xx^*}(\alpha)|H_0)} = \exp\left(-\frac{1}{2}M\hat{r}_{xx^*}(\alpha)\hat{\Sigma}^{-1}_{xx^*}(\alpha)\hat{r}^{\mathrm{T}}_{xx^*}(\alpha)\right). \quad (10)$$

Therefore, the detection statistic is obtained as following:

$$T_{xx^*}(\alpha) = -2\ln\xi = M\hat{r}_{xx^*}(\alpha)\hat{\Sigma}^{-1}_{xx^*}(\alpha)\hat{r}^{\mathrm{T}}_{xx^*}(\alpha), \quad (11)$$

where $\hat{\Sigma}^{-1}_{xx^*}(\alpha)$ is the generalized inverse matrix of covariance matrix of $\hat{r}_{xx^*}(\alpha)$.

The statistic will be obtained on the conditions of H_0 and H_1 from Refs. [3,11].

$$\begin{aligned} H_0 &: \lim_{M\to\infty} T_{xx^*}(\alpha) = \chi^2_{2N}, \\ H_1 &: \lim_{M\to\infty} T_{xx^*}(\alpha) = \chi^2_{2N}(\lambda), \end{aligned} \quad (12)$$

where $T_{xx^*}(\alpha)$ follows the gradual center chi-square distribution with $2N$ freedom degree in condition H_0, and $T_{xx^*}(\alpha)$ follows the non-central chi-square distribution with $2N$ freedom degree in condition H_1. Non-central parameter is deduced as following [11]:

$$\lambda = Mr_{xx^*}(\alpha)\hat{\Sigma}^{-1}_{xx^*}(\alpha)r^{\mathrm{T}}_{xx^*}(\alpha). \quad (13)$$

Therefore, the false-alarm probability and the detection probability are $P_f = Q_{\chi^2_{2N}}(\gamma)$ and $P_d = Q_{\chi^2_{2N}(\lambda)}(\gamma)$, respectively. According to Neyman-Pearson rule, the P_d can be obtained when given a target false-alarm probability P_{fa} as following:

$$P_d = Q_{\chi^2_{2N}(\lambda)}\left(Q^{-1}_{\chi^2_{2N}}(P_{fa})\right). \quad (14)$$

P_d is the performance of the single secondary user at single cycle frequency.

3.2 Weight optimization algorithm

Based on the cyclostationary properties of the primary user's signal, the algorithm adopts multiple secondary users to realize the weight cooperative detection according to the different cycle frequencies of the primary users' signals and optimized weight factors. The algorithm improves effectively the validity and reliability of the spectrum detection algorithm for cognitive radio. A modified detection algorithm is put forward on the basis of this idea. The block diagram of the algorithm is shown in Fig. 1.

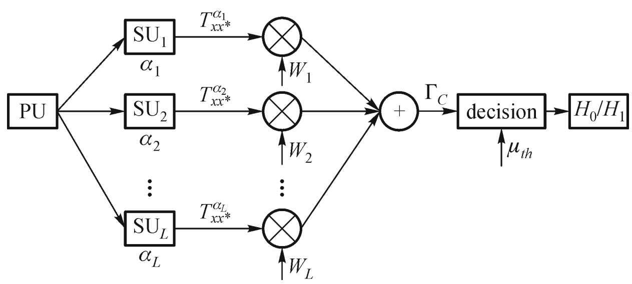

Fig. 1 Block diagram of MDCF-WCD algorithm

On the assumption that L secondary users detect the L different cycle frequencies in cycle frequency sets $\{\alpha_j\}_{j=1}^s$ respectively, the corresponding cyclostationary statistics of α_j is $T^{\alpha_j}_{xx^*}$, and the cyclic autocorrelation function estimations for different cycle frequencies are gradual irrelevant. The linear combination of the L detection statistical amounts is obtained from Ref. [3]:

$$\Gamma_c = \sum_{j=1}^{L} W_j T^{\alpha_j}_{xx^*} = W^T T, \quad (15)$$

where $W = [W_1,W_2,...,W_L]^{\mathrm{T}}$ is the weight vector, $W_j \geqslant 0$ and $\|W\|_2 = 1$. $T = [T^{\alpha_1}_{xx^*},T^{\alpha_2}_{xx^*},...,T^{\alpha_L}_{xx^*}]^{\mathrm{T}}$ is the detection statistics vector.

The next step is how to quantify the weight vector W to achieve the best performance of the detector. The deflection coefficient is selected as the standard of measurement in the algorithm because the final global detection statistic is a Gaussian random variable, and so the deflection coefficient can be applied to represent the influence of its probability density function to the detection performance. To get the deflection coefficient of the detector, first of all, the mean and variance of the statistic should be calculated under two assumptions conditions:

$$\begin{aligned} \mathrm{E}[\Gamma_c|H_0] &= 2N\sum_{j=1}^{L}W_j, \\ \mathrm{E}[\Gamma_c|H_1] &= \sum_{j=1}^{L}W_j(2N+\lambda_j), \\ \mathrm{var}[\Gamma_c|H_0] &= 4N\sum_{j=1}^{L}W_j = W^{\mathrm{T}}W, \\ \mathrm{var}[\Gamma_c|H_1] &= 4\sum_{j=1}^{L}W_j^2(N+\lambda_j) = 4W^{\mathrm{T}}\theta W, \end{aligned} \tag{16}$$

where $\theta \triangleq NI_L + \mathrm{diag}(\eta)$ and $\eta = [\lambda_1,\lambda_1,...,\lambda_L]$.

The deflection coefficient is an important index to evaluate the performance of the detector. It is defined as

$$DC(W) \triangleq \frac{(\mathrm{E}[\Gamma_c|H_1] - \mathrm{E}[\Gamma_c|H_0])^2}{\mathrm{var}[\Gamma_c|H_0]}. \tag{17}$$

Put the results (16) into the above equation and simplify:

$$DC(W) \triangleq \frac{1}{4N}\frac{(\eta^{\mathrm{T}}W)^2}{W^{\mathrm{T}}W}. \tag{18}$$

The essence of the detector based on the deflection coefficient optimization is to solve the following optimization problems:

$$\max_{W}\frac{(\eta^{\mathrm{T}}W)^2}{W^{\mathrm{T}}W}\ \text{s.t.}\ \|W\|_2 = 1, \tag{19}$$

where $\|W\|_2$ is the modulus of the weight vector. W_d^o is defined as the optimal solution of $\|W\|_2$. The optimal solution W_d^o is actually the maximum Rayleigh quotient [12] of the weight vector.

Assuming the largest variance $e_{\max}$ is an $L\times L$ symmetric matrix, the largest Rayleigh quotient is $\max\limits_{W\neq 0}\dfrac{W^{\mathrm{T}}bW}{W^{\mathrm{T}}W} = e_{\max}(b)$ for any $L\times 1$ vector W, where $e_{\max}(b)$ represents the largest variance of matrix b. Vector W which obtains the maximize Rayleigh quotient is the variance vector of the corresponding maximize variance. Here, $b = \eta\eta^{\mathrm{T}}$. Therefore, the deflection coefficient optimizing weight vector is deduced as

$$W_d^o = \frac{\eta}{\|\eta\|_2}. \tag{20}$$

3.3 Threshold determination of MDCF-WCD algorithm

To set the optimal threshold detector, the algorithm needs to figure out the distribution of weight summation to independent chi-square random variable. According to Ref. [12], we can obtain the approximate distribution of the linear summation to chi-square random variable. Assuming that $T_{xx^*}^{\alpha_j} \sim \chi_{2N}^2$ is the independent center chi-square distribution variables under H_0, $\Gamma_{c|H_0}$ will be obtained approximately:

$$\Gamma_{c|H_0} = \sum_{j=1}^{L}W_jT_{xx^*}^{\alpha_j} \overset{a}{\sim} p\chi_v^2, \tag{21}$$

where a represents the approximate distribution,

$$\begin{aligned} p &= \frac{1}{\sum_{j=1}^{L}W_j}, \\ v &= 2N\left(\sum_{j=1}^{L}W_j\right)^2. \end{aligned} \tag{22}$$

Then, the threshold is estimated as

$$\mu_{th} \approx pQ_{\chi_v^2}^{-1}(P_{fa}). \tag{23}$$

Therefore, the statistical detection decision between H_0 and H_1 can be performed as

$$\begin{cases} \text{if } \Gamma_c < \mu_{th},\ H_0 \text{ is decided;} \\ \text{if } \Gamma_c > \mu_{th},\ H_1 \text{ is decided.} \end{cases} \tag{24}$$

4 Simulation results and analysis

The orthogonal frequency division multiplexing (OFDM) signal is adopted as the primary users' signal in simulation because the OFDM signal is applied widely in wireless communication systems, such as the 3GPP long-term evolution (LTE) systems, IEEE 802.11a/g wireless LAN system, the DVB-T and DVB-H systems based on digital video broadcasting (DVB) standard, IEEE 802.16 and the WiMax wireless MAN system [10]. Without loss of generality, the signal of the IEEE 802.11a wireless LAN network is selected as the signal of the primary user, and the parameters of the signals are listed in Table 1.

The basic cycle frequency α_0 of the OFDM signal is the reciprocal of the useful OFDM symbol length, that is, $\alpha_0 = 1/N_u$. Then, the cycle frequencies set A is $\{\alpha = m\alpha_0\}$ [8], m is an integer and $N_u = N_{fft} + N_g$. In Ref. [13], the authors have proved that the OFDM signal has a strong cyclostationary property at time-delay $\tau = \pm N_{fft}$. The simulation is completed in additive white Gaussian noise (AWGN) channel. Other parameters are supposed as follows: number of signal samples is $N = 1024$, $\beta = 10$, and the Kaiser window with the length $L = N/4-1$. Monte Carlo simulation is independently implemented 10000 times with the false alarm probability $P_{fa} = 0.02$.

Table 1 OFDM signal parameters in simulation

parameters	value
sub-carrier modulation mode	quadrature phase shift keying (QPSK)
FFT length	$N_{fft} = 128$
number of occupied channels	$N_{OOC} = 128$
guard interval length	$N_g = 32$
symbol rate	250 ksym/s
sampling rate	$R_S = 20$ MHz
carrier frequency	$f_c = 5$ GHz

The detection performance of a single user at three different cycle frequencies is shown in Fig. 2. The three cycle frequencies selected at random are $\alpha_1 = 3\alpha_0$, $\alpha_2 = 5\alpha_0$, and $\alpha_3 = 6\alpha_0$. The detection performance of a single user is not the same at different cycle frequencies in Fig. 2. This is because different cycle frequency contains wealth different information of the cyclostationary signals. For example, the cycle frequency of the cyclostationary signal may be related with the carrier frequency, symbol rate, and coding rule. Therefore, the variations of detection performance exist for the detection at different cycle frequencies. Obviously, it will make full use of the cyclostationary properties of the primary user to improve the spectrum detection performance by adopting multiple cycle frequencies cooperative detection.

Figure 3 shows the simulation result of the detection performance when the number of the cooperation detection users involved is changed. The weight cooperative detection method proposed in this paper is applied by each multi-user at a different cycle frequency. From Fig. 3, it is obvious that the detection performance is improved with the increasing of the secondary users involved in cooperation detection. This is because the number of the different cycle frequencies is also increased to realize the signal detection while the cooperative users increase. The detection probability will reach 100% with −7 dB SNR when 4 secondary users participate in the cooperative detection. This shows that the multiple-secondary-user cooperative detection can produce cooperation gain.

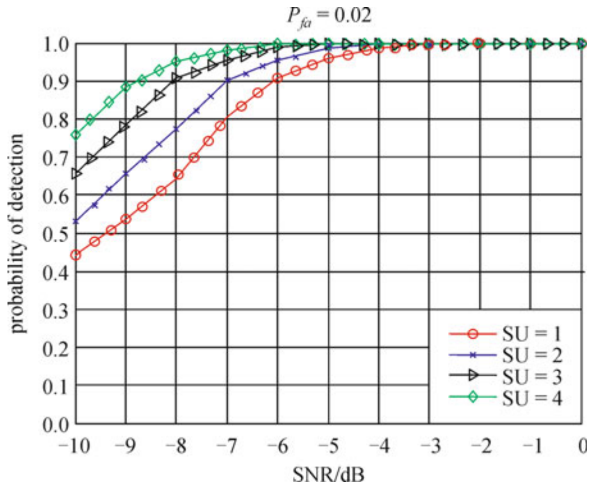

Fig. 3 Cooperative detection performance comparison when the detection users are changed

Figure 4 is the receiver operating characteristic (ROC) of cooperative detection algorithm proposed in this paper in AWGN channel compared with in slow flat Rayleigh fading channel while SNR is −7 dB. $h = k\sqrt{a^2 + b^2}$ is the channel factor of the slow flat Rayleigh fading channel, where a and b are the Gaussian random variables with independent and identically distributed, and variance is 1. K is the scale factor, and is set as $\sqrt{1/2}$ in order to keep the mean power of the flat Rayleigh fading to be 1. The data will be invariant in a sampling process because of the slow flat Rayleigh fading channel. It could be found out from Fig. 4 that the detection algorithm proposed in this paper

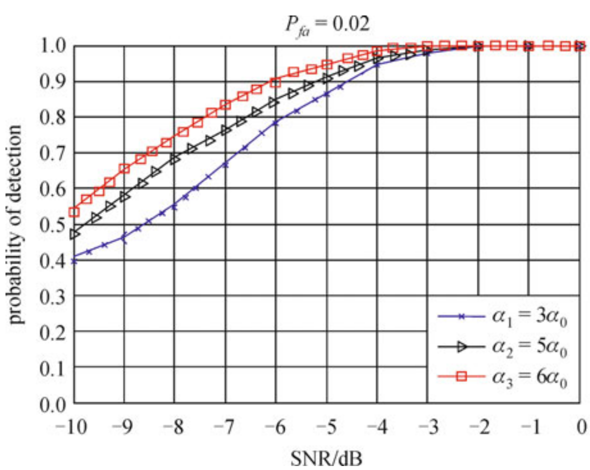

Fig. 2 Single-user detection performance comparison at three different cycle frequencies

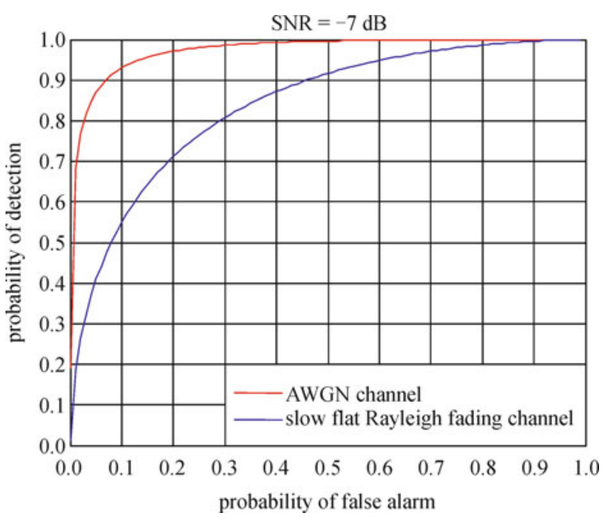

Fig. 4 ROC of cooperative detection algorithm proposed in this paper

still has better detection performance even in slow Rayleigh flat fading channel. This is because the multi-user cooperative detection at different cycle frequencies takes full advantage of multi-user cooperation gain and the primary users' signal cyclostationary properties, overcomes the adverse factors effectively in the wireless environment such as multipath fading and shadow effects, and improves the signal detection performance. Meanwhile, because the algorithm is a compromise of the two above algorithms, the computational complexity does not increase, which meets the real-time detection requirements of cognitive radio free spectrum.

In Fig. 5, the detection performance is compared among the multi-user detection at a single cycle frequency proposed in Ref. [6], the multi-user detection at different multiple cycle frequencies, the single-user detection at different multiple cycle frequencies proposed in Refs. [7,11], and the MDCF-WCD algorithm (DC method) presented in this paper. Three secondary users, three different cycle frequencies, and two different data fusion methods are selected in simulation. By the detection performance comparison of four different detection methods, the performance of multi-user EGC cooperative detection at different cycle frequencies is superior to single-user EGC cooperative detection at different cycle frequencies and multi-user EGC cooperative detection at single cycle frequency, meanwhile the MDCF-WCD algorithm is superior to the detection performance of the multi-user EGC cooperative detection at different cycle frequencies. The MDCF-WCD algorithm takes full advantage of cooperation gain produced by space diversity and the cyclostationary properties of the primary users' signals; therefore, the detection performance has got double gain, and the DC-based optimization in the data fusion stage for weight factor further improves the signal detection performance.

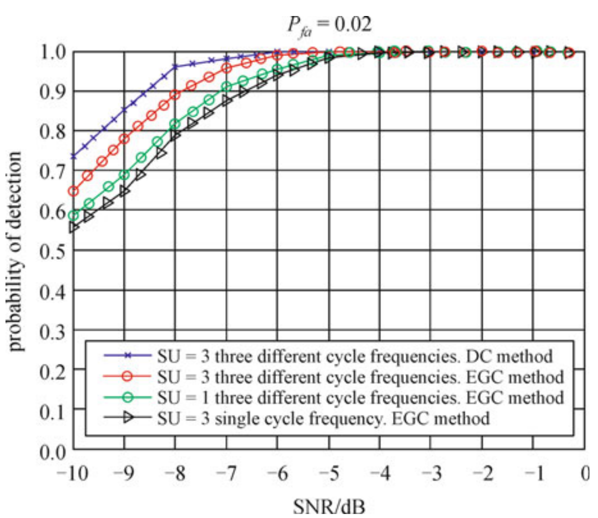

Fig. 5 Performance comparison of three detection methods

Finally, we will simply describe the complexity of the interrelated algorithms. The DC-based method presented in the paper has the approximate complexity with EGC method while at the same number of cycle frequencies. The difference between them is that the DC-based algorithm adopted the different cycle frequencies and the EGC method adopted the same cycle frequency. Meanwhile, the data fuse method of the DC-based algorithm is better than that of the EGC method. Being confined to the length of the paper, we do not compare the algorithm complexity in detail.

5 Conclusion

Cognitive radio is the most important way to improve the spectrum utilization ratio, and the reliable and effective detection of the primary user's signal is one of the most important requirements for cognitive wireless network performance. This paper adopts the signal's cyclostationary properties to implement weight cooperative detection by multiple secondary users at different signal cycles frequencies, and presents a DC-based weight optimization method. Simulation results show that even in low SNR, the detection algorithm mentioned in this article still has high detection performance.

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