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RESEARCH ARTICLE

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A design of multi-cycle detector for cognitive radios

Abstract Cognitive radio (CR) is a promising technology. The most fundamental problem of CR is spectrum sensing. Energy detector is often considered for spectrum sensing in CR, and if the noise power is exactly known, energy detector has admirable performance. However, in practice, noise power is always inexactly known. To solve this problem, Dandawate [Dandawate et al. IEEE Transactions on Signal Processing, 1994, 42(9): 2355–2369] has proposed a nonparametric single-cycle detector based on cyclostationarity, which is robust to noise uncertainty. In this paper, based on Dandawate's single-cycle detector, a joint multi-cycle detector is further proposed, which is also nonparametric and immune from noise uncertainty. Simulation results have shown the validity and superiority over single-cycle detector of the proposed detector.

Keywords cognitive radio (CR), cyclostationarity, noise uncertainty, spectrum sensing

1 Introduction

Cognitive radio (CR) has been proposed recently as the means to make an efficient use of the spectrum by exploiting the existence of unused spectrum. In spite of the brilliant prosperity, the most fundamental problem of CR is how to locate idle spectrum as quickly and accurately as possible. There are various methods for spectrum sensing existing in Refs. [1–3], such as energy detection method and feature detection method. Energy detection is the most commonly used sensing method because of its simplicity and admirable performance. However, if the noise power is not known exactly, the performance of energy detector deteriorates rapidly. In practice, noise is an aggregation of various sources and could change significantly over time so that noise uncertainty is always present and ranges from 1 to 2 dB according to Refs. [4,5].

Unlike energy detector, feature detector, such as a cyclic detector, exploits the unique patterns of specific signals and may be immune from noise uncertainty. In Ref. [6], Dandawate has presented some statistical tests to show how to use cyclostationarity to determine the presence of cyclostationary signals. However, Dandawate only considered the case of single-cycle detector, whereas cyclostationary signals usually have multiple cyclic frequencies. As a result, Dandawate's tests have not used the rich information contained in cyclostationary signals sufficiently. To solve this problem, Ref. [7] has proposed two methods for detecting multiple cyclic frequencies. One calculates the maximum of the test statistics over all cyclic frequencies, and the other calculates the sum. Reference [7] further gives a detailed performance analysis about the former one, but they fail to do so about the latter one, which is usually superior to the former one according to their simulation results.

In this paper, we propose a joint multi-cycle detection method that is different from both two methods of Ref. [7], except for the same complexity and further gives a detailed introduction to show how to implement spectrum sensing by using the proposed method. Simulation results demonstrate the reasonability and validity of our method.

2 Joint multi-cycle detector

2.1 Cyclostationarity

A continuous-time random process $x(t)$ is said to be cyclostationary in the wide sense if its autocorrelation function is a periodic function of the variable t and will therefore admit the Fourier series representation:

$$R_x(t,t+\tau) = \mathrm{E}\{x(t)x^*(t+\tau)\} = \sum_{\alpha\in\Omega} R_x^{\alpha}(\tau)\mathrm{e}^{\mathrm{j}2\pi\alpha t}, \quad (1)$$

where $R_x^{\alpha}(\tau)$ is called the cyclic autocorrelation function (CAF), and the set Ω contains all integer multiples of the fundamental frequency α. Furthermore, if $x(t)$ is a

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cycloergodic process, CAF can be given by the following formula:

$$R_x^{\alpha}(\tau)=\lim_{T\to\infty}\frac{1}{T}\sum_{t=0}^{T-1}x(t)x^*(t+\tau)\mathrm{e}^{-\mathrm{j}2\pi\alpha t}. \tag{2}$$

If $x(t)$ is stationary, then Eq. (2) becomes

$$R_x^{\alpha}(\tau)=\lim_{T\to\infty}\frac{1}{T}R_x(\tau)\sum_{t=0}^{T-1}\mathrm{e}^{-\mathrm{j}2\pi\alpha t}$$

$$=\begin{cases}R_x(\tau), & \alpha=0,\\ 0, & \alpha\neq 0.\end{cases} \tag{3}$$

This implies that the CAF of a stationary process is vanished at cyclic frequency α ($\alpha\neq 0$), while the CAF of a cyclostationary process is not, which shows the potential of cyclostationarity in signal detection.

2.2 Proposed algorithm

A typical signal detection problem usually formulated as a binary hypothesis testing problem:

$$\begin{cases}x(t)=n(t), & H_0,\\ x(t)=s(t)+n(t), & H_1,\end{cases} \tag{4}$$

where $s(t)$ is the cyclostationary signal, $n(t)$ is a stationary noise process with zero mean, $s(t)$ and $n(t)$ are independent with each other, $x(t)$ is the received signal, and H_0 or H_1 represents the absence or presence of the primary signal, respectively. Our goal is to distinguish between the two hypotheses. Moreover, in order to obtain the asymptotic results, we make the following assumption on $x(t)$:

Assumption 1

$$\sum_{\tau_1,\tau_2,\dots,\tau_{k-1}}|\tau_i c_{kx}(\tau_1,\tau_2,\dots,\tau_{k-1})|<+\infty, \tag{5}$$

where $c_{kx}(\tau_1,\tau_2,\dots,\tau_{k-1})$ is the kth order cumulant of $x(t)$.

Assumption 1 implies that samples of $x(t)$ are well separated in time and are approximately independent, and it is useful in characterizing the rate of convergence of polyspectra, as illustrated by Dandawate.

Based on finite samples T, a reasonable estimator of $R_x^{\alpha}(\tau)$ is

$$R_x^{\alpha(T)}(\tau)\triangleq\frac{1}{T}\sum_{t=0}^{T-1}x(t)x^*(t+\tau)\mathrm{e}^{-\mathrm{j}2\pi\alpha t}. \tag{6}$$

Dandawate further proved its asymptotic unbiasedness, consistency, and asymptotic normality in Ref. [6]. Hence, if the samples are large enough, the hypothesis testing problem becomes

$$\begin{cases}R_x^{\alpha(T)}(\tau)=\varepsilon^{(T)}(t), & H_0,\\ R_x^{\alpha(T)}(\tau)=R_s^{\alpha}(\tau)+\varepsilon^{(T)}(t), & H_1,\end{cases} \tag{7}$$

where $\varepsilon^{(T)}(t)$ denotes the estimation error that vanishes asymptotically as $T\to\infty$.

If $x(t)$ is zero mean (if not, one can estimate and subtract the mean), given N distinct cyclic frequencies $\alpha_1,\alpha_2,\dots,\alpha_N$ and N lag vectors $\boldsymbol{\tau}_1,\boldsymbol{\tau}_2,\dots,\boldsymbol{\tau}_N$ ($\boldsymbol{\tau}_i=\begin{bmatrix}\tau_i^1 & \tau_i^2 & \cdots & \tau_i^{n_i}\end{bmatrix}$). Then, define a $1\times 2M$ ($M=n_1+n_2+\cdots+n_N$) vector:

$$\begin{aligned}\hat{\boldsymbol{r}}_{2x}^{\Omega(T)}(\boldsymbol{\tau})\triangleq\Big[&\mathrm{Re}\left\{\hat{R}_{2x}^{\alpha_1(T)}(\tau_1^1)\right\},\dots,\mathrm{Re}\left\{\hat{R}_{2x}^{\alpha_1(T)}(\tau_1^{n_1})\right\},\dots,\\ &\mathrm{Re}\left\{\hat{R}_{2x}^{\alpha_N(T)}(\tau_N^1)\right\},\dots,\mathrm{Re}\left\{\hat{R}_{2x}^{\alpha_N(T)}(\tau_N^{n_N})\right\},\\ &\mathrm{Im}\left\{\hat{R}_{2x}^{\alpha_1(T)}(\tau_1^1)\right\},\dots,\mathrm{Im}\left\{\hat{R}_{2x}^{\alpha_1(T)}(\tau_1^{n_1})\right\},\dots,\\ &\mathrm{Im}\left\{\hat{R}_{2x}^{\alpha_N(T)}(\tau_N^1)\right\},\dots,\mathrm{Im}\left\{\hat{R}_{2x}^{\alpha_N(T)}(\tau_N^{n_N})\right\}\Big],\end{aligned} \tag{8}$$

where

$$\hat{R}_{2x}^{\alpha_i(T)}(\tau_i^j)\triangleq\frac{1}{T}\sum_{t=0}^{T-1}x(t)x^*(t+\tau_i^j)\mathrm{e}^{-\mathrm{j}2\pi\alpha_i t}$$

$$(\alpha\neq 0;\ i=1,2,\dots,N;\ j=1,2,\dots,n_i). \tag{9}$$

The $2M\times 2M$ covariance matrix of $\hat{\boldsymbol{r}}_{2x}^{\Omega(T)}(\boldsymbol{\tau})$ can be computed as

$$\hat{\boldsymbol{\Sigma}}_{2c}=\frac{1}{2}\begin{bmatrix}\mathrm{Re}\{\boldsymbol{Q}_{2c}+\boldsymbol{Q}_{2c}^*\} & \mathrm{Im}\{\boldsymbol{Q}_{2c}-\boldsymbol{Q}_{2c}^*\}\\ \mathrm{Im}\{\boldsymbol{Q}_{2c}+\boldsymbol{Q}_{2c}^*\} & \mathrm{Re}\{\boldsymbol{Q}_{2c}^*-\boldsymbol{Q}_{2c}\}\end{bmatrix}, \tag{10}$$

where the (m,n)th entries of $\boldsymbol{Q}_{2c}$ and $\boldsymbol{Q}_{2c}^*$ can be calculated as

$$\boldsymbol{Q}_{2c}(m,n)\triangleq\hat{S}_{2f_{\tau_m,\tau_n}}^{(T)}(\alpha_m+\alpha_n;\alpha_n),$$

$$\boldsymbol{Q}_{2c}^*(m,n)\triangleq\hat{S}_{2f_{\tau_m,\tau_n}}^{*(T)}(\alpha_m-\alpha_n;-\alpha_n). \tag{11}$$

Here, $\hat{S}_{2f_{\tau,\rho}}^{(T)}(\alpha;w)$ and $\hat{S}_{2f_{\tau,\rho}}^{*(T)}(\alpha;w)$ denote the estimated unconjugated and conjugated cyclic spectrum of $f(t;\tau)\triangleq x(t)x^*(t+\tau)$, respectively.

Given a symmetric spectral window $W(s)$ of odd length L, $\hat{S}_{2f_{\tau,\rho}}^{(T)}(\alpha;w)$ and $\hat{S}_{2f_{\tau,\rho}}^{*(T)}(\alpha;w)$ can be computed as follows:

$$\begin{aligned}&\hat{S}_{2f_{\tau_m,\tau_n}}^{(T)}(\alpha_m+\alpha_n;\alpha_n)\\ &=\frac{1}{TL}\sum_{s=-(L-1)/2}^{(L-1)/2}W(s)\\ &\quad\times F_{T,\tau_m}\left(\alpha_n+\frac{2\pi s}{T}\right)F_{T,\tau_n}\left(\alpha_m-\frac{2\pi s}{T}\right),\end{aligned} \tag{12}$$

$$\hat{S}^{(T)}_{2f_{\tau_m,\tau_n}}(\alpha_m-\alpha_n;-\alpha_n) = \frac{1}{TL}\sum_{s=-(L-1)/2}^{(L-1)/2} W(s) \times F^*_{T,\tau_m}\left(\alpha_n+\frac{2\pi s}{T}\right)F_{T,\tau_n}\left(\alpha_m+\frac{2\pi s}{T}\right), \quad (13)$$

where

$$F_{T,\tau}(w)=\sum_{t=0}^{T-1} x(t)x^*(t+\tau)\mathrm{e}^{-\mathrm{j}wt}. \quad (14)$$

Both Eqs. (12) and (13) can be derived from Ref. [8], and these spectrum estimators are also proved to be asymptotic unbiased, consistent, and asymptotically normal in Ref. [8].

According to Ref. [9], using the generalized likelihood ratio test (GLRT), the test statistic of this problem is

$$T''_{2c} = \ln\frac{\frac{1}{(2\pi)^{T/2}|\boldsymbol{\Sigma}_{2c}|}\exp\left(-\frac{1}{2}\left(\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})-\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})\right)'\boldsymbol{\Sigma}^{-1}_{2c}\left(\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})-\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})\right)\right)}{\frac{1}{(2\pi)^{T/2}|\boldsymbol{\Sigma}_{2c}|}\exp\left(-\frac{1}{2}\left(\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})\right)'\boldsymbol{\Sigma}^{-1}_{2c}\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})\right)}$$

$$= \left(\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})\right)'\boldsymbol{\Sigma}^{-1}_{2c}\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})-\frac{1}{2}\left(\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})\right)'\boldsymbol{\Sigma}^{-1}_{2c}\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau}). \quad (15)$$

To get the asymptotic distributions, ignoring the irrelevant items, a refined test statistic is defined as follows:

$$T'_{2c} = T\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})\boldsymbol{\Sigma}^{-1}_{2c}\hat{\boldsymbol{r}}^{\Omega(T)'}_{2x}(\boldsymbol{\tau}). \quad (16)$$

Replace $\boldsymbol{\Sigma}_{2c}$ and $\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})$ with their estimators $\hat{\boldsymbol{\Sigma}}_{2c}$ and $\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})$, respectively. We get the final test statistic of our proposed joint multi-cycle detector:

$$T_{2c} = T\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})\hat{\boldsymbol{\Sigma}}^{-1}_{2c}\hat{\boldsymbol{r}}^{\Omega(T)'}_{2x}(\boldsymbol{\tau}). \quad (17)$$

2.3 Asymptotic distributions

To set a threshold, we need the asymptotic distributions of T_{2c}. The following theorem can be found in Ref. [10, Chap. 3]:

Theorem 1 If the m-component vector $\boldsymbol{y}$ is distributed according to $\mathcal{N}(\boldsymbol{\mu},\boldsymbol{\Psi})$, then $\boldsymbol{y}\boldsymbol{\Psi}^{-1}\boldsymbol{y}'$ is distributed according to the noncentral χ^2_m distribution with noncentrality parameter $\boldsymbol{\mu}\boldsymbol{\Psi}^{-1}\boldsymbol{\mu}'$. If $\boldsymbol{\mu}=\boldsymbol{0}$, the distribution is the central χ^2_m distribution.

Here, $\boldsymbol{y}=\sqrt{T}\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})$, $\boldsymbol{\mu}=\boldsymbol{0}$ under H_0, and $\boldsymbol{\mu}=\sqrt{T}\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})$ under H_1, and $\boldsymbol{\Psi}=\boldsymbol{\Sigma}_{2c}$. Then, according to Theorem 1, the following asymptotic results come immediately:

$$\begin{cases} T_{2c}\sim\chi^2_{2M}, & H_0,\\ T_{2c}\sim\chi^2_{2M}\left(T\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})\boldsymbol{\Sigma}^{-1}_{2c}\boldsymbol{r}^{\Omega'}_{2s}(\boldsymbol{\tau})\right), & H_1. \end{cases} \quad (18)$$

In practice, we have no knowledge about the signal or the noise; therefore, we should replace $\boldsymbol{r}^{\Omega}_{2s}(\boldsymbol{\tau})$ and $\boldsymbol{\Sigma}^{-1}_{2c}$ with their estimators $\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})$ and $\hat{\boldsymbol{\Sigma}}^{-1}_{2c}$. Note that when T is large enough, we can further use Gaussian distribution to approximate the noncentral chi-square distribution according to Ref. [9], which may be more useful in engineering. Hence, Eq. (18) yields

$$\begin{cases} T_{2c}\sim\chi^2_{2M}, & H_0, \quad (19a)\\ T_{2c}\sim\mathcal{N}\Big(T\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})\hat{\boldsymbol{\Sigma}}^{-1}_{2c}\hat{\boldsymbol{r}}^{\Omega(T)'}_{2x}(\boldsymbol{\tau}), \\ \qquad 4T\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})\hat{\boldsymbol{\Sigma}}^{-1}_{2c}\hat{\boldsymbol{r}}^{\Omega(T)'}_{2x}(\boldsymbol{\tau})\Big), & H_1. \quad (19b) \end{cases}$$

From Eq. (19a), given false alarm probability P_{FA}, the establishment of the threshold of a cyclic detector is only related to M and has nothing to do with noise power, so it is robust to noise uncertainty.

Unlike the work in Ref. [7], we use multiple cyclic frequencies jointly, so we name it "joint multi-cycle detector". This proposed detector has the same complexity as the two detectors in Ref. [7], and the performance comparison of these different multi-cycle detectors is given in Sect. 4.

Summing up the above discussion, we finally propose the suggested algorithm of joint multi-cycle detector:

Step 1 For N given distinct cyclic frequencies $\alpha_1,\alpha_2,\ldots,\alpha_N$ and N given lag vectors $\boldsymbol{\tau}_1,\boldsymbol{\tau}_2,\ldots,\boldsymbol{\tau}_N$ ($\boldsymbol{\tau}_i=[\tau_i^1\ \tau_i^2\ \cdots\ \tau_i^{n_i}]$), using Eq. (8) to compute $\hat{\boldsymbol{r}}^{\Omega(T)}_{2x}(\boldsymbol{\tau})$, based on T samples of the received signal $x(t)$.

Step 2 Compute the covariance matrix $\hat{\boldsymbol{\Sigma}}_{2c}$ as discussed following Eq. (10).

Step 3 Compute the test statistics T_{2c} according to Eq. (17).

Step 4 For a given false alarm probability P_{FA}, set up the threshold by Eq. (19a), and then determine the presence of the signal. Moreover, if performance evaluation is needed, the detection probability can also be estimated by Eq. (19b).

3 Collaborative spectrum sensing

If noise uncertainty exists, for energy detector, many independent sensors are required to obtain a reasonably low probability of misdetection according to Ref. [5]. However, since cyclic detector is robust to noise uncertainty, the cooperation of a few CR users will achieve a satisfied performance in spectrum sensing for the proposed joint multi-cycle detection method.

Assume that there is a CR network with Z cooperative users, the total test statistic could be the sum of every individual user:

$$\Delta = \sum_{i=1}^{Z} T_i \hat{\boldsymbol{r}}_{2x}^{\Omega_i(T_i)}(\boldsymbol{\tau}_i)\left(\hat{\boldsymbol{\Sigma}}_{2c}^{\Omega_i}\right)^{-1}\hat{\boldsymbol{r}}_{2x}^{\Omega_i(T_i)'}(\boldsymbol{\tau}_i). \qquad (20)$$

If they sensing the spectrum independently, the asymptotic distributions can be given by

$$\begin{cases} \Delta \sim \chi^2_{2\sum_{i=1}^{Z} M_i}, & H_0, \\ \Delta \sim \mathcal{N}\left(\sum_{i=1}^{Z} T_i \hat{\boldsymbol{r}}_{2x}^{\Omega_i(T_i)}(\boldsymbol{\tau}_i)\left(\hat{\boldsymbol{\Sigma}}_{2c}^{\Omega_i}\right)^{-1}\hat{\boldsymbol{r}}_{2x}^{\Omega_i(T_i)'}(\boldsymbol{\tau}_i),\ 4\sum_{i=1}^{Z} T_i \hat{\boldsymbol{r}}_{2x}^{\Omega_i(T_i)}(\boldsymbol{\tau}_i)\left(\hat{\boldsymbol{\Sigma}}_{2c}^{\Omega_i}\right)^{-1}\hat{\boldsymbol{r}}_{2x}^{\Omega_i(T_i)'}(\boldsymbol{\tau}_i)\right), & H_1, \end{cases} \qquad (21)$$

which is a straightforward derivation of Eq. (19).

4 Simulation results and analysis

In this section, we will give some simulation results to show the validity and reasonability of our proposed joint multi-cycle detector. Note that in the following Figs. 2–4, "theo" means theoretical curves, "EG-x dB" means energy detection with x dB noise uncertainty, "x Freqs" means that x distinct cyclic frequencies are adopted by a cyclic detector, "x CRs" means that there are x cooperative CRs, and "P_{FA}" means that the simulated false alarm probability curves. All the simulation results are obtained from 2000 Monte Carlo runs.

An orthogonal frequency division multiplexing (OFDM) signal is adopted as a test signal in our simulations. OFDM is employed by many of wireless communications systems, such as 3GPP long-term evolution (LTE), IEEE 802.11a/g, digital video broadcasting (DVB) systems, ultra wideband (UWB) systems, and WiMax systems.

OFDM signals can be represented as follows:

$$x(t) = \sum_{k}\sum_{i=0}^{N_s} \gamma_{i,k} \mathrm{e}^{\mathrm{j}(2\pi/T_s)it} q(t - kT_{\mathrm{D}}), \qquad (22)$$

where $\gamma_{i,k}$ is an independent and identically distributed message symbol sequence, N_s is the number of subcarriers, T_s is the symbol length, $q(t)$ denotes the rectangular pulse of duration T_{D}, and T_g is the cyclic prefix length such that $T_{\mathrm{D}} = T_s + T_g$. OFDM signals exhibits cyclostationarity with cyclic frequencies of $\alpha = \pm k/T_{\mathrm{D}}$, $k = 1,2,\ldots$, according to Refs. [11,12].

The OFDM signal we used here has 32 subcarriers, and the length of the cyclic prefix is 1/4 of the symbol length. The subcarrier modulation employed is a 16-quadrature amplitude modulation (16-QAM). The spectral window $W(s)$ we have chosen is a length-251 Kaiser window with β parameter of 10.

The cyclic frequencies and the lag vectors we chose are $\alpha_1 = 1/T_{\mathrm{D}}$, $\alpha_2 = 2/T_{\mathrm{D}}$, $\alpha_3 = 3/T_{\mathrm{D}}$, and $\boldsymbol{\tau}_1 = \boldsymbol{\tau}_2 = \boldsymbol{\tau}_3 = [0]$. "1 Freq" means that α_1 has been adopted by a cyclic detector, while "3 Freqs" denotes a multi-cycle detector with three distinct cyclic frequencies α_1, α_2, and α_3.

Figure 1 shows CAF of the OFDM signal. As mentioned before, OFDM signals exhibits cyclostationarity with cyclic frequencies of $\alpha = \pm k/T_{\mathrm{D}}$, $k = 1,2,\ldots$. Figure 1 reveals this clearly.

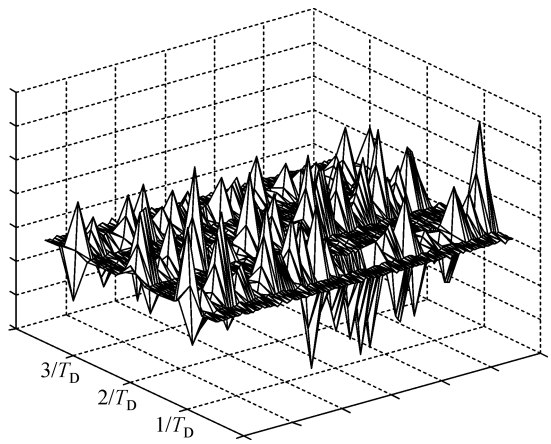

Fig. 1 CAF of an OFDM signal

Figure 2 shows a comparison between a single-cycle detector and a joint multi-cycle detector under different sample sizes. We set $P_{\mathrm{FA}} = 0.05$ and the signal-to-noise ratio SNR = −10 dB. We see clearly the joint multi-cycle detector that outperforms the single-cycle detector either in theory or in simulations. The estimation errors are also decreasing when the sample sizes are increasing. In addition, the false alarm probability is relatively stable since there are enough samples, and the chi-square distribution can be satisfied easily.

Figure 3 depicts the receiver operating characteristic (ROC) curves of joint multi-cycle detector and energy detector with different noise uncertainty. We set SNR =

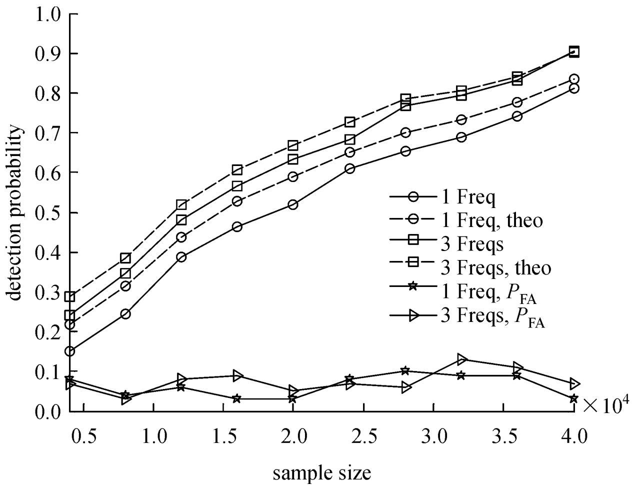

Fig. 2 Comparison between single-cycle detector and joint multi-cycle detector, $\boldsymbol{\tau} = [0]$, $P_{FA} = 0.05$, and SNR = −10 dB

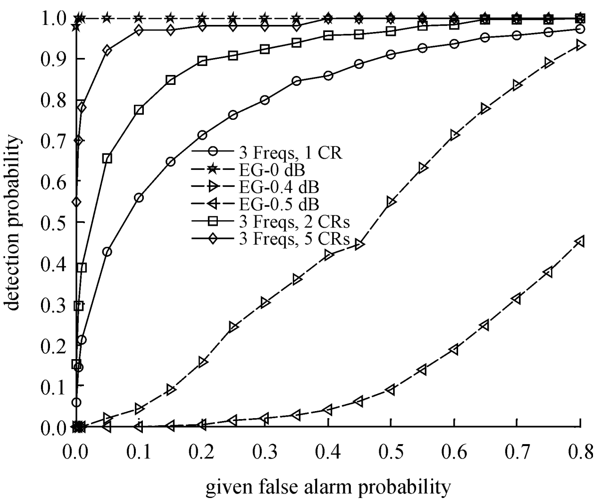

Fig. 3 ROC curves of a joint multi-cycle detector and an energy detector with different noise uncertainties, $\boldsymbol{\tau} = [0]$, SNR = −10 dB, and $T = 4000$

−10 dB and T = 4000. The energy detector is perfectly good if there is no noise uncertainty, but its performance deteriorates rapidly even if the noise uncertainty is as small as 0.4–0.5 dB. A joint multi-cycle detector is robust to noise uncertainty, and through cooperation, it may achieve a high performance as an ideal energy detector.

Figure 4 illustrates the SNR versus detection probability curves of different multi-cycle detectors and energy detector with different noise uncertainties. Note that in this figure, "JMC" is our proposed joint multi-cycle detector. "SMC" is the multi-cycle detector using the sum of all cyclic frequencies, and "MMC" is the multi-cycle detector using the maximum of them, which are both proposed in Ref. [7]. Here, we set $P_{FA} = 0.05$ and $T = 4000$. It also proves multi-cycle detectors are superior to energy detector if noise uncertainty exists. In addition, we can see that JMC detector is equivalent to SMC detector and both JMC and SMC detectors outperform MMC detector, about 0.5 dB in performance. Moreover, in Fig. 4, for a joint multi-cycle detector, through the cooperation of 2–5 CR users, we will gain an increase of about 1–2 dB in performance.

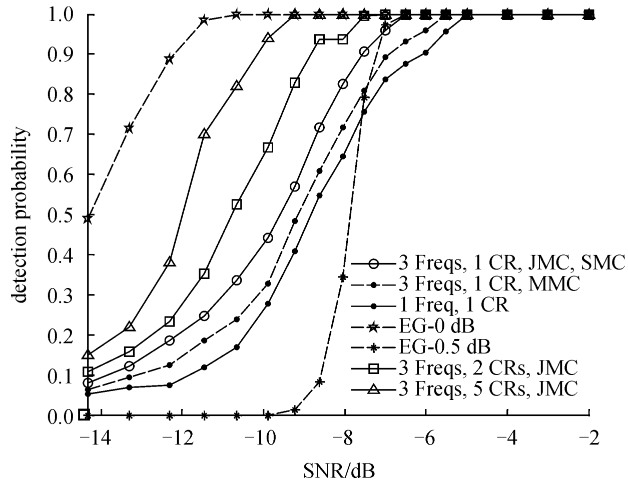

Fig. 4 SNR versus detection probability curves of different multi-cycle detectors and energy detector with different noise uncertainties, $\boldsymbol{\tau} = [0]$, $P_{FA} = 0.05$, and $T = 4000$

5 Conclusion

In this paper, we propose a joint multi-cycle detector based on Dandawate's single-cycle detector. According to our theoretical analysis and simulation results, it is robust to noise uncertainty and better than single-cycle detector. Furthermore, through the cooperation of a few CR users, it may achieve a high performance as an ideal energy detector. In conclusion, the joint multi-cycle detector has a wide range of application prospects.

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