Performance of Spectrum Sensing and Optimization Based on User Selection in Cognitive Radio

YANG OU †* YI-MING WANG †

***Abstract*—**The paper first proposes a fast novel spectrum sensing algorithm for cognitive radios based on cyclic autocorrelation. When only the existence of primary users in noise is detected, special cyclic frequency can be choosed to sense, which will significantly reduce the computational cost in applying the cyclostationarity detection. The paper also proposes to select the users with good detection performance for cooperative sensing so as to improve sensing sensitivity. It demonstrates that the throughput of CR system is also improved by user selection.

***Keywords*—**spectrum sensing, cyclostationary detection, cyclic autocorrelation, sensing-throughput, user selection

I. INTRODUCTION

Cognitive radio [1] has been proposed as a possible solution to improve spectrum utilization via opportunistic sharing. Cognitive radio users are considered lower priority or secondary users of spectrum allocation to a primary user. Their fundamental requirement is to avoid interference to potential primary users in their vicinity. That is, it is necessary to dynamically detect the existence of primary users' signals. Detecting the presence of primary users is currently one of the most challenging tasks in CR design and implementation.

There are several definitions of a vacant frequency band, but generally we can consider that a frequency band is unoccupied if the filtered radio signal within this band is only composed of noise. In the opposite case, this signal will consist of an unknown nonzero number of telecommunication signals in addition to the noise.

How to detect the existence of primary users in the given frequency bands? The solution to this problem was largely studied in the past and depends on the degrees of knowledge we have on the signal and the noise. Energy detection is a major and basic method. It needs the knowledge of accurate noise power. In practice, it is very difficult to obtain the accurate noise power. When noise power is unknown, the quality of detection is strongly degraded[2][3]. Matched filtering is the optimum method for detection of primary users. However, matched filtering requires the cognitive user/radio to demodulate the received signal hence it requires perfect knowledge of the primary users signal features. Moreover, since the cognitive radio will need receivers for all signal types, it is practically difficult to implement. For the case of unknown noise power, the cyclostationarity property of communication signals is exploited. In contrast to noise which is a wide-sense stationary random signal with no correlation, the modulated signals are in general coupled with sine wave carriers, pulse trains, hopping sequences or cyclic prefixes which result in periodicity of the mean and autocorrelation of such signals. These features can be used to discriminate the noise from modulated signal. The detection based on cyclostationarity property chooses a cyclostationarity model[4],[5] rather than a stationary one for the signal. This model is particularly attractive when the noise is of stationary type. Several works[6]-[10] are devoted to this kind of problem and propose various tests of cyclostationarity over a given set of cycle frequencies. Among these methods, cyclic spectrum or spectrum correlation density (SCD) function is the main estimator. To better depict cyclic spectrum, large estimation is needed. While the spectrum detection probability(P_d) and the probability of false alarm(P_{fa}) haven't been expressed in a closed analytical form.

In this paper, a sensing technique based on cyclic autocorrelation (CA) is proposed to detect the primary users in the given spectrum. The remainder of the paper is organized as follows. In section 2 the cyclic autocorrelation features are introduced and the detecting model of the primary users is presented. A fast spectrum sensing method is proposed in section 3 and probability distribution functions of the computed CA are given. In section 4, computer simulations are presented to verify the method. In section 5, cooperative spectrum sensing is discussed and user selection is proposed. Finally we present

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Yang Ou. Author is with Department of Electronic Engineering, University of Science and Technology of Suzhou, CO 215011 Suzhou China. Phone: 0816-0512-68247085. e-mail: qq00993@ 126.com.

Yi-Ming Wang. Author was with Department of Electronics and Information Engineering, Soochow University, CO 215011, Suzhou China.

our conclusion in section 6.

II. Cyclic Autocorrelation Features

A. The Definition and Features of Cyclic Autocorrelation

The cyclic autocorrelation (CA) of a complex-valued time series *s(t)* is defined by [11]

$$R_s(\alpha,\tau)=\lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} s(t+\tau/2)s^*(t-\tau/2)e^{-j2\pi\alpha t}dt \quad (1)$$

which can be interpreted as the Fourier coefficient of any additive sine wave component with frequency α that might be contained in the delay product (a quadratic transformation) of *s(t)*. α is called cycle frequency. It is a discrete set of values and can be writen as $\{\alpha_n\}$, which includes zero values and nonzero values. In the degenerate case of $\alpha=0$, the left member of (1) becomes the conventional autocorrelation.

B. Cyclic Autocorrelation of Ddigitally Modulated Signals

The basic mathematic model of digitally modulated signals can be described as [12]

$$s(t)=\sum_n a_n g(t-nT-\theta)e^{j2\pi f_c t},(n-1)T\le t<nT \quad (2)$$

$$a_n = a(t)e^{j\phi(t)} \quad (3)$$

where $a(t)$, $\phi(t)$ are narrow band modulating signals, $g(t)$ is the shaping signal. *T* is the symbol period and f_c is the carrier frequency. θ is the delay in a symbol period. Equation (2) can represent ASK, PSK, QAM signal and so on. a_n is kept constant in a symbol period. Complex stationary series $\{a_n\}$ satisfies the following equation

$$E\{a_n\}=0, E\{a_n a_m^*\}=\sigma_a^2\delta_{m,n} \quad (4)$$

where σ_a^2 is variance of $\{a_n\}$, $\delta_{m,n}$ is the discrete Dirac delta function.

When the shaping signal $g(t)$ is the square wave

$$U(t)=\begin{cases}1/T & -T/2\le t<T/2\\ 0 & otherwise\end{cases} \quad (5)$$

The CA of $s(t)$ can be

$$R_s(\alpha,\tau)=\sigma_a^2 e^{-j2\pi(f_c\tau-\alpha\theta)}\frac{1}{T}\frac{\sin(\pi\alpha(T-|\tau|))}{\pi\alpha},|\tau|<T \quad (6)$$

and

$$|R_s(\alpha,\tau)|=\sigma_a^2\frac{1}{T}\frac{\sin(\pi\alpha(T-|\tau|))}{\pi\alpha},|\tau|<T \quad (7)$$

III. Spectrum Sensing Based On Cyclic Autocorrelation

A. The estimation of cyclic autocorrelation

Define the numerical cyclic autocorrelation estimation of $s(t)$ as

$$\hat{R}_x(\alpha,\tau)=\frac{1}{N}\sum_{n=1}^{N} x(n)x^*(n+\tau)e^{-j2\pi\alpha n} \quad (8)$$

where *N* is the number of observations, τ is time delay.

B. Hypothesis testing

Spectrum sensing can be modeled as a hypothesis test problem. There are two possible hypotheses H_0 and H_1

$$x(n)=\begin{cases} w(n) & H_0\\ s(n)+w(n) & H_1\end{cases} \quad (9)$$

hypothesis H_1 refers to the presence of a primary user and hypothesis H_0 refers to the presence of vacant frequency bands, where $x(n)$ is the received signal, $s(n)$ is the possible primary user signal passed through a wireless channel (including fading and multipath effect), and $w(n)$ is a White Gaussian Process with zero-mean.

In section Ⅱ we analyzed the CA of general modulation signal, now we analyze the CA of the White Gaussian Process. Because $w(n)$ is a stationary process, it doesn't have cyclostationarity property, its CA function is given as [6]

$$R_w^\alpha(\tau)=\begin{cases}\sigma_w^2\delta(\tau) & \alpha=0\\ 0 & \alpha\ne 0\end{cases} \quad (10)$$

where σ_w^2 is noise variance.

Equation (10) clearly displays two meanings. One is that $w(n)$ hasn't nonzero cycle frequency or $w(n)$ has only one cycle frequency $\alpha=0$. The second is $R_w^\alpha(\tau)$ has nonzero value only at $\alpha=0$ and $\tau=0$. If $\alpha\ne 0$ or $\tau\ne 0$, then $R_w^\alpha(\tau)=0$.

According to (7), testing for the presence of primary user can change to test whether the estimated signal cyclic autocorrelation $\hat{R}_x(\alpha,\tau)$ is different from zero at $\alpha\ne 0$ or $\tau\ne 0$. There exists many cyclic frequencies, we can use their maximum value of CA as decision statistic.

$$\gamma=\max_\alpha|\hat{R}_s(\alpha,\tau)| \quad \begin{matrix}\ge\lambda & H_1\\ <\lambda & H_0\end{matrix} \quad (11)$$

where *r* is decision statistic, λ is threshold.

There exists many cyclic frequencies, when we want to distinguish different signals such as ASK, PSK and QAM etc, we should know the specific cyclic frequencies. While if we just detect the existence of primary users in noise, we can chose cyclic frequency $\alpha=0$ to sense.

C. Fast spectrum sensing

According to (7), we can find that $\hat{R}_s(\alpha,\tau)$ has maximum value at $\alpha=0$ and its value is

$$\hat{R}_{\max}(\alpha,\tau)=\sigma_a^2(1-\frac{|\tau|}{T}) \qquad |\tau|<T \quad (12)$$

where $\hat{R}_{\max}(\alpha,\tau)$ gradually reduces with the growth of τ. According to (10), we can see that the CA of $w(n)$ has nonzero value σ_w^2 only at $\alpha=0$ and $\tau=0$. If $0<|\tau|<T$, then $R_w^0(\tau)=0$, and

$$\hat{R}_x(0,\tau)=\hat{R}_s(0,\tau) \qquad \tau\neq 0 \tag{13}$$

so we can use $\hat{R}_x(0,\tau)$ as feature detector to detect the presence of primary user. For special cyclic frequency $\alpha=0$, $\hat{R}_x(0,\tau)$ has maximum value, so it has the best detecting performance. $\hat{R}_x(0,\tau)$ is one dimension function about τ, its search is simple. In practise, once given any nonzero τ_p, the computation complexity of $\hat{R}_x(0,\tau_p)$ is nearly as that of the energy detector. This method can be used to detect ASK, PSK, QAM signal and so on which can be represented by (2). In this regard it is easily applicable because it is also a blind detection method.

D. *Probability distribution function of the computed CA*

Upon substituting $s(n)$ in (8) with $w(n)$ which is a white Gaussian process with zero-mean and variance σ_w^2. Then $\hat{R}_w(\alpha,\tau)$ are circularly symmetric i.i.d. complex Gaussian random varibles with zero-mean and variance σ_w^4/N. So

$$H_0:\hat{R}_w(\alpha,\tau)\rightarrow CN\,(0,\sigma_w^4/N) \tag{14}$$

where $CN\,(\cdot,\cdot)$ represents the complex Normal distribution.

Hypothesis H_1 corresponds to the presence of user signal and noise, i.e., $x(n)=s(n)+w(n)$. $s(n)$ is the possible primary user passed through a wireless channel. Substituting $x(n)$ in (8) with $s(n)+w(n)$

$$\hat{R}_X(\alpha,\tau)=\hat{R}_s(\alpha,\tau)+\hat{R}_{sw}(\alpha,\tau)+\hat{R}_{ws}(\alpha,\tau)+\hat{R}_w(\alpha,\tau) \tag{15}$$

where $\hat{R}_s(\alpha,\tau)$ is the CA of the primary users' signals, it can been see as a constant of the time domain. $\hat{R}_{sw}(\alpha,\tau)$ and $\hat{R}_{ws}(\alpha,\tau)$ are cyclic cross correlation functions between s(n) and w(n), and $\hat{R}_{sw}(\alpha,\tau)=\hat{R}_{ws}(\alpha,\tau)$, they are nearly the complex Gaussian Normal distribution. Obviously

$$E[\hat{R}_X(\alpha,\tau)]=\hat{R}_s(\alpha,\tau) \tag{16}$$

It can be verified that

$$Var[\hat{R}_X(\alpha,\tau)]=\frac{2}{N}\sigma_w^2\sigma_s^2+\frac{1}{N}\sigma_w^4 \tag{17}$$

So

$$H_1:\ \hat{R}_x(\alpha,\tau)\rightarrow CN\,(\hat{R}_s(\alpha,\tau),\frac{\sigma_w^4}{N}(1+\frac{2\sigma_s^2}{\sigma_w^2})) \tag{18}$$

Equation (14) and (18) are obtained through statistics analysis under H_0 and H_1 cases. Next some simulation results which validate these important results are presented. 20000 Monte Carlo simulations are performed. The number of observations is N=2000.

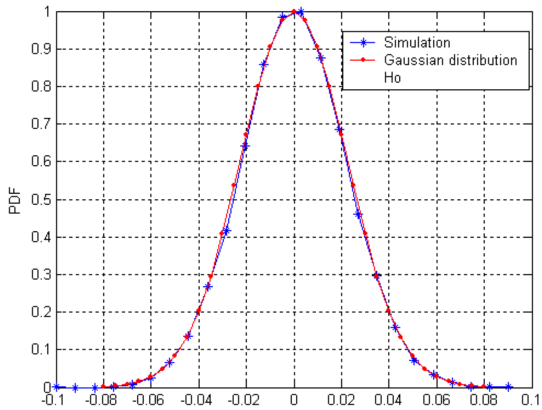

Fig.1 the distribution of CA under H_0, $\sigma_w^2=1$

Fig.1 shows the distribution of CA under H_0 case, suppose noise power $\sigma_w^2=1$. "*" represents simulated result. The simulated CA value under H_0 case is nearly zero and its distribution satisfies Gaussian Normal distribution. "." represents statistics analysis result of (14). The simulated results match to the theoretical results very well.

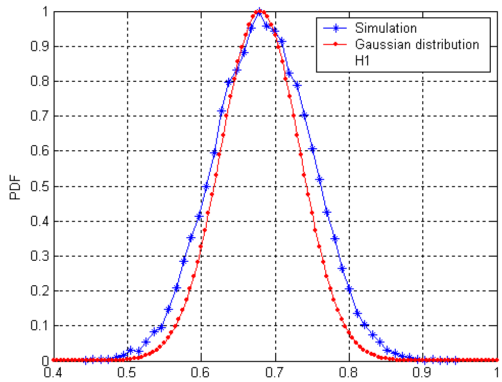

Fig.2 the distribution of CA under H_1 and SNR=0

Fig.2 displays the distribution of CA under H_1 case, suppose SNR=0dB. "*" represents simulated result. "." represents statistics analysis result of (18) and CA value is supposed as 0.68. The simulated distribution of CA value under H_1 nearly matchs to the statistics analysis.

IV. Numerical Results

A. *The Magnitudes of CA For Signal in Noise*

In this section the performance of the proposed cyclic autocorrelation based detector is discussed. As a signal of interest, a BPSK time series with baud-rate of $f_b=f_c/20$ is taken. f_c is the carrier frequency. Sampling frequency is $f_s=5f_c$. The number of observations is N=2000.

Fig.3 displays that the magnitudes of CA for signal in

Additive Gaussian White Noise at τ =0.1T and suppose SNR=0. It shows that the magnitudes of CA at cyclic frenquencies (such as 0, 40) are obviously larger than the CA magnitude of Gaussian White Noise. It also shows that the CA has maximum value at $\alpha = 0$ and this maximum value is 0.9 when τ =0.1T, which matches the (12).

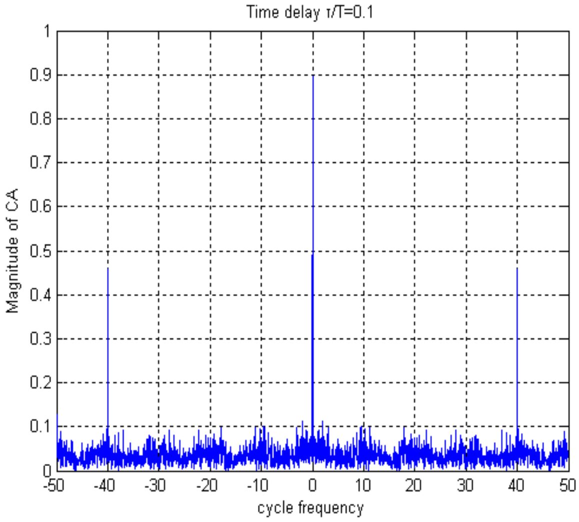

Fig.3 the magnitude of CA for BPSK signal in noise and SNR=0 dB

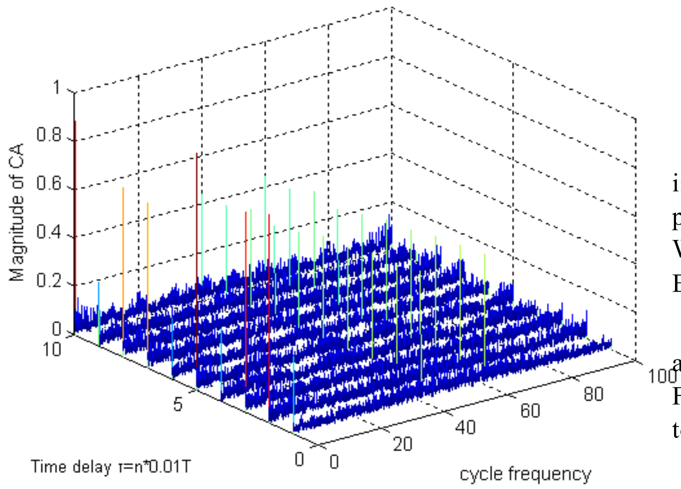

Fig.4 the CA at τ=0.1T for $s(n)+w(n)$, SNR=0

Fig.4 displays the magnitudes of CA for signal at different time delay τ and τ is from 0.01T to 0.1T. Suppose SNR=0. Fig.4 clearly dispalys that the magnitudes of CA are different at different cyclic frenquencies (such as 0, 40) and different time delay τ (such as 0.02T, 0.1T). These CA magnitudes obviously differentiate the noise，so can be used to detect the presence of primary users in a licensed spectrum.

In order to verify the performance of the proposed methed, theory results and computer simulations are made. We use constant false alarm rate (CFAR) method. First, we fix the thresholds based on probability of false alarm P_{fa}, then calculate and simulate the probability of detection P_d for various SNR cases. We set the target P_{fa}=0.1, choose τ =0.1T, 0.3T, 0.5T, 0.7T and N=2000. The threshold for energy detector (ED) is given in [13].

B. *Without Noise Uncertainty*

First the noise variance is exactly known, the detection performance made by these two methods are compared in Fig.5 and Fig.6.

The analytical results of the probabilities of detection for a pre-specified probability of false-alarm at given SNR and different time delay τ are shown in Fig.5.

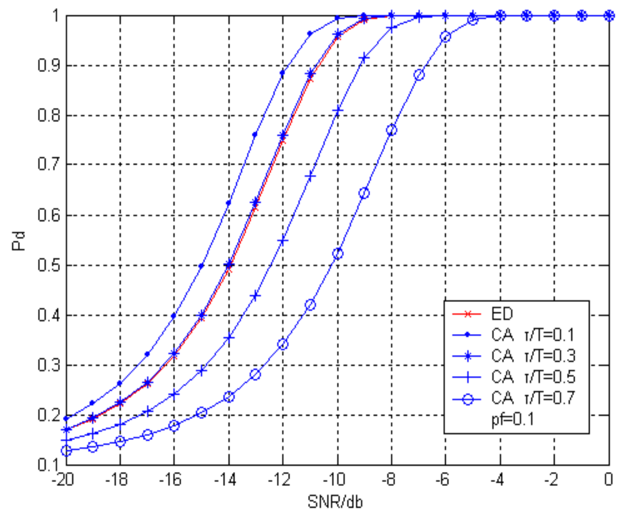

Fig.5 P_d versus SNR according to theory

From Fig.5 we can find that the detection performance of CA is more better than ED method when τ =0.1T. The detection performance of CA is equal to ED method when τ =0.3T. When τ =0.5T, 0.7T, its detection performance is worse than ED method.

Fig.6 is a simulation result. 10000 Monte Carlo simulations are performed. The number of observations is N=2000. From Fig.5 and Fig.6, it can be found that the simulated results match to the theoretical results very well.

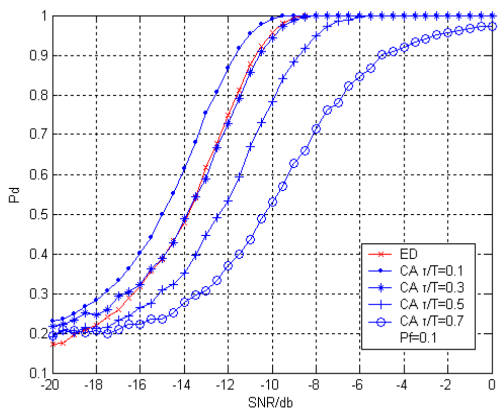

Fig.6 P_d versus SNR according to simulation

C. Noise Uncertainty Is Present.

However, in practice, noise uncertainty is always present. Due to noise uncertainty, the estimated (or assumed) noise power may be different from the real noise power. In practice, the noise uncertainty factor of a receiving device normally ranges 1dB. Environment/interference noise uncertainty can be much higher.

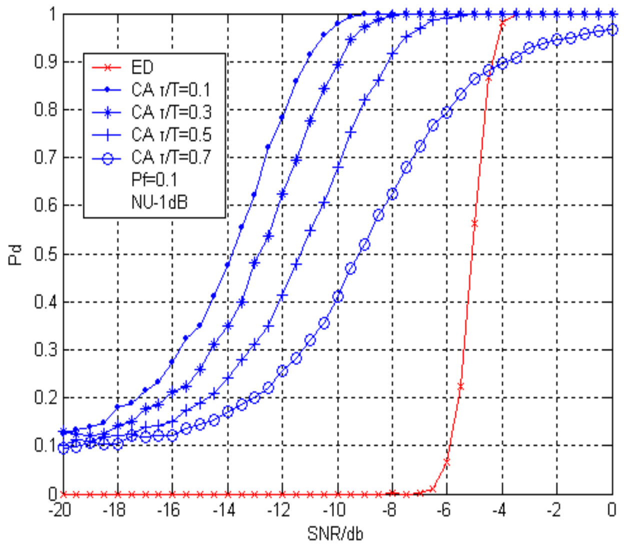

Fig.7 P_d versus *SNR* Noise uncertainty:1dB

When the noise uncertainty is 1dB, the detection performances maded by two methods are simulated in Fig.7. 10000 Monte Carlo simulations are performed. Compared with the case without noise uncertainty in Fig.6, it can be found that the performance of CA method has some subtle changes. In the case of τ/T=0.3 and *SNR*=-12dB, the P_d is near 72% in Fig.6, and it is near 62% in Fig.7. The detection performance declines 13.8%. While for Ed method, the P_d is near 72% in Fig.6 and it is 0% in Fig.7. The detection performance declines 100%. Fig.7 shows that the quality of energy detection is strongly degraded in the case with noise uncertainty, while quality of the CA method is still kept well.

Both simulation results and mathematical analysis show that this CA method outperforms the energy detector in the presence of noise power uncertainty.

V. Cooperative Spectrum Sensing

One of the great challenges of implementing spectrum sensing is the hidden terminal problem, which occurs when the cognitive radio is shadowed, in severe multipath fading or inside buildings with high penetration loss, while a primary user (PU) is operating in the vicinity [14]. Due to the hidden terminal problem, a cognitive radio may fail to notice the presence of the PU and then will access the licensed channel and cause interference to the licensed system. In order to deal with the hidden terminal problem in cognitive radio networks, multiple cognitive users can cooperate to conduct spectrum sensing. Cooperation in spectrum sensing can increase the reliability of detection of PU signals. In cooperative scenarios, each CR performs spectrum sensing and sends its sensing report to a data collector known as the fusion center. The problem how to combine the individual sensing results to make a final sensing decision at the fusion center is of great interest. The simplest fusion rules proposed in the literature for binary local decisions are “OR”, “AND” and “MAJORITY” rules. It has been shown that spectrum sensing performance can be greatly improved with an increase of the number of cooperative partners [15]–[20]. While a large number of cooperating CRs typically leads to an increase in total energy consumption and overhead in the sense that the entire reporting group cannot transmit until all the sensing reports are collected and combined by the fusion center so the average throughput is reduced. Moreover, a large number of CRs participating in cooperative spectrum sensing also increases the overall energy consumption of the CR network. Besides, because the classical and widely used fusion rules are not optimal, users with poor sensing performance may actually degrade the fused sensing performance [21],[22].

Therefore, low overhead and energy effcient cooperative spectrum sensing schemes are required to address the above mentioned issues.

In this section, the performance of spectrum sensing in terms of the throughput[23],[24] is analysised. We propose to select the users with good performances to cooperative sensing so as to optimize the throughput of the secondary users.

A. Muiti-secondary User for Spectrum Sensing

There are various cooperative schemes to combine the sensing information from the secondary users, such as the *k*-out-of-*N* fusion rule, soft decision based fusion, and weighted data based fusion [25]. In this section, using the *k*-out-of-*N* fusion rule as the basis, we formulate an optimization problem using the sensing time and the fusion parameter k as the optimization variables to jointly maximize the throughput of the secondary users while giving adequate protection to the primary user. Second, we propose an selective scheme for the optimization problem.

Suppose that the *k*-out-of-*N* fusion rule is adopted as the fusion scheme. By setting a common threshold λ for the CA detector at the sensor nodes, the overall probabilities of detection and false alarm of the cognitive radio network are respectively given as

$$P_{Kd}(\lambda, L, k) = \sum_{i=k}^{N} \binom{N}{i} P_d(\lambda, L)^i (1 - P_d(\lambda, L))^{N-i} \quad (19)$$

$$P_{Kf}(\lambda, L, k) = \sum_{i=k}^{N} \binom{N}{i} P_f(\lambda, L)^i (1 - P_f(\lambda, L))^{N-i} \quad (20)$$

Accord to (14) and (18), at hypothesis H_0. The probability of false alarm P_{fa} for the CA algorithm is

$$P_f = P(\gamma > \lambda | H_0) = Q\left(\frac{\gamma}{\sigma_w^2 / \sqrt{Lf_s}}\right) \tag{21}$$

$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{\mu^2}{2}} d\mu \tag{22}$$

And at hypothesis H_1. The probability of detection P_d for the CA algorithm is

$$P_d = P(\gamma \geq \lambda | H_1) = Q\left(\frac{\gamma - |\hat{R}_s(\alpha,\tau)|}{\sigma_w^2 \sqrt{\frac{1 + 2\sigma_s^2/\sigma_w^2}{Lf_s}}}\right) \tag{23}$$

where $Q^{-1}(\cdot)$ is the inverse function of $Q(x)$. L is the sensing time and fs is sampling frequency.

B. Optimization of Cooperative Sensing

A basic frame structure of a cognitive radio network consists of, at least, a sensing slot and a data transmission slot. Suppose the sensing duration is L and the frame duration is T, So the length of period T-L is used for data transmission. Denote C_0 as the throughput of the secondary network when it operates in the absence of primary users, and C_1 as the throughput when it operates in the presence of primary users.

If there is only one point-to-point transmission in the secondary network and the *SNR* for this secondary link is *SNR*s $=P_s/N_0$, where P_s is the received power of the secondary user and N_0 is the noise power. Let P_p be the interference power of primary user measured at the secondary receiver, and assume that the primary user's signal and secondary user's signal are Gaussian white Noise and independent of each other. According to [23]

$$C_0 = \log_2(1 + SNR_s) \tag{24}$$

$$C_1 = \log_2\left(1 + \frac{SNR_s}{1 + SNR_p}\right) \tag{25}$$

where $SNR_p = P_p / N_o$. Obviously $C_0 > C_1$.

For a given frequency band of interest, P(H_1) is defined as the probability for which the primary user is active, and P(H_0) is defined as the probability for which the primary user is inactive. Then P(H_1)+ P(H_0)=1.

There are two scenarios for which the secondary network can operate at the primary user's frequency band.

The first scenario: When the primary user is not present and no false alarm is generated by the secondary user, the achievable throughput of the secondary link is $\frac{T-L}{T}C_0$.

The second scenario: When the primary user is active but it is not detected by the secondary user, the achievable throughput of the secondary link is $\frac{T-L}{T}C_1$

The achievable throughput of the secondary users under these scenarios are respectively given as

$$O_0 = \frac{T-L}{T} C_0 (1 - P_{Kf}) P(H_0) \tag{26}$$

and

$$O_1 = \frac{T-L}{T} C_1 (1 - P_{Kd}) P(H_1) \tag{27}$$

then the average throughput for the secondary network is given by

$$O = O_0 + O_1 \tag{28}$$

Obviously, for a given frame duration T, the longer the sensing time L, the shorter the available data transmission time T- L.

Usually spectrum sensing optimization includes throughput optimization. That is making the achievable throughput of the secondary network maximized while the primary users are sufficiently protected. We suppose the activity probability P(H_1) of primary users is small, say less than 0.3, thus it is economically advisable to explore the secondary usage for that frequency band. Since $C_0 > C_1$, the first term in the right hand side of (28) dominates the achievable throughput. Therefore the optimization problem can be approximated by

$$\begin{aligned} &\max \quad \tilde{O} = O_0 \\ &s.t. \quad P_{Kd} \geq \overline{P}_d \end{aligned} \tag{29}$$

When CA detector is applied, using (19) and (23) we have

$$\tilde{O}(L, P_{Kd}) = C_0 P(H_0)(1 - \frac{L}{T})(1 - P_{kd}) \tag{30}$$

Thus, from (30) we can see that the achievable throughput of the secondary network is a function of the sensing time L and overall probabilities of detection P_{kd}. So the optimization problem can be approximated by

$$\begin{aligned} &\max \quad \tilde{O}(L, P_{Kd}) \\ &s.t. \quad P_{Kd} \geq \overline{P}_d \\ &\qquad 0 \leq L \leq T \\ &\qquad 1 \leq k \leq n \end{aligned} \tag{31}$$

C. Selective Cooperative Sensing

Because the classical and widely used fusion rules are not optimal, users with poor sensing performance may actually degrade the fused sensing performance.In this section, we propose to select the users with good detection performance to coopérative sense so as to improve sensing sensitivity.

D. Numerical Results

In IV section, it can be found that simulated results match to the theoretical results very well, because of this consistency, in the following evaluations, we will only consider the theoretical results.

In the following simulations, we set the number of secondary users to be N=6. and the frame duration to be T=20ms. The sampling frequency of the received signal is assumed to be 10 MHz, and P_d is set as 90%. The *SNR* of the primary user's signal received at the secondary users is varied from -20dB to -5dB. The fusion scheme is k-out-of-N fusion rule.

Fig.8 shows the overall P_{Kd} of the network versus SNR in k-out-of-N fusion scheme using different k for secondary network with six users. It can be found that P_{kd} is maximum when k=1, this is "OR" rule. P_{kd} is the least when k=6 and this is "And" rule. Comparing Fig.5 and Fig.8， it can be found that cooperative spectrum sensing obviously improves the system detection probabilities in the case of k=1.

Fig.9 shows the overall P_{Kd} of the network versus sensing time in k-out-of-N fusion scheme. The overall P_{Kd} of the network improves with the increase of sensing time and reduces with the increase of k.

Fig.10 shows the overall P_{Kd} of the network versus sensing time in the cases of selective cooperative users and unselective cooperative users. Six users channel gains are assumed as $\boldsymbol{h}$=[0.9, 0.8, 0.7, 0.6, 0.6, 0.5] and their SNR=[-5, -5, -5, -6,-7, -8]dB. In the cases of users k=3 and k=4, the detection performace of selective cooperative sensing is obviously better than unselective cooperative sensing.

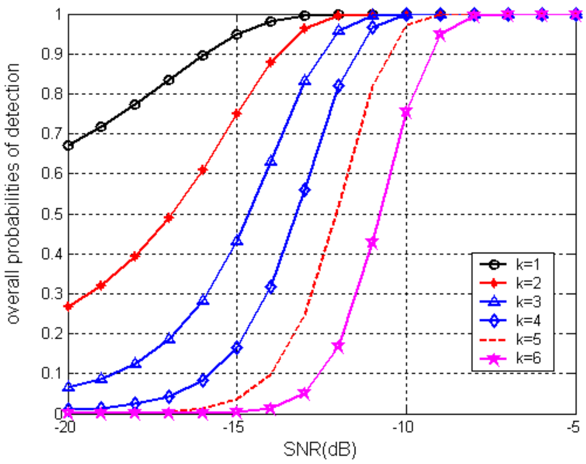

Fig.8 The overall P_{Kd} of the network versus SNR in k-out-of-N fusion scheme

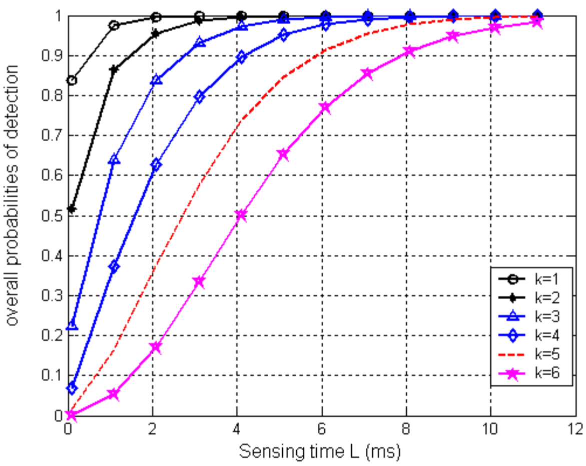

Fig.9 The overall P_{Kd} of the network versus sensing time in k-out-of-N fusion scheme

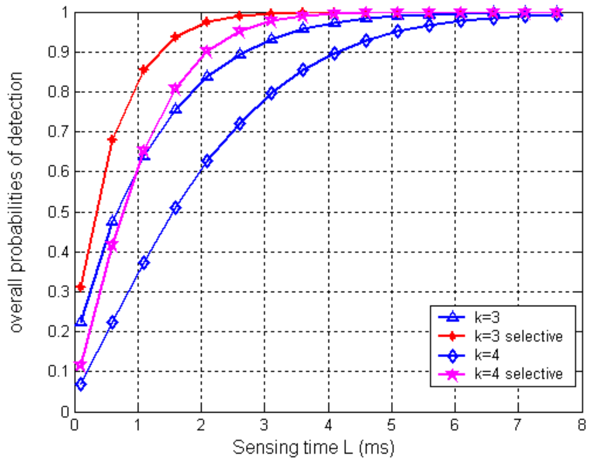

Fig.10 The overall P_{Kd} of the network versus sensing time in the cases of selective cooperative users and unselective cooperative users

Fig.11 shows the throughput for the secondary network according to (26), (27) and (28). In (28), O_0 dominates the achievable throughput, so system throughput can be approximated by O_0.

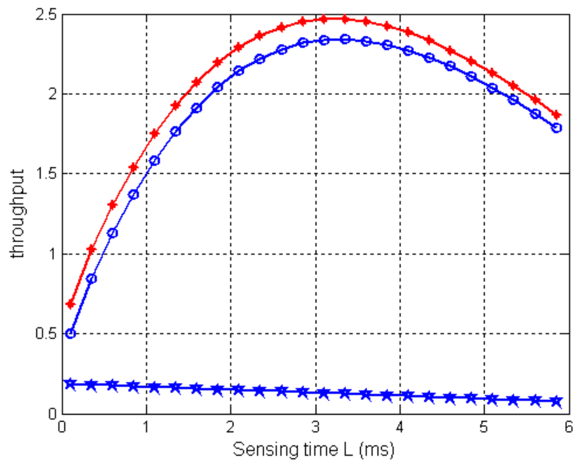

Fig.11 the throughput for the secondary network ("*" for O , " O" for O_0, "☆" for O_1)

Dealing with the optimization problem of spectrum sensing, the throughput of a CR system is considered. Fig.12 shows optimization throughput of the secondary network through user selection. "k=3 selective" expresses selecting three users with good performance to cooperate sensing from six users. "k=3" expresses any three users without selection. We can find that the maximum throughput with user selection is obviously larger than the maximum throughput without user selection in the case of k=3 and k=4.

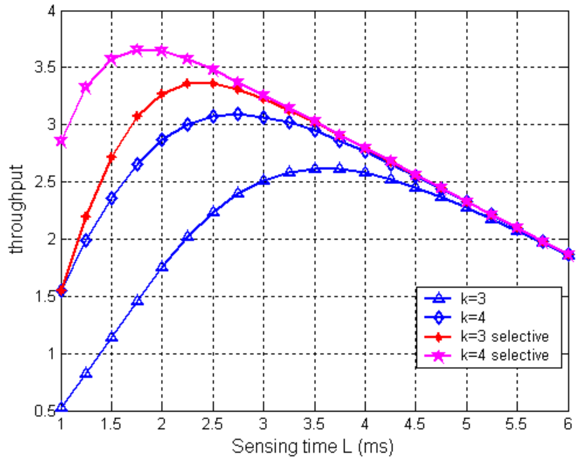

Fig.12 optimization throughput of the secondary network

VI. CONCLUSION

In this paper, a fast spectrum detecting algorithm based on cyclic autocorrelation (CA) of communication signals is proposed. Theoretical analysis and simulations have been carried out to evaluate the performance of the proposed methods. When only detect the existence of primary users in noise, special cyclic frequency $\alpha = 0$ is chosen to sense. In this way it is easily applicable because it is also a blind detection method. Based on this method, we proposes to select the users with good detection performance to cooprative sense so as to improve sensing sensitivity. It demonstrates that the throughput of CR system is also improved by user selection.

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Yang Ou received the M.S. degree in electrical engineering in 1996. She was an Associate Professor with the University of Science and Technology of Suzhou. Her research interests include cognitive radio, spectrum sensing, signal processing for communications, wireless networking and statistical signal processing.