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A Spectrum Sensing Method Based on Gabor Transform for Cognitive Radio

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Abstract: In order to improve the sensing performance for cognitive radio, this paper proposes a spectrum sensing method based on Gabor transform. Firstly, a continuous-time signal is transformed into a discrete-time signal, then, the discrete-time signal is converted into Gabor transform by over-sampling. Secondly, the Gabor transform coefficient of the discrete-time signal is obtained, and then a module value of the Gabor transform coefficient is computed. Finally, the module value is compared with the preset detection threshold. The simulation results show that the proposed method is better than the energy detection algorithm, especially in low SNR. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Cognitive radio, Energy detection, Gabor transform, Improved.

1. Introduction

With increasing for communications service, the spectrum resource is more and more lacking, however, the fixed spectrum allocation strategy leads to the spectrum utilization rate very low. Cognitive radio (CR) is a spectrum sharing technology, which can greatly ease the shortage [1, 2]. In CR systems, the cognitive user (CU) (also call second user, SU) senses some spectrum bands not being used by the licensed primary user (PU), called a spectrum hole, and use a part (or the whole) of the spectrum hole as their communication channel [3, 4]. These spectrum holes are potential opportunities for smartly using wireless spectrum resources [5].

For cognitive radio, spectrum sensing is a very key problem. Currently, there are a number of different spectrum sensing methods, which include matched filter detection, cyclostationary feature detection, energy detection, covariance-based detection, multitaper spectrum estimation and filter bank spectrum estimation, and so on [6, 7]. These methods have respectively the own advantages and disadvantages, and the matched filter detection need to know the channel information and precise synchronization from PU for the receiver, and the cyclostationary feature detection need to know the cycle frequency of PU and a strong analog to digital conversion capability [8]. The energy detection is the most popular detection method for spectrum sensing, because it has a simple design and wide application [7]. The energy detection does not need any prior information about the PU signals that may be present within a certain frequency band, but it commonly uses a spectrum sensing strategy with decision threshold, which cannot guarantee the optimal detection performance in any environments. Specially, in low signal-to-noise ratio (SNR) conditions, the error rate of energy detection is very high, and the sensing performance is limited in the strong noise conditions. In order to solve this problem, this paper proposes a spectrum sensing method based on Gabor transform.

The rest of this paper is organized as follows. In Section II, the reviews for the energy detection and Gabor transform are given. Section III gives the spectrum sensing method based on Gabor transform. In Section IV, the simulation analysis is given. Finally, the conclusion is drawn in section V.

2. Energy Detection and Gabor Transform

2.1. Energy Detection

The energy detection method uses the signal power as test statistics, and compares the statistics value with the preset threshold to judge whether existing a primary user within a detection band [7, 9-11]. The energy detection process can be performed in time domain or frequency domain, and these two processes are shown in Fig. 1.

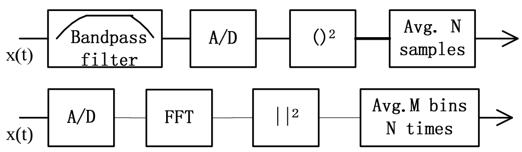

Fig. 1. The detection process implementation in time domain and frequency domain.

To let $x(t)$ represent the PU signal, and $n(t)$ be additive white Gaussian noise (AWGN), under two hypotheses, the received signal is given by

$$\begin{cases} H_0: r(t) = n(t) \\ H_1: r(t) = x(t) + n(t) \end{cases} \tag{1}$$

where H_0 is the null hypothesis indicating that the received signal corresponds to noise, and therefore there is not PU in the sensed spectrum band. H_1 states that some PUs are present.

If the signal bandwidth is W, and the sampling frequency is 2 W, the discrete signal is expressed as following

$$\begin{cases} H_0: r(n) = w(n) \qquad n = 1, 2, ..., N \\ H_1: r(n) = x(n) + w(n) \;\; n = 1, 2, ..., N \end{cases} \tag{2}$$

where N denotes the number of sampling point during the sensing period of the signal, $w(n)$ is the zero-mean white Gaussian noise. The CU will select hypothesis H_1 whenever a PU signal is present and hypothesis H_0 otherwise.

When the test statistics takes $T(x) = \sum_{n=1}^{N} |r(n)|^2$, the second user determine whether a PU signal is present (hypothesis H_1) or not (hypothesis H_0), i.e.

$$\begin{cases} H_0: T(x) = \sum_{n=1}^{N} |r(n)|^2 < \gamma \\ H_1: T(x) = \sum_{n=1}^{N} |r(n)|^2 \geq \gamma \end{cases} \tag{3}$$

where γ is the preset threshold. Because $r(n)$ obeys Gaussian distribution, and $T(x)$ is the sum of the square of Gaussian variables from 1 to N, therefore, $T(x)$ obeys chi–square distribution and the degree is N. According to the central limit theorem, when N has enough value (N>20), $T(x)$ approximately obeys Gaussian distribution and is written as

$$T(x) \sim \begin{cases} H_0 : Normal(N\sigma^2, 2N\sigma^4) \\ H_1 : Normal(N\sigma^2 + NP_s, 4N\sigma^4 P_s) \end{cases} \tag{4}$$

where σ^2 is the noise variance and $P_s = \frac{\sum_{n=1}^{N} |x(n)|^2}{N}$ represents that the second user receives the average signal power of primary user.

When N>20, the false alarm probability P_f and the detection probability are expressed respectively as following

$$P_f = P(T(x) > \gamma \mid H_0) = Q\left(\frac{\gamma - N\sigma^2}{\sigma^2\sqrt{2N}}\right) \tag{5}$$

$$\begin{aligned} P_d &= P(T(x) > \gamma \mid H_1) \\ &= Q\left(\frac{\gamma - N\sigma^2 - NP_s}{\sigma\sqrt{2N\sigma^2 + 4NP_s}}\right) \end{aligned} \tag{6}$$

where $Q(...)$ is the generalized Marcum function, and $Q(x) = \frac{1}{2\pi}\int_x^{\infty} \exp(\frac{-y^2}{2})$.

2.2. Gabor Transform

Gabor who is a British scientist has proposed a set of functions $\Psi_{m,n}(t) = \Psi(t - mT)e^{jn\Omega t}$ to describe the sectional feature of a signal in 1946 [12]. The set of functions are produced by the delay of a good generating function $\Psi(t)$ on the time and frequency domain, which have a good time-frequency aggregation. The Gabor transform is expressed as follows.

$$x(t) = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} c_{m,n} \psi_{m,n}(t) \tag{7}$$

where $c_{m,n}$ is the two-dimensional sequence called Gabor transform coefficients. Gabor has selected the Gaussian function $\psi(t) = Ae^{-\partial t^2}$ as the generating function, and ∂ is the resolution ratio to adjust $x(t)$.

A finite-length sequence can turn into a periodic sequence by the cycle extension, and the periodic sequence $x(k)$ with a cycle N_1 meets $x(k) = x(k+N_1)$. With the critical sampling frequency, the discrete Gabor transform can be defined as

$$x(k) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} c_{m,n}\tilde{\psi}_{m,n}(k) \tag{8}$$

where the transform coefficient $c_{m,n}$ that can be determined by the following equation.

$$c_{m,n} = \sum_{k=0}^{N_1-1} x(k)\tilde{\chi}^{*}_{m,n}(k) \tag{9}$$

where $N_1 = MN_2$, M and N_2 are the point number of time sampling and the point number of frequency sampling respectively.

$\psi_{m,n}(k)$ in the equation (8) can be expressed as following

$$\tilde{\psi}_{m,n}(k) = \tilde{\psi}(k - mN) W_N^{nk} \tag{10}$$

where $W_N^{nk} = e^{j\frac{2\pi}{N}nk}$, $\tilde{\psi}(k)$ is the periodic extension of $\psi(k)$, the window function $\psi(k)$ also meets the equation $\sum_{k=-\infty}^{+\infty} |\psi(k)|^2 = 1$.

$\tilde{\chi}(k)$ in the equation (9) is periodic sequence, and meets the following equation

$$\sum_{k=0}^{N_1-1} \tilde{\psi}_{-m,-n}(k)\tilde{\chi}^{*}(k) = \delta(m)\delta(n)$$
$$0 \le m \le M-1,\ 0 \le m \le N_2 - 1, \tag{11}$$

3. Spectrum Sensing Method Based on Gabor Transform

The process of the new method is given as follows:

Step 1: To convert a continuous time signal into a discrete time signal in time domain.

Step 2: To over-sample the discrete time signal in frequency domain and gain the Gabor transform of the signal.

Step 3: To calculate a module value of the Gabor transform coefficient obtained in *Step 2.*

Step 4: the module value is compared with the preset detection threshold to judge whether or not the PU signal exists.

Depended on the above process, the signal in the equation (2) can be converted into the Gabor transform as the equation (7) by the over-sampling in frequency domain. The Gabor transform coefficients are respectively calculated as following

$$c_{1m,n} = \sum_{k=0}^{N_1} w(n)\tilde{\chi}^{*}_{m,n}(k) \tag{12}$$

$$c_{2m,n} = \sum_{k=0}^{N_1} \left[w(n) + x(n)\right]\tilde{\chi}^{*}_{m,n}(k) \tag{13}$$

Depended on the equation (12) and (13), if $c_{1m,n} > \gamma$, It means a faulty judgment, which is the condition for the false alarm probability. If $c_{2m,n} > \gamma$, it represents that the result is right, which is the condition for the detection probability. So the spectrum hole can be found by the Gabor transform.

If the primary user exists, the signal SNR is

$$\frac{\sum_{k=0}^{N_1}[w(n)+x(n)]\tilde{\chi}^{*}_{m,n}(k)}{\sum_{k=0}^{N_1} w(n)\tilde{\chi}^{*}_{m,n}(k)}.$$

Depended on the equation (6), after Gabor transform, the detection probability is expressed as following

$$P_d = Q\left(\frac{\gamma - N_1\sigma^2 - |c_{2m,n}|}{\sigma\sqrt{2N_1\sigma^2 + 4|c_{2m,n}|}}\right) \tag{14}$$

4. Simulation

In the section, the numerical values of the proposed spectrum sensing method are evaluated through computer simulation.

The sample frequency takes 100, the simulation result is illustrated in the Fig. 2.

Form Fig. 2, the new method has a higher detection probability than energy detection in the low SNR condition. This reason is that Gabor transform enhances the signal intensity, and the increasing intensity can preferably show the detailed feature of the signal in a short time. Therefore, the spectrum sensing based on Gabor transform improves the signal quantity in the low SNR, so it has the higher detection probability than the energy detection method.

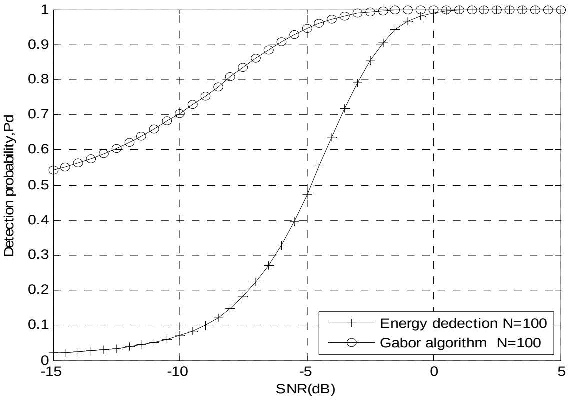

Fig. 2. The detection probability of the sample frequency taking 100.

To raise the sample frequency, the effective components of the signal also increase to lead to increasing of the signal SNR, and the detection probability also is improved. The sample frequency takes 200, the simulation result is illustrated in the Fig. 3.

The Fig. 2 and Fig. 3. show that the detection probability based on Gabor transform and energy detection are all constantly improved as the signal-to-noise ratio increasing, in which the higher the primary user has signal-to-noise ratio, the greater the cognitive user detects successfully the spectrum hole.

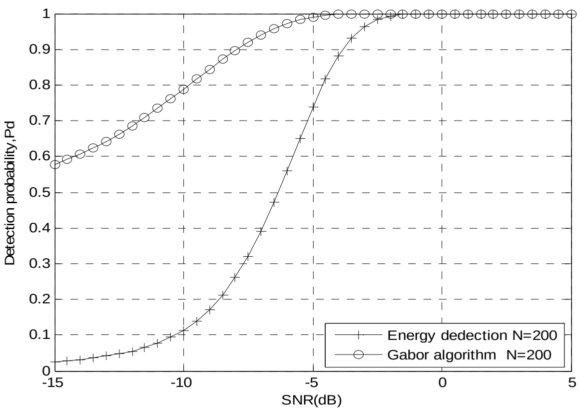

Fig. 3. The detection probability of the sample frequency taking 200.

5. Conclusion

Based on Gabor transform, the paper proposes a spectrum sensing method for improving the sensing performance in cognitive radio. The new method has a higher detection probability than energy detection in the low SNR condition, and the detection probability is even improved with the raising sample frequency. However, with the increasing of sample frequency, the calculation complexity and the sensing time would become larger. In practice, the SNR should be determine by comprehensive considering the channel state and geographical location conditions, and then the properly sample frequency is selected.

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References

[1]. Facilitating Opportunities for Flexible, Efficient, and Reliable Spectrum Use Employing Cognitive Radio Technologies, NPRM & ORDER, ET Docket no.03-108, FCC 03-322, *Federal Communications Commission,* 2003, pp. 2-53.

[2]. S. Haykin, Cognitive Radio: Brain-empowered Wireless Communications, *IEEE Journal on Selected Areas in Communication*, Vol. 23, Issue 2, 2005, pp. 216-217.

[3]. S. B. Wang, Z. Zhou, K. S. Kwak, Two Pulse Designs for Ultra Wideband-Cognitive Radio by Using Multiple Modified Transform Domain Communication System, *Applied Mathematics & Information Sciences*, Vol. 6, Issue 3, 2012, pp. 619-628.

[4]. W. S. Jeon, J. A. Han, D. G. Jeong, A Novel MAC Scheme for Multichannel Cognitive Radio Ad Hoc Networks, *IEEE Transactions on Mobile Computing*, Vol. 11, Issue 6, 2012, pp. 922-934.

[5]. N. Bouabdallah, B. Ishibashi, R. Boutaba, Performance of Cognitive Radio-Based Wireless Mesh Networks, *IEEE Transactions on Mobile Computing*, Vol. 10, Issue 1, 2011, pp. 122-135.

[6]. T. Yucek, H. Arslan, A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications, *IEEE Communications Surveys & Tutorials*, Vol. 11, Issue 1, 2009, pp. 116-130.

[7]. M. López-Benítez, F. Casadevall, Improved Energy Detection Spectrum Sensing for Cognitive Radio, *IET Communications*,Vol. 6, Issue 8, 2012, pp. 785-796.

[8]. W. R. Wang, S. B. Wang, X. Y. Zhao, A Dynamic Threshold Optimization Algorithm for Spectrum Sensing with Energy Detection in Cognitive Radio, *Applied Mechanics and Materials*, Vol. 236-237, Issue 11, 2012, pp. 917-922.

[9]. J. Ma, G. D. Zhao, Y. Li, Soft Combination and Detection for Cooperative Spectrum Sensing in Cognitive Radio Networks, *IEEE Transactions on Wireless Communications*, Vol. 7, Issue 11, 2008, pp. 4502-4507.

[10]. J. J. Lehtomaki, M. Juntti, H. Saarnisaari, S. Koivu, Threshold Setting Strategies for a Quantized Total Power Radiometer, *IEEE Signal Process Letter*, Vol. 12, Issue 11, 2005, pp. 796-799.

[11]. X. P. Zhai, J. G. Pan, Energy-detection Based Spectrum Sensing for Cognitive Radio, in

Proceedings of IET Conference on Wireless, Mobile and Sensor Networks (CCWMSN'07), 12-14 December 2007, pp. 944-947.

[12]. D. Gabor, Theroy of Communication, *Journal of the Institute for Electrical Engineers*, Vol. 93, 1946, pp. 429-457.

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