Sensors & Transducers, Vol. 181, Issue 10, October 2014, pp. 155-162

Sensors & Transducers

Spectrum Sensing for Unidentified Primary User Condition

[1] Yuelin Du, [2] Jingting Yao, [3] Lihua Gao
[1] College of Electronics Science and Engineering, Nanjing University of Posts and Telecommunications, Nanjing, China
[2] Overseas Education College, Nanjing University of Posts and Telecommunications, Nanjing, China
[3] China Telecom Co Jiangsu branch, Nanjing, China
[1] Tel.: 86 25 85866390, fax: 86 25 85866390
E-mail: duyl@njupt.edu.cn

Received: 10 July 2014 /Accepted: 30 September 2014 /Published: 31 October 2014

Abstract: Recently, a survey released by Federal Communications Commission (FCC) shows that the utilization rate of the allocated spectrum in the US is only 30 %, which means there is still a great proportion of spectrum that are expected to be made better use of. As an efficient spectrum utilization technique, Cognitive Radio (CR) is a temping solution to the spectral congestion problem by introducing opportunistic usage of the frequency band that are not heavily occupied by licensed users [1]. This research focuses on one of the three essential components of CR – spectrum sensing. The other two are dynamic spectrum management and adaptive communications. To be more specific, this research narrows the range of study into “unidentified” PUs as the title goes, implying the unknown circumstances of the information of the transmission channel and the PUs such as the power of the random Gaussian noise and the modulation type. Previous research has accomplished great advancement in spectrum sensing algorithms, however, seldom of which has ever put these techniques together and provide an overall review. The merit of this research lies in the combined evaluation of the selected four algorithms: energy detection based sensing, eigen-value based sensing, cyclostationary based sensing and entropy based sensing. Based on MATLAB, simulations were implemented using multiple types of signal sources as input to test the performances of the algorithms. Finally, an innovative comparison approach using the idea of correlation coefficient is adopted to evaluate the utility of the four different approaches.

Keywords: Cognitive radio, Spectrum sensing, Energy detection, Eigen-value based sensing, Cyclostationary based sensing, Entropy based sensing.

1. Introduction

The advancement in wireless communications promotes the drastic demand in related business and has led to the scarcity of the spectrum resources available. Traditionally, service providers adopt allocation policy based on a fixed and static mechanism in which only a small proportion of spectrum is used efficiently while the rest is idle. For a long time, the issue of improving the utilization rate of the allocated spectrum in multiple areas and time domains has become a common concern. Thus, the concept of Cognitive Radio (CR) was proposed. According to the definition raised by FCC, Cognitive Radio (CR) is “A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously adjust it radio operating parameters to modify system operation, such as maximize throughput, access secondary markets" [2]. Hence, the main problem that CR deals with is to intelligently exploit unused spectrum within regional area networks to provide utilize possibility for extra spectrum access.

It is showed in Fig. 1 that an empty spot/hole in frequency spectrum can be a candidate to be allocated with a new communication link.

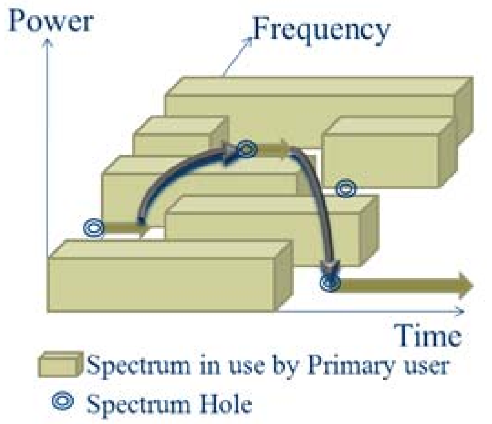

Fig. 1. Spectrum holes.

This paper consists of six parts. Except for the introduction which provides an overview of the research topic, related work is revealed in part two. Part three demonstrates the system design with specific parameter settings and structure of the system. The following sensing algorithm part discusses at length about four different sensing techniques along with simulation results and analysis based on MALTAB, respectively. Chapter five compares the four algorithms from both theoretical aspect and simulation results. The last part, chapter five, concludes the research in a broad perspective and provides suggestions to future works.

2. Related Work

Harry Urkowitz in his [3] has delivered a thorough description about energy detection technique for unknown deterministic signals in 1967. Yonghong Zeng et al [4] in their research proposed a covariance matrix theory (CMT) to overcome the noise uncertainty problem when the signals are highly correlated. Latest random matrix theories (RMT) have been used to set the thresholds and obtain the probability of detection. Y. Zhang et al [5] put forward a blind frequency-domain entropy based spectrum sensing scheme and concluded by simulation that outperforms classical energy detector and cyclostationary detector in low SNR region with 6 and 4 dB performance improvement, respectively. Tevfivk et al [6] provides a complete review of all the spectrum sensing algorithms. It also discussed about sensing features of some current wireless standards.

3. System Overview

The overall process of this research is shown in Fig. 2. In this research, the message source contains several different types of transmitted signals, including baseband, BASK, BPSK, BFSK, 16QAM, 4PSK and random signals. Four different detection techniques are applied in the detector side which will be discussed at length in part IV.

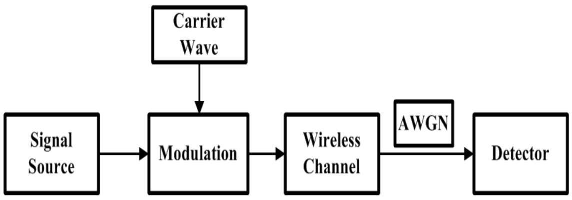

Fig. 2. System flow chart.

The simulation system of this research differs greatly from real-life environment. The following assumptions are made for simplicity in the simulated system in MATLAB:

- The signal goes through a frequency-flat band-limited addictive Gaussian noise channel. The channel is assumed to be static and in a form of a Rayleigh channel in which the signal passes through a single-path. Factors like Doppler shift, propagation delay, path gain are neglected.
- The carrier frequency of the carrier wave is set as 5000 Hz.
- The original frequencies of the source signals are limited within 3000 Hz, while in telephony the voice frequency ranges from 300 to 3400 Hz.
- The sampling rate is chosen around 6000 Hz on the basis of Nyquist Theory except for the wav audio which is sampled by the defaulted rate of MATLAB 44100 Hz, while in practical applications the Uniform Pulse Coding Modulation (UPCM) sampling rate is 8000 Hz.

4. Four Types of Spectrum Sensing Algorithms

In discrete domain, the received signal can be modeled as:

$$y(n) = x(n) + w(n), \tag{1}$$

where $x(n)$ is the signal that needs to be detected, and $w(n)$ is the additive white Gaussian noise (AWGN) sample and n is the sample index. $x(n)$ equals to zero in the situation when there is no primary user or transmitted signal.

Define two hypotheses and to represent the presence of a received signal, and then the corresponding signal model is given by

$$H_0 : y(n) = w(n)$$
$$H_1 : y(n) = x(n) + w(n)\,, \qquad (2)$$

4.1. Energy Detection Based Sensing Algorithm

Energy detection (ED) based sensing algorithm is the simplest and most popular signal detection algorithm. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. The key to applying ED technique is to select an appropriate threshold for the secondary user. There are also some other challenges brought about by ED technique such as the estimation of noise power and the ability to differentiate the primary users and noise. It is notable that ED technique does not work efficiently for detecting spread spectrum signals [7, 8]. Fig. 3 shows the block diagram of the energy detector. The noise prefilter serves to limit the noise bandwidth; the noise at the input to the squaring device has a band-limited, flat spectral density.

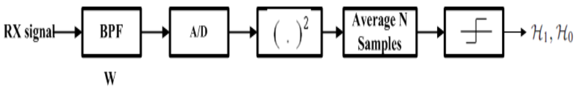

Fig. 3. Energy detector.

For the discrete signal, the energy based test statistic is given by

$$\varepsilon = T_s \sum_{n=0}^{N-1} |\, y(n)\,|^2\,, \qquad (3)$$

where N is the size of the observation vector.

The performance of the detection algorithm can be summarized into two probabilities: probability of detection and probability of False Alarm. P_F, P_D is the probability of detecting a licensed primary user which really exists. P_F is the probability of mistakenly concluding the presence of the PUs while they are actually inactive. For a good detection algorithm, the lower the P_F, the better the precision of the detector which offers a higher throughput for the secondary network.

Fig. 4, Fig. 5, Fig. 6 and Fig. 7 show the relationship among threshold, P_D and SNR under different sample numbers. By increasing the threshold, P_D increases; when SNR increases, P_D also increases, leading to the more accurate of judgment of the detector. According to the four figures, the value of threshold is narrowed within [0.366, 1.033], [0.370, 1.030], [0.372, 1.028], [0.374, 1.026], respectively. It is found that the more number of samples, the smaller the range of threshold, making it comparatively easier to fix the value of threshold.

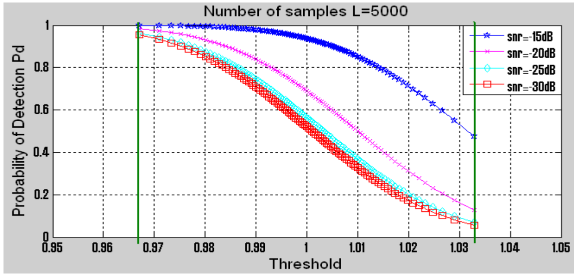

Fig. 4. Threshold vs. Pd when L=5000.

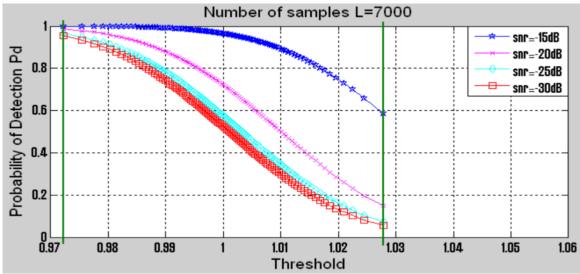

Fig. 5. Threshold vs. Pd when L=6000.

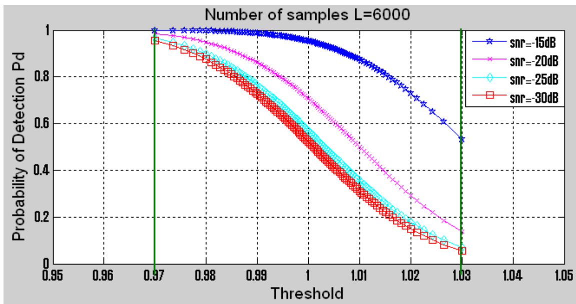

Fig. 6. Threshold vs. Pd when L=7000.

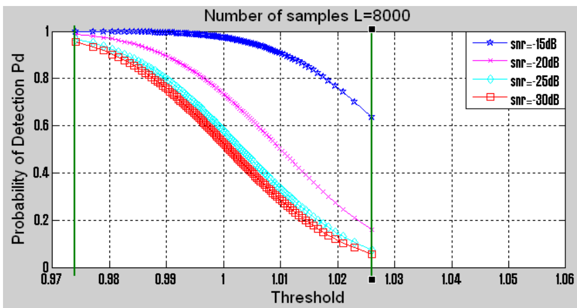

Fig. 7. Threshold vs. Pd when L=8000.

In order to compare the performances for different threshold values, receiver operating characteristic (ROC) curves can be used. ROC curves allow us to explore the relationship between the sensitivity (probability of detection) and specificity (false alarm rate) of a sensing method for a variety of different thresholds, thus allowing the determination of an optimal threshold.

Fig. 8 and Fig. 9 show that when P_F increases P_D also increases. The higher the SNR, the lower the P_F. It shows that more and more false alarm will give chances for PU to use their band or we can say that PU can use their band without much disturbance [9].

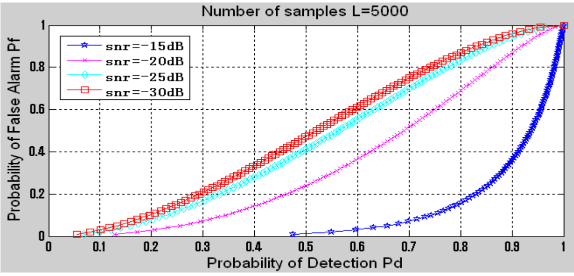

Fig. 8. ROC when L=5000.

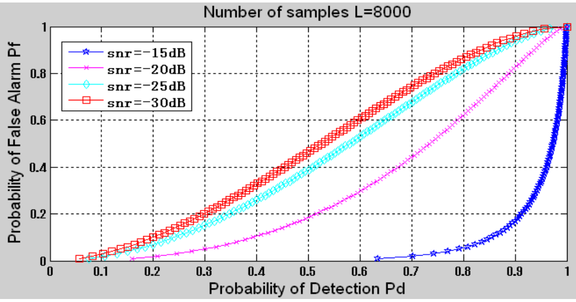

Fig. 9. ROC when L=8000.

4.2. Eigenvalue Based Sensing Algorithm

Different from that of the energy detection technique, without any pre-knowledge of the transmitted signal and the environment, eigenvalue based sensing algorithm uses the covariance matrix theories (CMT) to accomplish the task of sensing primary users.

In real life, only the sample covariance matrix is accessible rather than the statistic covariance matrix because the received signal obtained after the channel is a series of samples. The sample covariance matrix of the received samples can be expressed as follows:

$$\vec{R}_x(\mathrm{N}_s) = \frac{1}{N_s}\sum_{n=L-1}^{L-2+N_s} \vec{\mathrm{x}}(\mathrm{n})\overrightarrow{x^{\dagger}}(\mathrm{n})\,, \tag{4}$$

where N_s s the number of samples [4].

By calculating the eigenvalues of the covariance matrix, the maximum λ_{max} and minimum $\lambda_{\min}$ values of the eigenvalues can be obtained. The threshold is therefore achieved $T = \frac{\lambda_{\max}}{\lambda_{\min}}$. If $T \succ \gamma$, then the primary user exists; otherwise, the decision is that there is no primary user. γ is a constant that is larger than 1.

With the increase of the size of the matrix (corresponds to the increasing value of *L*), the rank of the covariance matrix reduces, thus leading to the overlap of some eigenvalues of the matrix. Table 1 and Table 2 show some of the eigenvalues of the different signal sources. Eigenvalues become very large after *L*>20, so analysis is going to be conducted within *L*=5 to *L*=20.

Table 1. Eigenvalues under SNR=25 dB, fs=2000 Hz, f=500 Hz, fc=5000 Hz.

	L=5	*L*=10	*L*=15	*L*=20	*L*=25	*L*=30	*L*=35	*L*=40	*L*=45
Baseband	12.348	25.298	38.540	67.550	62.615	89.787	171.305	199.665	367.425
BPSK	2.125	2.491	24.975	28.799	497.289	1657.706	2301.78	91.116	2517.39
BFSK	2.675	3.579	17.496	98.468	2183.667	2267.136	2893.713	322.4175	4037.035
16QAM	4.417	4.375	8.627	48.172	164.614	166.669	233.784	160.176	516.570
4PSK	2.364	2.001	5.887	34.533	96.132	131.762	122.339	150.096	296.852

Table 2. Eigenvalues under SNR=45 dB, fs=2000 Hz, f=500 Hz, fc=5000 Hz.

	L=5	*L*=10	*L*=15	*L*=20	*L*=25	*L*=30	*L*=35	*L*=40	*L*=45
Baseband	12.476	25.705	39.275	68.575	64.333	92.726	174.530	202.530	366.404
BPSK	2.139	2.505	25.022	30.772	699.926	4023.630	301899.9	96.558	226846.13
BFSK	2.668	3.577	17.322	98.092	2226.059	2234.655	2475.93	323.332	4423.423
16QAM	4.444	4.396	8.738	49.613	174.688	180.224	249.702	169.012	638.716
4PSK	2.368	1.999	5.907	34.391	95.906	130.985	121.776	150.198	308.656

* fc=5000 Hz does not apply to the baseband signal.

4.3. Cyclostationary Sensing Algorithm

Cyclostationary-Based detector is the very method for detecting primary user transmission via exploiting the cyclostationary features of the received signal at the cognitive node. Signals have cyclostationary features in the frequency domain that are not easily seen in the time domain. Instead using power spectrum density (PSD) in energy-based detector, cyclostationary-based detector uses cyclic correction function (CAF) to detect the signal present in a given spectrum. The mathematic definition of CAF is given in (5) as follows:

$$R_x^{\,a}(k) = \lim_{x\to\infty} \frac{1}{2N+1}\sum_{n=-N}^{N} x(n)x^*(n-k)e^{-j2\pi an}e^{j\pi ak}\,, \tag{5}$$

The spectral correlation function (SCD) is defined as

$$S_x^{\,a}(f) = \int_{-\infty}^{+\infty} R_x^{\,a}(\tau)e^{-j2\pi at}d\tau\,, \tag{6}$$

FFT Accumulation Method (FAM) method is based on modifications of time smoothed cyclic cross periodogram.

For testing, an AM baseband signal with frequency 50 Hz and carrier frequency 500 Hz is used as a source signal. Test the SCD for different SNR: SNR=25, 15, 5, -5. The results for different condition are shown in Fig. 10, as it is seen that cyclostationary features is more apparent for a higher SNR. A higher SNR brings a better wireless communication. When the SNR=-5 dB (the first plot), the cyclic power spectrum don't concentrate around cyclic frequency and it spreads widely. However, when SNR increase into 25 dB, we can see perfectly cyclostationary features of the AM signals. The same result can be obtained from the Fig. 11 for SCD 2-D contour plot of different SNR.

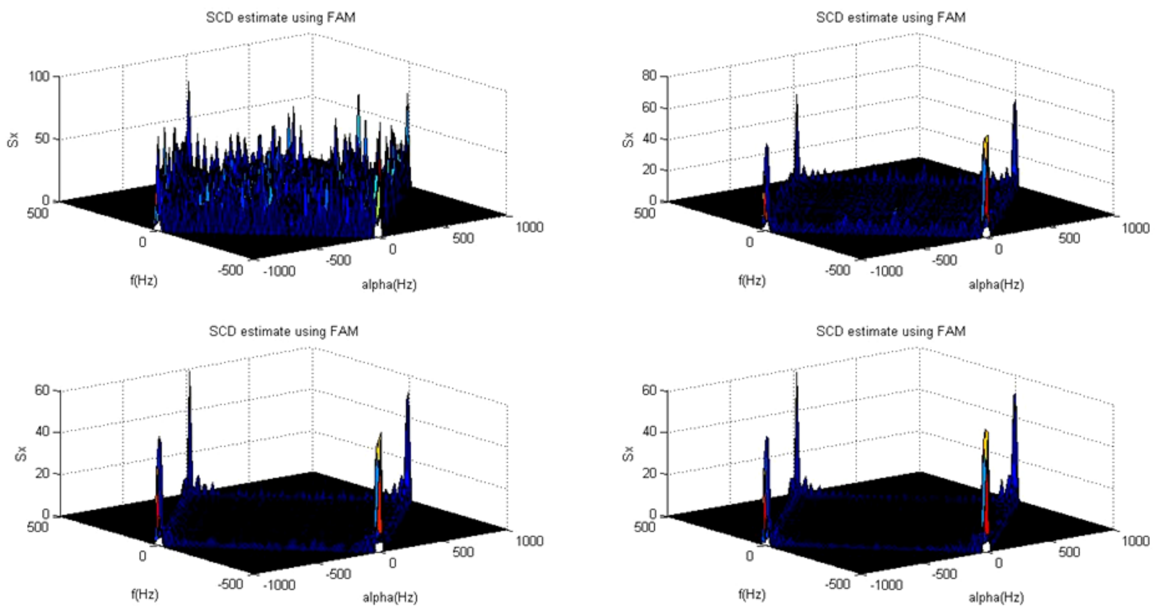

Fig. 10. The SCD-3D plot.

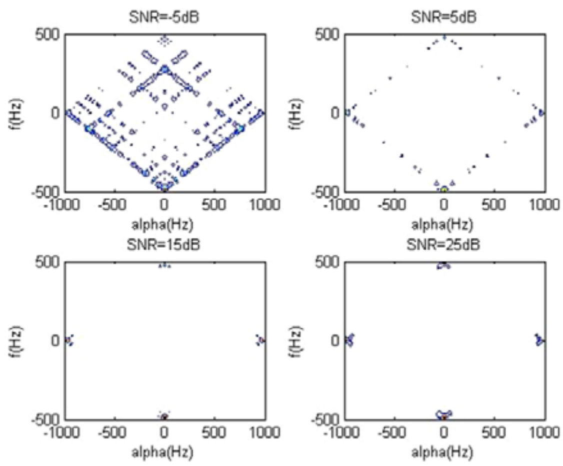

Fig. 11. SCD-2D contour plot.

4.4. Entropy Sensing Algorithm

In information theory, entropy is a measure of uncertainty associated with a random variable. The term by itself usually refers to the Shannon entropy, which qualifies the information contained in a message. In [10], the author investigated entropy-based detection to counteract noise certainty in frequency domain, and the Shannon entropy is first used as information measure of the received signal to detect the presence of primary user in a blind manner.

A probability space can represent a discrete random variable, and P represents the sample space, events, and the measure of the event. Let denote a possible state value, and denote the corresponding probability in state. Let L represents the total number of countable states. Then the information entropy can be represented as

$$X(k) = -\sum_{i=1}^{L} p_i \log_b p_i \,, \qquad (7)$$

where $\sum_{i=1}^{L} p_i = 1$ with $0 \le p_i \le 1$, b is the base of the logarithm. For simplicity, in the rest of the paper, we use log to denote base 2 logarithms. Basic histogram method is used for entropy estimation in our project. The number of states of the random variable is then equal to the bin number L.

In accordance to the requirements of IEEE 802.22 to digital television (DTV) spectrum sensing, the test parameters are set [11]: the false alarm probability is no more than 0.1 for better spectrum utilization.

Table 3, Table 4 and Table 5 show that the value of entropy of pure noise is larger than that of with transmitted signals/primary users. It is worth clarifying that when it comes to the baseband test signal, the parameter fc=5000 Hz is no longer applicable; and when it comes to calculating the entropy of noise, the setting of SNR is irrelevant. As observed from the tables, the entropy of a certain source is almost a constant – it does not change with SNR. However, except for the baseband signal, it becomes larger when the frequencies of the signals and the sampling rates are higher, which implies that the higher the frequency of the transmitted signals, the bigger the fluctuation of the signals is observed and the more complete nature of the signals is revealed.

5. Comparison of the Algorithms

5.1. Requirements Evaluation

Table 6 shows that summary for sensing algorithms.

Table 3. Entropy of different signals when fs=200 Hz, f=50 Hz, fc=5000 Hz.

SNR (dB)	Noise	Baseband	BASK	BPSK	BFSK	16QAM	4PSK
25	2.6108	0.6915	0.0385	0.2136	0.0793	0.0721	0.0783
35	2.5877	0.6915	0.0380	0.2125	0.0793	0.0721	0.0783
45	2.5680	0.6915	0.0380	0.2153	0.0798	0.0721	0.0784

Table 4. Entropy of different signals when fs=800 Hz, f=200 Hz, fc=5000 Hz.

SNR (dB)	Noise	Baseband	BASK	BPSK	BFSK	16QAM	4PSK
25	2.691	0.224	0.0027	0.0695	0.0153	0.0153	0.022
35	2.519	0.2158	0.0027	0.0695	0.0153	0.0153	0.022
45	2.5619	0.2158	0.0027	0.0695	0.0153	0.0153	0.022

Table 5. Entropy of different signals when fs=2000 Hz, f=500 Hz, fc=5000 Hz.

SNR (dB)	Noise	Baseband	BASK	BPSK	BFSK	16QAM	4PSK
25	2.5346	0.098	0.0025	0.0025	0.0085	0.0085	0.0097
35	2.6902	0.0938	0.0025	0.0025	0.0085	0.0085	0.0097
45	2.6416	0.1022	0.0025	0.0225	0.0085	0.0085	0.0097

Table 6. Compare and contrast summary for sensing algorithms.

Spectrum Sensing Algorithm	Using Conditions	Advantages	Disadvantages
Energy Detector-based Sensing	Unknown PU signal	Simple structure, and No requirements for knowledge of PU	Poor performance for low SNR condition
Eigenvalue-based sensing	Unknown PU signal	Better performance than ED, and no requirements for knowledge of PU	Accurate Synchronization
Cyclostationary-based sensing	PU signal has cycclostationary feature	Distinguish SCD between noise and PU easily	Complex
Entropy-based sensing	Unknown PU signal	Robust against uncertainty noise, and no requirements for knowledge of PU	Requirements for FFT

5.2. Performance Evaluation

Correlation efficient is a measure of the strength and direction of the linear relationship between two variables that is defined as the (sample) covariance of the variables divided by the product of their (sample) standard deviations [12].

Denote M_1 (*M=x, y or z*) the evaluation factors obtained from noise; M_2 (*M=x, y or z*) the evaluation factors obtained from source signals. Denote the correlation coefficient between M_1 and M_2 *rou* and the variance of M_2 *var*.

From the results of the Table 7, Table 8 and Table 9 it is found that:

rou(cyclostationary)<rou(eigenvalue)<rou(entropy),
var(entropy)<var(cyclostationart)<var(eigenvalue).

It shows that the cyclostationary technique has less correlation with the performance of pure noise while entropy has the most, which implies that cyclostationary may be a better choice of spectrum sensing technique in terms of correction rate. However, entropy technique is the most stable one while the eigenvalue is the least.

Table 7. Performance when SNR=25.

	Eigenvalue	Cyclostationary	Entropy
Rou	0.8077	0.7130	0.8821
Var	201.8505	0.0862	0.0047

Table 8. Performance when SNR=35.

	Eigenvalue	Cyclostationary	Entropy
Rou	0.8650	0.7142	0.8832
Var	213.6579	0.0212	0.0046

Table 9. Performance when SNR=45.

	Eigenvalue	Cyclostationary	Entropy
Rou	0.8649	0.7142	0.9998
Var	214.4176	0.0212	0.0019

6. Conclusions

The energy detector is known for its simplicity of implementing and low complexity. However, its weakest point is that it is not effective under the condition that SNR is an unknown, this leads to its unguaranteed accuracy. The eigenvalue based sensing technique is not as stable as the cyclostationary and entropy technique since its threshold various greatly as it needs to solve the problem of appropriately estimate the size of the covariance matrix, leading to its instability. Cyclostationary produces the test statics which can be used as testing the existence of the primary users the least correlated to that produced by pure noise signals, which implies that this technique make a clearer and better judgment as to the considering issue. Entropy algorithm is a comparatively new technique, although it is more stable, it has the most similarity with the performance of pure noise signals, which bring about potential mistakes in making decisions for the secondary users.

Future work of this field of research is still promising and scientists are looking for more innovative spectrum sensing techniques function in the frequency domain. It is also important to extend and optimize this research, either non-cooperative sensing, or more complicated cooperative sensing, to practical use of people's daily lives, and this has become another challenge for telecommunication scientists.

Acknowledgments

This work was supported by Jiangsu province Graduate student innovation (No.CXZZ11-0393) and National Natural Science Foundation of China (No. 61271240).

References

[1]. Mohd Sajid Imam, Sheetal Ingle, and Shabnam Ara, A review paper based on spectrum sensing techniques in cognitive radio networks, *Network and Complex Systems*, Vol. 3, No. 9, 2013, pp. 14-20.

[2] Notice of proposed rulemaking and order: Facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies, *Federal Communications Commission*, ET Docket, No. 03-108, February 2005.

[3]. Harry Urkowitz, Energy detection of the unknown deterministic signals, *Proceedings of the IEEE*, Vol. 55, Issue 4, 1967, pp. 523-531.

[4]. Zeng Yonghong and Yingchang Liang, Eigenvalue-based spectrum sensing algorithms for cognitive radio, *IEEE Transactions on Communications*, Vol. 57, Issue 6, 2009, pp. 1784-1793.

[5]. Y. Zhang, Q. Zhang, and S. Wu, Entropy-based robust spectrum sensing in cognitive radio, *IET Communications*, Vol. 4, Issue 4, 2010, pp. 428-436.

[6]. Tevfik Yucek and Huseyin Arslan, A survey of spectrum sensing algorithms for cognitive radio applications, *IEEE Communications Surveys & Tutorials*, Vol. 11, Issue 1, 2009, pp. 116-130.

[7]. D. Cabric, S. Mishra, and R. Brodersen, Implementation issues in spectrum sensing for cognitive radios, in *Proceedings of the Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, California, USA, November 2004, Vol. 1, pp. 772-776.

[8]. T. Yucek and H. Arslan, Spectrum characterization for opportunistic cognitive radio systems, in *Proceedings of the IEEE Conference on Military Communications*, Washington, D.C., USA, October 2006, pp. 1–6.

[9]. Vishakha Sood, and Manwinder Singh, On the performance of detection based spectrum sensing for

cognitive radio, *International Journal of Electronics & Communication Technology*, Vol. 2, Issue 3, 2011, pp. 140-143.

[10]. Andrea Mariani, Andrea Giorgetti, and Marco Chiani, Effects of noise power estimation on energy detection for cognitive radio applications, *IEEE Transactions on Communications*, Vol. 59, Issue 12, 2011, pp. 3410-3420.

[11]. S. Shellhammer, V. Tawil, G. Chouinard, M. Muterspaugh, M. Ghosh, Spectrum sensing simulation model, *IEEE 802.22-06/0028r10*, September 2006 (https://mentor.ieee.org/802.22/file/06/22-06-0089-05-0000-spectrum-sensing-simulation-Model.doc).

[12]. Y. L. Zhang, Q. Y. Zhang, T. Melodia, A frequency-domain entropy-based detector for robust spectrum sensing in cognitive radio networks, *IEEE Communications Letters*, Vol. 14, Issue 6, 2010, pp. 533-535.