International Journal of Future Generation Communication and Networking
Vol.7, No.3 (2014), pp.173-182
http://dx.doi.org/10.14257/ijfgcn.2014.7.3.16

Dynamic Double Energy Thresholds Detection for Cooperative Spectrum Sensing in Cognitive Radio

Tangsen Huang[1], Peng liu[2] and Ji-chen Yang[2]

*[1]Department of Computer and Communication Engineering,
Hunan University of Science and Engineering,
Yongzhou, China*
*[2]School of Electronic and Information Engineering,
South China University of Technology,
Guangzhou, China*
huang.ts@mail.scut.edu.cn, liu.p@mail.scut.edu.cn, NisonYoung@163.com

Abstract

This paper suggests a cooperative spectrum sensing using dynamic double thresholds energy detection and adaptive grid search to obtain the highest probability detection. The proposed double thresholds are adaptive to noise fluctuation. A new fusion method combined of weighting and voting is used in cooperative sensing. Further, in order to obtain the best sensing performance, we firstly use adaptive grid search to find the optimal double thresholds. Simulation results show that the proposed method has excellent robustness to noise fluctuation and good sensing performance even under low signal to noise ratio (SNR).

Keywords: *spectrum sensing, double thresholds, weighting and voting rule, grid search, cognitive radio*

1. Introduction

Spectrum sensing technology can alleviate the scarcity of spectrum resources. In cognitive radio networks, second user (SU) can utilize a licensed channel when the signal of primary user (PU) is absent. In order to estimate whether the primary user is present or absent, SU must perform spectrum sensing. The initial sensing method is single SU perform spectrum sensing independently. Due to path loss, Rayleigh fading and shadowing fading, single SU perform spectrum sensing poorly. So as to obtain better sensing performance, some SUs can jointly perform cooperative spectrum sensing.

Some studies are focusing on cooperative sensing using double energy threshold. In [1], a hierarchical cooperative sensing method was used to improve sensing performance. The distance between double thresholds was divided into four regions and all weights were same in a region. But this method was not taken the particularity of each SU into serious consideration. In [2], Eigen value of signal was used to improve sensing performance, but the distance between double thresholds was subjectively given and the double energy thresholds in this method were not robust to noise fluctuation. In [3], k-out-of-M fusion rule was used to improve sensing performance. In this method, the difference between double thresholds was important to optimize the detection performance, but the authors did not explain how to set the double thresholds appropriately.

In this paper, the proposed double thresholds have capability to adapt to the change of noise power. Due to the different SU estimates different noise power and SNR, all SUs perform local sensing will get different double thresholds. Because receiving energy of each

ISSN: 2233-7857 IJFGCN

SU is different, all SUs are respectively allocated weights according to their receiving energy, then participated in cooperative sensing. In proposed sensing method, cooperative sensing uses voting rule so that each SU can make the appropriate sensing contribution. Due to the proposed double thresholds is dynamic, it is necessary to solve how to set the double thresholds. In this paper, we set an impact factor to adjust the distance between the double thresholds. When the impact factor has been changed, the double thresholds and the sensing performance will be changed. Therefore, it is important to find out the optimal impact factor to improve sensing performance. Grid search algorithm [4] can find out the optimal impact factor. In order to improve search efficiency, we are the first one using adaptive grid search to find out the optimal impact factor for obtaining the best sensing performance. Simulation results show that the proposed cooperative sensing method achieves better sensing performance even under low SNR and noise fluctuation.

2. System Model

In the this section, we consider a cognitive system having N SUs, a PU and a cognitive b A spectrum sensing system model consists a PU, a cognitive base station (CBS) and N SUs. These SUs are uniformly distributed around the PU. CBS is a fusion center and it decides the PU is present or absent. The system model illustrated as Figure 1.

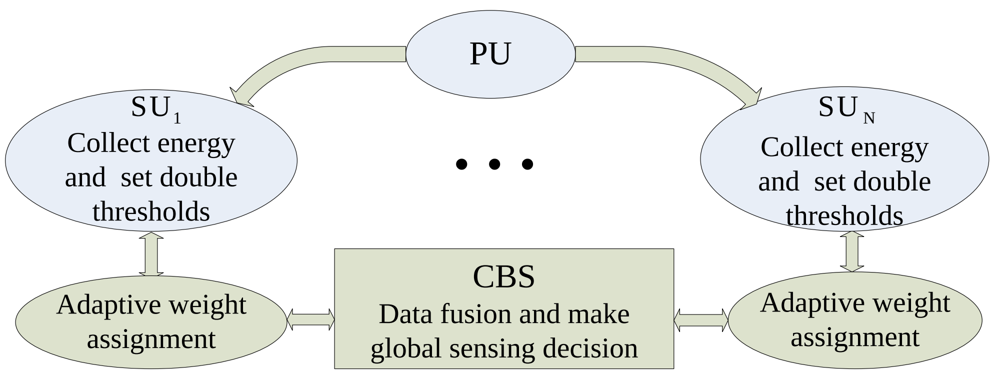


Figure 1. A Cognitive System

2.1. Calculate the Optimal Threshold

For spectrum sensing, every SU performs energy detection independently and the received signal of SU is given by [5]

$$x(m) = s(m) + v(m), \quad m = 0, 1, \cdots, M-1 \tag{1}$$

where $s(m)$ is PU's transmitted signal, $v(m)$ is AWGN with zero mean and variance of σ_v^2, and M is the number of samples. If the PU is absent, $s(m)=0$, denoted by H_0, otherwise, denoted by H_1. So they can be expressed as [5]

$$\begin{aligned} H_0 &: x(m) = v(m), & m = 0,1, \ldots, M-1 \\ H_1 &: x(m) = s(m) + v(m), & m = 0,1, \ldots, M-1 \end{aligned} \tag{2}$$

Assume E is the average energy of the SU received signal, it is expressed as [6]:

$$E = \frac{1}{M}\sum_{m=0}^{M-1}\left|x(m)\right|^2 \tag{3}$$

When M>250, E follows Gaussian distribution according to the central limitation theorem. If each SU makes its local decision depend on a single threshold λ_0, then the probability of detection (P_d) and the probability of false alarm (P_f) can be expressed as respectively [7]:

$$P_d = P\left\{E \geq \lambda_0 \middle| H_1\right\} = Q\left(\frac{\lambda_0 - (\sigma_s^2 + \sigma_v^2)}{(\sigma_s^2 + \sigma_v^2)\Big/\sqrt{M/2}}\right) \tag{4}$$

$$P_f = P\left\{E \geq \lambda_0 \middle| H_0\right\} = Q\left(\frac{\lambda_0 - \sigma_v^2}{\sigma_v^2\Big/\sqrt{M/2}}\right) \tag{5}$$

where σ_s^2 is PU's signal power, σ_v^2 is noise power, λ_0 is decision threshold, and $Q(x)$ is expressed as [7]:

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{\frac{-t^2}{2}}\,dt \tag{6}$$

In order to improve P_d and reduce P_f simultaneously, we put a limiting range on the threshold λ_0 as [8]:

$$\sigma_v^2 \leq \lambda_0 \leq \sigma_v^2 + \sigma_s^2 \tag{7}$$

If the probability of PU's presence signal is $P(H_1) = \beta$, $0 < \beta < 1$, the probability of PU's absent signal is $P(H_0) = 1 - \beta$ and the probability of error detection (P_e) is expressed as [9]:

$$P_e = P(H_1)(1 - P_d) + P(H_0)P_f = \beta(1 - P_d) + (1 - \beta)P_f \tag{8}$$

Let E_1 denote the estimation of the noise power, i.e. $E_1 = \hat{\sigma}_v^2$, E_2 denote the estimation of the sum of signal power and noise power, i.e. $E_2 = \hat{\sigma}_v^2 + \hat{\sigma}_s^2$. Thus the estimation of signal power is $\hat{\sigma}_s^2 = E_2 - E_1$, and the estimation of SNR of the received signal $x(m)$ is [8]:

$$\hat{\gamma} = \frac{\hat{\sigma}_s^2}{\hat{\sigma}_v^2} = \frac{E_2 - E_1}{E_1} \tag{9}$$

The optimal threshold $\hat{\lambda}_o$ is [9]

$$\hat{\lambda}_o = \frac{\hat{\sigma}_v^2 (1+\hat{\gamma}) \left[1 + \sqrt{1 + \frac{4(2+\hat{\gamma})}{M \cdot \hat{\gamma}} \ln \left[\frac{(1-\beta)(1+\hat{\gamma})}{\beta} \right]} \right]}{2+\hat{\gamma}} \tag{10}$$

2.2. Adaptive Double-Threshold Setting

The optimal threshold $\hat{\lambda}_o$ is the center point, and d ($d \geq 0$) is distance between $\hat{\lambda}_o$ and threshold λ_h larger than $\hat{\lambda}_o$ or threshold λ_l lower than $\hat{\lambda}_o$. Obviously, $\lambda_l = \hat{\lambda}_o - d$ and $\hat{\lambda}_o + d = \lambda_h$. In fact, noise power should be less than or equal to λ_l , and noise power adding signal power should be greater than or equal to λ_h . d is satisfied expression (11) and (12)

$$E_1 = \hat{\sigma}_v^2 \leq \hat{\lambda}_O - d \tag{11}$$

$$\hat{\lambda}_o + d \leq \hat{\sigma}_v^2 + \hat{\sigma}_s^2 = E_2 \tag{12}$$

By (11)+(12) obtaining [8]

$$0 \leq d \leq \frac{1}{2}(E_2 - E_1) \tag{13}$$

$$d = \varepsilon(E_2 - E_1) \tag{14}$$

where ε is a impact factor.

According to (13), $0 \leq \varepsilon \leq 0.5$. When $\varepsilon = 0$, double thresholds problem is changed to single threshold problem. λ_h and λ_l can be expressed as

$$\lambda_h = \hat{\lambda}_o + \varepsilon(E_2 - E_1) \tag{15}$$

$$\lambda_l = \hat{\lambda}_o - \varepsilon(E_2 - E_1) \tag{16}$$

3. Local Weight Assignment and Cooperative Spectrum Sensing Algorithm

N SUs are participated in cooperative spectrum sensing in cognitive radio networks. We assume the i^{th} SU receives the average energy of signal is E_i . $\lambda_{h,i}$, $\lambda_{l,i}$, $\hat{\lambda}_{o,i}$ and w_i are the i^{th} SU's larger threshold, lower threshold, the estimated value of the optimal threshold and weight, respectively.

All SUs are not the same distance with the PU, because path loss, multipath Rayleigh fading and shadows fading. Each SU receives different average energy of signal. That is to say, each SU maybe has different weight. The proposed method considers different SUs have different weights and roles in cognitive radio networks. All SUs contribute to the cooperative sensing according to their weights by fusion center.

The fusion rule is voting rule in the fusion center, and can be expressed as

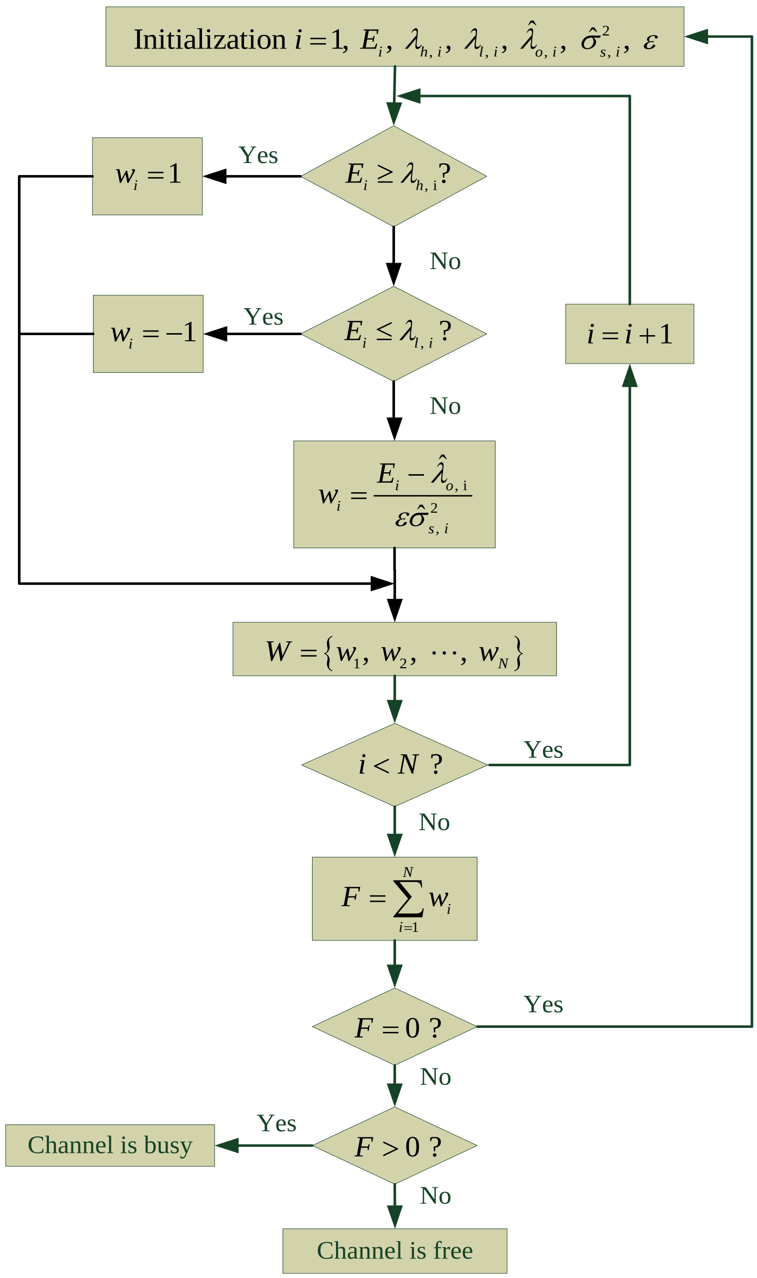


Figure 2. Weights Allocation and Cooperative Sensing Algorithm

$$F = \sum_{i=1}^{N} w_i,\quad i=1,\ 2,\ \cdots,\ N \tag{17}$$

where F is fusion result of the fusion center and equal to the sum of the weights of the all SUs, i is the index of SUs, w_i is i^{th} SU's weight. Fusion center decide whether the PU is present or absent according to the result of (18):

$$F = \sum_{i=1}^{N} w_i \begin{cases} > 0, H_1 \\ < 0, H_0 \\ = 0, \text{no decision and increase sensing time} \end{cases} \tag{18}$$

Only when F=0, fusion center can't decide whether the primary user is present or absent, and all SUs have to increase a sensing cycle time. Fig.2. summarizes the weights allocation and cooperative sensing.

From weights allocation and cooperative sensing algorithm, we discover that the fusion method combines soft fusion and hard fusion, and this algorithm can improve sensing performance while reducing communication overhead.

4. Adaptive Grid Search Algorithm for Optimal Control Parameter

For spectrum sensing, we need to choose an optimal control parameter ε to obtain the best global sensing performance. Grid search can find the optimal ε according to the feedback of global P_d. Its principle is:

1) Under a SNR k, search from $\varepsilon_0 = 0.0$ to $\varepsilon_{10} = 0.5$ in step 0.05, and obtain $\{P_{d,0}, P_{d,1}, \cdots, P_{d,10}\}$.

2) The $P_{d,\max}$ and the corresponding ε_{opt} are output according to:

$$\begin{cases} P_{d,\max} = \max\{P_{d,0}, P_{d,1}, \cdots, P_{d,10}\} \\ \varepsilon_{opt} = f^{-1}(P_{d,\max}) \end{cases} \tag{19}$$

where $f^{-1}(\cdot)$ denotes extracting ε_{opt} corresponding to $P_{d,\max}$.

3) The optimal parameter ε_{opt} and the SNR k will be saved as a group of prior knowledge to a knowledge base. Subsequent spectrum sensing will directly invoke the ε_{opt} according to the prior knowledge when the SNR k appears repeatedly. If SNR changes, go to step 1).

5. Simulation Results

In order to evaluate the sensing performance of the proposed scheme, we design two simulation experiments: *A*) parameter ε impacts on sensing performance; *B*) function testing of grid search.

In the simulation experiments, we assume the PU signal is a BPSK (Binary Phase Shift Keying) signal, sample frequency is 10 KHz, the sensing time is 0.1s, the presence probability of the PU is $\beta = P(H_1) = 0.5$, the transmission power of the PU is 0.01W and noise power fluctuation is modeled by changing SNR. Moreover, we consider an $2\text{ Km} \times 2\text{Km}$ area with a PU located at the center. There are 16 SUs uniformly distributed in the area. And assume the path loss exponent is 3, the standard deviation of the shadow is 6 dB and the mean of the multipath Rayleigh fading is 1.

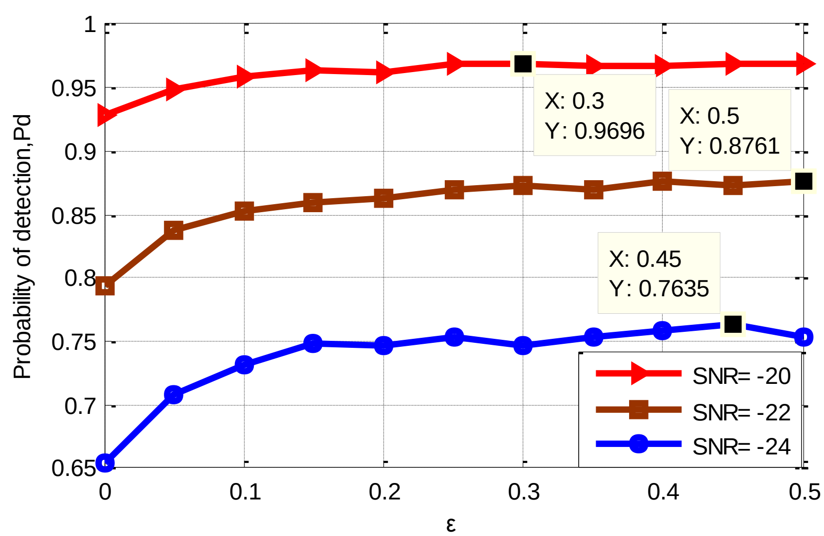
5.1. Investigating the Impacting of Parameter ε on Sensing Performance

In order to illustrate the control parameter ε impacting on sensing performance, we observe that probability of detection P_d and probability of error detection P_e will be how to change when ε is changed. Figure 3 illustrates the results of P_d and P_e versus ε . In Figure 3 (a), there is an optimal ε to make P_d maximum under a SNR, the optimal ε may be different under different SNR. In Figure 3 (b), there is also an optimal ε to make P_e minimum under a SNR. By comparing Figure 3 (a) and Figure 3 (b), we discover their optimal ε are the same under the same SNR. This is what we expect. Therefore, finding the optimal ε is very important to improve sensing performance.

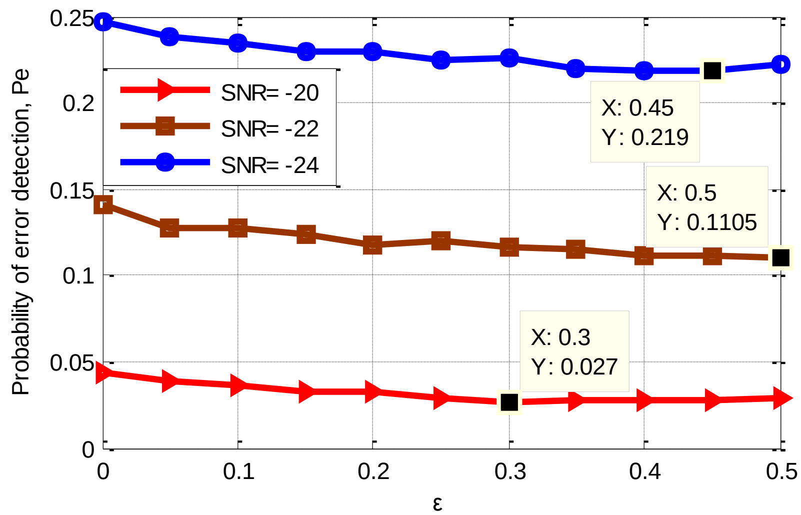
5.2. Function Testing of Grid Search

In order to test function of grid search, $P_{d,\max}$, $P_{d,d}$ and $P_{d,s}$ are obtained by using grid search (ε is changed), double thresholds ($\varepsilon = 0.25$) and single threshold ($\varepsilon = 0$) respectively. Figure 4 illustrates the results of comparison. We discover that $P_{d,\max}$ is the highest. Therefore, it is effective using grid search algorithm to obtain the best sensing performance. Further, we discover that $P_{d,d}$ is much larger than $P_{d,s}$ under different SNR. This is because each SU with double thresholds can make appropriate sensing contribution based on its weight, it is more reliable comparing with every SU with single threshold only have two weights (1 or -1).

Figure 5 shows different step of ε value versus the detection ratio $P_{d,\max}$, we can see that step of ε value doesn't impact the detection ratio $P_{d,\max}$. So , we only need suitable step of ε value can obtain the $P_{d,\max}$.



(a) P_d vs. ε for Cooperative Spectrum Sensing



(b) P_e vs. ε for Cooperative Spectrum Sensing

Figure 3. Parameter ε Impacts on Sensing Performance. P_d and P_e vs. ε for Cooperative Spectrum Sensing, $\Delta\varepsilon = 0.05$

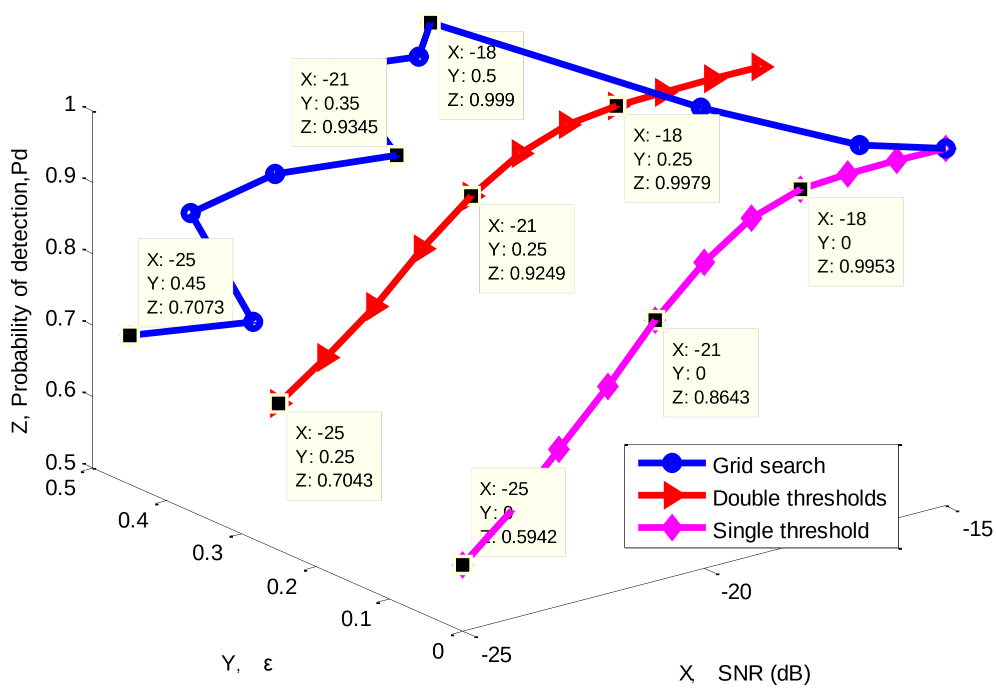


Figure 4. Function Testing of Grid Search Comparison of $P_{d,\max}$, $P_{d,d}$ and $P_{d,s}$

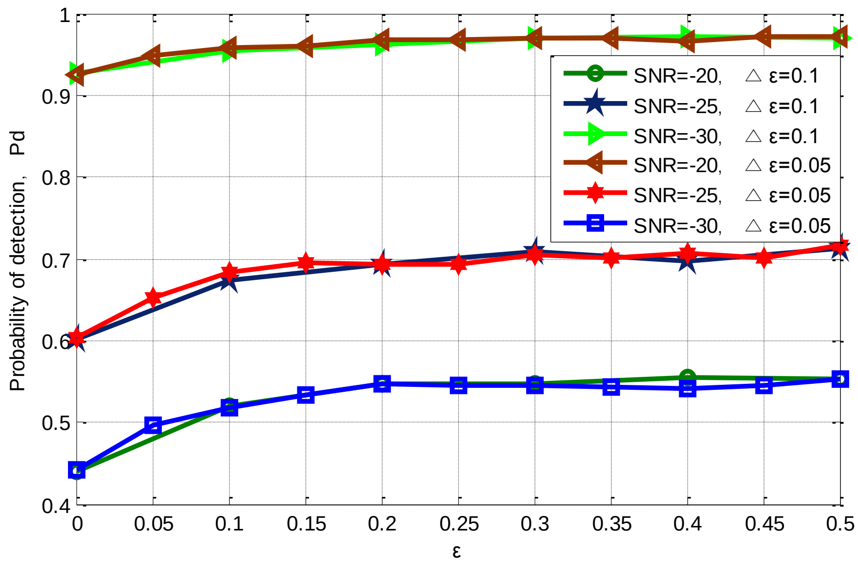


Figure 5. Different Step of ε VS $P_{d,\max}$

6. Conclusion

In this paper, we have studied a new cooperative spectrum sensing method. This method used adaptive double thresholds energy detection and adaptive grid search to obtain the highest probability of detection. In local sensing, SU obtained the optimal threshold through estimating noise power and SNR, and we set an impact factor to adjust the distance between the double thresholds. In cooperative sensing, all SUs are assigned weights according to the received average energy and participated in cooperative sensing. Adaptive grid search could find out the optimal double thresholds and obtained the best sensing performance. We also take the impact of path loss, multipath Rayleigh fading and shadows fading into consideration. Simulation results have demonstrated that the proposed spectrum sensing method have excellent sensing performance with low SNR and noise fluctuation.

Acknowledgements

This work was supported by the National Nature Science Foundation of China (No. 61301300), China Postdoctoral Science Foundation (No.2013M531850) and the Fundamental Research Funds for the Central Universities, SCUT, China (No. 2013ZM0097).

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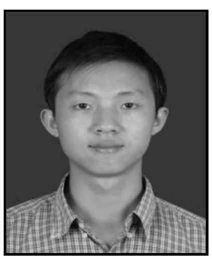
Authors

Tangsen Huang, received B.Eng. degree in Electronic Information Engineering from Hunan University of Technology, Zhuzhou, China, in 2004. He received M. Eng. Degree in Signal and Information Processing from Guilin University of Electronic Science and Technology, Guilin, China, in 2007. He worked as a teacher in Hunan University of Science and Engineering, Yongzhou, China. He is pursuing Ph.D. in the School of Electronic and Information Engineering, South China University of Technology, Guangzhou, China. His research interests are cognitive radio, ultra-wideband communication and compressed sensing.



Peng Liu, received the B.S. Degree in Institute of Electronics and Information from the South China University of Technology, Guangzhou China, in 2012. He is currently pursuing the Master's degree in the Institute of Electronics and Information, South China University of Technology. His current research interests include image super-resolution and compressive sensing.

Ji-chen Yang, received the B.Eng. degree in electronic and information engineering from Guangdong University of Petrochemical Technology, Maoming, China, in 2004. He received the M. Eng. Degree in system engineering from Guangdong University of Technology, Guangzhou, China, in 2007. He received the Ph.D. in Communication and Information System from South China University of Technology, Guangzhou, China, in 2010. Since Oct. 2011, he has been a post doc. researcher in South China University of Technology. His current interest is audio signal processing.

