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Cooperative Spectrum Sensing Optimization Algorithm Based on Adaptive Threshold Setting

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Abstract

Energy detection performance in the signal to noise ratio (SNR) fluctuation needs to be improved. In order to obtain the highest probability of detection, a new cooperative spectrum sensing algorithm is proposed. Dynamic double energy thresholds and adaptive grid search are utilized to obtain the highest probability detection. Double thresholds are adaptive to noise fluctuation, and in order to obtain the best sensing performance, adaptive grid search is used firstly to find the optimal double thresholds. Simulation results show that the proposed algorithm has excellent robustness to noise fluctuation and good sensing performance even under the low signal to noise ratio.

Keywords: *Cognitive radio, spectrum sensing, double thresholds, grid search*

1. Introduction

In cognitive radio networks, second user (SU) can utilize a licensed channel when the signal of the primary user (PU) is absent [1]. In order to assess whether the primary user is present or absent. SU must perform spectrum sensing [2]. The initial sensing method is single SU performance spectrum sensing independently. Due to path loss, Rayleigh fading and shadowing fading, single SU performance spectrum sensing poorly [3]. So as to obtain better sensing performance. Some SU can jointly perform cooperative spectrum sensing [4]. In this paper, considering the path loss, each SU collects different energy and need in order to adjust double energy thresholds for enhancing reliability of local decision. Therefore, a control parameter to accurately fine tune the double thresholds is introduced. Further, in order to reflect the difference of SU collected energy, each SU will be assigned a weight according to its collected energy. Fusion center will fuse their weights according to majority rule and make a final decision to determine the channel is free or busy. Simulation results show that the proposed sensing scheme has excellent performance and outperforms the conventional sensing schemes under low SNR.

Some studies are focusing on cooperative sensing using double energy threshold. In [5], hierarchical cooperative sensing method was used to improve sensing performance. The distance between double thresholds was divided into four regions and all weights in a region are same. But this method was not taken the particularity of each SU into serious consideration. In [6], eigenvalue of the 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 [7], 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, a new method of estimate noise power and SNR is proposed. The proposed double thresholds have capability to adapt to the change of noise power. Due to

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the different SU estimates noise power and SNR, all SU perform local sensing will get different double thresholds, and sensing results are more reliable compared with all SU have the same double thresholds. Energy of each SU received is different, all SU are respectively allocated weights according to their receiving energy, then participated in cooperative sensing. The 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, double thresholds and sensing performance will be changed. Therefore, it is important to find out the optimal impact factor to improve sensing performance. Grid search can find out the optimal impact factor [8]. In order to improve search efficiency, we are the first one using adaptive grid search to find out the optimal impact factor and obtain 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 following section, a system having N SUs is considered, a PU and a cognitive base station. All SUs communicate with the cognitive base station through a common control channel, and the cognitive base station is a fuse center and it decides PU is present or absent.

2.1. Calculate the Optimal Threshold

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

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

where $s(m)$ is transmitted signal of PU, $v(m)$ is additive white Gaussian noise (AWGN) with zero mean and variance of $\sigma_v{}^2$, and M is the number of samples. PU absence is denoted by H_0, and PU presence is denoted by H_1. So they can be expressed as [5]

$$H_0:\ x(m) = v(m), \qquad m = 0,1,\ ...,\ M\text{-}1 \tag{2-1}$$

$$H_1:\ x(m) = s(m) + v(m), \quad m = 0,1,\ ...,\ M\text{-}1 \tag{2-2}$$

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

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

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

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

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

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

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

If the probability of PU presence is $P(H_1) = \beta$, $0 < \beta < 1$ the probability of PU absent is $P(H_0) = 1 - \beta$ and the probability of error detection (P_e) is expressed as [8]

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

Because P_d, P_f and P_e are quadratic function of the λ_0, we can derive . There must have the optimal threshold λ_0 to minimize P_e, and then by letting $\frac{\partial P_e}{\partial \lambda_0} = 0$ to obtain the optimal threshold λ_o, it is expressed as

$$\lambda_o = \left| \frac{\sigma_v^2 (1+\gamma)\left[1 + \sqrt{1 + \frac{4(2+\gamma)}{M \cdot \gamma} \ln\left[\frac{(1-\beta)(1+\gamma)}{\beta}\right]}\right]}{2+\gamma} \right| \tag{9}$$

where $\gamma = \frac{\sigma_s{}^2}{\sigma_v{}^2}$ is the SNR of the receiving terminal of SU. If we know the signal power σ_s^2, noise power σ_v^2 and the SNR of the receiving terminal, it is easy to obtain the optimal threshold. If collecting the energy in a sensing cycle is E, and E can be divided into two equal sections E_1 and E_2.

If $E_1 < E_2$, we let $E_1 = \hat{\sigma}_v^2$, $E_2 = \hat{\sigma}_s^2 + \hat{\sigma}_v^2$ and the estimated value of SNR is

$$\hat{\gamma} = \frac{\hat{\sigma}_s^2}{\hat{\sigma}_v^2} = \frac{E_2 - E_1}{E_1} \tag{10}$$

Then the optimal threshold λ_o can be estimated by the following expression

$$\hat{\lambda}_o = \left| \frac{\hat{\sigma}_v^2 (1+\hat{\gamma})\left[1 + \sqrt{1 + \frac{4(2+\hat{\gamma})}{(M/2)\hat{\gamma}} \ln\left[\frac{(1-\beta)(1+\hat{\gamma})}{\beta}\right]}\right]}{2+\hat{\gamma}} \right| \tag{11}$$

2.2. Adaptive Double-threshold Setting

The optimal threshold $\hat{\lambda}_O$ is the center point, and d ($d \ge 0$) is distance between $\hat{\lambda}_o$ and threshold λ_h larger than $\hat{\lambda}_o$ or threshold λ_l lower than $\hat{\lambda}_o$.

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, so d should satisfy

$$E_1 = \hat{\sigma}_v^2 \le \hat{\lambda}_O - d = \lambda_l \tag{12}$$

$$\lambda_h = \hat{\lambda}_o + d \le \hat{\sigma}_v^2 + \hat{\sigma}_s^2 = E_2 \tag{13}$$

(12)+ (13) can obtain

$$0 \le d \le \frac{1}{2}\left(E_2 - E_1\right) \tag{14}$$

Let

$$d = \varepsilon\left(E_2 - E_1\right) \tag{15}$$

where ε is an impact factor, and $0 \le \varepsilon \le 0.5$. When $\varepsilon = 0$, double thresholds problem is changed to single threshold problem. λ_h and λ_l can be expressed as

$$\lambda_h = \hat{\lambda}_o + \varepsilon\left(E_2 - E_1\right) \tag{16}$$

$$\lambda_l = \hat{\lambda}_o - \varepsilon\left(E_2 - E_1\right) \tag{17}$$

3. Cooperative Spectrum Sensing Algorithm

N SUs take part in cooperative spectrum sensing in cognitive radio networks. 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 larger threshold, lower threshold, the estimated value of the optimal threshold and weight of i^{th} SU, respectively.

All SUs are not the same distance with the PU, because path loss, multipath Rayleigh 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, this is close to the actual situation. All SUs contribute to the cooperative sensing according to their weights by fusion center. Algorithm 1 summarizes the weights allocation and cooperative sensing.

Algorithm 1 Weights allocation and cooperative sensing

Initialization: obtain E_i , $\hat{\lambda}_{o,i}$, $\lambda_{h,i}$, $\lambda_{l,i}$, N

If $E_i \ge \lambda_{h,i}$, assign $w_i = 1$ and transmit 1 to the fusion center

Else if $E_i \le \lambda_{l,i}$, assign $w_i = -1$ and transmit -1 to the fusion center

Else $\lambda_{l,i} < E_i < \lambda_{h,i}$

If $\hat{\lambda}_{o,i} < E_i < \lambda_{h,i}$, assign $w_i = \dfrac{E_i - \hat{\lambda}_{o,i}}{\lambda_{h,i} - \hat{\lambda}_{o,i}}$, and transmit w_i to the fusion center

If $\lambda_{l,i} < E_i \le \hat{\lambda}_{o,i}$, assign $w_i = \dfrac{E_i - \hat{\lambda}_{o,i}}{\hat{\lambda}_{o,i} - \lambda_{l,i}}$, and transmit w_i to the fusion center

The value of F is calculated according to $F = \sum_{i=1}^{N} w_i,\ i = 1, 2, \cdots, N$

If $F > 0$, the fusion center output 1, and decide the PU is presence
Else if $F < 0$, the fusion center output 0, and decide the PU is absent
Else $F = 0$, the fusion center does not making decision and go to step 1
End

From algorithm 1, we discover that the fusion of all SUs are combined soft fusion with hard fusion, so algorithm 1 can improve sensing performance while reducing communication overhead.

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4. Adaptive Grid Search Algorithm

Setting of appropriate double thresholds will affect the sensing performance. The double thresholds are related to impact factor ε, that is to say which ε can impact the sensing performance. When $0 \le \varepsilon \le 0.5$, there must exist a ε making the best sensing performance. So it is important to ensure the optimal ε to obtain the best sensing performance. Adaptive grid search can find out it to obtain the best sensing performance. Algorithm 2 explains the process using the adaptive grid search to find the optimal ε and obtain the highest P_d.

Algorithm 2 Using the adaptive grid search to find the optimal ε and obtain the highest P_d

1: Initialization: SNR
2: For $j = 1:10$
3: Order ε_0=0.0, $\Delta\varepsilon = 0.05$ and $\varepsilon_j = \varepsilon_0 + \Delta\varepsilon \cdot j$
4: According to algorithm 1 to compute $P_{d,0} = f\left(\hat{\lambda}_o, \varepsilon_0\right)$ and $P_{d,j} = f\left(\hat{\lambda}_o, \varepsilon_j\right)$
5: Compare the $P_{d,j}$, $j = 0,1,\cdots,10$
6: Select the highest $P_{d,j}$ and the ε_j corresponding with the highest $P_{d,j}$, $j = 0,1,\cdots,10$
7: Save the optimal ε_j of the SNR
8: When SNR changed, go to step 2
9: The saved ε will be as a prior knowledge of later sensing
10: End

5. Simulation Results

For evaluating the sensing performance of the proposed sensing scheme, a lot of simulation results are shown. The signal of the PU is BPSK (Binary Phase Shift Keying) signal, the bandwidth is 10 KHz, the sensing time is 0.1 s. Assume the $P(H_1) = \beta = 0.5$ and the transmission power of the PU is 0.1 W. We consider a $1\,\text{Km} \times 1\,\text{Km}$ area, PU located at the center, there are 16 SUs uniformly distributed in the area, Figure 1 illustrates the distribution of PU and SUs, and consider the impact of path loss, multipath Rayleigh fading and shadows shade, 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 [15].

Figure 2 illustrates the results of the P_d versus ε, ε value is changed. Can be seen that when SNR is fixed, the P_d changes along with ε value changed from Figure 2, but there is an optimal ε value to maximize the P_d. And different SNR have a different optimal ε value. Due to SNR is often changing, need to use adaptive grid search algorithm to find out the optimal values.

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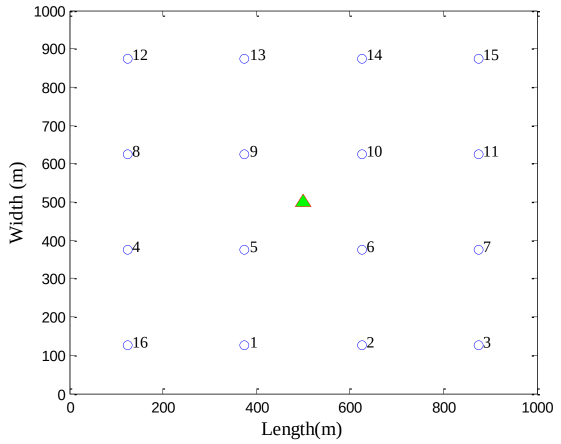

Figure 1. The Network used for Simulation, the Triangle Denote the PU, the Circles Denotes the SUs

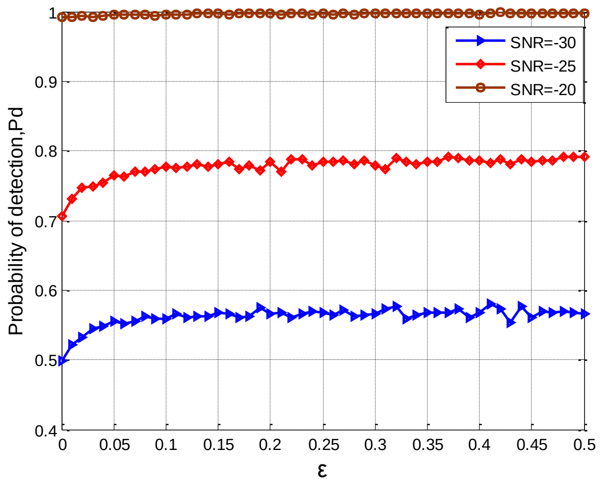

Figure 2. P_d versus ε for Cooperative Spectrum Sensing, $0 \le \varepsilon \le 0.5, \Delta\varepsilon = 0.01$, SNR=30 dB, -25dB and -20dB

Figure 3 illustrates the results of using adaptive grid search algorithm to find out the optimal ε values to maximize the P_d in different SNR. Table 1 show the data consistent with the characteristic curve in Figure 3. Table 1 illustrates the results of using grid search to find the optimal ε and obtain the highest P_d under different SNR, and compared with fixed ε. Using grid search to obtain the probability of detection is higher than this of fixed ε. It also shows that using grid search has obvious effect to improve probability of detection, and has excellent robustness to noise fluctuation.

Figure 4 illustrates the results of the proposed spectrum sensing method compare with others sensing methods. There are 5 kinds of comparison methods, respectively are hierarchical with quantization method [6], double thresholds detection using eigenvalue method [7], the proposed adaptive single threshold method, the proposed adaptive double threshold method and the proposed adaptive grid search algorithm. Can be seen that the P_d of obtain using adaptive grid search algorithm is highest from Figure 4, even using the proposed single threshold method, the P_d outperforms others sensing methods.

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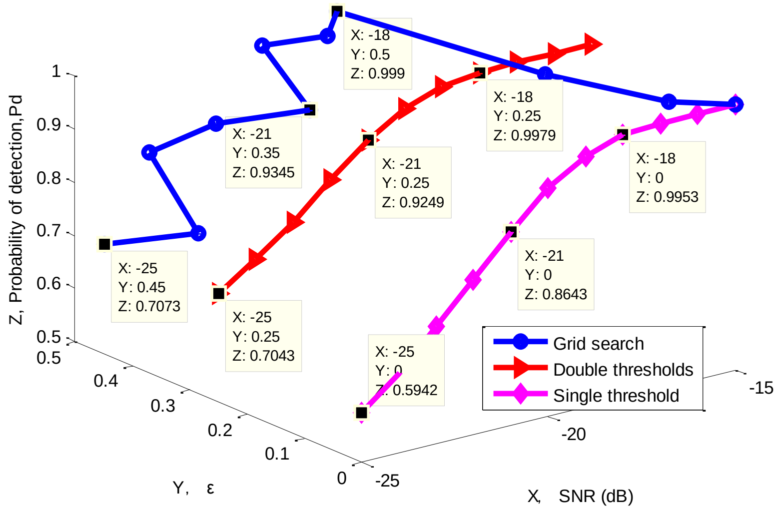

Figure 3. Comparison of $P_{d,\max}$, $P_{d,d}$ and $P_{d,s}$

Table 1. The Probability of Detection Comparison Using Grid Search and Using Fixed ε

SNR(dB)		-25	-24	-23	-22	-21	-20
Using grid search to obtain the highest probability of detection	ε	0.45	0.35	0.50	0.45	0.35	0.50
	P_d	0.7073	0.7545	0.8222	0.8815	0.9345	0.9761
Using fixed ε and double thresholds detection	ε	0.25	0.25	0.25	0.25	0.25	0.25
	P_d	0.7043	0.7489	0.8002	0.8589	0.9249	0.9681
Using fixed ε and single threshold detection	ε	0.0	0.0	0.0	0.0	0.0	0.0
	P_d	0.5942	0.6513	0.7203	0.7866	0.8643	0.9316

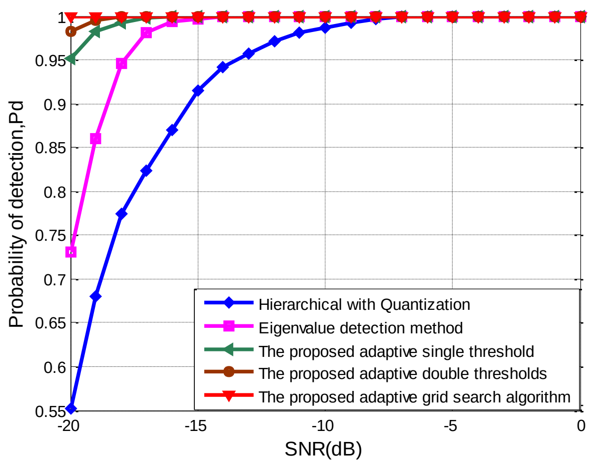

Figure 4. Performance Comparison of the different Sensing Methods

6. Conclusion

In this paper, a novel weighted cooperative spectrum sensing scheme is studied. This scheme used dynamic double energy thresholds to achieve better sensing performance. In local sensing, obtained an optimal energy threshold by minimizing the sum of the probabilities of false alarm and detection, and introduced a control parameter to adjust the local double energy thresholds. In cooperative sensing, each SU was assigned a weight depending on its collected average energy. Moreover, the path loss is taking into consideration in cooperation sensing. Simulation results showed that the proposed spectrum sensing scheme had excellent sensing performance under different SNR.

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References

[1] G. Ganesan and Y. G. Li, “Cooperative spectrum sensing in cognitive radio networks”, in Proc. IEEE Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN05), Baltimore, USA, pp.137-143, **(2010)**, pp. 561--565.

[2] J. Wu, T. Luo and G. Yue, “An energy detection algorithm based on double-threshold in cognitive radio systems,” Information Science and Engineering (ICISE), 2009 1st International Conference on. Kyoto, Japan, (1995), IEEE, Kyoto, Japan, **(2013)**, pp. 493-496.

[3] N. Meghanathan, "A Survey on the Communication Protocols and Security in Cognitive Radio Networks", International Journal of Communication Networks and Information Security (IJCNIS), Shanghai, China, **(2014)**, pp.118-124.

[4] S. A. Mousavifar and C. Leung, "Transient Analysis for a Trust-Based Cognitive Radio Collaborative Spectrum Sensing Scheme", IEEE Wireless Communications Letters, vol. 4, **(2015),** pp. 377-380.

[5] H. Vu-Van and I. Koo, “Cooperative spectrum sensing with double adaptive energy thresholds and relaying users in cognitive radio”, Telecommunications (AICT), 2010 Sixth Advanced International Conference on. IEEE, Xian, China, **(2013)**, pp. 52-56.

[6] Z. Shibing, Y. Jiaojiao and G. Lili, "Eigenvalue-Based Cooperative Spectrum Sensing Algorithm", in Instrumentation, Measurement, Computer, Communication and Control (IMCCC), 2012 Second International Conference on, Hong Kong, China, **(2012)**, pp. 375-378.

[7] A. Bagwari and G. S. Tomar, "Adaptive double-threshold based energy detector for spectrum sensing in cognitive radio networks", International Journal of Electronics Letters, **(2013)**, pp. 33-41.

[8] T. Kieu-Xuan and I. Koo, “A cooperative spectrum sensing scheme using adaptive fuzzy system for cognitive radio networks”, Information Sciences, vol. 220, **(2013)**, pp. 102-109.

[9] L. Xiang, W. Bin, W. Hong, H. Pin-Han, B. Zhiqiang and P. Lili, "Adaptive Threshold Control for Energy Detection Based Spectrum Sensing in Cognitive Radios", Wireless Communications Letters, IEEE, vol. 1, **(2012)**, pp. 448-451.

[10] N. Zhao, "A novel two-stage entropy-based robust cooperative spectrum sensing scheme with two-bit decision in cognitive radio", Wireless Personal Communications, **(2013)**, pp. 1-15.

[11] S. Zhang, X. Dong, Z. Bao and H. Zhang, "Adaptive Spectrum Sensing Algorithm in Cognitive Ultra-Wideband Systems", Wireless Personal Communications, vol. 68, **(2013)**, pp. 789-810.

[12] A. Mohammadi, M. R. Taban, J. Abouei and H. Torabi, "Fuzzy likelihood ratio test for cooperative spectrum sensing in cognitive radio", Signal Processing, vol. 56, **(2014)**, pp. 62-66.

[13] I. Sobron, P. S. R. Diniz, W. A. Martins and M. Velez, "Energy Detection Technique for Adaptive Spectrum Sensing", IEEE TRANSACTIONS ON COMMUNICATIONS, vol. 63, **(2015)**, pp. 617-627.

[14] A. Salman, I. M. Qureshi, K. Sultan and S. Saeed, "Joint spectrum sensing for detection of primary users using cognitive relays with evolutionary computing," Communications, IET, vol. 9, **(2015)**, pp. 1643--1648.

[15] D. Guoru, W. Qihui, S. Fei, and W. Jinlong, "Decentralized sensor selection for cooperative spectrum sensing based on unsupervised learning", in Communications (ICC), 2012 IEEE International Conference on, Gaungzhou, China, **(2015)**, pp. 1576-1580.

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