Cooperative Spectrum Sensing - Overview

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Резюме. *Когнитивното радио е технология, която отговаря на все по-нарастващите нужди на безжичните комуникации, като осигурява повече възможности за достъп до радиочестотния спектър. За да може нелицензираните потребители да реализират своето предаване, е необходимо да намерят свободно пространство в спектъра, но това не винаги е възможно поради несъвършенствата на каналите. Съвместното наблюдение на спектъра допринася за по-точното и надеждно откриване на сигналите на лицензираните потребители. В статията е направен преглед на повечето от съществуващите техники за съвместно наблюдение на спектъра и алгоритми за споделяне на данните.*

Abstract. *Cognitive radio is a technology that meets the growing needs of wireless communications, providing more opportunities to access the radio spectrum. In order for the unlicensed users to realize their transmission, they need to find free space in the spectrum, but this is not always possible due to channel imperfections. Cooperative spectrum sensing contributes to more accurate and reliable detection of the licensed users signal. The article reviews most of the existing cooperative spectrum sensing techniques and data sharing algorithms.*

Introduction

In recent years, there has been a tremendous growth in mobile communications. But spectrum is a scarce resource and its use cannot be extended indefinitely. At the same time, it is used irrationally, as licensed users having the permit to access the spectrum, called primary users (PU), do not realize their transmissions continuously. The cognitive radio comes help making spectrum usage more efficient. Users without permit to access, called secondary users (SU) or cognitive users (CU), also want to realize their transmission. For this purpose, they are constantly spectrum sensing, looking for free spaces where they can carry out their transmission, without interfering with the PU and when the PU appears to stop their transmission and immediately leave the bandwidth.

SUs may experience the hidden terminal problem, shadow fading, multipath, or receiver uncertainty, thereby impairing the spectrum sensing efficiency in a highly urbanized environment. Fig. 1 shows SUs with various problems [1]. For example, the SU4 is outside of the PU transmitter range, and it also experiences the receiver uncertainty, because it does not know about PU and does not suspect the PU Rx existence; SU2 is shadowed - there is no direct visibility with PU Tx; and SU1 is subjected to multipath fading because it receives many and different attenuating copies of the transmitted signal.

Cooperative Spectrum Sensing (CSS) contributes to more accurate detection of the PU signal, using spatial diversity of spatially located SUs. Several SUs share their own spectrum sensing information to make a more accurate combined solution for the presence of a PU signal in the channel.

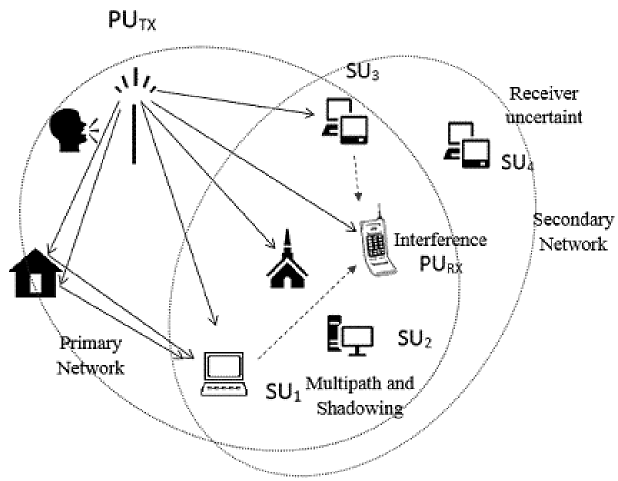

Fig.1 Receiver uncertanty, multipath, shadow fading[1]

Classification of cooperative sensing

The main types of CSS, depending on how SUs share their information from local sensing, are centralized, distributed, and relay-assisted. Fig. 2 shows a model of a cognitive network with centralized CSS. Such a network model is studied in [2],[3],[4],[5],[6].

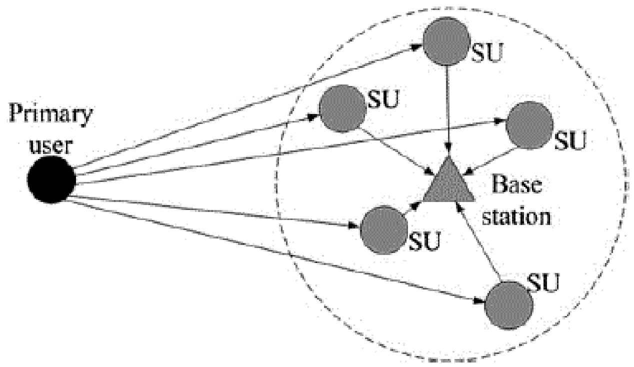

Fig. 2 Centralized cooperative spectrum sensing [3]

Centralized CSS has a common Fusion Center (FC). Connection between the PU transmitter and SUs in cooperation to observe the primary signal is called a sensing channel. For reporting data, all SUs are set for control channel. The point-to-point physical link between each SU and (FC) is called a reporting channel, and it sends the detection results. The FC controls and manages the CSS process in three steps. First, FC selects a channel or bandwidth of interest for detection and instructs all cooperating SUs to make individual local detection. Second, all cooperating SUs report their detection results through the control channel. Third, FC combines received information from local detection, selects SU, determines the presence of PU, and distributes the decision back to the SUs in cooperation.

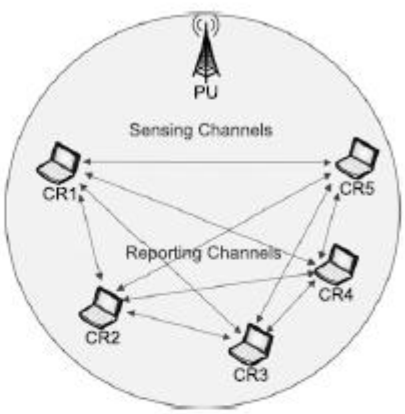

Fig. 3 Distributed cooperative spectrum sensing [1]

There is no FC in the distributed CSS, and each SU shares the local detection information with their neighbors to make a combined decision[7],[8]. A decentralized CSS network model is shown in fig. 3.

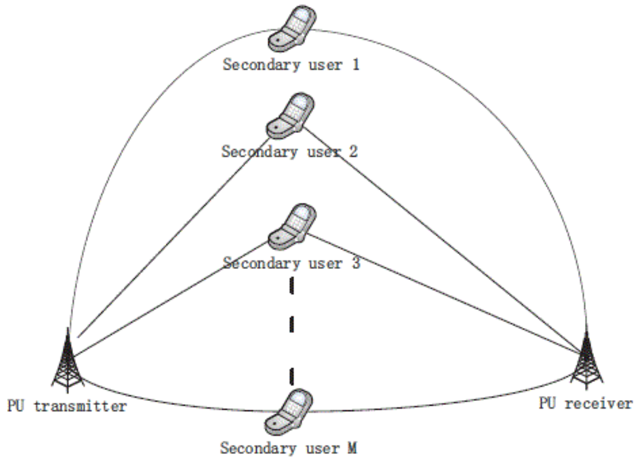

Fig. 4 Relay-assisted cooperative spectrum sensing [9]

In relay-assisted CSS, as shown in fig. 4, SUs cooperate to improve cooperative efficiency, as reporting and monitoring channels are not ideal [7],[9],[10],[11],[12]. Different strategies can be used for joint actions: decode and forward (DF) or amplify and forward (AF). The AF relay receives the signal and sends its amplified version at the same time interval. In the DF, the relay decodes the output message in one block and transmits the encoded message back to the next block or respectively in an odd and even time interval. The receiver can decode the data if there are no damaged or lost blocks.

Cooperation model

For CSS, different cooperative action models of SUs can be used. In [1]a classification of the main cooperative models is made. They are parallel fusion model [13] shown in fig. 5 and model based on game theory.

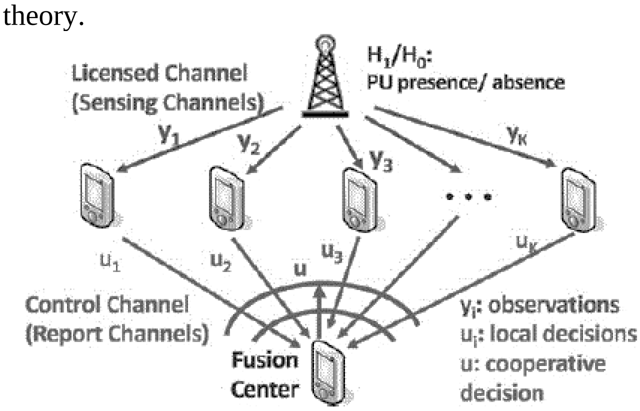

Fig. 5 Parallel cooperation model [1]

In the parallel cooperative model, a group of spatially distributed SUs make their local detections. They report their statistics testing or decisions to the FC, which combines the reported data and takes the global decision via the binary hypothesis testing.

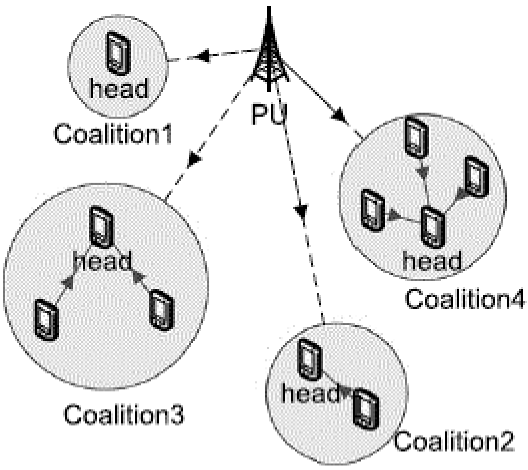

Fig. 6 Coalition cooperation model [1]

In topology, based on game theory [14], there is a coalitional and an evolutionary model. A CSS coalition model is displayed in fig. 6. SUs can form or split a coalition if the detection efficiency in the coalition is greater than the probability of local detection. An example of an evolutionary model is the distributed CSS. Each SU chooses their actions whether to participate or not in the collaboration. The most commonly used cooperative model is a parallel pattern in distributed detection and data fusion.

Detection Techniques

Regardless of the CSS model, at first all SUs make a local detection. There are different spectrum sensing techniques with different computational complexity.

Matched Filter

Block diagram of an implementation on matched filter based spectrum sensing is shown in fig. 7.

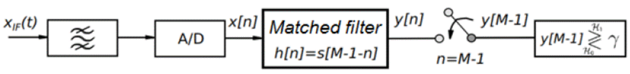

Fig. 7 Matched Filter block diagram [15]

The received signal is passed through a filter that increases the output signal-to-noise ratio (SNR) by reducing the output noise power. A matched filter generates a peak signal value and suppresses the noise amplitude. The disadvantage of this detector is that the signal should be demodulated in advance, but synchronization is required for this purpose. This means that before the sensing it is necessary to have preliminary information about the PU signal, such as type modulation, packet format, etc. Most PUs have pilot signals, distribution codes, or preambles that can be used. Another significant disadvantage is that for each type of PU is needed a particular receiver.

The main advantage of this technique is that less time for signal processing is required due to coordination - only samples are needed.

Cyclostationarity-Based Spectrum Sensing

Sine wave modulation, pulse sequences, wide-area codes, cyclic prefixes, or hoping sequences are used to modulate signals, resulting in built-in periodicity. They are characterized as cyclostationary because their statistics, mean value and autocorrelation are periodic. The cyclostationary signals transmitted by PUs have a spectral correlation that is not present at stationary noise or interference. A cyclostationary detector block diagram is shown in fig. 8.

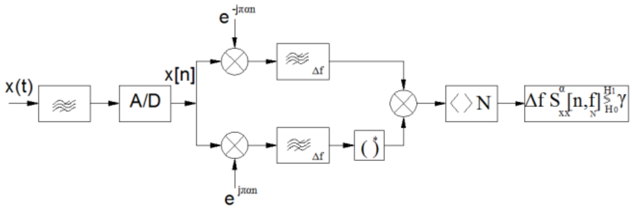

Fig. 8 Cyclostationarity-based detector block diagram [15]

Cyclostationarity-based detector works very well at low SNR, resists noise uncertainty and distinguishes transmissions from different types of PU signals. The main disadvantage is the length of spectrum sensing time to find a PU signal. Other disadvantages are the need for a prior knowledge of PU signal characteristics and high computational complexity.

Energy detection

The energy detection is based on the fact, that if there is a PU signal, the energy in the channel will be significantly more than if there is no signal. The energy detection method of spectrum sensing includes pre-filtering to separate the bandwidth, digitalizing the signal, collecting the energy for each channel, comparing this energy with a threshold that is used to decide if there is a signal in channel or not. An energy detector block diagram is shown in fig. 9.

The energy detection advantages are easy realization, which does not lead to complex mathematical calculations, and that the receiver does not need a priori information about the PUs signal parameters. Therefore, the energy detector is used very often in studies [2], [16], [17]. As a disadvantage, should be noted its poor performance at low SNR.

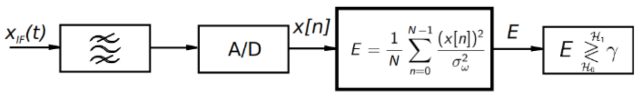

Fig. 9 Energy detector block diagram [15]

In [15] and [18], a cyclostationarity-based detector, an energy detector and a matched filter detector are compared at the local detection and CSS [2], [19].

Eigenvalues-Based Spectrum Sensing

The spectral holes are detected by eigenvalues-based spectrum sensing, using test statistics, based on the covariance matrix eigenvalues of the received signal Y. All eigenvalues-based methods rely on the fact that the covariance matrix is a diagonal matrix only in the noise presence and all its elements are equal to σ^2, therefore have one eigenvalue, also equal to σ^2. In the presence of a PU, this is no longer true [20].There are different algorithms based on the eigenvalues of the covariance matrix, such as the generalized likelihood ratio test (GLRT); the maximum-minimum eigenvalue detection (MMED), also known as the eigenvalue ratio detection ERD; maximum eigenvalue detection (MED), also known as the Roy's Largest Root Test (RLRT); and energy detection (ED).

In [21], two spectrum sensing algorithms based on the eigenvalues distribution in the random matrices with large dimensions theory are discussed: MMED and ED with the Minimum Eigenvalue (EME), in a local spectrum sensing scheme. Authors in [5] have submitted a CSS scheme using the RLRT algorithm.

The advantage of detecting the eigenvalues of the covariance matrix is that there is no need for a prior information about the PU signal characteristics. This detection is called blind. A significant disadvantage is the complex mathematical calculations.

Primary signal detection

The most commonly used system consists of one PU and one or more SUs. SUs spectrum sense for the PU signal. Thus, the system can be modeled as a binary hypothesis testing of the PU state:

H_0: y[n] = w[n] - signal absent

H_1: y[n] = w[n] +s[n] - signal present

n = 1, …, N

y[n] – Receiver signal samples,

w[n] – Noise samples,

s[n] – PU signal samples,

N – The interval of the interest length corresponding to the number of samples.

Detector performance is characterized by metrics based on test statistics in the binary hypothesis:

- Probability of detection - Pd: This is the probability that there is a signal in the channel when the hypothesis H_1 is true.
- Probability of false alarm - Pfa: The probability of having a signal with a valid hypothesis H_0. These are the undiscovered holes in the spectrum - a missed opportunity.
- Probability of miss detection - Pmd: The probability that a signal is not present when H_1 is true. If there is a signal in the channel, SUs indicate that the channel is free. These are free channel messages when it is busy.

Pmd = 1 - Pd

Data fusion

An important point of CSS is the data fusion from the local SUs detection when deciding on the presence of a PU signal in the channel. Local detection results may be of a different type, size, form, depending on the control channel bandwidth. Data sharing can be done in two ways: Soft Combining [22],[23] and Hard Combining [24],[25],[26],[27].

Soft Combining

SUs transmit to the control center the complete statistics from the local observation or all samples without any decision at the local detection. Various consolidation techniques can be applied in the FC, such as: Maximal Ratio Combining (MRC) [28], Equal Gain Combining (EGC) [29], Square Law Combining (SLC) [30], Selection Combining (SC) [31].

Fusion with the soft combination provides better performance than hard, but it requires more control channel bandwidth, and generates more costs than the fusion with the hard combination [23].

Hard Combining

The [26] has considered the hard combining policy efficiency when making decision on AWGN channels. Each SU takes a binary decision for the PU activity and the local decisions are reported in FC through the reporting channel.

$$\Delta_k = \begin{cases} 1, & E_k > \lambda_k \\ 0, & E_k \le \lambda_k \end{cases} \quad (1)$$

FC takes the final decision on either the OR, AND or the MAJORITY fusion rule, which can be summarized as a "k-out-of-n" dropping rule.

The OR function determines that the PU signal is present when at least one SU reports "1".

$$\begin{cases} H_1: & \sum_{k=1}^{K} \Delta_k \ge 1 \\ H_0: & \sum_{k=1}^{K} \Delta_k < 1 \end{cases} \quad (2)$$

The AND function determines that the PU signal is present when all SUs report a "1" decision.

$$\begin{cases} H_1: & \sum_{k=1}^{K} \Delta_k = K \\ H_0: & \sum_{k=1}^{K} \Delta_k \ne K \end{cases} \quad (3)$$

In the voting rule, if at least N of K users have detected a signal 1 ≦ N ≦ K. The test is formulated as:

$$\begin{cases} H_1: & \sum_{k=1}^{K} \Delta_k \geq N \\ H_0: & \sum_{k=1}^{K} \Delta_k < 1 \end{cases} \quad (4)$$

Rules AND and OR are a private case for N = K and N = 1.

For simplification two assumptions were made:

• the reporting channel is error-free;

• the SU has information about the SNR statistics of the received PU signals.

These assumptions are practically not real in the cognitive network.

The probability of CSS Qd and the common probability of a false alarm Qfa are defined as:

$$Q_d = Pr\{\Delta = 1|\, H_1\} = Pr\left\{\sum_{i=1}^{K} \Delta_k \geq M|H_1\right\} \quad (5)$$

$$Q_{fa} = Pr\{\Delta = 1|\, H_0\} = Pr\left\{\sum_{i=1}^{K} \Delta_k \geq M|H_0\right\} \quad (6)$$

where Δ is the final decision.

Energy efficiency and detection reliability

Conventional detection methods and schemes are not effective enough, especially for low SNR or for noise uncertainty in the channel [32]. Therefore, many studies have proposed new, optimized schemes to increase detector efficiency, while reducing detection costs. In [33] authors calculate the optimal number of SUs to obtain maximum energy efficiency. Similarly, [34] has introduced an effective optimization factor-number of SUs to minimize the probability of a complete error. The optimization of the number of collaborative SUs and the sensing time is done by increasing the size of the network [35]. In [36], a fast differential development algorithm is proposed to optimize CSS energy consumption, considering a sleep scheme and a censoring mechanism.

In [37]a decision censoring scheme is proposed that leads to better results than the conventional fusion rule “k-out-of-n”. The message "No solution" sent to FC by some sensor node leads to improved CSS. By censoring the collected local decisions, only users with sufficient information are sending their decisions to the common receiver [38].

For a more reliable detection in [39], a hybrid CSS is proposed that utilizes the diversity of reporting channels. SUs with good quality reporting channels carry the quantized statistics for local detection in FC, and the other SUs report their local decisions. FC takes the final decision by performing a hybrid combination. [16] is proposed a two-step scheme giving a two-bit decision. In [40], two-stage spectrum sensing detectors are proposed. The first stage consists of a multiple energy detectors (MED) where each energy detector (ED) has a single antenna with fixed threshold (MED_FT) for making a local binary decision and if necessary, includes the second stage consisting of an ED with an adaptive double threshold (ED_ADT). The scheme is shown in fig. 10.

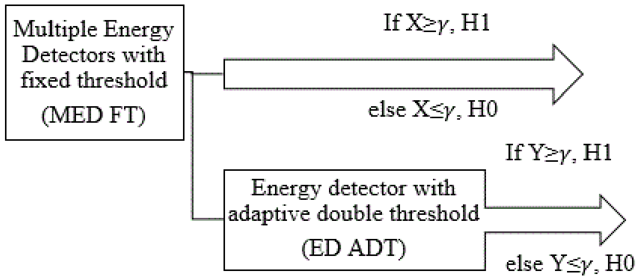

Fig.10 Two-Stage Detectors with Multiple Energy Detectors and Adaptive Double Threshold [40]

To improve the energy efficiency of detection in [3], a two-step CSS scheme using a one-bit decision, as shown in fig. 11, is proposed. If the SNR is high or no PU transmission is detected, only one coarse detection step is required to reduce the energy and detection time. When there is a PU signal, fine detection is performed to increase the precision. The authors also propose a second algorithm to improve energy efficiency at the same time of observation. It uses the local decision for coarse detection. These two algorithms are further developed in [41].

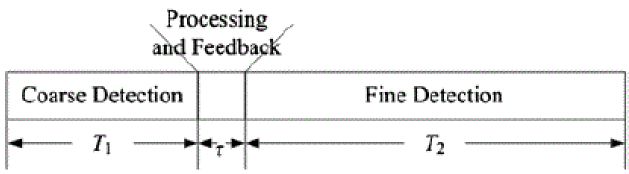

Fig.11 Two-stage one-bit CSS scheme [3]

In [23], a softened two-bit scheme is introduced for hard combining, as soft combining schemes require monitoring resources and feedback for each SU. In conventional hard data combining schemes, a threshold dividing the range of observed energy into two regions is introduced, and SUs fall into them even if they carry different energy values. A two-bit scheme is proposed, including three thresholds, dividing the range of four regions where SUs have energy with different weights. FC determines the presence of a signal using the following equation:

$$\sum_{i=0}^{3} w_i N_i \geq L, \quad (7)$$

where N is the number of observed energies falling in region i and w_i is the weight of region i. In [25], the idea is further developed and a three-bit scheme, including 7 thresholds, is proposed. This scheme has the benefits of both soft and hard combining, achieving a compromise between cost and detecting results. A modified double-threshold energy detection

(MDTED) for each cluster, location, and channel information is used to improve the detection algorithm in wireless sensor networks [42]. Due to the large amount of data, the algorithm is optimized by reducing the number of nodes in one cluster.

Security

An important part of the common decision is the accuracy of the SUs decisions. Incorrect data can lead to a generally wrong decision. Errors may be of a malfunction or due to intentional actions of some SUs, called malicious users. Fig. 12 shows a graph of the probability detection according to the SNR. One of the SUs gives the wrong solution for the presence of a PU signal in the channel [43].

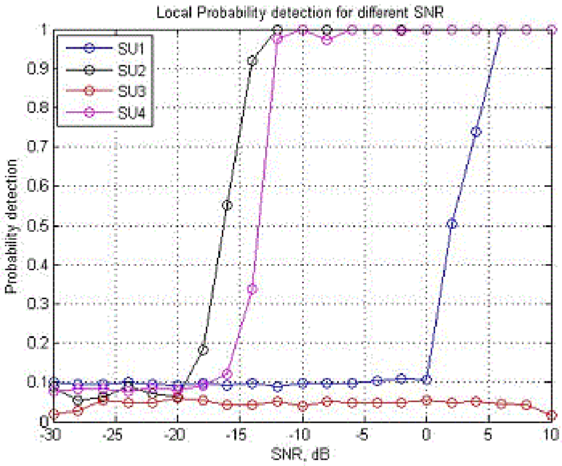

Fig. 12. Pd(SNR) curves for 4 SUs [43]

The malicious users are classified into three groups, depending on the result of the observation in [44]: always Yes, always No and the opposite result. Secure spectrum cooperation, based on a goodness-of-fit (GOF) test that summarizes the discrepancy between observed samples with theoretical distributions or empirical distributions and reference distribution is proposed. The concept of smart primary user emulation attacker (PUEA) is introduced in [45]. They imitate the PU signal to deceive SUs and not allow them to the free bands. CSS rules, working in the presence of such attackers are presented. The problem with the suppression of multiple malicious users, performing spectrum sensing data falsification (SSDF) attacks in cognitive radio network with CSS is studied in [46]. An algorithm to suppress these malicious users is used in FC. It may be an adaptive weighting algorithm, a Tietjen-Moore test, or Peirce's criterion.

Conclusions

CSS is an important part of the process of the spectrums rational utilization. This article reviews the spectrum sensing techniques and notes their advantages and disadvantages. Conventional CSS schemes using soft and hard data combining, as well as the benefits they bring, when there are fading, shadowing, and multipath in the channels, are shown. The optimization problems and reliability of detecting are discussed as different hybrid schemes, increasing the sensing efficiency, while maintaining or reducing energy costs are presented. Various strategies to increase security by reducing the impact of attacks by malicious users are also included in the review.

Acknowledgments

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References

[1] I. Akyildiz, B. Lo, R. Balakrishnan, Cooperative Spectrum Sensing in Cognitive Radio Networks, A Survey, Physical Communication 4 (2011) 40–62, 19 December 2010

[2] Y. Fu, Z. Li, D. Liu, Q. Liu, Implementation of Centralized Cooperative Spectrum Sensing Based on USRP, Int. Conf. on Logistics Engineering, Management and Computer Science (LEMCS 2014), 24-26 May 2014, Shenyang, China

[3] N. Zhao, F. Yu, H. Sun, A. Nallanathan, Energy-Efficient Cooperative Spectrum Sensing Schemes for Cognitive Radio Networks, EURASIP Journal on Wireless Communications and Networking 2013, 2013:120

[4] J. Du, D. Guo, B. Zhang, L. Shang, A Secure Cooperative Spectrum Sensing Scheme in Mobile Cognitive Radio Networks, Int. Journal of Distributed Sensor Networks, http://dx.doi.org/10.1155/2014/620196

[5] RS Yoshimura, FS Mathilde, JP Dantas, VA de S Jr., J.Bazzo, D.Melgarejo, A USRP based scheme for cooperative sensing networks, Anais do 4º Workshop de Redes de Acesso em Banda Larga – WRA 2014

[6] G.Ding, Q.Wu, J.Wang, F.Song, Y.Gong, Chapter 12 Joint Spectrum Sensing and Resource Scheduling for Cognitive Radio Networks Via Duality Optimization, of Foundation of Cognitive Radio Systems, www.intechopen.com/books/foundation-of-cognitive-radio-systems

[7] G. Ganesan, Y. Li, Cooperative Spectrum Sensing in Cognitive Radio, Part I Two User Networks, IEEE Transactions on Wireless Communications, Vol. 6, No. 6, June 2007

[8] H. Hu, H. Zhang, H. Yu, J. Jafarian, Throughput Optimization via Cooperative Spectrum Sensing with Novel Frame Structure, Mathematical Problems in Engineering, http://dx.doi.org/10.1155/2013/975860

[9] T.Jing, S. Zhu, H Li, X.Cheng, Y.Huo, Cooperative Relay for Cognitive Radio Networks, 2013 Proceedings IEEE Infocom, 14-19 April 2013, Turin, Italy, pp. 175-179

[10] D. Hu, S. Mao, Cooperative Relay in Cognitive Radio Networks Decode-and-Forward or Amplify-and-Forward, Global Telecommunications Conf. GLOBECOM, IEEE, 6-10 December 2010, Miami, FL, USA, pp. 1-5

[11] S. Atapattu, C. Tellambura, H. Jiang, Energy Detection Based Cooperative Spectrum Sensing in Cognitive Radio Networks, IEEE Transactions on Wireless Communications, Vol. 10, No. 4, April 2011

[12] N. Zarin, I. Khan, S. Jan, Relay Based Cooperative Spectrum Sensing in Cognitive Radio Networks over Nakagami Fading Channels, Int. Journal of Multidisciplinary Sciences and Engineering, Vol. 3, No. 4, Apr. 2012, pp 54 -58

[13] H. Hosseini, K.Raahemifar, S. Yusof, A. Anpalagan, Cooperative Spectrum Sensing for Cognitive Heterogeneous Networking Using Iterative Gauss-Seidel Process, Int. Journal of Distributed Sensor Networks, Volume 2015, Article ID 319164, http://dx.doi.org/10.1155/2015/319164

[14] W. Saad, Z. Han, M. Debbah, A. Hjørungnes, T. Basar, Coalitional Games for Distributed Collaborative Spectrum Sensing in Cognitive Radio Networks, INFOCOM 19-25 April 2009, Rio de Janeiro, Brazil

[15] LMG Diaz, LM Marrero, JT Gómez, Performance Comparison of Spectrum Sensing Techniques for Cognitive Radio Networks, 16th Int. Convention and Fair, 14-8 March 2016, Havana, Cuba

[16] N. Zhao, A Novel Two-stage Entropy-based Robust Cooperative Spectrum Sensing Scheme with Two-bit Decision in Cognitive Radio, Springer, 2012

[17] A. Haniz, M. Rahman, M. Kim, J. Takada, Implementation of a Cooperative Spectrum Sensing System using GNU Radio and USRP, IEICE General Conference, p.667, 2010

[18] R. Vadivelu, K. Sankaranarayanan, V. Vijayakumari, Matched filter based spectrum sensing for cognitive radio at low signal to noise ratio, Journal of Theoretical and Applied Information Technology, 10th April 2014. Vol. 62 No.1

[19] D. Cabric, S. Mishra, R. Brodersen, Implementation issues in spectrum sensing for cognitive radios, in: Proc. of Asilomar Conf.on Signals, Systems, and Computers, vol. 1, 2004, pp. 772–776.

[20] D. Guimaraes, R. Souza, A. Barreto, Performance of Cooperative Eigenvalue Spectrum Sensing with a Realistic Receiver Model under Impulsive Noise, Journal of Sensor and Actuator Networks, 2013, 2, 46-69; doi:10.3390/jsan2010046

[21] A. Nafkha, B. Aziz, M. Naoues, A. Kliks, Cyclostationarity-based versus eigenvalues-based algorithms for spectrum sensing in cognitive radio systems Experimental evaluation using GNU radio and USRP, IEEE 11th Int. Conf. on Wireless and Mobile Computing, Networking and Communications (WiMob), 19-21 October 2015, Abu Dhabi, United Arab Emirate

[22] M. Akbari, A. Reza, K. Noordin, K. Dimyati, M. Manesh, M. Hindia, Recent Efficient Iterative Algorithms on Cognitive Radio Cooperative Spectrum Sensing to Improve Reliability and Performance, Int. Journal of Distributed Sensor Networks, http://dx.doi.org/10.1155/2016/3701308

[23] J. Ma, G. Zhao, Y. Li, Soft Combination and Detection for Cooperative Spectrum Sensing in Cognitive Radio Networks, IEEE Transactions on Wireless Communications, Vol. 7, No. 11, November 2008

[24] S. Maleki, S. Chepuri, G. Leus, Energy and Throughput Efficient Strategies for Cooperative Spectrum Sensing in Cognitive Radios, 2011 IEEE 12th Int. Workshop on Signal Processing Adv. in Wireless Communications

[25] D. Teguig, B. Scheers, V. Le Nir, Data Fusion Schemes for Cooperative Spectrum Sensing in Cognitive Radio Networks, Military Communications and Information Systems Conf. (MCC), 8-9 Oct. 2012, Gdansk, Poland, pp. 1- 7

[26] M. Hossain, M. Rahman, M. Abdullah, M. Hossain, Hard Combination Data Fusion for Cooperative Spectrum Sensing in Cognitive Radio, Int. Journal of Electrical and Computer Engineering, Vol.2, No.6, Dec. 2012, pp. 811-818

[27] K. Umebayashi, J. Lehtomaki, Study on efficient decision fusion in OR-rule base Cooperative Spectrum Sensing, Wireless Communications and Networking Conf. (WCNC), 1-4 April 2012, Shanghai, China

[28] Q. T. Zhang, Maximal-Ratio Combining over Nakagami Fading Channels with an Arbitrary Branch Covariance Matrix, IEEE Transactions on Vehicular Technology, Vol. 48, No. 4, July 1999, pp. 1141–1150

[29] D. Hamza, S. Aïssa, G. Aniba, Equal Gain Combining for Cooperative Spectrum Sensing in Cognitive Radio Networks, IEEE Transactions on Wireless Communications, Vol.13, No 8, 16 April 2014, pp.4334 – 4345

[30] Y. Liu, D. Yuan, M. Jiang, W. Fan, G. Jin, F. Li, Analysis of Square-Law Combining for Cognitive Radios over Nakagami Channels, 5th Int. Conf. on Wireless Communications, Networking and Mobile Computing, 24-26 Sept. 2009, Beijing, China

[31] A. Singh, M. Bhatnagar, R. Mallik, Cooperative Spectrum Sensing in Multiple Antenna Based Cognitive Radio Network Using an Improved Energy Detector, IEEE Int. Conf. on Communications, IEEE Communications letters Vol. 16, No 1, 2012, pp. 64-67.

[32] S. Bahamou, A. Nafkha, Noise Uncertainty Analysis of Energy Detector: Bounded and Unbounded Approximation Relationship, Proceedings of the 21st European Signal Processing Conf., 9-13 Sept. 2013, pp. 1-4, Marrakech, Morocco

[33] S. Althunibat, M. Renzo, F. Granelli, Cooperative Spectrum Sensing for Cognitive Radio Networks Under

Limited Time Constraints, Computer Communications 43 (2014), pp. 55–63

[34] H. Thakkar, K. Parmar, New Optimization Scheme for Cooperative Spectrum Sensing Taking Different SNR in Cognitive Radio Networks, Int. Journal of Research in Engineering and Technology, Vol. 03, No 04, April 2014, pp 597-601

[35] H. F. Al-Doseri, M. A. Mangoud, Performance Analysis of Cooperative Spectrum Sensing under Guaranteed Throughput Constraints for Cognitive Radio Networks, Journal of Computer Networks and Communications, Vol. 2016, March 2016, Article No. 5

[36] W. Liu, G. Qin, S. Li, J. He, X. Zhang, A Multiobjective Evolutionary Algorithm for Energy-Efficient Cooperative Spectrum Sensing in Cognitive Radio Sensor Network, Int. Journal of Distributed Sensor Networks, Volume 2015, Article ID 581589, http://dx.doi.org/10.1155/2015/581589

[37] W. Wang, W. Zou, Z. Zhou, H. Zhang, Y. Ye, Decision Fusion of Cooperative Spectrum Sensing for Cognitive Radio under Bandwidth Constraints, Third Int. Conf. on Convergence and Hybrid Information Technology, 11-13 November 2008, Busan, South Korea, pp 733-736

[38] C. Sun, W. Zhang, K. Letaief, Cooperative Spectrum Sensing for Cognitive Radio under Bandwidth Constraints. Wireless Communications and Networking Conf., WCNC IEEE, 11-15 March 2007, Kowloon, China

[39] C. Yao, Q. Wu, A Hybrid Combination Scheme for Cooperative Spectrum Sensing in Cognitive Radio Networks, Mathematical Problems in Engineering, Volume 2014, http://dx.doi.org/10.1155/2014/106106

[40] A. Bagwari, G. S. Tomar, Cooperative spectrum sensing based on two-stage detectors with multiple energy detectors and adaptive double threshold in cognitive radio networks, Int. Journal of Distributed Sensor Networks, Vol. 9, No 8, 2013, http://dx.doi.org/10.1155/2013/656495

[41] A. Chaudhary, M. Dongre, H. Patil, Energy-Decisive and Upgrade Cooperative Spectrum Sensing in Cognitive Radio Networks, 7th Int. Conf. on Communication, Computing and Virtualization 2016, Procedia Computer Science 79 (2016), pp. 683 – 691.

[42] S. Wang, H. Liu, K. Liu, An Improved Clustering Cooperative Spectrum Sensing Algorithm Based on Modified Double-Threshold Energy Detection and Its Optimization in Cognitive Wireless Sensor Networks, Int. Journal of Distributed Sensor Networks, http://journals.sagepub.com/doi/full/10.1155/2015/136948

[43] Z. Tchobanova, G. Marinova, A. Nafkha Implementation of an Energy Detection Based Cooperative Spectrum Sensing on USRP Platforms for a Cognitive Radio Networks, Twelfth Adv. Int. Conf. on Telecommunications, May 2016, Valencia, Spain, pp 29-33

[44] H. Vu-Van, I. Koo, Goodness-of-Fit Based Secure Cooperative Spectrum Sensing for Cognitive Radio Network, The Scientific World Journal, Volume 2014, Article ID 752507, http://dx.doi.org/10.1155/2014/752507

[45] M. Haghighat, S. Sadough, Cooperative Spectrum Sensing for Cognitive Radio Networks in the Presence of Smart Malicious Users, Int. Journal of Electronics and Communications (AEÜ) 68 (2014) pp. 520–527

[46] N. Lavanis, D. Jalihal, Performance of p-Norm Detector in Cognitive Radio Networks with Cooperative Spectrum Sensing in Presence of Malicious Users, Wireless Communications and Mobile Computing, Vol. 2017, https://doi.org/10.1155/2017/4316029