IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 3, Issue 3, October 2014)

A Review on Cooperative Spectrum Sensing in Cognitive Radio Networks

Aakash Trivedi
M. Tech Scholar
Electronics & Communication Department
IES IPS Academy, Indore (India)

Rupesh Dubey
Associate Prof. & HOD,
Electronics & Communication Department
IES IPS Academy, Indore (India)

Rajesh Babu Ahirwar
Assistant Professor,
Electronics & Communication Department
IES IPS Academy, Indore (India)

Abstract –**Spectrum sensing is a key function of cognitive radio to prevent the harmful interference with licensed users and identify the available spectrum for improving the spectrum's utilization. However, detection performance in practice is often compromised with multipath fading, shadowing and receiver uncertainty issues. To mitigate the impact of these issues, cooperative spectrum sensing has been shown to be an effective method to improve the detection performance by exploiting spatial diversity. While cooperative gain such as improved detection performance and relaxed sensitivity requirement can be obtained, cooperative sensing can incur cooperation overhead. The overhead refers to any extra sensing time, delay, energy, and operations devoted to cooperative sensing and any performance degradation caused by cooperative sensing. In this paper, the state of-the-art survey of cooperative sensing is provided to address the issues of cooperation method, cooperative gain, and cooperation overhead. Specifically, the cooperation method is analysed by the fundamental components called the elements of cooperative sensing, including cooperation models, sensing techniques, hypothesis testing, data fusion, control channel and reporting, user selection, and knowledge base. Moreover, the impacting factors of achievable cooperative gain and incurred cooperation overhead are presented. The factors under consideration include sensing time and delay, channel impairments, energy efficiency, cooperation efficiency, mobility, security, and wideband sensing issues. The open research challenges related to each issue in cooperative sensing are also discussed.**

Keywords –**Cognitive Radio, Cooperative Sensing Spectrum Sensing.**

I. INTRODUCTION

A One of the major challenges in design of wireless networks is the use of the frequency spectrum. Recent measurements by Federal Communications Commission (FCC) show that 70% of the allocated spectrum is in fact not utilized [1]. Spectrum utilization can be improved significantly by allowing a secondary user (SU) to utilize a licensed band when the primary user (PU) is absent. Cognitive radio (CR) has been proposed as a promising technique for future wireless communication systems [2]–[4]. CR is able to fill in spectrum holes and serve its users (Secondary users) without causing harmful interference to the licensed user (PU). To do so, the CR must continuously sense the spectrum it is using in order to detect the reappearance of the PU. Once the PU is found to be active, the SU is required to vacate the channel. Therefore, spectrum sensing is of significant importance in CR networks. Moreover, periodic sensing is essential where the SU has to be aware of the channel status at all times. This is achieved by using a frame structure as in [5]–[6]. In this structure, each frame consists of a sensing period and a transmission period. At the end of each sensing period, the SU transmission starts when the licensed channel is idle. Otherwise, the SU will wait until the next frame to sense the licensed channel again.

There are two important parameters associated with spectrum sensing: probability of detection and probability of false alarm. From the primary user's perspective, the higher the detection probability, the better protection it will have from the SU. However, from the secondary user's perspective, the lower the false alarm probability, the more secondary transmission opportunities it will have. Therefore, a better sensing quality can be obtained by using a longer sensing period or, large number of samples. Cooperative communications refer to the class of techniques, where the benefits of multiple-input multiple- output (MIMO) techniques are gained via sharing information between multiple cooperating terminals in a wireless networks. Wireless relay networks that employ cooperative diversity have sometimes been referred to as virtual MIMO systems [7]–[8]. Multiple secondary users can cooperate to increase the reliability of spectrum sensing. The key challenge of spectrum sensing is the detection of weak signals in noise channels with a large probability of detection. Cognitive radio sensing performance can be improved using secondary users cooperation where users share their

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 3, Issue 3, October 2014)

spectrum sensing measurements. Having multiple cooperating users increases diversity by providing multiple measurements of the signal and thus guarantees a better performance at low signal-to-noise ratio (SNR). It also provides a possible solution to the hidden-terminal problem that arises due to shadowing or severe multipath fading environments [9]–[10].

From the above discussion it is clear that, increasing the number of cooperative secondary users will increase the number of collected samples during the sensing time and this will improve the reliability of spectrum sensing in terms of detection probability. On the other hand, the more the collected samples during the sensing time, the more the power would be consumed. Thus, there exists a trade-off between power consumption (power efficiency) and detection probability; we can get higher detection probability but we need to consume more power instead.

The authors in [11]–[12], considered the trade-off between the sensing quality and the achievable throughput. The spectrum sensing duration and the achievable throughput trade-off in a cooperative cognitive radio network over Nakagami fading conditions was introduced in [13].

However, none of these papers have examined the trade-off between detection probability and power efficiency in cooperative cognitive radio networks. Therefore, it is of great interest to consider this trade-off in this paper. In this paper, we first study the trade-off between sensing quality in terms of detection probability and power efficiency. Then we propose a new approach to optimize the trade-off between detection probability and power efficiency in cooperative cognitive radios over fading wireless channels. The basic idea of the proposed approach can be explained as follows; assume K cooperative secondary users each collect N samples during the sensing time. The proposed approach is based on dividing the spectrum sensing into two phases. In the first phase, we use only n of N samples, ($n \leq N$) to check the channels state, then k of K secondary users, ($k \leq K$) which are in deeply faded channels are discarded. We call this n, a check point of the sensing time. The spectrum sensing with relatively less-faded channels are continued during the second phase. Therefore, there is a check point at which the sensing time can be optimized in order to maximize the probability of detection and the power efficiency.

The remainder of this paper is organized as follows; Section 2 presents the classification and framework of cooperative sensing. The relation between probability of detection and probability of false alarm is also established in this section. In Section 3, presents the cooperation model. Classification of cooperative sensing is explained in Section 4. Finally, conclusions are drawn in Section 5.

II. Classification and Framework of Cooperative Sensing

In this section, we present the problem of the primary signal detection in cooperative sensing and introduce the classification and the framework of cooperative sensing.

Primary Signal Detection

The process of cooperative sensing starts with spectrum sensing performed individually at each CR user called local sensing. Typically, local sensing for primary signal detection can be formulated as a binary hypothesis problem as follows [2]:

$$x(t) = \begin{cases} n(t), & H_0 \\ h(t).s(t) + n(t), & H_1 \end{cases} \qquad (1)$$

Where $x(t)$ denotes the received signal at the CR user, $s(t)$ is the transmitted PU signal, $h(t)$ is the channel gain of the sensing channel, $n(t)$ is the zero-mean additive white Gaussian noise (AWGN), H_0 and H_1 denote the hypothesis of the absence and the presence, respectively, of the PU signal in the frequency band of interest. For the evaluation of the detection performance, the probabilities of detection P_d and false alarm P_f are defined as [9].

Elements of cooperative spectrum sensing as described in Section 3, conventional cooperative sensing is generally considered as a three-step process: local sensing, reporting, and data fusion. In addition to these steps, there are other fundamental components that are crucial to cooperative sensing. We call these fundamental and yet essential components as the elements of cooperative sensing. In this section, we analyse and present the process of cooperative sensing by seven key elements:

1. Cooperation models
2. Sensing techniques
3. Control channel and reporting
4. Data fusion
5. Hypothesis testing
6. User selection
7. Knowledge base

These elements are briefly introduced as follows:

- Cooperation models consider the modelling of how CR users cooperate to perform sensing. We consider the most popular parallel fusion network models and recently developed game theoretical models.

IJDACR
ISSN: 2319-4863

IJDACR International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 3, Issue 3, October 2014)

- Sensing techniques are used to sense the RF environment, taking observation samples, and employing signal processing techniques for detecting the PU signal or the available spectrum. The choice of the sensing technique has the effect on how CR users cooperate with each other.
- Hypothesis testing is a statistical test to determine the presence or absence of a PU. This test can be performed individually by each cooperating user for local decisions or performed by the fusion center for cooperative decision.
- Control channel and reporting concerns about how the sensing results obtained by cooperating CR users can be efficiently and reliably reported to the fusion center or shared with other CR users via the bandwidth-limited and fading-susceptible control channel.
- Data fusion is the process of combining the reported or shared sensing results for making the cooperative decision. Based on their data type, the sensing results can be combined by signal combining techniques or decision fusion rules.
- User selection deals with how to optimally select the cooperating CR users and determine the proper cooperation footprint/range to maximize the cooperative gain and minimize the cooperation overhead.
- Knowledge base stores the information and facilitates the cooperative sensing process to improve the detection performance. The information in the knowledge base is either a priori knowledge or the knowledge accumulated through the experience. The knowledge may include PU and CR user locations, PU activity models, and received signal strength (RSS) profiles.

Next, we discuss each element of cooperative sensing in detail.

III. Cooperation Models

The cooperation of CR users for spectrum sensing can be modelled by different approaches. The modelling in cooperative sensing is primarily concerned with how CR users cooperate to perform spectrum sensing and achieve the optimal detection performance. The most popular and dominating approach originated from the parallel fusion (PF) model in distributed detection and data fusion [27]. Nevertheless, recent studies [28, 29] model the behaviours of cooperating CR users in cooperative sensing by using game theory [30]. The PF models aim to achieve the detection performance by using the distributed signal processing techniques to determine how the observations are combined and tested and how the decisions are made.

Unlike the PF models, game theoretical models focus on improving the sensing-parametric utility function by analysing the interactions and the cooperative or non-cooperative behaviours of CR users. It can be informally stated that the parallel cooperation model emphasizes the ‘‘sensing’’ part while the game model focuses on the ‘‘cooperative’’ part in cooperative sensing. In this paper, we discuss these two approaches to the modelling of CR user cooperation.

$$P_d = P\{decision = H_1|H_1|\} = P\{Y > \lambda|H_1\} \quad (2)$$
$$P_f = P\{decision = H_1|H_0|\} = P\{Y > \lambda|H_0\} \quad (3)$$

Where Y is the decision statistic and λ is the decision threshold. The value of λ is set depending on the requirements of detection performance. Based on these definitions, the probability of a miss or miss detection is defined as $P_m = 1 - P_d = P\{decision = H_0|H_1\}$. The plot that demonstrates P_d versus P_f is called the receiver operating characteristic (ROC) curve, which is the metric for the performance evaluation of sensing techniques. In cooperative sensing, the probabilities of detection and false alarms for evaluating the performance of cooperative decisions are denoted by Q_d and Q_f, respectively.

IV. Classification of Cooperative Sensing

To facilitate the analysis of cooperative sensing, we classify cooperative spectrum sensing into three categories based on how cooperating CR users share the sensing data in the network: centralized [10,6,11], distributed [12], and relay-assisted [13–15]. In centralized cooperative sensing, a central identity called fusion center (FC)[2] controls the three-step process of cooperative sensing. First, the FC selects a channel or a frequency band of interest for sensing and instructs all cooperating CR users to individually perform local sensing. Second, all cooperating CR users report their sensing results via the control channel. Then the FC combines the received local sensing information, determines the presence of PUs, and diffuses the decision back to cooperating CR users.

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 3, Issue 3, October 2014)

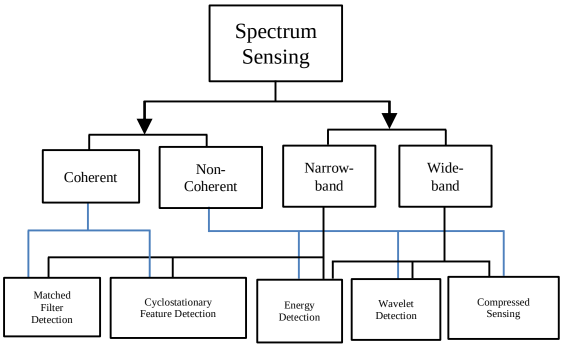

Figure 1: Classification of sensing techniques

A. *Matched filtering*

Matched filtering is used as an optimal method for detection of primary users when the transmitted signal is known [19]. Matched filtering method correlates the known primary signal with the received signal to detect the presence of the PU signal. It maximizes the signal-to-noise ratio (SNR). The matched filtering detector requires short sensing time to achieve good detection performance due to coherent detection. The matched filtering technique is not applicable when transmit signals by the PUS are unknown to the SUs [20]. In this method CR would need a dedicated receiver for every type of primary user.

B. *Energy Detection*

Energy detection is a non-coherent detection technique. The energy detector does not require a priori information of the PUs. The energy detector is optimal to detect the unknown signal if the noise power is known. In the energy detection, CR users sense the presence/absence of the PUs based on the energy of the received signals.

The energy detector is easy to implement. The energy detection suffers requires longer detection time compared to the matched filter detection. The energy detection depends only on the SNR of the received signal; hence its performance is susceptible to uncertainty in noise power [9] [21] [22].

The energy detector cannot distinguish the PU signal from the noise and other interference signals, which may lead to a high false-alarm probability. This method does not perform well under low signal-to-noise ratio conditions [23]. Energy detectors do not work efficiently for detecting spread spectrum signals.

C. *Cyclostationary Detection*

Cyclostationary detector is one of the feature detectors that utilize the cyclostationary feature of the signals for spectrum sensing. A signal is said to be cyclostationary if its mean and autocorrelation are a periodic functions [26]. Feature detection refers to extracting the features from the received signal and performing the detection based on the extracted features [27] [28]. It can be realized by analyzing the cyclic autocorrelation function (CAF) of the received signal $x(t)$, expressed as [24] where E[•] is the expectation operation, * denotes complex conjugation, and β is the cyclic frequency.

Cyclostationary detector can distinguish noise from the PU signals. It can be used for detecting weak signals at a very low SNR region. The main disadvantage of this method is the complexity of calculation and long sensing time.

V. CONCLUSION

Spectrum is a very valuable resource in wireless communication systems and it has been a major research topic from last several decades. Sensing provides awareness regarding the radio environment so that the spectrum opportunities can be efficiently reused while limiting the interference to the primary user. In this paper, a review of the CRs technology is presented. Different aspects of the spectrum sensing and various spectrum sensing techniques are reviewed. Cooperative sensing is an effective technique to improve detection performance. Cooperative sensing over Wideband has recently gained much attention. Cooperative sensing Spectrum sensing algorithms over Wideband need to be developed. CR technology will be applied to many real systems in the near future. Research can be possible for deriving a method for finding out how to minimize the energy consumption by the semiconductor chip while configuring the hardware into the CR.

REFERENCE

[1] I.F. Akyildiz, Y. Altunbasak, F. Fekri, R. Sivakumar,AdaptNet: "adaptive protocol suite for next generation wireless internet", IEEE Communications Magazine 42 (3) (2004) 128–138.
[2] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "NeXt generation / dynamic spectrum access / cognitive radio wireless networks: a survey," Computer Networks J. (Elsevier), vol. 50, Sept. 2006.
[3] J. Mitola III, "Software radios: survey, critical evaluation and future directions," IEEE Aerospace and Electronic Systems Magazine, vol. 8, no. 4, , 1993.
[4] S. Haykin, "Cognitive radio: brain-empowered wireless communications" ,IEEE Journal on Selected Areas in Communications 23 (2) (2005) 201–220.
[5] I. F. Akyildiz, W.-Y. Lee, K. R. Chowdhury: "CRAHNs: Cognitive Radio Ad Hoc Networks", Ad Hoc Networks, Elsevier, Vol. 7, No. 5,July 2009, pp. 810-836
[6] D. B. Rawat, G. Yan, C. Bajracharya (2010), "Signal Processing Techniques for Spectrum Sensing in Cognitive Radio Networks'', International Journal of Ultra Wideband Communications and Systems, Vol. x, No. x/x, pp:1-10.
[7] Tevfik Yucek and Huseyin Arslan (2009), ―"A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications‖", IEEE Communication Surveys & Tutorials, Vol.11, No.1, pp 116-130.

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 3, Issue 3, October 2014)

[8] A. Sahai, N. Hoven, R. Tandra, Some fundamental limits on cognitive radio, in: Proceedings of the Allerton Conference on Comm., Control, and Computing, 2004.

[9] D. Cabric, S. Mishra, and R. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in Proc. Asilomar Conf. onSignals, Systems and Computers, vol. 1, Pacific Grove, California, USA, Nov. 2004, pp. 772–776.

[10] E. Visotsky, S. Kuffner, R. Peterson. "On Collaborative Detection of TV Transmissions in Support of Dynamic Spectrum Sharing", In proc. of DySPAN'05, November 2005.

[11] S. M. Mishra, A.Sahai, R.W.Brodersen,Cooperative Sensing among Cognitive Radios", In proc. of International Conference on Communications, ICC'06, June 2006.

[12] J.C. Liberti, T.S. Rappaport, "Statistics of shadowing in indoor radio channels at 900 and 1900 MHz", In proc. Of Military Communications Conference, MILCOM'92,October 1992.

[13] Y. Xing, C. N. Mathur, M. Haleem, R. Chandramouli, and K. Subbalakshmi, ―"Dynamic spectrum access with qos and interference temperature constraints",‖ IEEE Transactions on Mobile Computing, vol. 6, no. 4, pp. 423–433, 2007.

[14] J. Bater, H.-P. Tan, K. Brown, and L. Doyle, "Modelling Interference Temperature Constraints for Spectrum Access in Cognitive Radio Networks",‖ in Proceeding of IEEE International Conference on Communications, 2007, ICC'07, Jun. 2007, pp. 6493 – 6498.

[15] B. Wild and K. Ramchandran, ―"Detecting Primary Receivers for Cognitive Radio Applications",‖ in proceeding of IEEE Dynamic Spectrum Access Networks, DySPAN 2005, November 2005, pp. 124–130.

[16] I. F. Akyildiz, B.F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: A survey," Physical Communication, vol. 4 no. 1 pp. 40-62, 2011. Elsevier DOI:10.1016/j.phycom.2011.12.003

[17] A. Garhwal, and P. P. Bhattacharya "A Survey on Dynamic Spectrum Access Techniques for Cognitive Radio," International Journal of Next-Generation Networks, vol. 3, no. 4, pp. 15-32, 2012.

[18] S. Ziafat, W. Ejaz, and H. Jamal, "Spectrum sensing techniques for cognitive radio networks: Performance analysis," 2011 IEEE MTT-S International Microwave Workshop Series on Intelligent Radio for Future Personal Terminals, pp. 1-4, 2011. IEEE

[19] J. G. Proakis, Digital Communications, 4th ed. McGraw-Hill, 2001.

[20] R. Tandra and A. Sahai, "Fundamental limits on detection in low SNR under noise uncertainty," in Proc. IEEE Int. Conf. Wireless Networks, Commun. and Mobile Computing, vol. 1, June 2005, pp. 464–469.

[21] A Sonnenschein, PM Fishman, "Radiometric detection of spread-spectrum signals in noise of uncertain power". IEEE J Sel Topics Signal Process. 2(1), (2008)

[22] R Tandra, A Sahai, SNR walls for signal detection. IEEE J Sel Topics Signal Process. 2(1), 4–17 (2008)

[23] W Jouini, Energy detection limits under log-normal approximated noise uncertainty. IEEE Signal Process Lett. 18(7), 423–426 (2011)

[24] H. Tang, "Some physical layer issues of wide-band cognitive radio systems," in Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, Baltimore,USA, Nov. 2005, pp. 151–159.

[25] PD Sutton, KE Nolan, LE Doyle, Cyclostationary signature in practical cognitive radio applications. IEEE J Sel Areas Commun. 26, 13–24 (2008)

[26] U. Gardner, WA, "Exploitation of spectral redundancy in cyclostationary signals," IEEE Signal Processing Mag., vol. 8, no. 2, pp. 14–36, 1991.

[27] A. Fehske, J. Gaeddert, and J. Reed, "A new approach to signal classification using spectral correlation and neural networks," in Proc.IEEE Int. Symposium on New Frontiers in Dynamic Spectrum AccessNetworks, Baltimore, Maryland, USA, Nov. 2005, pp. 144–150.

[28] M. Ghozzi, F. Marx, M. Dohler, and J. Palicot, "Cyclostationarity based test for detection of vacant frequency bands," in Proc. IEEEInt. Conf. Cognitive Radio Oriented Wireless Networks and Commun.(Crowncom), Mykonos Island, June 2006.

[29] A. Ghasemi and E. S. Sousa, "Spectrum sensing in cognitive radio networks: the cooperation-processing tradeoff," Wireless Communications and Mobile Computing, vol. 7, no. 9, pp. 1049–1060, 2007.

[30] K. B. Letaief and W. Zhang, "Cooperative spectrum sensing," in Cognitive Wireless Communication Networks, Springer, New York, NY, USA, 2007.

[31] Juan Andrés Bazerque and Georgios B. Giannakis "Distributed Spectrum Sensing for Cognitive Radio Networks by Exploiting Sparsity" IEEE Transactions on Signal Processing, Vol. 58, No. 3, March 2010.

[32] G. Ganesan and Y. Li, "Agility improvement through cooperative diversity in cognitive radio," in Proc. IEEE Global Telecomm. Conf. (Globecom), vol. 5, St. Louis, USA, Nov./Dec. 2005, pp.2505–2509.

[33] "Cooperative spectrum sensing in cognitive radio networks," in Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, Baltimore, Maryland, USA, Nov. 2005, pp. 137–143.

[34] D. Cabric, A. Tkachenko, and R. Brodersen, "Spectrum sensing measurements of pilot, energy, and collaborative detection," in Proc.IEEE Military Commun. Conf., Washington, D.C., USA, Oct. 2006, pp. 1–7.

[35] Zhi Quan, Shuguang Cui, Ali H. Sayed, andH. Vincent Poor, "Optimal Multiband Joint Detection for Spectrum Sensing in Cognitive Radio Networks" IEEE Transactions on Signal Processing, Vol. 57, No. 3, pp. 1128–1140, March 2009.

[36] Fanzi Zeng, Chen Li, and Zhi Tian, "Distributed Compressive Spectrum Sensing in Cooperative Multihop Cognitive Networks" IEEE journal OF selected topics in Signal Processing, Vol. 5, No. 1, February 2011

[37] Y. L. Polo, Y. Wang, A. Pandharipande, and G. Leus, "Compresive wideband spectrum sensing," in Proceedings of theIEEE International Conference on Acoustics, Speech, and SignalProcessing (ICASSP '09), Taipei, Taiwan, April 2009.

[38] Z. Quan, S. Cui, H. V. Poor, and A. H. Sayed, "Collaborative wideband sensing for cognitive radios," IEEE Signal ProcessingMagazine, vol. 25, no. 6, pp. 60–73, 2008.

[39] Y. Pei, Y.-C. Liang, K. C. Teh, and K. H. Li, "How much time is needed for wideband spectrum sensing?" to appear in IEEE Transactions on Wireless Communications.

[40] Q Zhang, G J M smit, L T Smit, A Kokkeler, F W Hoeksema, M Heskmp "A Reconfigurable Platform for Cognitive Radio".

[41] J Lotze, S A Fahmy, J Noguera, L. E. Doyle and R. Essar "An FPGA-based Cognitive Radio Network".

[42] J Lotze, S A Fahmy, J Noguera, L. E. Doyle and R. Essar "Development Framework for Implementating FPGA-Based Cognitive Network Nodes".