Spectrum Sensing Techniques for Cognitive radio-A Review

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Abstract

Cognitive Radio (CR) users need to sense the environment or channel at regular time interval for sharing the spectrum band of the primary users (PUs). Once find the spectrum idle, CR users start their transmission through it. Even while transmitting, they need to continue the sensing process so that they can leave the spectrum immediately whenever find a PU wanting to use the band. Therefore, detecting PUs is one of the main functions of cognitive radio before transmission and higher the detection probability ensures better protection to the primary users. However, it is not possible to attain a high detection probability (or a low miss detection probability) and low false alarm probability simultaneously as there is a tradeoff between false alarm probability (P_{fa}) and the probability of detection (P_d). In this paper, the author has provided a comprehensive study on different sensing techniques and discussed their advantages and disadvantages. Moreover, it is expected that, with this article, readers can have a through understanding of sensing techniques in CR and the current research trends in this area.

Keywords: Spectrum sensing; energy detection; probability of detection; probability of false alarm; sensing time.

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1. Introduction

Spectrum is a limited natural resource which is regulated by the government agencies such as Federal Communications Commissions (FCC) in the United States. Traditional approach to spectrum allocation is done by assigning the spectrum exclusively to a licensed user and the system has to operate within that frequency band. This leads to spectrum underutilization. In recent studies by the FCC, it is reported that there are vast temporal and spatial variations in the usage of allocated spectrum, which can be as low as 15% [1]. On the other hand, most of the licensed and unlicensed bands are rapidly filling up. Therefore, the efficient utilization of this limited natural spectrum-resource has dragged the attention of the researchers greatly, thus the concept of cognitive radio (CR) emerged.

Cognitive radio is a promising new technology which provides the scope of a more reliable, flexible and efficient spectrum sharing scheme with better utilization of the radio spectrum [46] using signal processing and adaptive procedures. It improves the spectrum utilization by allowing CR users to share the same licensed band that is allocated for the primary users. Utilization of spectrum holes by CR users within a limited interference to PU increases spatial diversity and improves spectrum efficiency due to the simultaneous transmission of PU and CR users. For best utilization of the available spectrum, the cognitive radios exploit side information (knowledge about the activity, channels, encoding strategies and/or transmitted data sequences of the PUs) about their environment and based on the nature of the available side information as well as a priori rules about spectrum usage, cognitive radio consider different degrees of interaction between PU and CR users which can be classified as: interweave, underlay and overlay. Interweave cognitive radio is the simplest one- the CR sense the environment to detect the presence of PUs and transmit opportunistically if PUs are idle. Underlay cognitive radio goes one step further and permits communication between CR users as long as the disturbance created to the PU is below some predefined threshold. Finally, in overlay, the CR users can assign part of their power for their own communication and the remainder of the power to assist (relay) the primary transmissions of data sequences. In such case, both PUs and CR users can transmit simultaneously.

Since CR users share the same spectrum band with PU, so chances of possible harmful interference remains and if CR senses presence of PU, it either has to leave the occupied spectrum for PU else it has to control its transmission parameters. Thus, the main challenge for the implementation of a CR network is to ensure high quality of service for the CR users so that they can transmit without any interruption and provide guaranteed security of licensed users from harmful interference caused due to CRs. To support this function, the CR users are required to sense the radio frequency environment at regular interval, and if the primary user is found to be active, the secondary users must vacate the channel within a set amount of time. Two parameters are related to channel sensing: probability of detection and probability of false alarm. The detection probability should be higher to protect the primary users better. On the other hand, if the false alarm probability is low, the chances to reuse the channel will more, thus the achievable throughput will be high for the CR users. When a false alarm happens, the secondary user does not exploit the spectrum that is actually empty and loses an opportunity to transmit its data. Hence, the lower the false alarm probability, the higher is the throughput of the secondary user. Conversely, the detection probability is defined as the probability of the energy detector making a correct decision. If the detection fails, or "miss detection" occurs, the secondary user starts an undesirable transmission in the primary spectrum where the primary user is also transmitting, and, therefore, causes a strong interference with the primary user signal. This degrades the signal quality of the primary communication and violates the fundamental doctrine of overlay spectrum sharing. Therefore, when the detection probability is higher, it is then possible to provide enhanced protection for the primary user. In order to get a better result from cognitive radio, it is, therefore, a prime problem to maintain a trade-off for better transmission both in primary and secondary user. Most of the papers related to spectrum sensing for cognitive radio [3-9] presents sensing performance. However, without considering increased sensing time, false alarm probability may have a chance to appear in larger limit that degrades the sensing performance.

Sensing time can be enhanced in full frame structure [13-14]. The basic of detection based on composite hypothesis testing is to accommodate unknown signal and noise parameters [1-2]. The most comprehensive overview of signal detection is available in the open literature. This paper focuses up-to-date introduction of optimizing detection algorithms and survey on spectrum sensing techniques. It starts with a quick review of the fundamental issues associated with the most important probability density functions and their properties of Gaussian, quadratic forms of Gaussian random variables, and Monte Carlo Performance Evaluations.

Energy detection of an unknown signal over a Gaussian channel [3], [9], [7] starts with the no-diversity case and presents some alternative closed-form expressions for the probability of detection in the literature. The whole duration of the time frame is used for both sensing and data transmission simultaneously, in which better sensing performance and maximum throughput both are possible [13].

Conventional frame structure for CR studied so far consists of a sensing slot and data transmission slot. According to this frame structure, a CR user senses the status of the frequency band for 'τ' units of time, whereas the remaining frame duration '$T - \tau$' is used for data transmission. According to the classical detection theory [1-2], an increase in the sensing time results in a higher detection probability and lower false alarm probability, which leads to better protection of the primary users from harmful interference in one hand, and improves utilization of the available unused spectrum, on the other hand, in the cognitive radio network. This paper is organized as follows. Section 2 presents Spectrum sensing summary. Section 3 describes transmitter detection based spectrum sensing techniques with a detail review of energy detection scheme. The relation between probability of detection and probability of false alarm is also established in this section. Furthermore, this section describes a comparison of various sensing methods. In Section 4, cooperative spectrum sensing technique, research issues and challenges have been discussed. Finally, conclusions are drawn in Section 5.

2. General Overview of Spectrum Sensing

Spectrum sensing is crucial in the development of cognitive radio. The sensing techniques can be classified as transmitter detection, cooperative detection, and interference based detection [17]. Among them, transmitter detection is based on the detection of a weak signal from the primary transmitter through the local observations of CR users. It is usually divided into three: energy detection, feature detection and matched filter. Feature detection has advantages over energy detector and matched filter, due to its ability to differentiate modulated signals, interference and noise in low signal to noise region. On the other hand, energy detector is simplest, computational efficient and is sufficient for wideband spectrum sensing. It is a non-coherent detection method that uses the energy of the received signal to determine the presence of primary signals. However, such individual sensing is not sufficient for reliable detection of PUs due to shadowing and multipath effects, and in such case, cooperative sensing is identified as the solution key to reduce interference to primary PUs. Cooperative sensing is theoretically more accurate because the uncertainty in a single user's detection can be minimized through collaborations [15].Cooperative spectrum sensing is classified into three- centralized, distributed, and relay-assisted. In centralized cooperative sensing, there is a central unit which collects sensing information from other cognitive radios and identifies the available spectrum. In distributed cooperative sensing, cognitive nodes share information among each other but make their own decisions to recognize the usable portion of the spectrum. Most of the conventional cooperative spectrum sensing methods are based on energy detection. It requires noise knowledge to perform spectrum sensing. But accurate noise estimation is difficult. Therefore, sensing algorithms that do not need noise information to perform spectrum sensing are referred as blind spectrum sensing algorithms, is now hot research topic [16]. However, spectrum sensing cannot resolve the interference issue perfectly. In some cases, CR users can not accurately detect spectrum holes because spectrum sensing is significantly affected by the channel fading or shadowing. So, interference estimation considering the number of CR users and their locations is very important to control the aggregation interference under the maximum tolerating interference power of the PU's receiver.

The detail of the different sensing techniques is explained in the subsequent sections.

3. Transmitter Detection based spectrum sensing

Cognitive radios must have the capability to determine if a signal from a primary transmitter is locally present in a certain spectrum. There are several approaches for transmitter based spectrum sensing which is mentioned earlier-

A. Matched Filter
B. Feature Detection
C. Energy Detector

In case of spectrum sensing, the need for signal processing is two-fold: improvement of radio front-end sensitivity by processing gain and primary user identification based on knowledge of the signal characteristics. In this section, we discuss advantages and disadvantages of three above techniques that are used for the identification of the presence of PUs.

3.1 Matched Filter

The matched filter (MF) is a coherent detector which correlates a known signal, or template with a unknown signal to detect the presence of the template in the unknown signal. It is a linear filter which maximizes the signal to noise ratio. The main advantage of matched filter detector (MFD) is that it requires less time to achieve high processing gain due to coherency. However, extra dedicated circuitry is required to achieve coherency with primary user signal.

3.2 Feature Detection

Feature detection is an alternative method for signal detection which extracts the spectral correlation due to the periodicity feature of modulated signals from the noise. Modulated signals are in general characterized by built-in periodicity or cyclostationarity. This periodicity is typically introduced intentionally in the signal format so that a receiver can exploit it for parameter estimation such as carrier phase, pulse timing, or direction of arrival. The advantage of feature detector is that it does not require priori knowledge about the primary signal. However, it is very complicated as it implements a 2-dimensional spectral correlation function (SCF) which leads to a slow detection.

3.3 Energy Detector (ED)

Energy detector based approach, also known as radiometry or periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities [4], [5], [6-10], [3], [11], [12], [13]. In addition, it is more generic (as compared to methods given in this section) as the receiver does not require any prior knowledge on the primary users' signal. The signal is detected by comparing the output of the energy detector with a threshold that depends on the noise floor [13]. The decision metric for the energy detector can be written as

$$P(yr) = \frac{1}{M} \sum_{m=1}^{M} |Yr(m)|^2 \underset{H_1}{\overset{H_0}{\gtrless}} \varepsilon_{ED} \tag{1}$$

Where, $P(yr)$ and ε_{ED} represents test statistics and decision threshold for ED sensing based on the decision rule defined in (1).

The performance of the detection algorithm can be summarized with two probabilities: probability of detection P_d and probability of false alarm P_{fa}. P_d is the probability of detecting a signal on the considered frequency when it is truly present. Thus, a large detection probability is desired. It can be formulated as

$$Pd,ed = Q\left(\left(\frac{\varepsilon}{No} - \gamma - 1\right)\sqrt{\frac{\tau fs}{2\gamma + 1}}\right) \tag{2}$$

where τ denotes the sensing time, ε the sensing threshold of the energy detector, γ the SNR of the primary user's signal at the secondary detector, N_o the noise variance and f_s the sampling frequency, such that M = τfs. As discussed in the previous section, [14] high probability of detection $P_{d,\,ed}$ is required for the protection of the quality of service (QoS) of the primary network.

P_f is the probability that the test incorrectly decides that the considered frequency is occupied when it actually is not, and it can be written as

$$Pfa,ed = Q\left(\sqrt{2\gamma+1}\right)Q^{-1}\left(Pd,ed\right)\sqrt{\tau f s\gamma} \tag{3}$$

There exists an optimal sensing time $0 < \tau < T$ which yields the maximum achievable P_d for a cognitive radio system that employs the frame structure. The probability of false alarm P_{fa}, ED (τ) is a decreasing function of the sensing time τ, which results from (3).

The analyzed scheme therefore ensures some advantages:

1. As the CR takes the right decision by sensing the band for a longer period, the probability of false alarm decreases, as a result detection probability increases.
2. Due to decrease of false alarm, the usage of band increases and we get an efficient band.
3. Misdetection decreases due to increase of detection probability.

3.3.1 Research Issue and Challenges

The detection problem using a threshold is illustrated with the help of **Fig. 1** where the horizontal axis is for the internal response and the vertical axis is the probability. The curve in the left side is for the noise alone whereas the curve on the right side is for the noise plus signal. The noise is additive white Gaussian noise (AWGN). The threshold level shown by the vertical line, divides the graph into four sections that corresponds to: probability of detection, probability of miss, probability of false alarm, probability of correct rejection. In the both case of probability of detection and probability of false alarm, the internal response curve exceeds the threshold level. Detection corresponds to the noise plus signal curve when the response exceeds the threshold level which is shown by the black shaded region in **Fig 1(a)**. False alarm corresponds to the noise only curve when the response exceeds the threshold level which is shown by the black shaded region in the **Fig 1(b)**.

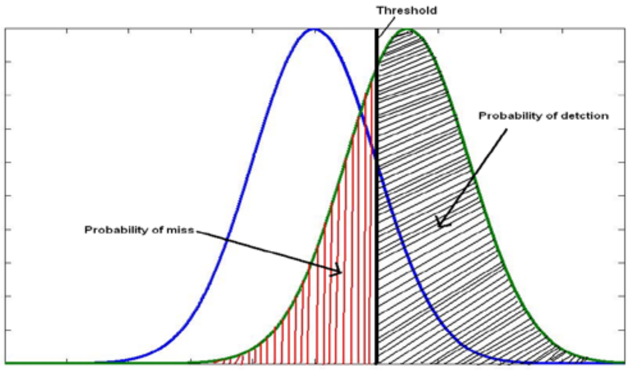

Fig. 1 (a). Probability of detection and probability of miss

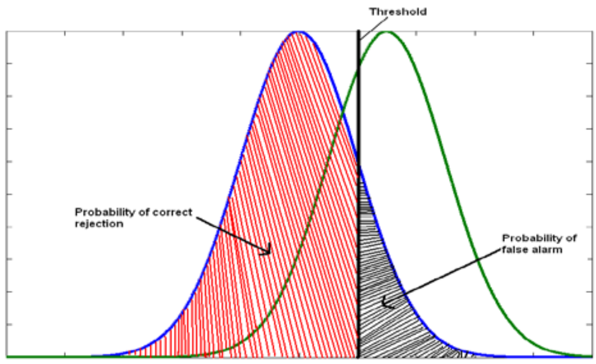

Fig. 1 (b). Probability of false alarm and probability of correct rejection

Probability of miss and correct rejection occurs when the threshold level exceeds the internal response curve. Probability of miss occurs in the case of noise plus signal curve where the threshold exceeds the response which is shown by the red shaded region in **Fig 1(a)**. Probability of correct rejection occurs in the case of noise only signal as soon as the threshold level exceeds the response of noise only curve which is shown by the red shaded region in **Fig 1 (b)**.

Some of the challenges of energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low signal to noise ratio (SNR) values [12].Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [6], [13].

Fig. 2 illustrates the changes in the probability of detection and probability of false alarm with variation of threshold value. It shows that both the probability of detection and probability of false alarm will increase if the threshold value increases. The goal of the detection system is to increase the probability of detection as much as possible while reducing the probability of false alarm (error). So, the threshold value setting is a very critical decision in signal detection system and an optimum value of threshold should be chosen to get the best performance.

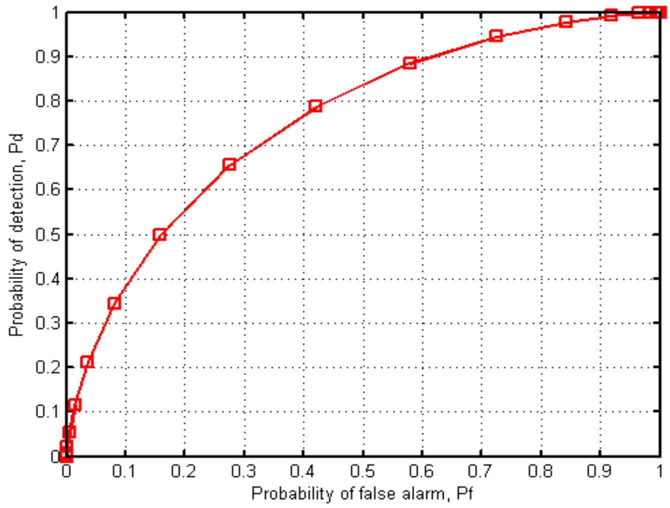

Fig. 2. Effect of threshold value setting

3.3 Comparison of Various Sensing Methods

Transmitter detection is the wide generic class of spectrum sensing methods and the selection of specific sensing method comes with a tradeoff between sensing accuracy and complexity while keeping in view the required sensing time. The basic comparison of different transmitter detection sensing methods is presented in **Fig. 3**. The energy detection offers less complexity as it does not require prior knowledge as a result low cost but correspondingly the accuracy is low because the criteria rely on some factors such as suitable threshold selection and noise steadiness. Other problems with the energy detector are baseband filter effects and spurious tones [41]. Whereas, the matched filter technique has shown good performance and high accuracy at the expense of more complexity and requires perfect knowledge. In contrast, Cyclostationary scheme has slightly better performance and possesses higher accuracy than energy detection but performs worse than energy detector based sensing methods when the noise is stationary. However, energy detector based schemes fail due to the presence of co-channel or adjacent channel interferers while cyclostationarity-based algorithms are not affected [43]. On the other hand, cyclostationary features may be completely lost due to channel fading [42], [44]. Furthermore, cyclostationarity based sensing is known to be vulnerable to sampling clock offsets [43].

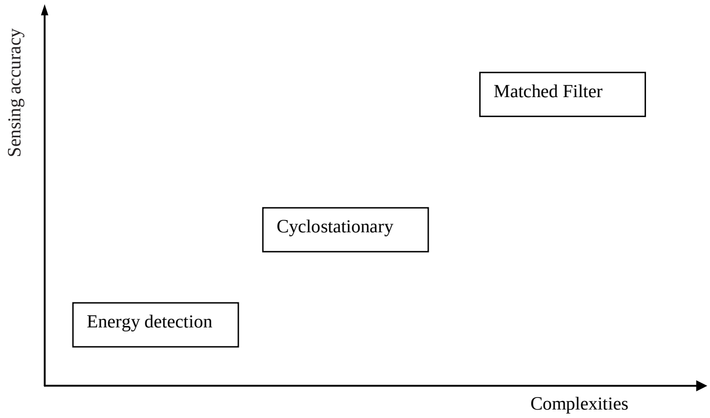

Fig. 3. Comparison of Spectrum sensing in terms of sensing accuracy and implementation complexities.

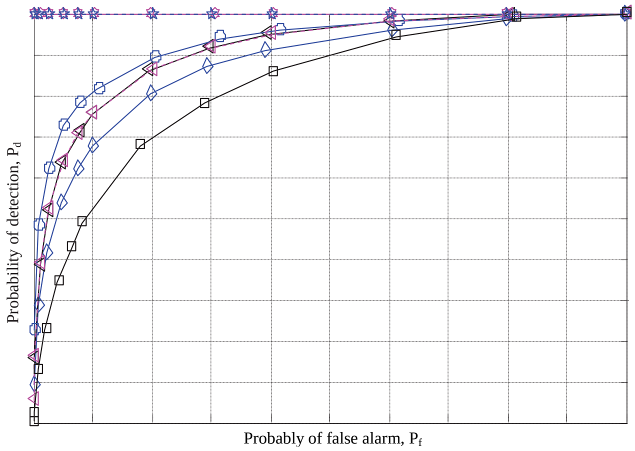

Fig. 4. ROC of MSC no overlap, ED, MSC 75% overlap, MFD ED theoretical, MFD theoretical, MFD (1.7 sample sync error) [SNR= -22dB]

The authors in [45] address two cyclostationalry feature detection methods which are based on estimating the Spectral Correlation Density (SCD) and the Magnitude Squared Coherence (MSC) of the signal and draw a performance comparison of different sensing methods in terms of probability of false alarm and probability of detection. The authors have shown that the cyclostationalry detectors are a good candidate for spectrum sensing in case of nonzero spectral correlation of the signal which is illustrated in **Fig. 4**.

The sensing performance has significant impact on the throughput of the CR system as high sensing performance ensures more opportunities for SUs to use licensed spectrum and the longer data transmission time guarantees the efficient use of PU's resources.

4. Cooperative Spectrum Sensing

In practice shown in **Fig. 5**, sensing performance of a single node often degrades due to multipath fading, shadowing and receiver uncertainty in the channel. As a result, multinode or cooperative sensing has attracted increased interest from researchers due to the fact that it can enhance the performance and mitigate the noise effects with different collaboration methods (soft and hard decision fusion) [18- 19]. While a network of CRs uses cooperative sensing to determine the availability of a specific frequency band, the local sensing information at individual CRs is forwarded to a FC which makes the final decision regarding the use of the sensed frequency band. In multinode sensing, two kinds of decision fusion logics (soft decision fusion and hard decision fusion) are being used in the central node or the fusion center. Among these, soft decision fusion techniques such as weighted gain combining (WGC) and equal gain combining (EGC) methods are shown to be reliable [20]. Recent research has focused on considerable effort on narrowband (single band) cooperative detection to enhance the sensing accuracy in low SNR environments [21]. But, in order to improve the opportunistic throughput, CR must sense the signals in multiple bands or wideband [22]. This also provides high spectrum mobility to cognitive users for their communication.

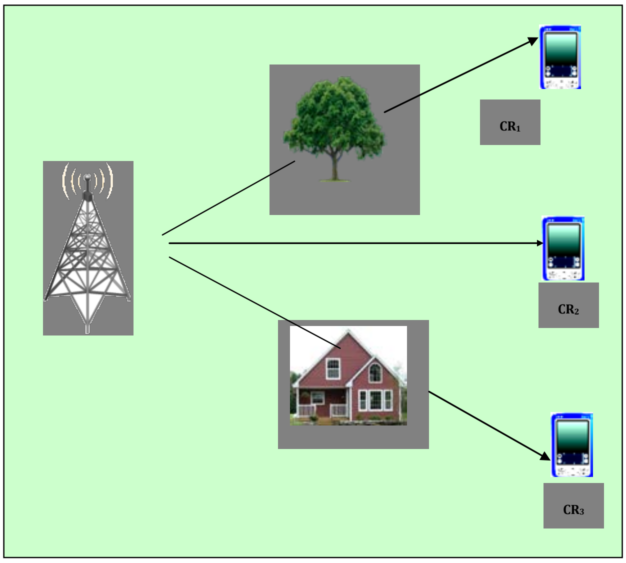

Fig. 5. Hidden node problem

4.1 Classification of Cooperative Sensing

Cooperative spectrum sensing can be classified into three- centralized, distributed and relay-assisted which is mentioned earlier. In this section, each cooperative sensing method is explained with figures.

Distributed cooperative spectrum sensing: In distributed approach shown in **Fig. 6**, each CR exchanges its sensing information with other CRs in the network. Finally, each of the CR in the network makes decision by combining their own sensing information with received signal from others.

In distributed cooperative sensing, though cognitive nodes share information among each other but they make their own decisions as to which part of the spectrum they can use. Reduced cost and rapid deployment makes distributive cooperative sensing an attractive option [23].

Centralized cooperative spectrum sensing: In centralized approach, each CR in the network individually performs spectrum sensing and sends sensed data to the central unit shown in **Fig. 7**, where the final decision is taken about the presence or absence of primary user by analyzing the received sensing information. AND, OR and Majority [8] are the rules used for combining results from various CR users to identify the available spectrum.

Relay-assisted Cooperative Sensing: **Fig. 8** shows relay-assisted cooperative sensing which overcomes the imperfection of both sensing channel and report channel. In relay-assisted approach, two CR users of which one CR experiences weak sensing channel and strong report channel, and the other one with a strong sensing channel and a weak report channel can cooperate with each other to improve the performance of cooperative sensing. However, the relay-assisted cooperative sensing incurs extra reporting delay because the sensing data is transmitted through multiple hops.

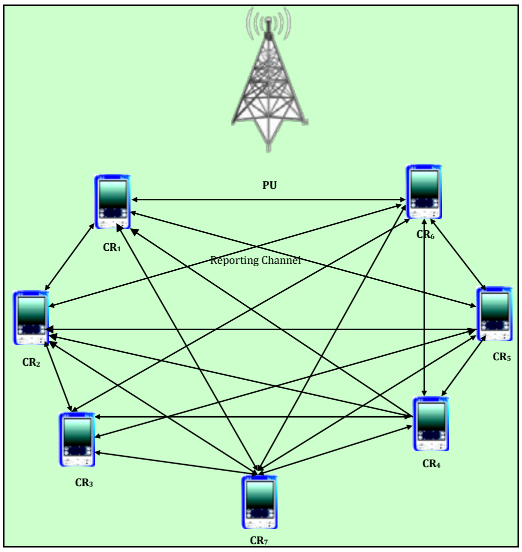

Fig. 6. Distributed Cooperative Sensing

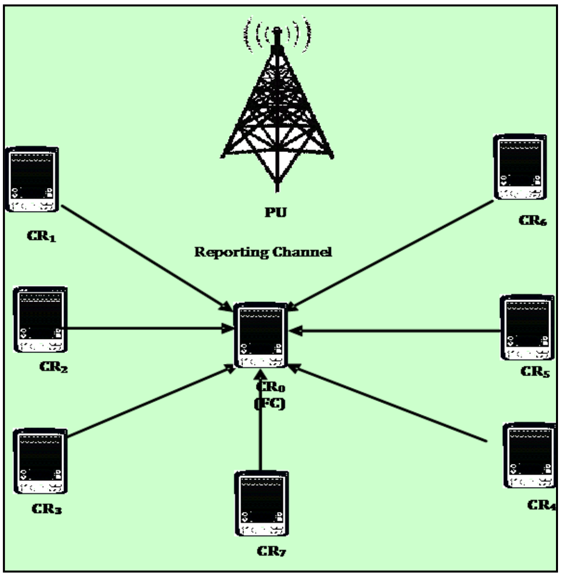

Fig. 7. Centralized Cooperative Sensing

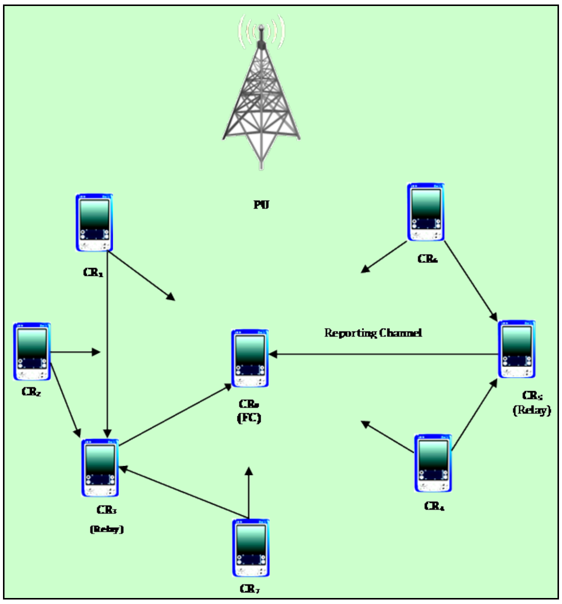

Fig. 8. Relay-assited Coopertive Sensing

4.2 Cooperative Sensing using Energy detection (ED) method

Cooperative sensing using ED method consists of PUs, CR users including Fusion Centre (FC). Each CR user is equipped with ED. ED has individual detection threshold and makes a decision based on its observation of PU's signal in compare to the predefined detection threshold. While an energy detection method is employed, missed detection probability and false alarm probability are widely used to evaluate spectrum sensing performance. Missed detections indicate that busy channels are detected as free, thus leading to the interference to

PUs. False alarms mean that free channels are considered to be busy, thereby overlooking some spectrum opportunities.

For any spectrum sensing algorithm, first a test statistic is calculated; defined as $P(yr)$. This test statistic is then compared with a decision threshold ε to decide if the 'transmit signal' is present; $P(yr) > \varepsilon$ indicates that a 'transmit signal' is present and vice versa. The receiver operating characteristics (ROC) curve is an important metric to evaluate the performance of a spectrum sensing algorithm.

The performance of cooperative wideband sensing using energy detection method is reported in [24- 25]. The authors in [26] tackle the spectrum sensing problem by using statistical test theory and derive novel spectrum sensing approaches. They apply the classical Kolmogorov–Smirnov (KS) test under the assumption that the noise probability distribution is known. Their simulations show that Anderson–Darling (AD) sensing performs superior to energy detection (ED) sensing for the system model defined in [27], that is, detection of non-zero mean in Gaussian noise.

4.3 Cooperative Spectrum Sensing Models

4.3.1. Parallel fusion (PF) model

In the distributed detection and data fusion [28], a group of spatially distributed sensors observes a physical phenomenon through the observations and report their observations to a central processor known as a FC [29]. The FC combines the reported data by data fusion and makes the global decision by using binary hypothesis testing. This PF model in the context of cooperative sensing is illustrated in **Fig. 9**. Due to the similarity to the process of distributed detection, a large number of proposed schemes [30-32] adopted the PF model or variations of this model for cooperative sensing. In these schemes, cooperative sensing follows the same three-step process: local sensing, data reporting, and data fusion. All CR users are assumed to be synchronized by the FC for sensing the channel or the frequency band of interest and reporting the sensing results. The FC combines the reported local sensing data and makes a cooperative decision. This decision is broadcast to all cooperating CR users. In addition, each cooperating CR user shares, collects, and combines the sensing data in distributed cooperative sensing is similar to the FC in the PF model. Thus, distributed cooperative sensing can also be represented by this model.

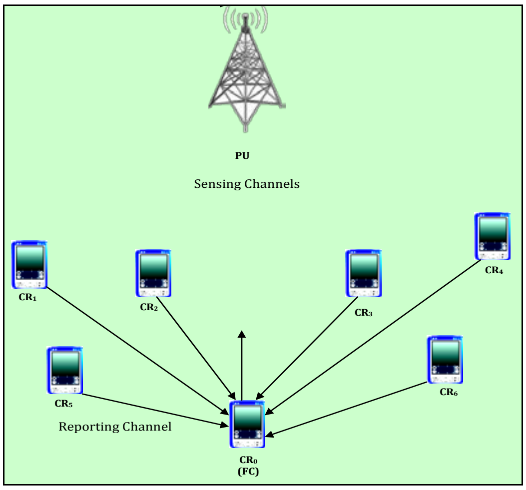

Fig. 9. Parallel Fusion model

4.3.2 Game Theoretical Model

In game theoretical models [33], cooperative sensing is designed as a game with a set of players, which are the cooperating CR users. In this model, each player has a probability of performing sensing. The strategy set for each player is to contribute or not to contribute. The payoff of each player is defined based on the throughput, which considers the time spent on spectrum sensing. Depending on the nature of the game, the behaviors of cooperating CR users are modeled differently. For example, in a coalitional game [34], CR users cooperate in the form of groups, called coalitions while in an evolutionary game [35], CR users are selfish users who may choose to cooperate or not cooperate depending on their own benefits.

4.4 Issues and Challenges in Cooperative sensing

To enforce cooperation in spectrum sensing, there are few approaches exist in the open literature such as grim trigger strategy, the punish and forgive strategy, tit-for-tat and fictitious play. In grim trigger strategy, the game jumps to the punishment stage where the selfish player is punished by other peers through non-cooperation forever. A less harsh alternative is known as “punish and forgive” strategy. In this strategy, the selfish CR is given limited punishment and cooperation will be resumed after enough punishment. In tit-for-tat strategy, a player chooses an action based on the behaviour of the previous round. Punishing a selfish node by not broadcasting the sensing results also affects other nodes which will in turn trigger punishments. A few works in [39-40] have focused on enforcing cooperative spectrum sensing. In [39], the author proposes the use of Carrot and Stick strategy in which all the nodes stop cooperating once a non-cooperating node is detected and they resume cooperation after every user stops cooperating. The biggest disadvantage of this strategy is that there will be frequent network shutdowns due to collision errors. Also, a malicious user can take advantage of the game model to disrupt the network by either being irrationally selfish or by causing collisions during the sharing period of the sensing results. Moreover, the game was not designed for multi-hop communication. Paper [40] deals with achieving cooperative spectrum sensing in a centralized cognitive radio network only. In summary, achieving cooperation in a multi-hop cognitive radio network has the following issues: traditional TFT strategy cannot be used, security attacks can be launched taking the advantage of an inefficient game model, and ensuring cooperation in a multi-hop scenario is complicated.

One of the issues in the cooperative sensing is the presence and possible emulation attacks of malicious/suspicious cognitive radio (SCR) users, where malicious cognitive users intentionally report/send the false measurement to other cognitive users, and thereby wrongly influences the multinode or global decision [36-37]. The performance of the cooperative sensing becomes unreliable due to suspicious users. Most of the works in the literature are concentrated to eliminate single suspicious user in the cognitive radio network (CRN) [36]. In practice, the network may contain multiple suspicious users. Hence, there is a need to develop an efficient technique to eliminate multiple malicious users in the cooperative network.

In paper [38], the authors have proposed multinode wideband spectrum sensing algorithm based on the entropy and cyclic properties of a received signal. From the simulation results, it is concluded that the proposed sensing method is robust against noise uncertainty. In addition, it has also been shown that the detection algorithm with multiple malicious user elimination can sense the spectrum efficiently and outperforms the three previous traditional sensing algorithms (detection based on generalised likelihood ratio with maximum likelihood estimation (GLR-ML), energy, entropy (FD), SCF method) (GLR-ML, energy, SCF, and entropy detection) methods.

5. Conclusion

As CR users are allowed to utilize licensed bands, it would not cause interference to the PUs. Therefore, spectrum sensing is important before data transmission. In this paper, the author focuses up-to-date introduction of optimizing detection algorithms and survey on spectrum sensing techniques. It starts with a quick review of the fundamental issues associated with the most important probability density functions and their properties. The higher the detection probability, the better PU transmission is protected. On the other hand, the lower the false alarm probability, the more opportunities for CR users to reuse the spectrum band. In view of that, we have to confirm the improved sensing capabilities with reasonable throughput in cognitive radio system. This paper also addresses the cutting edge research issues and challenges in spectrum sensing.

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