Spectrum Sensing Methods for Cognitive Radio Networks: A Review

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***Abstract*— Dynamic spectrum sensing is a challenging and necessary task in Cognitive Radio Networks (CRN). It can detect presence of primary user (PU) who is having legacy right on licensed spectrum. Secondary User (SU) continuously or periodically senses the PU's spectrum and when it finds the spectrum idle it starts transmitting its own data. When the SU detects presence of the PU in the spectrum it stops transmission or switches to another idle frequency spectrum. The SU must maintain its transmission parameters like power level, frequency band used for data transmission etc., in such a way that it must not cause any interference in PU's transmission. The spectrum utilization efficiency and throughput performance of SUs depend on robustness and accuracy of spectrum sensing algorithms. Hence, in this paper a survey of spectrum sensing algorithms for Cognitive Radio (CR) is presented with their merits and limitations. To improve spectrum sensing performance and accuracy, some cooperative sensing techniques have been developed where many SUs share their detected information. The cooperative sensing techniques also reduce shadowing and fading effects on spectrum sensing.**

***Keywords— Cognitive radio, spectrum sensing algorithms, cooperative spectrum sensing*.**

I. INTRODUCTION

The huge demand of frequency spectrum to support various types of real time and non-real time services using different type of technologies has created the scarcity of the frequency spectrum. To address the scarcity of frequency spectrum and to improve frequency spectrum utilization efficiency it has been proposed that unlicensed users (Secondary user/ Cognitive user) can be allowed to use the licensed frequency bands without affecting the communication performance of licensed user (Primary user) of the frequency band [1]. To improve the frequency spectrum utilization efficiency, In 1999, Mitola proposed the concept of Cognitive Radio which is also called as Software Defined Radio (SDR) [2]. A recent study by Federal Communication Commission (FCC) show that most of the fixed licensed spectrums are underutilized varies from 15 % to 85%, which is function of geographical and temporal dimensions [3]. The FCC recognized that there is significant amount of available spectrum that is currently not being used efficiently under the current fixed spectrum allocation policy. Therefore recently it has allowed the opportunistic access of the underutilized licensed spectrum to SUs [4]. The unused spectrum is often termed as "white space" and has been the focus of the IEEE 802.22 WRAN standard that aims to provide broadband wireless internet access to rural areas.

Hence in order to improve spectrum utilization efficiency and throughput of SUs, the robustness and accuracy of spectrum sensing methods are the key issues in CRN. The basics of spectrum sensing methods are surveyed in [5-7], which covers basics of energy detector, Cyclostationary feature detector, matched filter detector, Interference detector, cooperative detector etc. These methods are having their merits and limitations like, Energy detector is easy to implement but can't distinguish between PU's and SU's signals. The Cyclostationary feature based detector need prior knowledge of cyclic frequencies of PU and SUs to distinguish them. A matched filter based detector is a coherent detector that also need prior knowledge of PU's signal, like operating frequency, modulation etc. To address these limitations and improve detection probability some hybrid algorithms like Cyclo-energy detector [8] has been developed. To address the challenges posed by fading environment, hidden node, shadowing effect etc., centralized and distributed cooperative sensing algorithms have been proposed in [9-24]. A malicious SU may mislead a cooperative detector by hiding true information or sharing wrong information. So the possible attacks on Cooperative CRN and mitigating solutions [22] also have been surveyed in this paper. While several general and specific [5–7] reviews of the spectrum sensing methods and cooperative spectrum sensing literature exist; this paper is intended to provide the reader with a generic and comprehensive view of spectrum sensing techniques, as well as the most recent developments and emerging trends in the field.

II. SPECTRUM SENSING FRAMEWORK

In CRN the SUs can access the licensed spectrum using two main approaches: (i) the SUs are allowed to access a frequency band only when it is detected idle, and (ii) the SUs coexist with the PUs under the condition of protecting the latter from harmful interference.

A. Conventional spectrum sensing Architecture:

The CR system divides a frame into sensing (quiet time) and data transmission time slots as shown in Fig. 1. In sensing period SUs sense presence of PU' signal and start data transmission when they finds the spectrum idle. When the SUs detect presence of the PU in the spectrum they stop transmission or switch to another idle frequency spectrums as soon as possible [26]. The mathematical analysis of the sensing-throughput tradeoff is given in [27], which proves that the formulated problem has one optimal sensing time which yields the highest throughput for the secondary network**.**

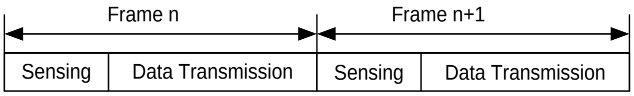

Fig.1. Frame structure of the conventional opportunistic spectrum access cognitive radio networks.

Since periodic spectrum sensing over the entire PU spectrum always interrupts the SU data transmission in the sensing interval, which degrades throughput of the SU, while the continuous sensing of the PU's spectrum improves spectrum detection probability. To alleviate the SU interruption problem during data transmission, the PU band is divided into two subbands, one for opportunistic SU data transmission, and the other for continuous spectrum sensing [28] as shown in Fig. 2 . Based on the PU band division, the average SU transmission delay is reduced by selecting the proper bandwidth for spectrum sensing within each frame. Since different SUs may have different requirements on their quality of services, so the achievable average SU throughput is maximized by choosing the optimal sensing bandwidth within multiple adjacent frames.

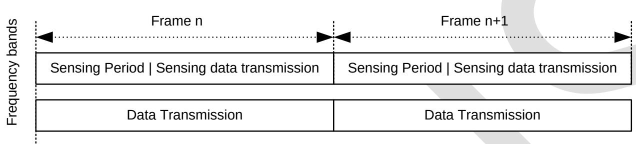

Fig. 2 data transmission and spectrum sensing using frequency division technique

A new Cognitive Radio design proposed to in [26, 33] to improve the spectrum detection probability and throughput of SUs. The SUs use signal feature based detectors / cyclostationary detector to distinguish PU and SUs from the received signal. The spectrum sensing and SUs data transmission are performed simultaneously as shown in Fig. 3. This technique allows SUs to sense and transmit data simultaneously for complete duration of the frame. Hence the large sensing and data transmission duration improves spectrum detection probability and SU's throughput greatly.

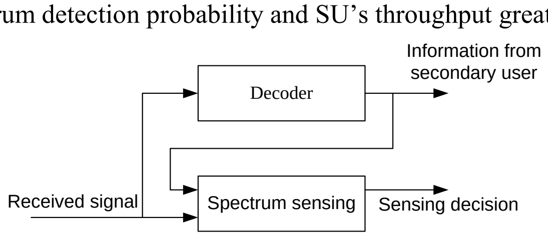

Fig. 3 Architecture for data transmission and spectrum sensing in parallel

B. External sensing framework:

In external sensing based cooperative cognitive radio network a separate control frequency band is used to share the spectrum sensing information among SUs while the sensed frequency band is used only for data transmission in perspective of SUs [5]. In external sensing architecture SUs continuously sense the licensed spectrum which improves detection probability and SUs throughput but at the cost of requirement of additional infrastructure as shown in Fig.4.

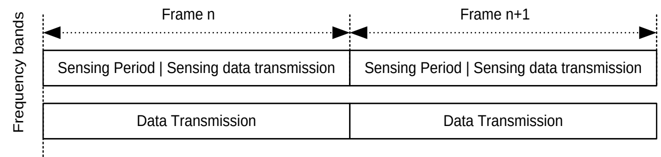

Fig.4 Frame structure of External sensing, having dedicated sensing frequency band

C. Spatial-temporal two dimensional sensing framework:

At a given time and different locations considering the heterogeneous spectrum availability, the SUs may experience different spectrum access opportunities. This framework improves the opportunity detection performance, which exploits correlations in time and space simultaneously by effectively fusing sensing results in a spatial-temporal sensing window [29]. In [30], PU localization algorithms are given that jointly utilizes received-signal strength (RSS) and direction-of-arrival (DoA) measurements by evaluating the Cramer-Rao Bound (CRB). The knowledge about location of PUs could enable several key features in cognitive radio (CR) networks including improved spatio-temporal sensing, intelligent location-aware routing, as well as aiding spectrum policy enforcement.

D. Underlay-Overlay Cognitive Radio Architecture:

In an underlay system, SUs are allowed to share the channel simultaneously with PUs (with the restriction on interference level) but not in an overlay system. In overlay system SUs are allowed to access spectrum only if PU's signal is absent or the spectrum is detected idle. In Underlay-Overlay Cognitive Radio networks SUs can switch between overlay and underlay modes of operation in order to improve its throughput with limited sensing capability (i.e. sensing only one channel at a time). It is found that proper selection of transmission mode can provide greater improvement in throughput for a secondary user. The mode selection depends on the transition characteristics of primary users and the throughput ratio between the two modes of operation [31].

E. Radiobot: Wideband spectrum sensing architecture

Autonomous cognitive radio architecture, referred as Radiobot [32], is a self-learning and self-reconfigurable without any prior knowledge of the RF environment used for wideband spectrum sensing. The Radiobot applies a blind energy detection followed by a Cyclostationary detection method to detect the active signals and extract their underlying periodic properties as reflected in cyclic frequencies. These extracted signal features are classified based on the Chinese restaurant process (CRP) and a learning algorithm is applied to achieve autonomous self reconfiguration of the sensing module.

III. SPECTRUM SENSING METHODS

Spectrum sensing is the most critical components of cognitive radio technology. By sensing and adapting to the environment, a cognitive radio is able to fill in spectrum holes and serve its users without causing harmful interference to the licensed user. The missed detection at the unlicensed user causes a channel conflict that causes interference to licensed users, and the false alarm in the detection causes the loss of channel opportunity for the unlicensed users. Therefore, the accurate spectrum sensing is a crucial mechanism to enable the cognitive radio. A number of different methods have been proposed in literature of spectrum sensing. These methods decide presence of signals based on energy detection, and some other characteristics of the signal. In this section, the most common spectrum sensing methods in the Cognitive Radio literature are explained.

A. Energy Detector Based Sensing:

This is the most common used method due to its simplicity, low computational and implementation complexities. In this method receiver do not need any knowledge of primary user's signal. The signal is detected by comparing the energy level of received signal and threshold level which depends on the noise floor [5]. The challenges associated with this method are poor detection performance under low Signal-to-Noise ratio (SNR), selection of the threshold level to detect primary user and inability to differentiate interference from primary users and noise.

For mathematical analysis of the energy detector [5], let us assume that the received signal has the following form

$$y(n) = s(n) + w(n) \tag{1}$$

Where y(n) is the received signal, s(n) is the signal to be detected, w(n) is the additive white Gaussian noise sample and n is sample index. The decision metric for energy detector can be written as

$$M = \sum_{n=1}^{N} |y(n)|^2 \tag{2}$$

By comparing the decision metric M with a threshold λ_E the spectrum occupancy decision is made. The decision is made by distinguishing between following hypothesizes:

$$H0 \quad : \quad y(n) = w(n), \tag{3}$$

$$H1 \quad : \quad y(n) = s(n) + w(n). \tag{4}$$

Probability of detection P_D and probability of false alarm P_F are used to analyze performance of the spectrum detector. P_D is probability of detecting a primary user signal on considered frequency spectrum when the signal is truly present. Thus a large detection probability is desired. It can be formulated as

$$P_D = \Pr(M > \lambda_E|H1) . \tag{5}$$

$$P_F = \Pr(M > \lambda_E|H0) . \tag{6}$$

P_F is the false detection probability which indicates that the test incorrectly decides that the primary user signal is present in the considered frequency spectrum. P_F should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λ_E can be selected in such a way that gives optimum values of P_D and P_F.

Missed probability detection is expressed as:

$$P_M = 1- P_D \tag{7}$$

The threshold level λ_E depends on noise variation. Thus to maintain performance of the detector it's necessary to measure noise dynamically. Then the noise value is used to choose the threshold level for constant false alarm rate. In [35], it is given that the sequential energy detector uses the smaller average number of samples than the energy detector. The sequential detector is designed using the iterative formulation of likelihood ratio of the sample energy for decision. The performance of the energy detector depends upon SNR of the received signal. Hence SNR can be improved by multi antenna secondary user [36], which results in improvement of spectrum detection probability. A goodness of fit test is applied for spectrum called as Anderson-Darling sensing [37]. Anderson-Darling sensing has much higher sensitivity to detect an existing signal than energy detector-based sensing, especially in a case where the received signal has a low signal-to-noise ratio (SNR) without prior knowledge of primary user signals. In [38], it is given that the Anderson-Darling sensing outperforms the energy detection method only when the primary user signal is assumed to be static during sensing interval, which is a very rare case in cognitive radio. The energy detection based sensing methods are simple and easy to implement because these methods don't require any prior knowledge of primary signal but can't distinguish PU's and SU's signals.

B. Waveform-based sensing

This method is applicable to systems with known signal patterns and it is also known as waveform-based sensing or coherent sensing because some known signal patterns like preambles, midambles, regularly transmitted pilot patterns, spreading sequences etc., are used for frequency synchronization and other purpose. A preamble is a known sequence transmitted before each burst and a midanble is transmitted in the middle of the burst or slot. In this method the sensing is performed by correlating the received signal with a known copy of itself. In [5], it is shown that the waveform

based sensing outperforms the energy detector based sensing in reliability and convergence time. It is also shown that the performance of the sensing algorithm increases as the length of the known signal pattern increases.
Using the same model in (1), the waveform-based sensing metric can be obtained as [5]

$$M = \mathrm{Re}[\sum_{n=1}^{N} y(n)s^*(n)] \tag{8}$$

Where * represent the complex conjugate operation. In the absence of primary user, the metric value becomes

$$M = \mathrm{Re}[\sum_{n=1}^{N} w(n)s^*(n)]. \tag{9}$$

Similarly in presence of primary user's signal, the sensing metric becomes

$$M = \sum_{n=1}^{N} |s(n)|^2] + \mathrm{Re}[\sum_{n=1}^{N} w(n)s^*(n)]. \tag{10}$$

The decision on the presence of the primary user's signal can be made by comparing the decision metric M against a fixed threshold λ_w. The waveform-based sensing requires short sensing measurement time but it is susceptible to synchronization error.

C. Cyclostationarity-Based Sensor

This is a method to detect primary user transmission based on cyclostationary features of the received signal. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation [5]. The periodicity can be induced intentionally to assist spectrum sensing. Cyclic correlation function is used to detect signals in the desired spectrum. The Cyclostationarity based detection algorithms can differentiate primary user signals from different type of transmissions and noise, which addresses the limitation of energy detection based sensing algorithms. This is due to fact that modulated signals are Cyclostationary with spectral correlation because of the redundancy of signal periodicities, while noise is wide sense stationary (WSS) with no correlation [5].
The cyclic spectral density (CSD) function of a received signal (1) can be calculated as [5]

$$S(f, \alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau)\, e^{-j2\pi f\tau}, \tag{11}$$

Where

$$R_y^{\alpha}(\tau) = E[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n} \tag{12}$$

is the cyclic autocorrelation function (CAF) and α is the cyclic frequency. The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of the transmitted signal s(n). Cyclic frequencies can be assumed to be known or they can be extracted and used as feature for identifying transmitted signals. However the merits of this methods comes at the expense of increased overhead and band width loss due to additional transmission required for preamble, midamble and spreading sequences etc. In OFDM based technology like WIMAX, Pilot subcarriers are used for channel synchronization and to generate system specific signatures or cyclic- frequencies at certain frequencies. Even some times the preamble sequence contains information of primary network. One limitation of this sensing method is all the SUs need prior knowledge of cyclic features of the PU's signals. The PU and SUs must have different cyclic frequencies to distinguish them.

D. Matched filter based sensing

Matched filtering is known as optimum method for detection of primary users when the transmitted signal is known [5]. The main advantage of matched filtering is the short time to achieve a certain probability of misdetection as compare to other methods discussed in this section. However, matched filtering requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping and frame format. Since cognitive radio needs receivers for all signal type, hence the power consumption and implementation complexity are large.

E. Radio Identification based sensing

A complete knowledge about the spectrum characteristic can be obtained by identifying the transmission technologies used by primary users [5]. Such types of identification methods provide higher spectrum sensing accuracy. For example, assume that a primary user's technology is identified as Bluetooth signal. Since the range of Bluetooth signal is around 10 meter so the cognitive radio can use this information for extracting some useful information in space dimension. In [34], OFDM based spectrum sensing algorithms are presented. These spectrum sensing algorithms are based on Time-Domain Symbol Cross-Correlation (TDSC-MRC and TDSC-NP methods) and can be applied to all existing wireless OFDM systems like WiFi, WiMAX, and LTE etc. The results in [34] show that the TDSC-MRC method outperforms the Cyclic prefix (CP) method for all values of CP ratio considered. The detection performance of the CP method degrades dramatically when the CP ratio becomes small, while the performance of TDSC methods remains same for different CP ratios. It is also given in the same paper that the spectrum sensing performance of the Cyclostationarity-based methods is either similar, or worse than that of the CP method. Hence, for OFDM systems the TDSC based sensing algorithm outperforms CP and Cyclostationary methods.

F. Hybrid detectors:

This type of detectors consists of combination of above given algorithms to address limitations of the individual sensing techniques and improves spectrum sensing probability. For example the energy detector can't distinguish between PU's and SU's signals, while Cyclostationary detector requires prior knowledge of Cyclostationary frequency of PU. So a Cyclo-energy detector (CED) [6], which is combination of Cyclostationary feature based detector and energy detector can address the limitations.

The CED can detect the PU when the PU and the SUs coexist in the same channel and When SUs don't know Cyclostatonaty frequency of PU, the CED still can sense presence of the PU. This sensing algorithm works on the principle that variance of noise has already been estimated by the sensors, the PU's received power can be calculated by subtracting the noise's and the SU's powers from the total received power on the condition that the power of SU is estimated by its Cyclostationary features. Thus, the presence of PU can be determined by comparing the PU's power with a threshold. The merits of this algorithm are: (i) it can detect the presence of the PU when the channel is being used by the SU. (ii) it requires that the SU's and PU's signals have different cycle frequencies when PU is Cyclostationary and (iii) it does not need to search the cyclic frequencies.

An algorithm for wideband Spectrum Sensing and Non-Parametric Signal Classification for Autonomous Self-Learning Cognitive Radios is given in [29]. This method is known as *Radiobot due to its* self-learning and self-reconfiguration properties. Without any prior knowledge of the RF environment, the Radiobot applies a sequence of increasingly sophisticated processing steps to detect and identify the sensed signals. This method applies a blind energy detection followed by a Cyclostationary detection method to detect the active signals and extract their underlying periodic properties as reflected in cyclic frequencies. These extracted signal features are classified based on the Chinese restaurant process (CRP) and a learning algorithm is applied to achieve autonomous self reconfiguration of the sensing module.

G. Other sensing methods

Other alternative spectrum sensing methods include multi-taper spectral estimation, wavelet transform based estimation, Hough transform and time frequency analysis. Random Hough transform [5] of received signal is used for identifying the presence of radar pulses in the operating channels of IEEE 802.11 system. Wavelets are used to detect edges between empty and occupied frequency band. In [35], a spectral covariance sensing (SCS) algorithm exploits the different statistical correlation of the received signal and noise in the frequency domain. To decide presence of primary signal the test statistics are computed from the covariance matrix of a partial spectrogram and compared with a decision threshold. The SCS is highly robust to noise uncertainty, improves sensitivity significantly for the same dwell time. In [36], a joint algorithm is given using cumulants based on fractional lower order statistics for spectrum sensing and automatic modulation classification (AMC). The spectrum sensing is done using cumulants derived from fractional lower order statistics and automatic modulation classification is done by maximizing the likelihood function among the multiple hypotheses created for the multiple modulation schemes. This algorithm can work when the cognitive radio receiver has no information about the channel or the modulation type.

IV. COOPERATIVE SENSING

Cooperative sensing techniques are used to mitigate fading over wireless channels, shadowing effect or hidden node problem in multistory building environment along with PU detection and improve the detection probability. In cooperative detection methods spectrum sensing information from multiple secondary users are incorporated for primary user detection. The SUs can use any of the above discussed sensing methods for PUs detection locally but the final decision is achieved by data fusion or decision fusion from the information received from SUs for cooperative sensing of PUs [9]. The cooperative detection can be implemented either in a centralized (infrastructure based) or in a distributed manner (infrastructure less) [1]. In the centralized method, the Cognitive Radio base-station plays a role to gather all sensing information from the SUs and detects the spectrum holes. On the other hand, distributed methods require exchange of observations among secondary users and based on shared information the SUs individually take decision regarding presence of PUs. Cooperative detection methods allow mitigating the multi-path fading and shadowing effects, which improves the detection probability in a heavily shadowed environment [1]. The benefits of cooperative sensing are reduction in detection time and improvement in agility [3-4]. The agility gain for spectrum sensing in two user and multi user cooperative cognitive networks are given in [12-13] with detailed mathematical analysis.

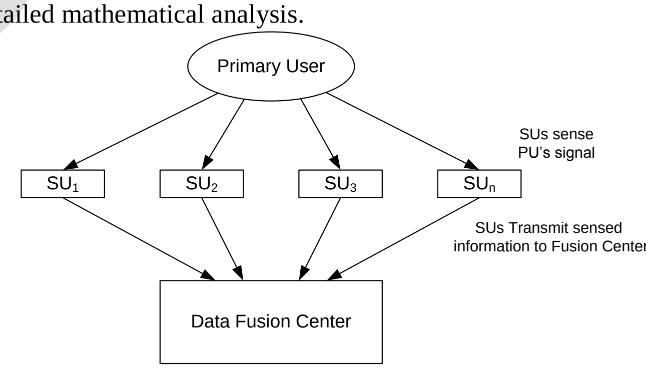

Fig. 5 Cooperative spectrum sensing model

In [8], a collaborative spectrum sensing using censored energy detection is analyzed. The censored energy detector selects measurements of different collaborating users by comparing them with two pre-determined limits and only uses measurements that are smaller than the lower limit or larger than the upper limit before applying them to collaborative spectrum sensing.

A transmit diversity based cooperative spectrum sensing method is given in [6]. In case of multiple CRs as a virtual antenna array, space-time coding and space frequency coding are applied into CR networks over flat-fading and frequencyselective fading channels, respectively. Relay diversity has been used to mitigate heavy shadowing based cooperative spectrum sensing. Hence the relay diversity can further improve the cooperative spectrum sensing performance [6,14]. In [37] SUs work cooperatively for optimal sensing and access policies that maximize the total secondary throughput on primary channels accrued over time. In Fig. 6 an optimum cooperative spectrum sensing framework is given for multiple PUs and multiple SUs for multi-channel spectrum sensing and channel access. In [38] hedonic coalition formation game is proposed, where a coalition corresponds to the SUs that have chosen to sense and access a particular channel. The value function of each coalition and the utility function of each SU take into account both the sensing accuracy and the energy consumption. An optimal multi-channel cooperative sensing strategy [17] with energy detection with soft decision rule is employed with two sensing modes: slotted time sensing mode and continuous-time sensing mode.

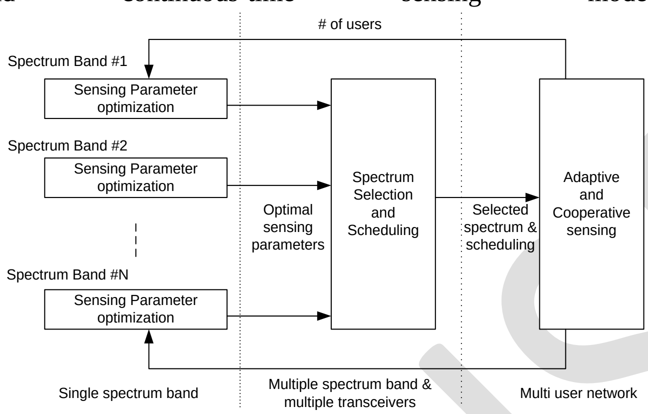

Fig. 6 Optimal cooperative spectrum sensing framework

An energy detection based cooperative spectrum sensing technique is given in [20], which optimizes the detection performance in an efficient and implementable way along with a customized algorithm for fast spectrum sensing for a large network which requires fewer than the total number of cognitive radios in cooperative spectrum sensing while satisfying a given error bound. In [11], Convex optimization is applied to trade sensing time samples for additional reporting time slots to increase the reporting signal to Noise ratio in cooperative sensing which minimizes the false alarm probability.

In cooperative sensing to minimize cooperation overhead the cooperative users sends only one bit decision to fusion center [23]. An adaptive and cooperative spectrum sensing method is proposed in [30], where the sensing parameters are optimized adaptively to the number of cooperating users.

A. Fusion schemes in cooperative spectrum sensing:

Fusion schemes are used to combine the sensing information from the cooperative secondary users and take final decision about presence of PUs. In centralized cooperative cognitive network, a central node or base station takes the decision based on the information collected from cooperative SUs in the network but in distributed cooperative cognitive network all the secondary users take the decision individually based on the information collected from cooperative SUs in the network. In case of decision fusion the SUs send their decision using one bit or multiple bit binary code but in data fusion the SUs send their actual data collected using local sensing techniques [15, 39]. At fusion centre received sensing data can be combined using logical OR-rule or AND-rule [39]. In case of the OR-rule, the fusion center only needs to be informed if any of the local decision of cooperating SU is a "1". While in case of the AND-rule, the fusion center needs binary information from all cooperating SUs in the network and if all the local decisions of cooperating SUs are "1" then only the fusion center decides presence of the PU. The AND-rule gives better detection accuracy but at the cost of higher missed detection rate. A moderate “k-out-of-n” fusion rule is given in [9] to get best of OR-rule and AND-rule.

The combination of sensing information is further classified as soft combination and hard combination [15]. In soft combination, CR users send their original sensing information to the base station without any local processing and the decision is made at the base station by combining them appropriately. While in hard combination, CR users send their processed sensing information in form of binary local decision and the final decision is made at the base station by combining the binary information using OR rule or AND rule. In [15], a new 2-bit hard combination technique which given better detection performance by dividing the whole range of the observed energy into more regions, and allocate larger weights to the upper regions and smaller weights to the lower regions. A weighted decision fusion center [8] is given, in which the weight for each SU is decided as per its detected SNR.

B. Attacks on cooperative Cognitive network and mitigations

In cognitive radio networks (CRN), cooperative spectrum sensing (CSS) is usually performed periodically due to the uncertain activity of PUs and all the SUs are expected to participate in CSS fairly. Generally in CRN all the SUs broadcast their sensed information; therefore a SU can read sensed information of its neighboring SUs. Hence a selfish SU may select a frequency (or number of times) for CSS participation to maximize its interest. Two solutions are suggested of this problem in [10]. The first solution is broadcasting only encrypted sensing information which can be read by base station of the CRN. The second solution is the base station of the CRN can schedule transmission time to SUs based on their frequency (or number of times) for CSS participation.

In CSS a malicious SU may send false sensing information and can degrade detection performance of the fusion centre. To detect the potential attacker and then exclude the attacker’s report for spectrum sensing an abnormality-detection approach, based on the abnormality detection in data mining, is proposed [7, 19, 59, 60, 61].For the case in which the attacker does not know the reports of honest secondary users (called independent attack) and for the case in which the attacker knows all the reports of other secondary users, based on which the attacker sends its report (called dependent attack). The mitigation approaches can be categorized into two types, namely passive and proactive. Passive approaches apply the techniques in robust signal processing, which limit the possible impact from attackers. Proactive approaches let honest secondary users detect malicious users and then reject their reports.

V. CONCLUSION

Now a day's huge public demand and economic potential of wireless communication services has created frequency spectrum scarcity. The development of different type of communication technologies, the limited and costly frequency spectrum, the demand of different type of real time and non-real time wireless services have raised new challenges and problems. The limited amount of available frequency spectrum and very high license cost has forced to develop solutions which can improve spectrum utilization efficiency. The Cognitive Radio Network (CRN) is solution to improve spectrum utilization efficiency. In CRN the performance of spectrum sensing techniques are very important to maintain QoS of primary users and provide transmission opportunity to secondary users.

In this paper, we have reviewed different type of spectrum sensing techniques, cooperative spectrum sensing techniques, their merits and limitations. The development of new and robust spectrum sensing techniques to address existing limitations, developing demand and suitability based cooperative sensing techniques, identifying possible attacks on CRN, developing mitigating solutions of the attacks, interference avoidance techniques for primary users, and sharing the sensed spectrum optimally among secondary users can be considered as some of the open research areas.

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