International Journal of Engineering and Technical Research (IJETR)
ISSN: 2321-0869 (O) 2454-4698 (P) Volume-7, Issue-7, July 2017

Centralized Cooperative Spectrum Sensing Optimization through Maximizing Network Utility and Minimizing Error Probability in Cognitive Radio: A Survey

Tarangini Shukla, Mr. Pradeep Yadav

***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 introduced to be an effective method to improve the detection performance by exploiting spatial diversity. Cooperative sensing is the most sophisticated approach in spectrum sensing depends on base of sharing information to eliminate error in spectrum sensing mechanism. 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 analyzed by the fundamental components called the elements of cooperative sensing, including cooperation models, sensing techniques, hypothesis testing, data fusion, control channel and user selection, and knowledge base. The open research challenges related to each issue in cooperative sensing are also discussed. In this review paper, we have discussed the Cooperative sensing approach, different optimization techniques for spectrum searching and sharing features in cognitive radio.**

***Index Terms*— cognitive radio, energy detection, Co-operative sensing, Optimization, Spectrum sensing.**

I. INTRODUCTION

The rapid growth in wireless communications has contributed to a huge demand on the deployment of new wireless services in both the licensed and unlicensed frequency spectrum. However, recent studies show that the fixed spectrum assignment policy enforced today results in poor spectrum utilization. To address this problem, cognitive radio (CR) [1,2] has emerged as a promising technology to enable the access of the intermittent periods of unoccupied frequency bands, called white space or spectrum holes, and thereby increase the spectral efficiency. The fundamental task of each CR user in CR networks, in the most primitive sense, is to detect the licensed users, also known as primary users (PUs), if they are present and identify the available spectrum if they are absent. This is usually achieved by sensing the RF environment, a process called spectrum sensing [1–4]. The objectives of spectrum sensing are twofold: first, CR users should not cause harmful interference to PUs by either switching to an available band or limiting its interference with PUs at an acceptable level and, second, CR users should efficiently identify and exploit the spectrum holes for required throughput and quality-of service (QoS). Thus, the detection performance in spectrum sensing is crucial to the performance of both primary and CR networks.

The detection performance can be primarily determined on the basis of two metrics: probability of false alarm, which denotes the probability that a PU is present when the spectrum is actually free, and probability of detection, which denotes the probability that a PU is present when the spectrum is indeed occupied by the PU. Since a miss in the detection will cause the interference with the PU and a false alarm will reduce the spectral efficiency, it is usually required for optimal detection performance that the probability of detection is maximized subject to the constraint of the probability of false alarm.

Fig.1 shows the spectrum access technique, it is a way to overcome the spectrum management and improve the efficiency. A spectrum hole or white space is band of frequencies assigned to a primary user but at a specific time and particular geographic area, the band is not being utilized by that user. These white spaces can occur in two fashions, in time or in space. When a primary user is not transmitting at a given specific time, then there is a temporal spectrum hole, if a primary user is transmitting in a certain portion of the spectrum but it is too far away from the secondary user so that the secondary user or cognitive user can reuse the frequency, then a spatial spectrum hole exists. The main concept of the cognitive radio is to continuously monitor the radio spectrum, detect the occupancy of the spectrum and then opportunistically use spectrum holes with minimum interference with primary user. [5] - [7].

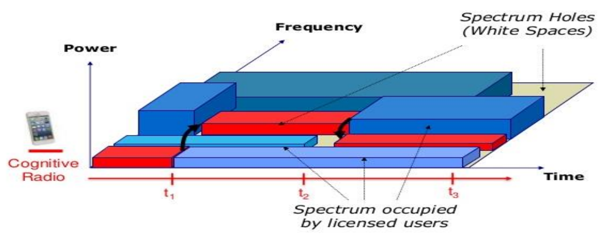

Fig.1: Spectrum Hole Concept

Tarangini Shukla, Department Electronics & Communication Engineering, M.Tech Scholar, Kanpur Institute of Technology, Kanpur, India.

Mr. Pradeep Yadav, Associate Professor, Department of Electronics & Communication Engineering, Kanpur Institute of Technology, Kanpur, India.

The main idea of cooperative sensing is to enhance the sensing performance by exploiting the spatial diversity in the observations of spatially located CR users. By cooperation, CR users can share their sensing information for making a combined decision more accurate than the individual decisions [8]. The performance improvement due to spatial diversity is called cooperative gain. The cooperative gain can be also viewed from the perspective of sensing hardware. Owing to multipath fading and shadowing, the signal-to-noise ratio (SNR) of the received primary signal can be extremely small and the detection of which becomes a difficult task. Since receiver sensitivity indicates the capability of detecting weak signals, the receiver will be imposed on a strict sensitivity requirement greatly increasing the implementation complexity and the associated hardware cost. More importantly, the detection performance cannot be improved by increasing the sensitivity, when the SNR of PU signals is below a certain level known as a SNR wall [9]. Fortunately, the sensitivity requirement and the hardware limitation issues can be considerably relieved by cooperative sensing.

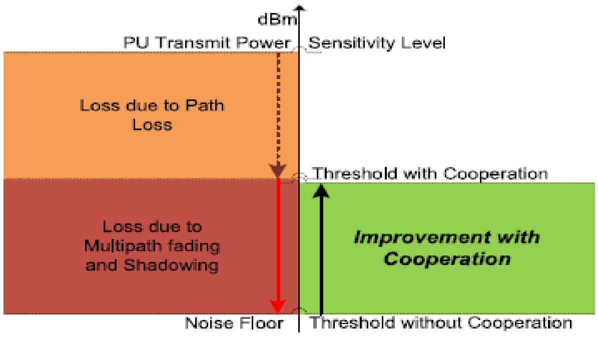

Fig. 2: Improvement of sensitivity with cooperative sensing

As shown in Fig. 2, the performance degradation due to multipath fading and shadowing can be overcome by cooperative sensing such that the receiver's sensitivity can be approximately set to the same level of nominal path loss without increasing the implementation cost of CR devices. However, cooperative gain is not limited to improved detection performance and relaxed sensitivity requirement. For example, if the sensing time can be reduced due to cooperation, CR users will have more time for data transmission so as to improve their throughput.

In this case, the improved throughput is also a part of cooperative gain. Thus, a well-designed cooperation mechanism for cooperative sensing can significantly contribute to a variety of achievable cooperative gain.

In [10], Cabric et al. identified the ''three main questions regarding cooperative sensing'' as follows [10]

- How can cognitive radios cooperate?
- How much can be gained from cooperation?
- What is the overhead associated with cooperation?

These three questions surrounding the issues of Cooperation Method, Cooperative Gain, and Cooperation Overhead, respectively, should be addressed in every cooperative sensing scheme. In this paper, we aim to survey the state of-the-art research in cooperative sensing centering these three issues by first analyzing the cooperation method with the fundamental components of cooperative sensing and then presenting the impacting factors of achievable cooperative gain and incurred cooperation overhead. In addition, we identify open research challenges related to each issue in cooperative sensing along with the discussion.

II. Classification and Framework of Cooperative Sensing

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

2.1. 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 given below,

$$x(t) = \begin{cases} n(t), & H0 \\ h(t) * s(t) + n(t) & H1 \end{cases} \quad (1)$$

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), H0 and H1 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 Pd and false alarm Pf are defined as [11]

$$P_d = P\{decision = H1|H1 = P\{y > \lambda\,|H1\} \quad (2)$$

$$P_f = P\{decision = H1|H0 = P\{y > \lambda\,|H0\} \quad (3)$$

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

$$P_m = 1 - Pd = P\{decision = H0|H1 \quad (4)$$

The plot that demonstrates Pd versus Pf 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 Qd and Qf , respectively.

2.2. 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]. These three types of cooperative sensing are illustrated in Fig. 3.

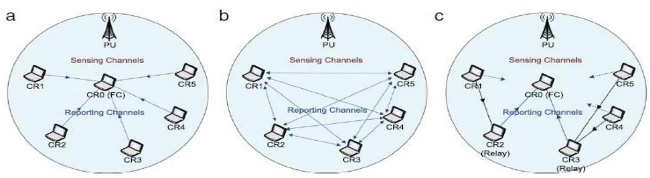

Fig.3: Classification of cooperative sensing: (a) Centralized, (b) Distributed, and (c) Relay-assisted

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. As shown in Fig. 3(a), CR0 is the FC and CR1–CR5 are cooperating CR users performing local sensing and reporting the results back to CR0. For local sensing, all CR users are tuned to the selected licensed channel or frequency band where a physical point-to-point link between the PU transmitter and each cooperating CR user for observing the primary signal is called a sensing channel. For data reporting, all CR users are tuned to a control channel where a physical point-to-point link between each cooperating CR user and the FC for sending the sensing results is called a reporting channel. Note that centralized cooperative sensing can occur in either centralized or distributed CR networks. In centralized CR networks, a CR base station (BS) is naturally the FC. Alternatively, in CR ad hoc networks (CRAHNs) where a CR BS is not present, any CR user can act as a FC to coordinate cooperative sensing and combine the sensing information from the cooperating neighbors.
Unlike centralized cooperative sensing, distributed cooperative sensing does not rely on a FC for making the cooperative decision. In this case, CR users communicate among themselves and converge to a unified decision on the presence or absence of PUs by iterations. Fig. 3(b) illustrates the cooperation in the distributed manner. After local sensing, CR1–CR5 shares the local sensing results with other users within their transmission range. Based on a distributed algorithm, each CR user sends its own sensing data to other users, combines its data with the received sensing data, and decides whether or not the PU is present by using a local criterion. If the criterion is not satisfied, CR users send their combined results to other users again and repeat this process until the algorithm is converged and a decision is reached. In this manner, this distributed scheme may take several iterations to reach the unanimous cooperative decision.
In addition to centralized and distributed cooperative sensing, the third scheme is relay-assisted cooperative sensing. Since both sensing channel and report channel are not perfect, a CR user observing a weak sensing channel and a strong report channel and a CR user with a strong sensing channel and a weak report channel, for example, can complement and cooperate with each other to improve the performance of cooperative sensing. In Fig. 3(c), CR1 CR4, and CR5, who observe strong PU signals, may suffer from a weak report channel. CR2 and CR3, who have a strong report channel, can serve as relays to assist in forwarding the sensing results from CR1, CR4, and CR5 to the FC. In this case, the report channels from CR2 and CR3 to the FC can also be called relay channels. Note that although Fig. 3(c) shows a centralized structure, the relay-assisted cooperative sensing can exist in distributed scheme. In fact, when the sensing results need to be forwarded by multiple hops to reach the intended receive node, all the intermediate hops are relays. Thus, if both centralized and distributed structures are one-hop cooperative sensing, the relay-assisted structure can be considered as multi-hop cooperative sensing.

2.3. Framework of Cooperative Sensing

The framework of cooperative sensing consists of the PUs, cooperating CR users including a FC, all the elements of cooperative sensing, which will be introduced in next section, the RF environment including licensed channels and control channels, and an optional remote database. Fig. 4 illustrates the framework of centralized cooperative sensing from the perspective of the physical layer. In this framework, a group of cooperating CR users performs local sensing with an RF frontend and a local processing unit. The RF frontend can be configured for data transmission or spectrum sensing. In addition, the RF frontend includes the down-conversion of RF signals and the sampling at Nyquist rate by an analog-to-digital converter (ADC). The raw sensing data from the RF frontend can be directly sent to the FC or be locally processed for local decision.

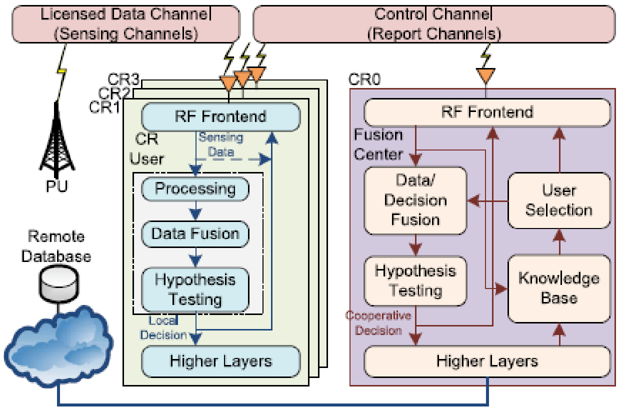

Fig. 4: Framework of centralized cooperative sensing

To minimize the bandwidth requirement of the control channel, certain local processing is usually required. The processing includes the calculation of test statistics, and a threshold device for local decision. Once the raw sensing data or the local decisions are ready, a medium access control (MAC) scheme is required to access the control channel for reporting the sensing results. The sensing results may also be used by higher network protocol layers for spectrum-aware routing selection [16] for example. The FC in the framework is a powerful CR user, which includes all the capabilities of a regular CR user and the additional user selection capability with the assistance of a embedded knowledge base. If the FC is as powerful as a base station, it may have the connection to the remote database for PU activity and white space information. For the framework of distributed cooperative sensing, all CR users are essentially the same and similar to the FC in the framework of centralized cooperative sensing with an optional and smaller knowledge base for local use.

3. Elements of Cooperative Spectrum Sensing(CSS)

The 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 analyze and present the process of cooperative sensing by seven key elements: (i) cooperation models, (ii) sensing techniques, (iii) control channel and reporting, (iv) data fusion, (v) hypothesis testing, (vi) user selection, and (vii) knowledge base. As shown in Fig. 5, these elements are briefly introduced as follows:

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

2. 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.*

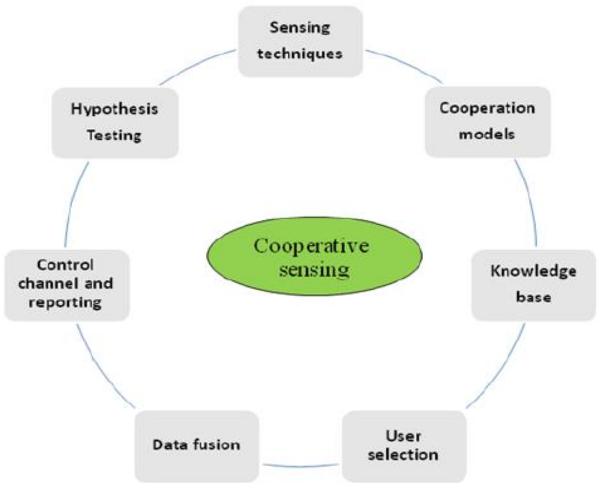

Fig. 5: Elements of cooperative spectrum sensing

3. 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.

4. 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.

5. 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.

6. 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.

7. 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.

4. Sensing Techniques

Regardless of the cooperation models, the process of cooperative sensing starts with local spectrum sensing at each cooperating CR user. Similar to traditional spectrum sensing without cooperation, the objective of the local spectrum sensing is primary signal detection. Sensing techniques are crucial in cooperative sensing in the sense that how primary signals are sensed, sampled, and processed is strongly related to how CR users cooperate with each other. Thus, sensing techniques are one of the fundamental elements in cooperative sensing.

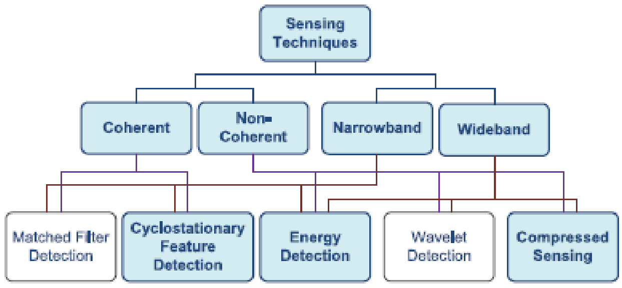

Fig. 6: Classification of sensing techniques

From the perspective of signal detection, sensing techniques can be classified into two broad categories: coherent and non-coherent detection. In coherent detection, the primary signal can be coherently detected by comparing the received signal or the extracted signal characteristics with a priori knowledge of primary signals. In non-coherent detection, no a priori knowledge is required for detection. Another way to classify sensing techniques is based on the bandwidth of the spectrum of interest for sensing: narrowband and wideband. The classification of sensing techniques is shown in Fig. 6. Note that our discussion here focus on the most popular sensing techniques in cooperative sensing rather than an exhaustive search for all primary detection methods. Thus, we discussed three most popular sensing techniques in cooperative sensing: energy detection, cyclostationary feature detection, and compressed sensing. The former two techniques are mainly for narrowband sensing while the latter is primarily used for wideband sensing.

5. Control Channel and Reporting

In cooperative sensing, a common control channel (CCC) [1,17] is commonly used by CR users to report local sensing data to the FC or share the sensing results with neighboring nodes. As a result, a control channel is the element of cooperative sensing. The control channel can be implemented as a dedicated channel in licensed or unlicensed bands, or an underlay ultra-wideband (UWB) channel [5]. A MAC scheme for multiple accesses is generally used by all cooperating CR users to access the control channel. From the perspective of the physical layer, a physical point-to-point link from a cooperating CR user to the FC is called a reporting channel. For reporting sensing data, three major control channel requirements must be satisfied in cooperative sensing: bandwidth, reliability, and security.

6. Data Fusion

In cooperative sensing, data fusion is a process of combining local sensing data for hypothesis testing, which is also an element of cooperative sensing. Depending on the control channel bandwidth requirement, reported sensing results may be of different forms, types, and sizes.

In general, the sensing results reported to the FC or shared with neighboring users can be combined in three different ways in descending order of demanding control channel bandwidth: (i) Soft Combining: CR users can transmit the entire local sensing samples or the complete local test statistics for soft decision. (ii) Quantized Soft Combining: CR users can quantize the local sensing results and send only the quantized data for soft combining to alleviate control channel communication overhead. (iii) Hard Combining: CR users make a local decision and transmit the one bit decision for hard combining. Obviously, using soft combining at the FC can achieve the best detection performance among all three at the cost of control channel overhead while the quantized soft combining and hard combining require much less control channel bandwidth with possibly degraded performance due to the loss of information from quantization. In this subsection, we first discuss soft combining and quantized soft combining techniques, and then focus on the fusion rules for decision fusion when the hard combining is used.

6.1 Soft Combining and Quantized Soft Combining

Existing receiver diversity techniques such as equal gain combining (EGC) and maximal ratio combining (MRC) can be utilized for soft combining of local observations or test statistics. In [61], an optimal soft combination scheme based on NP criterion is proposed to combine the weighted local observations. The proposed scheme reduces to EGC at high SNR and reduces to MRC at low SNR. Since such a soft combining scheme results in large overhead, a softened two-bit hard combining scheme is also proposed in [18] for energy detection. In this method, there are three decision thresholds dividing the whole range of test statistics into four regions. Each CR user reports the quantized two-bit information of its local test statistics. This method shows the comparable performance with the EGC scheme with less complexity and overhead.

6.2 Hard Combining and Decision Fusions

CSS deals with the hard decision and soft decision combining techniques. Totally there are six fusion rules are presented in the literature they are soft Optimal Linear mixing, Likelihood Ratio combining, soft Equal Weight combining, and hard decision combined with the AND, OR, and the MAJORITY counting rules. Because of simplicity most famous combining technique is hard decision combining contains OR, AND, and the Majority counting rules. In the implementation of hard decision rules, the fusion centre or central unit produce an n out of M rule that decides on the hypothesis testing at the secondary user. Whenever one secondary user sends output as one i.e., H1, then it comes under OR logic rule similarly if all the secondary users send output as one then it comes under AND logic rule. If majority secondary users send the decision as one then it comes under MAJORITY rule. Assuming uncorrelated decisions, the probability of detection, probability of false alarm and probability of miss detection at the fusion centre are given by [16]:

$$Q_f(K) = \sum_{j=n}^{K} \left(\frac{K}{j}\right) P_f^j \,(1 - P_f)(1 - P_f)^{k-j} \qquad (5)$$

$$Q_m(K) = 1 - \sum_{j=n}^{K} \binom{K}{J} P_{d^j} \,(1 - P_d)^{k-j} \qquad (6)$$

$$Q_m(K) = 1 - Q_m(K) \qquad (7)$$

OR Rule:

OR rule is implemented when the sensing threshold is high and thus only one or very few cognitive radios decision is considered for fusion. Performance of detection in CSS using this rule can be calculated by putting n=1 in the above Equations:

$$Q_d(K) = 1 - \prod_{i=1}^{k}(1 - P_{d,i}) \qquad (8)$$

$$Q_f(K) = 1 - \prod_{i=1}^{k}(1 - P_{f,i}) \qquad (9)$$

$$Q_m(K) = 1 - Q_d(K) \qquad (10)$$

AND Rule:

AND rule is implemented when the sensing threshold is low, and at that time all the cognitive radios decision is considered for fusion. Performance of detection in CSS using this rule will be calculated by putting n=N in the above equations:

$$Q_d(K) = P_{d,i^K} \qquad (11)$$

$$Q_f(K) = P_{f,i^K} \qquad (12)$$

$$Q_m(K) = 1 - Q_d(k) \qquad (13)$$

MAJORITY Rule:

The MAJORITY rule is implemented when more than half of the cognitive radios decision is considered for fusion. Performance of detection in CSS using this rule can be calculated by putting n= $\lfloor N/2 \rfloor$ in the above equations:

$$Q_{d,maj} = \sum_{\lfloor \frac{N}{2} \rfloor}^{N} \binom{N}{K} P_d j \,(1 - P_d)^{K-j} \qquad (14)$$

$$Q_{f,maj} = \sum_{\lfloor \frac{N}{2} \rfloor}^{N} \binom{N}{K} P_f j \,(1 - P_f)^{K-j} \qquad (15)$$

$$Q_m(K) = 1 - Q_d(K) \qquad (16)$$

It can be observed in (5) and (6) that when the value of k is taken as 1 and N, the k out of N rule becomes the OR and AND rules, respectively. The OR rule works best when the number of cooperating CR users is large. Similarly, the AND rule works well when the number of cooperating users is small. The majority rule can be obtained from the k out of N rule under the condition when k ≥ N/2. Thus, it is important to determine the optimal value of k for which the detection errors are minimized. It can be shown that the optimal value of k depends on the detection threshold. For a small fixed threshold, the optimal rule is the AND rule, i.e., k = N. Similarly, for a fixed very large threshold, the OR rule (k = 1) is said to be optimal. The k out of N rule is also equivalent to Counting Rule or Voting Rule when the threshold for determining H1 equals k. In [19], the proposed cooperative sensing scheme uses the k out of N rule for data fusion at the FC. The optimal value of k and the optimal sensing time are obtained by optimizing the average achievable throughput subject to the detection performance.

7. User Selection

The selection of CR users for cooperative sensing plays a key role in determining the performance of cooperative sensing because it can be utilized to improve cooperative gain and address the overhead issues. For example, when cooperating CR users experience correlated shadowing, it is shown in [7] that selecting independent CR users for cooperation can improve the robustness of sensing results. Moreover, removing malicious users from cooperation ensures the security and the reliability of the network. In Section 4, we will discuss how user selection can be used to address overhead issues such as correlated shadowing, cooperation efficiency, security, energy, and mobility. In this subsection, we present the centralized and cluster based user selection schemes in cooperative sensing.

8. Knowledge Base

The performance of cooperative sensing schemes largely depends on the knowledge of PU characteristics such as traffic patterns, location, and transmits power. The PU information, if available in a database, can facilitate the PU detection. The database that stores all the knowledge of the RF environments is called a knowledge base. Knowledge base is an indispensable element of cooperative sensing because it can be utilized to assist, complement, or even replace cooperative sensing for detecting PU signals and identifying the available spectrum.
Knowledge base serves as two roles in cooperative sensing: (i) to enhance the detection performance by utilizing the accumulated knowledge and the learned experience such as statistical models in the database and (ii) to alleviate the burden of cooperative sensing by retrieving the spectrum information such as a list of PU occupied channels from the database. As shown in Fig. 6, the knowledge base can provide PU information such as locations, tracking; transmit power, and activity in the forms of spatial–temporal–spectral maps for cooperative sensing. In this subsection, we discuss the following knowledge base approaches: radio environment map (REM) [20], received signal strength (RSS) profiles [21], channel gain map [22,23], and power spectral density (PSD) map [24].

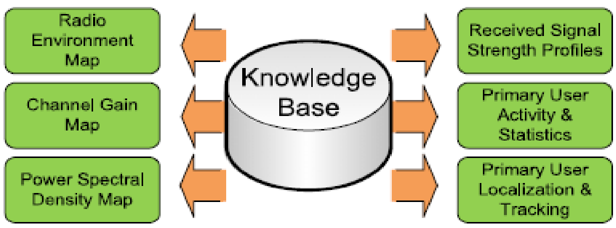

Fig 6: Knowledge base in cooperative sensing

III. OPTIMIZATION IN COGNITIVE RADIO NETWORK

Various modern heuristic algorithms have been developed for solving numeric optimization problems. These algorithms can be divided into different groups depending on the criteria being considered, such as population based, iterative based, stochastic, etc. There are mainly two groups of population based algorithms: evolutionary algorithms (EA) and swarm intelligence based algorithms.

1. Genetic Algorithm (GA)
The most reliable evolutionary algorithm is the genetic algorithm which is adaptable to the radio environment. Among the artificial intelligence techniques proposed in the research field of cognitive radio networks, there are expert systems, artificial neural networks, fuzzy logic, hidden markov model and genetic algorithm. These entire decision algorithms adopt different types of reasoning to achieve an optimal solution. But each algorithm has severe limitations that reduced their operational value in real time in cognitive radio network. Fuzzy logic allow approximate solutions to be found in uncertain inputs which do not permits proving that the system has an optimal behavior. Neural networks are most applicable in this field but their computational complexity is higher than other methods. Genetic algorithm is more popular for their rapidity to cover a large space of possible configuration, and thus find the most suitable solution.
What is genetic algorithm?
The genetic algorithm is a method for solving both constrained and unconstrained optimization problems, basically which is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly renovates a population of individual solutions. We can apply the genetic algorithm to solve a several optimization problems that are not well suited for standard optimization algorithms, including various problems in which the objective function is discontinuous, non-differentiable, or highly nonlinear. The main advantage of genetic algorithm is its rapidity to cover a large space of possible configuration and thus find most suitable optimal solution. More advantage of the GA is its random nature and flexibility. GA characterize a radio in form of a chromosomes and genes the users quality of service needs given as input to the GA procedure. We analyze two parameter, available spectrum resources size which is defined by the GA as a population size and the number of defined chromosome genes in the efficiency of spectrum allocation. This approach starts with the definition of the structure of a chromosome. The structure of a chromosome is a sets of genes i.e. frequency, modulation, bit error rate (BER)[13]. The main advantage of the GA is its multi-objective handling capacity [10]. Genetic algorithm has three main features for performing any optimal solution:

- Selection: It randomly selects individuals called parents which contribute to the population at the next generation.
- Crossover: crossover rule combines two parents to form a child for the next generation.
- Mutation: It is a process random change to individual parents to form children.

GA found that best value of parameter to obtain requires QOS specification for cognitive radio. [25-26].

2. Particle Swarm Optimization (PSO)

A popular swarm-intelligence-based algorithm is the Particle Swarm Optimization (PSO) algorithm. PSO is a population based stochastic optimization technique, which is inspired by social behavior of bird Flocking or fish schooling.PSO shares many similarities with evolutionary computation and search techniques such as Genetic Algorithms (GA).PSO is a simple, fast and efficient computational method that optimizes a problem iteratively and trying to improve a detection performance and other parameter‟s. PSO uses the behavior of these social organizations or so called swarm intelligence algorithm. In PSO, each single solution of given problem is a "bird" in the search space.it is called "particle". All of particles in the area have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.After finding the two best values, the particle updates its velocity and positions. PSO has two main features: position and velocity. These are changed according to the number of iteration and assign best value of position and velocity on each iteration into the current value of particle. [27]

3. Artificial Bee Colony

Artificial bee colony (ABC) algorithm of spectrum sensing was proposed by Karaboga in 2005. It is a swarm intelligent optimization algorithm inspired by honey bee foraging.ABC algorithm is better than to other population-based algorithms with the advantage of employing fewer control parameters. In ABC algorithm, the colony of the artificial bees mainly contains three groups of bees: employed bees, onlookers and scouts.The first half of the colony consists of the employed bees and second half includes the onlookers. Each employed bee is associated with a food source, in other words, the number of the employed bees is equal to the food sources. An employed bee finds a food source or position by modifying the position in her memory and calculates the nectar amount of each new source and memorizes the better one, i.e. greedy selection. Employed bees share information related with the quality of the food source they are exploiting information, on the dance area. Onlooker bees find food sources based upon the information coming from employed bees. More profitable food sources are more likely to be chosen by onlookers. An onlooker bee chooses a food source depending on this information and produces a modification on this source. Greedy selection is applied for finding better food source in ABC algorithm. The ABC algorithm is very simple and flexible, especially suitable for engineering application. C. Firefly Algorithm Firefly is a met heuristic algorithm that is inspired by the Behavior of fireflies. There are about two thousand firefly species, and most fireflies produce short and rhythmic flashes. The primary purpose for a firefly's flash is to act as a signal system to attract other fireflies. The pattern of flashes is often unique for a particular category. Females respond to a male's unique pattern of flashing in the same category. We know that the light intensity at a particular distance from the light source obeys the inverse square law. The air absorbs light becomes weaker and weaker as the distance increases. Here, the attractiveness is proportional to the brightness. The flashing light can be formulated in such a way that it is associated with the objective function. For the simplicity fireflies uses three idealized rules:

- All fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex.
- Attractiveness is proportional to their brightness, thus for any two flashing fireflies, the less brighter one will move towards the brighter one. If there is no brighter one than a particular firefly will move randomly.
- The brightness of fireflies is determined by the landscape of the objective function.

IV. CONCLUSION

The Cooperative sensing is an effective technique to improve detection performance by exploring spatial diversity at the expense of cooperation overhead. In this paper, we dissect the cooperative sensing problem into its fundamental elements and investigate in detail how each element plays an important role in cooperative sensing. Moreover, we define a myriad of cooperation overheads that can limit the achievable cooperative gain. We further identify the research challenges and unresolved issues in cooperative sensing that may be used as the starting point for future research.

REFERENCES

[1] I.F. Akyildiz, W.-Y. Lee, M.C. Vuran, S. Mohanty, NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey, Computer Networks 50 (13) (2006) 2127–2159.
[2] I.F. Akyildiz, W.-Y. Lee, K.R. Chowdhury, CRAHNs: cognitive radio ad hoc networks, Ad Hoc Networks 7 (5) (2009) 810–836.
[3] J. Ma, G. Li, B.H. Juang, Signal processing in cognitive radio, Proceedings of the IEEE 97 (5) (2009) 805–823.
[4] T. Yucek, H. Arslan, A survey of spectrum sensing algorithms for cognitive radio applications, Communications Surveys Tutorials, IEEE 11 (1) (2009) 116–130.
[5] Yue Wang, Chunyan Feng, Caili Guo and Fangfang Liu, "optimization of Parameters for Spectrum Sensing in cognitive radios (Conference style)," IEEE, 2009
[6] Wei Zhang, Ranjan K. Mallik,and Khaled Ben Letaief, "Optimization of Cooperative Spectrum Sensing with Energy Detection in Cognitive Radio Networks(Translation Journals style)," IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, vol. 8, no. 12, Dec. 2009.
[7] Wenjie Zhang, Yiqun Yang, and Chai Kiat Yeo, "Cluster-Based Cooperative Spectrum Sensing(Translation Journals style)," IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, vol. 64, no. 6, June 2015
[8] D. Cabric, S. Mishra, R. Brodersen, Implementation issues in spectrum sensing for cognitive radios, in: Proc. of Asilomar Conf. on Signals, Systems, and Computers, vol. 1, 2004, pp. 772–776.
[9] R. Tandra, A. Sahai, SNR walls for signal detection, IEEE Journal of Selected Topics in Signal Processing 2 (1) (2008) 4–17.
[10] D. Cabric, S. Mishra, R. Brodersen, Implementation issues in spectrum sensing for cognitive radios, in: Proc. of Asilomar Conf. on Signals, Systems, and Computers, vol. 1, 2004, pp. 772–776.
[11] F.F. Digham, M.-S. Alouini, M.K. Simon, On the energy detection of unknown signals over fading channels, IEEE Transactions on Communications 55 (1) (2007) 21–24.
[12] Z. Li, F. Yu, M. Huang, A cooperative spectrum sensing consensus scheme in cognitive radios, in: Proc. of IEEE Infocom 2009, 2009, pp. 2546–2550.
[13] G. Ganesan, Y.G. Li, Cooperative spectrum sensing in cognitive radio—part I: two user networks, IEEE Transactions on Wireless Communications 6 (6) (2007) 2204–2213.
[14] G. Ganesan, Y.G. Li, Cooperative spectrum sensing in cognitive radio—part II: multiuser networks, IEEE Transactions on Wireless Communications 6 (6) (2007) 2204–2213.

[15] W. Zhang, K. Letaief, Cooperative spectrum sensing with transmit and relay diversity in cognitive radio networks— [transaction letters], IEEE Transactions on Wireless Communications 7 (12) (2008) 4761–4766.
[16] K.R. Chowdhury, I.F. Akyildiz, CRP: A routing protocol for cognitive radio ad hoc networks, IEEE Journal of Selected Areas in Communications (JSAC), 2011 (in press).
[17] B.F. Lo, I.F. Akyildiz, A.M. Al-Dhelaan, Efficient recovery control channel design in cognitive radio ad hoc networks, IEEE Transactions on Vehicular Technology 59 (9) (2010) 4513–4526.
[18] J. Ma, G. Zhao, Y. Li, Soft combination and detection for cooperative spectrum sensing in cognitive radio networks, IEEE Transactions on Wireless Communications 7 (11) (2008) 4502–4507.
[19] E. Peh, Y.-C. Liang, Y.L. Guan, Y. Zeng, Optimization of cooperative sensing in cognitive radio networks: a sensing-throughput tradeoff view, IEEE Transactions on Vehicular Technology 58 (9) (2009) 5294–5299.
[20] J. Wei, X. Zhang, Energy-efficient distributed spectrum sensing for wireless cognitive radio networks, in: INFOCOM IEEE Conference on Computer Communications Workshops, 2010, 2010, pp. 1–6.
[21] Y. Zhao, J. Gaeddert, K.K. Bae, J.H. Reed, Radio environment map enabled situation-aware cognitive radio learning algorithms, in: Proceedings of Software Defined Radio, SDR, Technical Conference, 2006.
[22] A. Min, K. Shin, An optimal sensing framework based on spatial RSS profile in cognitive radio networks, in: Proc. of IEEE SECON 2009, 2009, pp. 1–9.
[23] S.-J. Kim, E. Dall'Anese, G. Giannakis, Sparsity-aware cooperative cognitive radio sensing using channel gain maps, in: Conference Record of the Forty-Third Asilomar Conference on Signals, Systems and Computers 2009, 2009, pp. 518–522.
[24] S.-J. Kim, E. Dall'Anese, G.B. Giannakis, Cooperative spectrum sensing for cognitive radios using kriged kalman filtering, IEEE Journal of Selected Topics in Signal Processing, 2010 (in press).
[25] Subhasree Bhattacharjee, Priyanka Das, Swarup Mandal and BhaskarSardar, "Optimization of Probability of False alarm and Probability of Detection in Cognitive Radio Networks Using GA (Conference style)," IEEE, 2015
[26] Yasmina El Morabit, FatihaMrabti and El Houssain Abarkan, "Spectrum Allocation UsingGenetic Algorithm in Cognitive Radio Networks (Conference style)," IEEE, 2015
[27] Ayman A. El-Saleh, MahamodIsmail,MohsenAkbari, Mohsen RiahiManesh, Seyed Ahmad RafieiTabaZavareh, "Minimizing the Detection Error of Cognitive Radio Networks Using Particle Swarm Optimization (Conference style)," International Conference On Computer and Communication Engineering (ICCCE 2012), Kuala Lumpur, Malaysia, July 2012,pp 3-5

Tarangini Shukla, Department Electronics & Communication Engineering, M.Tech Scholar, Kanpur Institute of Technology, Kanpur, India.

Mr. Pradeep Yadav, Associate Professor, Department of Electronics & Communication Engineering, Kanpur Institute of Technology, Kanpur, India.