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A Survey on Data and Decision Fusion Strategies on Spectrum Sensing in Cognitive Radio Networks

Megha Motta
Department of Electronics and Communication
Acropolis Institute of Technology And Reserch

Abstract—Cognitive radio is a promising technology which provides a novel way to improve utilization of available spectrum. Spectrum sensing is a fundamental problem for cognitive radio. Cooperative spectrum sensing is an efficient way to detect spectrum holes in cognitive radio network. In this paper we review that in cooperative sensing for data and decision fusion we conduct some hypothesis test in which we study different methods of hypothesis testing based on various fusion rules, Likelihood ratio test (LRT) and Neymon Pearson Criteria. Some serial and parallel topologies of distributed network in which secondary users are connected to each other for performing their operation are also shown. Soft combination scheme exceeds hard combination scheme at the cost of complexity. Therefore quantized combination scheme provides a better compromise between detection performance and complexity.

Index-Cognitive radio (CR), Dynamic Spectrum Access (DSA), Cooperative spectrum sensing, Energy detection, Like- lihood ratio test (LRT), Fusion rules, Decision fusion, Data fusion.

I. INTRODUCTION

The radio spectrum which is very essential for wireless communication is a nature limited resource. Fixed Spectrum Access(FSA) policy has traditionally been adopted by spectrum regulators to support various wireless applications. According to FSA each part of spectrum with definite bandwidth will be hand over to one or more dedicated users also known as licensed user's. Only these users have right to use the allocated spectrum and other users are not allowed to use it. On the other hand, recent studies of spectrum utilization measurements shows that a large segments of licensed spectrum experiences less utilization ,i.e, most of the time spectrum is in ideal condition and is not used by ts licensed users[1]-[3]. To overcome this situation Dynamic Spectrum Access(DSA), was introduced. It allows radio spectrum to be used in a more effective manner. According to DSA a small part of spectrum can be allocated to one or more users, which are called primary users (PUs); however the use of that spectrum is not fully granted to these users, although they have higher priority in using it. Other users, which are referred to as secondary users (SUs),can also access the allocated spectrum as long as the PUs are not temporally using it.
This opportunistic access should be in a manner that it does not interrupt any primary user in band. Secondary users must be aware of the activities done by the primary user so that they could spot the spectrum holes and the ideal state of the primary users in order to utilize the free band and also rapidly evacuate the band as soon as the primary users becomes active. Very low utilization of spectrum from 0-6 GHz is shown in Fig. 1 The rest of the paper is organized

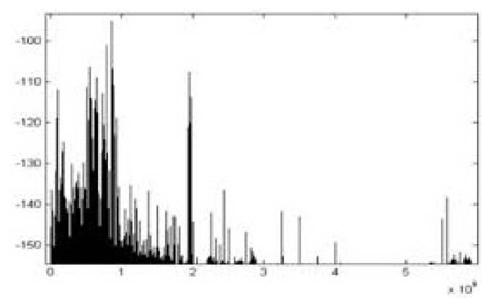

Fig. 1. Spectrum Utilization Measurements [4]

as follows. In section II, we revealed cognitive functionalities which includes cognitive cycle too. Formulation methods for hypothesis is being examined in Section III. Section IV, illustrates different types of spectrum sensing techniques. In Section V, we formulate the system model in CR networks. Then we investigate different fusion rules and propose a new quantized foue-bit hard combination scheme in Section VI. Comparision between one to four bit hard combination scheme is shown in Section VII, respectively. Conclusions are given in Section VIII

II. COGNITIVE RADIO FUNCTIONALITIES

According to S.Hykin "Cognitive Radio is an intelligent wireless communication system that is aware of its surrounding environment (i.e. outside world), and uses the methodology of understanding by building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters in real-time, with two primary objectives in mind:

- Highly reliable communications whenever and wherever needed.
- Efficient utilization of the radio."[5]

From the above mention definition two characteristics of cognitive radio can be summarized as cognitive radio can be

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summarized as cognitive and recofigurability. The first one enables the cognitive radio to interact with its environment in a real-time manner, and intelligently determine based on quality of service (QoS) requirements. Thus these tasks can be implemented by a basic cognitive cycle: Spectrum sensing, spectrum analysis and spectrum decision as shown in Fig. 2

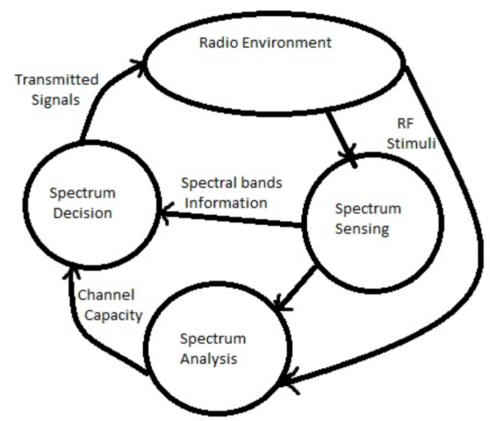

Fig. 2. The Cognitive Capability of cognitive radio enabled by a basic cognitive cycle

Spectrum Sensing: It is done by either cooperative or non cooperative technique in which cognitive radio nodes continuously monitor the RF environment.

Spectrum Analysis: It estimates the characteristics of spectral bands that are sensed through spectrum sensing.

Spectrum Decision: An appropriate spectral band will be chosen according to the spectrum characteristics analyzed for a particular cognitive radio node. Then the cognitive radio determines new configuration parameters.

The other feature of cognitive radio is reconfigurability. Therefore in order to get adapted to RF environment, cognitive radio should change its operational parameters[5]:

- Operating Frequency: Cognitive radio is capable of varying its operating frequency in order to avoid the PU to share spectrum with other users.
- Modulation Scheme: According to the user requirements of the user and channel condition cognitive radio should adaptively reconfigure the modulation scheme.
- Transmission Power: In order to improve spectral efficiency or diminish interference transmission power can be reconfigured.
- Communication Technology: By changing modulation scheme interoperability among different communication systems can also be provided by cognitive radio.

III. FORMULATION METHODS FOR HYPOTHESIS

A. Neyman Pearson Decision Criterion:

It is considered for the estimation of minimum error probability when information of a priori probabilities is not available [6]. Thus in this type of situation two different types of probabilities are of importance. One is the probability of False Alarm and the other is the probability of Miss Alarm. Therefore both probabilities are defined on the basis of two hypothesis H_1 and H_0. H_1 hypothesis is considered when signal and noise both are present where as H_0 hypothesis is considered when only noise is present. Errors take place in either of two situations. First type of error arises when choice is made in favor of H_1 but H_0 is true. It is denoted by $P(D_1/H_0)$ and is known as probability of false Alarm P_f. And the other error occurs when choice is made in favor of H_0 although H_1 is true. This is denoted by $P(D_0/H_1)$ and is known as Miss Alarm P_m [6]. Probability of correct decision is denoted in equation 1

$$P_D = 1 - P(D_o/H_1) = 1 - P_m \qquad (1)$$

In Neyman Pearson criterion an approach is made to maximize probability of of detection for an consigned probability of false alarm. Effectively, a function defined by $Q_{NP} = P_m + \mu P_f$ is minimized for an assigned P_f and a given constant. Thus the plot between P_D versus P_f is known as Receiver Operating Characteristics (ROC) as shown in Fig. 3

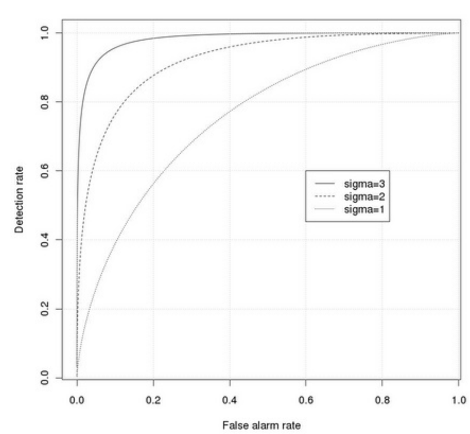

Fig. 3. ROC

B. Likelihood Ratio Test:

For establishing the receiver decision rule for the case of two signal classes a practical starting point is

$$P(S_0|Z) \gtrless_{H1}^{H0} P(S_1|Z) \qquad (2)$$

This equation states that we should choose hypothesis H_0 if the posterior probability $P(S_0|Z)$ is greater than the posterior

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probability $P(S_1|Z)$. Otherwise we should choose hypothesis H_1. Above equation can also be written as:

$$P(Z|S_0)P(S_0) \gtrless^{H0}_{H1} P(Z|S_1)P(S_1) \qquad (3)$$

Thus now we have a decision rule in terms of likelihoods. This equation can also be written as :

$$\frac{P(Z|S_0)}{P(Z|S_1)} \gtrless^{H0}_{H1} \frac{P(S_1)}{P(S_0)} \qquad (4)$$

Therefore, the left-hand ratio is known as the likelihood ratio and the entire equation is often referred as Likelihood Ratio Test. Thus a decision is based on a comparison of a measurement of a received signal to a threshold.

IV. Spectrum Sensing

Spectrum sensing is a key element in cognitive radio network. In fact it is a major challenge in cognitive radio for secondary users to detect the presence of primary users in a licensed spectrum and quit the frequency band immediately if the corresponding primary user emerges in order to avoid interference to primary users.[7]

Spectrum sensing technique can be further categorized as Non-cooperative and Cooperative as shown in Fig. 4

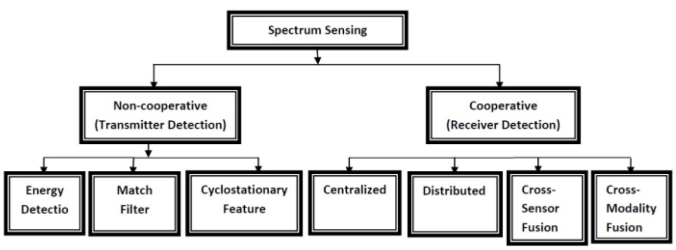

Fig. 4. Spectrum Sensing Techniques

A. Hypothesis Test

Spectrum sensing can be simply reduced to an identification problem modeled as hypothesis test. The signal detection problem is solved by the decision between the two hypothesis:

$$H_0 : \text{primary user not present} \qquad (5)$$

$$H_1 : \text{primary user present} \qquad (6)$$

The signal under hypothesis takes the form:

$$H_0 : y[n] = w[n], n = 1, 2, ..., N \qquad (7)$$

$$H_1 : y[n] = x[n] + w[n], n = 1, 2, ..., N \qquad (8)$$

where y[n] is the signal received by the secondary users, w[n] is a zero mean Additive White Gaussian Noise (AWGN) with variance σ^2_n, i.e. $w(n) \sim N(0, \sigma^2_n)$, and x[n] the signal sent by the primary user after attenuation and distortion from the channel. N is the number of samples of the received signal in the spectrum sensing process. hypothesis H_0 indicates absence of primary user and that the frequency band of interest only has noise whereas H_1 points towards presence of primary user. Thus for the two state hypothesis number of important cases are:

- H_1 turns out to be TRUE in case of presence of primary user i.e. $(H_1|H_1)$ is known as Probability of Detection (P_d).
- H_0 turns out to be TRUE in case of presence of primary user i.e. $P(H_0|H_1)$ is known as Probability of Miss-Detection (P_m).
- H_1 turns out to be TRUE in case of absence of primary user i.e. $P(H_1|H_0)$ is known as Probability of false Alarm (P_f).

The probability of detection is of main concern as it gives the probability of accurately sensing for the presence of primary users in the frequency band. Probability of miss alarm is just the complement of detection probability. The goal of the sensing is to maximize the detection probability for a low probability of false alarm. But there is always a trade-off between these two probabilities. Receiver Operating Characteristics (ROC) as shown in Fig. 5 presents very valuable information as observe the behavior of detection probability with changing false alarm probability (P_d v/s P_f)or miss alarm probability (P_d v/s P_m).

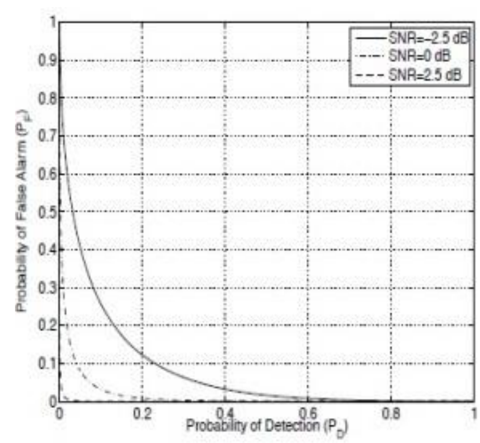

Fig. 5. ROC between Probability of Miss alarm and Prabability of Detection

A number of schemes have been developed for detecting the presence of primary user in a particular frequency band.

B. Non-Cooperative Spectrum Sensing

There are various spectrum sensing techniques which are suggested in non-cooperative spectrum sensing. Various methods are Energy detector, Matched filter and cyclostationary feature. The choice between these sensing method depends greatly on the context and the CR system requirements.[8]. Thus in transmitter detection each CR must Independently have the ability to determine the presence or absence of the PU in a specified spectrum. [9-10].

1) Energy Detection: Energy Detection (ED) is one of the most basic sensing schemes. It is the signal detection mechanism using an energy detector to specify the presence or

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absence of signal in the band. Neyman-Pearson (NP) lemma is the most often used approach in energy detection. Thus it increases the probability of detection (P_d) for a given probability of false alarm (P_f).It is optimal if both the signal and the noise are Gaussian, and the noise variance is perfectly known. However, its performance degrades rapidly when there is uncertainty in the noise power value and is also incapable to differentiate between signals from different systems and between these signals and noise. Its advantage lies in its simplicity and not requiring prior knowledge of the PU's signal making it best suited for fast spectrum sensing.
The energy detection process can be made in the time domain or frequency domain through a FFT block. The advantage of the frequency domain testing lies in the flexibility the FFT can provide by trading temporal resolution for frequency resolution. This means that a narrowband signal's bandwidth and central frequency can be estimated without requiring a very flexible pre-filter.
The ED test statistics can be defined as follows:

$$T^{ED} = \frac{1}{N}\sum_{n=0}^{N-1} y[n]^2 = \frac{1}{N}\sum_{l=0}^{L-1}\sum_{k=0}^{N_{fft}-1} Y_k(l)^2 \gtrless \gamma \quad (9)$$

where N_{fft} is the size of the FFT employed using FFT-based detection and L the number of samples used in the average of each FFT output bin ($N = L.N_{fft}$). Since $y[n]^2$ has a central chi-square distribution under H_0 and non-central chi-square distribution under H_1, the probabilities of false alarm and detection becomes [11].

$$P_f = P(T_i^{ED} > \gamma | H_0) = \frac{\Gamma\left(N, \frac{\gamma}{2\sigma_n^2}\right)}{\Gamma(N)} = P\left(N, \frac{\gamma}{2\sigma_n^2}\right) \quad (10)$$

$$P_d = P(T_i^{ED} > \gamma | H_1) = Q_L\left(\sqrt{\frac{\mu}{\sigma_n^2}}, \sqrt{\frac{\gamma}{\sigma_n^2}}\right) \quad (11)$$

where $\Gamma(.,.)$ is the lower incomplete gamma function, $\Gamma(.)$ the complete gamma function, $P(.,.)$ the regularized gamma function and $Q_L(.)$ is the generalized Marcum-Q function. From second equation it can be inferred that defining a threshold based on the probability of false alarm requires perfect knowledge of noise power (σ_n^2).
Considering the central limit theorem for a desired P_d and P_f a , the number of required samples can be approximated by the equation:

$$N = 2[Q^{-1}(P_f) - Q^{-1}(P_d)(1 + SNR)]^2 SNR^{-2} \quad (12)$$

2) Matched Filter: Matched filtering based methods are optimal for stationary Gaussian noise scenarios as they maximize the received SNR [12-13]. Matched filter requires prior knowledge about primary users waveform. Hence, it requires less sensing time for detection. The main advantage of this method is the short time to achieve a certain probability of false alarm or probability of miss detection as compared to other methods. For this optimal performance, they require perfect knowledge of channel responses from the primary user to the secondary user. The structure and waveforms of the primary signal is accurate synchronization at the secondary user. In cognitive radios, such knowledge is not readily available to secondary users and implementation cost and complexity of this detector is high especially as the number of the primary bands increases. Another disadvantage of match filtering is large power consumption as various receiver algorithms need to be executed for detection.

3) Cyclostationary Feature Detection: Another detection method that can be applied for spectrum sensing is the cyclostationary feature detection. This detector can distinguish between modulated signals and noise [12-17]. It exploits the fact that the primary modulated signals are cyclostationary with spectral correlation due to built-in redundancy of signal periodicity (e.g., sine wave carriers, plus trains, and cyclic prefixes), while the noise is a wide-sense stationary signal with no correlation [16,17]. This task can be performed by analyzing a spectral correlation function. Therefore, cyclostationary feature detectors are robust to the uncertainty in noise power. This is at the price of excessive computational complexity and long observation times. Moreover, it requires the knowledge of the cyclic frequencies of the primary users, which may not be available to the secondary users. Table I compares above spectrum methods in brief.

TABLE I
SUMMARY COMPARISION OF SPECTRUM SENSING METHODS

Sensing Methods	Advantages	Disadvantages
Energy Detection	Low complexity, no primary knowledge required	Vulnerable to noise uncertainity
Matched Filter	Optimum Performance	Requires full primary signal knowledge, high power consumption and implementation complexity
Cyclostationary Feature Detection	Robust to interference and noise uncertainty	High computational complexity,valnerable to sampling clock offsets and model uncertainties, observation time.

C. Cooperative Spectrum Sensing

CR cooperative spectrum sensing occurs when a group or network of CRs contribute to sense the information they gain for PU detection. It plays a very important role in the research of CR due to its ability of improving sensing performance especially in the shadowing, fading and noise uncertainty.[18][19].Probabilities of miss-detection and false alarm can be decreased using cooperative sensing. It can also decrease sensing time and solve the problem of hidden primary user.[20-22]. There are different cooperative sensing categories based on how CRs share data in the network: centralized approach, distributed approach, same sensor and different sensor.

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1) Centralized Approach: In centralized cooperative sensing, an entity called fusion centre (FC) controls all the co-operative sensing process by selecting the frequency band of interest, asking, through a control channel, for the individual sensing results of other CRs and receiving and combining those sensing results to make a decision on the presence or absence of a PU. Then, the unified decision is broadcasted to the neighbor CRs. FC finally evaluate the information and determines the bands that cannot or can be used as shown in figure 6

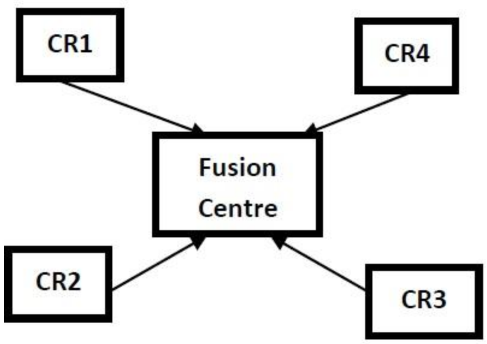

Fig. 6. Centralized Cooperative Sensing

2) Distributed Approach: In the case of distributed cooperative sensing, no FC is defined and the CRs communicate among themselves by sending their specific data of sensing to other CRs, merges its data with the received data of sensing, and decides whether PU is present or not by local condition as shown in figure 7 . Now this decision is conveyed to other users and all the steps are again followed until all converge to a common decision. Distributed sensor network with signal processing is gaining more importance now a days. This system was originally motivated by their applications in the field of military surveillance with respect to command, control and communications but now they are being employed in a wide variety of applications. Some preliminary processing of data is carried out at each sensor and compressed information

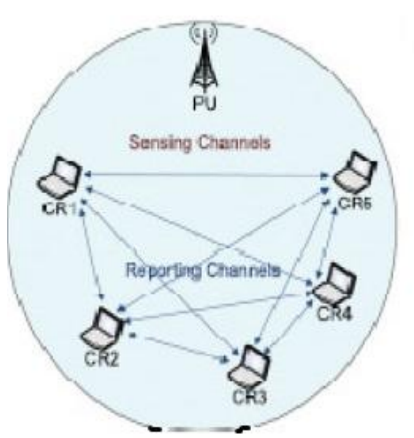

Fig. 7. Distributed Spectrum Sensing[23]

is sent from one sensor to the other sensor and ultimately to the central processor which is often known as the fusion centre[23]. In distributed sensor network there is intelligence at each node. There is a issue of choice of topology facility which has to be addressed by distributed sensor network to reconfigure the structure in the case of sensor/link failures, existence of communication between sensors and feedback communication between the fusion centre and the sensors. Therefore, there are three major topologies used for distributed signal processing. These are called parallel, serial and tree configurations. Topologies used for distributed approach:

1) Parallel Configuration: Let us assume the parallel configuration of N sensors in figure 8.Therefore we assume that from the fusion centre to any sensor there is no feedback connected and the sensors do not communicate with each other.[23] Now y_i denote either a single observation or local observation that is available at the i^{th} sensor or in the case of multiple observations, a sufficient statistic that might exist for the given binary hypothesis testing problem. Thus the i^{th} sensor occupy the mapping rule $u_i = \gamma_i(y_i)$ and passes the quantized information u_i to the fusion centre. Based on the received information $U = (u_1, u_2, ..., u_N$,the fusion centre arrives at the global decision $u_0 = \gamma_0(U)$ that favours either H_1 (say $u_0 = 1$) or H_0 (say $u_0 = 0$). The NP formulation of distribute detection problem can now be stated as follows: for a prescribed bound on the global probability of false alarm, P_f, find local and global decision rules $\Gamma = (\gamma_0, \gamma_1, ...\gamma_N)$ that minimize the global probability of miss P_m.

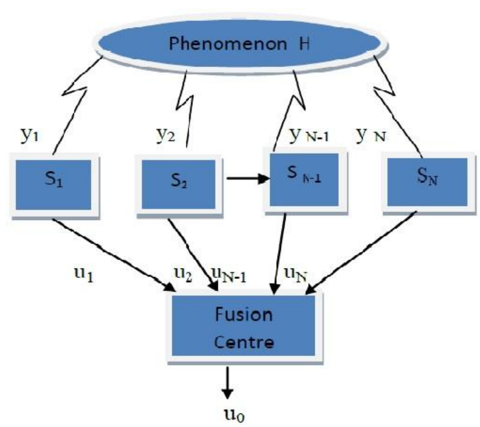

Fig. 8. Parallel topology with fusion centre

2) Serial Configuration: Serial configuration is also known as tandem configuration of N sensors. Now let us assume the tandem configuration of N sensors, the $(j-1)^{th}$ sensor passes its quantized information to the j_{th} sensor which generates a quantized information based on its own observation and the quantized data received from the previous sensor as shown in figure 9.This can be also understand as the first sensor in the network uses only its own observation to develop its quantized data for the

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use of next sensor. Thus, the last sensor in the network makes a decision that which one of the two possible hypothesis the observations at the sensors corresponds to optimal solution to the NP problem corresponding to the serial configuration.

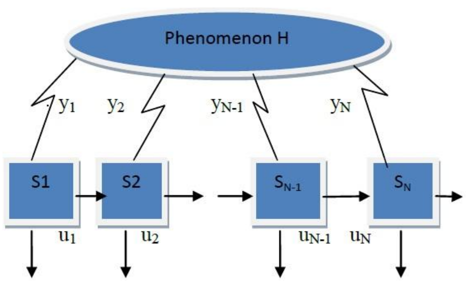

Fig. 9. Serial Topology

3) Tree Configuration: In the case of tree networks it can be seen that an optimal solution to the NP problem give up threshold tests based on likelihood ratios. Solving for

which becomes complicated in general thus we prefer much parallel or serial topology instead of tree.

3) Cross- Sensor Fusion: When the data fusion takes place within the same type of sensor in an active senor neighborhood then it is considered as cross-sensor fusion, conceptualized as "cooperative fusion". This data fusion is embedded in the likelihood function derivation.

4) Cross- Modality Fusion: When the combination of signals is collected by multiple type of sensors then it is considered as cross-modality fusion. It is "complementary", and represented by the contribution of their likelihood functions to the state update.[24]

V. System Model

Let there be a cognitive network with K cognitive users (such that K = 1,2,3,.....K) to sense the spectrum in order to detect the presence of PU. Assume that each CR performs local spectrum sensing independently by using N samples of the received signal. By taking two possible hypothesis H_0 and H_1 in binary hypothesis testing problem the problem of spectrum sensing can be formulated as:

$$H_0 : x_k(n) = w_k(n) \tag{13}$$

$$H_1 : x_k(n) = h_k s(n) = w_k(n) \tag{14}$$

where s(n) are samples of transmitted signal also known as primary signal, $w_k(n)$ is the receiver noise for the k^{th} CR user, which is assumed to be an i.i.d. random process with zero mean and variance σ_n^2 and h_k is the complex gain of the channel between the PU and the k^{th} CR user. H_0 and H_1 represents whether the signal is present or absent correspondingly. Using energy detector, the k^{th} CR user will calculate the received energy as [25] :

$$E_k = \sum_{n=1}^{N} x_k^2(n) \tag{15}$$

If we consider the case of soft decision, each CR user forwards the entire result E_k to the FC where as in case of hard decision, the CR user makes one-bit decision given by Δ_k by comparing the received energy Ek with the predefined threshold λ_k.

$$\Delta_k = \{1, E_k > \lambda_k\} \tag{16}$$

$$\Delta_k = \{0, \text{otherwise}\} \tag{17}$$

Detection probability $P_{d,k}$ and false alarm probability $P_{f,k}$ of the CR user K are defined as:

$$P_{d,k} = Pr\{\Delta_k = 1 | H_1\} = Pr\{E_k > \lambda_k | H_1\} \tag{18}$$

$$P_{f,k} = Pr\{\Delta_k = 1 | H_0\} = Pr\{E_k > \lambda_k | H_0\} \tag{19}$$

Let $\lambda_k = \lambda$ for all CR users, the detection probability, false alarm probability and miss detection $P_{m,k}$ over AWGN
channels can be expressed respectively[26].

$$P_{d,k} = Q_m\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) \tag{20}$$

$$P_{f,k} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \tag{21}$$

$$P_{m,k} = 1 - P_{d,k} \tag{22}$$

where γ is the signal to noise ratio (SNR), m=TW is the time bandwidth product, Q_N (., .) is the generalized Marcum Q function(.) and $\Gamma(.,.)$ are complete and incomplete gamma function respectively.

VI. Fusion Rules

This section describes the fusion rules that are used by the sensors for taking decision in spectrum sensing.

A. Hard decision fusion

In decision fusion, each user sends its one-bit or multiple-bit decision to a central processor, which deploys a fusion rule to make the final decision. Specifically, if each user only sends one-bit decision (1 for signal present and 0 for signal absent) and no other information is available at the central processor, some commonly adopted decision fusion rules are described as follows [27-28]

1) "Logical-AND (LA)" Rule: In this rule, the FC decides 1 if and only if all decisions from the cognitive radios are 1 . Hence, using this rule, the probability of false alarm is minimized, but the risk of causing interference will increase. The cooperative test using the AND rule can be formulated as follows :

$$H_1 : \sum_{k=1}^{K} \Delta_k = K \tag{23}$$

$$H_0 : \text{otherwise} \tag{24}$$

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2) "Logical-OR (LO)" Rule: In this rule, the FC gives decision 1 (PU present) if any one of decisions from the cognitive radios is 1. Thus, using this rule, the probability of false alarm (when PU is absent, cognitive radios think that PU is using that band) will increase. Meanwhile, the probability of missed detection (when PU is present, cognitive radios sense that PU is not using this band) is reduced. Since cognitive radio occupying a frequency band used by the PU may interfere with the PU, the risk of cognitive radios causing interference to the PU is minimized using the logical OR rule. The cooperative test using the OR rule can be formulated as follows :

$$H_1 : \sum_{k=1}^{K} \Delta_k \geq 1 \tag{25}$$

$$H_0 : \text{otherwise} \tag{26}$$

3) "K out of M" Rule: If and only if M decisions or more are 1s out of K, the final decision is 1.The test is formulated as:

$$H_1 : \sum_{k=1}^{K} \Delta_k \geq M \tag{27}$$

$$H_0 : \text{otherwise} \tag{28}$$

A majority decision is a special case of the voting rule for $M = K/2$, the same as the AND and the OR rule which are also special cases of the voting rule for M=K and M=1 respectively. Cooperative detection probability Q_d and cooperative false alarm probability Q_f are defined as:

$$Q_d = P_r\{\Delta = 1|H_1\} = P_r\left\{\sum_{i=1}^{K} \Delta_k \geq M |H_1\right\} \tag{29}$$

$$Q_f = P_r\{\Delta = 1|H_0\} = P_r\left\{\sum_{i=1}^{K} \Delta_k \geq M |H_0\right\} \tag{30}$$

Where Δ is the final decision. Note that the OR rule corresponds to the case $M = 1$, hence

$$Q_{d,or} = 1 - \Pi_{k=1}^{k}(1 - P_{d,k}) \tag{31}$$

$$Q_{f,or} = 1 - \Pi_{k=1}^{k}(1 - P_{f,k}) \tag{32}$$

The AND rule can be evaluated by setting $M = K$.

$$Q_{d,and} = \Pi_{k=1}^{k} P_{d,k} \tag{33}$$

$$Q_{f,and} = \Pi_{k=1}^{k} P_{f,k} \tag{34}$$

B. Soft data fusion

In Data Fusion or Soft Combining the CR users transmit the entire local sensing samples or their test statistics to the FC or other CRs. The shared data is then combined using diversity techniques such as square law combining (SLC), maximum ratio combining(MRC),selection combining (SC). Soft combining brings the best sensing performances since there is more information to process by the FC, however, it also incurs in the greatest overhead to the control channel in terms of required bandwidth.[26]

1) Square Law Combining (SLC): SLC is the simplest linear soft combining schemes. In this scheme, the outputs of the square-law devices (energy detectors) are combined and compared with a threshold to set a certain level of False Alarm probability. Decision statistic is given by

$$E_{slc} = \sum_{k=1}^{K} E_k \tag{35}$$

where E_k denotes the statistic from the K^{th} CR user. The detection probability and false alarm probability are formulated as follow

$$Q_{d,slc} = Q_{mk}\left(\sqrt{2\gamma_{slc}}, \sqrt{\lambda}\right) \tag{36}$$

$$Q_{f,slc} = \frac{\Gamma(mK, \lambda/2)}{\Gamma(m, K)} \tag{37}$$

where,

$$\gamma_{slc} = \sum_{k=1}^{K} \gamma_k \tag{38}$$

and γ_k is the received SNR at k^{th} CR user.

2) Maximum Ratio Combining (MRC): This method focuses on Maximum Ratio Combining (MRC) to increase spectral efficiency for cognitive radios. In this method, the normalized weight is considered and is added with the energy received in the center fusion from each user[29] .The weight depends on the received SNR of the different CR user. The statistical test for this scheme is given by:

$$E_{mrc} = \sum_{k=1}^{K} W_k E_k \tag{39}$$

Over AWGN channels, the probabilities of false alarm and detection under the MRC diversity scheme can be given by:

$$Q_{d,MRC} = Q_m\left(\sqrt{2\gamma_{mrc}}, \sqrt{\lambda}\right) \tag{40}$$

$$Q_{f,MRC} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \tag{41}$$

where,

$$\gamma_{mrc} = \sum_{k=1}^{K} \gamma_k \tag{42}$$

3) Selection Combining (SC): selection combining method is applied to an energy detection based spectrum sensing system. In this method cognitive radio is assumed to have the knowledge of channel state information and thus chooses the branch with the highest SNR. Then simply the received data is applied to an Energy Detector.

$$\gamma_{sc} = \max(\gamma_1, \gamma_2, \ldots\ldots\gamma_k) \tag{43}$$

Over AWGN channels, the probabilities of false alarm and detection under the SC diversity scheme can be written by:

$$Q_{d,sc} = Q_m\left(\sqrt{2\gamma_{sc}}, \sqrt{\lambda}\right) \tag{44}$$

$$Q_{f,sc} = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \tag{45}$$

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C. Quantized data fusion

In this method a better detection performance is obtained by increasing the number of threshold to get more regions of observed energy. Whereas in one bit hard combining, there was only one threshold dividing the whole range of the detected energy into two regions. Therefore a better tradeoff is realized between the overhead and the detection performance.

1) One Bit Hard Combination Scheme: In the conventional one-bit hard combination scheme, there is only one threshold dividing the whole range of the observed energy into two regions. As a result, all of the CR users above this threshold are allocated the same weight regardless of the possible significant differences in their observed energies

A better detection performance can be achieved if we divide 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. From the above discussion we develop a softened two-bit hard combination scheme.[30]

2) Two Bit Hard Combination Scheme: A two-bit hard combining scheme is proposed in which the whole range of the detected energy is divided into four regions. The presence of the signal of interest is decided at the FC by using the following equation:

$$\sum_{i=0}^{3} w_i n_i \geq L \qquad (46)$$

where L is the threshold and it is equal to the weight of the upper region, n_i is the number of observed energies falling in region i and w_i is the weight value of region i with $w_0 = 0, w_1 = 1, w_2 = 2$ and $w_3 = 4$ as shown in figure 10.

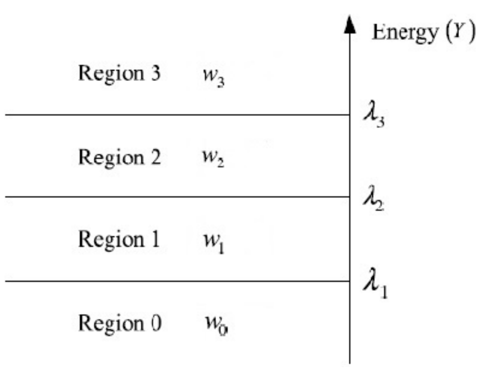

Fig. 10. 2-bit hard combination

3) Three Bit Hard Combination Scheme: In the three-bit scheme, seven threshold λ_1, λ_2, ...and λ_7, divide the whole range of the statistic into 8 regions, as depicted in figure 11. Each CR user forwards 3 bit of information to point out the region of the observed energy. Nodes that observe higher energies in upper regions will forward a higher value than nodes observing lower energies in lower regions. The final decision is made by comparing this sum with a threshold L.

$$\sum_{k=1} w_{i,k} \geq L \qquad (47)$$

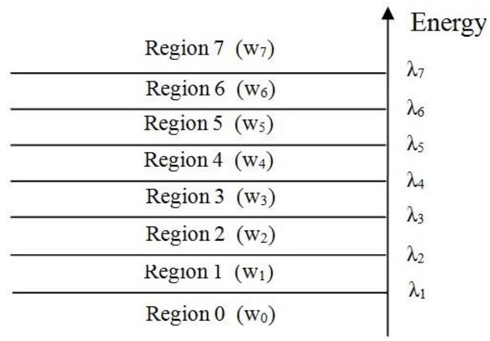

Fig. 11. 3-bit hard combination scheme

4) Four Bit Combination Scheme: In the four-bit scheme, fifteen threshold λ_1, λ_2, ...and λ_{15}, divide the whole range of the statistic into 16 regions. Each CR user forwards 4 bit of information to point out the region of the observed energy. Nodes that observe higher energies in upper regions will forward a higher value than nodes observing lower energies in lower regions. The final decision is made by comparing this sum with a threshold L.

$$\sum_{m=1} w_{i,m} \geq L \qquad (48)$$

VII. Conclusion

In this paper, the effect of fusion rules for cooperative spectrum sensing is shown. We have seen the data and decision fusion in cooperative sensing using some hypothesis test. These hypothesis testing was based on various fusion rules, Likelihood ratio test (LRT) and Neymon Pearson Criteria.Some serial and parallel topologies of distributed network in which secondary users are connected to each other for performing their operation are also shown. The hypothesis testing and all fusion rules are applied in centralized network of secondary users. We have extended the combination of bits till 4 bits. The proposed quantized four-bit combination scheme wins advantage of the soft and the hard decisions schemes with a tradeoff between overhead and detection performance. Simulation comparison will be done between various fusion rules. With the help of simulation we will see that soft combination scheme exceeds hard combination scheme at the cost of complexity. Therefore quantized combination scheme provides a better compromise between detection performance and complexity.

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