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Performance Analysis and Comparative Study of Cognitive Radio Spectrum Sensing Schemes

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Abstract : *In cognitive radio, spectrum sensing is an emergent technology to find available and unused spectrum for increasing spectrum utilization and to overcome spectrum scarcity problem without harmful interference to licensed users. Cooperative spectrum sensing is used to give reliable performance in terms of detection probability and false alarm probability as well as in order to reduce fading, noise and shadowing effects on cognitive radio users. In this paper according to detection performance and complexity various cooperative spectrum sensing schemes have been discussed. We have analyzed spectrum sensing with different fusion rules and their comparative behavior has also been studied. Furthermore, we introduced AND-OR fusion rules in 2-bit and 3-bit hard combination schemes.*

Keywords *- Cognitive radio, cooperative spectrum sensing, energy detector, spectrum sensing, hard combination*

I. INTRODUCTION

Radio spectrum is a very scarce and important resource for wireless communication systems. The tremendous 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. Recently, a Cognitive Radio (CR) access technology has been proposed as a promising solution for improving the efficiency of spectrum usage by adopting dynamic spectrum resource management concept [4], [13].

The main functions of a cognitive radio can be addressed as follows [14]:

- Spectrum sensing is the process of a cognitive radio sensing the channel and determining if a primary user is present, detecting the spectrum holes
- Spectrum management is selecting the best available channel (for a cognitive user) over the available channels.
- Spectrum sharing is the allocation of available frequencies between the cognitive users.
- Spectrum mobility is the case when a secondary user rapidly allocates the channel to the primary user when a primary user wants to retransmit again.

Among these functions, spectrum sensing is the one that has driven most interest. The role of spectrum sensing in the CR system is to locate unoccupied spectrum segments as quickly and accurately as possible. Inaccurate or delayed sensing results deter communication of the primary user occupying the spectrum. Thus, spectrum sensing speed and accuracy are extremely important. From a CR system commercialization standpoint, minimizing hardware complexity as well as power consumption is also critical.

Spectrum scarcity problem [1],[2] due to the growth of demand for the spectrum, is suggested to be solved by increasing the spectrum utilization which can be done by allowing cognitive users (unlicensed users) to occupy the spectrum band when the primary users (licensed users) do not use it. CR system [3], [4] can be suggested to use the spectrum band efficiently. In spectrum sensing [5] there are several sensing methods. One from these methods is the energy detection [6], [7]. Other methods were described briefly in Ref. [4], [8], [9]. Energy detection will be used here due to its simplicity and no need for any prior information about the primary users' signals. Therefore, it has been thoroughly studied both in local spectrum sensing [6],[7],[8],[9],[10] and cooperative spectrum sensing [11],[12],[13],[14].In cooperative spectrum sensing, local spectrum sensing information from multiple CRs are combined for Primary User (PU) detection. In centralized CR network, a common receiver plays a key role in collecting these information and detecting spectrum holes which were described in details in [12].

Cooperative spectrum sensing was proposed to overcome noise uncertainties, fading and shadowing in primary user signal detection. It can be as a solution to hidden node problem and decrease sensing time as well [15]. In this technique, CR users/nodes are collaborated to sense spectrum hole and detect PUs signal. Then, with or without sharing local detection information among users, they forward them to data fusion centre. The fusion centre decides the final result in accordance with the decision rules whether primary signal is present or absent.

The paper is organized as follows: Section 2 reviews spectrum sensing schemes. In section 3, we provide comparison of spectrum sensing schemes. Conclusion is presented in Section 4.

II. SPECTRUM SENSING SCHEMES

Several methods have been proposed to perform local spectrum sensing [14], [16], [17], and [18]. The following section highlights three of the most relevant methods from the literature [18]: 1) energy detection based spectrum sensing, 2) cyclostationary-based spectrum sensing, and 3) matched filtering. A brief overview of each technique is provided below along with the relative advantages and disadvantages of each.

2.1 Energy Detection Based Spectrum Sensing

Due to its low complexity and computational cost, energy detection based spectrum sensing is the most common spectrum sensing method [16]. It is performed by comparing the received energy of the signal against a predefined energy detection threshold to determine the presence or absence of the user in the frequency band of interest [16], [17], [19]. The energy of the received signal is determined by squaring and integrating the received signal strength (RSS) over the observation time interval [14], [16], [19]. The energy detection threshold is determined using the noise variance of the environment [14]. Thus, small errors in the noise variance estimation can cause significant performance degradation [14]. Energy detection based spectrum sensing is the optimal detection method for zero-mean constellation signals when no information is known in advance about the user occupying the channel [14], [19]. However, energy detection based spectrum sensing cannot distinguish the type of user occupying the frequency band [14], [16]. In addition, under low signal-to-noise ratio (SNR) conditions, energy detection performs poorly [14], [16].

The principle of energy detection is shown in fig. 1. Energy detector has a band-pass filter which limits the bandwidth of the received signal to the frequency band of interest, a square law device which squares each term of the received signal and a summation device which adds all the squared values to compute the energy.

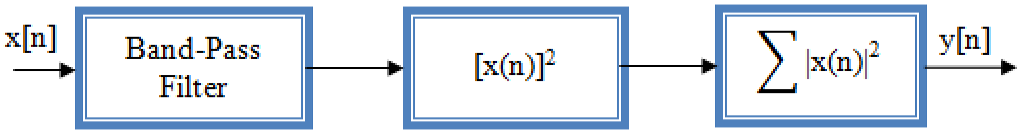

Figure 1: Energy Detector-based Sensing

The energy is calculated as:

$$E = \sum_{n=0}^{N} |x(n)|^2 \tag{1}$$

The Energy is now compared to a threshold for checking which hypothesis turns out to be true.

$$E > \lambda \Rightarrow H_1$$
$$E < \lambda \Rightarrow H_0 \tag{2}$$

The probability of detection (P_d) and probability of false alarm (P_{fa}) can be given as :

$$P_d = Q_m\left(\sqrt{2\gamma},\ \sqrt{\lambda}\right) \tag{3}$$

Where $Q_m(a, b)$ is generalized Marcum Q-function.

$$P_f = \frac{\Gamma(m,\lambda/2)}{\Gamma(m)} \tag{4}$$

Where Γ (a) is the complete gamma function and Γ (a,b) is the incomplete gamma function. γ and λ represents SNR and detection threshold respectively.

1.2 Cyclostationary-Based Spectrum Sensing

Given the disadvantages of energy detection based spectrum sensing, cyclostationary-based spectrum sensing offers an attractive alternative [14], [16]. By exploiting the cyclostationary features of the received signal [16], cyclostationary-based spectrum sensing is capable of discriminating which type of user is present [14], [16] and detecting the presence of a user under low SNR conditions [14]. Such benefits come at the cost of additional hardware complexity and a lengthier detection process when compared to energy detection based spectrum sensing [14]. Cyclostationary features are the result of periodicity in the received signal or its statistical properties [16]. As such, detection is accomplished by finding the unique cyclic frequency of the spectral correlation function of the received signal [14], [16]. The spectral correlation function is determined by taking the Fourier transform of the cyclic autocorrelation function.

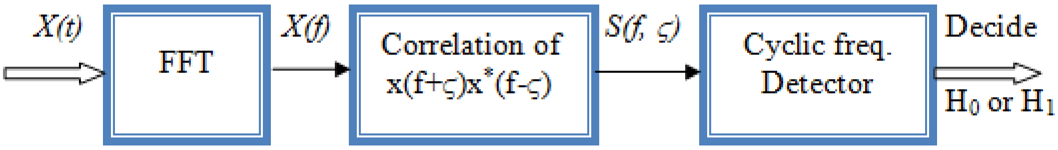

Figure 2: Cyclostationary-based Sensing

1.3 Matched Filter Detection

The Matched Filter is used to maximize the signal to noise ratio (SNR). This method incorporates a filter matched to the primary user's signal at the cognitive radio receiver. Obviously, this method is optimal in the sense that it maximizes the SNR, minimizing the decision errors. However, this method is not practical since it requires the cognitive user to know the primary user's signalling type.

It is a linear filter and prior knowledge of the primary user signal is very essential for its operation. The operation performed is equivalent to a correlation. Matched filter correlates the signal with time shifted version and compares between the final output of matched filter and predetermined threshold will determine the PU presence.

1.4 Waveform-Based Sensing

Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns include preambles, midambles, regularly transmitted pilot patterns, spreading sequences *etc*. A preamble is a known sequence transmitted before each burst and a midamble is transmitted in the middle of a burst or slot. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [24], [25], [27]. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing or coherent sensing. In [24], it is shown that waveform based sensing outperforms energy detector based sensing in reliability and convergence time. Furthermore, it is shown that the performance of the sensing algorithm increases as the length of the known signal pattern increases.

1.5 Radio Identification Based Sensing

A complete knowledge about the spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. Such identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [26]. For example, assume that a primary user's technology is identified as a Bluetooth signal. Cognitive radio can use this information for extracting some useful information in space dimension as the range of Bluetooth signal is known to be around 10 meters. Furthermore, cognitive radio may want to communicate with the identified communication systems in some applications.

For radio identification, feature extraction and classification techniques are used in the context of European transparent ubiquitous terminal (TRUST) project [33]. The goal is to identify the presence of some known transmission technologies and achieve communication through them. The two main tasks are initial mode identification (IMI) and alternative mode monitoring (AMM). In IMI, the cognitive device searches for a possible transmission mode (network) following the power on. AMM is the task of monitoring other modes while the cognitive device is communicating in a certain mode.

In radio identification based sensing, several features are extracted from the received signal and they are used for selecting the most probable primary user technology by employing various classification methods. In [20], [34], features obtained by energy detector based methods are used for classification. These features include amount of energy detected and its distribution across the spectrum. Channel bandwidth and its shape are used in [35] as reference features. Channel bandwidth is found to be the most discriminating parameter among others. For classification, radial basis function (RBF) neural network is employed. Operation bandwidth and centre frequency of a received signal are extracted using energy detector based methods in [26]. These two features are fed to a Bayesian classifier for determining the active primary user and for identifying spectrum opportunities. The standard deviation of the instantaneous frequency and the maximum duration of a signal are extracted using time-frequency analysis in [22], [23], [36], [37] and neural networks are used for identification of active transmissions using these features. Cycle frequencies of the incoming signal are used for detection and signal classification in [30]. Signal identification is performed by processing the (cyclostationary) signal features using hidden Markov model (HMM). Another cyclostationarity based method is used in [28], [29] where spectral correlation density (SCD) and spectral coherence function (SCF) are used as features. Neural network are utilized for classification in [29] while statistical tests are used in [28].

III. COMPARISON OF SENSING SCHEMES

A basic comparison of the sensing methods given in this section is presented in Fig. 3. Waveform-based sensing is more robust than energy detector and cyclostationarity based methods because of the coherent processing that comes from using deterministic signal component [24]. However, there should be a priori information about the primary user's characteristics and primary users should transmit known patterns or pilots.

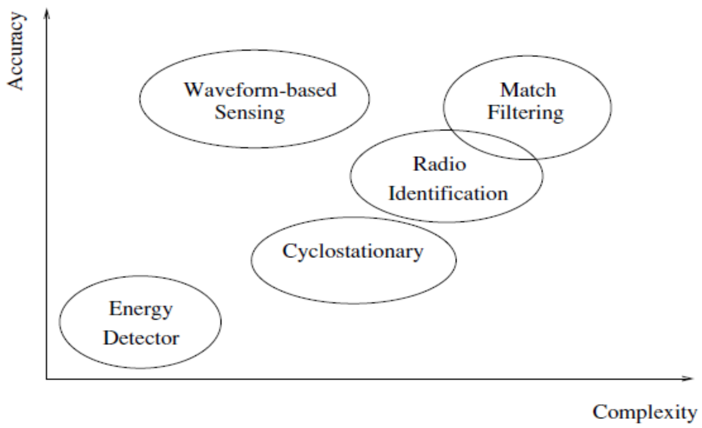

Figure 3: Main sensing methods in terms of their sensing accuracies and complexities.

The performance of energy detector based sensing is limited when two common assumptions do not hold [24]. The noise may not be stationary and its variance may not be known. Other problems with the energy detector include baseband filter effects and spurious tones [27]. It is stated in literature that cyclostationary-based methods perform worse than energy detector based sensing methods when the noise is stationary. However, in the presence of co-channel or adjacent channel interferers, noise becomes non-stationary. Hence, energy detector based schemes fail while cyclostationarity-based algorithms are not affected [32]. On the other hand, cyclostationary features may be completely lost due to channel fading [31], [39]. It is shown in [39] that model uncertainties cause an SNR wall for cyclostationary based feature detectors similar to energy detectors [38]. Furthermore, cyclostationarity based sensing is known to be vulnerable to sampling clock offsets [32].

IV. RESULT AND DISCUSSION

As described earlier, cooperative technique was proposed to combat noise uncertainty, fading, and shadowing. These all can cause sensing errors such as false detection and miss-detection. False detection senses idle channel as a busy channel and CR users refrain to transmit data. On the other hand, miss detection senses busy channel as an idle channel and cause CR users collide to PU transmission.

There are three rules commonly used in hard decision combining based cooperative spectrum sensing. OR rule decides primary user is present when at least one user detects primary user signal while AND rule decides primary user is present if all cognitive radio users forward their bit-1 local detections. MAJORITY rule decides primary user is present when X out of N secondary users detect primary user present. Through computer simulation, we model cooperative spectrum sensing and obtain numerical results.

First we have discussed the relationship of the probability of detection (P_d) and probability of false alarm (P_{fa}) based on AND rule, OR rule and MAJORITY rule. The simulation conditions are shown below: the number of cognitive users is 5, constant losses are 1, the probability of false alarm (p_{fa}) of each single cognitive user is p_{fa} =0.1 and SNR=15dB.

Fig.4 shows Complementary ROC of Cooperative sensing with AND fusion rule under AWGN. AND rule has lower probability of false alarm (P_{fa}) , but also has lower probability of detection (P_d).

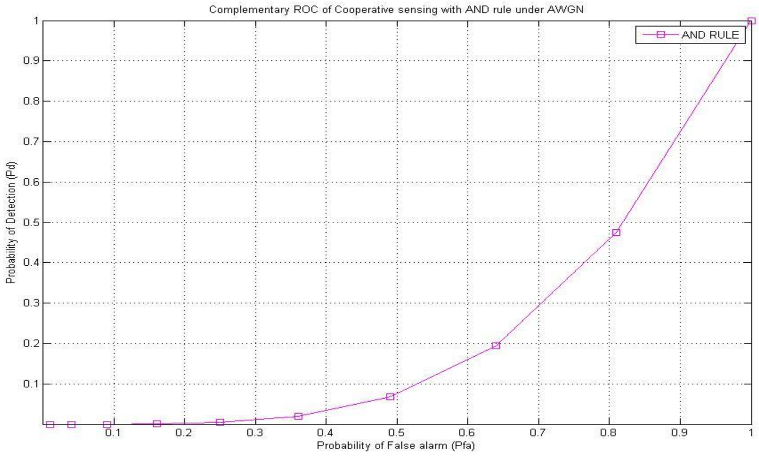

Figure 4: Complementary ROC of Cooperative sensing with AND fusion rule under AWGN

Fig.5 shows Complementary ROC of Cooperative sensing with OR fusion rule under AWGN. OR rule has high probability of detection (P_d) but also has high probability of false alarm (P_{fa}).

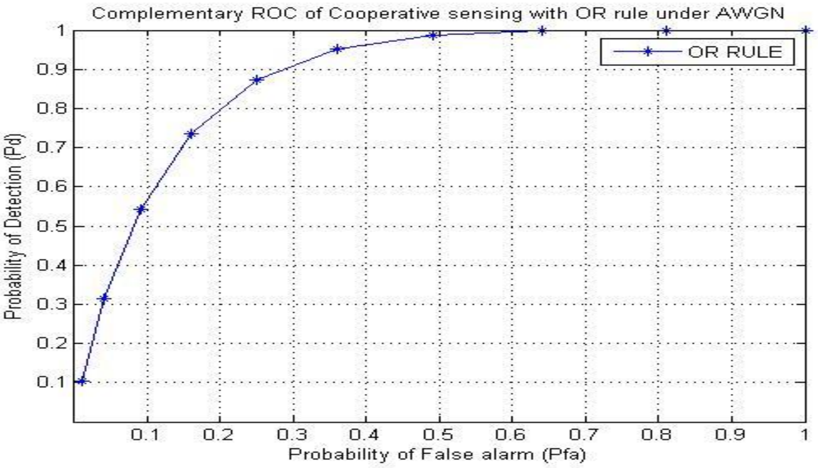

Figure 5: Complementary ROC of Cooperative sensing with OR fusion rule under AWGN

Now, OR and AND rule are studied. We define P_{fa} values from 0.1-1.0. The information of local detection from each cognitive radio users are forwarded to data fusion centre and combined to obtain final decision. The simulation is performed by using probability of detection as a metric at different SNR values.

Fig.6 describes the probability of detection by employing AND and OR rule. We assume 5 CR users are collaborated to detect primary user signal. As shown in the figure that OR rule has better probability of detection than AND rule. The data fusion centre decides H1 when at least there is one CR user detects primary user signal for OR rule while in AND rule, all local detection of CR users must be H1 to decide the presence of primary user signal. From fig.6 it is clear that as probability of false alarm (P_{fa}) is low, OR fusion rule has better probability of detection (P_d) than AND fusion rule. The reason is that data fusion centre decides H_1 i.e. primary user is present when at least there is one CR user detects primary user signal for OR fusion rule while in AND fusion rule, all local detection of CR users must be H_1 i.e. primary user is present to decide the presence of primary user signal. As probability of false alarm (P_{fa}) increases OR and AND fusion rules show similar results. At SNR values less than 10dB OR fusion rule exhibits better detection performance than AND fusion rule.

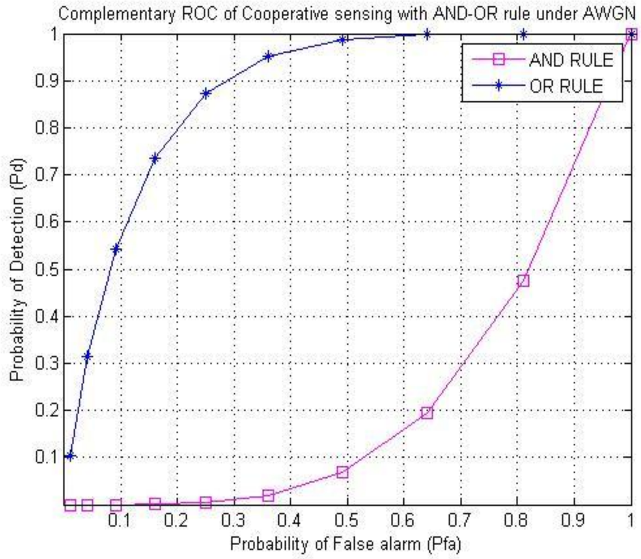

Figure 6: Probability of detection for AND and OR rule.

Then, In Fig.7 we evaluate probability of detection with different number of cognitive radio users in each decision fusion rule. Number of 5 and 10 collaborated users is implemented for this evaluation.We used here two important spectrum sensing detection parameters i.e. Probability of Missed Detection (P_{md}) and Probability of False alarm (P_{fa}).

A missed detection occurs when a primary signal is present in the sensed band and the spectrum sensing algorithm selects hypothesis H_0, which may result in harmful interference to primary users. On the other hand, a false alarm occurs when the sensed spectrum band is idle and the spectrum sensing algorithm selects hypothesis H_1, which results in missed transmission opportunities and therefore in a lower spectrum utilization. Based on these definitions, the performance of any spectrum sensing algorithm can be summarized by means of two probabilities:

The probability of missed detection
$P_{md} = P\ (H_0=H_1)$,
and the probability of false alarm
$P_{fa} = P\ (H_1=H_0)$

In Fig.7 we have used two different number of cognitive users n=5 and n=20.All the results obtained after 1000 run of simulations. As number of cognitive users increases, both fusion rules show different results. At low false alarm values OR fusion rule shows better results for number of cognitive users n=20 than number of cognitive users n=5.Probability of missed detection (P_{md}) also decreases for number of cognitive users n=20.So total detection probability (P_d) increases accordingly.

At low false alarm values AND fusion rules shows almost similar characteristics for both number of cognitive users i.e. n=5 and n=20.But as values for false alarm increases it shows better performance for number of cognitive users n=5 than number of cognitive users n=20.It means Probability of missed detection(P_{md}) increases as number of cognitive users increases according to Probability of false alarm(P_{fa}).For AND fusion rule total detection probability(P_d) decreases with increment of number of cognitive users(n).

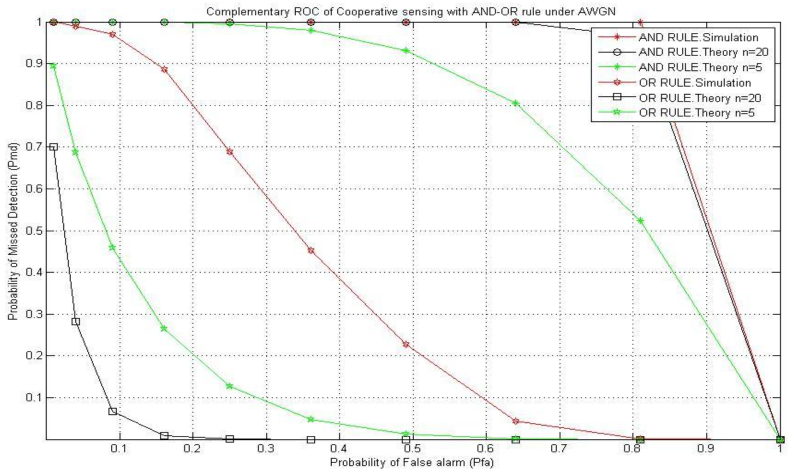

Figure 7: Probability of detection for AND and OR rule for different no. of secondary users

Fig.8 describes the probability of detection by employing AND, OR and MAJORITY rules. We assume 5 CR users are collaborated to detect primary user signal. As shown in the figure that OR rule has better probability of detection than AND and MAJORITY rules. The data fusion centre decides H1 when at least there are X out of N. CR users detect primary user signal for MAJORITY rule.When comparing the performances of all fusion rules, performance of the MAJORITY fusion rule is considerably worse but much better than the performance of the AND rule. It clearly seen that performance of MAJORITY fusion rule lies between OR fusion rule and AND fusion rule. At low values of Probability of false alarm (P_{fa}), OR fusion rule exhibits best results over MAJORITY and AND fusion rules. Probability of detection (P_d) for OR rule is also much better than other fusion rules at low false alarm values. For better primary user detection, Probability of detection (P_d) should be maximum and Probability of false alarm (P_{md}) should be minimum so that spectrum could be utilized efficiently. AND fusion rule shows worst performance among all fusion rule as final decision of primary user presentation depends on all cognitive users while in OR fusion rule one cognitive user is sufficient for final decision making. Final decision can be obtained in MAJORITY fusion rule by k out of n rule.

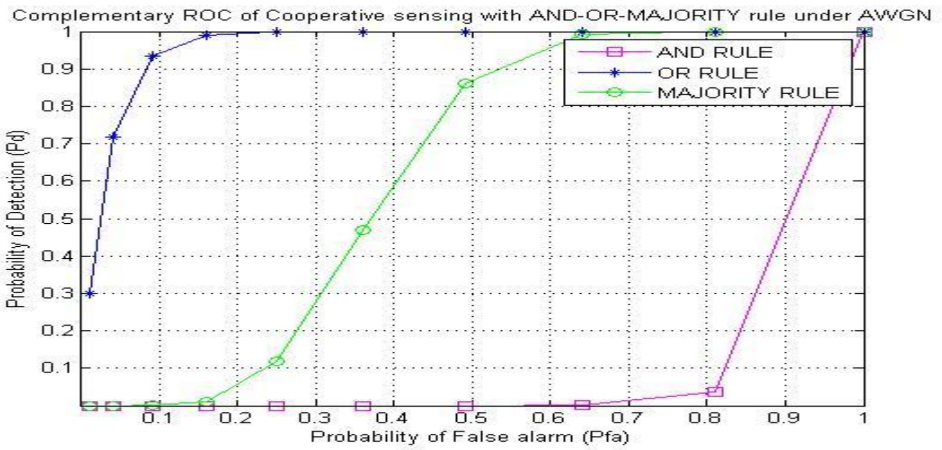

Figure 8: Probability of detection for AND, OR and MAJORITY rule.

The main idea behind the 2-bit hard combination scheme is to divide the whole range of observed energy into more than two regions and to assign different weights to these regions [18]. By doing this, nodes that observe higher energies in upper regions have greater weights than nodes that observe lower energies in lower regions [6]. Using the main idea of the 2-bit hard combination scheme proposed in [18], in 3-bit case the whole range of observed energy is divided into more than four regions. In particular, seven thresholds are used to divide the whole range of observed energy into eight regions. Each node sends to the decision maker a 3-bit information that indicates the region in which it's observed energy fell.

Fig.9 represents 2-bit and 3-bit combination comparison at SNR=-10dB. Comparing both hard combination schemes, 3-bit combination schemes shows better probability of detection (P_d) in terms of probability of false alarm (P_{fa}) over 2-bit combination schemes.3-bit combination scheme has low false alarm value than 2-bit combination scheme but when we consider probability of detection (p_d), 3-bit combination scheme outperforms than 2-bit combination scheme due to low false alarm value for particular probability of detection (P_d).

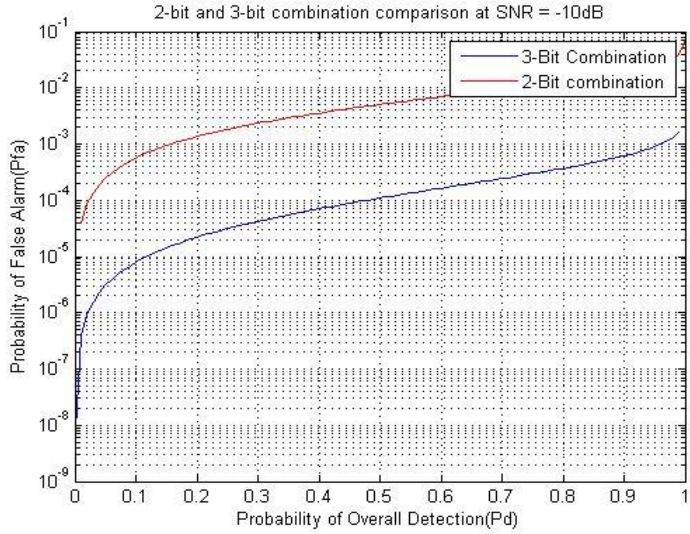

Figure 9: 2-bit and 3-bit combination comparison at SNR=-10dB

At low probability of detection (P_d), 2-bit OR combination scheme has highest false alarm value than 2-bit AND combination schemes and both 3-bit combination schemes. When probability of detection (P_d) increases for both 2-bit and 3-bit combination schemes, 3-bit combination AND and OR schemes show less false alarm values than other two of 2-bit combination schemes as shown in fig. 10.

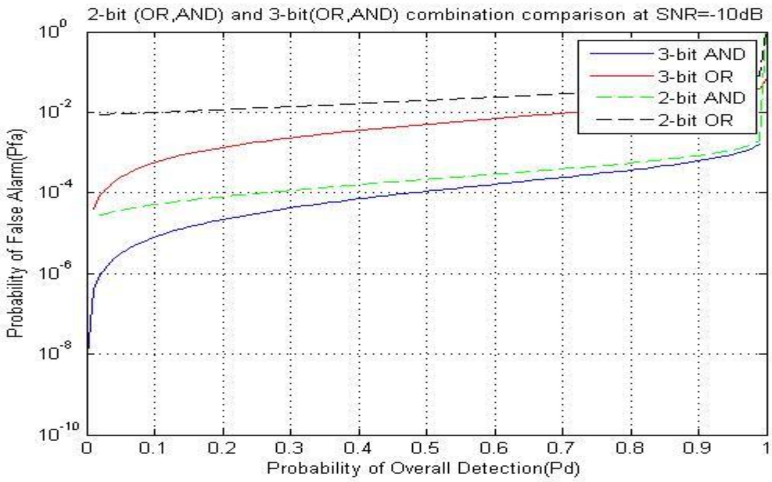

Figure 10: 2-bit (OR, AND) and 3-bit (OR, AND) combination comparison at SNR=-10dB

V. CONCLUSION

Spectrum Is A Very Valuable Resource In Wireless Communication Systems, And It Has Been A Focal Point For Research And Development Efforts Over The Last Several Decades. Cognitive Radio, Which Is One Of The Efforts To Utilize The Available Spectrum More Efficiently Through Opportunistic Spectrum Usage, Has Become An Exciting And Promising Concept. One Of The Important Elements Of Cognitive Radio Is Sensing The Available Spectrum Opportunities. Several Sensing Methods Are Studied.

The numerical results OR rule can improve probability of detection than AND rule and MAJORITY rule. Cooperative technique is more effective when received SNR in cognitive radio users is low due to fading and shadowing.

There are several ideas for future work from this thesis. First, simulation models can be improved. Multipath fading effects could be added and their effects on the performance of the fusion rules could be investigated. Instead of generating the RF signals in MATLAB, actual transmitted signals could be collected in the field. The 3-bit hard combination scheme could be compared with the 2-bit hard combination scheme with actual signal collected in the field. In the simulation results, probability of detection could be illustrated as a detection performance measure.

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