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Performance analysis of Maximum Eigen value and Energy Detection Techniques

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ABSATCT; The main motive to design this to implementation and analysis Cognitive Radio technology (CR) is spectrum sensing. The characteristic of this spectrum sensing the electromagnetic atmosphere to settle in their operation for better radio operating parameters. One of the challenges for CR is to detect the primary users present over the spectrum. That presents the Maximum Eigen value Based energy detection and .Also highlighted the effect of different parameters like number of samples, signal to noise ratio in addition apply comparison between the two methods using the simulation technique. In these Paper spectrums sensing technique is introduced but the main work is carried for energy detection methods. Energy detection technique is implemented using MATLAB simulation and the obtained results are plotted using MATLAB simulation

KEYWORDS: Energy detection. Maximum Eigen value ma, CR, OR rule, AND rule, majority rule

I. INTRODUCTION

Spectrum is a scarce resource, and licensed spectrum is intended to be used only by the spectrum owners. However, various measurements of spectrum utilization have shown unused resources in frequency, time and space. Cognitive radio is a new concept of reusing licensed spectrum in an unlicensed manner. The unused resources are often referred to as spectrum holes or white spaces. These spectrum holes could be reused by cognitive radios, sometimes called secondary users. However, the introduction of cognitive radios will inevitably create increased interference and thus degrade the quality of service of the primary system. The impact on the primary system, for example in terms of increased interference, must be kept at a minimal level. To keep the impact at an acceptable level, secondary users must sense the spectrum to detect whether it is available or not. Secondary users must be able to detect very weak primary user signals [8]

Spectrum sensing is the ability to find available frequencies or timeslots to transmit in, and is therefore a fundamental component in cognitive radio. However, there are several factors which make the sensing problem difficult to solve. First, the Signal-to-Noise Ratio (SNR) of the primary users received at the secondary receivers may be very low. Secondly, fading and time dispersion of the wireless channel may complicate the sensing problem. In particular, fading will cause the received signal power to fluctuate dramatically while an unknown time dispersed channel will cause unreliable coherent detection [10][3]. Thirdly, the noise/interference level changes with time which results in the noise uncertainty [10][1][5] there are two types of noise uncertainty: receiver device noise uncertainty and environment noise uncertainty. The sources of receiver device noise uncertainty include [13] (a) non-linearity of components (b) thermal noise in components, which is non-uniform and time-varying. The environment noise uncertainty may be caused by

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transmissions of other users, including near-by unintentional transmissions and far-away intentional transmissions. Because of the noise uncertainty, in practice, it is very difficult to obtain the accurate noise power Under this paradigm, the onus is entirely on the secondary network to detect if the incumbent network is utilizing the channel, and to access the channel only if the incumbent is silent, or access it in such a way that it causes an unnoticeable performance drop for the primary network. Consequently, this creates the very challenging problem of designing a detector capable of producing high probabilities of detection at very low signal-to-noise ratios

FUNCTIONS OF CR: There are four major functions of Cognitive Radio. Figure 1 shows the basic cognitive cycle the principal step of spectrum sensing is that it decides the presence of primary user on a band. The cognitive radio has the capacity to impart the result of its detection with other cognitive radios in the wake of sensing the spectrum. The main objective of spectrum sensing is to discover the spectrum status and activity by periodically sensing the target frequency band

. **A-SPECTRUM MANAGEMENT:** Provides the reasonable spectrum scheduling technique among coexisting users. The available white space or channel is quickly chosen by cognitive radio if once found. This property of cognitive radio is described as spectrum management.

B- SPECTRUM SHARING: Cognitive Radio doles out the unused (spectrum hole) to the secondary user (SU) as

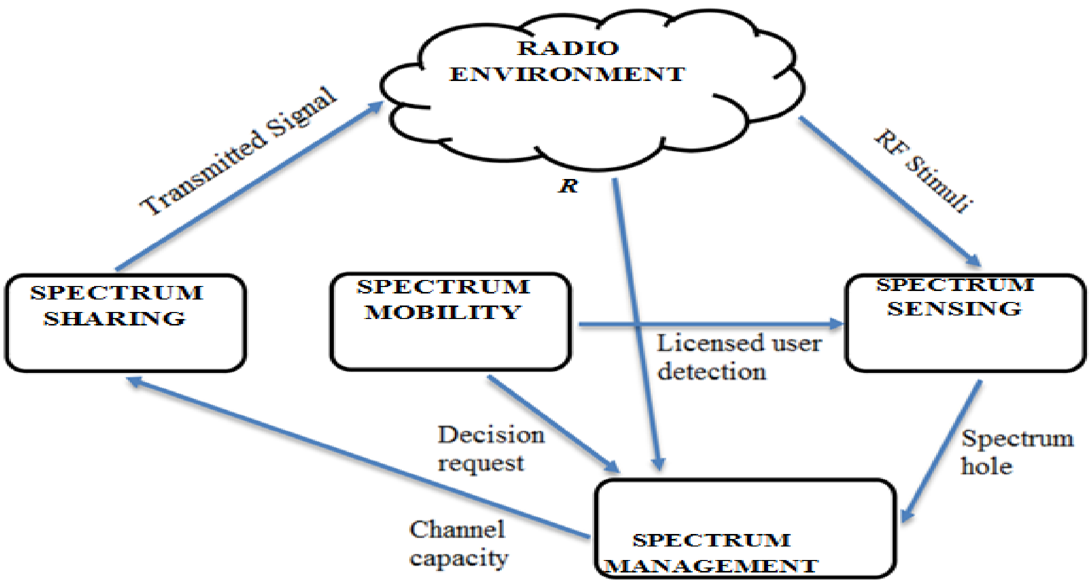

Figure 1.4 Basic cognitive cycles

Long as primary user (PU) does not utilize it. This property of cognitive radio is described as spectrum sharing.

C- SPECTRUM MOBILITY: When an authorized (Primary) user is detected, the Cognitive Radio (CR) empties the channel. This property of cognitive radio is depicted as the spectrum mobility, also called handoff.

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II. PROPOSED METHOD

In communication theory it is often assumed that the transmitted signals are distorted by some noise. The most common noise is Additive Gaussian noise, i.e. the so called Additive White Gaussian Noise channel, AWGN. Even though the noise in reality is more complex, this model is very efficient when simulating for example background noise or amplifier noise. Then the model can be complemented by e.g. impulse noise or other typical noise models that are out there. In this chapter we will have a closer look at AWGN channels and see how the previous theory applies here. We will derive a fundamental limit of the signal to noise ration (SNR) specifying when it is not possible to achieve reliable communication. Spectrum Sensing Model The algorithm of spectrum sensing depends on many parameters like number of samples, signal to noise ratio and noise uncertainty. It aims to make decision between two hypotheses (choose H0 or H1) based on the received signal.

$$H0: X(N) = W(N) \ldots\ldots\ldots\ldots\ldots 1$$

$$H1: X(N) = S(N) + W(N) \ldots 2$$

Where N is number of samples, X(N) is the received signal , S(N) is the primary users signal, W(N) is the noise , H0 Gaussian noise (AWGN) with zero mean [4]. The key metric in spectrum sensing are the probability of correct detection probability of alarm (occurs when the channel is empty (H0) but spectrum sensor decides that the channel is occupied and probability of misdetection occurs when the channel is occupied (H1) but spectrum sensor decides that the channel is unoccupied [5] A signal in a digital communication system can be represented as by a continuous random variable. This value can be decomposed in two parts added together

$$Y = X + Z$$

Where X is the information carrier component and Z noise component. The average power allocated by the variable X is defined as the second moment,

$$P = E[X2]$$

A Gaussian channel is a time-discrete channel with input X and output Y = X + Z, where Z models the noise and is Normal distributed,

The communication signalling is limited by a power constraint on the transmitter side,

$$E[X2] \leq P$$

Without the power constraint in the definition we would be able to choose as many signal alternatives as far apart as we like. Then we would be able to transmit as much information as we like in a single channel use. With the power constraint we get a more realistic system where we need to find other means that increasing the power to get a higher information throughput over the channel.1 To see how much information is possible to transmit over the channel we again maximizes the mutual information between the transmitted variable X and the received variable Y, with the side condition that the power is limited by P

III. EVALUATION RESULT

The evaluation results. Is relevant for checking the correctness and completeness of the results and to validate these against theoretical findings. The results should be presented with estimated confidence intervals that present uncertainties in measurements and statistical analysis. Signal detection methods .a signal detector makes a binary decision based on the observed signal values on the channel during a limited time window. In analog implementations,

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the observed values can be represented as a continuous function x (t) defined for t ∈ [0, ts]. In digital implementations a more useful representation is a vector x of Ns observed signal samples in the time domain:

x = [xn] = {x0, x1, xNs-1}   (1)

The null hypothesis $\mathcal{H}0$ for the detector is that a channel is vacant. Alternative hypothesis $\mathcal{H}1$ is that the channel is occupied by another user. In the case of a vacant channel it is assumed that the observed samples consist of only noise. In the case of an occupied channel, the observed samples contain noise in addition to some information-carrying signal SNR. Various spectrum sensing methods make different assumptions about the properties of SNR to distinguish it from noise.

H0:xn=unH1:xn=un+snn∈[0,Ns-1]

An event when the detector reports an occupied channel and $\mathcal{H}1$ is true is called a correct detection. Alternatively, a false alarm event happens if $\mathcal{H}0$ is true while the detector reports the occupied channel. Both of these events are assigned probabilities, Pd and Pfa respectively. Probabilities are given in relation to the signal power:

Pin=1Ns∑n=0Ns-1sn2

A good spectrum sensing method will keep Pd high even for low Pin and short sensing time Ns. In practical applications, to have a useful detection method, the probability of detection should stay above a certain threshold.

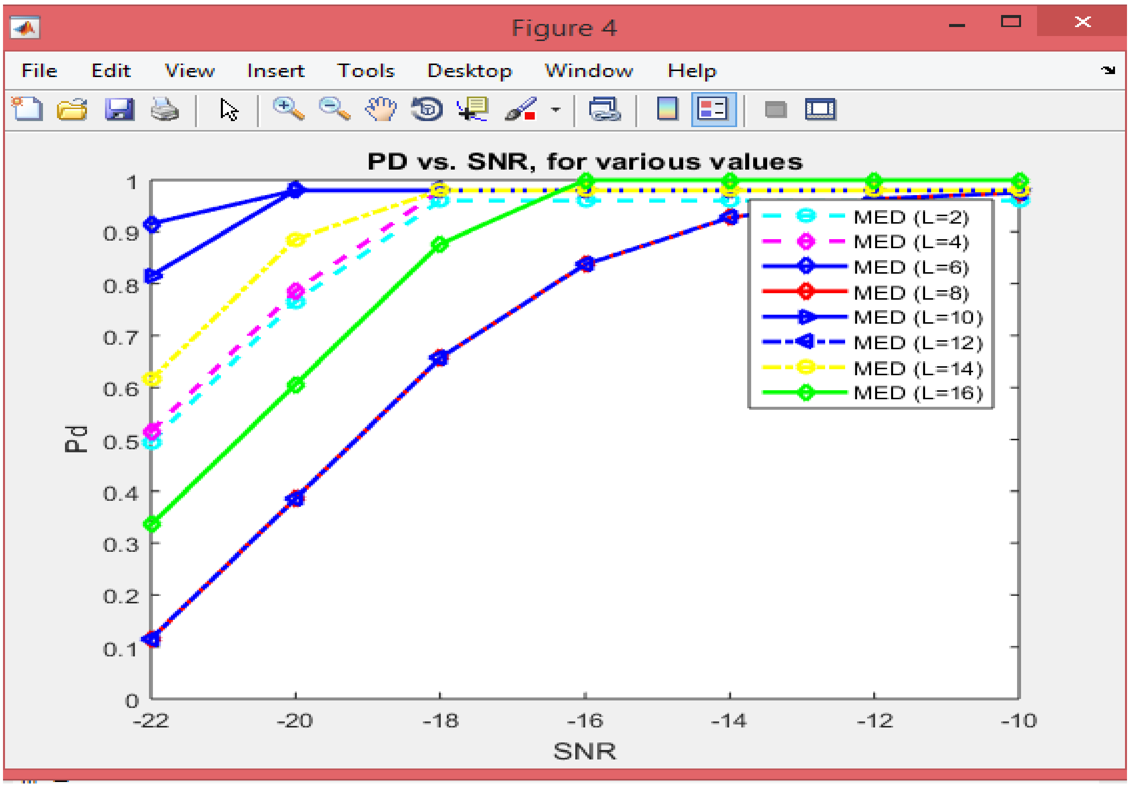

Fig. 2. PD vs. SNR, for various values of smoothing factor L

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The signal detection methods considered in this paper operate by defining a scalar test statistic $\gamma = \gamma(x)$ as a function of observed signal samples. A threshold $\gamma 0$ is then defined, which is used to make the binary decision as follows:

$$H0 if \gamma(x) \leq \gamma 0 H1 if \gamma(x) > \gamma 0$$

Threshold selection can be challenging. In our evaluation we used the empirical constant false alarm rate (CFAR) method [1]. A large number of signal sample vectors x was obtained for a known-empty channel. Using these measurements we approximated the complementary cumulative distribution function (CCDF) for γ in the case of $\mathcal{H}0$. The approximate $\gamma 0$ for a desired probability of false alarm Pfa can then be read from the graph,

SIGNAL-TO-NOISE-RATIO (SNR): Type I and type II errors are linked to each other through sensing time, SNR, and detection threshold. The SNR at the SUs depends on the PU transmitted power and the spectrum environment. The detection performance improves with an increase in the SNR.

In Fig. 4.1 we evaluate the detection probability of the two compared methods as a function of SNR and using different values of the smoothing factor (L varying from 1 to 16) in order to analyze its effect. These figures show that the detection probability in the case of the MED method decreases by increasing the SNR and increases by increasing the smoothing factor compared to the energy detection method which is not affected by L. Indeed, we can note that the PD in the case of the maximum eigenvalue detection method is not very sensitive to the smoothing factor for $L \geq 8$.First, randomly generated signals are used. We consider a system with 4 receivers/antennas ($M = 4$) and 2 signals ($P = 2$). The channel orders are $N1 = N2 = 4$ (5 taps). Assume that all the channel taps are independent with equal power. The smoothing factor is chosen as $L = 6$. 50000 samples are used for computing the sample covariance matrix. The probabilities of detection (Pd) for the MED method and energy detection (with or without noise uncertainty) If the noise variance is exactly known ($B = 0$), the energy detection is pretty good.

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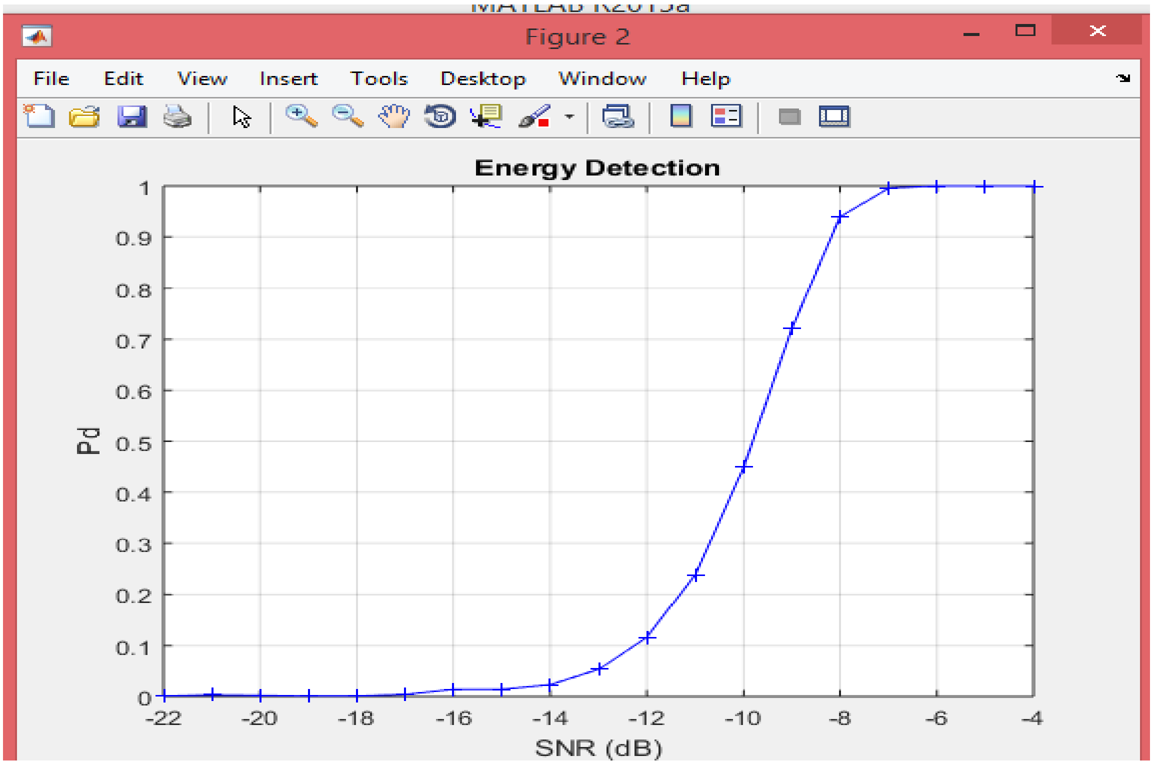

Fig. 3 PD vs. SNR, for various values of energy detection

The results are taken for = 0.1 , and SNRs varying from -22dB to -4dB. It is shown that the detection performance becomes better when increases However, when turns to 48, the However, if there is noise uncertainty, the detection probability of the energy detection is much worse than that of the proposed method. The Pfa for the proposed method and the energy detection without noise uncertainty meet the requirement (Pfa 6 0.1), but the Pfa for the energy detection with noise uncertainty far exceeds the limit. This means that the energy detection is very unreliable in practical situations with noise uncertainty performance detection declines. Therefore, should be relatively small while using this technique for a given number of samples. Therefore, choosing a proper temporal smoothing factor for a given number of samples is important. Figure 4.4 shows the performance comparison of the optimal-detection technique, the MED detection and energy detection. In MED detection, 4 receiving antennas are used for sensing in the radio environment while the optimal detector has a temporal smoothing factor of 16.

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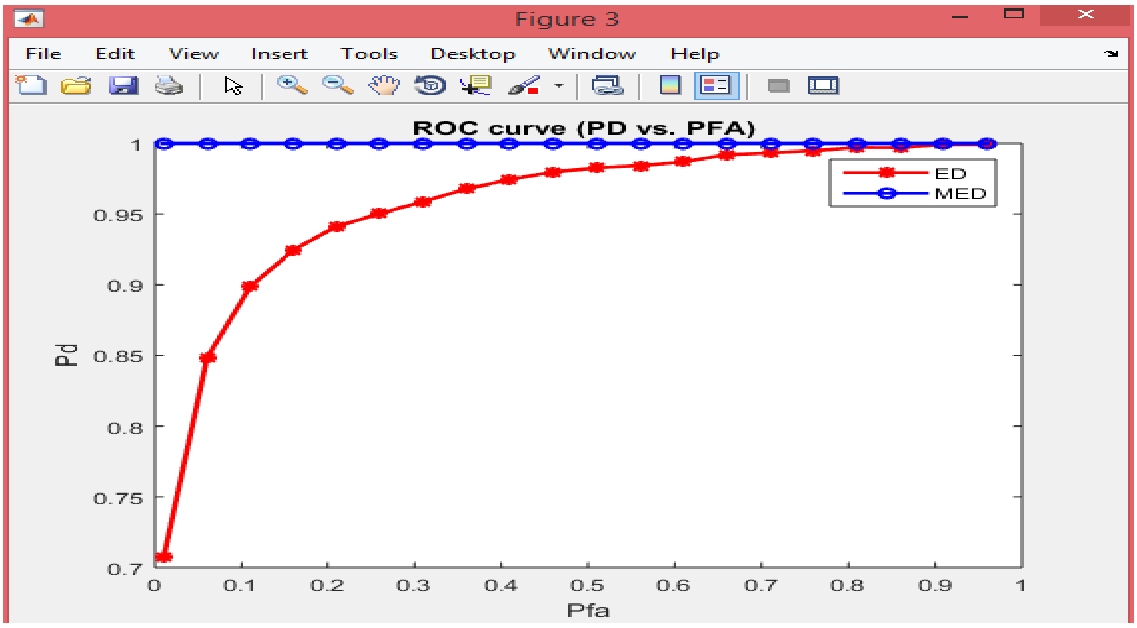

Fig. 4. PD vs. SNR, for various values of energy detection and MED

From the figure, we can also see that for the same SNR, the probability of detection improves as probability of false alarm increases. This reflects the trade-off between false alarm and detection probability. The graph probability of false alarm on X-axis and probability of detection on Y-axis as shown in Figure 3.4. Here we have taken probability of false alarm is (0,1), N=2000 and the Figure 4.2 clearly illustrates this tradeoffs. When increases there is a high likelihood of the algorithm detecting a signal even when there is no signal present. Obviously, for a good detection algorithm, the probability of detection should be high and the probability of false alarm should be low. The requirements of and depend on the application he Fig. 4 represents the detection probability of the ED and the MED methods as a function of the SNR with a false alarm probability fixed to PFA=0.1. From this figure, we can note that the detection probability is better in the case of the maximum eigenvalue detection whatever the value of the SNR

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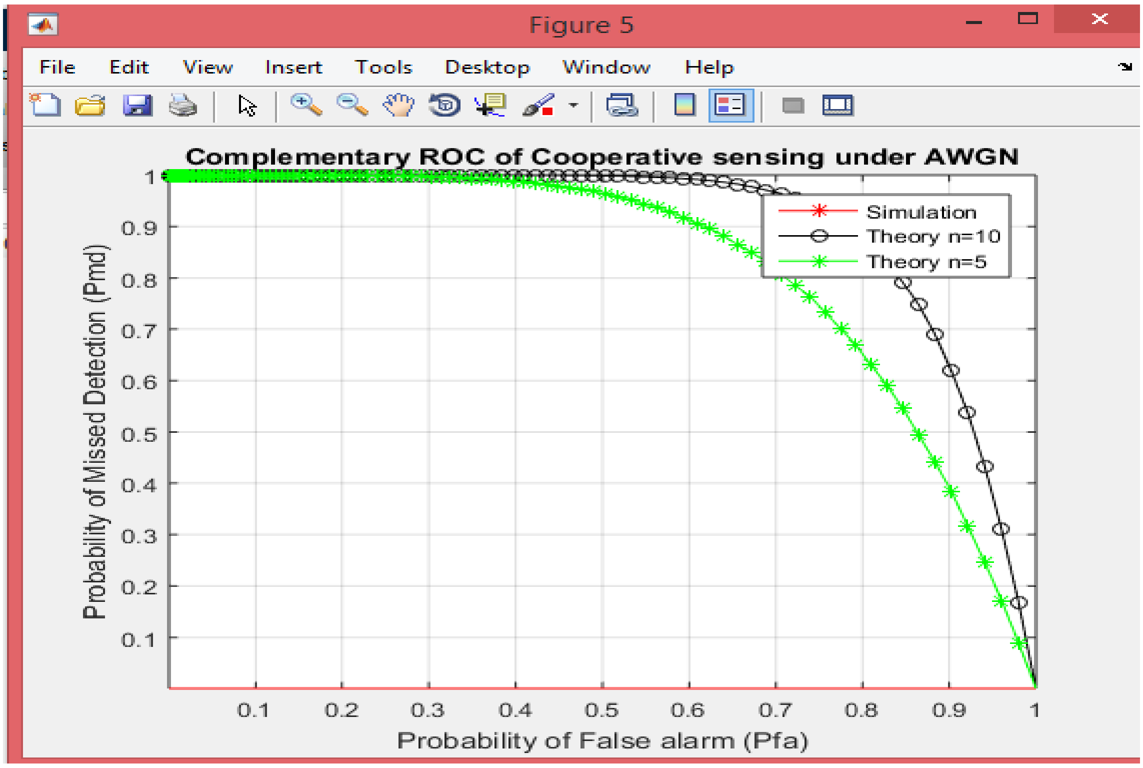

Fig. 5 PD vs.Pmd, for various values of energy detection and MED

Next energy detection mechanism was analyzed. The graph of P_{md} values on X-axis and probability of false alarm on Y-axis shown in the Figure 4.4.The graph shows that simulation and theoretically values of probability of detection for different values of SNR curves. Here we have taken probability of false alarm is 0.1 missed detection and number of sample points N=10.from the figure it is observed that performance is better at higher SNR 4.5 the ROC curves of the „AND" and the „OR" rule and majority rule ,. Each user has a SNR of -2db. As shown in Fig.4.6 the OR rule has better detection performance than the AND rule,

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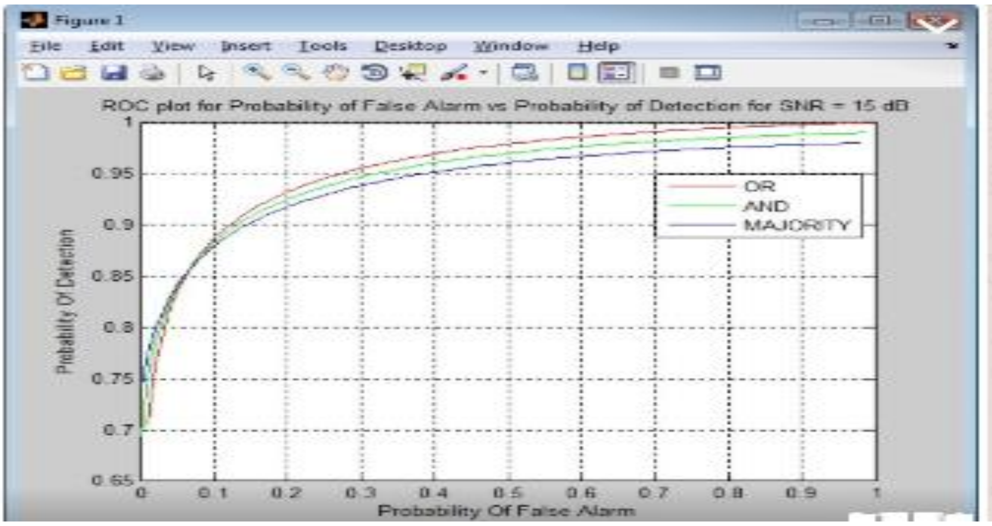

Fig.6 The ROC curves of the „AND" and the „OR" rule and majority rule

we evaluate the detection probability of the two compared methods as a function of SNR and using different values of the smoothing factor (L varying from 1 to 14) in order to analyze its effect. These figures show that the detection probability in the case of the MED method decreases by increasing the SNR and increases by increasing the smoothing factor compared to the energy detection method which is not affected by L.

Table 1 Comparison table

	PREVIOUS WORK		**PROPOSED WORK**	
L FACTOR	**SNR**	**PD**	**SNR**	**PD**
2	-16	0.1	-16.1	0.1
4	.-21	0.5	-19	0.5
6	-18	0.51	-18.12	0.51
8	-18	0.61	-18.1	0.61
10	-20	0.81	-20	0.81
16	-20	0.91	-20.12	0.91
ED	-16	0	-15.1	0

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IV. CONCLUSIONS

The main purpose of the thesis was to study the performance of energy detection algorithm for spectrum sensing in cognitive radio by drawing the curves between probability of false alarm vs. probability of detection, SNR vs. probability of detection and the performance of dynamic threshold on spectrum detection techniques(Matched filter detection, Energy detection) in cognitive radio systems. the future of wireless communications will be characterized by highly varying environments with multiple available radio access technologies exhibiting diverse features. So cognitive radio is a paradigm for new wireless communications to meet their standards.

The energy detector performance can be improved by increasing the SNR values and by increasing the number of sample points the detection performance is much better even at lower SNR values. the detection performance can be improved by using dynamic threshold based spectrum detection algorithm in cognitive radio systems. Energy detection based on fixed threshold are sensitive to noise uncertainty, a fractional change of average noise power causes decreasing the performance quickly. Matched filter which not sensitive to noise uncertainty, by using dynamic threshold the performance can be improved as compared with the fixed threshold. A method based on the eigenvalues of the sample covariance matrix of the received signal has been proposed using a single antenna for cognitive radio networks. A temporal smoothing technique is utilized to form a virtual multi-antenna structure.

Simulations using randomly generated signals are presented in order to illustrate the performance of the Optimal-detection method. It has been shown that the performance of Optimal-detection is very close to that of the MED detection with multiple antennas. The method can be used for various signal detection applications without knowledge of signal, channel and noise power. Besides, the proposed optimal-detection method can reduce system overhead and avoid the eigenvalue decomposition processing by utilizing power method.

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