PERFORMANCE EVALUATION OF DIFFERENT SPECTRUM SENSING TECHNIQUES FOR REALISTIC IMPLEMENTATION ORIENTED MODEL IN COGNITIVE RADIO NETWORKS

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ABSTRACT

In this paper, the performance assessment of five different detection techniques from spectrum sensing perspective in cognitive radio networks is proposed and implemented using the realistic implementation oriented model (R-model) with signal processing operations. The performance assessment of the different sensing techniques in the existence of unknown or imprecisely known impulsive noise levels is done by considering the signal detection in cognitive radio networks under a non-parametric multisensory detection scenario. The examination focuses on performance comparison of basic spectrum sensing mechanisms as, energy detection (ED) and cyclostationary feature detection (CSFD) along with the eigenvalue-based detection methods namely, Maximum-minimum eigenvalue detection (MMED), Roy's largest Root Test (RLRT) which requires knowledge of the noise variance and Generalized Likelihood Ratio Test (GLRT) which can be implemented as a test of the largest eigenvalues vs. Maximum-likelihood estimates a noise variance. From simulation results it is observed that the detection performance of the GLRT method is better than the other techniques in realistic implementation oriented model.

KEYWORDS

Cognitive Radio, Cyclostationary feature detection, Energy detection, GLRT, RLRT, Spectrum Sensing

1.INTRODUCTION

The demand for the radio spectrum is dramatically increasing and is estimated to rise rapidly in the near future with reference to the rapid development of different wireless communication applications. The radio frequency spectrum is a limited natural resource to enable wireless communication between transmitters and receivers and it is already very packed. It appears that it is tough to accommodate more wireless applications within this limited resource. The frequency bands of the wireless communication spectrum are not currently used very efficiently, mainly due to the current static spectrum allocation policy is based on a fixed frequency allocation policy in which the licensed spectrum bands remains underutilized. The report of Federal Communications Commission (FCC) [1], exposes that in some locations or at some times of day, almost 70% of the allocated spectrum may be sitting idle. To deal with the discrepancy between spectrum congestion and spectrum under-utilization, cognitive radio (CR) has been recently proposed as the capable solution for improving the utilization of the available spectrum to current low usage of licensed spectrum problem [2]. A CR sense and identify spectrum opportunities unoccupied by a primary user (PU) and improve the spectrum utilization while reducing the white spaces in the spectrum. Also it must prevent interference with the licensed PUs. The spectrum sensing is one of the main issues from the spectrum management perspective as the CR needs to sense the spectrum holes in wireless environments before accessing the channel. [3].

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Major problems for CR like multipath fading, receiver uncertainty hidden terminals and correlated shadowing observed in a non-cooperative spectrum sensing can be solved by cooperative spectrum sensing techniques. Cooperative sensing decreases the probabilities of miss-detection and probability of false alarm considerably. Furthermore the hidden PU problem can also be solved which results in decrease in sensing time [4]. The basic spectrum sensing mechanisms are matched filter detection (MFD) [5-8], energy detection [9-12] and cyclostationary feature detection [13-15]. Every technique is unique in itself with certain advantages and limitations. The basic knowledge of cyclic frequencies of the primary signal is essential in CSFD, which may not be available to the secondary users in practice. Also, it has high computational complexity. MFD is considered to be an optimal signal-detection method. The MFD is assumed to be an optimal signal-detection method. However the prior knowledge of the PU such as, modulation type, pulse shaping, and synchronization of timing and carrier is indispensable. And in MFD, for each PU, the CR will require a committed receiver and this requirement is makes it difficult for practical implementation [16]. From [17- 19] it is observed that the eigenvalue–based spectrum sensing techniques is found as the best amongst existing sensing methods. The eigenvalue-based spectrum sensing methods has overcome the limitations of the previously discussed methods. The prior knowledge of the transmitted signal is not essential in this method. Also the most basic sensing method the ED is reasonably sensitive to the accuracy of the expected noise variance [20]. We have considered the effect of impulsive noise for investigating the performance of the eigenvalue- based spectrum sensing scheme in perspective of spectrum sensing.

Impulsive noise (IN) consists of repetitive or non-repetitive pulses with a random intensity, duration and occurrence. The major sources of IN generation are household appliances, heating systems, ignition devices and dropouts or surface degradation of audio recordings, clicks from computer keyboards [21-22]. Via selection and equal gain combining the performance of the ED is investigated and concluded that impulsive noise can degrade the sensing performance. The GLRT method of detection is also proposed. In the non-realistic conventional model no analysis has been made considering the different eigenvalue-based spectrum sensing methods.

1.1. Conventional discrete time memory less linear MIMO fading channel model (C-Model)

It is static model in which channel remains idle, we consider Additive White Gaussian Noise (AWGN) channel. The memory-less linear discrete-time multiple input multiple output (MIMO) fading channel for single-receiver, multi-sensor and multiple-receiver, single-sensor cognitive devices is considered. It is also known as conventional model (C-model) [23]. Because of limitation of no signal processing performed by the C-model, it cannot be used for multiple CR receivers, as the samples collected by each CR are considered and forwarded to the fusion centre directly. Hence modifications are essential in the C-model.

1.2. The Realistic Implementation oriented model (R-Model)

The more realistic implementation- oriented MIMO (R-model), in which signal processing operations like filtering , quantization and automatic gain control (AGC) are used within direct-conversion CR receiver architecture as shown below [24-25].

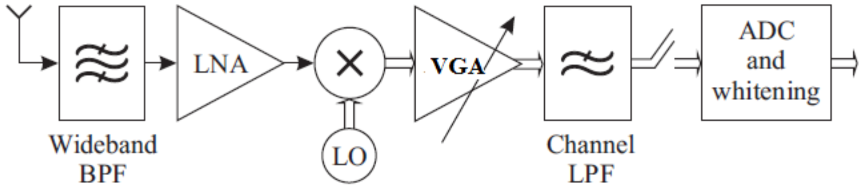

Figure 1. CR Receiver Diagram

Fig. 1 is considered for construction of the realistic model. In which the spectrum-sensing directed functions are combined with the direct conversion receiver (DCR). The wideband band-pass filter (BPF), low-noise amplifier (LNA) and quadrature local oscillators (LO) and mixers are used for direct conversion of the desired channel to in-phase and quadrature (I&Q) baseband signals. The drawbacks like I&Q imbalance are present in the DCRs, because it suffers from, flicker noise and DC- offset [26]. The DC-offset can effortlessly saturate succeeding amplification stages [27]. It is a DC signal appearing at the mixer output is composed of a static and a dynamic part, primarily due to LO self-mixing processes and in-band interfering signals. The static part can be removed by the careful circuit design and modern DC-offset compensation algorithms, but still some residual dynamic DC-offset will always remain [28]. The signal is held in reserve within the dynamic range of the analog-to-digital converters (ADC) in I&Q signal paths which passed through the variable gain amplifier (VGA) with the help of the automatic gain control (AGC) method. The I&Q low-pass filters (LPF) is used to select the preferred bandwidth to be sampled.

The effect of impulsive noise (IN) is considered for investigating the performance of the eigenvalue-based spectrum sensing scheme. Efforts are put in investigation about the influence of impulsive noise in the CR receivers in perspective of spectrum sensing.
Various models are proposed to exemplify the IN [29-33]. The model presented in [30] is used for performance evaluation in which the white noise signal is used to generate the IN waveform and shown in Fig.2.

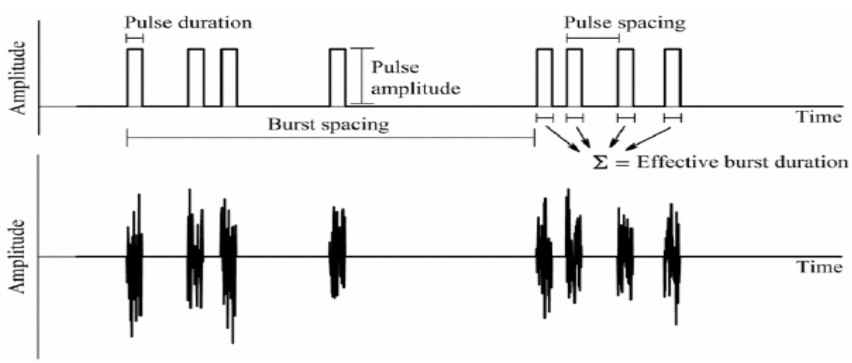

Figure 2. Impulsive Noise waveform

Considering the above mentioned issues, it is clear that the IN can cause degradation in performance of eigenvalue based spectrum sensing. Our work focus point is to assess the performance of spectrum sensing techniques by addressing the effect of IN and investigate the comparative performance in realistic implementation oriented model (R-model).The work contributes examination of the effect of impulsive noise in five different detection techniques namely GLRT, RLRT, CSFD, MMED and ED .

The rest of the paper is organized as follows. Section 2 briefly describes the system model for spectrum detection techniques under examination. Simulation setup for performance analysis of the five spectrum sensing techniques with configuration of parameters is presented in Section 3 .Simulation results with comparative sensing performance is illustrated in Section 4. Finally conclusions are drawn in Section 5.

2. SYSTEM MODEL

The system model of detection is under the test of following two hypotheses H_0 and H_1 [34-35].

H_0 : signifies the absence of the signal and presence of only noise.

H_1: signifies the presence of both signal and noise.

Thus, for the two state hypothesis numbers of cases are:-

1) Probability of Detection (P_d): i.e P (H_1 / H_1) , corresponds H_1 to be true for the presence of primary signal.
2) Probabilty of Missed Detection (P_{md}): i.e P (H_0 / H_1) , corresponds H_0 to be true for the presence of primary signal.
3) Probabilty of False Alarm (P_{fa}): i.e P (H_1/ H_0) , corresponds $H_1$to be true for the presence of primary signal.

Probability of detection P_d and Probability of false alarm P_{fa} can be expressed as [12],

$$P_d = P(T > \gamma | H_1) \tag{1}$$

$$P_{fa} = P(T > \gamma | H_0) \tag{2}$$

Where, P denotes the probability of a given event, T is the detection-dependent test statistic and γ is the decision threshold. The value of γ is selected depending on the requirements for the spectrum sensing performance, which is typically evaluated through receiver operating characteristic (ROC) curves that show P_{fa} versus P_d as they vary with the decision threshold γ.
For constructing test statics, the multi-sensor detection setting situation is considered, with K sensors (receivers or antennas) and N time samples. Let $y(n) = [y1(n)\ldots yK(n)]^T$ be the $K \times 1$ received vector at time n, where the element $yk(n)$ is the discrete baseband complex sample at receiver k. Under H_0, the received vector consists of K complex Gaussian noise samples with zero mean and variance σ_v^2.

$$y(n)|H_0 = v(n) \tag{3}$$

Where $v(n) \sim NC(0_{K\times1}, \sigma_v^2 I_{K\times K}$. Under H_1, in contrast, the received vector contains signal plus noise,

$$y(n)|H_1 = x(n) + v(n) = hs(n) + v(n) \tag{4}$$

The $s(n)$, represent the transmitted signal sample, modelled as a Gaussian2 random variable with zero mean and variance σ_s^2 and h is the $K \times 1$ unknown complex channel vector. The assumption for the channel is made to be memory less and constant during the detection time. Under H_1, the SNR at the receiver is defined as,

$$\rho \cong \frac{E\|x(n)\|^2}{E\|v(n)\|^2} = \frac{\sigma_s^2\|h\|^2}{\sigma_v^2\ K}, \tag{5}$$

where, $\|.\|$ denotes Euclidean (L2) norm.

The received samples are stored by the detector in the $K \times N$ matrix

$$Y \cong, [y(1) \dots y(N)] = hs + V \tag{6}$$

Where , $s \cong, [s(1)\dots s(N)]$, is a $1 \times N$ signal vector and $V \cong, [v(1)\dots v(N)]$ is a $K\times N$ noise matrix. The sample covariance matrix R is then defined as,

$$R \cong \frac{1}{N} YY^H \tag{7}$$

Let $\lambda_1 \geq \cdots \geq \lambda_K$ be the eigen values of R (without loss of generality, sorted in decreasing order).

We focus on the difference in detection performance between the cases of known and unknown noise level.

The test statistics for GLRT, CSFD, MMED, ED and RLRT are respectively calculated according to [25].

$$T_{GLRT} = \frac{\lambda_1}{\frac{1}{m}tr(R)} = \frac{\lambda_1}{\frac{1}{m}\sum_{i=1}^{m}\lambda_i} \tag{8}$$

$$T_{CSFD} = \frac{\lambda_1}{\lambda_m} \tag{9}$$

$$T_{MMED} = \frac{\lambda_1}{\sigma^2}, \tag{10}$$

$$T_{ED} = \frac{\|Y\|_F^2}{mn\sigma^2} = \frac{1}{m\sigma^2}\sum_{i=1}^{m}\lambda_i, \tag{11}$$

$$T_{RLRT} = \frac{\lambda_1}{\sigma_v^2} \tag{12}$$

Where, σ^2 is the thermal noise power, expected to be known and with equal value in each sensor input, and $tr(\,)$ and $\|\,\|_F$ are the trace and the Frobenius norm of the underlying matrix, respectively.

3. SIMULATION SETUP

With reference to receiver architecture shown in the Fig.1, the simulation setup is build and the, performance parameters configured are as follows,

- m: Antennas in CR / CR with one antenna each.
- n: Number of received samples collected from primary transmitter.
- Ne: The number of Monte Carlo simulation events.
- The sensing techniques under analysis are ED, MFD, CSFD, GLRT and RLRT.
- The type of transmitted signal (noise, BPSK, QAM or user defined modulation).
- N_q: Number of quantization levels .
- D: ADC dynamic range.
- f_{od}: overdrive factor.

For impulsive noise (IN) following additional parameters have to be set,

- p_{IN} : Probability of IN occurrence.
- p_{CR} : Fractions of CR hits by IN.
- N_s : Number of IN blurts.
- K : The ratio between average IN power and average thermal noise power.
- β : The average number of samples between impulsive noise pulses.
- A : The mean of the log-normal impulsive noise amplitudes.
- B : The standard deviation of the log-normal amplitudes.

Two different simulation processes are carried out. For the first simulation type, the SNR is kept at fixed value in dB and the decision threshold range is varied between minimum and maximum threshold values. While the second process of simulation is carried out by defining three parameters, like the fixed threshold level , and the minimum and the maximum SNR values in dB with the number of points within the SNR range.

4. SIMULATION RESULTS

Two major parameters used as a performance measurement metrics to analyse the performance of detection process are, Probability of Detection (P_d) and Probability of False alarm(P_{fa}). The performance of a spectrum sensing techniques is illustrated by the receiver operating characteristics (ROC) curve which is a plot of P_d versus P_{fa}.

The performance measurements parameters set for simulation type one as, $m = 8,\ n = 50,$ $SNR = -10\ dB,$ no. of monte carlo events simulated = 1000 and minimum to maximum threshold levels set in the range from $\gamma = 0.78$ to $\gamma = 1.1$ with 8 different threshold events. In the second simulation scenario the threshold level is kept fixed at value $\gamma = 1.4$ and SNR is varied in between the range of -10 dB to 20 dB.

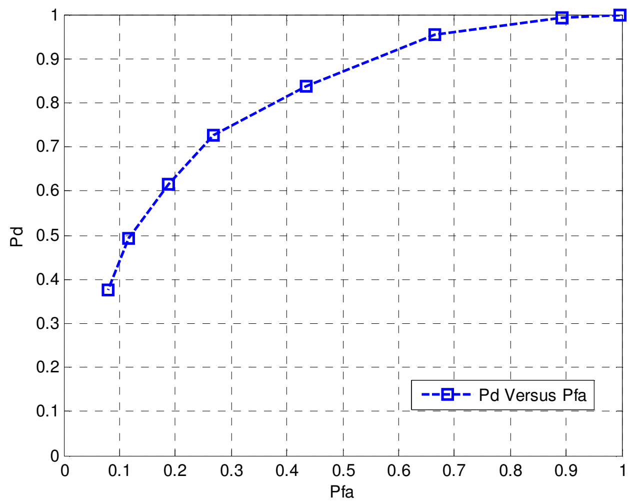

Figure 3. ROC curve with SNR=10dB for m=8 and n=50

Fig. 3, represents the ROC curve for ED method, it is evident from the graph that for less P_{fa} values, P_d is comparatively high. But, as P_{fa} increased, there is increased significant improvement is observed in P_d . Thus, it can be seen that the detection performance is improved in ED at low SNR values.

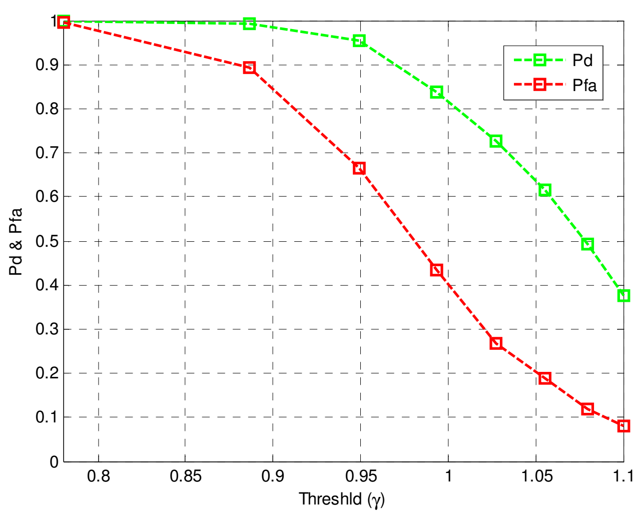

Figure 4. Pd, Pfa Vs Threshold

Fig.4. presents comparison of P_d P_{fa}, with respect to change in threshold levels. Fixed a given threshold, the behaviour of the P_{fa} is shown, it is evident from the results that the P_d is improved.

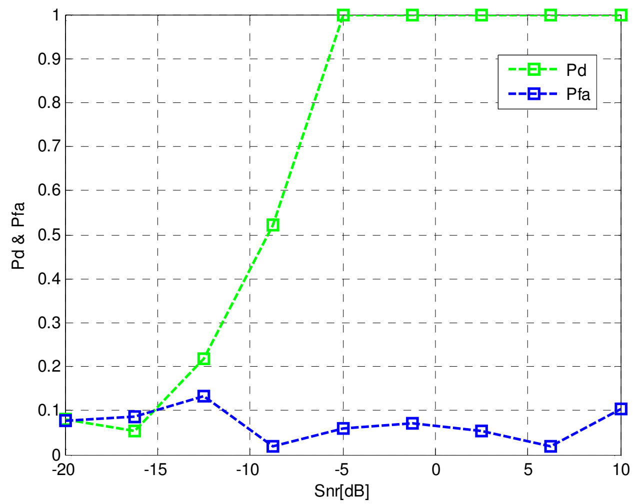

Figure 5. Pd, Pfa Vs SNR

In Fig.5 the relation between the P_d, P_{fa} with SNR is verified. With increase in SNR the value of P_d is also increased. Also as the value of P_{fa} vary there is significant improvement in P_d is obtained. Although the results presented in Figure 3-5 are only for ED method, but we retried that this is valid for all detection techniques considered here.

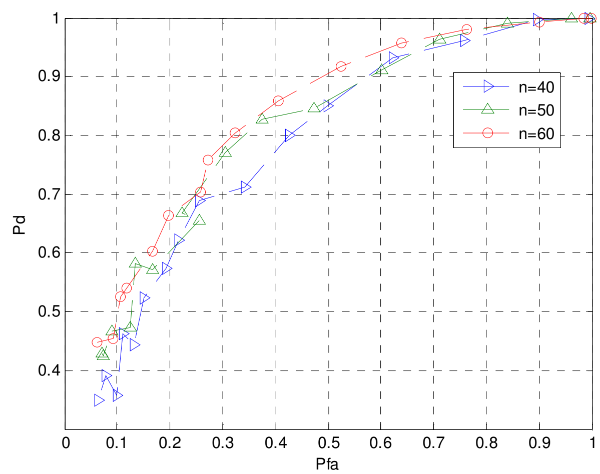

Figure 6. ROC curve for ED method with m=8 and SNR=10dB

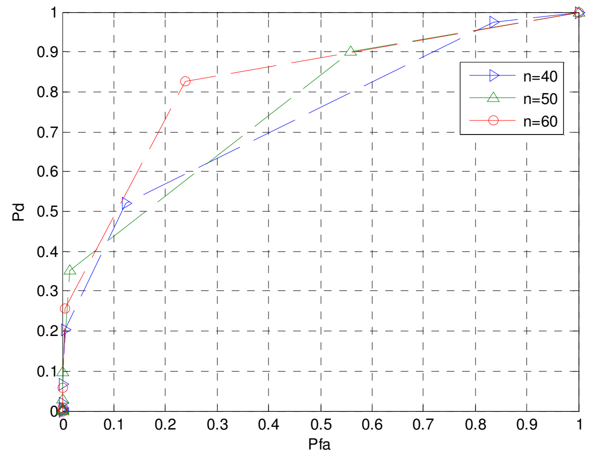

Figure 7. ROC curve for GLRT method with m=8 and SNR=10dB

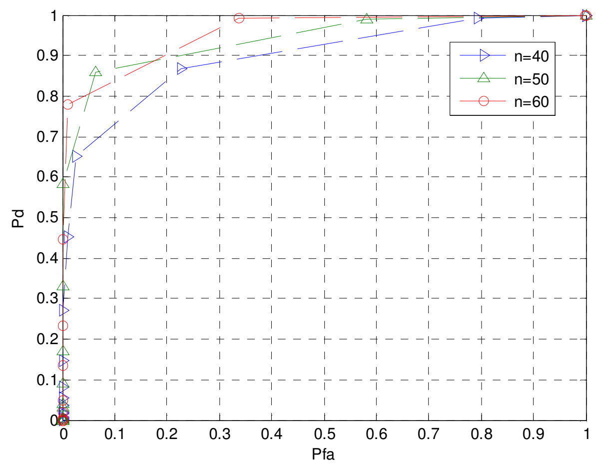

Figure 8. ROC curve for CSFD method with m=8 and SNR=10dB

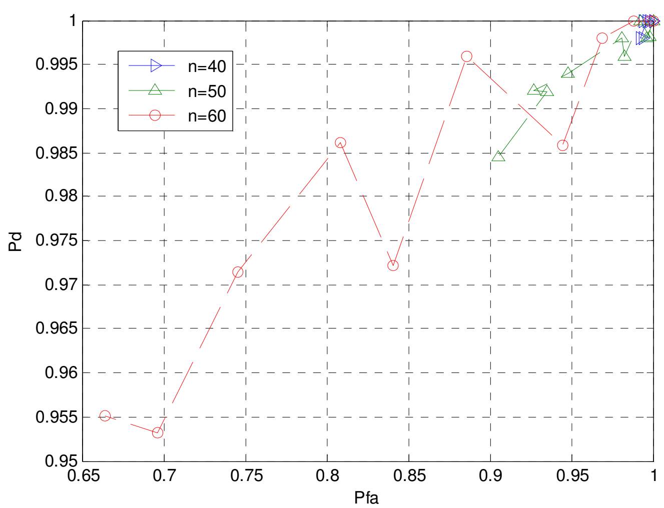

Figure 9. ROC curve for MMED method with m=8 and SNR=10dB

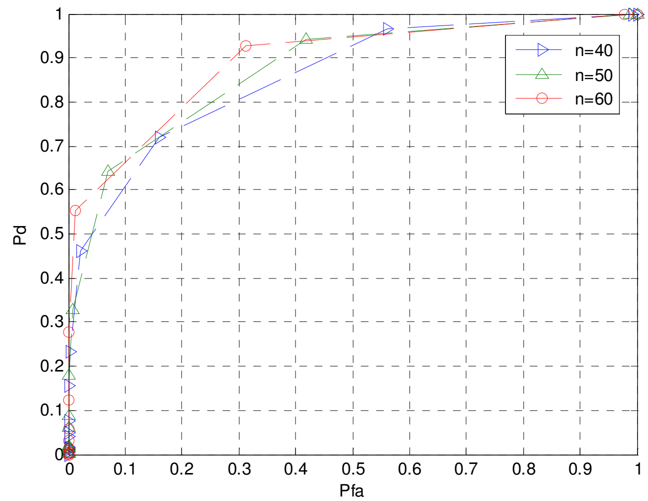

Figure 10. ROC curve for RLRT method with m=8 and SNR=10dB

Fig. 6-10, shows ROC curve with effect of IN for all the detection methods under test. Different values of the number of collected samples (n), concerning the probability of false alarm (P_{fa}) and the probability of detection (P_d) are measured. The results illustrate system performance under IN conditions. With reference to the number of collected samples (n), we set different minimum to maximum threshold levels as follows. For $n = 40$ the threshold levels are $\gamma_{min} = 2.8$ and $\gamma_{max} = 6.5$, for $n = 50$, $\gamma_{min} = 2.8$ and $\gamma_{max} = 6.5$, and for $n = 60$ $\gamma_{min} = 2$ to $\gamma_{max} = 4.5$. Also $m = 8$ and SNR is kept at -10 dB. The number of primary transmitters p =1,$K = 0$, $L = 1 - 20$,$D = 2$, $f_{od} = 1 - 2$ and N_q is varied as 4,8 and 256. It is clear from the results that with reference to greater threshold value, the values of P_d and P_{fa} are smaller. Similarly, for smaller threshold, P_d and P_{fa} tends to 1. Increase in sensing performance is observed with increase in n . It can be further confirmed from ROC curves that, the influence of increasing the number n of collected samples per CR is a performance improvement, considering as fixed the remaining system are identified in the graph.

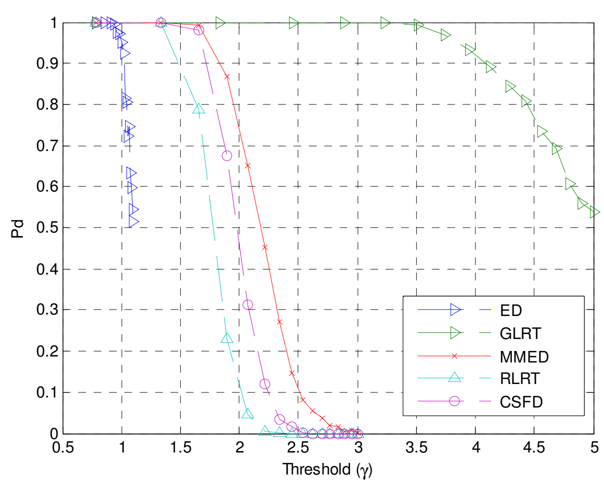

Figure 11. Pd Vs Threshold for all sensing methods

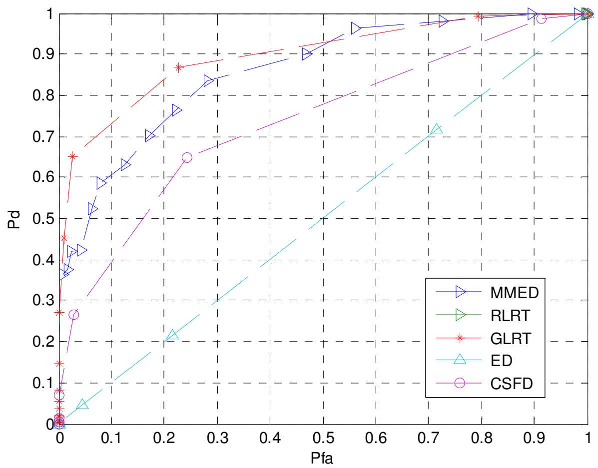

Figure 12. ROC Curve for all sensing methods under parameter variations

Fig. 11-12, illustrates the performance comparison of all the detection methods under test namely, GLRT, CSFD, MMED, ED and RLRT. Different threshold values from $\gamma_{\min} = 0.5$ and $\gamma_{\max} = 5$ are used for plotting the probability of detection Pd in Fig.11. From the comparative plot, it is clear that the GLRT method demonstrate better detection performance than the other detection methods for variable threshold level with fixed SNR value. Fig.12 presents ROC curves relating (P_{fa}) and the (P_d) for the investigated detection techniques, for p = 1, m = 6, SNR = −10 dB, and variable $N_q = 8$, and for f_{od} and L ranging from 1 to 2, and 1 to 20, respectively. And analysis of the results indicates that, the sensing performance is improved in GLRT and MMED methods for realistic implementation oriented model in the presence of impulsive noise.

5. CONCLUSIONS

In this paper, performance of five different detection methods for spectrum sensing in cognitive radio networks is evaluated by implementing the realistic model with typical signal processing is involved in implementation. Closed form expressions for probability of detection and false alarm over different sensing methods are evaluated. Simulation results shows that, the effect of

impulsive noise is less in GLRT method as compare to the other detection methods and thus the performance of GLRT method is improved in realistic implementation model.

In comparison with the conventional model the realistic implementation oriented model provide reasonably better results. Moreover the comparison of results helps for performance evaluation and of sensing methods in cognitive radio networks. It is believed that the work carried out in this paper is useful to understand the performance in cognitive radio network for selection of best sensing method. In future work attention can be given on the computation of closed form analysis by using more realistic approach with typical CR signal processing tasks.

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