

# SIMULATION OF IMPROVED ENERGY DETECTION BASED SPECTRUM SENSING

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**Abstract**— With tremendous growth of wireless communication technology, the spectrum utilization is one of the prime challenges. Cognitive radio has been emerged as a key technology which can resolve the issue by sensing, analyzing and allocating the spectrum. There are different spectrum sensing algorithms suggested in the literature. In this thesis, an overview of major sensing techniques is discussed. Although having practical limitations, Energy detection is a popular technique because of its simplicity, low computational complexity and mainly due to no necessity of prior information from primary user. This research is focused on an improved version of energy Detection Technique. The results prove that the improved energy detection based technique gives better performance under lower SNR values.

**Index Terms**— cognitive radio; spectrum sensing, Energy Detection, ROC

## I. INTRODUCTION

The phenomenal development of wireless communication services and requirement of high data rates over time, lead to growing spectrum demand. Considering mobile networks, as per the Cisco's Visual Networking Index (VNI) reports Mobile data traffic increased 63 percent at global level in 2016. At the end of 2016, it reached 7.2 billion gigabytes/month from 4.4 billion gigabytes/month at the end of 2015. The growth is 18-fold over the past five years and data transfer speed over mobile networks grew 3 folds last year. Predictions show that by 2021, mobile data traffic will reach 49 billion gigabytes/month and data transfer speed will exceed 20Mbps [1]. The scenario for other wireless services is similar or even more demanding.

In contrast to the exponential increase in spectrum demand, the spectrum provided for communication is limited and new allotment is done at quite a moderate pace. In today's scenario where large part of spectrum is allotted to licensed users, there have been two techniques to enhance spectral efficiency of wireless networks: to design more spectrally efficient wireless systems; and to increase the size of spectrum [2]. Plenty of research has been done to increase spectral efficiency in terms of throughput per bandwidth for example by implementing Multiple Input Multiple Output (MIMO) systems. However the advanced systems brings their own challenges. Similarly frequency bands between few KHz to hundreds of GHz have been allocated already (by FCC - Federal Communications Commission), so it is difficult to increase the size of spectrum further. Due to these limitations static frequency allocation is not capable to accommodate more users or new services with high data rates. However the study of spectrum shows that some of the licensed spectrum bands remain free for large time, some are partially used and very few frequency spectrum is fully occupied. Thus the frequency bands are not utilized fully and resulting in spectrum wastage. The underutilization of the spectrum causes spectrum holes. Spectrum hole is a frequency bandwidth provided to licensed user but at some geographic area or at particular times it not being used by the user [3].

Utilization of spectrum can be increased significantly by allowing secondary users who are not registered for a service to access the blank spectrum unoccupied by the licensed (primary) user at right time(temporal) and at right location(spatial). Cognitive Radio (CR) has been proposed as a promising solution to the problem. One of the most prime challenges of cognitive radio is not to cause harmful interference to primary users. To provide interference free spectrum access, secondary user should reliably identify the presence of primary users within a certain band of spectrum. This identification process is known as spectrum sensing.

In literature, various spectrum sensing algorithms have been proposed including energy detection, covariance based detection, matched filter based detection, cyclostationary feature detection [4-6]. Energy Detection is the most general spectrum sensing method due to its computation simplicity and mainly because it does not require pre information about primary user signal. But performance of energy detector is limited by low SNR, shadowing and multipath fading. Here improved version of energy detection which is proposed in [7] known as "Improved energy detection (IED) is simulated.

## II. MATHEMATICAL MODEL OF IMPROVED ENERGY DETECTION

### Energy detection

As per the working principle of the energy detection, the detector(cognitive radio) measures the energy of received signal from interested channel, compares it with threshold energy and selects either of the hypothesis  $H_0$  and  $H_1$ . Mathematically it can be represented by,

$$T_i(y_i) = \sum_{n=1}^N |y_i[n]|^2 > \text{or} < H_1 \text{ or } H_0 \quad \square \square \square$$

The performance parameters Pfa and Pd can be indicated by,

$$P_{fa} = P(H_1 \square H_0) \quad \square \square \square$$

$$P_d = P(H_1 \square H_0 \square) \quad \square \square \square$$

Where  $P(-/-)$  shows the conditional probabilities. The test statistic  $T_i(y_i)$  can be approximated as Gaussian by considering the sample size  $N$  very high and applying central limit theorem. Considering  $\sigma_x^2$  as signal variance (received average primary signal power when mean is zero) and  $\sigma_w^2$  as the noise variance (noise power as zero mean) power, the equation of test statistics is [7].

$$T_i(y_i) = \begin{cases} N(N\sigma_w^2, 2N\sigma_w^4), & H_0 \\ N(N(\sigma_x^2 + \sigma_w^2), 2N(\sigma_x^2 + \sigma_w^2)^2), & H_1 \end{cases} \quad \square \square \square$$

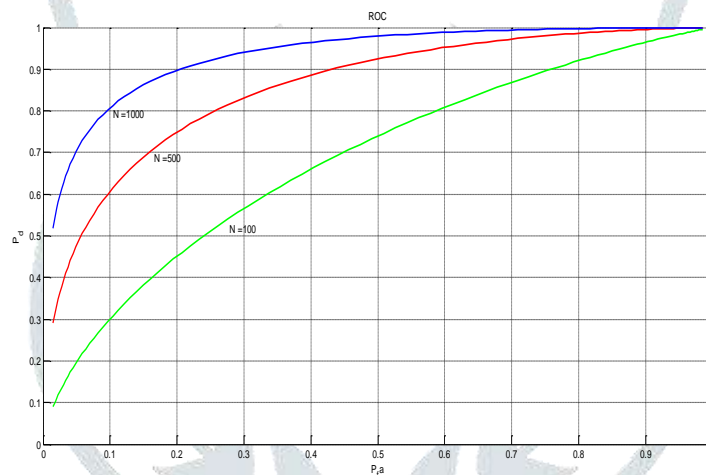
Now the probabilities  $P_d$  and  $P_{fa}$  can be derived by integrating the test statistics  $T_i(y_i)$  with respect to threshold (Considering  $H_0$  for  $P_{fa}$  and  $H_1$  for  $P_d/P_{md}$ ). These probabilities can be expressed as,

$$P_d^{CED} = Q\left(\frac{\lambda - N(\sigma_x^2 + \sigma_w^2)}{\sqrt{2N(\sigma_x^2 + \sigma_w^2)^2}}\right) \quad \square \square \square$$

$$P_{fa}^{CED} = Q\left(\frac{\lambda - N\sigma_w^2}{\sqrt{2N\sigma_w^4}}\right) \quad \square \square \square$$

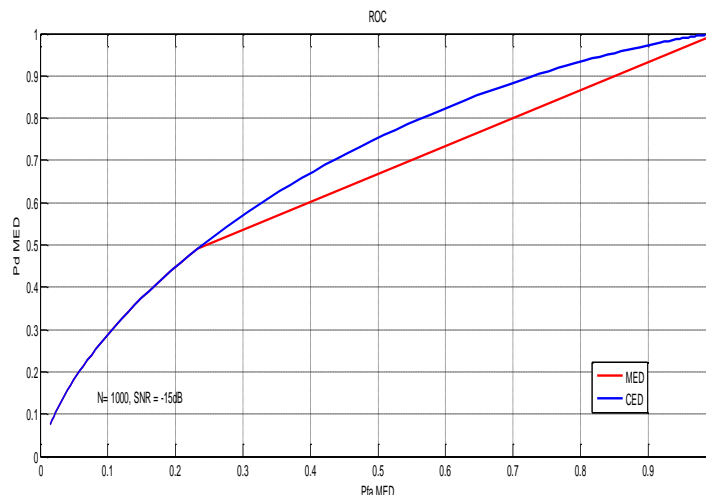
**Improved energy detection**

Although the classical energy detector is having advantages like low computational complexity, the performance degrades for lower value of  $N$  as shown in Figure 1. This is motivation to develop new version of energy detectors which avoids the problem. This improved version is suggested in [7] in two steps – Modified Energy Detection (MED) and its extension - Improved Energy Detection (IED). To improve the detection performance, MED is developed to avoid the misdetection due to instantaneous energy drops. The first step of MED is same as CED to find test statistic  $T_i(y_i)$ . In next step, the MED considers the last  $L$  sensing events to find an average test statistic value  $T_i^{avg}(T_i)$ . The decision is taken based on both  $T_i(y_i)$  and  $T_i^{avg}(T_i)$ . If the energy of sensed channel is lower than threshold, an additional check is performed where the average energy is compared with threshold. If the average is higher than threshold, it is likely that a channel is actually busy but due to instantaneous energy drop the idle channel is detected, which is a detection error. The MED detects idle channel only if both  $T_i(y_i)$  and  $T_i^{avg}(T_i)$  are lower than threshold. Thus MED reduces the misdetections due to instantaneous energy drop.



**Figure 1 : Effect of sample size N on ROC of Classical Energy Detection**

The test statistic  $T_i(y_i)$  is assumed to have normally distributed values. As  $T_i^{avg}(T_i)$  is the average of independent  $T_i(y_i)$ , it is also normally distributed. The improvement in detection probability is at the expense of probability of false alarm. The overall performance comparison (based on ROC) as shown in figure.2 indicates that the MED is inferior to CED.



**Figure 2 : Comparison of CED and MED based n ROC**

To overcome the limitation of MED that increasing  $P_d$  without increasing  $P_{fa}$  much, Improved energy detection (IED) is proposed in [7]. To avoid the false alarms, an additional check is included in IED which is based on the previous sensing event  $T_{i-1}(y_{i-1})$ . When  $T_i(y_i) < \lambda$  and  $T_i^{avg}(T_i) > \lambda$ , the situation  $T_{i-1}(y_{i-1}) > \lambda$  indicates that  $T_i(y_i) < \lambda$  may be because of instantaneous energy drop and  $H_1$  should be selected. And if  $T_{i-1}(y_{i-1}) < \lambda$ , it indicates that  $T_i(y_i) < \lambda$  may be due to channel release and  $H_0$  should be selected. Thus IED improves the false alarm performance of MED and also increases detection probability of CED.

The test statistics  $T_i(y_i)$ ,  $T_i^{avg}(T_i)$  and  $T_{i-1}(y_{i-1})$  are considered as normally distributed.  $P_d$  and  $P_{fa}$  for IED can be found based on these statistics as :

$$P_d^{IED} = P\{T_i(y_i) > \lambda\}_{H1} + P\{T_i(y_i) \leq \lambda, T_i^{avg}(T_i) > \lambda, T_{i-1}(y_{i-1}) > \lambda\}_{H1}$$

$$P\{T_i(y_i) > \lambda\}_{H1} + P\{T_i(y_i) \leq \lambda\}_{H1} * P(T_i^{avg}(T_i) > \lambda) * P\{T_{i-1}(y_{i-1}) > \lambda\}_{H1}$$

$$P_{fa}^{IED} = P\{T_i(y_i) > \lambda\}_{H0} + P\{T_i(y_i) \leq \lambda, T_i^{avg}(T_i) > \lambda, T_{i-1}(y_{i-1}) > \lambda\}_{H0}$$

$$= P\{T_i(y_i) > \lambda\}_{H0} + P\{T_i(y_i) \leq \lambda\}_{H0} * P(T_i^{avg}(T_i) > \lambda) * P\{T_{i-1}(y_{i-1}) > \lambda\}_{H0}$$

If we assume  $T_i(y_i)$ ,  $T_i^{avg}(T_i)$  and  $T_{i-1}(y_{i-1})$  are mutually independent, above equations 7 and 8 can be rewritten as,

$$P_d^{IED} = P_d^{CED} + P_d^{CED} (1 - P_d^{CED}) * Q\left(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\right)$$

$$P_{fa}^{IED} = P_{fa}^{CED} + P_{fa}^{CED} (1 - P_{fa}^{CED}) * Q\left(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\right)$$

As  $0 < Q(-) < 1$ , we can indicate  $P_d^{CED} \leq P_d^{IED}$  and also  $P_{fa}^{CED} \leq P_{fa}^{IED}$  meaning that in IED also the improvement in  $P_d$  is on cost of degraded  $P_{fa}^{CED}$  but the degradation is not severe as MED. Where,  $\mu_{avg}$  and  $\sigma_{avg}^2$ ,

$$\mu_{avg} = \frac{M}{L} N(\sigma_x^2 + \sigma_w^2) + \frac{L - M}{L} N\sigma_w^2$$

$$\sigma_{avg}^2 = \frac{M}{L^2} 2N(\sigma_x^2 + \sigma_w^2)^2 + \frac{L - M}{L^2} 2N\sigma_w^4$$

Here,  $M \in [0, L]$  indicating the number of sensing events where a primary signal is actually present.  $M$  is not known for practical case but can be bounded between 0 and  $L$ .  $M=0$  indicates always idle and  $M=L$  indicates always busy during past  $L$  sensing events.

**III. SIMULATION AND ANALYSIS**

**Methodology**

Two Matlab functions are created for probability of false alarm and probability of detection for CED(as per equations 5 and 6 ) and IED (based on equations 9 and 10) as a function of signal and noise powers(variances) ,threshold level and sample size. Here the equations indicate that the  $P_{fa}$  depends only on noise power and  $P_d$  depends on both the noise and signal powers.  $P_d$  and  $P_{fa}$  calculated by these functions are used to plot the receiver operating characteristics (ROC) of ED and IED. Here the following parameters are considered: Receiver bandwidth = 10MHz, Receiver noise figure = 5dB. The signal to noise ratio and sample size is varied to check the performance of all three sensing schemes.

**Results**

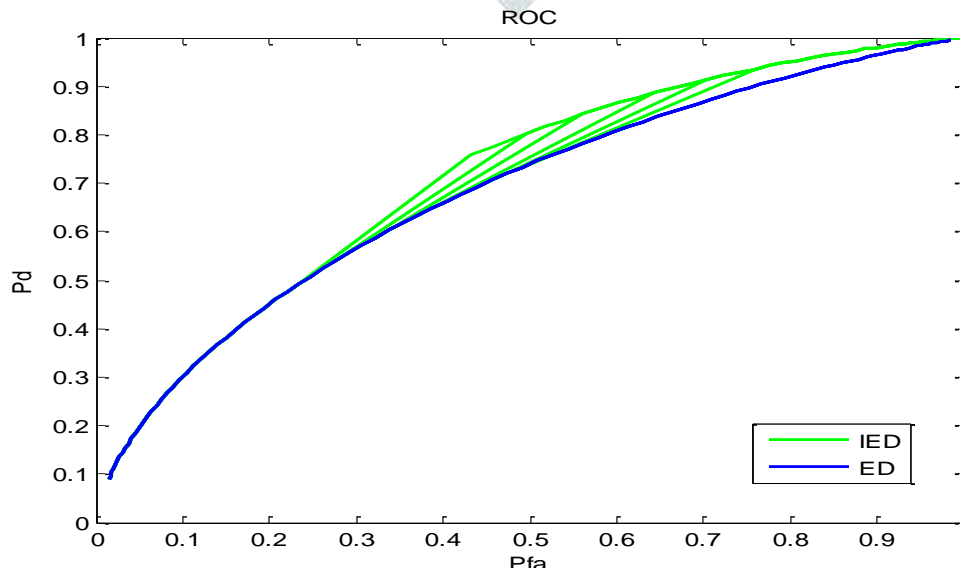


Figure 3(a) : ROC for N = 100, SNR = -10dB, L =5 , M= 0 to L

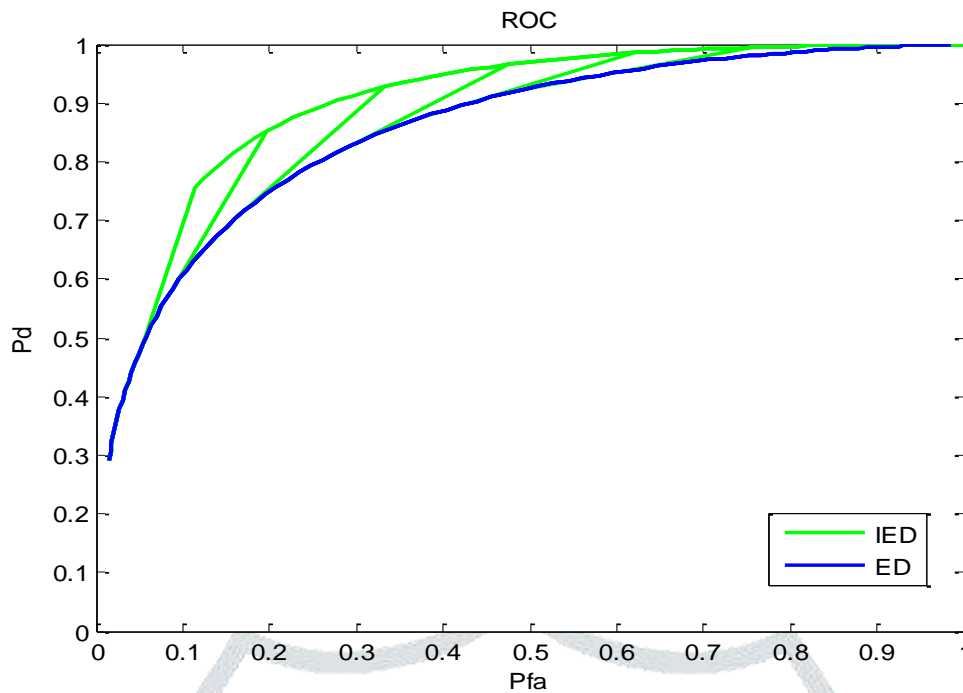


Figure 3(b) : ROC for N = 500, SNR = -10dB, L =5 , M= 0 to L

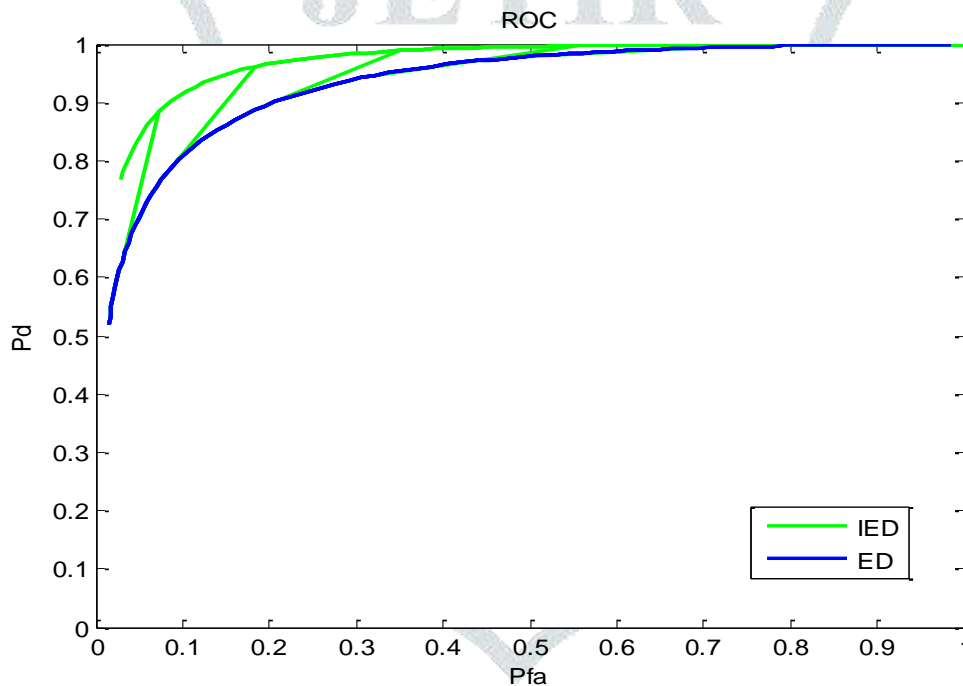


Figure 3(c): ROC for N = 1000, SNR = -10dB, L =5 , M= 0 to L

The figures 3(a),(b) and (c) are indicating the performance of CED and IED by changing the sample size. With increase in sample size, the performance of detection is increased. If N is low, the test statistic follows the instantaneous variations of the signal energy. This implies that higher signal energy variance means the instantaneous energy level falls below the threshold more times and probability that the channel is declared idle even if it is occupied is also increased. Thus the misdetection probability increases which degrades the detection performance. The figure 3.1(a) represents the same. For lower value of sample size N, the sensing schemes can not provide proper estimation.

The figure 4(a) and (b) are indicating that the performance of sensing technique degrades under low SNR conditions. IED performs quiet better at high SNR conditions but its performance is same as CED under low SNR conditions. Even the channel status in previous events (value of M) effect the performance of IED. If the channel is idle during previous event(M=0), IED performs same as CED but if the channel is busy during previous sensing events (M>0), performance of IED is superior than CED.

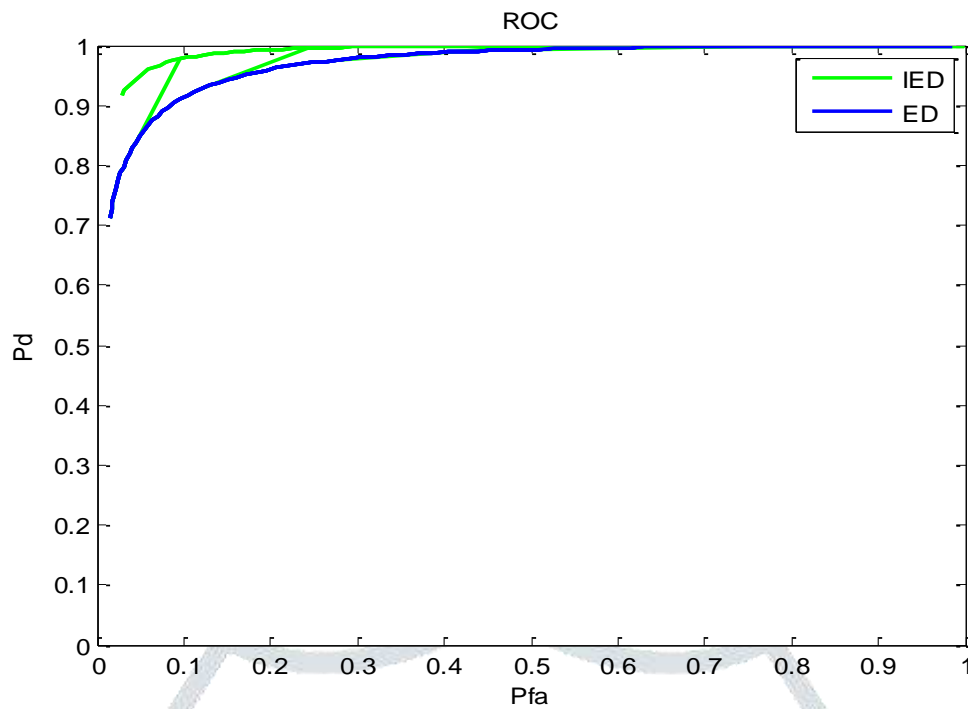


Figure 4(a) : ROC for  $N = 1000$ ,  $SNR = -9dB$ ,  $L = 5$ ,  $M = 0$  to  $L$

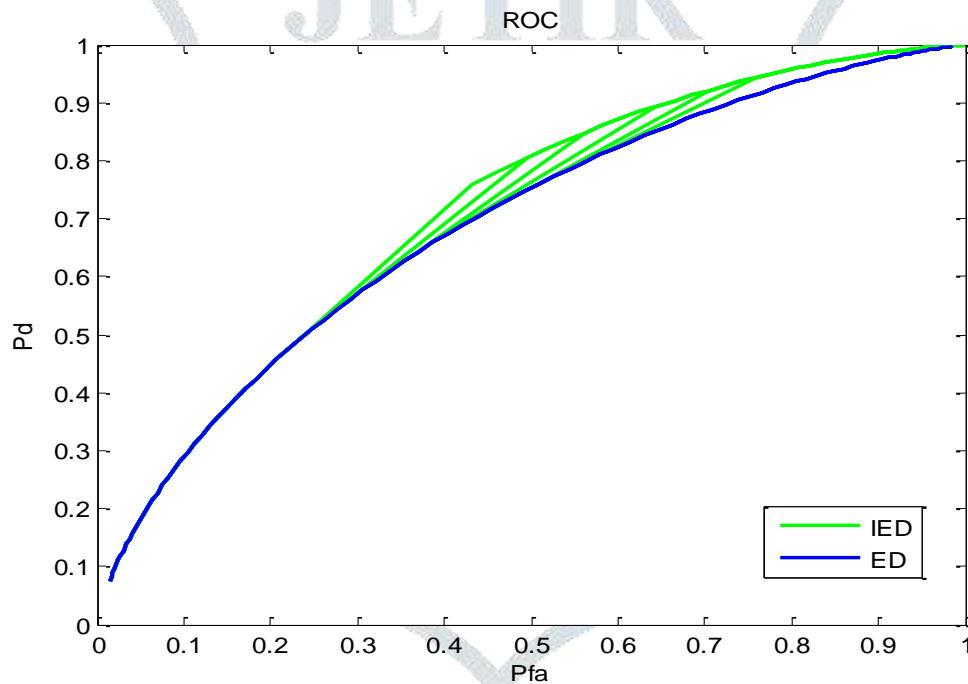


Figure 4(b): ROC for  $N = 1000$ ,  $SNR = -15dB$ ,  $L = 5$ ,  $M = 0$  to  $L$

The computational cost can be calculated by the set of mathematical operations in algorithms of CED and IED. The calculation of  $T_i(y_i)$  needs  $N-1$  additions and  $N$  multiplications. These calculations are required in both the algorithms. In addition IED algorithm computes  $T_i^{avg}$  and  $T_{i-1}(y_{i-1})$ . The  $T_i^{avg} > \lambda$  needs  $L-1$  additions and one division. IED also needs two more comparators and memory that stores the last  $L-1$  test statistics. This increased computational complexity is negligible if we compare it with other spectrum sensing methods like cyclostationary or covariance based detectors because they require more complex operations like autocorrelation or covariance matrices.

#### IV. CONCLUSION

Energy detection is widely used spectrum sensing technique for cognitive radio because of its low complexity and compatible performance for all type of signals. Its main limitation is lower detection performance under low SNR. The improved energy detection technique is able to outperform the classical energy detection while preserving the complexity level and general applicability. Implementation of mathematical model for IED local spectrum sensing confirms the improvement in detection probability under different values of SNR for AWGN channel.

#### REFERENCES

- [1] Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2016–2021
- [2] Richard N. Clarke, Expanding mobile wireless capacity: The challenges presented by technology and economics, [www.elsevier.com/locate/telpol](http://www.elsevier.com/locate/telpol).

- [3] Simon Haykin, Cognitive Radio: Brain-Empowered Wireless Communications, IEEE Journal on Selected areas in communication, VOL. 23, NO. 2, February 2005.
- [4] Tefvik Yucek and Huseyin Arslan, A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications , IEEE Communication Surveys and Tutorials, VOL. 11, NO. 1, First Quarter, 2009.
- [5] Lu Lu, Xiangwei Zhou, Uzoma Onunkwo and Geoffrey Ye Li Ten years of research in spectrum sensing and sharing in cognitive radio EURASIP Journal on Wireless Communications and Networking 2012.
- [6] Ian F. Akyildiz, Won-Yeol Lee, Mehmet C. Vuran, Shantidev Mohanty, NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey , Elsevier - computer networks 50 2006 2127-2159.
- [7] Miguel López-Benítez and Fernando Casadevall, Improved Energy Detection Spectrum Sensing for Cognitive Radio , IET Communications (Special issue on Cognitive Communications), 2012.

