Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.777645

GENERALIZED ENERGY DETECTOR- DUAL THRESHOLDING (GED-DT) FOR COOPERATIVE SPECTRUM SENSING IN CRNS

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Abstract: Spectrum sensing is a major task in Cognitive Radio Networks which determines the presence or absence of Primary User (PU) such that the Secondary User (SU) or opportunistic user can use the unoccupied spectrum. Energy based Primary user Detection is the mostly employed strategy for spectrum sensing while it suffers from ambiguous results due to single threshold based decision making strategy. Hence, this paper proposes a new thresholding mechanism called as Dual Thresholding and applied on the Generalized Energy Detection (GED) to identify whether the Primary user is present or not. In addition, we also introduce a new fusion concept in cooperative spectrum sensing where the decision of Secondary User not only depends on his/her own decision but also on the decisions of other secondary users. Simulation experiments reveal the efficiency of proposed approach in terms of bit error rate, probability of false alarm, probability of detection.

Keywords: Cognitive Radio Networks, cooperative spectrum sensing, Single Thresholding, Dual thresholding, Fusion, Probability of false alarm, Probability of detection.

I. Introduction

In the wireless communication system, radio spectrum is regarded as a natural and finite precious resource. Recently, due to the advances in the wireless communication technologies, the demand for the utilization of radio spectrum is raising continuously. However, the traditional fixed spectrum allocation methods allow only licensed users to access the spectrum. But, several studies on the utilization of spectrum reported that most of the spectrum is underutilized in terms of different parameters like space, time and frequency [1], [2]. In order to make the spectrum utilization in more effective manner, in 1999, Joseph Mitola III introduced a new concept called as Cognitive Radio (CR) [3]. A device with CR capability can adjust its parameters like modulation strategy, carrier frequency and transmits power according to the situations. Due to these advantages, the Federal Communication Commission (FCC) suggested to use the CR technology in TV bands (UHF and VHF) because the TV bands have seldom changes in the location and frequency.

Next, the Cognitive Radio Network (CRN) is defined as network formulated with CR devices where the adaptive reconfiguration of communication parameters is happened. Basically, the CRN consists of two types of users; they are licensed user (or) Primary User

(PU) and opportunistic user (or) Secondary User (SU)[4]. Figure.1 shows an example of CRN with primary users and secondary users. PU has exclusive right to access the spectrum while the SU has to use the spectrum in an opportunistic way. SU can occupy the spectrum if it found that the PU is not present but SU needs to vacate once the PU arrives. In other words, the cognitive user uses the licensed spectrum in a given location and time when the PU is either absent or idle [5], [6]. So, the SU has only temporary permission to use the spectrum which is considered as a significant component in CRNs. CR uses the spectrum in an intelligent way when the radio spectrum is unused based on the observation.

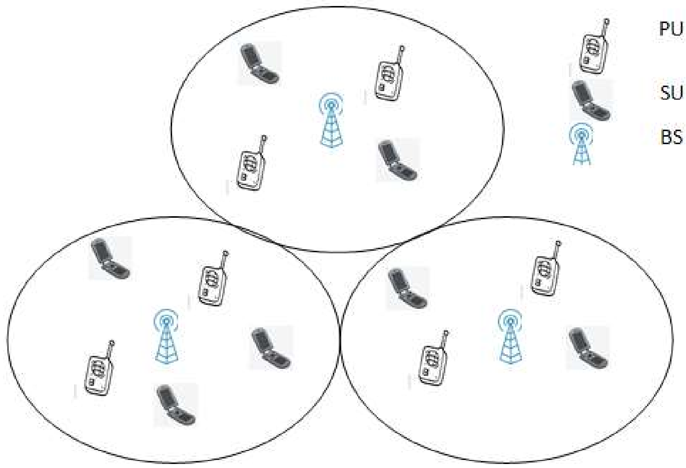

Figure.1 Samples CRN with PUs and SUs

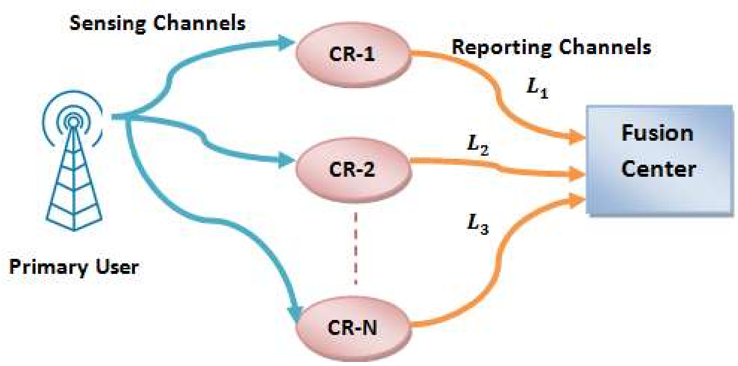

Figure.2 schematic of CSS

According to the network architecture, CRNs are classified into two types; they are Infrastructure-based CRN (ICRN) [7] and the Cognitive Radio Adhoc Networks (CRAHNs) [8]. ICRN consist of central network termed as an access point in wireless local area networks (LANs) whereas base station in cellular networks. On the other hand, the CRAHNs don't have any infrastructure backbone. So, the CR users communicate each other over ADHoc connection between the unlicensed and licensed spectrum bands. Towards such utilization, the SU needs to sense the presence of PU and most of primary research on CRN is done in such direction only [9]. Recently a new type of spectrum sensing is evolved called as Cooperative Spectrum Sensing (CSS) in which the SU not only depends on his/her own decision but also seeks the opinions of other SUs in the determination of presence or absence of PU. Unlike the simple independent spectrum sensing, the cooperative spectrum sensing improve she accuracy of detection. In this model, more than two SUs execute the spectrum sensing process and produce a binary decision. Then the obtained decisions re sent to a fusion center to get the final decision regarding the presence of absence of PU. CSS ensure more guarantee towards the perfect spectrum utilization by increasing the probability of PU detection and decreasing the probability of false alarm. CSS totally executes in two phases; they are sensing and reporting. In the former phase, the SUs sense the spectrum for a specific period of time to get the decisions on the occupancy of PU. Next, in the reporting phase, all the SUs forwards their decisions to fusion center to get the final decision on occupancy of PU. A sample demonstration about CSS is shown in Figure.2.

From the past few years, several researchers have been proposed several methods for spectrum sensing in CRN. However, most of the methods employed threshold based detection to identify whether the PU is present of not. However, optimal threshold designing is a challenging task. An improper threshold design lowers probability of correct detection and raises the probability of misdetection. Hence the design of optimal threshold is the main motivation of this paper. Towards such objective, we propose a new and dynamic threshold based on the energy of PU signals. The overall contributions of this work are outlined as follows;

- To increases the spectrum utilization efficiency in CRN, this paper proposes a new thresholding mechanism called a Dual Thresholding (DT) in CSS assisted CRN. DT ensures a perfect differentiation between the absence and presence of PU such that the SU can occupy and utilize the spectrum effectively.
- To lessen the ambiguity at the fusion center in CSS with multiple decisions, this work proposed a new fusion mechanism which considers two values; they are local decisions and local energy values obtained from multiple SUs.

Organization of rest of the paper is as follows; the details of related work are explored in 2nd section. The details of proposed method are explored in 3rd section. 4th section provides the details of experimental investigations and last section concludes the paper.

II. Related Work

In CRAHN, spectrum sensing has become challenging task due to very low received Signal to Noise Ratio (SNR)[10]. To provide the solution for spectrum sensing under noisy environments, various researchers suggested various techniques. For instance Pandya *et al.* [11] proposed a spectrum sensing technique through energy detection for non-fading channel. The authors computed sensing node's false alarm probability, probability of detection expressions theoretically over non-fading (AWGN) channel. They used static thresholding to determine whether the primary user occupied or not. Next, D. M. M. Plata *et al.* [12] suggested energy detection based spectrum sensing technique where the threshold is selected dynamically. The authors considered the Constant False Alarm Rate (CFAR) and noise levels to evaluate the threshold. They obtained good probability of detection but uncertainties in the noise and estimation errors affects the threshold parameter.

H. Patil *et al.* [13] suggested an Energy detection spectrum sensing technique by deriving mathematical formulas for probability of false alarm, probability of detection at various SNR levels. Further, the simulation results of are compared with theoretic models under

Rayleigh fading environment. Finally, they concluded that as SNR rises, the probability of false alarm increases and probability of detection decreases. Next, M. Deshmukh *et al.* [14] proposed a Wishart matrix based covariance matrix to detect the independent random signals through Chi-Square distributed technique. Further, to scale the sample covariance matrix, a centering matrix is employed with Wishart distribution. Finally, the performance is evaluated under various fading random signals using the proposed algorithm.

Next, to tackle the problems like random variation of noise and noise instability, M. B. Usman *et al.* [15] proposed an entropy based energy detection for spectrum sensing. They derived few mathematical equations under AWGN channel for false alarm probability, probability of miss-detection, and probability of detection. Even though they achieved better spectrum detection at low SNRs but it used a predetermined threshold. Due to such kind of thresholding, false alarm rate increases. Similarly, Jun Luo *et al.* [16] suggested a spectrum sensing technique based on detected energy to decrease the effect of noise variance uncertainties. The authors considered two c

hannel models to evaluate the noise variance through multiple antennas; they are Rayleigh fading channel and Gaussian channel. Finally, they proposed a mechanism to obtain the threshold which is completely independent of noise variances. However, it is regarded as a blind spectrum sensing in which noise variances can affect the original signal occasionally.

Irma Uriarte *et al.* [17] suggested an energy detection mechanism to improve the robustness under various noise uncertainty and low SNR environment conditions. The authors used Spectral Minima Tracking (STM) mechanism to compute the noise power in each sensing interval to propose adaptive threshold detection. Further, they maintained correlation between the STM parameters and estimated noise power. However, the correlation increases computational complexity and estimation errors. K. M. Captain and M. V. Joshi [18] proposed an energy detection spectrum sensing mechanism called as Generalized Energy Detector (GED) which is implemented by squaring the amplitudes of received samples with an arbitrary positive power p. The authors examined the SNR wall for Cognitive Spectrum Sensing (CSS) in the case where all Cooperating Secondary Users (CSUs) use GED. They considered soft and hard decision combinations to analyze their method. In both the combinations, they derived the expressions under various AWGN, SNR wall, and Nakagami fading environments for arbitrary power p. However as the fading increases it shows impact on the threshold.

To select suitable threshold for Cognitive Radio Networks, Kumar *et al.* [19] proposed an algorithm based on critical SNR under fading environment such as Nakagami-m and Rayleigh fading. They analyzed the performance of their method through two different scenarios through total error rate and throughput. Under the cooperative scenario for lower SNR regions, they achieved higher throughput based on constant false-alarm rate (CFAR) threshold selection approach. However, under non cooperative scenario for higher SNR regions, their method minimized the total error or sensing error with the help of Minimizing Error Probability (MEP) threshold selection method.

Recently, Machine Learning (ML) and Deep Learning (DL) techniques are found as good approaches for spectrum sensing in CRAHN as it does not necessitate fixing any threshold [20]. Few researchers applied ML and DL techniques to extract the features and making the decisions under various noise environments. For instance, Y. Arjoune and N. Kaabouch [21] suggsted several ML techniques for spectrum sensing in cognitive radio networks. The authors prepared one large scale dataset for training, then validated and tested through various ML techniques like random forest , K-nearest neighbors, support vector machine, Naïve Bayes, and logistic regression. Further, they compared each technique by measuring the performance metrics such as classification accuracy, probability of miss-detection, probability of detection, and false alarm rate. Further, to identify the presence of primary user under low SNR conditions, Yue Geng *et al.* [22] proposed DL based binary classification method. Various features are extracted to prepare the dataset under different noise environments. Even though, the authors attained good accuracy but sensing time is also important feature and it should be considered before making the decision.

Next, S. Zheng *et al.* [23] proposed DL assisted classification through which spectrum sensing is analyzed. Next, to overcome the effects of uncertainties in the received normalized signal power, they trained the numerous signals and noise data. Further, they used new strategy called as transfer learning to evaluate the performance of proposed work through real-world signals. Further, to improve the spectrum sensing performance, Kenan kockaya and Ibrahim Develi [24] introduced ML based threshold detection mechanism. The authors evaluated the sensing performance for energy detection mechanism and matched filter technique. They obtained the threshold based on the historical detection data. Later, based on the obtained threshold, they tested the proposed method over various noise uncertainties at lower SNRs.

III. Generalized Energy Detector (GED)

In the CR, the PU detection is formulated as a binary hypothesis. According to the classical detection theory [25], it is expressed as

$$y(n) = \begin{cases} hs(n) + w(n), & H_1 \\ w(n), & H_0 \end{cases} \quad (1)$$

Where $y(n)$ denotes the n^{th} sample of signal received at SU, $s(n)$ is the n^{th} sample of signal of an unknown PU, $w(n)$ denotes Additive White Gaussian Noise with zero mean and σ^2 variance, *n* varies as $n = 1, \ldots, N$ are the indexes of the samples of the signal received at SU and *h* denotes the fading coefficient of the channel propagating between SU and PU. Next H_0 and H_1 represents the hypotheses denoting the presence and absence of primary user respectively. Further, the primary signal's average power is denoted as σ_s^2 and the primary signals are considered to be independent of fading and noise. As well, the samples of both primary signal and noise signal are also assumed as independent. To ensure a simplified computation, we consider the noise, fading coefficients and primary signal samples are real numbers because the extension of computations for complex signals can be easily done.

Here, the spectrum sensing major intention is to determine whether the PU is present or absent based on the above-mentioned hypothesis, i.e., selection of one hypothesis from H_0 and H_1. Such determination is done based on the PU's signal received at SU. Generally, two performance metrics are used t asses the effectiveness of spectrum sensing method, they are Probability of False Alarm (P_F) and Probability of Detection (P_D). P_D is defined as the probability of selecting the hypothesis H_1 when the true hypothesis is H_1, i.e., $P_D = \Pr(H_1|H_1)$ while the P_F is defined as the probability of selecting the hypothesis H_1 when the true hypothesis is H_0, i.e., $P_F = \Pr(H_1|H_0)$. So larger the P_D value and smaller the P_F value signifies that the spectrum sensing method is effective.

GED [26], [27] based spectrum sensing is the most popular method which employs energy detection because it does not need any additional knowledge about the signals of PU and low complex in nature. GED is an extended version of conventional energy detector (CED) in which the PUs signal samples are initially squared and then summed followed by normalized. Then the obtained value is compared with a predefined threshold to determine the presence or absence of PU. Mathematically the CED is expressed as

$$E_{CED} = \frac{1}{N}\sum_{i=1}^{N}|y(n)^2| \quad (2)$$

Based on the Eq.(3), the GED is obtained by replacing the 2 in the squaring operation with an arbitrary constant p. Mathematically the GED is expressed as

$$E_{GED} = \frac{1}{N}\sum_{i=1}^{N}|y(n)^p| \quad (3)$$

Where p is a real number having the values always greater than zero. Based on the Eq.(3), it can be stated that the CED is a special case of GED.

In the case of a PU signal with larger number of samples, the Central Limit Theorem (CLT) [28] is invoked to define the Probability of detection and probability of false alarm for GED as

$$P_D = \Pr(E_{GED} > T|H_1) = Q\left(\frac{T-m_1}{s_1/\sqrt{N}}\right) \quad (4)$$

$$P_F = \Pr(E_{GED} > T|H_0) = Q\left(\frac{T-m_0}{s_0/\sqrt{N}}\right) \quad (4)$$

Where

$$Q(t) = \frac{1}{2\pi}\int_t^{\infty} e^{-(x^2/2)}dx \quad (5)$$

Where T is called as predefined threshold derived after fixing the P_F, m_1 and m_0 are the mean of E_{GED} under two hypothesis H_0 and H_1 respectively, s_1^2 and s_0^2 are the variances of E_{GED} under two hypothesis H_0 and H_1 respectively. They are computed as follows;

$$m_0 = \frac{2^{p/2}}{\sqrt{\pi}}\,\Gamma\left(\frac{p+1}{2}\right)s^p \quad (6)$$

$$s_0^2 = \frac{2^p}{\sqrt{\pi}}\left[\Gamma\left(\frac{2p+1}{2}\right) - \frac{1}{\sqrt{\pi}}\Gamma^2\left(\frac{p+1}{2}\right)\right]s^{2p} \quad (7)$$

$$m_1 = \frac{2^{p/2}(1+\gamma)^{p/2}}{\sqrt{\pi}}\,\Gamma\left(\frac{p+1}{2}\right)s^p \quad (8)$$

$$s_1^2 = \frac{2^p(1+\gamma)^p}{\sqrt{\pi}}\left[\Gamma\left(\frac{2p+1}{2}\right) - \frac{1}{\sqrt{\pi}}\Gamma^2\left(\frac{p+1}{2}\right)\right]s^{2p} \quad (9)$$

Where γ denotes the average Signal to Noise Ratio (SNR) of received signal at SU and $\Gamma(.)$ denotes the complete Gamma function. Based on the obtained mean and variances, two parameters are derived for threshold computation; they are shape parameter (k') and scale parameter (θ'). For Hypothesis H_0, the scale parameter k' is written as k_0' and computed as

$k_0' = \frac{(m_0)^2}{s_0^2}$ while for H_1, k' is written as k_1' and computed as $k_1' = \frac{(m_1)^2}{s_1^2}$. Next, For Hypothesis H_0, the shape parameter θ' is written as θ_0' and computed as $\theta_0' = \frac{s_0^2}{m_0}$ while for H_1, θ' is written as θ_1' and computed as $\theta_1' = \frac{s_1^2}{m_1}$. Based on these four values, the threshold is computed as

$$T = \frac{1}{F(1-P_F, k_0', \theta_0')} \quad (10)$$

Where $F(x, k_0', \theta_0')$ is a cumulative distribution function of a Gamma Distribution and it is expressed as

$$F(x, k_0', \theta_0') = \int_0^x \frac{1}{\theta_0'^{k_0'}\Gamma(k_0')} t^{k_0'-1} e^{\frac{-t}{\theta_0'}} dt \quad (11)$$

Based on the Eq.(11), the probability of detection is derived as

$$P_D = 1 - F(T, k_1', \theta_1') \quad (12)$$

From this expression, we can state that the p value is liked with the ASNR, P_D, P_F and the size of samples. The determination of optimal value for *p* can ensure maximum P_D by fixing the values of P_F, ASNR and samples count. Similarly, the determination of optimal value for *p* can ensure minimum P_F by fixing the values of P_D, ASNR and samples count. Hence, Eq.(12) can be called as generalize expression which can be used in different applications.

IV. Dual Thresholding

In the real time communication scenario, there exist several problems like shadowing, fading and hidden node etc. which deteriorates the performance of spectrum sensing of secondary user. In most of the past methods, it was assumed that there exists one fusion center and *N* number of secondary users in a CRN. Every user has its own experience about the fading and shadowing with same average SNR and uses same threshold T for the determination of PU. The information related to all secondary users receives at the fusion center and then it takes a decision about the PU's presence or absence. The conventional fusion methods apply OR-rule for the determination of PU. For instance, if any primary user is found by the SU, then the fusion center verifies whether it is true or not [29].

In the conventional GED based spectrum sensing, the PU's presence or absence is determined based on the single threshold. Each SU takes a local decision by comparing the energy of signal received with a predefined threshold, as shown in Figure.3. Here, E_{GED}^i denotes the acquired energy value of a signal received at i^{th} SU. The decision is taken as H_1 when the E_{GED}^i value is found as greater than or equal to the threshold T and decision is taken as H_0 when the E_{GED}^i value is found as less than the threshold T. However such kind of decision making results in larger spectrum unutilized. For example, consider E_{GED}^i value is just greater than the T, then the SU considers it as the presence of PU and won't occupy the corresponding spectrum. Similarly, consider E_{GED}^i value is just less than the T, then the SU considers it as the absence of PU and tries to occupy it. In both of these cases, the spectrum is being unutilized properly and results in the degraded communication performance. Hence, we propose a new threshold called as Dual threshold which ensures a perfect differentiation between the presence and absence of PU.

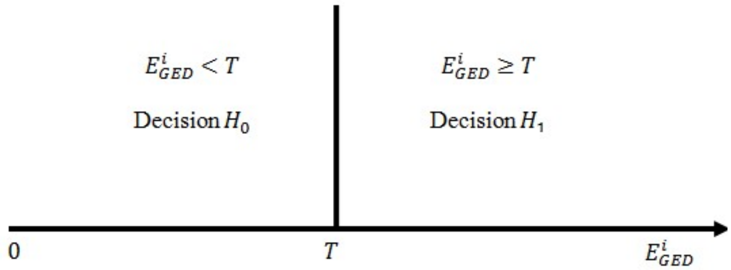

Figure.3 GED with Single Threshold

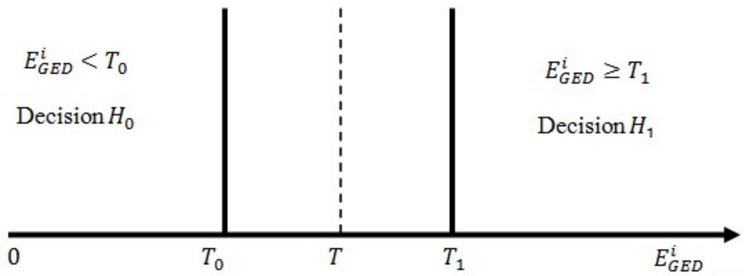

Figure.4 GED with Dual Threshold

Figure.4 shows the concept of dual thresholding with GED mechanism. Here, two new thresholds are derived from T, they are upper threshold T_1 and Lower threshold T_0. These two thresholds are computed based on T as $T_1 = T \times \beta$ and $T_0 = T/\beta$ [30]. These two thresholds help the SUs in decision making towards the presence of absence of PU. The presence of PU is identified if the energy value exceeds the upper threshold T_1, i.e., H_1. On the other hand, the absence of PU is identified if the energy value is lower than the lower threshold T_0, i.e., H_0. Otherwise, the energy value lie sin between T_0 and T_1. In such case, the SU is allowed to report its observed energy value to the fusion center. Thus, in the proposed model, the fusion center receives two types of information; they are local decisions and observational local energy values. In such case, the fusion center performs the following operations to take the decision.

1. For Every i^{th} SU initially the spectrum sensing is carried out in an individual fashion, i.e., E_{GED}^{i} is computed for the received unknown PUs signal. Then the energy values are compared with individual thresholds and takes local decisions and they are denoted as L_i. If the energy is found in between the two thresholds, i.e., $T_0 < E_{GED}^{i} \leq T_1$, then the corresponding SU reports the energy value to fusion center. Here we use R_i to signify the information received at the fusion center based on the threshold equalities, as

$$R_i = \begin{cases} E_{GED}^{i}, T_0 < E_{GED}^{i} \leq T_1 \\ L_i, \; Otherwise \end{cases} \quad (13)$$

Where

$$L_i = \begin{cases} 0, 0 < E_{GED}^{i} \leq T_0 \\ 1, \; E_{GED}^{i} \geq \; T_1 \end{cases} \quad (14)$$

2. Hence, the Fusion center receives totally K local decisions and N-K local energy values from the N SUs. Based on the N-K local energy values, the fusion center takes the decision, as

$$D = \begin{cases} 0, & 0 \leq \sum_{i=1}^{N-K} E_{GED}^{i} \leq T \\ 1, & \sum_{i=1}^{N-K} E_{GED}^{i} > T \end{cases} \qquad (15)$$

Where T is the threshold of energy detection derived based on the Eq.(10). Eq.(15) reveals that the N-K SUs are not able to take proper decision regarding the absence or presence of PU. Hence, the local energy values are collected by fusion center to make an upper decision unlike the local decisions of themselves, i.e., energy fusion operation can be executed by fusion center with the help of N-K SUs local observational energy values [31].

3. Based on the Decision value D obtained from Eq.(15) and local decisions such as L_is, the fusion center takes a final decision as follows;

$$F = \begin{cases} 1, & D + \sum_{i=1}^{K} L_i > 1 \\ 0, & otherwise \end{cases} \qquad (16)$$

In Eq.(16), F=1 denotes the presence of PU and F = 0 denotes the absence of PU. Since the proposed method applied a dual thresholding mechanism, every SU in eh network can take an appropriate decision regarding the occupancy of PU. Such kind of decisions makes the efficient spectrum utilization.

V. Experimental Analysis

This section describes the proposed work's experimental analysis. Simulation carried out by varying the range of different parameters such as Probabilities of detection and false alarm, ASNR and number of samples in the received at SU.

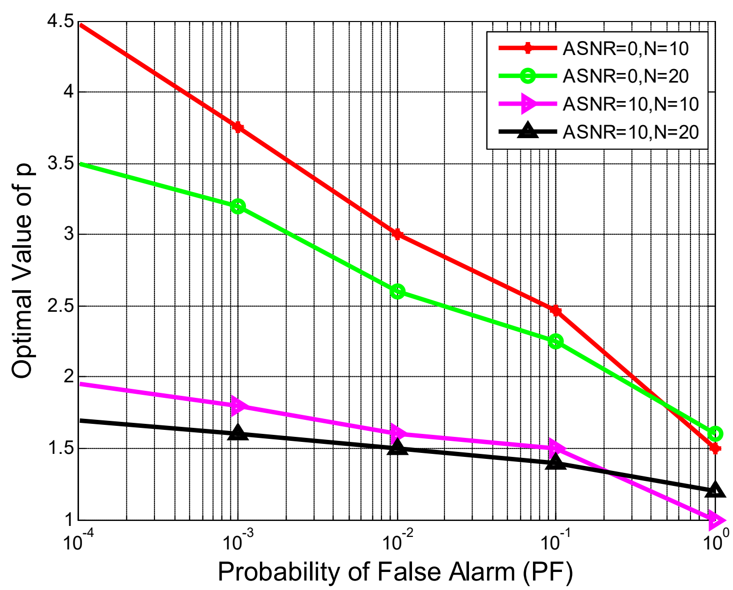

Figure.5 Optimal value of p for varying PFs at different ASNR and N values.

Figure.5 shows the determination of optimal value of p with varying ANSR and Number of samples N. Here we tried to found the optimal p value that maximize the probability of detection with varying probability of false alarm for different values of ASNR(γ) and N. the value of p is tested by varying its range from 0.01 to 10 with the step size of 0.01. From the results, we can see that the optimal p value decreases with an increase in the P_F value. At the lower value of P_F, a slow decrement is observed in the value of p while it drops instantaneously when the P_f is reaching to 1. Further, it can also be observed that at $\gamma = 10$ dB, the lower values of p experienced lesser P_D. On the other hand, at $\gamma = 0$ dB, the optimal value of p=2 is observed at $P_F = 0.2$. Based on the constraint, i.e., $P_F = \Pr(H_1|H_0)$, the P_F is considered as the probability at where the CR devices can take a decision saying that the licensed spectrum is occupied but actually it was free. Such decision signifies a missed opportunity to CR device from using the spectrum and making it to lose the transmission opportunity. From the perspective of CR, the P_F must be very less value and $P_F = 0.2$ is a larger value. Hence, the practical P_F values must be small and the optimal value of p =2 is not a vital solution. Based on the results, we can say that the Proposed approach needs to considered larger values of p to get better spectrum sensing performance.

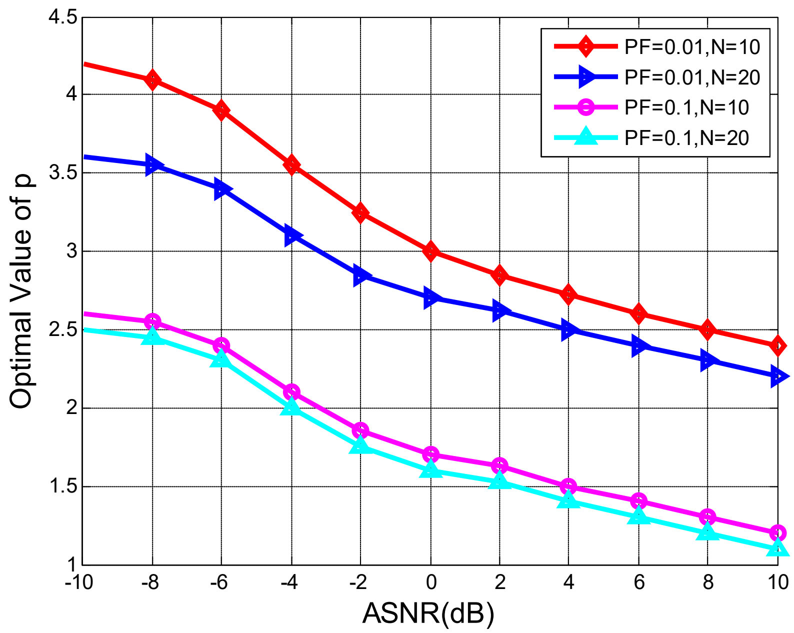

Figure.6 Optimal value of p for varying ASNRs at different PFs and N values

Figure.6 shows the determination of optimal value for p at different fixed values of N and P_F through which the probability of false alarm vs. ASNR minimizes. As shown in the Figure. 6, we observe that the optimal value of p is decreases as ASNR increases and the rate decrement is slow at medium range of ASNR compared to larger values of ASNR. Figure.7 shows the determination of optimal value for p at different fixed values of N and P_D through which the probability of detection vs. ASNR maximizes. From the values, we can see that the optimal value of p increases with an increase in the ASNR value. The rate of increase for optimal value of p is slow at the lower ASNR values than at the larger values. The optimal value of p that maximizes the probability of detection reaches to a common round off value when the ANSR is lager. On the other hand, the optimal value of p that minimizes the probability of false alarm reaches to a common round off value when the ANSR is smaller.

Further, the p value is not equal to 2 in most of the situations. From these results we can state that the optimal p value is completely depend on four parameter they are P_F, P_D, γ and N. In real time application, P_F, P_D, and N are predetermined while the γ value is determined based on the SNR estimation approaches discussed in [32] and [33] based on the structure of communication system. With the help of predetermined P_F, P_D, and N values and computed γ values, we can derived an optimal p value in any circumstances.

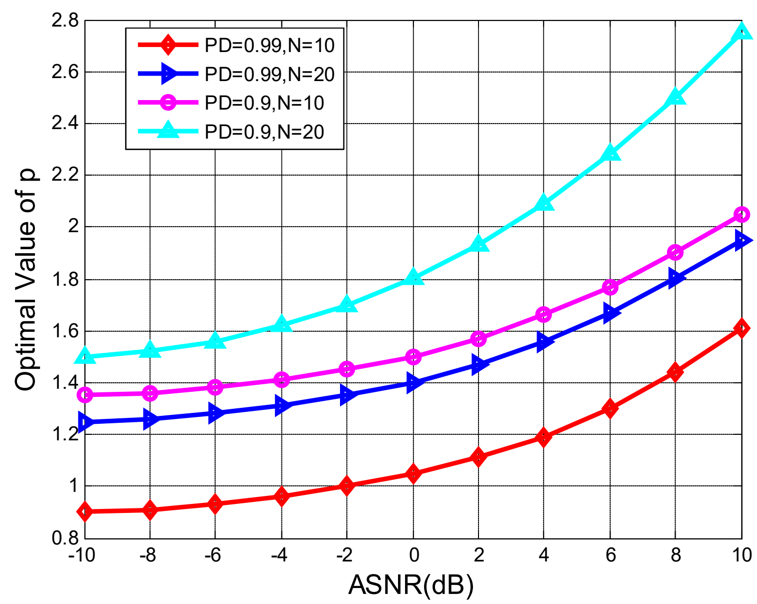

Figure.7 Optimal value of p for varying ASNRs at different PDs and N values

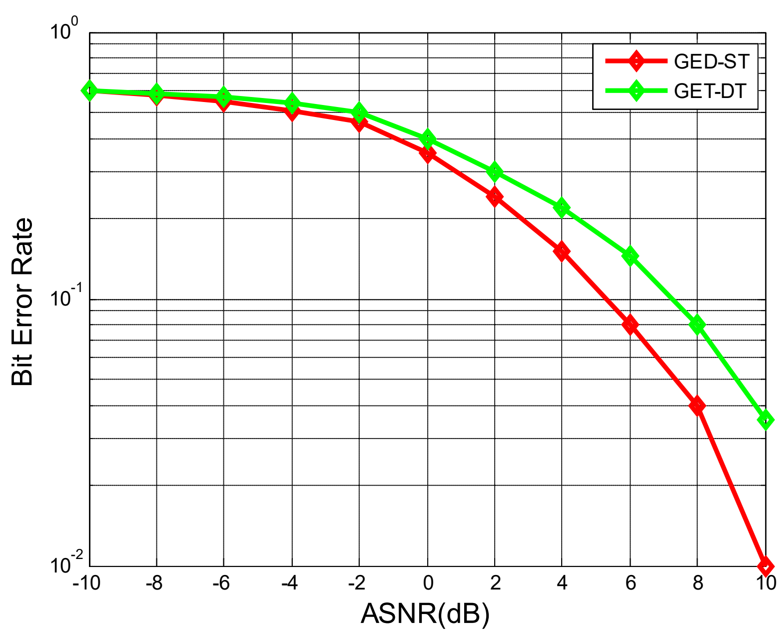

Figure.8 Bit error rate comparison between GED-ST and GED-DT at different ASNRs

Figure.8 shows the evaluation of proposed method's performance by comparing it with existing method through Bit Error Rate (BER) for varying ANSR values. Here we employed the GED with Single Thresholding (GED-ST) and GED with Dual Thresholding (GED-DT) for comparison. As the single threshold provides ambiguity about the PU's absence or presence, the SU cannot use the spectrum confidently. In such case upon the arrival of PU, the entire information of SU may get lost or corrupted in turn results in the BER. However, the proposed dual thresholding concept ensure a better discrimination between presence and absence of PU, the SU can use the spectrum more confidently. In such case, the SU can control is accessibility of the spectrum. Hence, the proposed GED-DT experienced less BER than the GED-ST. Further, the BER follows an inverse relation with SNR, as the SNR increases, BER decreases and vice versa. In the current simulation, the ASNR value is varied from -10 to 10 and the maximum BER is observed at lower SNR. The GED-ST has a larger BER than the GED-DT at fixed values of p ranging from 2.5 to 4. Hence, the GED-DT outperforms the GED-ST even at fixed values of p without any additional knowledge about the ASNR for determining the p value. .

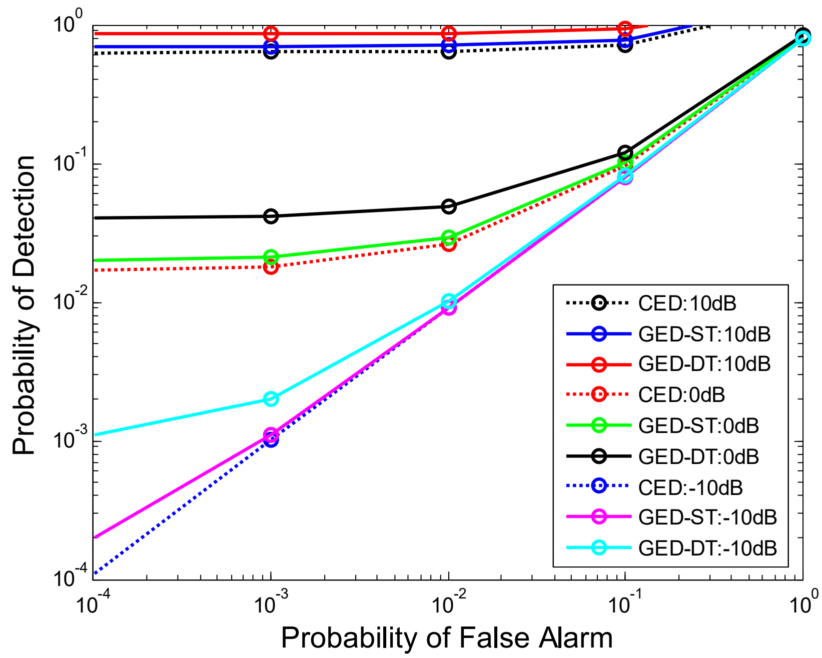

Figure.9 ROC analysis for CED, GED-ST and GED-DT at different ASNRs.

Figure.9 shows the evaluation of proposed method's performance by comparing it with existing methods through ROC curve at different ASNRs. From the results, we observe that the proposed GED-DT outperformed the traditional GED-ST at all ASNRs. However, it is not clear at ASNR = 10dB where the proposed GED-DT and GED-ST maintained a very negligible difference. As the value of Probability of false alarm decreases, the performance gain increases and we observed the significance in the gain at the less than or equal value of $P_F = 10^{-3}$. This value indicates that the probability of false alarm must be lower than 10^{-3} in order to get maximum gain through the proposed GED-DT. Otherwise, it must be larger than 10^{-3} to control the significant loss through the GED-ST and CED. Further, I can be noticed that the maximum performance gain is observed at $\gamma = 10$ dB. At lower values of γ, both the CED and GED had shown limited performance.

VI. Conclusion

This paper presented a new Mechanism for spectrum sensing on CRN based on CSS and Dual thresholding. The suggested combination intends towards the improvisation of probability of detection and accuracy at spectrum sensing. This method is an extension of traditional GED in which we have introduced a new thresholding concept based on two thresholds. Further, we suggested a new fusion mechanism which considers two parameters for deriving final decision, they are local decisions and local energy values of SUs. The local decisions are perfect decision made by SUs based on GED while the local energy values are ambiguous values observed for the signal received at SUs. At fusion, the fusion center acquired these two types of values and derives a final decision regarding the primary user's presence or absence. Extensive simulations on the developed mechanism ensure better probability of detection with lower probability of false alarm.

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