Performance Estimation of Improved Cooperative Spectrum Sensing in Cognitive Radio

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Abstract*: The applications of wireless communication are growing day by day; utilization of the spectrum is one of the prime challenges. Cognitive radio is the new era of wireless communication and acts as an immerging solution to the problem. It senses, analyzes and, allocates the vacant frequency band to secondary users (cognitive Radios). Energy detection (E.D.) has been accepted as the most suitable spectrum sensing technique due to its lower complexity, simplicity and majorly because of its blind detection. But the performance of the E.D. is limited by low SNR, shadowing, and multipath fading, so there is a tradeoff between complexity and performance in this conventional Energy detection technique. In this paper improved version of E.D. –Improved Energy Detection (IED)is used as a significant method for the case of cooperative sensing scenario. The proposed framework is also analyzed and compared for the case of different SNR and decision fusion rules. The Simulation result shows that the proposed framework gives excellent performance compared to conventional energy detection (CED) technique with lower complexity which meets the real-time requirement of cooperative spectrum sensing in wireless communication

***Keywords*: cognitive radio, spectrum sensing, Energy Detection, cooperative spectrum sensing.**

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I. INTRODUCTION

In the current era, there is a very high spectrum demand due to the expansion of wireless communication applications, which also require high data rates. This situation leads to growing spectrum demand. The requirement in spectrum demand is exponential, but the total available allocated spectrum is inadequate, and it is very difficult to increase the size of the spectrum further. By designing more efficient wireless systems, spectral efficiency can be improved. However, the advanced systems bring their own challenges. Because of these drawbacks, the static distribution of frequencies would not be effective in supporting new services / new users with high data rates.

The spectrum analysis indicates that the frequency bands are not fully utilized, which causes wastage of spectrum (spectrum holes). Spectrum efficiency can be improved by allowing unregistered users (secondary users) to use the vacant spectrum at the right location (spatial domain) and at the right time (temporal domain) [1]. One of the most prime challenges of the process is not to have interference to primary users and to achieve that, the secondary user should be able to sense the presence of primary users reliably within a specific spectrum range. In literature, various spectrum sensing algorithms have been proposed. From which, the most accepted spectrum sensing methods are energy detection, cyclostationary feature detection,covariance-based detection, and matched filter-based detection.

The most popular spectrum sensing method is Energy detection (E.D.) due to its simplicity of measurement and because it does not require knowledge of P.U. signal. However, E.D. efficiency is restricted by multipath fading, shadowing, and low Signal to Noise Ratio (SNR). Many researchers have introduced enhancement in energy detection-based spectrum sensing algorithms like double threshold-based energy detector [4] and adaptive double threshold-based energy detector [5], Improved energy detector based on arbitrary positive power [6], Three steps decision making based improved energy detector [7], Adaptive (dynamic) threshold-based energy detection [8],[13] and Memory based energy detection[14]. Various factors like fading and time variation of radio channels (noise uncertainty) also degrade the performance of spectrum sensing; cooperative sensing can ease the problems with additional analytical complexity and traffic between cooperative nodes[2], [3].

II. ANALYSIS OF IMPROVED ENERGY DETECTION

A. Energy detection(ED)

According to the working method of E.D., A signal from the channel of interest is received by the Secondary User (SU), which is also known as Cognitive Radio (C.R.). The energy of that signal is measured, and it is compared with predefined threshold energy. Based on which one of the hypothesis H_0 or H_1 is, decided to indicate absence or presence of Primary User (PU) over the channel of interest. It can be interpreted mathematically by equation (1).

The performance of the sensing technique can be indicated by the Probability of false alarm (P_{fa}) and Probability of detection (P_d). If we consider the sample size N high enough, we can approximate the test statistic $T_i(y_i)$ as Gaussian (as per the central limit theorem). Considering the signal variance (average signal power of received primary signal considering zero mean) of σ_x^2 and the noise variance (noise power considering zero mean) of σ_w^2, the equation of test statistics can be indicated mathematically by equation (2) [7],[9].

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

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

If we integrate the test statistic $T_i(y_i)$ with reference to the threshold, we can derive P_d and P_{fa}. These probabilities can be indicated mathematically by equations (3) and (4) respectively [7][9],

$$P_d^{CED} = Q\left(\frac{\lambda - N(\sigma_x^2 + \sigma_w^2)}{\sqrt{2N(\sigma_x^2 + \sigma_w^2)^2}}\right) \quad (3)$$

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

B. *Improved Energy Detection*

While the CED has benefits like adaptability and low complexity, the efficiency decreases to a lower value of N. This motivates the development of Improved Energy Detector (IED), which can solve such issues. As per the improved version suggested in [4], The initial step of IED is the same as CED, where the test statistic $T_i(y_i)$ is derived. In the next step, the IED finds an average test statistic $T_i^{avg}(y_i)$ based on the last L sensing measures. The Ti(yi) here is believed to have normally distributed values. So, $T_i^{avg}(y_i)$ can also be considered normally distributed because it is independent of $T_i(y_i)$.

In order to prevent the rise in the false alarm, an extra check based on previous sensing event $T_{i-1}(y_{i-1})$ is included in IED. When the test statistic $T_i(y_i)$ is less than the threshold(λ), and the average test statistic $T_i^{avg}(T_i)$ is greater than λ, and the situation indicates that a decrement in the received energy may be due to an instantaneous energy drop, but the decision should be H_1. In the third step, the previous sensing event $T_{i-1}(y_{i-1})$ is measured. If it is less than the threshold (λ), it shows that the decrement in received signal energy is indicating that the channel is now released and the channel is vacant now. So, the decision should be H_0.

The test statistics $T_{i-1}(y_{i-1})$ is also considered as normally distributed. By assuming Ti(yi), $T_i^{avg}(T_i)$ and $T_{i-1}(y_{i-1})$ Mutually independent. P_d and P_{fa} for IED can be indicated mathematically by equations (5) and (6), respectively:

$$P_d^{IED} = P_d^{CED} + P_d^{CED}(1 - P_d^{CED}) * Q\left(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\right) \quad (5)$$

$$P_{fa}^{IED} = P_{fa}^{CED} + P_{fa}^{CED}(1 - P_{fa}^{CED}) * Q\left(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\right) \quad (6)$$

Where, μ_{avg} and σ_{avg}^2,

$$\mu_{avg} = \frac{M}{L} N(\sigma_x^2 + \sigma_w^2) + \frac{L-M}{L} N\sigma_w^2 \quad (7)$$

$$\sigma_{avg}^2 = \frac{M}{L^2} 2N(\sigma_x^2 + \sigma_w^2)^2 + \frac{L-M}{L^2} 2N\sigma_w^4 \quad (8)$$

Here, M ∈ [0, L] is a number of sensing events for which the primary signal is present in real. For practical cases, M is not known but can be restricted between 0, and L.M=L shows always busy channel, and M=0 shows always idle channel considering previous L sensing events [7].

III. Cooperative Improved Energy Detection

The performance of spectrum sensing can be determined by two main factors: the probability of false alarm and the probability of misdetection. Misdetection causes interference with P.U., and so it is more severe. It is desired that a sensing algorithm provides a higher detection probability with a lower false alarm probability. But many other factors in real affect the detection performance like shadowing, multipath fading, and receiver uncertainty problem.

When a C.R. receives multipath signals and experiences shadowing due to blocking by an obstacle/obstacles, due to that, the P.U. signal may not be properly detected. Again, whenever a receiver is outside the range of the network, it is affected by receiver uncertainty issues because it is unaware of the P.U. transmitter and receiver. Such CR determines the channel as a free channel, although it is busy, which creates the misdetection.

But as all C.R. users are spatially diversified, it is unlikely that all C.R. experience the same fading/multipath effect. If C.R. users cooperate and share their sensing results with other C.R.s to take the combined cooperative decision, overall spectrum sensing performance can be improved. Thus, cooperative spectrum sensing is emerged as an effective and attractive solution to reduce the effect of multipath fading and receiver uncertainty [9],[11].

The performance improvement due to cooperative sensing is called cooperative gain. With the advantage of cooperative gain, the cooperative network also brings limitations of cooperation overhead. The overhead can be in the form of sensing time, bandwidth, and delay.

The cooperation of C.R. users can be modeled by various approaches. Different models are based on how C.R. users are cooperating to have optimal spectrum sensing. The cooperative sensing can be either centralized where the decision is taken by a fusion center or distributed where each C.R. is intelligent to take the decision.

In the data fusion (soft combination) model, each C.R.s receives the signal, amplifies it, and sends it to the fusion center, while in the decision fusion (hard combination) model, each C.R. makes a decision in the form of 1/0 (presence/absence) based on the status of P.U., and individual decisions are sent to fusion center through reporting channel.

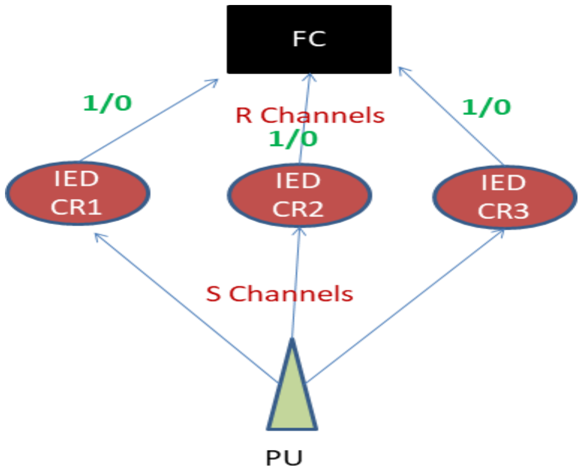


Fig.1 System model of cooperative decision fusion.

In this paper, we have used the decision fusion model of cooperation by considering a centralized fusion center. The OR and the AND rules have been evaluated. The system model of the scenario is shown in Fig.1.

Let us consider d_i as the local decision by C.R. use i and the d as the cooperative decision by the fusion center. d_i, d$\in$ {0,1}, and "0" and "1" represent the absence(H_0) and presence(H_1) respectively.According to the AND rule, the F.C. determines the cooperative decision d = 1if for all i, local decision d_i = 1. Similarly, for the OR rule, F.C. determines cooperative decision d = 1if for any i, local decision d_i = 1. The majority rule cooperative decision d =1 is determined if at least half of the C.R. users take local decision d_i = 1. In general, the fusion rules can be indicated by the k out of N rule. The false alarm probability of cooperative spectrum sensing can be indicated mathematically by equations (9) [9], [11]

$$Q_f = \sum_{l=k}^{N} \binom{N}{l} P_f^l (1 - P_f)^{N-l} \quad (9)$$

The detection probability of cooperative spectrum sensing can be indicated mathematically by equations (10) [9],[11],

$$Q_d = \sum_{l=k}^{N} \binom{N}{l} P_d^l (1 - P_d)^{N-l} \quad (10)$$

From equations (9) and (10), it can be shown that for k = 1, the generalized k out of N rule turns out to be OR rule, and for k = N, the k out of N rule turns out to be AND. For a network with higher numbers of C.R. users, the OR rule is more efficient, and for the smaller number of C.Rs, AND rule performs better. By considering k $\geq$ N/2, the k out of N rule turns out to be the majority rule. It is important to get the optimal value of k for which the majority rule performs better considering k out of N rule. If we select the cooperative rule base on threshold level, for a fixed small threshold level AND is the optimal rule and for fix large threshold level OR rule is optimal [2], [9].

Cooperative detection probability for AND, OR, and majority rule can be obtained from equation (10) by setting k = N, k =1, and l = k/2, respectively.

$$Q_{d,AND} = P_{d,i}^N \quad (11)$$

$$Q_{d,OR} = 1 - (1 - P_{d,i})^N \quad (12)$$

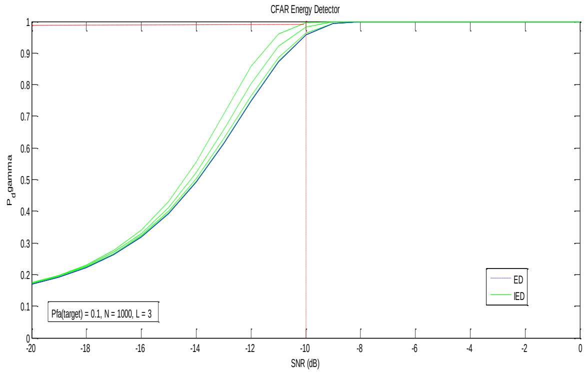
$$Q_{d,maj} = \sum_{l=k/2}^{N} \binom{N}{l} P_{d,i}^l (1 - P_{d,i})^{N-l} \quad (13)$$

IV. RESULTS AND PERFORMANCE ANALYSIS

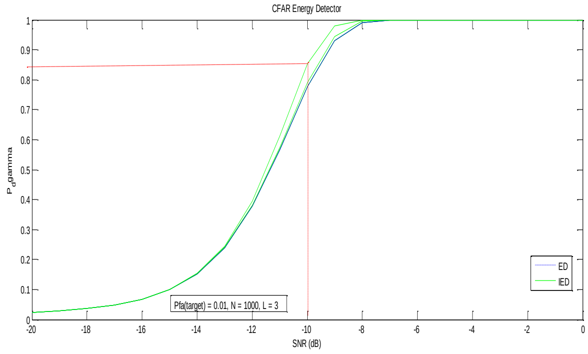
A. *Performance comparison based on mathematical implementation*

For implementation, MATLAB functions of the probability of detection P_d and Probability of false alarm P_{fa} are formed based on equations (3), (4) and (5), (6) as a function of sample size, threshold, signal power (variance), and noise power (variance). The equations here illustrate that the P_{fa} is dependent only on noise power while the P_d is dependent on the noise and signal powers both. Here decision threshold is set by using the Constant False Alarm Rate (CFAR) technique in which the value of P_{fa} is kept constant at the required value. The function to calculate CFAR for CED and IED is created, which depends on the target P_{fa}, SNR, and sample size. The function is created based on equations (3) for CED and (5) for IED to get threshold valueλ. Substituting λ in equation (3) and (5), and dividing the numerator and denominator by σ_w^2 gives the detection probability as a function of SNR (γ), where $\gamma = (\sigma_x^2/\sigma_w^2)$. P_d is calculated to have the constant desired value of P_{fa}. For two values of $P_{fa,}$ which are 0.1 and 0.01. Here SNR values are varied from -20dB to 0dB to check the performance of both CED and IED for N =1000. The graph of P_d v/s SNR is plotted, which is shown in Fig. 2.

Fig. 2 shows that the P_d increases with SNR. To achieve the lower P_{fa}, under the same conditions, lower P_d is achieved. In other words, a better SNR value is required to achieve better $P_{fa.}$



$P_{fa,target}$ = 0.1 , N = 1000, L =3, M = 0 to L

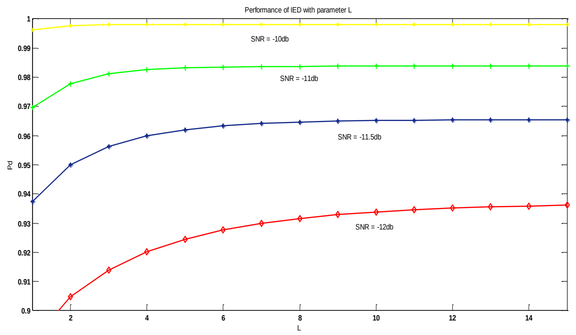


$P_{fa,target}$ = 0.01 , N = 100, L =3, M = 0 to L

Fig.2 CFAR curve for CED and IED

B. Performance Evaluation of IED based on the value of L.

IED performance is indicated as a function of the algorithm's parameter L. CED and IED schemes are equivalent for L = 1. The performance has been achieved by changing the values of L by considering P_{fa_target}= 0.1 for different values of SNR.



N = 1000, Pfa_target = 0.1, M = L

Fig. 3 Performance of IED with variable L under different SNR.

Fig. 3 shows the change in performance of IED with a change in L. With the increase of L, more sensing events are considered while calculating $T_i^{avg}(T_i)$, and so the average value can be calculated more accurately, which increases the probability of detection. But after increasing L after a sufficiently large value, the true average value remains the same, and so further increase in L does not change the detection efficiency. For lower SNR, L should be sufficiently large. Increasing L also increases the memory requirement, so the selection of L is a tradeoff between detection accuracy and memory requirement.

C. Cooperative Improved Energy Detection

The simulation for cooperative spectrum sensing was performed using the mathematical equations (11) and (12) by considering $P_{d,i}$ is the probability of detection for each C.R., which detects the channels by improved energy detection algorithm. The simulation is designed for the different cognitive devices under consideration. N is the number of C.R. users and results for N =1,5, and 10 are obtained. SNR value is assumed at -15dB, and local sensing is done by the IED algorithm for the sample size of 1000. The target false alarm probability is assumed to be 0.1. The path loss is considered for different C.R.s by applying random distances to each. The reporting and sensing channels are assumed to be AWGN channels. The cooperative P_d and P_{fa} are calculated by using AND and OR rules, and the ROC curve is plotted for both the rules. The results are shown in Fig. 4 and Fig. 5.

As per the OR rule, if any one of C.R.s detects the presence of the P.U. in the cognitive network, the F.C. decides that the P.U. is present, so no other C.R.s will start their communication. Thus, there are very few chances of interferences (misdetection) which can be observed from Fig. 4. The detection probability is higher in the OR rule, and it increases with an increase in the number of C.R. users in the network. The limitation of the OR rule is that the channel utilization is lower.

In the AND rule, in contrast with the OR rule, if all of C.R.s detects the presence of the P.U. in the cognitive network, then only F.C. decides the P.U. is present. In other words, if any of the C.R.s detects the absence of P.U., F.C. considers it as the absence of P.U. and allows other C.R. to start communication. This situation can cause interference, and so the misdetection probability of AND rule is higher (Lower detection probability), which can be observed from Fig.5. The advantage of AND rule is that it provides higher channel utilization.

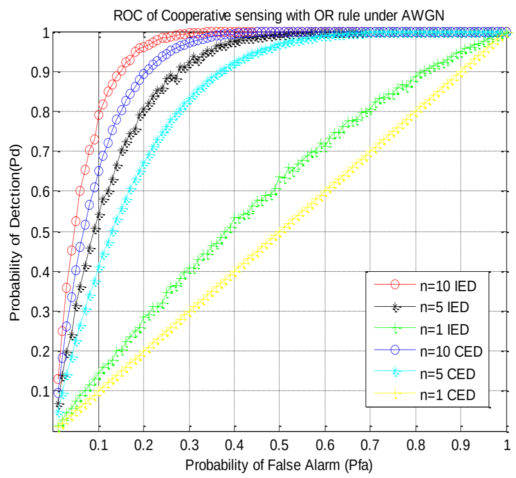


Fig. 4 P_d V/s P_{fa} for cooperative(OR Rule)IED

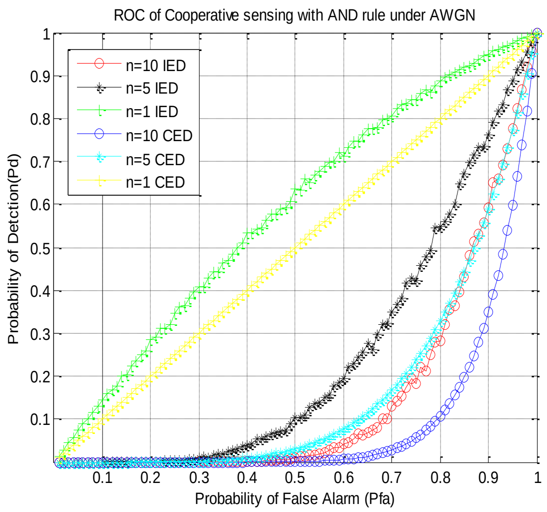


Fig. 5 P_d V/s P_{fa} for cooperative(AND Rule) IED

V. CONCLUSION

To solve the hidden primary user problem and to improve robustness towards noise uncertainty, IED-based cooperative sensing is used. The Decision fusion by AND rule, OR rule, and the k out of N rule are applied and analyzed with respect to CED for the different number of cognitive radios in the network. Simulation results indicate that the OR rule performs well for a low number of C.R.s the AND rule for a large number of C.R.s.

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