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Performance Improvement of Generalized Energy Detection For Cognitive Radio

[1]P.Venkatapathi, [2]Dr.Habbulla Khan, [3]Dr.S.Srinivasa Rao

Abstract--- *An efficient spectrum utilization has been an important topic of interest because of the improved usage of wireless communications in governmental, commercial and personal capacities.Cognitive Radio (CR) is a potential solution to this inefficiency problem. The spectrum sensing issignificant function of CR. It is used to detect primary user. Energy Detection(ED) is a most commonly used technique for spectrum sensing.*

Keywords--- *Cognitive Radio,Spectrum sensing, Energy Detection.*

I INTRODUCTION

Cognitive radio (CR) technology is an embryonic technology that talksabout the spectrum scarcity problem which is major issue in several countries by providing the Dynamic Spectrum Access (DSA). Spectrum utilization can be greatly improved by allowing secondary users (SU's) to access spectrum holes which are unoccupied by primary users (PU's).

Cognitive radiocarry out two impartment tasks. Firstly, it searches the spectrum and determines which parts are vacant,this methodis known as spectrum sensing. Secondly, it determines a method of assigning secondary users to the vacant spectrum without interfering with the primary users. Cognitive radio networks can drastically change the prevailing methods that wireless communications operate in the future by dynamically allocating spectrum usage and eventually provide a better quality of service to users.

In this paper, the Energy detection is reviewed for spectrum sensing since it does not require prior information of primary signals and is simple to implement because of low complexity. The remaining of the paper is planned as follows. Section II gives the system model while the algorithm is presented in Section III.Section IV demonstrates selected numerical results and final section V concludes the paper.

II SYSTEM MODEL.

The binary hypothesis model for PU detection in Cognitive radio[1] is given as

$$y(n) = \begin{cases} h_S(n) + w(n), & H1 \\ w(n), & H0 \end{cases} \qquad (1)$$

Where

1, Research Scholar, KL University,Green Fields, Vaddeswaram,Guntur District, A.P., India.
2, *Dean (Student Affairs), Malla Reddy College of Engineering and Technology, Hyderabad, Telangana, India.*
3, *Professor & HOD, University,Green Fields, Vaddeswaram,Guntur District, A.P., India*

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y(n) is the nth received signal sample by SU

n = 1,…., N indexes the samples of received signal by SU.

s(n) is the nth unknown primary signal sample.

his the fading coefficient of the channelbetween PU and SU.

w(n)is additive white Gaussian noise (AWGN) with mean zero and variance σ^2.

H1 and H0 are the hypotheses appreciate presence and absence of PU respectively. The typical power of primary signal is σ_s^2. We assume that primary signal is irregular of noise and attenuation. It's thought of that primary signal samples square measure irregular. Noise samples are assumed to be irregular. For simplicity, we tend to think about primary signal, attenuation coefficients and noise square measure imaginary number. Extension of the results for advanced signals will simply be done.

The aim of spectrum sensing is to determine the presence or absence of PU supported aforesaid binary hypothesis downside (choose H1 or H0). The choice is taken supported received signal by the secondary user. Spectrum sensing algorithmic performance is typically measured by 2 probabilities.

One is probability of detection (P_D) and the other is probability of false alarm (P_{FA}) which are defined as

$$P_D = P_r(H1|H1) \qquad (2)$$

$$P_{FA} = P_r(H1|H0) \qquad (3)$$

Thus the chance of detection is that the chance of selecting H1 once verity hypothesis is H1 and chance of false is that the chance of selecting H1 once verity hypothesis is H0. A decent sensing rule is that the one that achieves high chance of detection and low chance of warning, for a given variety of samples.

III PROPOSED ALGORITHM.

In this paper, the energy detection is used for spectrum sensing is energy detectionbecause it doesn't need previous information of primary signals and low complexness. In case of Conventional Energy Detector (CED), the received signal samples areInitial Square, then summed over the amount of samples collected and so compared with a preset threshold to require call on presence or absence of PU. The data point T_{CED} for standard energy detector is given as

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

Where N is the number of samples.

By exchange squaring operation by positive operation p we can remodel typical energy detector to Generalized Energy Detector(GED) [2]. Then the check data point for GED is given as

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$$T_{GED} = \frac{1}{N}\sum_{n=1}^{N}|y(n)|^{P}$$

Where p >0 is an arbitrary constant. It can be understood that CED is a special case of GED with p = 2.

For large N and therefore invoking central limit theorem (CLT) [3], we are able to outline chance of detection P_D and chance of false alarm P_{FA} for GED as

$$P_D = P_r(T_{GED} > T\backslash H1) = Q(\frac{T-\mu 1}{\sigma 1/\sqrt{N}})$$

And

$$P_{FA} = P_r(T_{GED} > T\backslash H0) = Q(\frac{T-\mu 0}{\frac{\sigma 0}{\sqrt{N}}})$$

Where

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

And T is the predetermined threshold which can be obtained by fixing probability of false alarm, ¹1 and ¹0 are means of T_{GED}under $H_1$and H_0respectively, $\sigma_1^2$and $\sigma_1^2$are variances of T_{GED}under $H_1$and H_0respectively, which can be given as [2]

$$\mu_0 = \frac{2^{P/2}}{\sqrt{\pi}}\sqrt{\frac{P+1}{2}}\sigma^P$$

$$\sigma_0^2 = \frac{2^P}{\sqrt{\pi}}[\sqrt{}(\frac{2P+1}{2}) - \frac{1}{\sqrt{\pi}}\sqrt{}^2(\frac{P+1}{2})]\sigma^{2P}$$

$$\mu_1 = \frac{2^{\frac{P}{2}}(1+\gamma)^{P/2}}{\sqrt{\pi}}\sqrt{}(\frac{P+1}{2})\sigma^P$$

$$\sigma_1^2 = \frac{2^P(1+\gamma)^P}{\sqrt{\pi}}[\sqrt{}\left(\frac{2P+1}{2}\right) - \frac{1}{\sqrt{\pi}}\sqrt{}^2(\frac{P+1}{2})]\sigma^{2P}$$

With $\gamma$is average received signal-to-noise ratio (ASNR).

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IV SIMULATION RESULTS.

Here simulation is done using MATLAB**.**Fig.1 shows thatthe Receiver Operating Characteristic (ROC) curve where average probability of detection $\bar{P}_D$is plotted against average probability of false alarm $\bar{P}_{FA}$for different values of p with noise uncertainty L = 0.1 dB, N = 10000 and ASNR =-15 dB . It can be seen that the best energy detector that gives maximum area under ROC curve is the one with p = 2,that is CED. For any values of p other than 2, the detection performance degrades compared to that of CED. This can also be verified from Fig.2 where $\bar{P}_D$is plotted against ASNR for fixed$\bar{P}_{FA}$. CED (p = 2) is the best energy detector among all energy detectors and the detection performance degrades as p deviates from 2.

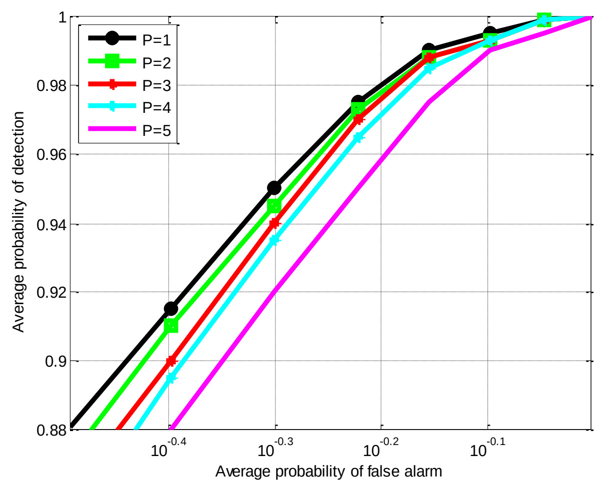

Fig.1.ROC curve for different values of p for L=0.1 dB, N=10000,ASNR=-15dB.

Probability of false alarm	Probability of detection				
	P=1	P=2	P=3	P=4	P=5
$10^{-0.4}$	0.9152	0.9102	0.9002	0.8952	0.8802
$10^{-0.3}$	0.9502	0.9452	0.9402	0.9352	0.9202
$10^{-0.2}$	0.9752	0.9732	0.9702	0.9652	0.9502
$10^{-0.1}$	0.9932	0.9882	0.9786	0.9932	0.9902
10^{0}	0.9982	0.9932	0.9882	0.9786	0.9932

Table 1: Probability of false alarm versus probability of detection for various P values

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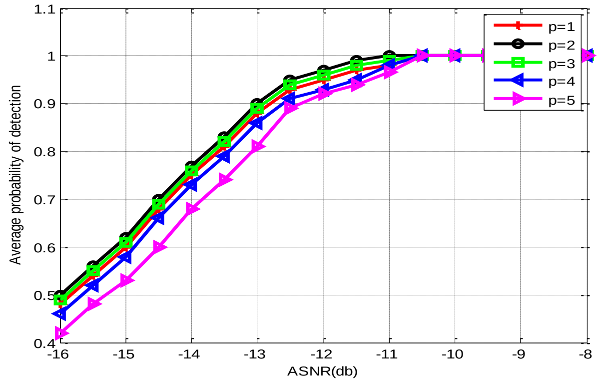

Fig.2.$\bar{P}_D$ vs. ASNR(dB) for different values of p for L=0.1dB,N=10000,$\bar{P}_{FA}$=0.1.

ASNR	Probability of Detection				
	P=1	P=2	P=3	P=4	P=5
-16	0.49	0.5	0.49	0.46	0.42
-15	0.6	0.62	0.61	0.58	0.53
-14	0.76	0.77	0.76	0.73	0.68
-13	0.89	0.9	0.89	0.86	0.81
-12	0.95	0.97	0.96	0.93	0.92
-11	0.98	0.99	0.99	0.98	0.96
-10	1.0	1.0	1.0	1.0	1.0
-9	1.0	1.0	1.0	1.0	1.0
-8	1.0	1.0	1.0	1.0	1.0

Table 2: Probability of detection versus Average signal to noise ratio forP=[1, 2, 3, 4, 5].

Fig.3 compares energy detectors with p = 2 and p = 5 for the cases when there is no noise uncertainty (L = 0 dB), L =0.2 dB and L = 0.5 dB. When there is no noise uncertainty, thedetection performance gap between GED with p = 2 and GED with p = 5 is large, former performing better than that of the latter. But as the noise certainty increases, the performance gap decreases. For significant noise uncertainty (L=0.5 dB), this gap is negligible and all energy detectors perform almost the same, that is, the detection performance becomes independent of p for significantly large noise uncertainty.

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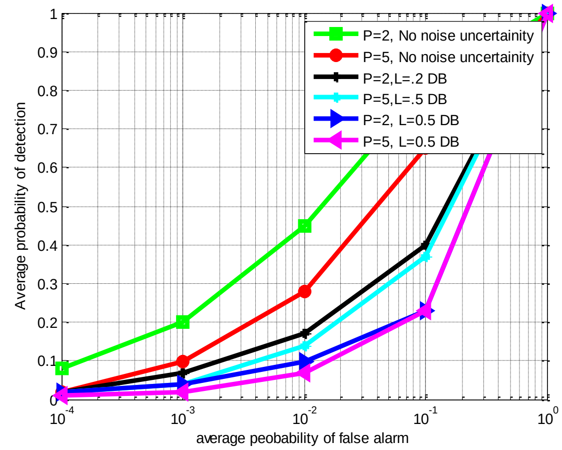

Fig.3.Comparison of ROC curve for p=2.5 with no noise uncertainty, L=0.2dB and L=0.5dB,N=10000,ASNR=-15dB.

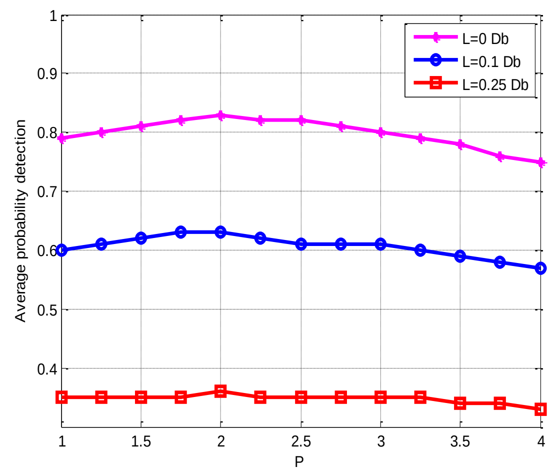

Fig.4.$\bar{P}_D$ vs.p for L=0.1dB.0.25dB for $\bar{P}_{FA}$=0.1,N=10000,ASNR=-1.5dB.

Fig.4 shows the variation of $\bar{P}_D$versus power constant p for L = 0.1 dB, L = 0.25 dB and no noise uncertainty (L = 0 dB) with $\bar{P}_{FA}$= 0.1, N = 10000 and ASNR = -15 dB.

We consider two cases:

Case 1: When noise uncertainty is present

In this case, from Fig. 4, it can be verified that GED with p = 2 is the best detector for both L = 0.1 dB and L = 0.25 dB. For L = 0.1dB, the detection performance degrades significantly as the p deviates from 2. For p = 2, $\bar{P}_D$is 0.6262 which deteriorates to 0.5773 for p = 4. However, for L = 0:25 dB,$\bar{P}_D$deteriorates not significantly, from 0.3496 to 0.3380 as p changes from 2 to 4. This highlights the fact that more the noise uncertainty,lesser is the effect of p on the detection performance and with significantly high value of noise uncertainty, the detection performance becomes independent of p, which is also shown in Fig. 3.

Case 2: When there is no noise uncertainty

In this case we can be observed from Fig.4 is that the best ED that has the maximum $\bar{P}_D$, corresponds to p = 2 and CED (p = 2) is not the best ED. But when the noise uncertainty is present, CED is the best ED.

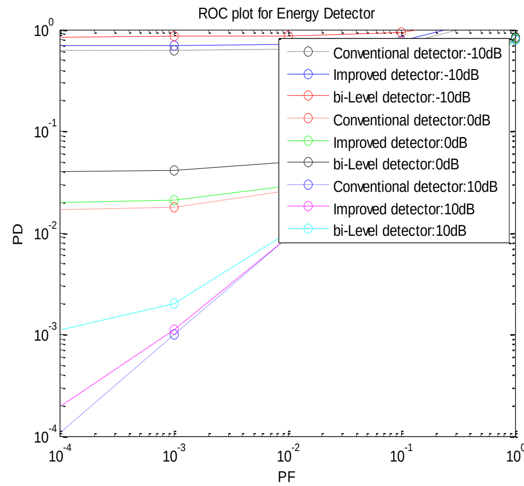

Fig.5. ROC plot for energy detectors

Fig.5 shows Receiver Operating Characteristic (ROC) curve where average probability of detection $\bar{P}_D$is plotted against average probability of false alarm $\bar{P}_{FA}$for different energy detectors with N=1000, ASNR=[-10db, 0db, 10db], and L=0.1. From the above figure the average probability of detection for the bi-level energy detector is better compared to earlier energy detectors at all ASNRs.

Fig. 6 shows receiver operating characteristic (ROC) curve where average probability of detection $\bar{P}_D$is plotted against average probability of false alarm $\bar{P}_{FA}$for different values of p with noise uncertainty L = 0.1 dB, N = 10000 and ASNR =-15 dB.

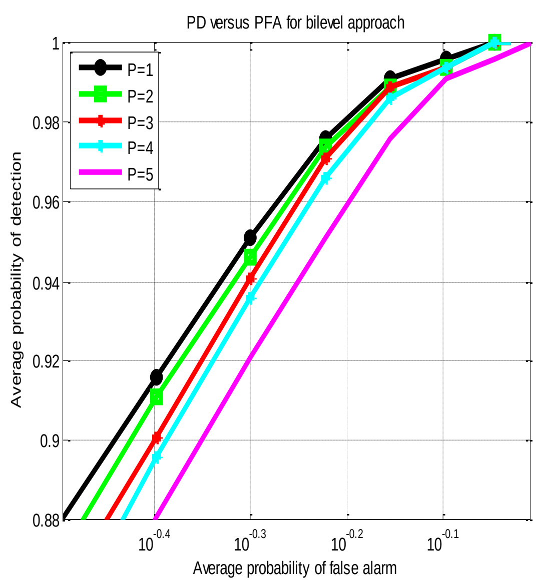

Fig.6.6. ROC curve for different values of p for L=0.1 dB, N=10000,ASNR=-15dB.

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From the above figure it is clear that compared to the figure 1. ROC curves the PD for the bi-level thresholding approach is better compared to GED.

V CONCLUSION.

The detection performance of the traditional energy detector has been improved by selecting the worth of the ability operation of the signal sample in step with the system settings. During this paper, the detection performance of generalized energy detector is analyzed, beneath the worst case of noise uncertainty and beneath the idea that noise uncertainty is uniformly distributed. For the worst case of noise uncertainty, analytically it's shown that SNR wall remains unchanged for all values of p. beneath the noise uncertainty with uniform distribution, generalized energy detector with p = 2 i.e. standard energy detector, is that the best energy detector. However standard energy detector might not be the most effective energy detector within the absence of noise uncertainty. Additionally because the noise uncertainty will increase and becomes important (generally bigger than zero.5 dB), the detection performance of generalized energy detector becomes freelance of p.

Numerical results have shown that the optimum power operation depends on the chance of warning, the ASNR moreover because the sample size. mistreatment the relationships between the optimum power operation and also the chance of warning, the ASNR and also the sample size, new energy detectors that shell the traditional energy detector are derived. Future works embrace examination of different nonlinear varieties of the signal samples to boost the detection performance of the energy detector any.

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