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# Advanced Energy Detection Method Using LO Algorithm

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**ABSTRACT:** We drive the optimal detector structure of MPSK modulated primary signal with known order over AWGN channels and given its corresponding suboptimal detector in both low and high SNR regimes. Through approximation , it is found that , in low SNR regimes, for MPSK(M>2) signals the sub optimal detectors on the real part . In the high SNR regimes, it is shown that , for BPSK signals, test statistics the sum of signal magnitude, but uses the real part of the phase-shifted signals as the input. We provide the performance analysis of the suboptimal detectors in terms of probabilities of detection and false alarm and selection of detection threshold and number of samples.

**KEYWORDS** : Spectrum sensing , Likelihood ratio test ,Cognitive radios, Fading channels.

### I. INTRODUCTION

Radio frequency spectrum is an expensive and limited resource for wireless communication. The increasing demands for additional bandwidth have to study that indicates the spectrum assigned to primary license holders is under-utilized. Cognitive radio technology helps us to use the RFspectrum more efficiently, by introducing secondary usage of the spectrum licensed to the primary usage but with the lower priority. A cognitive radio is able to change its transmitter parameters based on interaction with the environment. Secondary users equipped with cognitive radios cansense the spectrum and dynamically use spectrum holes inPU frequency bands for data transmission.

Secondary users are not allowed to introduce any interference to the primary license holders. Therefore, before starting their transmission, they need to be aware of the presence of the PUs. Spectrum sensing is one method for detecting the presence or absence of a primary license holder. This is a challenging task because the PU signal is usually very weak due to fading, shadowing etc.

There are a few main categories of spectrum sensing including matched filtering energy detection, cyclo-stationarybased detection an eigenvalue-based detection. Energy detection is the simplest method but it is optimized for impairment with additive white Gaussian noise (AWGN).

General optimum detection in the presence of correlated noise models have been considered i for the e-mixing noise model, for m-independent noise model and for moving average non-Gaussian noise models. In case of dependence is weak, the first order moving average (MA) of an i.i.d. random process is considered as a weakly correlated noise model, detection schemes are designed for known signals.

The work in this paper a Locally Optimum (LO) detection of random signals under a weakly correlated noise model over fading channels. And simple energy detection is often preferred over more complex detection techniques, with an LO detection technique with comparable complexity to energy detection for correlated noise environments.

The performance of LO detection is measured using false alarm and detection probabilities. In fading channel, these two probabilities depend on the channel gain hand we need to perform averaging overhin order to find final average false alarm and detection probabilities.



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Theoretical averages for these probabilities under fading condition in order to validate these theoretical results and to perform simulations over a large number of channel gains and obtain averages. Hence the simulation results are in good match with theoretical results.

The performance of the proposed locally optimum detection is shown to be better compared to the simple energy detection like Bayesian approach. If the estimated correlation between noise samples is different from the real correlation of the detection and false alarm probabilities and their theoretical averages in terms of bothestimated and actual correlations and investigated the effect of correlation mismatch on the performance of the proposed detection method.

### **II. COGNITIVE NETWORKS**

The wireless spectrum has been a hot research topic in the wireless communications community in recent years ,due to the intense competition for the use of spectrum at frequencies below 3 GHz.Cognitive network has a cognitive process that can perceive current network conditions, and then plan decide and act on those conditions. Network can learn from these adaptations and use them to make future decisions.

A cognitive network consists of a number of traditional wireless service subscribers and they are called as cognitive users. The traditional wireless service subscribers have the legacy priority access to the spectrum and are usually called primary users in this network. Cognitive users presented in this system are also known as the secondary users, are allowed to access the spectrum only ,if communication does not create significant interference to the licensed primary users.

A cognitive radio is a kind of two-way radio that automatically changes its transmission or reception parameters, in such a way that the entire wireless communication network of which it is a node communicates efficiently, while avoiding interference with licensed orun licensed users. The Cognitive Radio (CR) concept is a new wireless communication paradigm that improves the spectrum usage efficiency by exploiting the existence of spectrum holes. The Cognitive Radio (CR) concept is a new wireless communication paradigms that improves the spectrum sage efficiency by exploiting the existence of spectrum sage.

Devices using CRs referred to as Secondary Users (SUs), are aware of their spectrum environments and change their transmission and reception parameters to avoid interference with licensed spectrum users referred to as Primary Users (PUs).Networks consisting of nodes equipped with CRs are referred to as Cognitive Radio Networks (CRNs).CRNs are networks that have cognitive and reconfigurable properties and the capability to detect unoccupied spectrum holes and change frequency for end-to-end communication

### **SPECTRUM HANDOFF IN CRN:**

In CRNs, spectrum mobility causes a new type ofHandoff n referred to as spectrum handoff, which is different from traditional cellular handoff and mainly caused by the presence of PUs. In cellular networks and mobile devices transfer an ongoing connection from one channel to another channel between base stations due to user mobility or channel degradation.

The concept of user movement has also new meanings in CRNs because the number and characteristic of available spectrum at a new location may vary with PU spectrum usage. Moreover, the spectrum handoffs in CRNs are likely to incur longer delays or temporary communication disruptions because SUs must search for spectrum holes and choose anproper channel at every spectrum handoff. We are developing a new type of spectrum handoff to reduce temporary communication disruption disruptions.



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### **APPLICATIONS:**

We use wireless communication in variety of fields like Bluetooth, GSM, Zig-bee, WI-Max, Tetra etc.

### **III.TEST STATISTICS**

The Test statistic can be written as summation of random variables  $Y_iN$ ,

$$\Lambda_{|H_1} = S_N = \sum_{i=1}^N y_{iN}$$

$$y_{iN} = \kappa_i \left| e_{iN} + h \sum_{k=0}^{i-1} (-\rho)^k s_{(i-k)N} \right|^2$$

Here,Nis the number of samples and, if  $Y_i$  Nsample .when Nsamples are selected, corresponding noise  $e_iN$  and signals s(i-k)n components are defined similarly and is a summation of dependent random variables. Inorder to prove that  $\Lambda/H$  can be considered asymptotically as Gaussian random variable for large N, can use the centrallimit theorems for dependent random variables. For a timeindexedarray of dependent random variables, the main idea is that as long as the random variables temporally far enoughfrom each other are nearly independent, there are theorem that prove for the summation of the array of random variables.

$$S_{N}(a,b) = \sum_{j=a+1}^{a+b} (y_{jN} - E[y_{jN}]),$$
  

$$0 \le a, 1 \le b \le N - a$$
  

$$\tilde{c}_{N}(k) = \sup_{\substack{(l,m:|l-m|\ge k, 1 \le l, m \le N)}} |Cov(y_{lN}, y_{mN})|$$
  

$$0 \le k < N$$
  

$$\tilde{c}(k) = \max_{N} \tilde{c}_{N}(k)$$
  

$$C_{N}(k) = \sum_{j=k}^{N-1} \tilde{c}_{N}(j)$$

where Cov(.,.) is the covariance between two random variables and cN(k) is the maximum covariance between two samples among Ntotal samples that are at least k samples apart.

### SYSTEM MODEL:

The noise samples and the fading gains and the PU signal are mutually independent. In this paper we assume that the noise samples are temporally dependent. first-order bilateral and unilateral moving averages (MAs) an (i.e.) random process are used to model the weakly correlated noise. They are simple and good approximations to a weakly correlated noise.

We consider a weakly dependent scenario using the unilateral (MA)of (i.e.). random variables. Assuming that ei,i=1,

2, . . . , N, are the (i.e.). random variables with common probability density function (pdf)  $f_{e}(.)$ , the noise samples w<sub>1</sub>, w<sub>2</sub>, . . . , w<sub>n</sub>can be modeled.



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### IV.AVERAGE DETECTION AND FALSE ALARM PROBABILITIES OF LO DETECTOR

**1.Average Detection Probability**: In order to deal with the averaging in a low SNR regime where  $\sigma^2 \rightarrow 0$  which leads to  $\sigma^2 \rightarrow \sigma^2 0$ . By using this approximation the following relationship is between  $\mu_0$  and  $\mu_1$ .

$$\hat{P}_d = E_h \left[ Q \left( \epsilon_d - \delta \right) \right] = \int_0^\infty Q \left( \epsilon_d - \delta \right) f_\delta(\delta) d\delta$$

And its Q-function are determined below;

$$Q(x) = \frac{1}{\pi} \int_0^{\pi/2} e^{-\frac{x^2}{2\sin^2\theta}} d\theta$$

**2.Average False Alarm Probability :** In order to deal with the averaging in alow SNR regime where  $\sigma^4 s \rightarrow 0$  meaning in the expression for  $\sigma^2 1$ , all the terms with coefficient  $\sigma^4 s$  can be neglected.

 $\sigma_1^2 \cong \sigma_0^2 + \phi |h|^2$ 

In first-term of Q-function;

$$\sqrt{\frac{\sigma_1^2}{\sigma_0^2}}\epsilon_f = \epsilon_f \sqrt{1 + \frac{\phi}{\sigma_0^2} |h|^2}$$

By using the Taylor series:  $\sqrt{1+x} = 1 + \frac{1}{2}x - \frac{1}{8}x^2 + \frac{1}{16}x^3 - ..., \qquad |x| < 1$ 

$$\frac{\mu_1-\mu_0}{\sigma_0}=\alpha |h|^2$$

In second terms of Q-function;  $\sigma_0$ And average false alarm probabilities are specified below:

$$\hat{P}_f = E_h \left[ Q \left( \epsilon_f + \eta |h|^2 \right) \right]$$
$$\eta = \left( \frac{1}{2} \frac{\phi}{\sigma_0^2} \epsilon_f + \alpha \right).$$

### 3. Average Detection Probability for Energy Detector and Average False Alarm Probability for Energy Detector

$$\hat{P}_{d-e} = E_h \left[ Q \left( \epsilon_{d-e} - \alpha_e \, |h|^2 \right) \right] \, ; \, \hat{P}_{f-e} = E_h \left[ Q \left( \sqrt{\frac{\sigma_{1-e}^2}{\sigma_{0-e}^2}} \epsilon_f + \frac{\mu_{1-e} - \mu_{0-e}}{\sigma_{0-e}} \right) \right] \, ;$$

the same steps can be performed to find the final expression for average detection probability of LO energy detector. For the highest detection probability and the lowest false alarm probability.

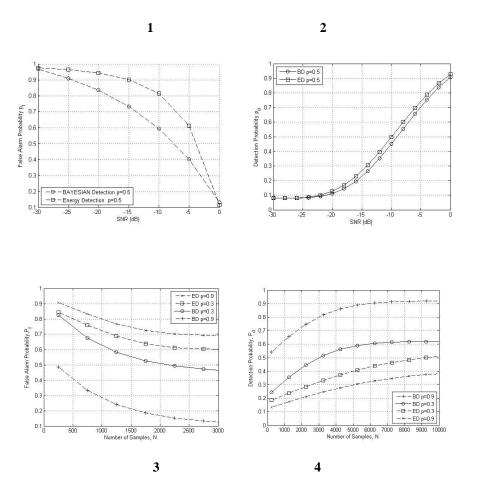


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The performance degradation depends on the absolute value and the difference between the estimated and the actual correlation values. The correctness of the analytical derivations has been verified using simulation results for false alarm and detection probabilities.

### V. SIMULATION RESULTS



Average false alarm probabilities using analytic result for detection probability of 0.95 and p=0.5 in fig .1, and in the fig.2 average detection probabilites using analytic results for false alarm probabilities of 0.05 and p=0.5, and in the Fig.3 average false alarm probabilities versus the number of samples for the detection probabilities of 0.95 and in fig.4 average detection probabilities versus the number of samples for false alarm probability of 0.05 are mentioned above for the high SNR ratios are analysed.

#### **VI.** CONCLUSION

We have implemented an advance LOenergy detection technique from an modulated signal for SNR value detection. Our techniques successfully detects the low SNR values from the signal which consists of modulated signal to form high SNR value. We have applied our technique on many energy detections processand found that it successfully detect the low SNR values.



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