International Journal for Innovative
Engineering and Management Research
A Peer Revieved Open Access International Journal
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Volume 08, Issue 05, Pages: 104–111.

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RELIABLE SPECTRUM SENSING OVER FADING CHANNELS IN PRESENCE OF CORRELATED NOISE CONDITIONS

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Abstract - In modern-day cognitive radio networks, to avoid interference from secondary customers to primary holders with license in spectrum, it is want to have the correct spectrum sensing. In methods like spectrum sensing, where samples of noise are correlated, the impairments from unbiased noise samples do now not offer surest performances. So, in case of random indicators over a weakly correlated noise version in fading channels calls for a locally finest detection approach has been proposed in this paper. A low sign to noise ratio regime has derived based totally at the chances of false alarm and detection of proposed detector. The common probabilities of false alarm and detection of proposed detector are derivated for exceptional channel gains. The simulation and numerical effects enables to compare and outline that the proposed method is greater suitable than the traditional strength detection approach. Finally we take a scenario wherein the expected and actual correlations are exceptional. The effect of correlation mismatch at the probabilities of false alarm and detection in proposed approach are envisioned.

Key Words: Cognitive radio networks, spectrum sensing, fading channels, domestically top-quality detection, fake alarm, correlation mismatch, electricity detection**.**

I. INTRODUCTION

The most expensive and limited resource for wireless communications are Radio Frequency (RF) spectrums The increase in demands for additional bandwidth has lead to these studies which will indicate the spectrum assigned to primary license holders are not utilized properly. RF's spectrums are efficiently utilized by Cognitive radio technology and the spectrums secondary usages to primary users have lower priority. Based on the interaction with the environment, a cognitive radio signals will change the transmitter parameters. In data transmission, secondary users can sense the spectrum and use spectrum holes dynamically from primary users with the help of cognitive radio signals. Any interference of secondary users are not allowed in primary users frequencies. Therefore secondary users must be aware of the primary user's presence. Primary license holders are detected by their presence and absence with methods like spectrum sensing. The method of spectrum sensing is tedious task as primary users suffer from fading, shadowing, etc. There are other types of spectrum sensing techniques like matched filtering, energy detection, cyclostationarity-based detection and Eigen value-based detection .Among these energy detection is simple technique and optimized with impairment of additive white Gaussian noise (AWGN).The additive noise samples are statistically independent. In this paper we consider AWGN exhibits correlation significantly. In applications like smart grid monitoring, noise are experimentally measured has several characteristics one of them was correlations of the time domain. These noise models are complex and need Markov transition models. Any real type cognitive radio environment signals will have some level of noise correlation. The correlation noise models are considered for ϵ-mixing noise model, for m−independent noise model and for average moving non-Gaussian noise models. First order moving average (MA) of an i.i.d is considered as weakly correlated noise when the dependence is weak. In all these above studies the implementation of detection schemes are designed for known signals. A detection mechanism like locally optimum (LO) of random signals over a weakly correlated noise model over fading channels is implemented. In case of correlated noise environments, rather than simple detection techniques we use to implement LO detection techniques. False alarm and detection probabilities are used to define LO detection. The above said probabilities depend on channel gain hand we need to take average of h in order to get final average false alarm and detection probabilities. In this paper, we derive some averages of these two probabilities in a large no. of channel gains and averages are taken. From the probabilities we can determine that simulation results obtained are matching well with theoretical results. When compared simple energy detection with locally optimum detection it is clear that later has better performance. Section II in this paper includes two hypotheses which details about the presence and absence of primary user and also about the model for correlated noise samples. Section III includes the derivation of locally optimum test statistic in the presence of correlated noise. In section IV, we compare locally Most effective detector and simple electricity detector and the overall performance of energy detector are analyzed and parameters required are derivated. All the effects above those sections are not real scenarios in which there may be some errors in the estimation of correlation coefficient.In section VI we give false alarm and detection possibilities in Numerical and simulation effects. In section VII conclusions are finally presented.

II. SYSTEM MODEL

The two hypotheses assumed are, H0 in which the primary user is said to be absent and H1 once the first user is said to be present, the received signal samples (n = 1, 2, . . .,N) at the secondary user for these two types of hypotheses could also be shapely in equivalent complex baseband illustration as: H0 : xn = wn H1 : xn = hsn + wn where, xn, h, and wn denote the received signal, the third Baron Rayleigh attenuation channel gain, and also the noise samples at the secondary user and Sn is that the primary user signal. The channel gain h is assumed to be constant throughout the detection method with zero mean and also the variance of E[|h|2] = σh2. The primary user signal used to has zero mean, variance σs2, and it's real and unreal elements square measure statistically freelance and has each variance σs2 /2.The zero mean noise samples square measure assumed to own identical variance σn2. The element samples square measure assumed to be temporally freelance, identically distributed (i.i.d.) .Moreover, we tend to assume that the noise samples, the fading gains, and also the primary user signals square measure reciprocally freelance. In this paper we tend to assume that the noise samples square measure temporally dependent. In straightforward first-order bilateral associate degreed unilateral moving averages (MAs) of an i.i.d. random method square measure accustomed model the feeble correlate noise. They're straightforward and sensible approximations to a feeble correlate noise. We tend to contemplate feeble dependent situation victimization the unilateral MA of i.i.d. random variables. Presumptuous that ei, i = 1, 2, . . .,N, are the i.i.d. random variables with common Probability density perform (pdf) fe(.), the noise samples w1, w2, . . ., wn can be defined as:

$$w_1 = e_1$$
$$w_n = e_n + \rho e_{n-1}, n = 2, \ldots, N,$$

Where |ρ| < 1 is the parameter that defines the noise Correlation.

III. TEST STATISTIC

In order to derive a test statistic to recognize between two hypothesis H0 and H1, we start with the globally optimal (GO) decision statistic expressed as

$$\Lambda = \frac{p(X|H_1)}{p(X|H_0)} = E_{h,S}\left[\frac{f_W(X - hS)}{f_W(X)}\right]$$

Where fW is the multivariate pdf of the noise samples and X = x1, . . . , xN, S = s1, . . . , sN. For the hypothesis H1, we have

$$f_W(X - hS) = f_W(x_1 - hs_1, x_2 - hs_2, \ldots, x_N - hs_N).$$

Since the noise samples are dependent, it is not possible to write the above multivariate pdf as a multiplication of pdfs of its elements.

IV. ENERGY DETECTOR

We have also analyzed an energy detector (ED) used for detection in the presence of correlated noise samples, in order to compare its performance with the proposed LO detector based on We plan to demonstrate the superiority of the proposed locally optimum detector in terms of performance compared to the conventional energy detection, based on analytical expressions. The test statistic for an energy detector can be expressed as follows:

$$\Lambda = \sum_{i=1}^{N} |x_i|^2 .$$

$$\Lambda_{|H_0} = \sum_{i=1}^{N} |w_i|^2 ,$$

$$\Lambda_{|H_1} = \sum_{i=1}^{N} |hs_i + w_i|^2 .$$

We explicitly derive expressions for the false alarm probability and detection probability when this energy detector statistic is used under noise conditions that match our correlated noise model.

V. CORRELATION MISMATCH

So far, all the presented results are based on the assumption that we have the perfect knowledge about the correlation coefficient ρ between noise samples at different times. This may not be valid in real scenarios where it is possible to have error in estimating the correlation coefficient. In order to investigate the effect of correlation mismatch in our proposed detector, we denote the real correlation coefficient with ρ and the estimated one with ˆρ. In order to include these two quantities in our analysis, we can start with the test statistics in Equation

$$\Lambda = \sum_{i=1}^{N} \frac{1-\hat{\rho}^{2i}}{1-\hat{\rho}^{2}} |\hat{y}_i|^2$$

For H_0 hypothesis,

$$\hat{y}_i = \sum_{k=0}^{i-1} (-\hat{\rho})^k w_{i-k} = \sum_{k=0}^{i-1} (-\hat{\rho})^k ($$

$$= e_i + \left(1 - \frac{\rho}{\hat{\rho}}\right) \sum_{k=1}^{i-1} (-\hat{\rho})^k e_{i-k}$$

and therefore

$$\Lambda_0 = \sum_{i=1}^{N} \frac{1-\hat{\rho}^{2i}}{1-\hat{\rho}^{2}} \left| e_i + \left(1 - \frac{\rho}{\hat{\rho}}\right) \right.$$

As we can see Λ_0 is a summation of dependent random variables. Similar arguments can be made as the ones to prove that Λ_0 can be considered a asymptotically Gaussian random variable when the number of samples N is large enough. It can be proved that the random variables in this summation are ρ-mixing. By defining

$$d_i = \left| e_i + \left(1 - \frac{\rho}{\hat{\rho}}\right) \sum_{k=1}^{i-1} (-\hat{\rho})^k e_{i-k} \right|^2$$

Calculate the mean μ_{0-m} and variance σ^2_{0-m} of the Gaussian random variable Λ_0.Same approach can be followed for Λ_1, and the parameters of these distributions can be used to compute false alarm and detection probabilities under mismatch conditions.

VI. RESULTS AND DISCUSSIONS

At secondary user a fading channel with weakly correlated noise, N=500 samples are taken. In case of slow fading channel, the fading coefficient h is constant for a given sampling period. Let the detection probability is taken as 0.95 and different signal to noise ratios(SNRs, defined as SNR = **σ**h2**σ**s2 /**σ**n2)) are calculated to find average false alarm probabilities for both proposed locally optimum detector model and conventional energy detector model. Theoretical analysis are found and compared with analytical results from the average false alarm probabilities from simulations over one lakh independent realizations of the Rayleigh fading channels.Fig1 shows average false alarm probability for correlation coefficient ρ = 0.5.Primary users can be implemented by 8-PSK.From Fig1,we can compare false alarm probability of the locally optimum detector are lower than the energy detector and also there are very small errors when simulation and analytical results are verified. Now let us take the false alarm probability as 0.05 and also average detection probabilities for different SNR's are defined. From Fig 2, the energy detector and proposed detector are compared where the proposed detector has higher detection probability and results of simulation are very closer to the analytical results. The effects of no. of samples on the detection performance are also considered. Different correlations for energy detection and LO detection are considered. -30

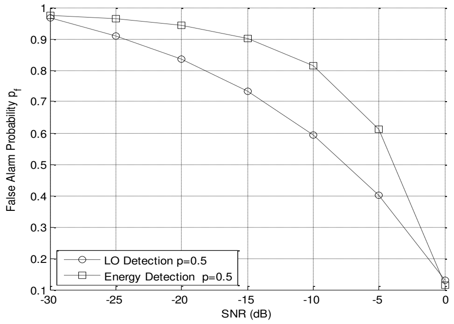

Figure 1: Average false alarm probabilities using analytical results as well as simulation results at different SNRs for detection probability of 0.95 and ρ = 0.5.

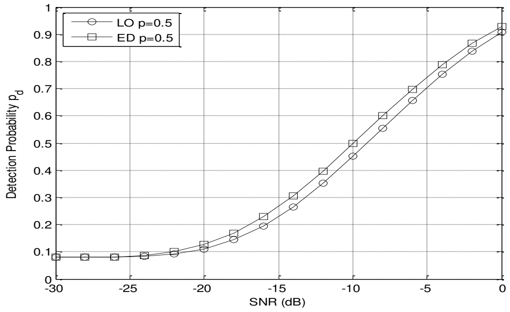

Figure 2 Average detection probabilities using analytical results as well as simulation results at different SNRs for false alarm probability of 0.05 and ρ = 0.5.

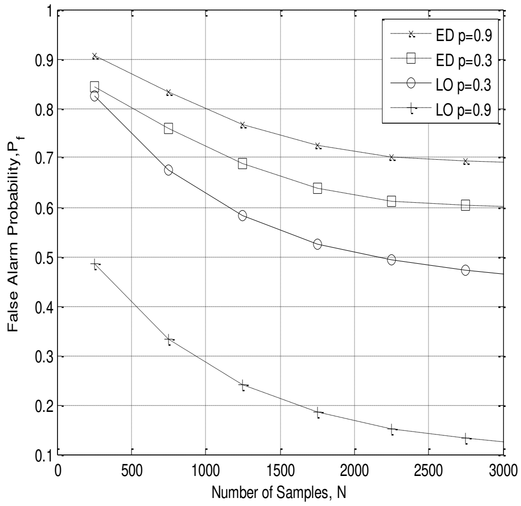

Figure 3 Average false alarm probabilities versus the number of samples for detection probability of 0.95

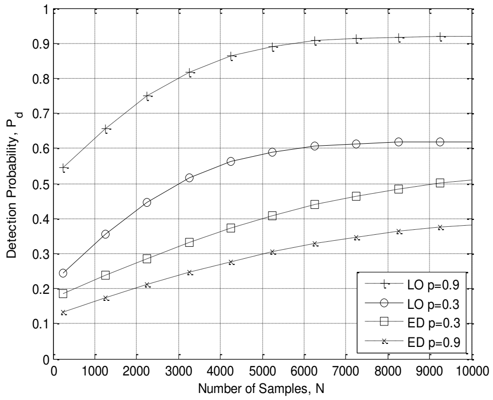

Figure 4 Average detection probabilities versus the number of samples for false alarm probability of 0.05

The above two graphs explains about average false alarm and detection probabilities and it is clear that when the number of samples gets lower and detection probability gets higher.In the graphs all the curves have rate of increasing Pd with decreasing Pf and is higher at beginning with lower samples and decreases when number of samples increases.

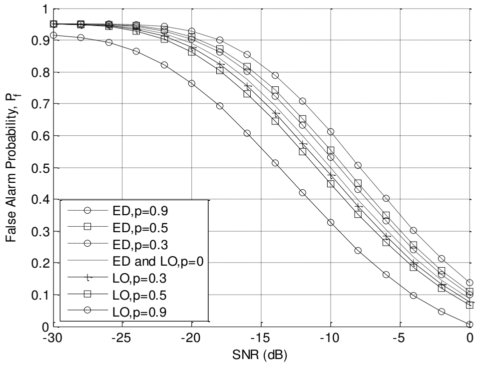

Figure 5 Average false alarm probabilities at different SNRs for detection probability of 0.95 and different correlation coefficients.

From the above graph, it is clear that the gain of proposed detector becomes high with increase in correlation coefficient for various SNR's with detection probability of 0.95.

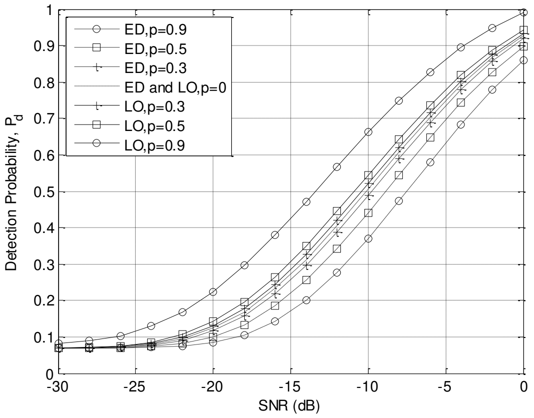

Figure.6 Average detection probabilities at different SNRs for false alarm probability of 0.05 and different correlation coefficients.

From the graph the gain becomes higher when the correlation gets higher in proposed detector than in energy detector for various SNR's and false alarm probability of 0.05

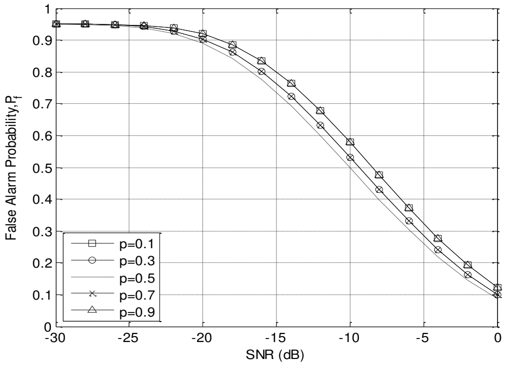

Figure7 Detection probabilities at different SNRs for false alarm probability of 0.05, for the case the estimated correlation is 0.5 and the actual correlations of [0.1:0.2:0.9].

The above graph shows detection probabilities when false alarm probability is 0.5 with estimated correlation as 0.5 and actual correlations of [0.1:0.2:0.9].Here the detection probabilities decreases with increase in differences between estimated and actual correlation coefficients.

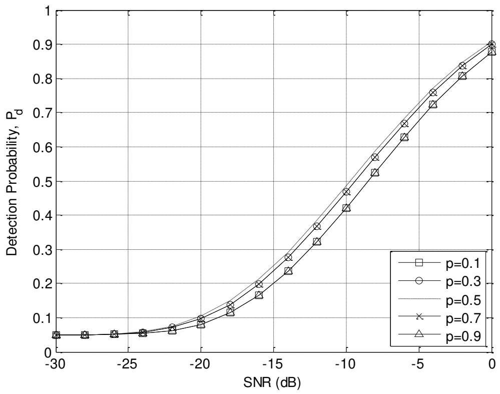

Figure 8 False alarm probabilities at different SNRs for detection probability of 0.95, for the case the estimated correlation is 0.5 and the actual correlations of [0.1:0.2:0.9].

The above graph shows the false alarm at various SNR's with detection probability of 0.95 and estimated correlation as 0.5 and actual correlations of [0.1:0.2:0.9]. When $\hat{}\rho = \rho = 0.5$ is said to be the perfect estimation case with highest detection probability. Performance degradation depends on the absolute value of the difference between the estimated and actual correlation values. $\rho = 0.1$ and $\rho = 0.9$ have the same performance

VII. CONCLUSION

A locally gold standard detector for detection of random indicators beneath a weakly correlated noise version over fading channels has been proposed. For a correlation mismatch, everyday situations wherein the envisioned correlations among noise samples aren't equal to real correlations are taken into consideration. For various channel profits, the fake alarm and detection probabilities are derived for a selected channel benefit h and then average of those chances are derived. In order to evaluate the overall performance of proposed version over power detector not unusual correlated noise are taken. The numerical and simulation consequences received from the possibilities of false alarm and detection really explains that LO detector has much less false alarm probability and excessive detection chance whilst in comparison with electricity detector. Higher the correlation coefficient, benefit also becomes higher in case of proposed detector whilst in comparison to electricity detector. The overall performance of proposed detector and power detector could be equal when there's no correlation. When there may be a mismatch of correlation, the fake alarm and detection possibilities are calculated. It is apparent from the consequences that if correlation mismatches are higher then the detection probabilities becomes lower and false alarm chances gets higher. The value$\hat{}\rho = \rho$ is an ideal estimation case which ends up maximum detection opportunity and lowest fake alarm chance. The degradation inside the performance is dependent on absolute price of the versions among estimated and actual correlated values.

The correctness of analytical outcomes over simulation consequences are verified based totally on false alarm and detection chances. In this paper, the maximum crucial assumption is primary user samples are independent over the years. For situations where time correlation among primary consumer pattern are more, a spectrum sensing approach may be carried out.

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