RF Signal Detection And Analysis Of Correlated Noise In Detection

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Abstract: *In cognitive radio networks, to avoid interference from secondary users (SU) to the first license holders (PU) of the spectrum, reliable spectrum sensing is important. In some situation when the noise samples are correlated, the spectrum sensing methods optimized considering impairment by way of independent noise samples will not offer finest performances. To deal with this difficulty, a domestically most reliable detection approach for random alerts under a performance analysis noise over channels is proposed. To implement this problem, a Locally Optimum (LO) detection method of random signals in presence of correlated noise model for fading channels is used. The performance parameters of Locally Optimum detection are measured using probabilities of detection and false alarm by performing averages over channel gain.*

Keywords: ***signal detection,spectrum sensing,optimum Detection ,spectrum sensing.***

1. Introduction*:*

RF spectrum is used resource in wireless communication and it extends from low frequency radio waves to high frequency gamma signals. The frequencies starting from the range of 3MHz-300GHz have innumerable applications in the field of wireless communication, RADAR and Communication Satellites. It becomes difficult to meet the growing demands for spectral resource. This leads to study the spectrum usage assigned to Primary License holders (PU). Cognitive Radio (CR) is associate rising communication theme that improves the spectrum utilization by up spectrum potency and exploiting the prevailing spectrum holes. It consists of variety of psychological feature users. The users having the psychological feature, the authorization to access the spectrum area unit known as primary users, and people with no authorization to spectrum area unit known as secondary users, and may access the authorized band while not intrusive with primary users [10][12][14].

The Cognitive Radio helps to use the frequency spectrum additional expeditiously, by allocating the accredited spectrum of primary users (PU) to the secondary user with a lower priority. On interaction with the setting the psychological feature radio is in a position to vary its transmitter parameters. Secondary users (SU's) equipped with psychological feature radios will sense the availability of spectrum and dynamically use spectrum holes in frequency bands for information transmission. As secondary users have restrictions to introduce any interference to the first license holders. Thus they have to bear in mind of the

presence of the PUs, before beginning their transmission [20, 21, 22, 23]. Spectrum sensing is employed for detection of the presence or absence of a primary / license holder. It is a difficult task as a result of the element signal is typically terribly weak attributable to attenuation channel and shadowing result, etc. The various classes of spectrum sensing embrace Matched Filter (MF), Energy Detection (ED), Cyclostationarity detection in and Eigen value-based method. Among this Energy detection proved the optimized for method to be impairment with additive white noise (AWGN)[18].

2. Related Work:

The main challenge for the cognitive radios is that it should not interfere with the authorised users and may vacate the band when required. For this it is necessary to sense the signals with fast speed. This work focus on the RF band sensing techniques which is based on primary signal transmitter detection. The RF band sensing and its estimation is the first important step to implement Cognitive Radio Technology.

Locally optimum detector (LOD) [24] is the simplest non-coherent method among all. The statistical analysis of the LOD is developed to model the faintly dependent noise model. In the comparison Locally Optimum detector has better performance than other methods.

Range choice is the capacity of an intellectual radio (CR) to choose the best accessible range band to fulfill optional clients' (SUs') nature of administration (QoS) necessities, without making destructive impedance authorized or essential clients (PUs). Every CR performs range detecting to distinguish the accessible range groups and the range choice procedure chooses from these accessible groups for entrepreneurial use. Range choice establishes a significant point which has not been enough investigated in CR look into. Range choice includes range portrayal, range determination and CR reconfiguration capacities. After the accessible range has been recognized, the initial step is to describe it put together not just with respect to the present radio condition conditions, yet in addition on the PU exercises [3][5].

3. Description Of Correlated Noise:

The detection theory works with the detection of signal and parameter estimation. The general environmental scenario for detection of signal and estimation of parameters is shown in Fig.1. It can be seen that for making decisions of presence or absence of PU activity, signal processor is required with inputs of signal plus noise signals.

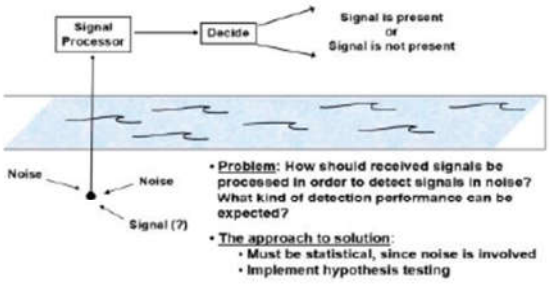

Fig. 1: Detection of signal.

Fig.2 shows the detection of signal in presence of noise. The requirements are expressed in terms of Pd and Pfa. The threshold for declaring detection is set based on models for signal and noise. Noise background estimation can be performed on data to improve the model. Outputs of detector are threshold crossings but these criteria are not independent so it results in a lower threshold which increases PD, but also increases PFA. The Performance defined by receiver operating characteristic (ROC) curve is Pd vs. Pfa for a particular SNR.

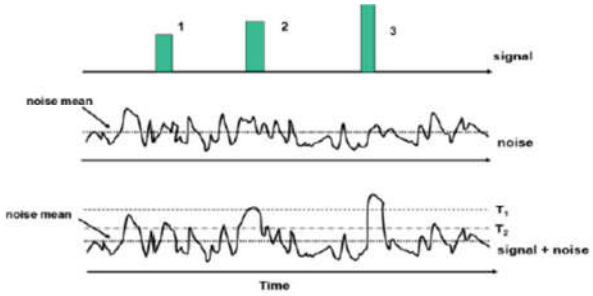

Fig. 2: Detection in Noise.

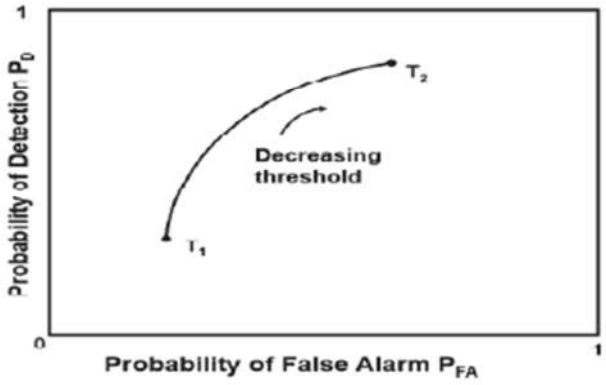

Fig. 3: Receiver Operating Curve (ROC).

4. 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 that secondary user for two types of hypotheses could also be shapely in the equivalent complex baseband illustration as:

H_0 : Xn = Wn
(1)

H_1 : Xn = hsn + Wn
(2)

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 $E[|h|2] = \sigma h^2$. The primary user signal used to has zero mean, variance σs^2, and it's real and unreal elements square measure in the statistically freelance and has each variance $\sigma s^2/2$. The zero mean noise samples square measure assumed to own identical variance σn^2. The element samples square measure assumed to be temporally freelance, identically distributed (i.i.d.). In this paper, we will assume that the weakly dependent noise e_i, i=1,2……,N, are unilateral MA of i.i.d. random variables The element samples square measure assumed to be temporally freelance, identically distributed (i.i.d.). In this paper, we will assume that the weakly dependent noise e_i, i=1,2……,N, are unilateral MA of i.i.d. random variables.

$$W_1 = e_1 \quad (3)$$

$$W_n = e_n + \rho e_{n-1},\ n = 2, \ldots, N, \quad (4)$$

Where $|\rho| < 1$ is the parameter that defines the noise Correlation.

5. 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

$$\Lambda = \frac{P(X/H1)}{P(X/H0)} = E_{h,s}\left[\frac{f_W}{f_W}\frac{(X-hs)}{(X)}\right] \quad (5)$$

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

$$F_W(X\text{-}hS) = f_W(x_1\text{-}hs_1, x_2\text{-}hs_2 \ldots\ldots x_n\text{-}hs_n). \quad (6)$$

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

6. Performance Analysis:

Using the test statistic obtained in Eq.(05) we analyze the performance of the proposed detector by calculating the false alarm and detection probabilities.

$$Pf=Pr(\Lambda>\tau|H_0)=Q(\tau-\frac{\mu 0}{\sigma 0}) \quad (7)$$

$$Pd=Eh[Q(\tau-\frac{\mu}{\sigma 1})] \quad (8)$$

6.1. Local optimum Detection:

The locally optimum detector (LOD) is used to achieve maximum spectrum utilization in cognitive radio networks. It derives the optimal detector using MPSK modulation for primary signals over AWGN type of channels whose order is known. It also calculates parameters of respective sub-optimal detectors in both high and low SNR values.

For the low SNR, using MPSK (M > 2) signals, the sub-optimal detector is the ED, but for Binary-PSK signals the sub-optimal detector is that the ED is on the important half. In high SNR conditions, using Binary- PSK, the test statistic is the sum of, real part of the phase-shifted signals as the i/p and signal magnitudes. It analyses the performance of sub-optimal detectors in terms of possibilities, warning, sampled levels and choice of threshold level and.

The simulated outcome shows that Bayesian Detector performs in a similar way as that of energy detector for low SNR values. For high SNR values it gives much better performance in terms of spectrum band utilization and SU throughput. To model the faintly co-related noise, simple first-order first order and second order moving averages of an i.i.d. RV are used. The Pd using Gaussian value can be given as:

$$Pd=Pr(\Lambda>\tau|H1)=Q(\tau-\frac{\mu 1}{\sigma 1}) \quad (9)$$

Where,

τ is defined as threshold ,vQ is the mono-tonically decreasing function.

7. 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 Equatio

$$\Lambda = \sum_{i=1}^{N} \frac{1-\hat{\rho}2i}{1-\hat{\rho}2} \left| yi \right|^2 \quad (10)$$

And therefore,

$$\Lambda_0 = \sum_{i=1}^{N} \frac{1-\hat{\rho}2i}{1-\hat{\rho}2} \left| e_i + (1-\frac{\rho}{\rho^{\wedge}}) \sum_{K=1}^{N} (-\rho^{\wedge}) \right| \quad (11)$$

As we can see Λ0 is a summation of dependent random variables. Similar arguments can be made to prove that Λ0 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

$$d_i = \left| e_i + (1-\frac{\rho}{\rho^{\wedge}}) \sum_{K=1}^{N} (-\rho^{\wedge})^k e_i - K \right|^2 \quad (12)$$

A similar approach can be followed for Λ1, and the parameters of these distributions can be used to compute false alarm and detection probabilities under mismatch conditions.

6. Results And Discussion

A fading channel is considered with weakly correlated noise and N=127 samples have been collected at the secondary user.

Assume a slow attenuation channel wherever the attenuation constant h is constant throughout the sampling amount. The detection probability is fixed to 0.95. The average false alarm probability for correlation coefficient ρ = 0.5 shown in fig. 4 as it can be seen in from fig. 4.

Locally optimum detector has lower false alarm probability. Now we fix the false alarm probability to 0.05 and find the average detection probability at signal to noise ratio (SNR). As it can be seen from fig. 5 the proposed detector has higher detection probability.

When correlation coefficient is equal zero the proposed have the same false alarm and detection probability it is shown in fig. 4 and fig. 5.

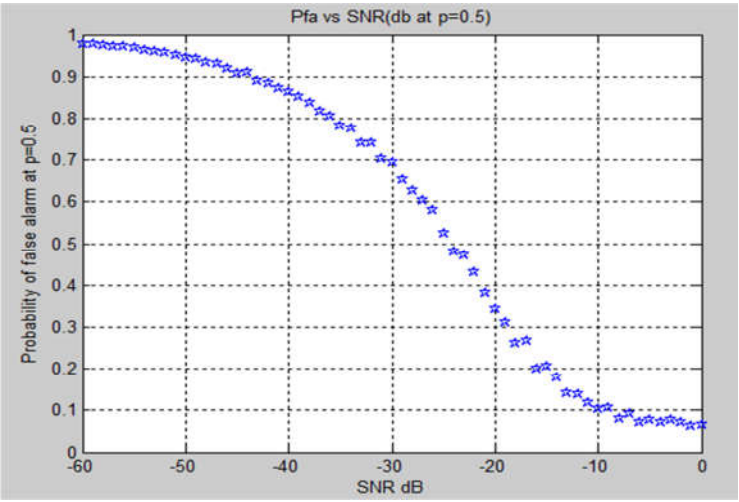

Fig. 4. Pfa Vs SNR db at ρ = 0.5.

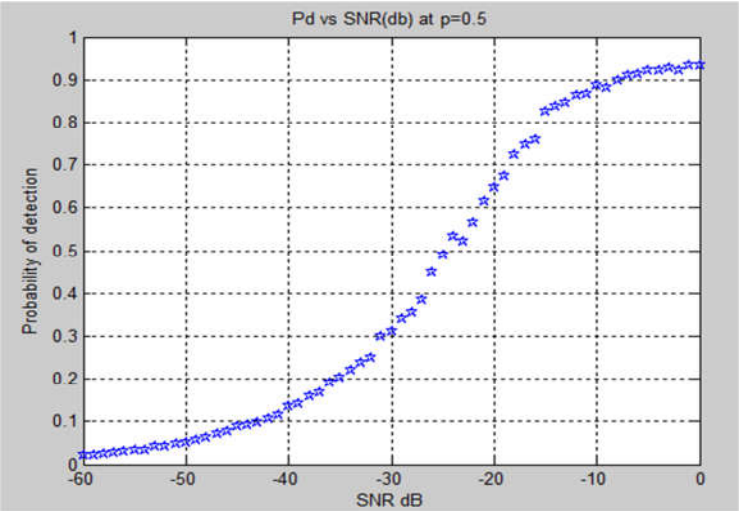

Fig. 5. Pd Vs SNR db at ρ = 0.5.

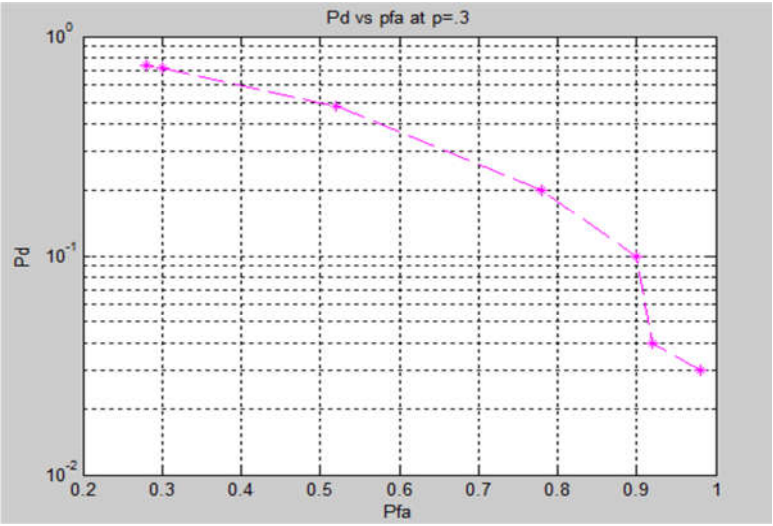

Fig. 6. Pd Vs pfa at ρ=0.3.

Pd vs pfa graph in fig 6 is decreasing in nature, it indicates inversely proportion of pd and pfa to each other.

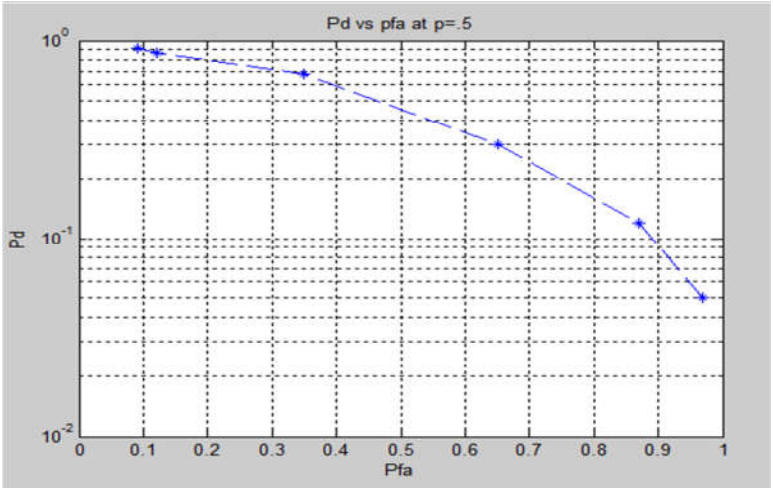

Fig. 7. Pd Vs pfa at ρ = 0.5.

With respective to correlation coefficient ρ = 0.5, pd gets increased with increased correlation coefficient. Fig. 7 is also indicates that inversely proportion of pd and pfa to each other.

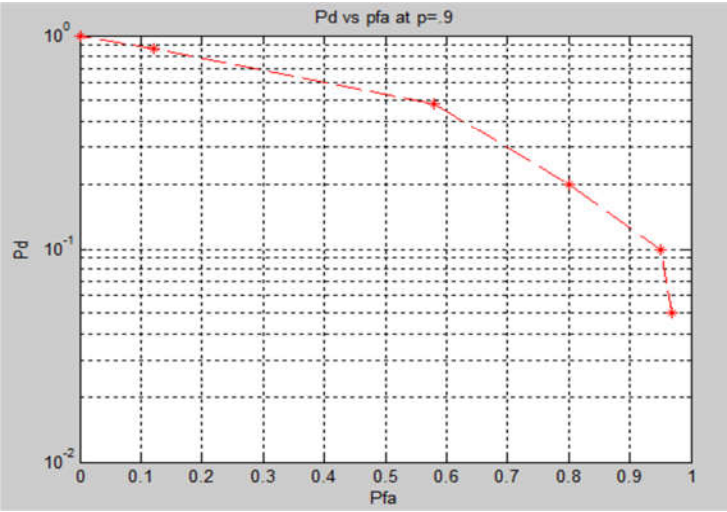

Fig. 8. Pd Vs pfa at ρ = 0.9.

In fig. 8 pfa decreases with respective to increased correlation coefficient ρ = 0.9. Fig. 6, Fig. 7 and Fig. 8 it shows that pfa get decreases with increase of correlation coefficient. The Detection probability as well as false alarm probability at noise correlation coefficient ρ = 0.5 is shown in fig. 5 and fig. 4 for LO. The BPSK modulation technique is used for the primary user.

The Performance of receiver operating characteristic such as probability of detection and false alarm probability has shown in fig. 4, fig. 5 and fig 6. Simulated results indicate that at low false alarm probability performance of both the detector is nearly same but as the false alarm probability increases detection by LO detection.

7. Conclusion:

In this paper, LO detection of random signals in additive weakly dependent noise is considered. The test statistic of the LO detector for that random signal in weakly dependent noise is simulated using receiver operating characteristic. The performance analysis of the LO detector is analysed and results suggest it will perform better than other methods.

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