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SPECTRUM DETECTION IN COGNITIVE RADIO OVER FADING CHANNELS USING LOCALLY OPTIMUM DETECTION

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ABSTRACT

In Cognitive Radio (CR) networks, reliable spectrum sensing is highly necessary to determine the presence of primary user (PU) in order to avoid interference from secondary users (SU).Spectrum sensing allows opportunistic secondary (unlicensed) users to access the spectral resources unused by their primary (licensed) owners. It is equally important to have trusted spectrum access methods even under low signal to noise ratio environments. To solve this issue, Locally Optimum (LO) Detection of random signals under weakly correlated noise model over fading (Rayleigh) channels is proposed. This method allows the detection of PU signal even under low SNR conditions where average probabilities are measured under different channel gains. On analysis, it can be seen that numerical and simulation results shows better results of the proposed method over known energy detection with certain complexities under correlated noisy environments.

Index Terms—**Cognitive Radio, Spectrum Sensing, Locally Optimum Detection, Correlated noise samples**

I. INTRODUCTION

Electromagnetic spectrum consists of range of frequencies extending from low frequency radio waves to higher frequency gamma radiations. In that, Radio Frequency(RF) typically ranging from 3MHz-300GHz have innumerable applications especially in Wireless Communication, RADAR and Communication Satellites. Of all available spectrum in RF band only certain part have commercial uses which is mainly used in Wireless Communication. Thus the spectrum availability is limited and is a precious resource. Also it will not be feasible to increase the bandwidth with ever growing demands growing for spectral resource[1].This demand had paved opportunities to study under utilization of the spectrum assigned to Primary License holder who is referred to as Primary User(PU).

Cognitive Radio (CR), also known as Intelligent Radio is the sensing device installed at SU end to detect the presence or absence of PU signal. Hence, CR's have to regularly perform reliable radio scene analysis [2] to detect the presence of primary user signals with high detection and low false alarm probability as well as to know allowable RF noise limit in PU signal. This is mainly done to avoid interference from the SU to PU that allows opportunistic usage of the unused spectrum to SU's for data transmission. For this dynamic spectrum sensing, we shall need to detect spectral spaces among various PUs licensed bands which is given in Fig.1 [3]

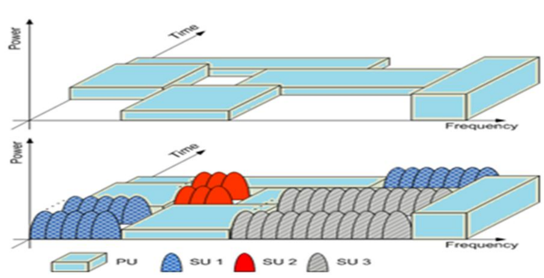

Fig. 1 Spectral opportunity for secondary access: A spectrum space

According to Federal Communications Commission, "A radio or system that senses its operational electromagnetic environment and can dynamically and autonomously

SPECTRAL SPACES

adjust its radio operating parameters to modify system operation, such as maximize throughput, mitigate interference, facilitate interoperability, access secondary markets"[4]. Henceforth, question arises when CR's have to sense and detect the PU signal even under fading and shadowing problems which is inevitable. So, a number of methods proposed including matched filtering [5], energy detection [6], cyclo stationarity-based detection [7], [8]. This is summarized in the following classification provided in Fig2.

Energy detection is the simplest method but it is optimized for disturbance with Additive White Gaussian Noise (AWGN) and only in high SNR values. Generally, we often consider the noise samples to be statistically independent. But in real practice, AWGN assumption does not hold good in some situations where the noise exhibits significant correlation in time domain. For this we require a cognitive radio environment that takes into account certain level of noise correlation. However studies on spectrum sensing reveals that prior knowledge of the PU signal is needed for detection in environments where noise samples are correlated [9].

In this paper, we propose a Local Optimum (LO) detection of random signals under weakly correlated noise models over fading channels being Rayleigh fading environment considered here. On investigation, we find that performance of LO detection measured using false alarm and detection probabilities is superior over existing energy detection methods with comparable complexities. Here we find that the probability values depend upon the channel gain 'h'. For this purpose we need to derive theoretical average probabilities and for the validation of these results obtained we perform simulations showing good agreement. In case, the estimated correlation between noise samples is different from real correlation, we need to derive average detection and false alarm probabilities for both estimated and actual correlations and study the effect of this mismatch in the performance of LO detector.

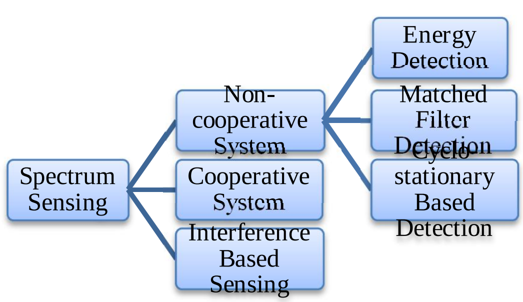

Fig. 2 Classification of spectrum sensing techniques

In the forthcoming modules let us discuss the following:

1. System Model
2. Energy detector structure through the approximations in different SNR regimes
   (i) False alarm probability
   (ii) Detection probability
3. Locally optimum detector structure through the approximations in different SNR regimes
   (i) False alarm probability
   (ii) Detection probability

II . SYSTEM MODEL

Assuming there are two hypotheses, let H_0 represents primary user being absent and H_1 represents primary user being present, the received signal samples (n = 1, 2, . . ., N) at the secondary user for these two hypotheses may be provided in equivalent complex baseband representation as:

H_0: $x_n = w_n$ (PU is absent) (1)

H_1: $x_n = hs_n + w_n$ (PU is present) (2)

where, x_n, h, and w_n denote the received signal, the Rayleigh fading channel gain, and the noise samples at the secondary user and Sn is the PU signal. The channel gain "h" is assumed to be constant during the detection process with zero mean and the variance of $E[h^2] = \sigma^2_h$. The PU signal has zero mean, variance σ^2_s, and its real and imaginary parts are statistically independent and with both having variance $(\sigma^2_s)/2$. The zero mean noise samples are assumed to have identical variance σ^2_n. Here PU samples are assumed to be independent over time, independent identically distributed (IID). Furthermore, we assume that the noise samples, the fading gains, and the PU signal are mutually independent to each other.

In this paper, we assume the noise samples being correlated under time domain. For this purpose, we consider a weakly dependent environment using unilateral Moving Average of IID random variables. Assuming that e_i with i=1,2,3,…N are the IID random variables with common probability density function (PDF) $f_e(;)$, the noise samples $w_1, w_2, ..w_n$ in this case may be expressed as,

$w_1=e_1$; $w_2=e_2+\rho e_1$ (3)

$w_n=e_n+\rho e_{n-1}$ (4)

where n=2,…N with | |<1,denotes the noise correlation co-efficient value.

A. ENERGY DETECTOR

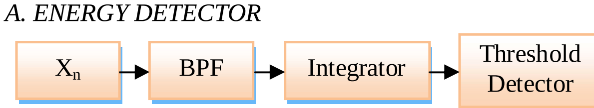

Fig. 3 Block Diagram of Energy Detector

Energy detection based sensing had been widely used due to its low cost and less computational complexity. The presence or absence of Primary Users signal is detected by pre-defining a known threshold limit. As shown in fig 3 , here the received signal sample X_n is initially passed through the Band Pass Filter (BPF) to limit the bandwidth to the interested value of frequency. Now the band-limited signal is sent to square law device to squares the PU's signal. Now the collected samples are summed and then sent to threshold detector circuit. This performs the decision making depending upon the energy value of the summed samples. This decision is taken by,

E > Ʈ, H_1 (PU is present) (5)

E < Ʈ, H_0 (PU is absent) (6)

Although the fact that the prior knowledge of PUs signals is not required in this spectrum sensing method makes it simple to implement, but it suffers from the following disadvantages:

(i) Time required to sense and detects the spectrum availability.

(ii) Poor performance under low SNR environment and in cases where the noise samples exhibit significant correlation.

(iii) ED cannot be used to detect spread spectrum signals [10].

1) PERFORMANCE OF ENERGY DETECTOR UNDER CORRELATED NOISE CONDITIONS

Consider 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. We plan to examine the advantage of the proposed local optimum detector in terms of performance compared to the conventional energy detection, based on following analytical expressions. The test statistic or the energy value for an energy detector can be expressed as follows. When the PU is absent then we obtain test statistic as,

$\Lambda=\sum |\ \ |^2$ (7)

$=\sum |\ \ |^2$ (8)

When the PU is present, then the test statistic obtained is,

$=\sum |\ \ + h\ \ |^2$ (9)

We 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.

From (8),

$=\sum |\ \ |^2$

Similarly the expression of noise samples w_i under correlated noise environments is expressed in equation (4),

$=\sum |\ \ +\rho\ \ |^2$

$= |\ \ |^2+|\ \ +\rho\ \ |^2+|\ \ +\rho\ \ |^2+..+|\ \ +\rho\ \ |^2$

Using Central Limit Theorem(CLT),we can prove that both and as asymptotically Gaussian random variable(RV) for large values of samples N,provided the RVs are far enough from each other in time domain and are nearly independent.[11]Now let us calculate both mean and variance of asymptotically Gaussian RVs and . For hypothesis H_0,we obtain the following results,

$(\ )= [N+ (\ -1)$

$(\ )= [N+(N-1)(4+\ )\rho^2]$ (10)

For hypothesis H_1,we have,

$(\ )= [N\frac{|\ |}{}+N(1+\rho^2)-\rho^2]$

(11) $(\ )=E[\Lambda^2_{|H1}] - (\ )$

Using equations (10),(11),(38),(40),we can able to calculate the $P_{f(ed)}$ and $P_{d(ed)}$for the provided channel gain "h".

Now,we will calculate the average detection probability and false alarm probability for the Energy Detector,

$(\ )=E_h\ Q\ \frac{}{}$

Assuming low SNR region,

$(\ )=E_h[Q(\in\ \ -\ \ |h|\ )]$

where,

$\in (\ ) = \frac{}{}$ and $=N\frac{}{}$.

Similarly,

$(\ )=E_h\ Q\ \in -\ \ |h|$

where, $= -\frac{}{(\ )}\in +$.

B. PROPOSED DETECTOR

In this module, an locally optimum detector for spectrum sensing is proposed to achieve higher spectrum utilization in cognitive radio networks. The optimal detector structure for

MPSK modulated primary signals with known order over AWGN channels is derived and its corresponding suboptimal detectors in both low and high SNR (Signal-to-Noise Ratio) is also given. Through approximations, it is found that, in low SNR regime, for MPSK (M > 2) signals, the suboptimal detector is the energy detector, while for BPSK signals the suboptimal detector is the energy detection on the real part. In high SNR regime, it is shown that, for BPSK signals, the test statistic is the sum of signal magnitudes, 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.

The simulations have shown that Bayesian detector has a performance similar to the energy detector in low SNR regime, but has better performance in high SNR regime in terms of spectrum utilization and secondary user's throughput. We assume that the noise samples are temporally dependent. In simple first-order bilateral and unilateral moving averages (MAs) of an IID 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 IID random variables.

1) 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

$$\Lambda=\frac{p(X/H_1)}{p(X/H_0)}=E_{h,s}\frac{[\ \ (X-hS)]}{[\ \ (X)]} \quad (12)$$

Where f_W is the multivariate pdf of the noise samples and $X = x_1, \ldots, x_N$, $S = s_1, \ldots, s_N$. For the hypothesis H1, we have

(X-hS)= $(x_1\text{-}hS_1, x_2\text{-}hS_2, \dots, x_N\text{-}hS_N)$ (13)

As the noise samples are not independent, the multivariate PDF cannot be expressed as multiplication of PDF of its elements.

Using equation (3),

$w_1=e_1=x_1-hs_1$ (14)

$w_2=e_2+\rho e_1=x_2-hs_2$, (15)

i.e; $e_2=x_2-hs_2-\rho(x_1-hs_1)$ (16)

So,the generalized form is obtained as,

$w_N=e_N+\rho e_{N-1}=x_N-hs_N$; (17)

$e_N=\sum \;(-\rho)\;(\;\;-h\;\;)$ (18)

Therefore,

$(x_1\text{-}hS_1, x_2\text{-}hS_2, \dots, x_N\text{-}hS_N)$

$= f_e(x_1\text{-}hS_1)^*,..^*\sum \;(-\rho)\;(\;\;-h\;\;))$

$= f_e(x_1\text{-}hS_1)^*\dots{}^*f_e(\sum \;(-\rho)\;(\;\;-h\;\;))$

$= \prod \;(\;\;-h\;\;)$. (19)

Where, $y_i=\sum \;(-\rho)\;(\;\;)$ (20)

and $c_i=\sum \;(-\rho)\;(\;\;)$. (21)

Similarly for hypothesis H_0,

(X) = $(x_1, x_2, x_3, \dots x_N)$

$= f_e(x_1,\; x2\text{-}\rho x_1, \dots, \sum \;(-\rho)\;(\;\;)$

$= f_e(x_1)^*\dots{}^*f_e(\sum \;(-\rho)\;(\;\;)$

$= \prod \;(\;\;)$. (22)

Replacing the above equations of PDF's (19) and (22) in (12), we get,

$\Lambda=\frac{p(\;\;)}{p(\;\;)} = Eh, s \prod \frac{(\;\;)}{(\;\;)}$ (23)

It is necessary to simplify furthermore the above expression where we use Taylor's series of the joint PDF of the real and imaginary parts of a complex RV[12]. Let us consider R and I denote the real and imaginary parts of complex RV, we have,

$f(y\text{-}u) \equiv f(y_R,y_I) - u_R\frac{}{}f(y_R,y_I) - u_I\frac{}{}f(y_R,y_I) +$

$1/2\; u_R^2\frac{}{}f(y_R,y_I) + 1/2\; u_I^2\frac{}{}f(y_R,y_I) + u_R u_I\frac{}{}f(y_R,y_I)$

(24)

Here $u_i=hc_i$ relating to PU signal has zero mean and has uncorrelated real and imaginary parts. Considering low SNR regime, the value of $\sigma^2_h\, \sigma^2_s$ is almost zero and due to this u_i also becomes zero. Hence the general approximation can be done as,

$\prod\;(1+\;\;) \approx 1+\prod\;(\;\;)$ with i=1...M. (25)

This is done to approximate the (8),

$$\Lambda=1+\frac{\sum \;\; - \;\frac{}{}\; + - \;\frac{}{}\;\;(\;\;)}{(\;\;)} \quad (26)$$

Using $c_i=\sum \;(-\rho)\;(\;\;)$, we may simplify further by using the following calculation,

$E[\;\;]=E[\;\;]=\frac{\sigma\;\sigma}{}\sum$ (27)

which results in following statistic,

$$\Lambda=1+\frac{\frac{\sigma\;\sigma}{}\sum\;(\sum\;\;)\;\;\frac{}{}+\;\frac{}{}\;\;(\;\;)}{(\;\;)} \quad (28)$$

Now, let us consider Gaussian model for PDF f_e,

$f_e(y)=\frac{}{\sqrt{}}\;(\frac{}{})$ (29)

Finding first and second derivative with respect to Y_R and Y_I, the most suitable LO test statistic may be obtained as,

$= \sum\;(\sum\;\;)|\;\;|^2$ (30)

$= \sum\;\frac{}{}|\;\;|^2$ (31)

2) FALSE ALARM AND DETECTION PROBABILITIES FOR LO DETECTION:

For hypothesis H_0,

$=\sum\;(\sum\;\;)|\sum\;(-\;\;)\;\;|^2$ (32)

where, $k_i=\sum$ (33)

Hence, we obtain test statistic for H_0 as,

$= \sum\;\;|\;\;|^2$ (34)

Since e_i'with i=1,…N and for large values of samples N, they are independent which allows us to use Central Limit theorem, and so can be approximated as Gaussian RV with mean and variance .

The test statistic for H_1 is given by,

$=e_i+h\sum\;(-\;\;)$

(35)

Similar procedure shall be used to show as Gaussian RV with mean and variance . Using Gaussian parameters of each hypothesis, we shall represent the false alarm and detection probability as,

$P_f=P_r(\;\;>\;\;|H_0)=Q\;\frac{}{}$ (36)

$P_d=P_r(\;\;>\;\;|H_1)=Q\;\frac{}{}$ (37)

where denotes threshold.

Here Q function is a monotonically decreasing function, and hence both false alarm and detection probability values increase and decrease at the same time. In order to have high detection values, we must tolerate higher false alarm values and hence it is important to keep false alarm probability value to be kept under limit given by two proposals,

$P_f \leq$ (38)

(i.e), $\geq\;\;(\;\;)+$ (39)

For maximum detection probability,

$P_{d\text{-}max}=Q\;\frac{(\;\;)}{}$ (40)

$P_f \leq$ (41)

Similarly for the detection probability to be above specific value, we have,

$P_{f\text{-}min}=Q\;\frac{(\;\;)}{}$ (42)

$Pd \geq$ (43)

3) PARAMETERS OF THE HYPOTHESES

For hypothesis H_0, The mean and variance ^{2} is given as,

$= \sum$ (44)

$= \sum$ (45)

Similarly for hypothesis H_1,

$= \sum\;\;1+\frac{|\;\;|}{}$ (46)

The variance ^{2} is given by,

$^2=E[\Lambda^2_{|H1}]\; -$ (47)

From the above parameters, it is very clear that both the values of and does not depend on the channel gain "h". But the expressions of and do depend on channel gain h". Using these values in equations (38) and (43), helps us to determine the detection and false alarm probabilities for a specific gain "h", when LO detection is done.

4) AVERAGE FALSE ALARM AND DETECTION PROBABILITIES FOR LO DETECTION

Incase to find average false alarm and detection probabilities, we use following expressions averaged over channel gain "h",

$$=E_h \; Q \; \text{——} \qquad (48)$$

In low SNR regions, the expression for average detection probability becomes,

$$=E_h[Q(\in - \; |h| \;)] \qquad (49)$$

where,

$$\in \; = \text{——} \text{ and } \; =\text{—}\sum \; (\text{——})^2 \qquad (50)$$

The average false alarm probability expression is given as,

$$=E_h \; Q \; \text{——} \qquad (51)$$

$$=E_h \; Q \; \frac{(\;)}{\text{————}} \qquad (52)$$

Therefore,

$$=E_h \; Q \; \in - \; |h| \qquad (53)$$

where, $\in = \; (\;)$ and $= -\text{—} \in + \; .$ (54)

III . SIMULATION RESULTS

Considering a fading channel with weakly correlated noise and N = 500 samples have been collected at the secondary user end. In this simulation, we assume a slow fading channel where the fading coefficient h is constant during the sampling period. Initially, we fix the detection probability to 0.95 and find the average false alarm probabilities at different signal to noise ratios (SNRs, defined as $SNR = \sigma^2_h\sigma^2_s / \sigma^2_n$) for both cases of our proposed locally optimum detector as well as the existing energy detector. In order to verify our theoretical analysis, we also find the average false alarm probability using simulations over 100,000 independent realizations of the Rayleigh fading channel and compare with analytical results. The average false alarm probability for correlation coefficient ρ = 0.5 is shown in Figure 4. We use an 8-PSK modulation for the PU.

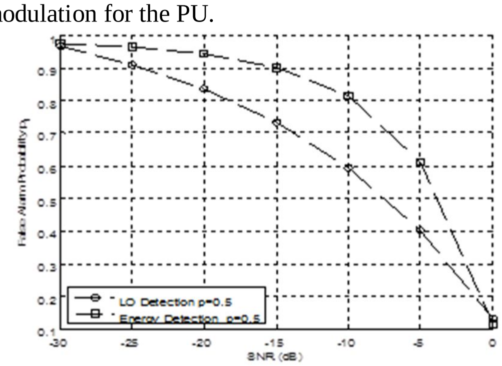

Fig.4 Average false alarm probabilities using theoretical and simulation results for detection probability of 0.95 and $= 0.5$ at different SNRs.

Table 1 False alarm probability figures at different SNRs

SNR (dB)	LO Detector	Energy Detector
-30	0.9679	0.9754
-25	0.9105	0.9641
-20	0.8343	0.9432
-15	0.7320	0.9018
-10	0.5926	0.8140
-5	0.4001	0.6131
0	0.1297	0.1132

Table 2. Detection probability figures at different SNRs

SNR (dB)	LO Detector	Energy Detector
-30	0.0800	0.0800
-28	0.0803	0.0800
-26	0.0819	0.0806
-24	0.0874	0.0834
-22	0.1007	0.0918
-20	0.1265	0.1104
-18	0.1685	0.1438
-16	0.2286	0.1952
-14	0.3061	0.2653
-12	0.3975	0.3520
-10	0.4976	0.4505
-8	0.6000	0.5546
-6	0.6988	0.6575
-4	0.7887	0.7534
-2	0.8662	0.8377
0	0.9296	0.9078

As it can be seen from Figure 4, our locally optimum detector has lower false alarm probability compared to the energy detector. Also, the simulation results almost match the analytical results with very small errors which will verify the validity of our analysis. In the following case, we fix the false alarm probability to 0.05 and find the average detection probabilities at different signal to noise ratios (SNRs).

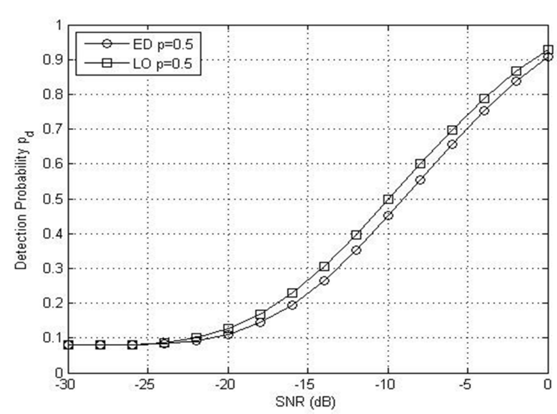

Fig. 5 Average detection probabilities using theoretical as well as simulation results for false alarm probability of 0.05 and $= 0.5$

As it can be seen from Figure 5, the proposed detector has higher detection probability compared to the energy detector. Similarly, the simulation results are very close to the analytical results.It is also important to take into account the effect of the number of samples on the performance of detection. Both energy detection and the proposed LO detection is considered with different correlations. The average false alarm and detection probabilities are shown in Figures 6 and 7 respectively.

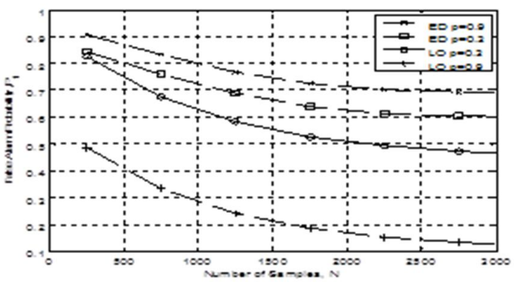

Fig. 6 Average false alarm probabilities Vs the number of samples for the detection probability of 0.95

As expected, increasing the number of samples results in lower false alarm and higher detection probabilities. For all curves shown in simulation, the rate of decreasing *Pf*(increasing *Pd*) is higher at the beginning (lower samples) and it decreases when the number of samples gets higher. For each correlation, the proposed LO detection is better than the energy detection for all values of *N*. The higher the correlation the more the difference between *Pf* values of both methods. This can be proved using Fig.6 and 7 for the given value of correlation co-efficient $= 0.9$ and $= 0.3$. Also, for each curve, simulation results have also been provided and as it can be seen they match the theoretical results with very small errors, thus validating the assumption made in the theoretical derivations.

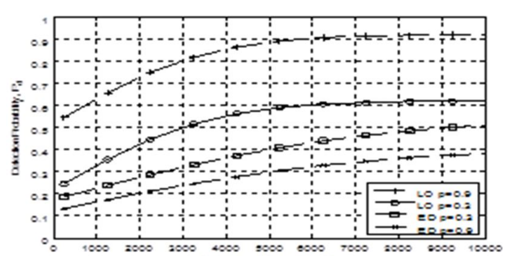

Fig. 7 Average detection probabilities Vs the number of samples for false alarm probability of 0.05

IV . CONCLUSION

Hence signal detection in Cognitive Radio over fading channels using Locally Optimum Detection under weakly correlated noise models had been proposed. This is done through the calculation of false alarm and detection probabilities for specific channel gain "h" and averaged under different channel gains. In order to compare the superiority of proposed LO detector over traditional energy detector, we have analyzed it's performance under the same correlated noise model. Through our simulations, we can conclude that LO detection technique gives lower false alarm probability and higher detection probability value compared to energy detection method under low SNR conditions. It can be inferred that the detection probability values in turn increases with the increasing channel gain "h". However, in this paper we did not take into account the effect of correlation mismatch on the probability values, which needs to be addressed.

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