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To analyze and compare the different spectrum sensing techniques over the primary channels from the study of CRN concept

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***Abstract*—**. The motive behind this paper is to utilize the RF Spectrum properly and to reduce the false alarm rate and to employ various techniques for cognitive radio network(CRN). In cognitive radio networks, to eliminate interference form other than primary users to the users who hold primary license of the spectrum, reliable spectrum sensing is needful. In endeavor, where the samples of noise are correlated, the spectrum sensing methods enhance considering impairment by the noise samples which are not dependent will not provide optimum performances. The probabilities of FA and detection of the designed detector in the low signal to noise ratio reign are visualized. The average probabilities are designed over distinct channel gains. Numerical and simulation results determine the better of the designed method over the known energy detection method and local optimum method with analogous convolution. Furthermore, we consider the endeavor where the calculated correlation is different from the ideal correlation and investigate the effect of this correlation mismatch on the probabilities of constant false alarm and detection of the purposed method. On comparing with the conventional techniques feature detection algorithm, cyclostationary approach is more accurate i.e. it can change the computational hazard according to current electromagnetic environment by motility its sampling times and the cyclic frequency step size.

Keywords- *CRN, Cyclostationary, False Alarm (FA), RF (radio frequency) spectrum*

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I. Introduction

RADIO Frequency (RF) spectrum is an exclusive and restricted resource for wireless communications. The ontogeny demands for increased bandwidth have led to studies that shows the spectrum distributed to primary users who hold license is under-utilized. Cognitive radio technology helps to use the RF spectrum more effctively, by implementing secondary usage of the spectrum certified to primary users (PU) but with a lesser priority. Secondary users (SU's) implemented with cognitive radios can sense the spectrum and vigorously use spectrum holes in PU frequency bands for data transmission. Secondary users cannot make any interference to the primary license holders. Since, before starting the transmission, they should be aware of the ubiquity of the PUs. Spectrum sensing is one technique for intentive the presence or absence of a primary license holder. This is a difficult task because the PU signal is weak due to fading, shadowing, etc. There are some main types of spectrum sensing techniques which includes matched filtering, cyclostationarity detection, energy detection . Energy detection is the easiest method but it enhances for deterioration with additive white Gaussian noise (AWGN). It is understood that the additional noise samples are statistically not dependent. Although the AWGN assumption is valid in some circumstances, the work in this paper is mainly motivated by scenario that we have encountered where the noise indicates substantial correlation. Any realistic cognitive radio atmosphere would at least take into account at approximate level the noise correlation. CR is an vital key to the shortage of spectrum resource, and it has been widely examined over years. In CR networks, the cognitive users (CUs) sense the spectrum every time for adaptation or for changing frequency access to develop the spectrum without agitating LUs, which allows good spectrum utilization [1, 2] On the other hand, collaborative networks may serve CR networks with the method of cooperative spectrum sensing, which can increase the performance of detection.

II. SYSTEM MODEL

We consider that there are two hypotheses, H0 when the primary user is not present and H1 when the primary user is present, the received signal samples (n = 1, 2, . . .,N) at the secondary user for these two hypotheses may be designed in identical complex baseband representation as:

H0 : xn =wn ------------(1)

H1 : xn = hsn + wn -----------(2)

where, xn, h, and wn denote the received signal, the Rayleigh fading channel gain, and the noise samples at the user other than primary and Sn is the PU signal. The channel gain h is assumed to be constant through out the detection process with zero mean and the variance of E[|h|2]= σ 2h .

A. ENERGY DETECTOR

We have also induced an energy detector (ED) used for finding in the presence of correlated noise samples, in order to match its performance with the designed LO detector based on the manifestation the superiority of the designed locally optimum detector is based on performance matched to the conventional energy detection, peculiar to analytical expressions. The test statistic for an energy detector is expressed as follows

$\Lambda=\sum^{N}_{i=1}|x|^{2}$……….(3)

$\Lambda=\sum^{N}_{i=1}|w_i|^{2}$………(4)

$\Lambda = \sum_{i=1}^{N} |w_i + hs_i|^2$…….(5)

B.LOCALLY OPTIMUM DETECTOR

We design an ideal locally finest detector for spectrum sensing to gain higher spectrum exploitation in cognitive radio networks. We derive the ideal detector structure for MPSK modulated license holder signals with known order over AWGN channels and calculate its consistent suboptimal detectors in both low and high SNR (Signal-to-Noise Ratio) regimes. Through approximations, it is analyzed that, in low SNR , 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 ideal part.

C. CYCLOSTATIONARY DETECTION

The periodicity of signals is usually induced by the sine waves or pulse successions during modulation. Although data which is transmitted in the system keeps a stationary stochastic process, some statistical structure of modulated signal can be cyclic e.g. correlation functions. Moreover, noise is usually supposed to be wide-sense inert with no correlation. So detectors can esteemed it from modulated signal by comparability the spectral correlation function of the signal. The received signal is called cyclostationary if it fulfills the following conditions:

$m_s(t)=E[s(t)]=m_s(t+T0)$
$R_s(t,\tau)=E\{s(t+\tau/2)s^*(t-\tau/2)\}$
$=R_s(t+T0,\tau)$

where is the period of signal, and the operator E(·) means calculating the average of signal. Function is the autocorrelation function of , and represents for the time offset.

Assume there is a complex sine wave signal s(t) defined as:

$S(t)=e^{(j2\pi f_0 t+\theta)}$

we usually apply the theory of Fourier transformation on CAF and get that:

In this technique, it's not essential to calculate the cyclic autocorrelation function of signal. Instead, we add a factor , which is related to cyclic frequency , to the received signal. And then calculate its average on a certain cyclic frequency to get the corresponding result. Assume that is the signal received by CU, and because of the influence caused by electromagnetic environment, may contain both signal and noise . So there are two hypotheses of given as follows:

$$r(t)=\begin{cases} n(t) & H0 \\ s(t)+n(t) & H1 \end{cases}$$

Where H_0 represents for the assumption of absence of LU when the signal contains noise only; while H_1 represents for the hypothesis of presence of LU, and in this situation both signal and noise are received by CU.

III. SOFTWARE IMPLEMENTATION

Matlab (Matrix Laboratory) is used to implement code which is high-performance language for scientific and technological calculations. Computation and programming are integrated in an easy-to-use environment where problems and solutions are expressed mathematically and visualized graphically. The version which is used in MATLAB is 7.14. Some typical applications are

1. system simulations,
2. algorithm outcome,
3. data acquisition, analysis, exploration, and visualization, as well as
4. Modeling, analyzing, simulation and prototyping.

IMPORTANCE OF MATLAB :-

Matlab was originally designed as a more convenient tool (than BASIC, FORTRAN or C/C++) for the manipulation of matrices. It was originally written to provide easy access to matrix software developed by the LINPACK and EISPACK projects. After- wards, it gradually became the language of general scientific calculations, computation,visualization and program design. Nowadays, Matlab engines incorporate the LAPACK and BLAS libraries, embedding the state of the art in software for matrix computations. It received more functionalities and it still remains a high-quality tool for scientific computation. Matlab excels at numerical calculations, especially when dealing with vectors or matrices of data. It is a procedural and computational language, combining an efficient programming structure with a bunch of predefined mathematical commands. While simple problems can be solved interactively with Matlab, its real power is its ability to create large program structures which can describe complex technical as well as non-technical systems. Mat- lab has evolved over a period of years with input from many users. In university environments, it is the standard computational tool for introductory and advanced courses in mathematics, engineering and science. In industry, Matlab is the tool of choice for highly-productive research, development and analysis.

IV. RESULTS AND DISCUSSIONS

We consider a fading channel with weakly correlated noise and N = 500 samples have been collected at the secondary user. We assume a slow fading channel where the fading coefficient h is constant during the sampling period. We fix the detection probability to 0.95 and find the intermediate false alarm probabilities at distinct signal to noise ratios (SNRs,defined as SNR = σ2hσ2s /σ2n) for cases of our proposed locally optimum detector,energy detector and cyclostationary. In order to verify our theoretical analysis, we also find the average false alarm probability using simulations over 100,000 not dependent realizations of the Rayleigh fading channel and compare with interpretive results. Figure 1 shows the intermediate false alarm probability for correlation coefficient ρ = 0.5 is shown in Figure 1. We use an 8-PSK modulation for the PU. As it can be seen from Figure 1, our cyclostationary detector has lower false alarm probability compared to the energy detector and local optimium. Also, the simulation results match the analytical results with very small errors which will verify the validity of our analysis. Now, we fix the false alarm probability to 0.05 and find the average detection probabilities at different signal to noise ratios (SNRs). As it can be seen from Figure 2, the cyclostationary detector has higher detection probability compared to the energy detector and local optimum. Similarly, the simulation results are very close to the analytical results. We should also consider the effect of the number of samples on the performance of detectionThe proposed techniques are considered with different correlations. The average false alarm and detection probabilities are shown in Figures 3 and 4 respectively. As expected, increasing the number of samples will result in lower false alarm and higher detection probabilities. For all curves, 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 cyclostaionary is better than the energy detector and local optimum for all N.

The higher the correlation the more the difference between Pf values of both methods. Also, for each curve, simulation results have also been provided and as it can be seen they match the analytical results with very small errors, thus validating the assumption made in the analytical derivations. Different correlation coefficients ρ are considered in Figures 5 and 6 where average false alarm and detection probabilities are shown respectively. From Figure 5, the higher the correlation coefficient, the higher the gain achieved by the cyclostationary compared to the energy detector and local optimum. For example, in order to achieve a false alarm probability of 0.2, the locally optimum detector has 1.2 dB, 3 dB and 11 dB gain over the energy detector for correlation coefficients of 0.3, 0.5 and 0.9 respectively. From Figure 6, the higher the correlation coefficient, the higher the gain achieved by the proposed detector compared to the energy one. For example, in order to achieve a detection probability of 0.2, the locally optimum detector has 1.2 dB, 3 dB and 12 dB gain over the energy detector for correlation coefficients of 0.3, 0.5 and 0.9 respectively. When, correlation coefficient is equal zero, the cyclostationary, local optimum and energy detector have the same false alarm and detection probabilities. All the figures so far have been obtained assuming perfect knowledge of the correlation coefficient at the detector. In case the estimated correlation coefficient ˆρ is different from the actual correlation coefficient ρ, we can calculate false alarm and detection probabilities.

A. Figures :-

Figure 1: False alarm probabilities at distinct signal to noise ratio's for detection probability of 0.95, for the case the estimated correlation is 0.5 and the actual correlations.

Figure 2: 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.

Figure 3: Average detection probabilities versus the samples for false alarm probability of 0.05

Figure 4: Average false alarm probabilities versus the number of samples for detection probability of 0.95

Figure 5: 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 6: Average false alarm probabilities from analytical results as well as simulation results at different SNRs for detection probability of 0.95 and ρ = 0.5

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FIGURE 1

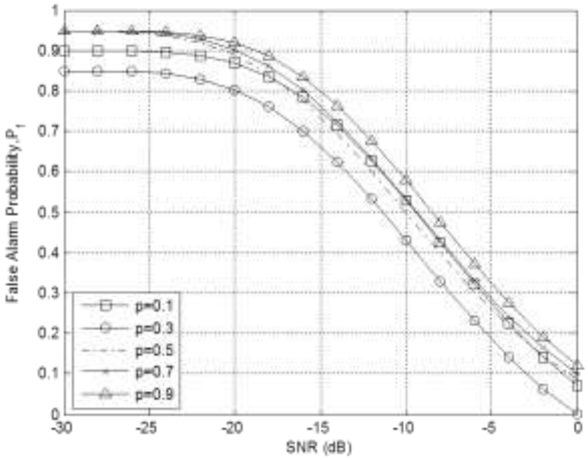

FIGURE 2

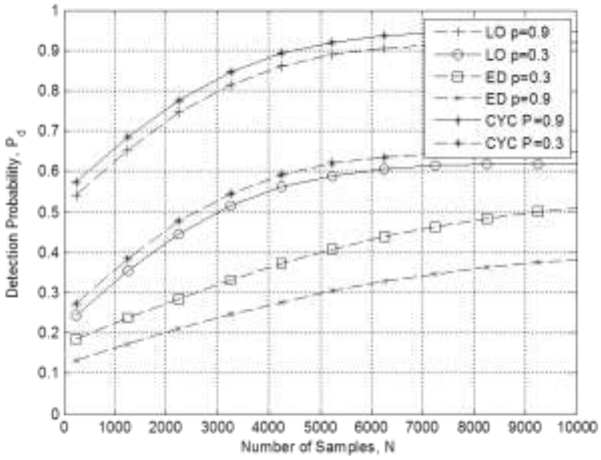

FIGURE 3

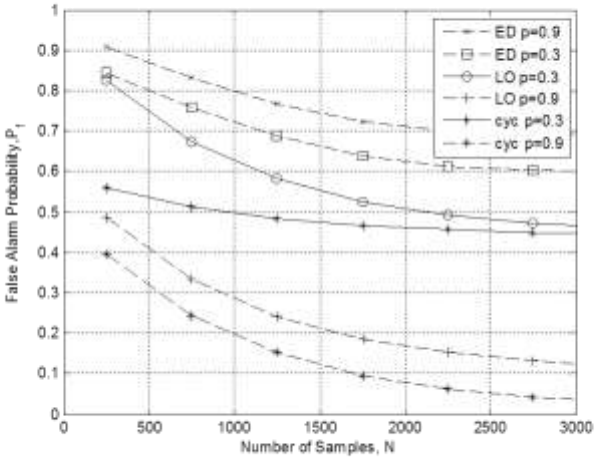

FIGURE 4

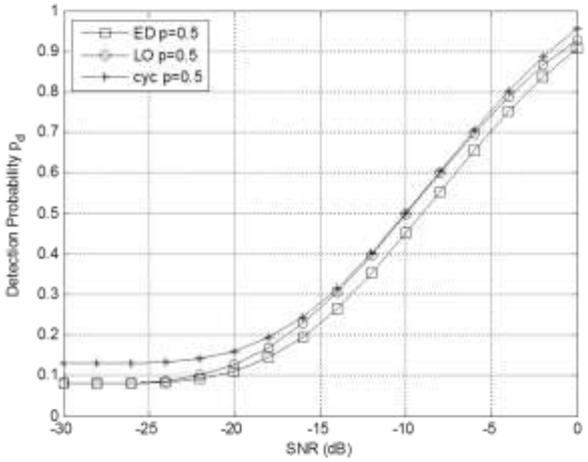

FIGURE 5