Detection of Primary User in Cognitive Radio Using Bayesian Approach

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Abstract - ***Using cognitive radios (CRs), the secondary users (SUs) is allowed to use the spectrum originally allocated to primary users (PUs) as long as the primary users are not using it temporarily. This operation is called opportunistic spectrum access (OSA). To avoid interference to the primary users, the SUs have to perform spectrum sensing before their attempts to transmit over the spectrum. In this paper we use energy detector, Bayesian detector and Approximate Bayesian detector for digitally modulated primary user to maximize the spectrum utilization, without prior information of transmitted sequence of the primary signals. We provide the performance analysis of the suboptimal detectors in terms of probabilities of detection and false alarm. In spectrum utilization and secondary user's throughput performance of the Bayesian and approximate Bayesian detector are better when compared with the energy detector. For the performance estimation we use MATLAB simulation environment.***

Key Words: *Bayesian, probability of detection, probability of false alarm, cognitive radio, spectrum sensing, primary user, secondary user.*

1. INTRODUCTION

The popularity of wireless technologies is skyrocketing as more devices are being connected and more technologies being deployed [9]-[10]. However, the underlying transmission medium of wireless technology, the radio spectrum, is a limited resource. While radio spectrum is theoretically unlimited, the frequency ranges that are suitable for commercial application is limited but required to support an ever increasing consumer base [1].

The term 'cognitive radio' is given to an emerging wireless access scheme that is 'an intelligent wireless communication system that is aware of its surrounding environment to allow changes in certain operating parameters for the objective of providing reliable communication and efficient utilization of the radio interference to PU activity is minimal and confined [2]. Since the first mentioning in 1999 [3], cognitive radio has become the focus of significant research from industry, research centers and universities alike [4]. In fact, the popularity and potential of cognitive radio is acknowledged by IEEE to promote and develop a standard based on cognitive radio technology, ' IEEE 802.22 wireless region area networks ', to deliver wireless broadband to regional area using UHF/VHF TV bands between 54-862 MHz in America [5].

Spectrum sensing is the task where the SU identifies possible spectrum opportunities and is one of the most crucial components of cognitive radio. Spectrum sensing is performed by the SU to sense a spectrum of interested, with the objective of detecting the presence of any PU signals to prevent interference and identify spectrum opportunity for secondary access [2, 5].The SU uses spectrum sensing detectors to analyze the signal captured or observed during the sensing period, and based on the detection results, decides whether or not to utilize the spectrum the transmission period. Spectrum sensing results in one of two decisions: false alarm where the SU declares PU is present when the spectrum is empty and detection where the SU correctly declares a PU is using the spectrum. The performance of sensing detection is thus measured through the probability of these two events.

Various conventional detectors have been adapted for the application of spectrum sensing for cognitive radio, including energy detector [6], waveform or matched filter based detector [6,7], cyclostationarity-based detector [8], wavelet and time frequency based detector. Each of the detectors have their advantages and disadvantages with varying detection performance, implementation complexity, detection time, assumptions/ requirements on PU signal, etc.

2. Spectrum Sensing Using Energy Detection And Bayesian Detector

A). Energy- Detection Based Spectrum Sensing

The energy detection method is simple in implementation since it does not require the knowledge about the structure of the primary signal. The energy detection method calculates the energy of the input signal and compares it with a threshold energy value. The signal is said to be present at a particular frequency if the energy of the signal exceeds the Energy level of the threshold

A decision statistic for energy detector is:

$$T = \sum_{N} (Y[n])^2$$

Note that for a given signal bandwidth *B*, a pre-filter matched to the bandwidth of the signal needs to be applied. This implementation is quite inflexible, particularly in the case of narrowband signals and sinewaves.

It is well known that under the common detection performance criteria (most notably, the Neyman-Pearson criteria) likelihood ratio yields the optimal hypothesis testing solution and performance is measured by a resulting pair of detection and false alarm probabilities (P_D, P_F). Each pair is associated with the particular threshold γ that tests the decision statistic:

$T > \gamma$ *decide signal present*

$T < \gamma$ *decide signal absent*

When the signal is absent, the decision statistic has a central chi-square distribution with N degrees of freedom. When the signal is present, the decision statistic has a non-central chi-square distribution with the same number of degrees of freedom. Since we are interested in the low SNR regime, the number of required samples is large. If N >250 we can use the central limit theorem to approximate the test statistic as Gaussian.

$$T \sim Normal(N\sigma_w^2,\ 2N\sigma_w^4) \quad \text{under} \quad H_0$$
$$T \sim Normal(N(\sigma_w^2 + \sigma_x^2),\ 2N(\sigma_w^2 + \sigma_x^2)^2) \quad \text{under} \quad H_1$$

Then P_D and P_F can be evaluated as:

$$P_F = Q\left(\frac{\gamma - N\sigma_W^2}{\sqrt{2N\sigma_W^4}}\right)$$

$$P_D = Q\left(\frac{\gamma - N(\sigma_W^2 + \sigma_x^2)}{\sqrt{2N(\sigma_W^2 + \sigma_x^2)^2}}\right)$$

B). Bayesian Detector

Bayesian detection method makes use of the prior statistics of PU activity and the signaling information of the PU such as symbol rate and modulation order to improve the SU throughput and the overall spectrum utilization of both PUs and SUs. It is shown that the Bayesian detector has the exact same structure as Neyman-Pearson detector , but the design principle of Neyman-Pearson detector is to maximize the detection probability for a given maximal false alarm probability, which results in the difference in detection threshold selection for the two schemes.

Starting from the so-called Bayesian inference that is the posterior likelihood or probability of q, the form of the detector and the corresponding ing detection rules will be presented.

The overall received vector is the concatenation of real and maginary parts, written here as $Y = [y_1^{re}, \ldots\ldots y_N^{re}, y_1^{im}, \ldots\ldots, y_N^{im}$ .The pdf of y is in the form of standard multivariate normal distribution of the form $p\left(\frac{y}{\vartheta}\right) \alpha\ \vartheta^{-N} e^{-N}$The proportionality sign is used to omit the scaling constant and such notation will be used for most of the upcoming probability distributions. This is because constant scaling does not have any influence on the final results. In the case where the variance is known perfectly once q is provided, the conditional distribution of v is $p(\vartheta\,|\theta) = \delta(\vartheta - \vartheta_0)$.

Furthermore, the prior of θ is denoted in the continuation as $\pi_1 \coloneqq \Pr\ (\theta = 1)$ and $\pi_0 \coloneqq \Pr\ (\theta = 0)$. Now, using the Bayes rule, the joint posterior distribution of θ and v is given as

$$p(\theta, v \mid \mathbf{y}) \propto p(\mathbf{y} \mid v) p(v \mid \theta) p(\theta) \propto v^{-N} e^{-N\frac{s}{v}} p(v \mid \theta) \pi_\theta$$

Marginalising out v and then inserting $p(v \mid \theta) = \delta(v - v_\theta)$ yields

$$p(\theta \mid \mathbf{y}) \propto \pi_\theta \int v^{-n} e^{-N\frac{s}{v}} p(v \mid \theta) dv \propto p(\theta \mid \mathbf{y})$$
$$\propto \pi_\theta v_\theta^{-N} e^{-N\frac{s}{v_\theta}}$$

The threshold value for Bayesian detection is

$$\gamma_{BD} = \gamma_{ED} = Q^{-1}(P_{FA}) v_0 \,/\, \sqrt{N} + v_0 \,.$$

We consider the MPSK primary signals with known order over additive white Gaussian noise (AWGN) channels. In low SNR regime, BD is approximated to energy detector for BPSK and MPSK (M> 2) signals in general. In high SNR regime and for BPSK signals, BD is approximated to a detector which employs the sum of the received signal

amplitudes to detect the primary signals. As an application,the proposed approach can be extended to detect M-QAM signals (e.g. DVB-T signals). Taking into consideration the fact that spectrum utilization of allocated spectrum could be very low, we determine the detection threshold based on the unequal probabilities of the two hypotheses. This detector is a likelihood ratio test (LRT) detector which can be approximated by its corresponding suboptimal structure in the low and high SNR regimes.It is well-known that the optimal detector for binary hypothesis testing based on Bayesian rule or Neyman-Pearson theorem is to compute the likelihood ratio and then make its decision by comparing the ratio with the threshold. The likelihood ratio test (LRT) of the hypotheses H1 and H0 can be defined as:

$$T_{LRT}(\boldsymbol{r}) = \frac{p(\boldsymbol{r}|\mathcal{H}_1)}{p(\boldsymbol{r}|\mathcal{H}_0)}.$$

Denote Cij as the cost associated with the decision that accepts Hi if the state is Hj ,fori, j =0, 1. Based on Bayesian decision rule to minimize the expected posterior cost which is defined as

$$\sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij} p(\mathcal{H}_j) p(\mathcal{H}_i|\mathcal{H}_j),$$

it is convenient to derive the optimal detector (BD):

$$T_{LRT}(\boldsymbol{r}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \epsilon,$$

Where

$$\epsilon = \frac{p(\mathcal{H}_0)(C_{10} - C_{00})}{p(\mathcal{H}_1)(C_{01} - C_{11})}.$$

If $C_{00} = C_{11} = 0$ and $C_{01} = C_{10}$, which is a uniform cost assignment (UCA),

$$\epsilon = \frac{p(\mathcal{H}_0)}{p(\mathcal{H}_1)}.$$

The Bayesian decision rule for an optimal Bayesian detector to minimize the Bayesian risk can be easily reduced to maximize the spectrum utilization

$$\max P(\mathcal{H}_0)(1 - P_F) + P(\mathcal{H}_1) P_D$$

To decide whether primary signals are present, we need to set a threshold ϵ, for each test statistic, such that certain objective can be achieved. If we do not have prior information on the signals, it is difficult to set the threshold based on PD. A normal practice is to choose the threshold based on PF under hypothesis H0. For the detector maximizing the spectrum utilization, it is easy to determine the detection threshold . However, in order to determine ϵ, for the ED/NPD with a given design parameter PF ,we have to find out the relationship between PF and ϵ,

The optimal detector (BD) for MPSK signals as:

$$T_{\mathrm{BD}} = \frac{1}{N}\sum_{k=0}^{N-1} \ln\left(\sum_{n=0}^{M/2-1} \cosh(v_n(k))\right) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma + \ln\frac{M}{2} + \frac{\ln\epsilon}{N}$$

Although the detector is optimal, it is too complicated to use in practice. In the following, we will simplify the detector when the SNR is very low or very high.

3. Suboptimal Bayesian Detector

If N is sufficiently large, according to central limit theorem (CLT), sum of all the independent identical distributed random variables can be approximated by a Gaussian distribution. Therefore, based on the optimal detector (BD) described , we can derive the approximate Bayesian detector (ABD) structure through the approximations in the low and high SNR regimes. We also give the theoretical analysis (detection performance and threshold) for the suboptimal detector to detect complex MPSK (M =2 and M> 2) in low SNR regime and compare with the results for real BPSK primary signals.

A). Approximation in low SNR Region

We study the approximation of our proposed detector for MPSK modulated primary signals in the low SNR regime. Through approximation, the detector structure becomes:

$$\frac{1}{N}\sum_{k=0}^{N-1}\sum_{n=0}^{\frac{M}{2}-1} \left(\Re\left[r(k) h^* e^{-j\phi_n(k)}\right]\right)^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{M N_0^2}{4}\left(\gamma + \frac{\ln\epsilon}{N}\right)$$

The proposed detector is an energy detector in the low SNR regime for MPSK signals (M> 2).The detector can be normalized to

$$T_{\mathrm{L-ABD-1}} = \frac{1}{N}\sum_{k=0}^{N-1} |r(k)|^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{N_0}{\gamma}\left(\gamma + \frac{\ln\epsilon}{N}\right)$$

When the signal is BPSK, the detector is equivalent to

$$T_{\mathrm{L-ABD-1}} = \frac{1}{N|h|^2}\sum_{k=0}^{N-1} (\Re[r(k)h^*])^2 \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{N_0}{2\gamma}\left(\gamma + \frac{\ln\epsilon}{N}\right)$$

B). Approximation in high SNR Region

Through approximation in the high SNR regime, the detector structure (H-ABD) becomes

$$T_{\mathrm{H-ABD}} = \frac{1}{N}\sum_{k=0}^{N-1}\ln\left(\sum_{n=0}^{M/2-1} e^{\frac{2}{N_0}\Re[r(k)h^* e^{-j\phi_n(k)}]}\right) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \gamma + \ln M + \frac{\ln\epsilon}{N}.$$

The suboptimal BD detector employs the sum of received signal magnitudes to detect the presence of primary signals in the high SNR regime, which indicates that energy detector is not optimal in this regime. Similar to the derivation we can derive the suboptimal detector as shown in which also uses the sum of the real part of the received signal magnitudes to detect primary signals. The detector H- ABD is as follows:

$$T_{\mathrm{H-ABD}} = \frac{1}{N}\sum_{k=0}^{N-1}|\Re[r(k)h^*]| \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \frac{N_0}{2}\left(\gamma + \ln 2 + \frac{\ln\epsilon}{N}\right)$$

4. Simulation Results

We assume a range for P_f and P_D for which the range of SNR values are calculated. In this simulation we used 1000 samples and BPSK modulation. The figure 1 shows the simulation plot for detection and false alarm both theoretical and practical values for the energy detection based spectrum sensing.

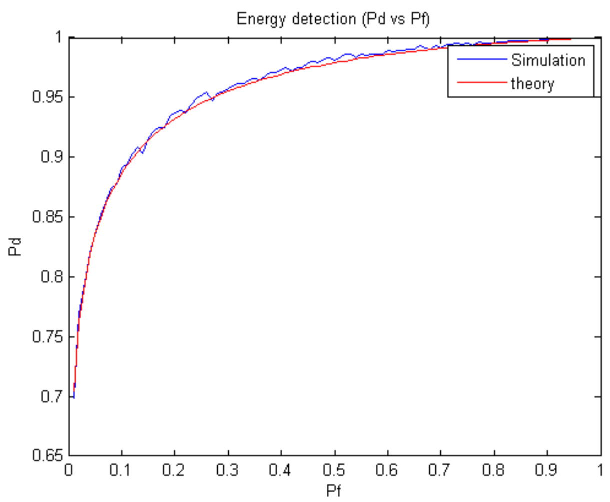

Figure.1 detection vs false alarm plot for energy detector spectrum sensing

Figure 2,3 gives the performance estimation of spectrum sensing for energy detection based and Bayesian based spectrum sensing for low SNR using BPSK modulation for 1000 samples.

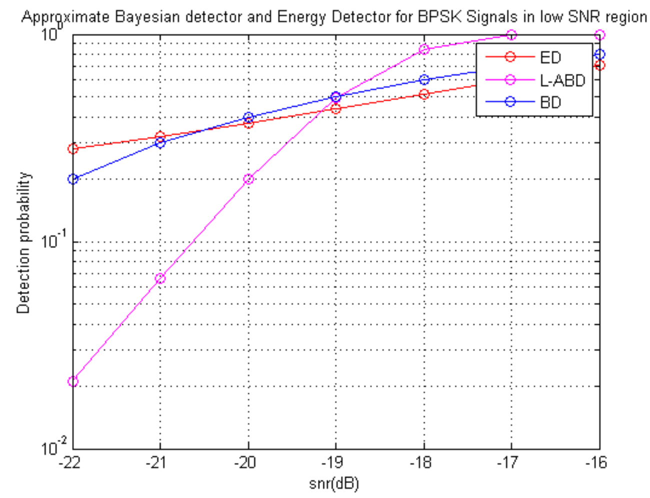

Figure 2 probability of detection for low SNR

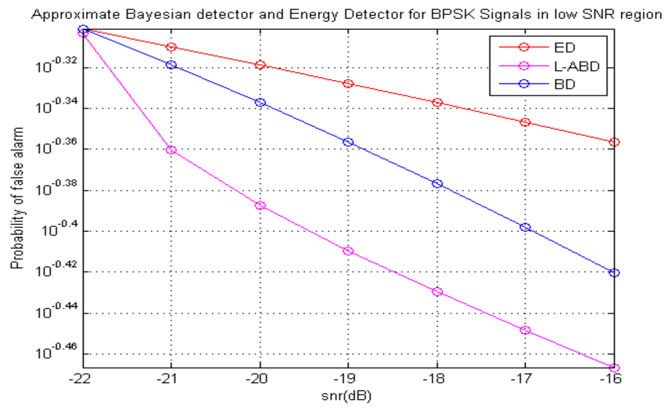

Figure.3 probability of false alarm for low SNR

Figure 4, 5 gives the performance estimation of spectrum sensing for Energy detection based and Bayesian based spectrum sensing for high SNR using BPSK modulation for 1000 samples.

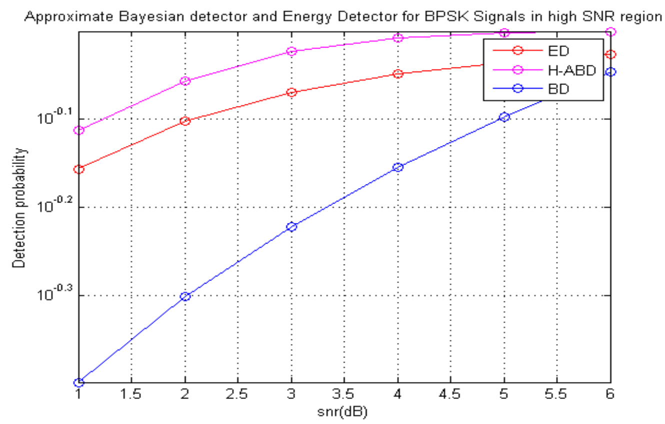

Figure 4 probability of detection for high SNR

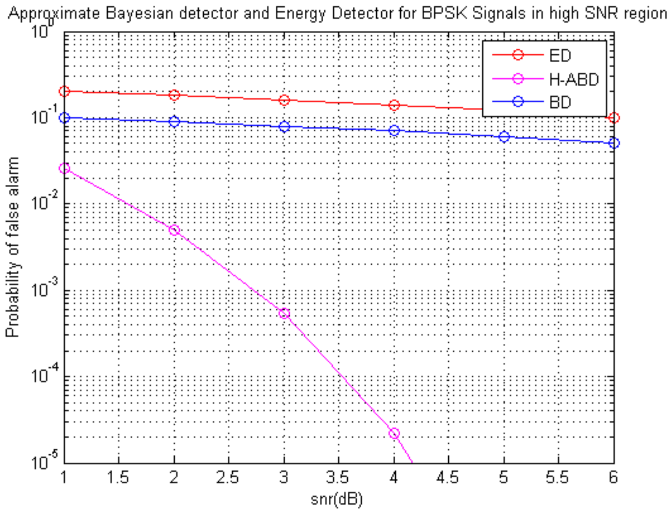

Figure 2 probability of false alarm for high SNR

5. Conclusion

Using MATLAB simulation environment spectrum sensing in cognitive radio is implemented. The performance estimation of the system for the detection of spectrum and probability of false alarm using Energy based detection and sub optimal based Bayesian detector. From the simulation results it is clearly shown that the performance of Bayesian based detector is far better than Energy based detector.

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