# Bayesian Approach for Spectrum Sensing in Cognitive Radio

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**Abstract:** ***Unused portions of allocated fixed spectrum are called spectrum holes or white spaces. These spectrum holes or white spaces are used by cognitive radio technology in an opportunistic manner. It will solve the global problem of spectrum scarcity. Cognitive radio assigns spectrum or radio resources in a manner to keep interference between CR devices and licensed users within limit. The scope of this paper is to achieve higher spectrum utilization in cognitive radio networks, using an optimal Bayesian Detector. If the primary user is highly inactive and the primary signals are digitally modulated, we will derive the optimal detector structure. And further suboptimal detectors in low and high SNR scenario. The Bayesian Detector has better performance than the Energy Detector in high signal to noise ratio and same performance as ED in low SNR for spectrum utilization. We provide Detection probability and false alarm probability analysis.***

**Keywords:** Cognitive radio, Spectrum sensing, spectrum utilization, Energy Detector, Bayesian Detector

## 1. Introduction

The shortage of spectrum is often a spectrum access problem. It means a spectrum is available, but its use is limited by traditional technologies. New technologies may allow sharingof spectrum resources which will increase available spectrum utilization.Federal communications commission would form policies to permit access of presently under-utilized spectrum while protecting legitimate needs of licensed users.This somehow could meet many of the nation's growing spectrum needs for a long time [1].

The current spectrum use indicates that often the spectrum is not being fully utilized, even though the spectrum in a general area may be licensed. By permitting spectrum access to other uses will add to capacity and increase spectrum efficiency. New operations could be permitted when the current user is not using the spectrum. Frequency sensitive operations could be moved to less crowded spectrum bands. Existing primary users studies the business potential in various service areas and accordingly mounts only enough radio transmitters. In this case, the remote area doesn't get the radio service. The lack of service in those areas called white spaces, which can be made available to other licensees who want to provide service in that area. Spectrum utilization survey in Europe [2] suggests thatspectrum usage is 6.5% to 10.7% for the frequency band of 400MHz to 3 GHz.

Measurement results in Singapore [3] show that most of the frequencies from 80MHz to 5.85GHz of allocated spectrum are under-utilized. Only the broadcasting and cell phone frequencies are an exception to it. The average occupancy was found only 4.5%. In all we can say that there is high probability that the primary users are likely idle for most of the time. To increase the spectrum efficiency, we need to improve access to spectrum. FCC promotes following steps in this regard

1) Flexible use of spectrum
2) Development and deployment of advanced technologies and
3) Secondary markets for spectrum.

Using cognitive radios, the secondary users are allowed to use the spectrum originally allocated to primary users as long as primary users are not using it temporarily. It's 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 [4].The secondary unlicensed users keep sensing the spectrum to determine the PU is transmitting or not. Upon detecting PUidle, the SUs can use those frequencies for transmission. This will increase overall spectrum utilization and in turn increase the spectrum efficiency. So it becomes extremely important to employ efficient and robust techniques to sense the spectrum which are reliable.

The detection of a signal in the presence of noise requires processing which depends upon what is known of the noise characteristics and signal characteristics. The energy detection is easy to implement since it does not require the knowledge about the structure of the primary signal. Urkowitz [5] discussed the detection of unknown structured signal in the presence of flat, band limited Gaussian noise of known power density. The decision statistic has non central chi-square distribution. Here the received signal often has random amplitude due to atmospheric turbulence, multichannel wave propagation and other. Further in [6] used sampling theory approach for an energy detector under both AWGN and fading channels. Matched filter based detection method is infeasible for practical applications as it needs complete knowledge of primary signals. Cyclostationarity properties of primary signal are needed in Cyclostationarity based detection which is not fully used. In this paper, we propose a Bayesian Detector for digitally modulated primary signals to maximize spectrum utilization. We don't need prior information on the transmitted sequence of the primary signals. It used the prior statics of primary user activity and signaling information such as symbol rate and modulation in order to improve the secondary user's throughput and overall spectrum utilization. The Neyman-Pearson has the same structure as Bayesian detector. The design principle of Neyman-Pearson method is to maximize the detection probability for a given maximal false alarm probability, which results in the difference in detection threshold selection for them.

We consider the primary signals over additive white Gaussian noise channels. These signals are MPSK modulated. In low SNR regime, Bayesian detector is same as energy detector of BPSK modulated signal and MPSK for M>2. In high signal to noise ratio for BPSK signals Bayesian detector is approximated to detector which employees the sum of the received signal amplitudes to detect the primary signals. The maximum likelihood ratio test detector can be approximated by its corresponding suboptimal structure in the low and high SNR regimes. We will analyze the detection and false alarm probabilities...

In section II we will discuss some conventional detection methods. Section III will give system model along with assumptions and Bayesian detector for MPSK modulated primary signal. Suboptimal detector structure is derived in section IV. We also analyze the probabilities of detection and false alarm in section V. Finally, we conclude in section VI.

## 2. Conventional Detectors

Energy Detector: Energy detection method is the simplest of all, so widely used and easy to implement. This method calculates the energy of input signal and compares it with some 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. In presence of noise and interference power uncertainty, the performance of energy detection severely degrades and the detector fails to differentiate primary signal from interference [6].

Matched filter: It matches or correlates a known signal or template with unknown signal to detect presence of template in unknown signal. The matched filter is the optimal linear filter for maximizing the SNR in the presence of additive noise. These filters are commonly used in radar. But it needs prior knowledge of primary signal, such as modulation type, signal shape,and then matched filter can be used. Here we don't have any prior knowledge about the primary signal. So we cannot use matched filter detection.

Waveform based sensing: In wireless systems, known patterns are often used to assist synchronization. Regularly transmitted pilot patterns, preamble, midamble are such known patterns. Sensing is performed by correlating received signal with its known copy. In terms of reliability and convergence time these detectors have better performance than energy detectors. Its performance increases as the length of the known signal pattern increases. The presence of primary signal is detected by comparing the decision metric against a fixed threshold. The disadvantages of this method are the susceptibility to synchronization errors and short measurement time.

Cyclostationarity feature detector: Spectral correlation function is the one of the special characteristics of modulated signal. It is used for various signal processing tasks like detection, synchronization and so on. An analysis of random signal is done using autocorrelation function. However, Cyclostationary signals reflect correlation between distinct spectral components because of periodicity. Spectral correlation function will separate noise from the signal. It is easy to detect primary signal which use longer transmission length. But this detection method involves high computational complexity and long observation time [7, 8, and 9].

## 3. Bayesian Detector For MPSK Modulated Primary Signals

We have two hypotheses for spectrum sensing: H0 denotes that the primary user is absent and H1 denotes the primary user is present. So we have now two important design parameters for spectrum sensing: probability of detection (Pd) and probability of false alarm (Pf). Here Pd is the probability that SU accurately detects the presence of active primary signals and Pf is the probability that SU falsely detects primary signals when PU is in fact absent. We define spectrum utilization as

$$P(H0)(1-Pf)+P(H1)Pd \qquad (1)$$

And the normalized SU throughput as

$$P(H0)(1-Pf) \qquad (2)$$

Note that P(H1)Pd is PU throughput when there are primary signals and the SUs detect the presence of the primary signals. Let consider Td, as the detection statistic to determine whether the spectrum is being used by the primary user. Td is compared with a predetermined threshold ϵ. Pf the probability of false alarm that the hypothesis test chooses H1 while it is in fact H0:

$$Pf = P(T_D > \epsilon|l \qquad (3)$$

Probability of detection Pd is the probability that the test correctly decides H1 when it is H1:

$$Pf = P(T_D > \epsilon|H0) \qquad (3)$$

### 3.1 Detection Statistics

As per the signal model in [6], we consider time-slotted primary signals where N primary signal samples are used to detect the existence of primary signals. The PU symbol duration is T which is known to the SU and the received signal r(t) is sampled at 1/T at the secondary receiver. For MPSK modulated primary signals, the received signal of k-th symbol at the CR detector, r(k) is

$$r(k) = \begin{cases} n(k), & H0 \\ he^{j\varphi n(k)} + n(k), & H1 \end{cases} \qquad (5)$$

Wheren(k) is a complex AWGN signal with variance N0, have real and imaginary parts.

$\varphi n(k) = \frac{2\pi n}{M}, n = 0,1,..M$ with equi-probability, h is the propagation channel that is assumed to be constant within the sensing period. Denote $r = [r(0), \ldots. r(N -$. Assume that the secondary user receiver has no information with regards to the transmitted signals by the PU and $\varphi n(k), k = 0,1, \ldots, N$ is independent and identically distributed and independent of Gaussian noise.

Energy detector detection statistics can be defined as the average energy of observed samples as

$$T_{ED} = \frac{1}{N}\sum_{k=1}^{N} |r(k)|^2 \quad (6)$$

Even though the energy detector does not require knowledge of the symbol rate, we assume that the sample rate is identical to the symbol rate.

The optimal detector based on Bayesian rule or Neyman-Pearson theorem is to compute the likelihood ratio[10] and then make its decision by comparing the ratio with the threshold. The likelihood ratio test(LRT) of theN hypothesis H1 and H0 can be defined as:

$$T_{LRT}(r) = \frac{P(\frac{r}{H1})}{P(\frac{r}{H0})} \quad (7)$$

Lets denote Cij as the cost associated with the decision that accepts Hi if the state is Hj, for i,j=0,1. As per Bayesian decision rule to minimize the expected posterior cost which is defines as

$$\sum_{i=0}^{1}\sum_{j=0}^{1} C_{ij} p(Hj) p(Hi/Hj) \quad (8)$$

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

$$T_{LRT}(r) \underset{H0}{\overset{H1}{\gtrless}} \epsilon \quad (9)$$

Where the threshold

$$\epsilon = \frac{p(H0)(C_{10}-C_{00})}{p(H1)(C_{01}-C_{11})} \quad (10)$$

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

$$\epsilon = \frac{p(H0)}{p(H1)} \quad (11)$$

In general case, we can consider $C_{01} \neq$ . In CR networks, when the spectrum is under-utilized then $p(H0) > p($

Thus by (1) and (8) the Bayesian decision rule for an optimal detector is

$$\max P(H0)(1 - Pf) + P(H1)Pd \quad (12)$$

this is equivalent to maximizing spectrum utilization.

To find the presence of primary signals, set a threshold $\epsilon$ for each 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 . So normally we choose the threshold based on under hypothesis . For the detector maximizing the spectrum utilization, it is easy to determine the detection threshold using equation (8).

### 3.2 Optimal Detector Structure

We can find the pdf of received signal, r when PU is absent over N symbol duration as below

$$p(r|\mathcal{H}0) = \prod_{k=0}^{N-1} \frac{e^{-|r(k)|^2/N_0}}{\pi N_0} \quad (13)$$

Since the noise signals n(k), k=0,...N-1 are independent.

Similarly, when PU is present, the pdf becomes

$$p(r|\mathcal{H}1) = \prod_{k=0}^{N-1}\sum_{\varphi_n(k)} p(r(k)|\mathcal{H}1, \varphi_n(k))\, p(\varphi_n(k)) \quad (14)$$

Where $\varphi n(k) = \frac{2\pi n}{M}, n = 0,1,..M$

So the BD structure becomes as below

$$T_{BD} = \frac{1}{N}\sum_{k=0}^{N-1} \ln\left(\sum_{n=0}^{\frac{M}{2}-1} \cosh(vn(k))\right) \quad (15)$$

The above equation is quite complicated to use in practice, we will simplify it in below section.

## 4. SUBOPtimal Detector structure Through The Approximations in Low and High SNR Regimes

The theoretical analysis (detection performance and threshold) for the suboptimal detector to detect complex MPSK( M=2 & M>2) in low SNR regime and high SNR regime and then comparison with real BPSK primary signal.

### 4.1 Approximation in the low SNR regime

When $\rightarrow 0, \cosh(x) \approx 1 + \frac{x^2}{2} and \ln(1+x)$ , we can obtain:

$$\sum_{k=0}^{N-1} \ln\left(\sum_{n=0}^{\frac{M}{2}-1} \cosh(v_n(k))\right) \quad (16)$$

Through approximation the detector structure becomes:

$$T_{L-ABD} = \frac{1}{N}\sum_{K=0}^{N-1} |r(k)|^2 \underset{H0}{\overset{H1}{\gtrless}} \frac{N}{\gamma}\left(\gamma + \frac{\ln\epsilon}{N}\right) \quad (17)$$

Above detector uses the real part of the received signal as input and has the same structure as the suboptimal detector for BPSK signals.

### 4.2 Approximation in high the SNR regime

At high SNR, when $x \gg 0, cosh(x) \approx$ the detector structure becomes

$$\sum_{k=0}^{N-1} \ln\left(\sum_{n=0}^{\frac{M}{2}-1} \frac{e^{|vn(k)|}}{2}\right) \quad (18)$$

It shows that presence of primary signals is detected by summing the received signalsmagnitude, indicating ED is not optimal at high SNR. So is ABD.

## 5. Analysis of Detector Performance and False Alarm Probability using simulation results

We assume that the primary network operates on an AWGN channel for BPSK modulated primary signals. The signal to noise ratio is varied to evaluate the performance of the energy detectors and Bayesian detectors. The detection threshold for BD is determined by the ratio of P(H0)=0.85 and P(H1)=0.15

The detection performance is given in terms of Pf and Pd. The detector for complex MPSK signals is energy detector, while the detector for BPSK signals is the real part of the ED[11]. We study the performance of approximate BD for 8PSK and BPSK channels at low and high SNR regime.

### 5.1 At Low SNR

We have plotted Pd and Pf versus SNR for ABD for 8PSK signals in Figs. 1 to 2 respectively, with number of samples N is set to 5000. It shows that when SNR is larger than -13 dB , ABD has a high detection probability larger than 0.9,and Pf of much less than 0.3.It shows that PUs are most likely idle than busy indicating highest spectrum utilization. We observe that the performance difference between ED and BD is insignificant due to their detector structures are quite similar. Surprisingly, false alarm probability of L-ABD in low SNR regime first becomes worse and gradually becomes better due to the threshold defined to maximize spectrum utilization given by (12).

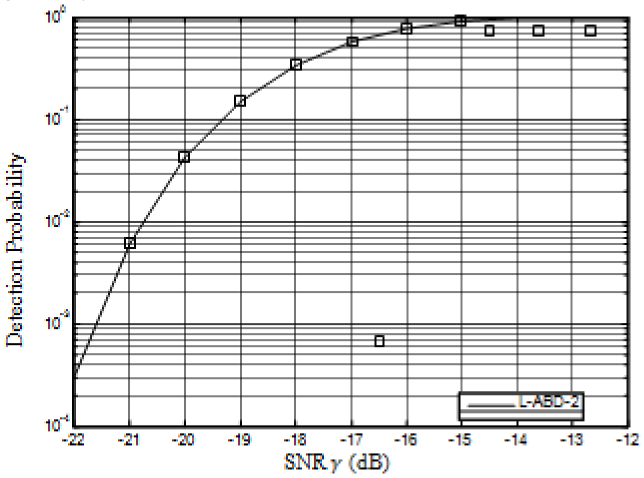


**Figure 1:** Detection probability of L-ABD vs. SNR(dB) for MPSK signal in low SNR regime.

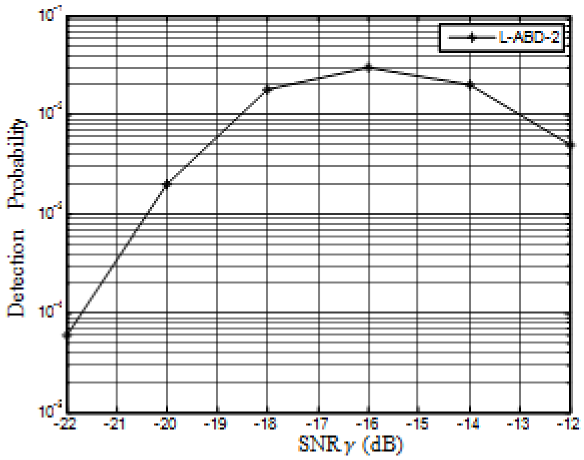


**Figure 2:** False alarm probability of L- ABD vs. SNR(dB) for MPSK signal in low SNR regime

### 5.2 At High SNR

For 10 samples and 20 million simulation runs the results are shown Fig. 3 and 4 for 8PSK signal in high SNR regime. The approximation becomes accurate when SNR is higher than 3dB. The false alarm probability is maximum 0.2 and decreases with SNR It's clear that Bayesian detector has better performance, better spectrum utilization and the energy detector is not optimal in high SNR regime.

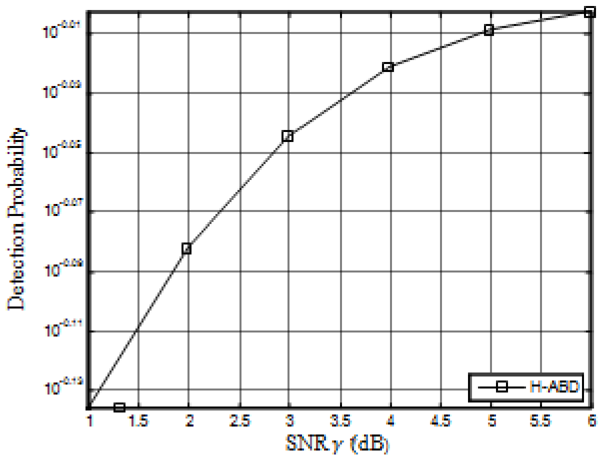


**Figure 3:** Detection probabilityof H-ABD vs. SNR(dB) for 8PSK signal in high SNR regime

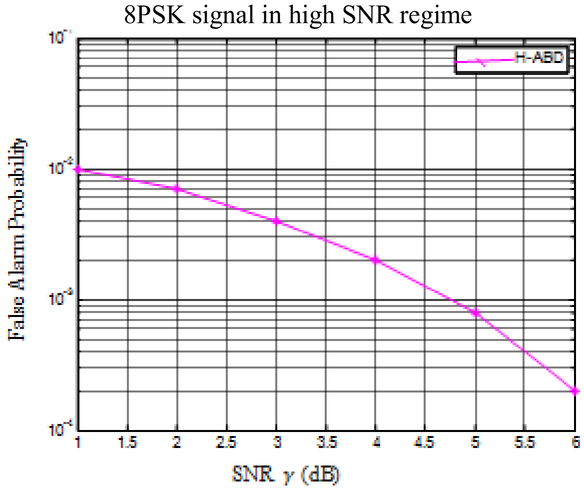


**Figure 4:** False alarm probability of H-ABD vs. SNR(dB) for 8PSK signal at high SNR

Simulation results of BPSK signal is shown in Figs. 5and 6. The false alarm probability is much lower and higher probability of signal detection. Figs. 7 and 8 shows that H-ABD has better spectrum utilization and secondary user's throughput

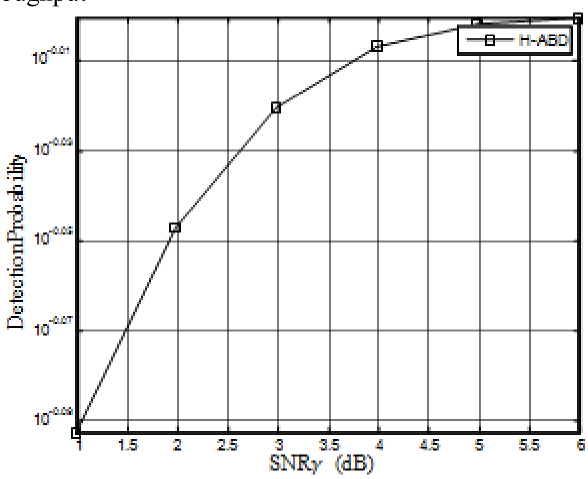


**Figure 5:** Detection probability of H-ABD vs.SNR(dB) for BPSK signal at high SNR

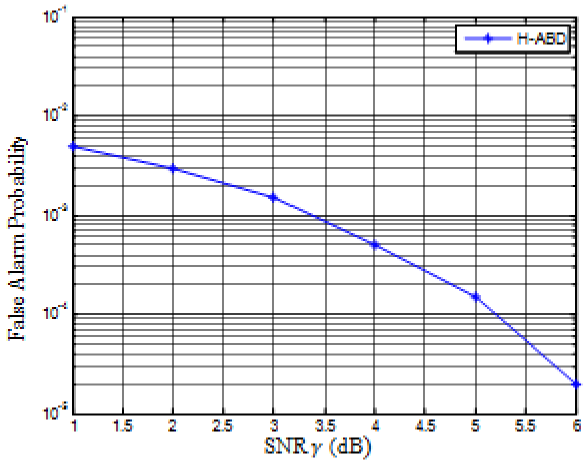


**Figure 6:** False alarm probability of H-ABD vs. SNR(dB) for BPSK signal at high SNR

## 6. Conclusion

Based on Bayesian rule, detector structure is presented here to detect known order MPSK modulated primary signals over AWGN channels. We have found that at low SNR regime energy detector is the same as Bayesian detector. But at high SNR energy is the sum of signal magnitudes. Bayesian detector has advantages over ED and NP detector due to the difference in detection threshold. It also maximizes the detection probability for a given false alarm probability.

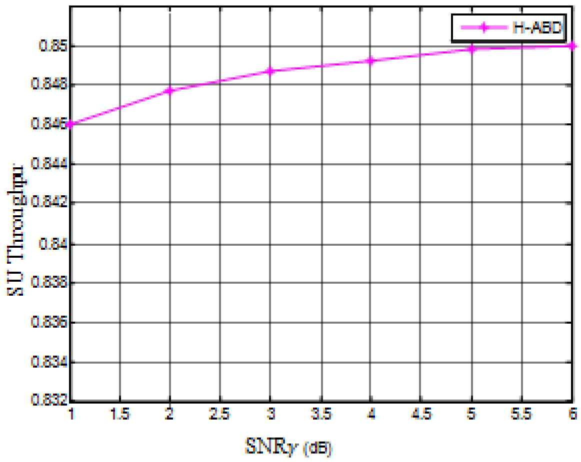


**Figure 7:** Secondary users throughput of H-ABD vs. SNR(dB) for BPSK signal at high SNR

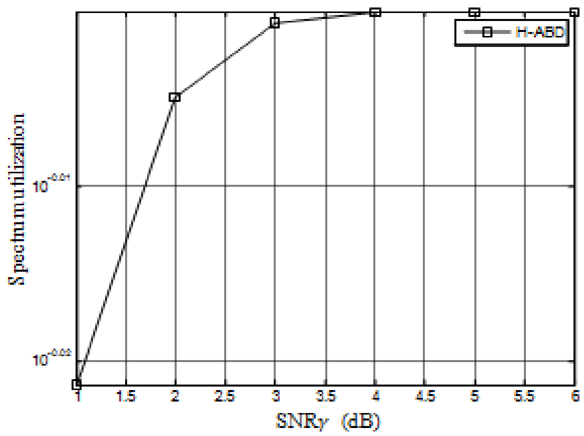


**Figure 8:** Spectrum utilization of H-ABD vs. SNR(dB) for BPSK signal at high SNR

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