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Spectrum Sensing Using Bayesian Method for Maximum Spectrum Utilization in Cognitive Radio

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Abstract

With increase demand for spectrum, it is necessary to detect the spectral holes in the static frequency assignment. Using cognitive radio the spectrum can be sensed to increase the efficient usage of spectrum by secondary users when the MPSK (M>2) modulated primary user is idle. In this paper we have derived an optimal Bayesian detector for MPSK modulated primary user over AWGN channel with corresponding suboptimal detector in low and high SNR walls. We give an analysis of detection based methods like energy detector, cyclostationary detector, and matched filter detector with Bayesian method. The performance of spectrum sensing methods is verified using the simulation results.

Keywords: *Cognitive radio, energy detector, matched filter detector, cyclostationary detector, Bayesian method*

1. Introduction

Increasing demand for mobile communications and new wireless applications raises the need to efficient use of the available spectrum resources. Spectrum scarcity is due to inefficient spectrum management rather than spectrum shortage. Cognitive Radio (CR) is a paradigm that enables a network to use spectrum in a dynamic manner. The term, cognitive radio, can formally be defined as, "Cognitive Radio is a radio for wireless communications in which either a network or a wireless node changes its transmission or reception parameters based on the interaction with the environment to communicate efficiently without interfering with licensed users". This changing of parameters is based on the active monitoring of external and internal radio environment such as radio frequency spectrum, user behavior trends and network state [2].

Spectrum sensing is the process used by a cognitive radio to identify available channels of both licensed and unlicensed spectrum in order to wirelessly communicate. The frequency spectrum is a dynamic system that changes with time and location. The availability of a channel in the licensed spectrum depends on the activity of the primary user (PU), which has priority, to the licensed spectrum. The underutilization of the licensed spectrum presents an opportunity for secondary users (SU) to transmit on these unused channels. This type of capability is the research motivation of spectrum sensing. When SU detects the presences of PU, it should vacate the channel within the stipulated time period.

Common algorithms that enable spectrum sensing: energy detection, cyclostationary detection, and matched filtering. Energy detection compares the received energy in frequency band to a threshold. If the threshold is exceeded, then signal detection is asserted. Cyclostationary detectors search for periodicity that exist in modulated signals and which do not exist in background noise. Cyclostationary detectors can achieve a high probability of signal detection with a low signal-to-noise ratio (SNR). Matched filtering correlates the received signal with the known waveform of the primary user in order to find a match.

In this paper we consider MPSK signals (M >2) as primary user in both low and high SNR walls with AWGN noise for the proposed Bayesian method and compare it with best method among the detection based methods. The paper is organized as follows: the detection based methods along with the bayesian method are discussed along with the simulated results in section 2. The proposed suboptimal bayesian detection method is discussed in section 3. The simulated results along with the comparison tables are given in the section 4.

2. Detection based methods:

Spectrum sensing is based on a well-known technique called signal detection. Signal detection can be described as a method for identifying the presence of a signal in a noisy environment. Signal detection can be reduced to a simple identification problem, formalized as a hypothesis model from [1]. There are two hypotheses: $\mathcal{H}_0$ for the hypothesis that the PU is absent and $\mathcal{H}_1$ for the hypothesis that the PU is present. The important parameters used in spectrum sensing are probability of detection $\mathcal{P}_d$ which is the probability that SU detects the presence of active primary signals, and probability of false alarm $\mathcal{P}_f$ which is the probability that SU falsely detects primary signals when PU is in fact absent. Spectrum utilization can be defined as

$$\mathcal{P}(\mathcal{H}_0)\left(1-\mathcal{P}_f\right)+\mathcal{P}(\mathcal{H}_1)\mathcal{P}_d \quad (1)$$

and normalized SU throughput as

$$\mathcal{P}(\mathcal{H}_0)(1-\mathcal{P}_f) \quad (2)$$

respectively. In hypothesis model the received signal of *t* symbols at the receiver r(t) is

$$r(t) = \begin{cases} n(t), & \mathcal{H}_0 \\ he^{j\phi_n(t)} + n(t), & \mathcal{H}_1 \end{cases} \qquad (3)$$

Where $n(t) = n_c(t) + jn_s(t)$ is the complex AWGN with variance N_0, $n_c(t)$ and $n_s(t)$ are respectively the real and imaginary parts of $n(t)$, $\phi_n(t) = \frac{2n\pi}{M}, n = 0,1, \dots\dots\dots\dots\dots . M-1$ with equi-probability, h is the propagation channel that is assumed to be constant within the sensing period.

2.1. Energy detector

Energy detection is an optimal way to detect primary signals when priori information of the primary signal is unknown to secondary users. It measures the energy of the received waveform over a specified observation time. The energy detector consists of square law device followed by a finite time integrator[4]. The noise pre-filter serves to limit the noise bandwidth; the noise at the input to squaring device has a band-limited, flat spectral density. A threshold value is required for the comparison of the energy found by the detector. Energy greater than the threshold values indicates the presence of the primary user. Energy is calculated as

$$E = \sum_{n=0}^{N} |x(n)|^2 \qquad (4)$$

The energy detector is now compared to a threshold ε for checking which hypothesis turns out to be true.

$$E > \varepsilon \Rightarrow \mathcal{H}_1$$
$$E > \varepsilon \Rightarrow \mathcal{H}_0 \qquad (5)$$

Under hypothesis $\mathcal{H}_0$ the probability of false alarm $\mathcal{P}_f$ can be calculated as

$$\mathcal{P}_f = \mathcal{Q}\left(\left(\frac{\varepsilon}{\sigma_n^2} - 1\right)\sqrt{N}\right) \qquad (6)$$

Similarly, under hypothesis $\mathcal{H}_1$, the probability of detection $\mathcal{P}_d$

$$\mathcal{P}_d = \mathcal{Q}\left\{\left(\frac{\varepsilon}{\sigma_n^2} - (\gamma+1)\right)\sqrt{\frac{N}{2\gamma+1}}\right\} \qquad (7)$$

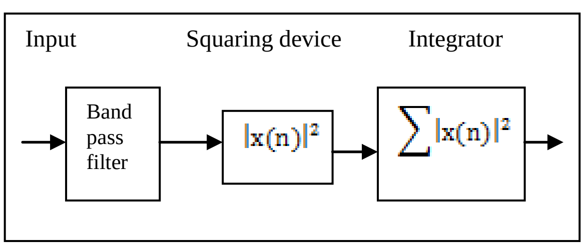

Fig 1: Energy detector method

The simulation result of the energy detector compared with the theoretical values is as shown in Fig 2. The energy detector performance is good in Low SNR walls and worst in High SNR walls.

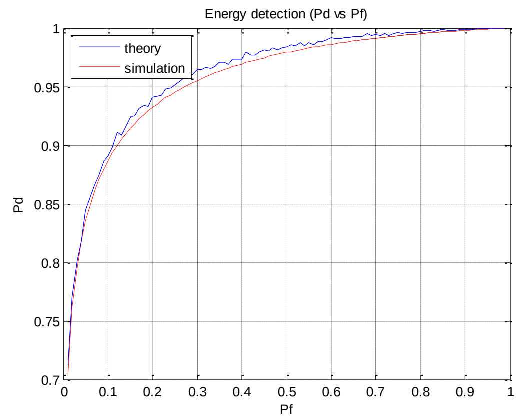

Fig 2: Detection probability vs false alarm probability of energy detector for 8PSK primary signal over AWGN channel in low SNR walls

This periodicity trend is used for analyzing various signal processing tasks such as detection, recognition and estimation of received signals.

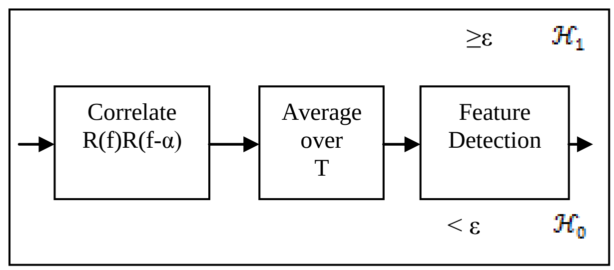

Fig 3: Principle of Cyclostationary method

In order to implement the cyclostationary detector steps are to be followed as

1) Determine the cyclic frequency for the signal, carrier frequency, window size, overlap number and fft size.
2) The signal say x(t) is shifted in time domain by –α/2 and α/2.
3) Both of the shifted signals are multiplied by a sliding window (hamming window).
4) Find Fourier transform of the windowed signals.
5) Spectral correlation function for each frame is found out and then it is normalized by its mean.
6) Maximum of the spectral correlation function is found and compared to a threshold to find the presence of a primary user.

The probability of false alarm for cyclostationary detection method is given [5] as

$$\mathcal{P}_f = exp\left(-\frac{(2N+1)\varepsilon^2}{2\delta^4}\right) \qquad (8)$$

From the above equation the threshold ε can be calculated as

$$\varepsilon = \sqrt{\frac{2\delta^4}{(2N+1)} ln(\mathcal{P}_f)} \quad (9)$$

The threshold value is used to calculate the probability of detection as

$$\mathcal{P}_d = Q\left(\sqrt{\frac{2\gamma}{\delta^2}}, \frac{\varepsilon}{\delta_b}\right) \quad (10)$$

where, $\delta_b = \frac{(2\gamma+1)\delta^4}{2N+1}$

where 'δ' is the variance of the received signal, 'N' is the number of samples values of the signal and 'γ' is the SNR.

This method performances better for low SNR walls but as the values of SNR walls increases there is a larger deviation of the values between the theoretical and simulated values as shown in the Fig 4 and Fig 5.

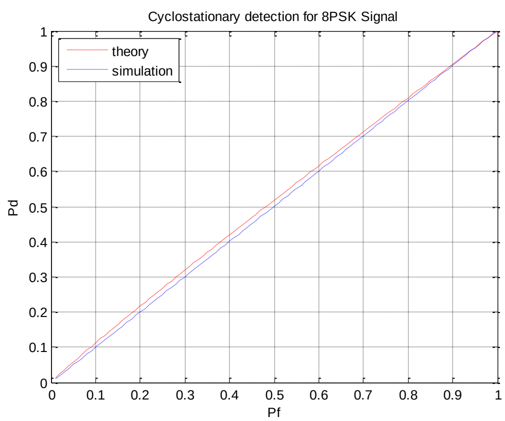

Fig 4: Detection probability vs false alarm probability of cyclostationary detector for 8PSK primary signal over AWGN channel in low SNR walls for SNR = -15dB

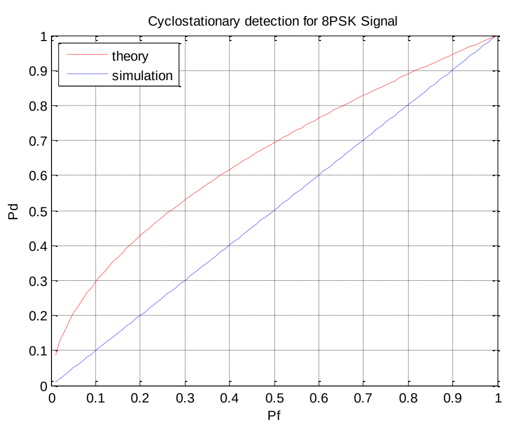

Fig 5: Detection probability vs false alarm probability of cyclostationary detector for 8PSK primary signal over AWGN channel in low SNR walls for SNR = -10dB

Since all cyclic frequencies are calculated so the computational complexities is higher than the energy detector and is not susceptible to noise levels as energy detection. This method is based on exploiting the cyclostationarity feature of primary signals, but it does not make full use of the characteristics of the modulated signals.

2.3. Matched filter detection method

The matched filter technique is very important in communications as it is an optimum filtering technique which maximizes the signal to noise ratio (SNR). It is a linear filter and prior knowledge of the primary user signal is very essential for its operation. The operation performed is equivalent to the correlation.

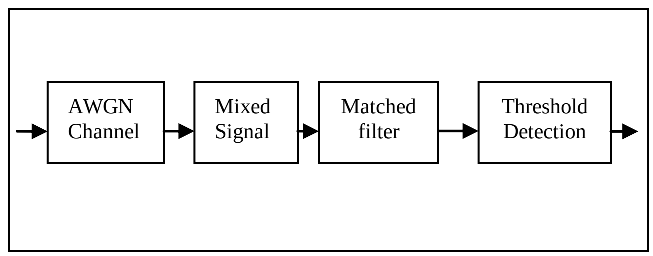

Fig 6: Principle of Matched filter operation

The transmitted signal is passed through the channel where the additive white Gaussian noise is getting added to the signal and the outputted the mixed signal. The mixed signal is given as input to the matched filter. The matched filter is convolved with the impulse response of the matched filter and the output is then compared with the threshold of the primary user detection. The signal component at the output of the filter in [6], at observation time instant T is given by

$$s(T) = {}^1/_{2\pi} (r(t))^2 = Energy \quad (11)$$

The threshold of signal is determined as in []. Estimate the energy of the signal and reduce it to half, fix it as a threshold.

This method requires perfect a prior knowledge of the primary users feature such as bandwidth, frequency, modulation type, etc. to demodulate the received signals. Therefore it needs dedicated signal receivers for each signal type that leads to implementation complexity and large power consumption it's very impractical to implement in cognitive radios which is illustrated in the simulation results as shown in the Fig 7.

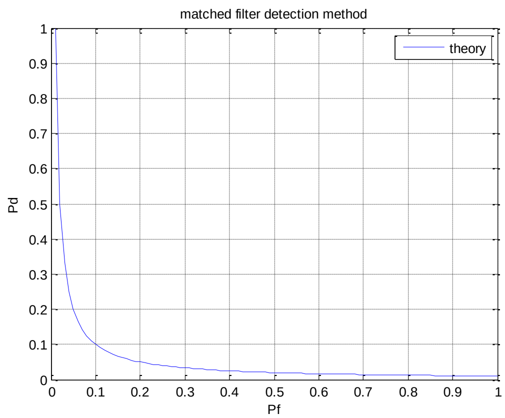

Fig 7: Theoretical detection probability vs false alarm probability of matched filter detector for 8PSK primary signal over AWGN channel in low SNR walls.

From all the three detection based methods, energy detection is the best. So we compare the proposed Bayesian method and the approximate Bayesian method with the energy detector for 8PSKprimary signals over AWGN channel in both low and high SNR walls.

2.4. Bayesian detection method

Detector for binary hypothesis testing is based on the Bayesian rule is to compute the likelihood ratio test and then it is compared with threshold to take the decision of whether secondary user (SU) can use the network or not as in [11]. The likelihood ratio test (LRT) can be defined as:

$$T_{LRT} = \frac{p(r|\mathcal{H}_1)}{p(r|\mathcal{H}_0)} \qquad (12)$$

Based on the Bayesian rule, it is convenient to derive the likelihood ratio test for optimal detector (BD) as:

$$T_{LRT}(r) \lessgtr \varepsilon \qquad (13)$$

Where

$$\varepsilon = \frac{p(\mathcal{H}_0)(C_{10}-C_{00})}{p(\mathcal{H}_1)(C_{01}-C_{11})} \qquad (14)$$

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

$$\varepsilon = \frac{p(\mathcal{H}_0)}{p(\mathcal{H}_1)} \qquad (15)$$

As the spectrum is underutilized in Cognitive radio networks it is likely that $p(\mathcal{H}_0) > p(\mathcal{H}_1)$.

3. Proposed method: 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) for the suboptimal detector to detect complex MPSK (M =2 and M > 2) in low and high SNR walls compare with the results for real 8PSK primary signals.

3.1. Approximation in low SNR Region

We study the approximation of our proposed detector for 8PSKmodulated primary signals in the low SNR regime. Through approximation, the detector structure becomes:

$$\frac{1}{N}\sum_{k=0}^{N-1}\sum_{n=0}^{\frac{M}{2}-1}\left(\Re\left[r(k)h^{*}e^{-j\emptyset_n(k)}\right]\right)^2 \lessgtr \frac{MN_0^2}{4}\left(\gamma+\frac{\ln\varepsilon}{N}\right) \qquad (16)$$

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

$$T_{L\_ABD\_1} = \frac{1}{N}\sum_{k=0}^{N-1}|r(k)|^2 \lessgtr \frac{N_0}{\gamma}\left(\gamma+\frac{\ln\varepsilon}{N}\right) \qquad (17)$$

When the signal is BPSK, the detector is equivalent to

$$T_{L\_ABD\_1} = \frac{1}{N|h|^2}\sum_{k=0}^{N-1}(\Re[r(k)h^{*}])^2 \lessgtr \frac{N_0}{2\gamma}\left(\gamma+\frac{\ln\varepsilon}{N}\right) \qquad (18)$$

3.2 Approximation in high SNR Region

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

$$T_{H\_ABD} = \frac{1}{N}\sum_{k=0}^{N-1} ln\left(\sum_{n=0}^{M/2-1} e^{\frac{2}{N_0}\Re\left[r(k)h^{*}e^{-j\emptyset_n(k)}\right]}\right) \lessgtr \gamma + \ln M + \frac{\ln\varepsilon}{N} \qquad (19)$$

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:

$$T_{H_{ABD}} = \frac{1}{N}\sum_{k=0}^{N-1}|\Re[r(k)h^{*}]| \lessgtr \frac{N_0}{2}\left(\gamma+\ln\ 2+\frac{\ln\varepsilon}{N}\right) \qquad (20)$$

4. Simulation results:

It is assumed that the primary network operates on a channel. The P_d versus P_f values of Energy detector, cyclostationary detector and matched filter methods are shown in Fig 2, Fig 4, Fig 5 and Fig 6 in low SNR walls over AWGN channel. From the results it is clear that the energy detector performances better in low SNR walls. In this section, we study the performance of ED, BD and ABD over AWGN channels for 8PSK modulated primary signals.

4.1 Low SNR walls

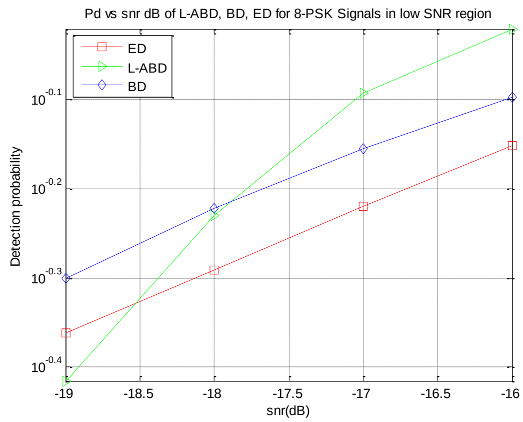

Fig 8: Detection probability vs SNR (dB) for 8PSK modulated primary user over AWGN channel in low SNR walls

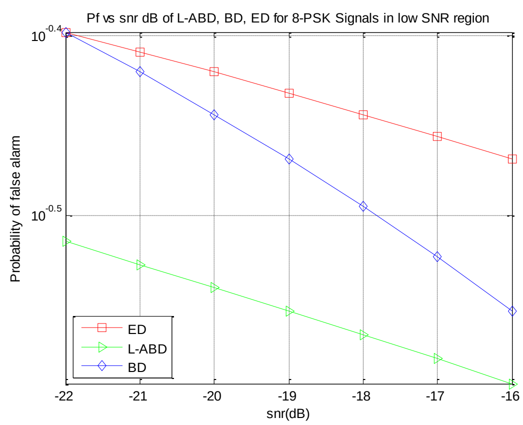

Fig 9: False alarm probability vs SNR (dB) for 8PSK modulated primary user over AWGN channel in low SNR walls

The numbers of samples taken are 5000 for low SNR walls over AWGN channel and the values of detection probability and false alarm probabilities are of L-ABD, BD and ED are compared as shown in Table 1. The performance of the L-ABD is better than that of EB and BD.

Table 1: Comparison of detection and false alarm probabilities

SIMULATION OF 8PSK						
	Probability of detection			Probability of false alarm		
SNR values	ED	BD	ABD	ED	BD	ABD
-22	0.2786	0.20	0.0961	0.40	0.4	0.3062
-21	0.3205	0.30	0.1494	0.39	0.38	0.2971
-20	0.3716	0.40	0.2393	0.38	0.36	0.2883
-19	0.4345	0.50	0.3841	0.37	0.34	0.2798
-18	0.5112	0.60	0.5884	0.36	0.32	0.2715
-17	0.6024	0.70	0.8087	0.35	0.3	0.2633
-16	0.7051	0.80	0.9543	0.34	0.28	0.2551

4.2 High SNR walls

The numbers of samples taken are 10 for high SNR walls over AWGN channel and the values are as shown in Table 2. The detection probability and false alarm probability are as shown in Fig 10 and Fig 11.

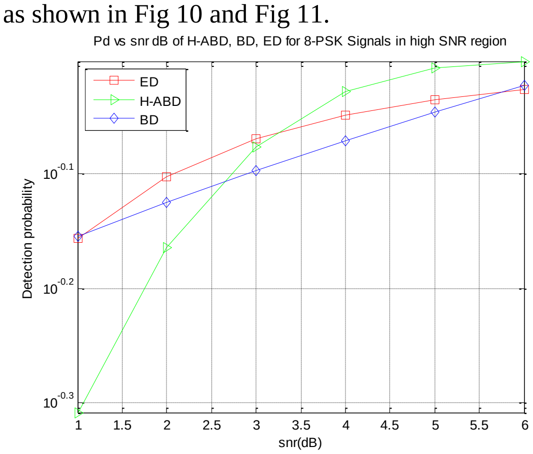

Fig 10: Detection probability vs SNR (dB) for 8PSK modulated primary user over AWGN channel in high SNR walls

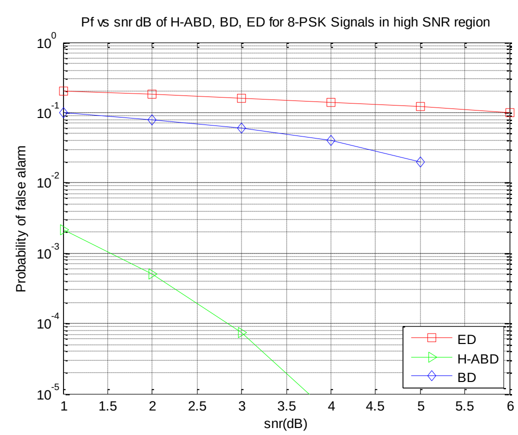

Fig 11: False alarm probability vs SNR (dB) for 8PSK modulated primary user over AWGN channel in high SNR walls

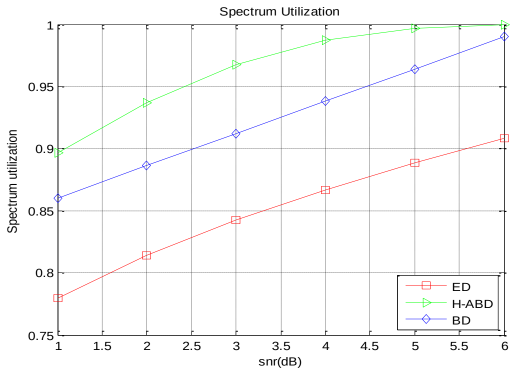

Fig 12: Spectrum utilization of 8PSK modulated primary signal over AWGN channel in High SNR walls

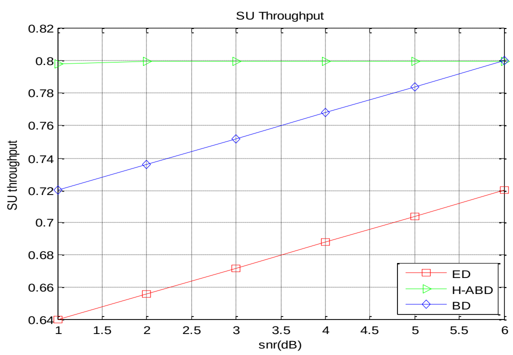

Fig 13: Secondary users' throughput of 8PSK modulated primary signal over AWGN channel in High SNR walls

Table 2: Comparison of detection and false alarm probabilities

SIMULATION OF 8PSK						
	Probability of detection			Probability of false alarm		
SNR VALUES	ED	BD	ABD	ED	BD	ABD
1	0.697762	0.7	0.491343	0.2	0.1	0.002137555
2	0.790801	0.75	0.685567	0.18	0.08	0.00050608
3	0.85211	0.8	0.83827	0.16	0.06	7.33E-05
4	0.893775	0.85	0.937841	0.14	0.04	5.19E-06
5	0.92211	0.9	0.983567	0.12	0.02	1.29E-07
6	0.941377	0.95	0.997261	0.1	0	6.71E-10

The performance of H-ABD is better than that of BD and ED, having better Pd values avoiding the interference of secondary users with the primary users. The false alarm values are very much less, providing opportunity for the secondary users to utilize the spectrum efficiently. The secondary user throughput has been increased and is as shown in Fig 13 and tabulated in Table 3.

Table 3: Comparison of spectrum utilization and SU throughput

	SPECTRUM UTILIZATION			SU THROUGHPUT		
SNR	ED	BD	ABD	ED	BD	ABD
1	0.77955241	0.86	0.850268586	0.64	0.72	0.798289956
2	0.81416029	0.886	0.885113477	0.656	0.736	0.799595136
3	0.84242194	0.912	0.911653977	0.672	0.752	0.799941395
4	0.86675508	0.938	0.927568187	0.688	0.768	0.799995848
5	0.88842206	0.964	0.932713422	0.704	0.784	0.799999897
6	0.90827546	0.99	0.931452232	0.72	0.8	0.799999999

5. Conclusion:

The advantages of using approximate bayesian detector are as follows:

(i) No prior information on the transmitted sequence of primary signals is required.
(ii) Prior statistics and Signaling information of Primary user such as symbol rate and modulation order are required to improve Spectrum utilization and SU Throughput.
(iii) Performs well in both Low SNR and High SNR regions.
(iv) Good Performance for Spectrum utilization and SU Throughput.
(v) Maximizes detection probability.

With the use of the approximate Bayesian method the spectrum is being utilized effectively by the secondary users and the throughput has been increased compared to all previous methods.

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