Analysis of Spectrum Sensing Based on Energy Detection Method in Cognitive Radio Networks

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Abstract - Spectrum sensing is an important aspect that maximizes the opportunistic usage of available spectrum. The cognitive/secondary users have to sense the spectrum repeatedly to prevent interference to licensed users. In this paper, an improved spectrum sensing model is proposed using energy detection technique. Using Central Limit theorem, an appropriate threshold is derived and the test statistics is obtained for Additive White Guassian Noise channel. The relation between detection probability and false alarm probability is derived. Computer Simulations were shown that an improved Pd can be obtained for QPSK and DVB-T signals. It has been observed that the SNR wall can be increased by increasing the number of samples of the primary signal.

Keywords - Cognitive radio, Energy detection, Additive White Guassian Noise (AWGN), DVB-T

1. INTRODUCTION

In most of the countries, the government bodies allocate the radio frequency band to the licensed users. The licensed users may transmit in their respective bands. But the spectrum measurements have shown that, the licensed frequency bands are not effectively utilized. In order to improve the spectrum efficiency, these licensed users may allow several other users to use its frequency band for reuse. The un-utilized frequencies in the radio frequency band are termed as spectrum holes.Cognitive Radios is an upcoming solution to the spectrum overcrowding problem which uses the spectrum holes that are not accommodated by the licensed users (also called primary users) [1].

Cognitive radios (or secondary users) have to sense the spectrum incessantly and find the areas where the frequency band is not used and adapt it for the transmission (specified by Federal Communications Commission (FCC))[2]. The licensed bands such as television bands, amateur radio, paging and wireless microphone bands are not fully utilized in remote areas. The usage varies from 15% to 85% [3].The IEEE 802.22 working group developed an air interface to television bands for providing a Point to Multi point service (PMP) to the secondary users. The WRAN standard is in developing stage available at [4]. In PMP network, there is one base station and a number of client stations (called as customer premise equipment (CPE)). So the sensing is done at the base stations. Based on the sensing results, the base station decides the channel availability. The operating frequency is varied, providing less hindrance to the licensed users. Spectrum sensing is therefore a crucial task for cognitive radios. And moreover, the most stimulating hypotheses are to detect the presence of primary user in very low SNR values. There are different spectrum sensing methods including Energy detection[7], Cyclostationary detection[8], Covariance detection[9], [10], Matched filtering[1], Eigen value detection[11]. Matched filtering gives desirable results, but requires some characteristics of the licensed user signal in the spectrum. They are carrier frequency, sampling frequency, bandwidth, pulse shaping [1]. However, it is impractical to access them. Another drawback is its complex receiver circuit and large power consumption.

Cyclostationary detection is another method that makes use of cyclic properties like periodicity and rate of transmission of the signal. This detection method is strongly valid against noise and averts interferences from adjacent channel. But this method involves complex computations. The above two methods are coherent detection techniques. On the other hand, many non-coherent detection techniques are available. one such technique is Eigen value detection[11]. In this technique, a sample covariance matrix of the received signal is computed and the maximum and minimum eigen values are obtained from it to find the detection threshold. This method uses random matrix theory. The Energy detection scheme is another non-coherent technique that does not need any prior characteristics of the signal. Moreover, Energy detector sensing is easier to apply and instigate. This paper is organized as follows. Section II presents the earlier work on Energy detection. Section III gives a common spectrum sensing model. Section IV presents the simulation results for different cases of SNR and probability of false alarm and finally Section V discusses the conclusions.

2. EARLIER WORK

In Ref [12], the authors estimated the sensing duration in order to achieve high throughput. As stated the minimum the sensing duration, the maximum is the throughput. A MAC frame structure for spectrum sensing is developed.

The simulations considered a QPSK signal of 6MHz bandwidth with P(H1) = 0.2 and 90% probability of detection. The technique used is Energy detection sensing with Rayleigh fading.Sensing times for single and multiple time slots are compared and an optimal sensing time of 3.6ms is achieved at SNR =-15dB. When five sensing slots were considered, a maximum Throughput of 0.94 is attained in 3.6ms. Distributed spectrum sensing is also performed with logic AND fusion rule. The results heve been pictorially shown that for one secondary user, the sensing time increased from 2.55ms to 14.5ms and for four secondary users, the sensing time increased from 1.5ms to 9.5ms.In paper[13], the fundamental limits of signal detection were derived. The input primary signal considered was a binary PSK signal. The results were shown both in the presence and absence of noise-uncertainity. The test statistic considered here was based on moment detector.In paper[5], the sensing of DVB-T signal using Energy and Eigen value detection were discussed. The performance of different non-parametric tests were shown. The analysis of various types of fading channels have shown that, the Roy's largest root test (RLRT) is better than Generalized likelihood ratio test(GLRT) for known noise variance and GLRT is the best algorithm for unknown noise variance. The DVB-T signal is detected at an SNR of -10dB with 10% false alarm rate under Rayleigh and guassian flat fading channels. A number of sensing algorithms were proposed in [6] for detection of DVB-T signal. The threshold and detection probability was derived here using chi-square distribution. The signal is sensed under several fading channels by varying the sensing time. Out of all methods pilot based detection and energy based detection depicted improved results.In this paper, we considered a QPSK signal as the primary user signal and noise as Additive White Guassian Noise. Also the results were compared with guassian and DVB-T signal respectively. Specifically, we are interested in the problem of improving Pd by varying Pf for low SNR values.

3. SPECTRUM SENSING MODEL

In today's Signal Processing systems, the continuous time waveforms are sampled and converted into discrete samples.

Let us consider L-point data as [x(0),x(1),. . . x(L-1)]. The decision is made by forming a function of the available data set or T[x(0),x(1),. . . x(L-1)]. Based on the detection theory[14], the function T is evaluated and mapped to take a proper decision. The Statistical Hypothesis testing addresses this issue of decision making. We have two possible hypothesis, signal and noise both present against noise only present. This is reffered as Binary hypothesis testing problem. Under this testing, the probability of detection can be modeled as in[12],[9]: When primary user is absent,

$$H0 : z(n) = w(n) \tag{1}$$

$$H1 : z(n) = s(n) + w(n) \tag{2}$$

Where z(n) is the received signal at the secondary user, s(n) is the signal component and w(n) is the noise component. The noise component is assumed to be guassian and independent and identically distributed with zero mean and variance (_!2).In Hypothesis testing, there are two types of errors that may occur. One is the probability of false alarm and another probability of missed detection. The probability of false alarm is defined as the rate at which the signal is wrongly detected when it is actually not present[15]. Conversely, the probability of missed detection(PMD) is defined as the rate at which the signal is wrongly rejected when it is actually present. But to focus on detection performance, we interpret the complement of PMD as probability of detection(Pd). The test statistic for energy detector is given by,

$$E(z) = \frac{1}{N}\sum_{n=1}^{L}|y(n)|^2 \tag{3}$$

Where E(z) is a random variable with guassian distribution. Under Hypothesis H1, the probability of detection is given by,

$$P_d = Pr(E(z) > \tau | H_1) \qquad (4)$$

Where E(Z) is detection threshold . Similarly, under Hypothesis H0, the probability of false alarm is given by,

$$P_f = Pr(E(z) > \tau | H_0) \qquad (5)$$

the detection threshold [8] for guassian noise with variance 1 is

$$\tau = Q^{-1}\left(\frac{P_f(m)}{\sqrt{L}}\right) + 1 \qquad (6)$$

where Q(x) is a complementary function i.e.,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{\frac{-t^2}{2}} dt \qquad (7)$$

the equations for Pd and Pf are obtained using central limit theorem [12]. As stated the theoretical value of Pd is,

$$P_d = Q\left(\frac{(\tau - (snr+1))\sqrt{L}}{\sqrt{2(snr+1)}}\right) \qquad (8)$$

The figure 1 and figure 2 shows the setup and the process of proposed Energy detection method. The simulation model consists of a primary transmitter, a AWGN communication channel and a secondary receiver. The proposed method evaluates the energy of the received signal (H1) over L samples .Using this energy over k simulations, the test statistic for energy detection is derived. Next by assuming suitable range for Pf , the detection threshold is computed. Finally the test statistic is compared with the threshold and the number of detection are observed.

At the end of simulation, the Pd is evaluated as

$$\text{Pd(m)} = \frac{\text{Number of detections}}{\text{Number of simulations}} \qquad (9)$$

Fig. 1 Energy detection setup

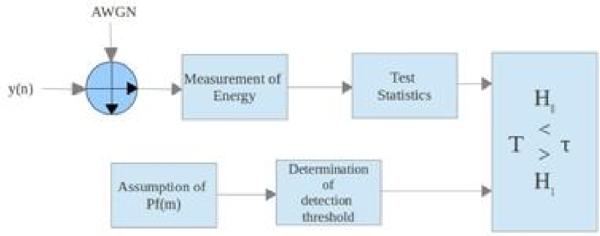

Fig. 2 Energy detection setup

4. COMPUTER SIMULATIONS

In this section, the simulation results have shown that, an improved Pd of 0.99 is obtained for different values of Pf .The primary user signal used here is a QPSK signal. The results were also compared with DVB-T signal. First we generate a QPSK signal of 1000 samples with 1KHZ carrier frequency and 8KHZ sampling frequency. Then a random guassian noise with zero mean and unity variance is generated. Using this secondary user signal, the test statistic for energy detection over L = 1000 samples is computed.

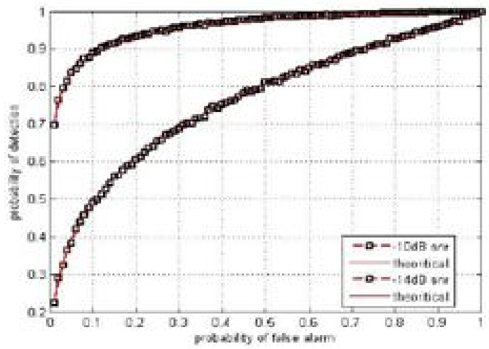

Fig. 3 Evaluation of probability of detection and probability of false alaram practically and theorectically for real guassian primary user signal for SNR-10dB and –14db with P_f = 0.1

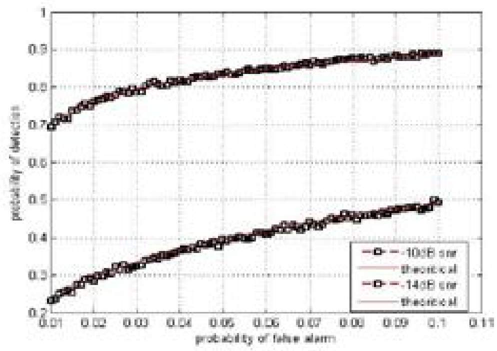

Fig. 4 Evaluation of probability of detection and probability of false alaram practically and theorectically for real guassian primary user signal for SNR-10dB and –14db with P_f = 0.01

Table 1 : Performance of proposed method

SNR in dB	P_f	Published Guassian primary user signal	Proposed QPSK signal
-10	0.13	0.9	0.99
	0.28	0.95	0.99
	0.68	0.99	0.99
-10	0.01	0.7	0.99
	0.02	0.76	0.99
	0.04	0.81	0.99
-14	0.01	0.24	0.55
	0.1	0.49	0.79
	0.7	0.9	0.98

Next a threshold is computed for 100 values of Pf ranging from 0.1 to 1.Finally the detection probability is calculated by comparing the test statistics with the threshold _ from detection threshold proposed in [9]. The results are also compared theoretically using equation(8). Fig.3 shows the theoretical and practical computations of Pd over different values of Pf for guassian signal.

The curves indicate that a Pd = 0.9 is achieved with Pf = 0.1 for -10Db SNR, whereas the detection probability decreases for -14 dB SNR. The results are also shown for 10 percent Pf in Fig. 4. In the next case, a QPSK signal is applied to attain an improved Pd = 0.99 as shown in fig. 5 and fig. 6 for Pf values of 0.1 and 0.01. By considering 10000 Monte Carlo simulations,the results were also generated for -12dB and -14dB SNRs as shown in Fig. 5 and Fig. 6. SNR wall is defined as the minimum value below which the detection is not possible. Fig. 9 shows the SNR wall upto which our QPSK signal is successfully detected is -13dB for false alarm rate of 0.1.Table 1 shows the published and proposed Energy detection sensing results of guassian and QPSK signal. At -10 dB, the Pd is improved from 0.9 to 0.99 with same Pf of 0.13. If the Pf is still reduced to 0.01, the detection probability has been decreased to 0.7 for guassian signal, whereas it remained the same for QPSK signal. At -14 dB Pd is decreased to 0.49 at Pf = 0.1 for guassian signal. This can be further increased to 0.9 for an increased Pf = 0.7. The Pd is proportionally decreasing even with the proposed QPSK signal but at a lesser rate. A Pd of 0.98 can be obtained for the same Pf of 0.7. The results are still decaying for low snr of -20dB as shown in the table1. A DVB-T signal is generated in simulink and applied to the algorithm. There are three specifications pertained to DVB-T signal namely bandwidth, mode and cyclic prefix length. The bandwidth of the signal may vary from 5MHz to 8MHz. There are two modes either 2k or 8k mode deciding the number of subcarriers used in coded OFDM modulation. The 2k mode assumes 2048 and 8k mode assumes 8192 subcarriers. A cyclic prefix is commonly used in the modulation to mitigate interference. We used 2k mode for our simulations. Fig. 10 shows the DVB-T signal with Resolution bandwidth of 6.7 MHz and a span of 9.14 MHz. The threshold(6) and probability of detection(8) derived in above section are used for simulation.

By increasing the number of samples from 256 to 4096, the SNR wall was increased from -6.6dB to -13dB. The SNR wall for detecting a DVB-T signal for L=4096 is shown in Fig. 11.

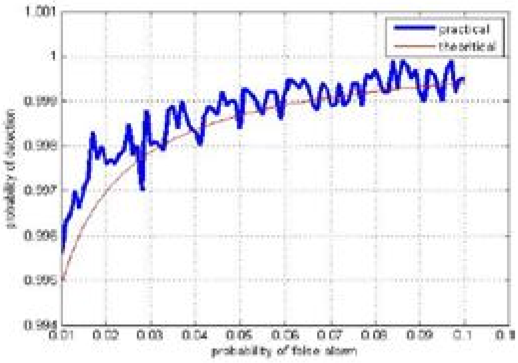

Fig. 6 Detection probability for QPSK signal with P_f = 0.01

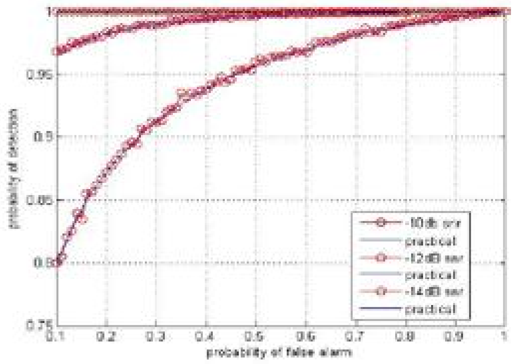

Fig. 7 Comparison of detection probability for QPSK signal at –10dB-12db and –14dB SNR with P_f = 0.1

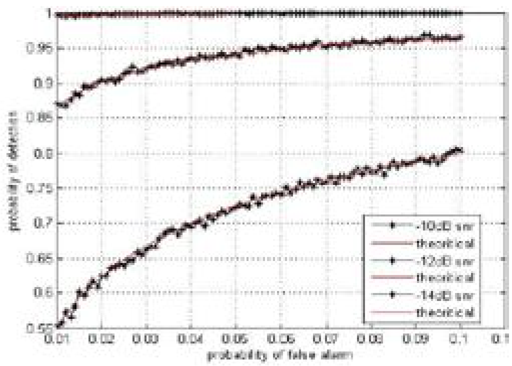

Fig. 8 Comparison of detection probability for QPSK signal at –10dB-12dB and –14dB SNR with P_f = 0.01

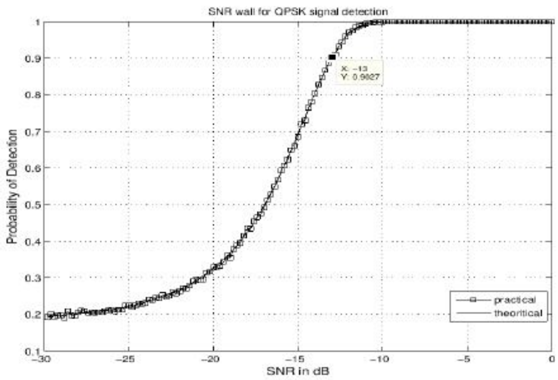

Fig. 9 Detection probability for QPSK signal with P_f = 0.1

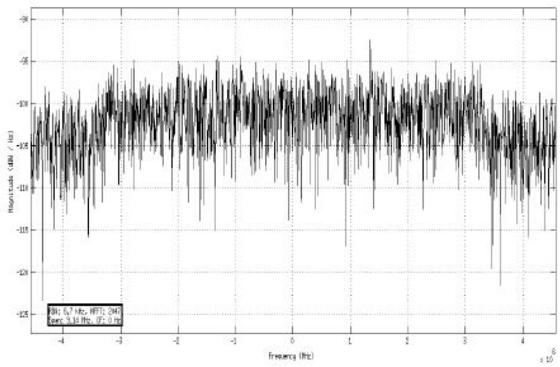

Fig. 10 DVB-T signal

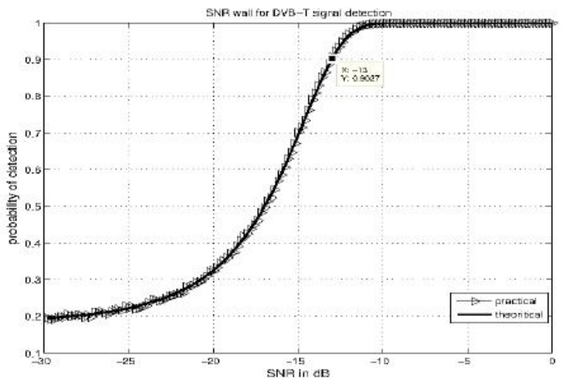

Fig. 11 Decision probability for DVB T-signal with P_f = 0.1

Table 2: shows the SNR walls for different values of L

No. of Samples (L)	SNR wall in dB
256	-6.6
512	-8.2
1024	-9.8
2048	-11.4
4096	-13

5. CONCLUSION

In this paper, the detection performance of Energy detection sensing is studied. The proposed sensing technique can be used to detect arbitrary signals with appropriate parameters of licensed signal. The detection threshold and probability of detection is derived based on [12]. The theoritical and practical results were verified using QPSK signal. The roposed energy detection sensing is tested with different values of Pf . The sensing performance was compared with real guassian signal. An improved Pd of 0.99 is obtained for a QPSK signal. Computer simulations have shown that a Pd of 0.99 is reached with a Pf of 0.1 at SNR of -10dB. The same detection probability was obtained even for less Pf of 0.01. The theoritical and practical values of Pd were shown for -12dB and -14dB SNR. An optimal Pd of 0.98 is attained for low SNR of -14dB. The proposed technique improves sensitivity by 4dB. The results of this paper show that Energy detection is a simple and efficient sensing technique which does not need any prior information of the signal.

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