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Detection of Untenanted Spectrum in Cognitive Radio Using Non Cooperative Spectrum Sensing

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***Abstract*—** Cognitive radio (CR) technology is a new way to compensate the spectrum shortage problem of wireless environment.This work explores the implementation of Non Cooperative Spectrum Sensing using blind detection technique to detect whether the primary user (PU) signals is present or not in the tested channel. In this technique, estimated energy of the received signal is compared with threshold (predefined) value by using decision rule.Simulation results show that the probability of detection increases when signal to noise ratio increases and also probability of detection will increases in the decrease of probability of false alarm detection.

***Keywords*—** Primary User, predefined value, spectrum shortage, dynamic spectrum access

I. Introduction

Due to increasing spectrum demand for new wireless communication applications, the available radio frequency spectrum has become scarce. Government agencies assign the spectrum to licensed users on a long term basis to avoid interference among wireless systems. Some band of spectrum remains largely underutilized; some are sparingly utilized, while the remaining bands of the spectrum are heavily occupied. It is recognized that this kind of static allocation policy has resulted in poor spectrum utilization, and created a severe shortage of spectrum for unlicensed users. Furthermore, spectrum underutilization by licensed users exacerbates spectrum scarcity [3].

The main reason of spectrum underutilization is that licensed users typically do not fully utilize their allocated bandwidths for most of the time, while unlicensed users are being starved for spectrum availability [3]. To deal with this dilemma, cognitive radio is a paradigm created in an attempt to enhance spectrum utilization, by allowing unlicensed users to coexist with licensed users and make use of the spectrum holes. In this paper, we propose Non cooperative spectrum sensing using energy detection technique to address these challenging issues. The main objective of this work is to prevent the interference with primary Users and also identifies the available white spaces to lift the spectrum utilisation. The cognition processes which carry out the activities of primary user after sensing, the function of spectrum management is started to take decision about the medium as shown in Fig 1

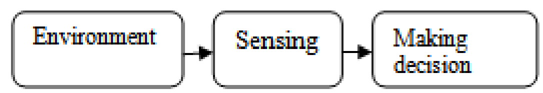

Fig.1Block diagram of Cognition process

Thispaper isorganised as follows: Section II explores problem formulation, energy detection system model and its performance under AWGN channel. Section III deals our practical work, which builds a CR prototype using energy detector based sensing model. The results are thoroughly investigated and analysed. Section IV gives the performance evaluation of energy detection techniques using ROC curves. Section Vgives the conclusions and future work and directions of the cognitive radio technology.

II. Problem FormulATION

Spectrum sensing is based on well-known called signal detection. In nutshell, signal detection can be described as a method for identifying the presence of a signal in a noisy environment. Analytically, signal detection can be reduced to a simple identification problem, formalized as a hypothesis test [1]

$Y(k)=n(k)$ $\quad H_0 \quad (1)$

$Y(k)=s(k)+n(k)$ $\quad H_1 \quad (2)$

Where,

$Y(k)$ is the sample to be analyzed at each instant k , $k=1,2,\ldots\ldots,N$

$n(k)$ is the noise(not necessarily white Gaussian noise) of variance σ^2.

$s(k)$ is the primary user(PU) signal which the network wants to detect.

H_0 and H_1 are the noise-only and signal-plus-noise hypothesis, respectively.

H_0 and H_1 are the sensed states for the absence and presence of PU signal, respectively. Then, as shown in Fig. 2.2 we can define four possible cases for the detected signal:

1. Probability of Deciding H_0 when H_0 is true $P(H_0|H_0)$
2. Probability of Deciding H_1 when H_1 is true $P(H_1|H_1)$
3. Probability of Deciding H_0 when H_1 is true $P(H_0|H_1)$

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4. Probability of Deciding H_1 when H_0 is true $P(H_1|H_0)$

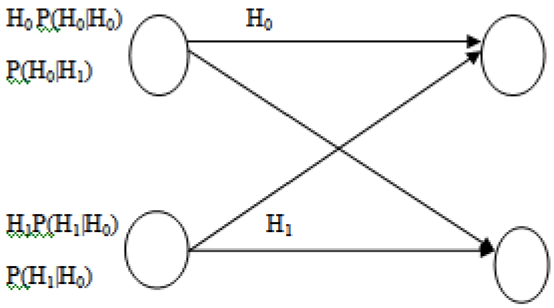

Fig 2Hypothesis test and possible outcomes with their corresponding probabilities

Cases 1 and 2 are known as a probability of correct detection, whereas cases 3 and 4 are known as a probability of missed detection (P_{MD}) and a probability of a false alarm (P_{FA}), respectively.

The performance of the spectrum-sensing technique is usually influenced by the probability of false alarm $P_{FA} = P(H_1|H_0)$, because this is the most influential metric. Usually, the performance is presented by receiver operation characteristic (ROC) curves, which plot the probability of detection $P_D = P(H_1|H_1)$ as a function of the probability of false alarm P_{FA}. Where $P_D=1-P_{MD}$. [1].

III. Non Cooperative Spectrum Sensing

In a realistic spectrum-sensing scenario, there are situations in which only one sensing terminal is available or in which no cooperation is allowed due to the lack of communication between sensing terminals.

The energy detection (ED) is the most popular spectrum sensing method since it is simple to implement and does not require any prior information about the primary signal. In practice, the energy detection is especially suitable for wideband spectrum sensing.

In energy detection, we compare the energy of some collected samples with predefined threshold (denoted as λ). If the energy exceeds the threshold, we say there is a signal transmitting in the channel; otherwise the channel is deemed as quiet. Where, the threshold Z is derived from the statistics of the noise (σ^2).

Let Y(k) be a sequence of received samples at the signal detector where k={0,1,2,…..,N},

The decision rule can be stated as:

$$\begin{cases} H_0, & \text{If } M > \lambda \\ H_1, & \text{If } M < \lambda \end{cases}$$

Where,

M is the estimated energy of the received samples.

λ is the threshold which chosen to be the noise variance (σ^2)

$$M = \frac{1}{N}\sum_{k=1}^{N}\left|y(k)\right|^2 \quad (3)$$

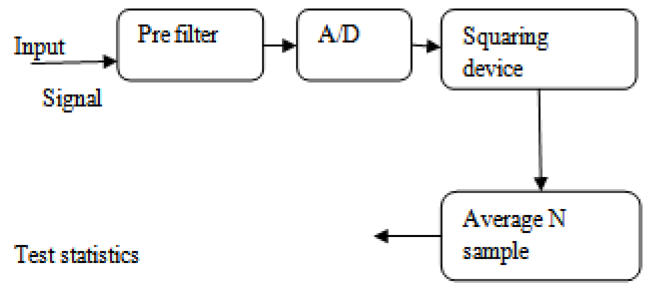

Fig.3: Block diagram of energy detection model

Figure 3.illustrates the general block diagram of the energy detector of the signal preserved in both time domain and frequency domain. Theoretically, whichever representation is used for signal detection and analysis makes no difference in result. But in time domain representation, for a given bandwidth signal, a pre-filter matched to the bandwidth of the signal needs to be applied. These need make this representation quite inflexible compared to the frequency domain representation, particularly in the case of narrowband signals and sine-waves. Therefore, it is intended to use the second representation in near future for analyzing the received signal via simulation.

We will consider second representation where,

A/D: converts the received signals to samples

FFT: gets the frequency domain of the received samples

Square device: takes the squared-magnitude of the FFT points to get the power spectral density. Then, taking the average and compare the results with a predefined threshold (calculated from noise variance).

The proposed model shows a primary user where each message is modulated by using amplitude modulation. However, PU’s signal is transmitted through additive white Gaussian noise (AWGN) channel in the Environment block**,** but it’s first multiplied with gain (gain=5 dB).This gain represents the PU antenna gain.

Periodogram method is used to estimate the power spectral density of the transmitted signal by using Fast Fourier Transform analysis. Firstly, N points from the received samples to be analyzed using Buffer(choosing buffer size=512) are taken, where the buffer size is exactly proportional to sensing time. The signal is converted from time domain to the frequency domain by the FFT block. The required band of frequencies is allowed by a hamming window. The magnitude of the received signal is then taken and it is squared also through the FFT block. The power spectral density of the signal is obtained by vector scope. Computation energy of the received signal is done by calculating the mean value along with specified dimension of the input. The result is visualised in the display**.** The value is expressed in dB, by taking log (base 10) using mathfunction block, then multiplying it with gain=10.

IV. PERFORMANCE UNDER AWGN CHANNEL

The performance of any detection algorithms is measured by a pair of detection and false alarm probabilities (P_D,P_{FA}). Each pair is associated with a particular threshold λ, representing the Receiver Operating Characteristics (ROC)

Where,

$P_D = P_r(M > \lambda \mid H_1)$ (4)

$P_{FA} = P_r(M > \lambda \mid H_0)$ (5)

Now we want to derive the probability of detection P_D and probability of false alarm P_{FA} under the assumption of additive white Gaussian noise channel [1].

At the noise only case H_0

$$M = \frac{1}{N}\sum_{k=1}^{N}\left|n(k)\right|^2$$

The noise n(k) follows a Gaussian distribution with zero mean and variance σ^2. *Y* can be viewed as the sum of the squares of 2*N* standard Gaussian varieties with zero mean and unit variance. Therefore, the decision statistics *M* follows a central chi-square $\chi 2$ distribution with 2N degrees of freedom [9].

Therefore, the probability density function will be:

$$f_M(y) = \frac{y^{N-1}e^{-y/2}}{2^N\Gamma(N)} \quad (6)$$

Where Γ is gamma function. Hence, the probability of false alarm is given by

$P_{FA} = P_r(M > \lambda \mid H_0)$

$$= \int_{\lambda}^{\infty} f_M(y)dy$$

$$= \int_{\lambda}^{\infty} \frac{y^{N-1}e^{-y/2}}{2^N\Gamma(N)}$$

Let y/2=u, dy=2du, then the limit of integration will be changed. Hence,

$$P_{FA} = \frac{1}{\Gamma(N)}\int_{\lambda/2}^{\infty} u^{n-1}e^{-u}du \quad (7)$$

Therefore, by the definition of incomplete gamma function, we have

$P_{FA} = 1-\Gamma(N, \lambda/2)$ (8)

from equation (8) we can get expression for theoretical threshold, where

$$\lambda = 2\Gamma^{-1}(1-P_{FA}, N) \quad (9)$$

$P_D = P_r(M > \lambda \mid H_1)$

$$= \int_{N}^{\infty}\frac{1}{2}\left(\frac{y}{2\Upsilon}\right)^{\frac{N-1}{2}}\exp\left(\frac{-(y+2\gamma)}{2}\right)I_{N-1}\left(\sqrt{2\gamma y}\right)dy \quad (10)$$

V. RESULT AND DISCUSSION

Table 1 gives the parameter used for Non cooperative spectrum sensing. The primary user is assumed to be frequency of 9 kHz. Sub block of Environment block shown in table 2

Table 1 Block Parameter values of Noncooperative spectrum sensing.

PARAMETER	**VALUES**	**BLOCK**
Operating frequency	9 kHz	carrier signal
Antenna Gain	1.5dB	environment
SNR	15dB	AWGN block
Buffer size	512 points	buffer block
FFT length	512 points	FFT block
Window function	Hamming	window function

Table 2 Sub block parameter values of Environment block

Parameter	Values
Sampling time	1/e^5
Input signal power	1 watt
Initial speed	67
SNR	10(dB)

Fig. 4shows the Power Spectral Density (PSD) of the received signal, in that the frequency peak for primary user, which implies that PU is present. And also the power spectral density of noise is considered to be the threshold shown in Fig. 5

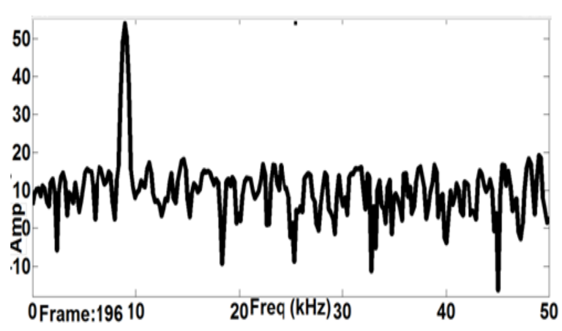

Fig. 4Power spectral density of transmitted signal

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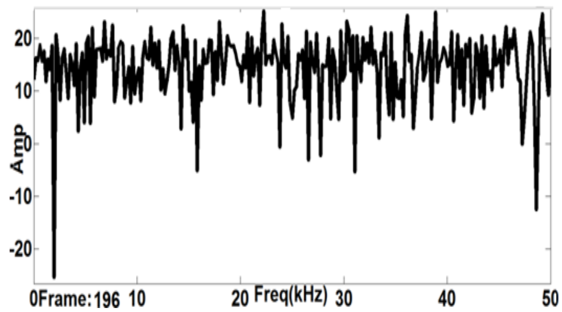

Fig. 5PSD of noise

Effect of SNR is shown in the further figures, Fig 6, 7, 8 represents PSD of the received signal when SNR value is 0dB, -20 dB and -40dB respectively. Figures 7and 8 show the PSD of received signal when SNR is -20 dB and -40 dB, reflecting that the signal becomes more distorted when SNR is as low as -20 dB than when it is -10 dB, proving that when SNR values become low, it leads to distortion of signals and hence increasing the P_{fa}, as well as degrading the $P_{d,}$ i.e., the performance of the energy detector degrades as the value of SNR falls down.

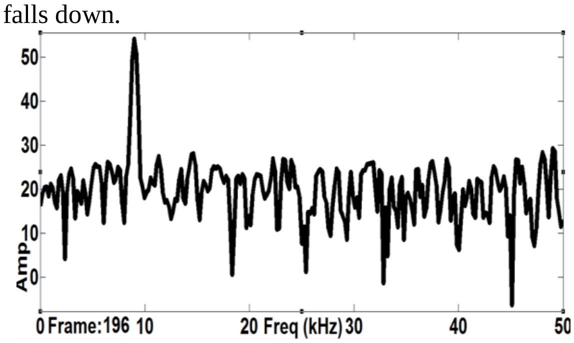

Fig.6 PSD of received signal at SNR=0 dB

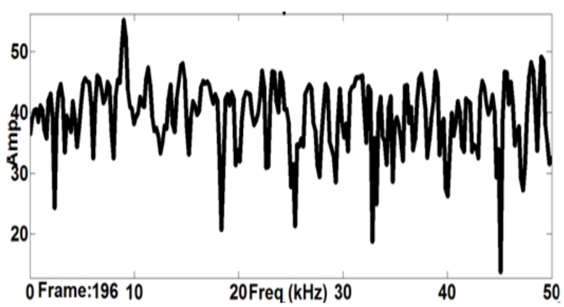

Fig. 7PSD of received signal at SNR=-20 dB

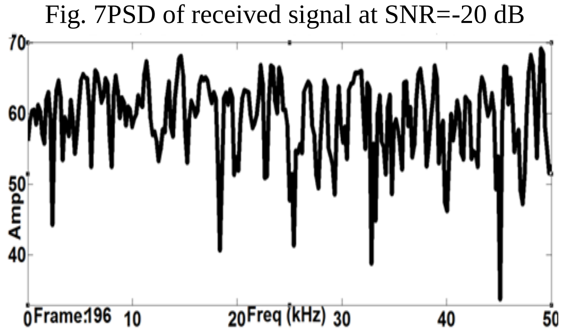

Fig 8 PSD of received signal at SNR=-40dB

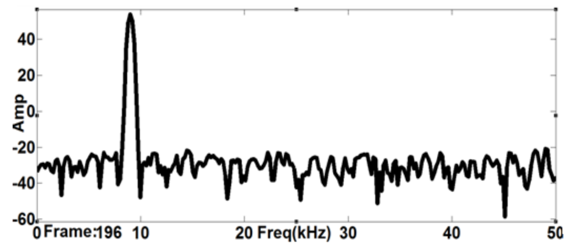

Fig. 9 PSD of received signal at SNR=50dB

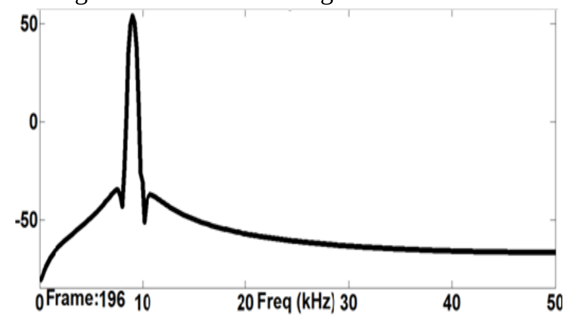

Fig. 10PSD of received signal at SNR=200dB

Another parameter that may affect on performance of energy detectors is buffer size. Buffer size is exactly proportional to sensing time. The previous measurements taking number of samples is equal to N=1024. If we make N=128 points at SNR=0dB, the power spectral density as shown in Fig. 10When the sample number is low, it's more difficult to get the actual PSD of the signal which is extremely distorted. In addition, it is more difficult to estimate the energy around the interested channel carrier frequency.

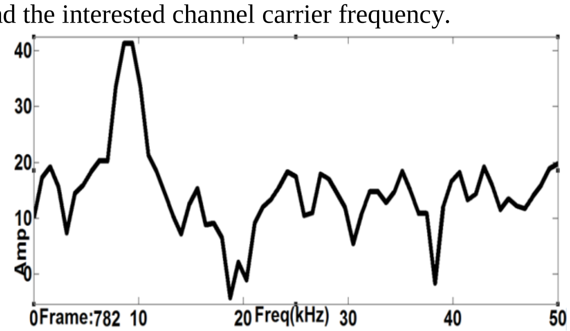

Fig 11 PSD of received signal at N=128, SNR=0dB

At the end, in the presence of PU signal and SNR and buffer size are large enough, the energy of PU signal is estimated, and it will be greater than the noise energy. The detection performance of the energy detector in the additive white gaussian noise channel is plotted by (C-ROC) curve.The Fig.12 shows the C-ROC curves for the energy detector for various values of signal to noise ratio levels. Fig.13 represents the relationship between probability of detection and false alarm detection.

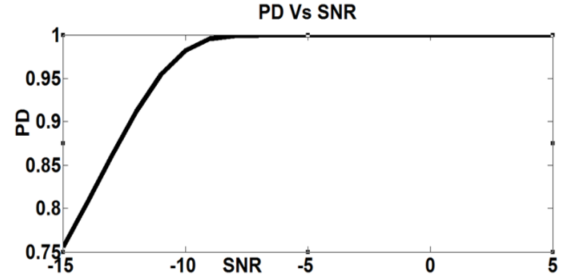

Fig 12 Probability of Detection Vs Signal to Noise ratio

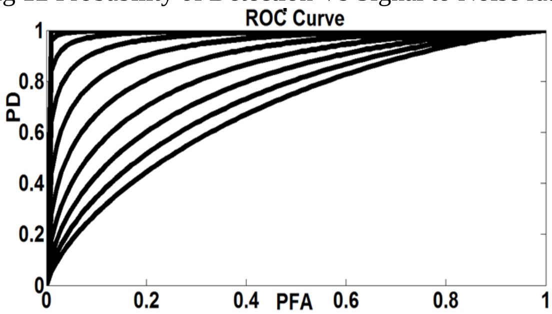

Fig 13ROC curve (N=1000)

Table 3explains when values of SNR are increased, then there is a dramatically increases in the probability of detection.

SNR(dB)	-15	-13	-12.5	-10	-5
P_d(%)	0.75	0.8	0.9	0.95	1

VI. Conclusion and Future Scope

Cognitive radio was introduced to utilize the unused spectrum efficiently to improve the spectrum utilization and hence to reduce spectrum scarcity. Non cooperative spectrum sensing is implemented using energy detection method which is discussed in detail. The energy detection method of spectrum sensing has its advantages as it is simple and easy to implement. Since no previous information about the signal is required for detection, it is also known as semi blind spectrum sensing. This will help in increasing the efficiency of spectrum utilisation without wasting unnecessary time and also reduce the cost. Simulation results found that it performs well only at high SNR values.

In future this work can be done by combine both methods to obtain the best performance at low cost and also detecting the malicious user in the cognitive radio network and minimising their effect.

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