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Spectrum Sensing based on Energy Detection in Cognitive Radio

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Abstract-In cognitive radio networks, dynamic spectrum access allows an unlicensed (secondary) user to use the frequency bands that are statically allocated to licensed (primary) users under condition of causing no harm to the primary transmission. For the process of the dynamic spectrum access to succeed, spectrum sensing becomes of great importance for the secondary user to capture the under-utilized frequency bands. In this paper the energy detection technique for spectrum sensing is investigated and the sensing throughput tradeoff for cognitive radio systems is examined. Receiver operating characteristic curve is used to examine the relation between probability of detection and false alarms for the Cognitive Radio. Probability of detection and probability of false alarm are the important factors used in this paper to evaluate this technique.

***Index Terms*-Cognitive Radio, Energy Detection, probability of detection, probability of false alarm.**

I. INTRODUCTION

Cognitive Radio (CR) is a system/model for wireless communication. It is built on software defined radio for Personal Communication Services (PCS) [1]. It uses the methodology of sensing and learning from the environment and adapting to statistical variations in real time. The network or wireless node changes its transmission or reception parameters to communicate efficiently anywhere and anytime avoiding interference with licensed or unlicensed users for efficient utilization of the radio spectrum [2].

CR arises to be a tempting solution to spectral crowding problem by introducing the opportunistic usage of frequency bands that are not heavily occupied by licensed users since they cannot be utilized by users other than the license owners at the moment [3]. Figure 1 shows a typical cognitive scenario in which the central unit coordinates for collecting the sensing information from cognitive devices in the centralized sensing. It directly controls the CR traffic by recognizing the vacant spectrum and broadcasts this information to other CRs [4-5].

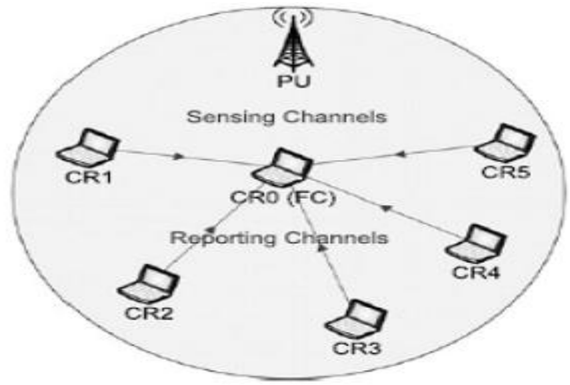

Fig 1: Centralized cooperative sensing

II. KEY BENEFITS OF COGNITIVE RADIO

Cognitive Radio offers optimal diversity (in frequency, power, modulation, coding, space, time, polarization and so on) which leads to:

- Spectrum Efficiency
- Higher bandwidth services
- Graceful Degradation of Services
- Improved Quality of Service (QoS)
- Commercial Exploitation
- Benefits to the Service
- Future-proofed product
- Common hardware platform
- Flexible regulation
- Emergency service communications
- Benefits to the Licensee

III. NEED OF SPECTRUM SENSING

The overcrowding of unlicensed frequency bands, given the underutilization of licensed bands has motivated research in cognitive networks. It is projected that cognitive networks will improve the efficient use of licensed spectrum by allowing SU and PU to coexist. The Federal Communications Commission (FCC) 2002 report on TV and Cellular communications reports that these bands are either unoccupied or underutilized [2] which calls for efficient techniques to harness the unused

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spectrum. Furthermore cognitive radio prototypes, capable of sensing spectrum holes in TV bands, have been designed [7]. The research community is also collaborating towards the implementation of a cognitive network standard, the IEEE 802.22, Wireless Regional Network [5]. Thus, the coexistence of PUs and SUs is feasible.

The efficiency of spectrum sensing has been identified as one of the performance metrics of cognitive networks. Spectrum sensing requires optimization to reduce false alarms while availing large portions of whitespaces [8] for data transmission. The need to optimize the sensing and transmission times is discussed in [9]. In [10], the capability of the infrastructure-based cognitive networks is contrasted to the infrastructure-less cognitive networks.

The existing spectrum sensing techniques can be broadly divided into three categories [11]: energy detection, matched filter detection, and cyclostationary detection. Matched filter [12] [13], energy detection [14] [15] and cyclostationary detection are widely used techniques as detection techniques. Among them, energy detection has been widely applied since it does not require any a prior knowledge of the primary signals and has much lower complexity than the other two schemes. In addition, it does not need any prior information about the PUs' signals. Therefore, it has been thoroughly studied both in local spectrum sensing. The matched-filter-based detection is the optional way for any signal detection [13]. A significant drawback of the matched filter-based detection is that a cognitive radio would need a dedicated receiver for every primary user class.

Cyclostationary feature detection method is recognized as a more effective way for the detection of very weak signals in a background of noise [4]. The computational complexity of cyclostationary feature detection needs further researches. Energy detection is a sub-optional technique which performs non-coherent detection. In this paper, we focus on the energy detection based spectrum sensing for cognitive radio. The performance of energy detection is analyzed under noise uncertainty. Simulation and analysis shows the great benefits of the proposed scheme.

IV. ENERGY DETECTION BASED SPECTRUM SENSING

Energy Detection is the most common way of spectrum sensing because of its low computational and implementation complexities. It is a more generic method as the receivers do not need any knowledge on the primary user's signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. The received signal sample of a secondary user can be represented as

$$Y(n)=\begin{cases} w(n); user & H0 \\ h(n)s(n)+w(n); & H1 \end{cases}$$

Where n denotes the sample index, h(n) denotes the impulse response of the channel between the primary and secondary users, s(n) is the signal from the primary user, w(n) denotes zero-mean additive white Gaussian noise and H_0 and H_1 represent hypothesis corresponding to the absence and presence of the primary user's signal, respectively. We consider the use of an energy detection for the spectrum sensing. Then, the probability of false alarm and probability of detection for the energy detector can be represented as

$$P_f=Q((\gamma-\sigma_n^2)/(2\sigma^4{}_n/N)^{1/2})$$

$$P_d=Q((\gamma-(p+\sigma^2{}_n))/(2(p+\sigma^2{}_n)^2/N)^{1/2})$$

Where N is the number of samples, Q is the standard Gaussian complementary cumulative distribution function,p is the average signal power, $\sigma^2{}_n$ is the noise variance and γ is the threshold level to be determined. The important challenge with the energy detector based sensing is the selection of the threshold for detecting primary users [16]. The other challenges include inability to differentiate interference from primary users and noise and poor performance under low signal-to-noise ratio values. P_d (probability of detection) and P_f (probability of false alarm) are the important factors for energy based detection which gives the information of the availability of the spectrum [17-19].

V. RESULTS AND DISCUSSION

A MATLAB code is used to plot receiver operating characteristic (ROC) curve for simple energy detection, when the primary signal is real Gaussian signal and noise is Additive White Real Gaussian in Fig. 2. Another case is considered when the primary

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user is a BPSK modulated signal. The ROC in this case is shown in Fig. 3. ROC is a plot of the true positive rate against the false positive rate for the different possible cut points. The closer the curve follows the left-hand

border and then the top border of the ROC space, tends to more accurate results. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test. In this case, the curve has shifted towards left axis i.e. probability of detection which proves the wellness of our algorithm. Figure 3 shows the relation between probability of detection and signal to noise ratio for a BPSK modulated user. It is evident from the graph that P_d increases with an increase in SNR. Some numerical values from the graph are shown in Table 1.

Table 1: numerical values of Probability of false alarm v/s Probability of detection

Probability of false alarm	Probability of detection
.1	0.4939
.2	0.6117
.3	0.6913
.4	0.753
.5	0.804
.6	0.8481
.7	0.8874
.8	0.9324
.9	0.958

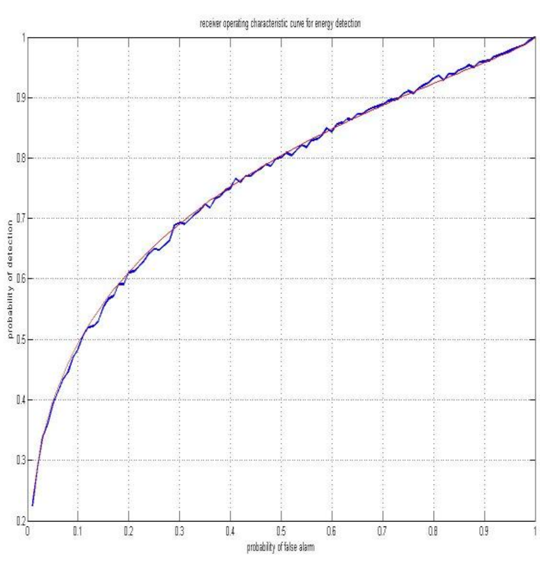

Fig 2: Receiver operating characteristic curve

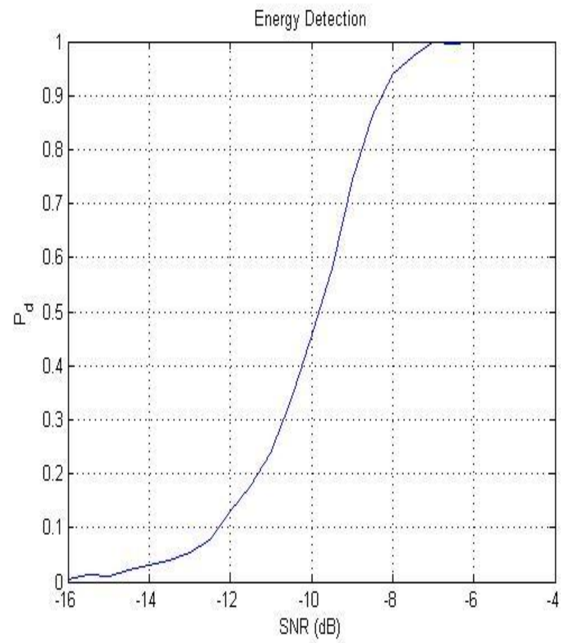

Fig 3: Receiver operating characteristic curve for BPSK modulated user

VI. CONCLUSION

In this paper, we have discussed spectrum sensing based on energy detection in CR networks. ROC curves are used to plots of the probability of detection v/s the probability of false alarm. Some theoretical background is provided for CRs. The probability of detection varies based on SNR and false alarm probability. We have discussed two different cases when the primary user is a pure Gaussian signal and in the other case, it is a BPSK modulated signal.

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