Spectrum sensing techniques and power control algorithm using power swarm optimization for cognitive radio

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Abstract—**The spectrum sensing problem has gained new aspects with cognitive radio and opportunistic spectrum access concepts.In this paper, an analytical study of spectrum sensing techniques for cognitive radio is presented. Various aspects of spectrum sensing problem are studied from a cognitive radio perspective. Results of spectrum sensing techniques like, energy detection, matched filter detection and cyclostationary feature detection are given. we have been solved the problem of optimal power allocation in cognitive radio systems. The proposed algorithm maximizes secondary networks' utilities that are based on SINR. The proposed approach is based on PSO (power swarm optimization) which is an evolutionary algorithm. Our approach is stable but generates superior results. In our future work, we will eliminate the base station and assume that each user can make a decision using local information.**

Keywords-**Cognitive radio, Spectrum sensing, Cyclostationary Feature detection, Energy detection, Matched filter detection, power swarm optimization.**

1. INTRODUCTION

Cognitive radio is an intelligence wireless communication system that allows unlicensed user to use spectrum without degrading quality of service of primary user. Cognitive radio is crucial device where primary user occupancy is less which lead]s to low spectrum efficiency. Cognitive radio provides unused frequencies to secondary users so that frequency appropriate spectrum efficiency is acquired. One of the most important components of the cognitive radio concept is the ability to measure, sense, learn, and be aware of the parameters related to the radio channel characteristics, availability of spectrum and power, radio's operating environment, user requirements and applications, available networks (infrastructures) and nodes, local policies and other operating restrictions. In cognitive radio terminology, primary users can be defined as the users who have higher priority or legacy rights on the usage of a specific part of the spectrum. On the other hand, secondary users, which have lower priority, exploit this spectrum in such a way that they do not cause interference to primary users. Therefore, secondary users need to have cognitive radio capabilities, such as sensing the spectrum reliably to check whether it is being used by a primary user and to change the radio parameters to exploit the unused part of the spectrum. Transmit power of secondary users in cognitive radio networks will inevitably introduce interference to primary users. Hence, a critical design challenge for cognitive radio is to establish a balance between transmit power and interference.

2. SPECTRUM SENSING METHODS FOR COGNITIVE RADIO

The present literature for spectrum sensing is still in its early stages of development. A number of different methods are proposed for identifying the presence of signal transmissions. In some approaches, characteristics of the identified transmission are detected for deciding the signal transmission as well as identifying the signal type. In this section, some of the most common spectrum sensing techniques in the cognitive radio literature are explained.

2.1. Energy Detection Based Sensing

Energy detector based approach, also known periodogram, is the most common way of spectrum sensing because of its low computational and implementation complexities. In addition, it is more generic (as compared to methods given in this section) as receivers do not need any knowledge on the primary users' signal. The signal is detected by comparing the output of the energy detector with a threshold which depends on the noise floor. Some of the challenges with energy detector based sensing include selection of the threshold for detecting primary users, inability to differentiate interference from primary users and noise, and poor performance under low signal-to-noise ratio (SNR) values. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals.

Let us assume that the received signal has the following simple form

$$y(n) = s(n) + w(n) \tag{1}$$

where s(n) is the signal to be detected, w(n) is the additive white Gaussian noise (AWGN) sample, and n is the sample index. Note that s(n)=0 when there is no transmission by primary user. The decision metric for the energy detector can be written as

$$M=\sum_{n=0}^{N} |y(n)|^2 \tag{2}$$

where N is the size of the observation vector. The decision on the occupancy of a band can be obtained by comparing the decision metric M against a fixed threshold λ_E. This is equivalent to distinguishing between the following two hypotheses:

$$H_0 : y(n) = w(n) \tag{3}$$
$$H_1 : y(n) = s(n)+w(n) \tag{4}$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection P_D and probability of false alarm P_F. P_D is the probability of detecting a signal on the considered frequency when it truly is present. Thus, a large detection probability is desired. It can be formulated as

$$P_D = P_r(M > \lambda_E | H_1) . \tag{5}$$

P_F is the probability that the test incorrectly decides that the considered frequency is occupied when it actually is not, and it can be written as

$$P_F = P_r(M > \lambda_E | H_0) . \tag{6}$$

P_F should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λ_E can be selected for finding an optimum balance between P_D and PF. However, this requires knowledge of noise and detected signal powers. The noise power can be estimated, but the signal power is difficult to estimate as it changes depending on ongoing transmission characteristics and the distance between the cognitive radio and primary user. In practice, the threshold is chosen to obtain a certain false alarm rate. Hence, knowledge of noise variance is sufficient for selection of a threshold.

The white noise can be modeled as a zero-mean Gaussian random variable with variance $\sigma_w,^2$ i.e. $w(n) = N(0,\sigma^2_w)$. For a simplified analysis, let us model the signal term as a zero-mean Gaussian variable as well,i.e. $s(n)=N(0,\sigma_s^2)$.The model for s(n) is more complicated as fading should also be considered. Because of these assumptions, the decision metric (2) follows chi-square distribution with 2N degrees of freedom χ^{2N} and hence, it can be modeled as

$$M = \begin{cases} \frac{\sigma_w^2}{2}\chi^2_{2N} & H_0 \\ \frac{\sigma_w^2+\sigma_s^2}{2}\chi^2_{2N} & H_1 \end{cases} \tag{7}$$

For energy detector, the probabilities P_F and P_D can be calculated as

$$P_F = 1 - \Gamma(L_f L_t, \frac{\lambda_E}{\sigma_w^2}) \tag{8}$$
$$P_D = 1 - \Gamma(L_f L_t, \frac{\lambda_E}{\sigma_w^2+\sigma_s^2}) \tag{9}$$

Where λ_E is the decision threshold, and $\Gamma(a, x)$ is the incomplete gamma function. In order to compare the performances for different threshold values, receiver operating characteristic (ROC) curves can be used. ROC curves allow us to explore the relationship between the sensitivity (probability of detection) and specificity (false alarm rate) of a sensing method for a variety of different thresholds, thus allowing the determination of an optimal threshold..

The threshold used in energy detector based sensing algorithms depends on the noise variance. Consequently, a small noise power estimation error causes significant performance loss .As a solution to this problem, noise level is estimated dynamically by separating the noise and signal subspaces using multiple signal classification (MUSIC) algorithm. Noise variance is obtained as the smallest eigen value of the incoming signal's autocorrelation. Then, the estimated value is used to choose the threshold for satisfying a constant false alarm rate. An iterative algorithm is proposed to find the decision threshold. The threshold is found iteratively to satisfy a given confidence level ,i.e. probability of false alarm. Forward methods based on energy measurements are studied for unknown noise power scenarios. The proposed method adaptively estimates the noise level. Therefore, it is suitable for practical cases where noise variance is not known.

Measurement results are analyzed using energy detector to identify the idle and busy periods of WLAN channels. The energy level for each global system for mobile communications (GSM) slot is measured and compared for identifying the idle slots for exploitation. The sensing task in this work is different in the sense that cognitive radio has to be synchronized to the primary user network and the sensing time is limited to slot duration.The power level at the output of fast Fourier transform (FFT) of an incoming signal is compared with a threshold value in order to identify the used TV channels. FFT is performed on the data sampled at 45 kHz around the centered TV carrier frequency for each TV channel. The performance of energy detector based sensing over various fading channels is investigated. Closed-form expressions for probability of detection under AWGN and fading (Rayleigh, Nakagami, and Ricean) channels are derived. Average probability of detection for energy detector based sensing algorithms under Rayleigh fading channels is derived. The effect of log-normal shadowing is obtained via numerical evaluation in the same paper. It is observed that the performance of energy-detector degrades considerably under Rayleigh fading.

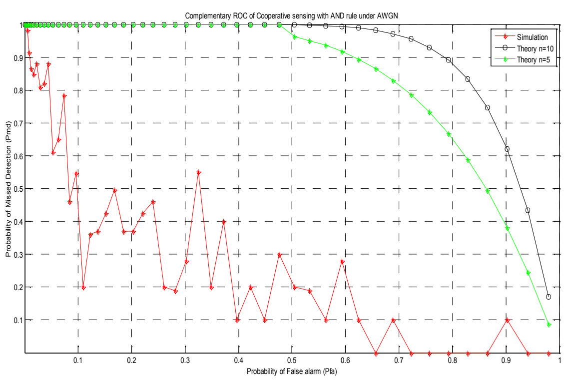

Figure 1 Complementary ROC of Cooperative sensing under AWGN channel

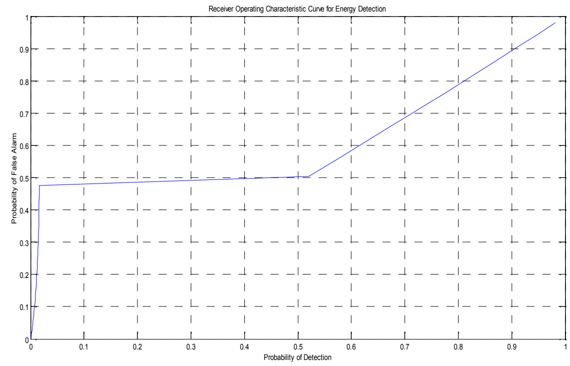

Figure 2 ROC of Energy detection

2.2. Cyclostationarity-Based Sensing

Cyclostationarity feature detection is a method for detecting primary user transmissions by exploiting the cyclostationarity features of the received signals. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing Instead of power spectral density (PSD), cyclic correlation function is used for detecting signals present in a given spectrum. The cyclostationarity based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities. Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users.

The cyclic spectral density (CSD) function of a received signal (1) can be calculated as

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^{\alpha}(\tau) e^{-j2\pi f\tau} \qquad (10)$$

where

$$R_y^{\alpha}(\tau) = E[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n}] \qquad (11)$$

is the cyclic autocorrelation function (CAF) and α is the cyclic frequency. The CSD function outputs peak values when the cyclic frequency is equal to the fundamental frequencies of transmitted signal x(n). Cyclic frequencies can be assumed to be known or they can be extracted and used as features for identifying transmitted signals.

The OFDM waveform is altered before transmission in order to generate system specific signatures or cycle-frequencies at certain frequencies. These signatures are then used to provide an effective signal classification mechanism. The number of features generated in the signal is increased in order to increase the robustness against multipath fading. However, this comes at the expense of increased overhead and bandwidth loss.

2.3. Matched-Filtering

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of miss detection as compared to other methods that are discussed in this section. In fact, the required number of samples grows as O(1/SNR) for a target probability of false alarm at low SNRs for matched-filtering. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signaling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format. Moreover, since cognitive radio needs receivers for all signal types, the implementation complexity of sensing unit is impractically large. Another disadvantage of match filtering is large power consumption as various receiver algorithms need to be executed for detection.

3 POWER CONTROL

The majority of power-control works have focused on devising policies for cellular networks where satisfying a QoS constraint is a premium. In such a framework, transmitters increase power to cope with channel impairments and increasing levels of interference in an inconsiderate and competitive manner. Within the spectrum sharing framework, a network will strongly oppose of secondary users transmitting with arbitrarily high power and interfering with the QoS of the primary users. Such intrusion clearly violates the sense of the primary users' QoS being oblivious to the presence of the secondary users. Haykin introduces and advocates the notion of interference temperature as being critical in decision making within a cognitive radio network. It appears natural that power allocation decisions should rely on interference levels. What is not as obvious is the differing dynamics of primary network users and secondary network users in response to their respective perceived interference levels. We shall discuss the necessity of interference-aware power control for users in a cognitive radio paradigm. Due to the existence of two classes of users, primary and secondary, the traditional problem of interference management through power control is different from that of cellular systems and ad hoc networks. Duo Priority Class Power Control (DPCPC) policies can protect primary users from the entrance of secondary users, provide opportunism to secondary users, and prevent the most adverse types of admission errors is presented. Autonomous Interference aware Power Control (AIPC), which belongs to the general class of DPCPC policies. Furthermore, the algorithm supports our notion of versatility and provides a licensing mechanism among users.

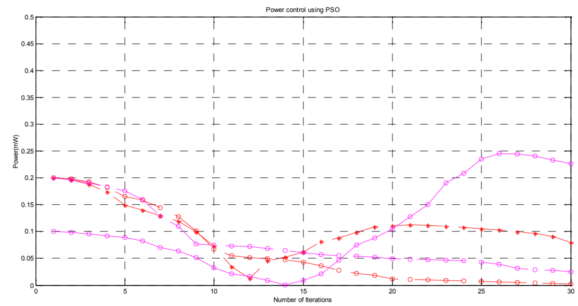

Figure 6 MATLAB simulation of Power control algorithm for 1 PU and 4 SU using PSO

4 CONCLUSION

Spectrum is a very valuable resource in wireless communication systems, and it has been a focal point for research and development efforts over the last several decades. Cognitive radio, which is one of the efforts to utilize the available spectrum more efficiently through opportunistic spectrum us-age, has become an exciting and promising concept. One of the important elements of cognitive radio is sensing the available spectrum opportunities. Various aspects of the spectrum sensing task are explained in detail. Several sensing methods are studied. Also, we have been studied the problem of optimal power allocation in cognitive radio systems. The PSO algorithm maximizes secondary networks' utilities that are based on SINR. The proposed approach is based on PSO which is an evolutionary algorithm. Our approach is stable but generate superior results.

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