



NOVEL SPECTRUM SENSING AND ALLOCATION USING COGNITIVE RADIO AD HOC NETWORKS

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ABSTRACT: A cognitive radio is a radio that can change its transmitter parameters based on interaction with the environment in which it operates. If the primary base station is busy or it is in congestion, the spectrum sensing and allocation will become difficult to perform. In order to avoid this cognitive radio based on ad hoc networks is introduced. In this the communication among the devices is performed without the support of the fixed component. The secondary users will allocate the channels within themselves. Cooperative spectrum sensing is usually employed to achieve accuracy and improve reliability, but at the cost of cooperation overhead among CR users. This overhead can be reduced by improving local spectrum sensing accuracy. Several signal processing techniques for transmitter detection have been proposed in the literature but more sophisticated approaches are needed to enhance sensing efficiency. This article proposes a two-stage local spectrum sensing approach. In the first stage, each CR performs existing spectrum sensing techniques, i.e., energy detection, matched filter detection, and cyclostationary detection. In the second stage, the output from each technique is combined using fuzzy logic in order to deduce the presence or absence of a primary transmitter. Simulation results verify that our proposed technique outperforms existing local spectrum sensing techniques.

Keywords: Cognitive radio, Spectrum sensing, Primary user, Secondary user, Cooperative spectrum

1. INTRODUCTION

The wireless communication systems are making the transition from wireless telephony to interactive internet data and multi-media type of applications, for desired higher data rate transmission. As more and more devices go wireless, it is not hard to imagine that future technologies will face spectral crowding, and coexistence of wireless devices will be a major issue. Considering the limited bandwidth availability, accommodating the demand for higher capacity and data rates is a challenging task, requiring innovative technologies that can offer new ways of exploiting the available radio spectrum. Cognitive radio is the exciting technologies that offer new approaches to the spectrum usage. Cognitive radio is a novel

concept for future wireless communications, and it has been gaining significant interest among the academia, industry, and regulatory bodies.

Cognitive Radio provides a tempting solution to spectral crowding problem by introducing the opportunistic usage of frequency

bands that are not heavily occupied by their licensed users. Cognitive radio concept proposes to furnish the radio systems with the abilities to measure and be aware of parameters related to the radio channel characteristics, availability of spectrum and power, interference and noise temperature, available networks, nodes, and infrastructures, as well as local policies and other operating restrictions.



2. RELATED STUDY

Spectrum sensing plays a critical role for the efficient utilization of the radio spectrum. Researchers currently focus on two major aspects in spectrum sensing: (1) how to improve local sensing results and (2) cooperative spectrum sensing for better data fusion results.

Cooperative spectrum sensing is a two-stage process composed of (1) local sensing and (2) fusion of local sensing results. In the first stage, each SU sniffs the spectrum and deduces the presence or absence of PU. In

the second stage, local decisions of multiple users are

fused together for making the final decision on whether

a PU is absent or present. For improving cooperative sensing, researchers focus on how to optimally fuse local

sensing results. Several optimal fusion schemes for cooperative spectrum sensing have been summarized in [6]. Although fusion rules may improve the final decision, the decision is highly dependent on the result of the first stage.

Therefore, improving the first stage can improve cooperation results. Researchers have recently

focused on how to achieve reliable results with less mean sensing time. The most promising reforms applied to local spectrum sensing are:

using multiple antennas, using two-stage sensing schemes, and improving existing techniques. In [9,10], the improvement of the sensing performance of energy detection is

achieved using multiple antennas at the sensing node. In [11-14], two-stage spectrum sensing techniques are explored, in which the first stage

involves coarse sensing and the second one involves fine sensing. In the majority of two-stage sensing techniques, coarse sensing performs energy detection while fine sensing is

later performed to verify the presence or absence of PUs.

3. SPECTRUM SENSING TECHNIQUES

The most commonly employed spectrum sensing techniques for transmitter detection are: matched filtering,

energy detection, and cyclostationary detection. These

spectrum sensing techniques are used for detection in

parallel and then the fuzzy logic approach is used to determine spectrum holes. First, we will discuss each of

the transmitter detection techniques including their pros

and cons.

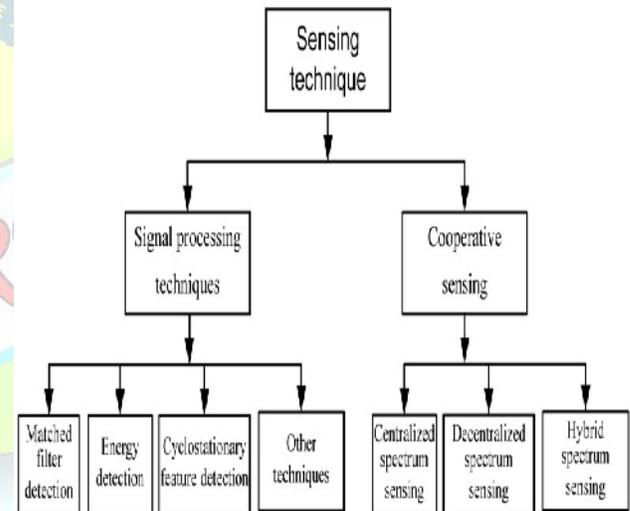


Figure 1: Classification of Spectrum Sensing Techniques

3.1 MATCHED FILTER DETECTION

The matched filter is the linear optimal filter used for coherent signal detection to maximize the signal-to-noise ratio (SNR) in the presence of additive stochastic noise. It is obtained by correlating a known original PU signal $s(t)$ with a received signal $r(t)$ where T is the symbol



duration of PU signals. Then the output of the matched filter is sampled at the synchronized timing. If the sampled value Y is greater than the threshold k , the spectrum is determined to be occupied by the PU transmission.

This detection method is known as an optimal detector in stationary Gaussian noise. It shows a fast sensing time, which requires $O(1/\text{SNR})$ samples to achieve a given target detection probability [6]. However, the matched filter necessitates not only a priori knowledge of the characteristics of the PU signal but also the synchronization between the PU transmitter and the CR user. If this information is not accurate, then the matched filter performs poorly. Furthermore, CR users need to have different multiple matched filters dedicated to each type of the PU signal, which increases the implementation cost and complexity.

For more practical implementation, a pilot signal of PU systems is used for the matched filter detection in [7].

In this method, PU transmitters send the pilot signal simultaneously with data, and CR users have its perfect knowledge, which may not still be feasible in CRAHNS. For this reason, energy detection and feature detection are the most commonly used for spectrum sensing in CRAHNS.

3.2 ENERGY DETECTION

The energy detector is optimal to detect the unknown signal if the noise power is known. In the energy detection, CR users sense the presence/absence of the PUs based on the energy of the received signals. The measured signal $r(t)$ is squared and integrated over the observation interval T . Finally, the output of the integrator is compared with a threshold k to decide if a PU is present.

While the energy detector is easy to implement, it has

several shortcomings.

The energy detector requires $O(1/\text{SNR}^2)$ samples for a given detection probability. Thus, if CR users need to detect weak PU signals (SNR: -10 dB to -40 dB), the energy detection suffers from longer detection time compared to the matched filter detection.

Furthermore, since the energy detection depends only

on the SNR of the received signal, its performance is susceptible to uncertainty in noise power. If the noise power is uncertain, the energy detector will not be able to detect the signal reliably as the SNR is less than a certain threshold, called an SNR wall. In addition, while the energy detector can only determine the presence of the signal but cannot differentiate signal types. Thus, the energy detector often results in false detection triggered by the unintended CR signals.

For these reasons, in order to use energy detection, CRAHNS need to provide the synchronization over the sensing operations of all neighbors, i.e., each CR user should be synchronized with the same sensing and transmission schedules. Otherwise, CR users cannot distinguish the received signals from primary and CR users, and hence the sensing operations of the CR user will be interfered by the transmissions of its neighbors.

When it is difficult for the SU to bring adequate information about the PU waveform, matched filter detection is not a favorable choice. However, if the SU is given the power of random Gaussian noise, energy detection becomes a better alternative for spectrum sensing.

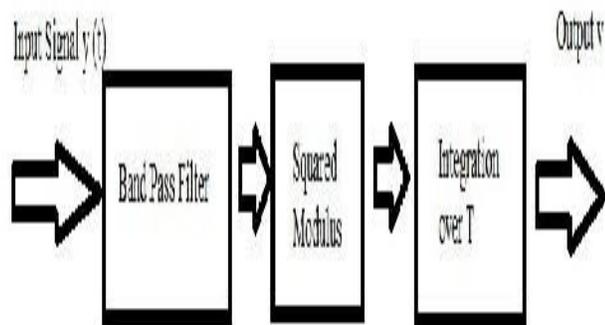


Figure 2 Energy detector

3.3 CYCLOSTATIONARY FEATURE DETECTION

Feature detection determines the presence of PU signals

by extracting their specific features such as pilot signals,

cyclic prefixes, symbol rate, spreading codes, or modulation types from its local observation.

These features introduce built-in periodicity in the modulated signals, which can be detected by analyzing a spectral correlation function. The feature detection leveraging

this periodicity is also called cyclostationary detection. Here, the spectrum correlation of the received signal $r(t)$ is averaged over the interval T , and compared with the test statistic to determine the presence of PU signals, similar to energy detection.

The main advantage of the feature detection is its robustness to the uncertainty in noise power. Furthermore,

it can distinguish the signals from different networks. This method allows the CR user to perform sensing operations independently of those of its neighbors without synchronization. Although feature detection is most effective for the nature of CRAHNS, it is computationally complex and requires significantly long sensing

time. In, the enhanced feature detection scheme combining cyclic spectral analysis with pattern recognition based on neural networks is proposed. The distinct features of the received signal are extracted using cyclic spectral analysis and represented by both spectral coherent function and spectral correlation density function.

The neural network, then, classifies signals into different modulation types. It is shown that the feature detection enables the detection of the presence of the Gaussian minimum shift keying (GMSK) modulated GSM signal (PU signal) in the channel under severe interference from the orthogonal frequency division multiplexing (OFDM) based wireless LAN signal (CR signal) by exploiting different cyclic signatures of both signals. A covariance-based detection scheme based on the statistical covariance or auto-correlations of the received signal is proposed in [92]. The statistical covariance matrices or autocorrelations of signal and noise are generally different. The statistical covariance matrix of noise is determined by the receiving filter. Based on this characteristic, it differentiates the presence of PU users and noise. The method can be used for various signal detection applications without knowledge of the signal, the channel and noise power.

4. SYSTEM MODEL

It is assumed that the PU signal structure is unknown but it allocates fraction of its power to transmit a deterministic pilot tone. This model is suitable for many practical communication systems in which the pilot tone is used for the data frame synchronization. A digital television (ATSC) signal is considered as the PU in which there is a strong pilot tone signal which is a sinusoidal signal in time domain.

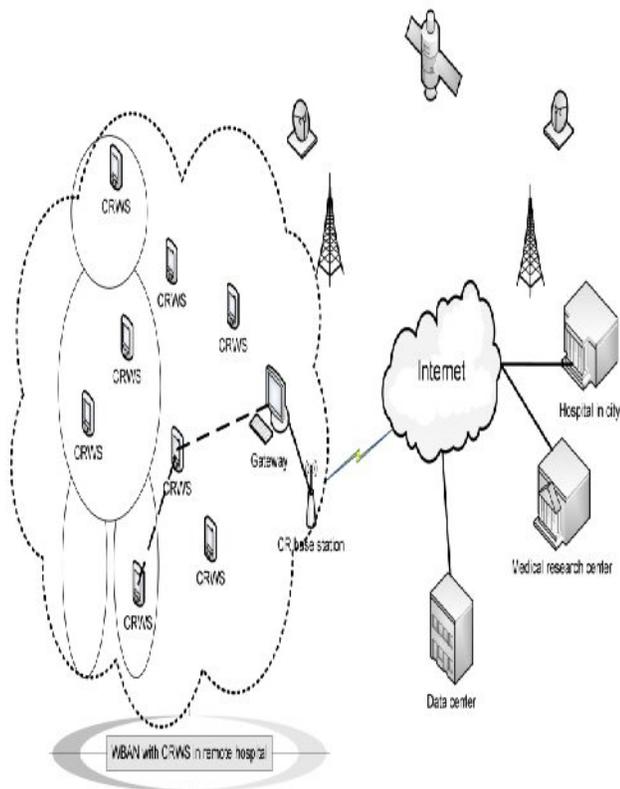


Figure 3 System model

4.1 FUZZY LOGIC DETECTOR

Traditional set theory has crisp concept of membership, i.e., an element either belongs to a set or it does not. In contrast, fuzzy set theory allows for partial membership. Fuzzy logic was initially proposed to cover the problem of reasoning under uncertainty. Decisions based on fuzzy logic are made using vague information, human understandable fuzzy sets, and inference rules (e.g., IF, THEN, ELSE, AND, OR, and NOT) instead of complicated mathematics [8].

In order to test the applicability of fuzzy logic for the mathematical hypothesis given in (1) and increase the

performance of local sensing, we propose an FLD scheme for the final decision (presence or absence of a PU). FLD offers several unique features that make itself a particularly good choice for PU detection. It does not require precise inputs therefore it is inherently robust.

Because the FLD system is governed by user-defined

rules, it can be modified easily to improve system performance.

Figure 4 shows the structure of FLD system. When the input is applied to the FLD, the output is computed by the fuzzy inference engine corresponding to each rule. The crisp output is then computed by defuzzification from output sets. The system has three inputs and one output using singleton fuzzification, Max-Product, as the conclusion method and the center of area as the defuzzification method [7]. The FLD is designed to detect the PU accurately in order to increase reliability of the detection and to avoid interference with PU transmission. The detection of PU is based on three antecedents, i.e., descriptors

1. Antecedent 1: Normalized output of energy detector
2. Antecedent 2: Normalized output of matched filter
3. Antecedent 3: Normalized output of cyclostationary detector

The linguistic variance used to represent each antecedent

is labeled high, medium, or low, indicating the possibility of the presence of the PU. Each antecedent uses two thresholds for the label choice.

The fuzzy if-then rules in this FLD scheme are of these types:



R^l : IF x_1 is F_l^1 , and x_2 is F_l^2 and x_3 is F_l^3
THEN the possibility (y) that the PU is present is D^l where $l=1,2, \dots, 27$.

The output y from the FLD system is

$$y(x_1, x_2, x_3) = \mu_{F1}(x_1) + \mu_{F2}(x_2) + \mu_{F3}(x_3) / N$$

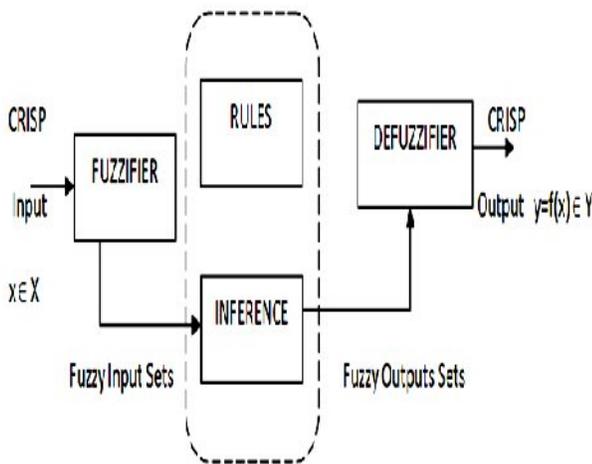


Figure 4 Structure of FLD system

4.2 ANALYSIS OF SENSING PERFORMANCE

In this section, we analyze the sensing performance of proposed FLD scheme with respect to detection performance.

In order to evaluate the agility of the FLD scheme, mean detection time is compared with matched filter detection, energy detection, and cyclostationary detection. The number of samples during observation periods is known in each sensing technique. The symbol duration is known in the case of the matched filter and the channel bandwidth is known for energy detection and

cyclostationary detection. Using this information, we can calculate the mean detection time represented as T_1 , T_2 , and T_3 for matched filter, energy detection, and cyclostationary detection, respectively. The mean sensing time for each channel for the matched filter, T_1 , can be calculated as

$$T_1 = \frac{M_1}{W}$$

where M_1 is the number of samples during the observation interval and T is the symbol duration.

The mean sensing time for each channel for energy detection, T_2 , can be calculated as

$$T_2 = \frac{M_2}{W}$$

where M_2 is the number of samples during the observation interval and W is the channel bandwidth.

The mean sensing time for each channel for cyclostationary detection, T_3 , can be calculated as

$$T_3 = \frac{M_3}{W}$$

where M_3 is the number of samples during the observation interval and W is the channel bandwidth. In the FLD scheme, all transmitter detection schemes run in parallel. The FLD will wait till all three detection algorithms finish their sensing. By doing so, the performance is increased and is better than individual performance of all the detectors. Main objective of this proposed FLD scheme is to increase reliability of detection at the cost of more hardware for each detector. Therefore, the total



detection time of the proposed scheme can be expressed as $T_{\max} = \text{Max} (T_1, T_2, T_3)$

5. SIMULATION

Figure 5 compares the probability of detection for transmission detection techniques with the proposed FLD scheme. The FLD scheme has a better performance over the entire SNR range compared to the other transmitter detection techniques. The FLD scheme detects the PU with 100% certainty even under a very low SNR value of -22 dB. In order to achieve the same degree of accuracy as a fuzzy logic scheme, the cyclostationary feature detector and the matched filter require relatively higher SNR values of -8 and 2 dB, respectively.

The performance of energy detection seems to be better than all other mentioned techniques over the entire SNR range at the cost of high probability of false alarms. Due to inherent limitation of the energy detector, it is unable to discriminate between signal and noise energy.

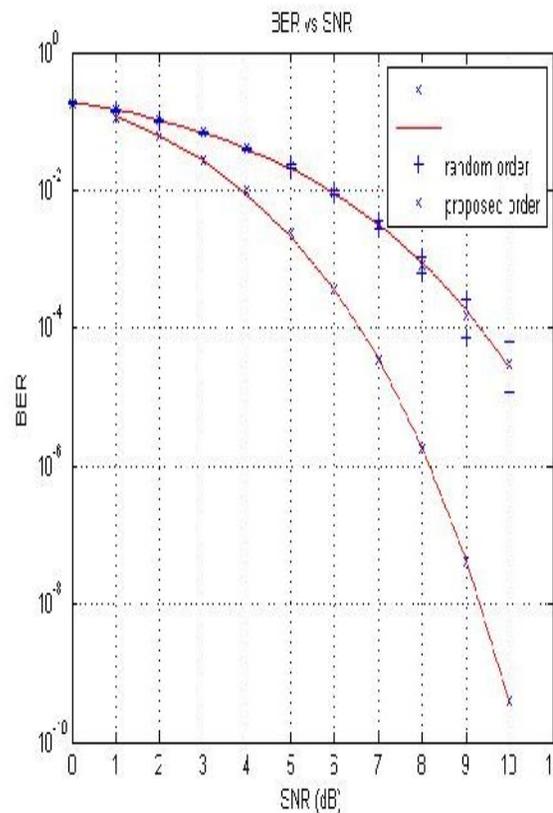


Figure 5 Comparison of transmitter detection and FLD schemes.

6. CONCLUSION

CR networks are envisaged to solve the problem of spectrum scarcity by making efficient and opportunistic use of frequencies reserved for the use of licensed users of the bands.

To realize the goals of truly ubiquitous spectrum-aware communication, the CR devices need to incorporate the spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility functionalities. The main challenge in CRAHNS is to integrate these functions in the layers of the protocol stack, so that the CR users can communicate reliably in a distributed manner, over a multi-hop/multi-spectrum environment, without any infrastructure support.



In this article, a new FLD scheme for local spectrum sensing is proposed. In the first stage of FLD, each SU performs existing spectrum sensing techniques, i.e., energy detection, matched filter detection, and cyclostationary detection, in parallel. In the second stage, the outputs of those detection approaches are combined using fuzzy logic in order to deduce the presence or absence of PU. Every detection technique has an SNR threshold below which robust operation is not possible. We find that by simultaneously combining the results of different detection techniques using fuzzy logic, better results can be obtained.

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