Analyze the Cooperative Spectrum Sensing in Cognitive Radio Networks

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***Abstract*-The cognitive radio is a network to alleviate spectrum scarcity; cognitive radios (CRs) have attracted intensive research attention recently. While great strides have been made in spectrum sensing techniques in cognitive radio networks, these approaches are susceptible to unconventional attacks that may result in catastrophic performance degradation of the spectrum usage efficiency. For example, primary user emulation, intelligent jamming and denial of service for spectrum usage may impact the performance of classical spectrum sensing approaches. A sensing quality metric is defined as a measure of the correctness of spectral availability information based on the fact that spectrum sensing information at a given space and time can represent spectrum information at a different point in space and time. A distributed Selective-(CORN)2 (S-(CORN)2) is introduced by extending the distributed algorithm to allow secondary users toselect collaboration neighbours' in densely populated cognitive radio networks. Challenges associated with spectrum sensing are given and enabling spectrum sensing methods are reviewed. The paper explains the cooperative sensing concept and its various forms. External sensing algorithms and other alternative sensing methods are discussed.**

Keywords:(CORN)2,WSN,Spectrum sensing and sharing in cooperative networks, scheduling.

I. INTRODUCTION

Cognitive radio (CR) is the enabling technology that allows unlicensed secondary users (SUs) to exploit idle licensed frequency bands, forming thus a cognitive radio network (CRN). CRs can autonomously adjust their transmission parameters and modify their behaviour based on the electromagnetic environment conditions. Spectrum sensing is a key phase in the operation cycle of a CR [1], leveraging the radio's ability to measure, sense and be aware of the channel characteristics. It can be performed either individually or cooperatively in order to detect idle frequencies, referred to as spectrum holes, and minimize interference to the licensed or primary user (PU) activities [2]. The accuracy on detecting spectrum holes determines the efficiency of exploiting the spectrum. Thus, either sensing errors related to hardware outages [3], [4] or susceptibility to specialized attacks on the sensing functionality can result in significant performance degradation. Existing works on security in CR mainly address concerns of designs for cryptography, intrusion detection system and authentication. However, these security measures are not sufficient to preserve the correctness of spectrum sensing results against attacks and intrusions [4]. Preventive security mechanisms, as cryptography, provide confidentiality, integrity and authentication, but they are inefficient against data injection overload, interception, manipulation or impersonation attacks, such as Denial of Services (DoS), PU emulation (PUE) attacks and jamming. Reactive security mechanisms, as intrusion detection systems (IDS), are based on network behaviour analysis, or previously known attack patterns, being inflexible to handle unpredictable misbehaviours. Furthermore, since new communication technologies are more dynamic and adaptive, attacks are also becoming smarter, often bypassing common security mechanisms [4]. This paper presents a cooperative spectrum sensing framework to effectively provide resilience against both faults and attacks. Applying a low-cost multi-criteria analysis technique, the framework is adaptable to radio environment and flexible to consider unpredictable behaviours that emerge from various practical deployment scenarios. Also, it is able to handle multi-dimensional (e.g. frequency, time, geographical space, security) data in order to effectively sense the spectrum, and detect or mitigate faults and attacks in an optimal way. In the framework, CRs share their initial estimation of the likelihood of an attack with neighbors to gather a collective perception of the network. Thus, they apply the non-parametric Bayesian inference technique to classify spectrum holes and indicate the ones that are least susceptible to failures and attacks, being then resilient in the sense that nodes do not simply rely on majority voting by a collection of nearby nodes. Our approach is evaluated under network disconnections and PUE attacks, considering different sets of physical layer features and their corresponding thresholds that indicate a deviation from the expected results. Simulation results, founded on real traces, show the benefit of the proposed framework in terms of attack detection and its adaptation to network conditions.

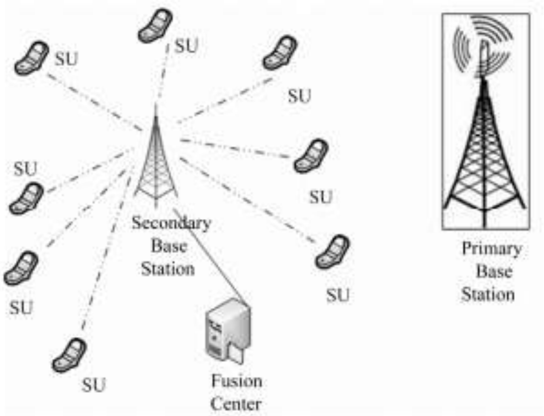

Fig.1.1 A typical collaborate spectrum sensing in cognitive radio network.

One of the most important challenges in cognitive radio is reliable spectrum sensing. It has attracted far-reaching attention recently. Spectrum sensing procedure can be accomplished individually or cooperatively. If spectrum sensing procedure is used by cooperative decision, it could be more reliable because there might happen something to several users and they couldn't sense the spectrum well and their local decisions don't be true.

II. ((CORN)2) ALGORITHM

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 is explained. The CRN from the perspective of individual SUs and their requirements of sensing quality. Accordingly, we develop a provably arbitrarily close to optimal sensing scheduling algorithm through a novel sensing deficiency virtual queue concept and introduce its distributed implementation.

A. Energy Detector Based Sensing

Energy detector based approach, also known as radiometry or period gram, 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 [64]. 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 [48]. Moreover, energy detectors do not work efficiently for detecting spread spectrum signals [26], [59]. Let us assume that the received signal has the following simple form

$$y(n) = s(n) + w(n) \quad (1)$$

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

$$M = N\ n{=}0\ |y(n)|\ 2\ , \quad (2)$$

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 λE. This is equivalent to distinguishing between the following two hypotheses:

$$H0 : y(n) = w(n), \quad (3)$$

$$H1 : y(n) = s(n) + w(n). \ (4)$$

The performance of the detection algorithm can be summarized with two probabilities: probability of detection PD and probability of false alarm PF . PD 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

$$PD = Pr\ (M>\lambda E\ |H1). \ (5)$$

PF 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

$$PF = Pr\ (M>\lambda E|H0). \quad (6)$$

PF should be kept as small as possible in order to prevent underutilization of transmission opportunities. The decision threshold λE can be selected for finding an optimum balance between PD 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 going 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 [65]. Hence, knowledge of noise variance is sufficient for selection of a threshold. The white noise can be modelled as a zero-mean Gaussian random variable with variance σ2 w, i.e. w(n) = N (0, σ2 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, σ2 s). 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 χ2 2N and hence, it can be modelled as

$$M = \sigma 2\ w\ 2\ \chi 2\ 2N\ H0,\ \sigma 2\ w{+}\sigma 2\ s\ 2\ \chi 2\ 2N\ H1. \ (7)$$

B. Waveform-Based Sensing

Known patterns are usually utilized in wireless systems to assist synchronization or for other purposes. Such patterns include preambles, midambles, regularly transmitted pilot patterns, spreading sequences etc. A preamble is a known sequence transmitted before each burst and a midamble is transmitted in the middle of a burst or slot. In the presence of a known pattern, sensing can be performed by correlating the received signal with a known copy of itself [48], [58], [63]. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing or coherent sensing. In [48], it is shown that wave form based sensing outperforms energy detector based sensing in reliability and convergence time. Furthermore, it is shown that the performance of the sensing algorithm increases as the length of the known signal pattern increases. Using the same model given in (1), the waveform-based sensing metric can be obtained.

The decision on the presence of a primary user signal can be made by comparing the decision metric M against a fixed threshold λW . For analyzing the WLAN channel usage characteristics, packet preambles of IEEE 802.11b [71] signals are exploited in [55], [56]. Measurement results presented in [25] show that waveform-based sensing requires short measurement time; however, it is susceptible to synchronization errors. Uplink packet preambles are exploited for detecting Worldwide Interoperability for Microwave Access (WiMAX) signals.

C. 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 [80] 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 [74]. Furthermore, cyclostationarity can be used for distinguishing among different types of transmissions and primary users.

D. Radio Identification Based Sensing

A complete knowledge about the spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. Such an identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [59]. For example, assume that a primary user's technology is identified as a Bluetooth signal. Cognitive radio can use this information for extracting some useful information in space dimension as the range of Bluetooth signal is known to be around 10 meters. Furthermore, cognitive radio may want to communicate with the identified communication systems in some applications. For radio identification, feature extraction and classification techniques are used in the context of European transparent ubiquitous terminal (TRUST) project [86]. The goal is to identify the presence of some known transmission technologies and achieve communication through them. The two main tasks are initial mode identification (IMI) and alternative mode monitoring (AMM). In IMI, the cognitive device searches for a possible transmission mode (network) following the power on. AMM is the task of monitoring other modes while the cognitive device is communicating in a certain mode.

E. Matched-Filtering

Matched-filtering is known as the optimum method for detection of primary users when the transmitted signal is known [91]. The main advantage of matched filtering is the short time to achieve a certain probability of false alarm or probability of miss detection [92] 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 [92]. However, matched-filtering requires cognitive radio to demodulate received signals. Hence, it requires perfect knowledge of the primary users signalling features such as bandwidth, operating frequency, modulation type and order, pulse shaping, and frame format.

F. Other Sensing Methods

Other alternative spectrum sensing methods include multitaper spectral estimation, wavelet transform based estimation, Hough transform, and time-frequency analysis. Multitaper spectrum estimation is proposed in [93]. The proposed algorithm is shown to be an approximation to maximum likelihood PSD estimator, and for wideband signals, it is nearly optimal. Although the complexity of this method is smaller than the maximum likelihood estimator, it is still computationally demanding. Random Hough transform of received signal is used in [94] for identifying the presence of radar pulses in the operating channels of IEEE 802.11 systems.

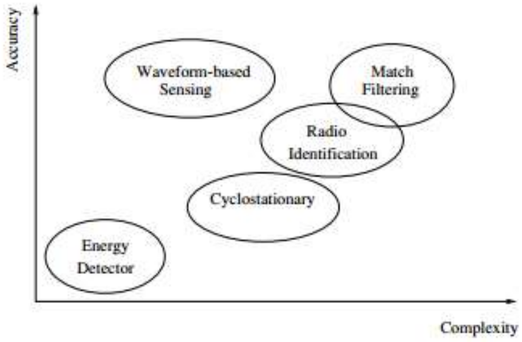

Fig.1.2 Main sensing methods in terms of their sensing accuracies and complexities.

This method can be used to detect any type of signal with a periodic pattern as well. Statistical covariance of noise and signal are known to be different. This fact is used in [95] to develop algorithms for identifying the existence of a communication signal. Proposed methods are shown to be effective to detect digital television (DTV) signals.

III. COGNITIVE RADIO NETWORK

A cognitive radio is an intelligent radio that can be programmed and configured dynamically. Its transceiver is designed to use the best wireless channels in its vicinity. Such a radio automatically detects available channels in wireless spectrum, then accordingly changes its transmission or reception parameters to allow more concurrent wireless communications in a given spectrum band at one location. This process is a form of dynamic spectrum management.

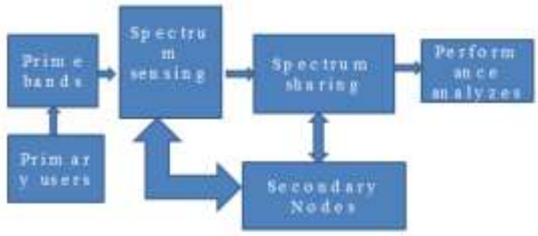

Fig.1.3 CR Network((CORN)2)

The main functions of cognitive radios are:

Power Control**:** Power control is used for both opportunistic spectrum access and spectrum sharing CR systems for finding the cut-off level in SNR supporting the channel allocation and imposing interference power constraints for the primary user's protection respectively.

Spectrum sensing**:** Detecting unused spectrum and sharing it, without harmful interference to other users; an important requirement of the cognitive-radio network to sense empty spectrum. Detecting primary users is the most efficient way to detect empty spectrum. Spectrum-sensing techniques may be grouped into three categories:

Transmitter detection**:** Cognitive radios must have the capability to determine if a signal from a primary transmitter is locally present in a certain spectrum. There are several proposed approaches to transmitter detection:

Energy detection: Energy detection is a spectrum sensing method that detects the presence/absence of a signal just by measuring the received signal power. This signal detection approach is quite easy and convenient for practical implementation. To implement energy detector, however, perfect noise variance information is required. And surprisingly when there is noise uncertainty, there is an SNR wall below which the energy detector cannot reliably detect any transmitted signal. In a new energy based spectrum sensing algorithm with noise variance uncertainty is proposed. This algorithm does not suffer from SNR wall and outperforms the existing signal detectors (see for example and its USRP implementation). And most importantly, the relationship between the energy detector of and that of is quantified analytically. Also when the noise variance is known perfectly these two energy detectors achieve the same probability of detection and false alarm rates.

Cooperative detection**:** Refers to spectrum-sensing methods where information from multiple cognitive-radio users is incorporated for primary-user detection.

Null-space based CR**:** With the aid of multiple antennas, CR detects the null-space of the primary-user and then transmit within this null-space, such that its subsequent transmission causes less interference to the primary-user

Spectrum management**:** Capturing the best available spectrum to meet user communication requirements, while not creating undue interference to other (primary) users. Cognitive radios should decide on the best spectrum band (of all bands available) to meet quality of service requirements; therefore, spectrum-management functions are required for cognitive radios. Spectrum-management functions are classified as:

- Spectrum analysis
- Spectrum decision

IV. SPATIAL-CORRELATION BASED SENSINGSCHEDULING ALGORITHMS

We compare (CORN)2 with respect to a spatial-correlation-based cooperative sensing algorithm, where we do not require a minimum sensing rate constraint (i.e.,RS= 0). Different from (CORN)2, the spatial-correlation based algorithm is developed to minimize the energy consumption employing spatial correlations only.3 Specifically, the centralized spatial-correlation-based algorithm.

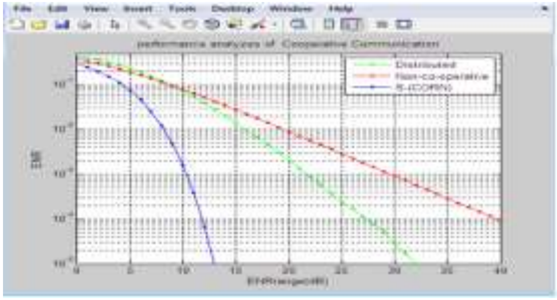

Fig.1.4 Performance of CORN

Under the above spatial-correlation-based algorithm, at each time slot *t*, if an SU is scheduled to sense a channel, it will broadcast its sensing data to its neighbour. However, an SU *i* does not utilize its neighbour SU *j*'s sensing data if SU *j* is not scheduled to perform sensing at the current time slot *t* (i.e., if $\mu j,c(t) = 0$), as is captured by the constraint (24). That is, under this algorithm a node does not utilize any sensing information before the current timeslot (either from its local sensing history or its neighbour's broadcasted data in the past). Hence, this algorithm optimizes the total energy consumption only based on the current spatial correlations.

V. CONCLUSION

In this paper, a new cooperative spectrum sensing for cognitive radio based on S-(CORN)2 algorithm was proposed. In our proposed scheme the weights of secondary users were updated in time and finally the sensing results were combined in the fusion centre based on their trusted weights. The developed algorithm and its variants are theoretically shown to minimize the sensing cost and stabilizing all queues in the network, which in turn guarantees desired sensing quality levels.

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