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Performance Analysis Of Cooperative Spectrum Sensing Schemes In Cognitive Radio:A Survey

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Abstract:

In cognitive radio, spectrum sensing is an emergent technology to find available and unused spectrum for increasing spectrum utilization and to overcome spectrum scarcity problem without harmful interference to licensed users. Cooperative spectrum sensing is used to give reliable performance in terms of detection probability and false alarm probability as well as in order to reduce fading, noise and shadowing effects on cognitive radio users. In this paper according to detection performance and complexity various cooperative spectrum sensing schemes have been discussed.

Key words*: Cognitive radio,spectrum sensing,cooperative spectrum sensing,enery detecto*

1.Introduction

Radio spectrum is a very scarce and important resource for wireless communication systems. The tremendous growth in wireless communications has contributed to a huge demand on the deployment of new wireless services in both the licensed and unlicensed frequency spectrum.

Recently, a Cognitive Radio (CR) access technology has been proposed as a promising solution for improving the efficiency of spectrum usage by adopting dynamic spectrum resource management concept [4, 13].

The main functions of a cognitive radio can be addressed as follows [14]:

Spectrum sensing is the process of a cognitive radio sensing the channel and determining if a primary user is present, detecting the spectrum holes

Spectrum management is selecting the best available channel (for a cognitive user) over the available channels.

Spectrum sharing is the allocation of available frequencies between the cognitive users.

Spectrum mobility is the case when a secondary user rapidly allocates the channel to the primary user when a primary user wants to retransmit again.

Among these functions, spectrum sensing is the one that has driven most interest. The role of spectrum sensing in the CR system is to locate unoccupied spectrum segments as quickly and accurately as possible. Inaccurate or delayed.

sensing results deter communication of the primary user occupying the

spectrum. Thus, spectrum sensing speed and accuracy are extremely important. From a CR system commercialization standpoint, minimizing hardware complexity as well as power consumption is also critical.

Spectrum scarcity problem [1,2], due to the growth of demand for the spectrum, is suggested to be solved by increasing the spectrum utilization which can be done by allowing cognitive users (unlicensed users) to occupy the spectrum band when the primary users (licensed users) do not use it. CR system [3, 4] can be suggested to use the spectrum band efficiently. In spectrum sensing [5] there are several sensing methods. One from these methods is the energy detection [6, 7]. Other methods were described briefly in Ref. [4, 8, 9]. Energy detection will be used here due to its simplicity and no need for any prior information about the primary users' signals. Therefore, it has been thoroughly studied both in local spectrum sensing [6-10] and cooperative spectrum sensing [11-14].In cooperative spectrum sensing, local spectrum sensing information from multiple CRs are combined for Primary User (PU) detection. In centralized CR network, a common receiver plays a key role in collecting these information and detecting spectrum holes which were described in details in [12].

Cooperative spectrum sensing was proposed to overcome noise uncertainties, fading and shadowing in primary user signal detection. It can be as a solution to hidden node problem and decrease sensing time as well [15]. In this technique, CR users/nodes are collaborated to sense spectrum hole and detect PUs signal. Then, with or without sharing local detection information among users, they forward them to data fusion centre. The fusion centre decides the final result in accordance with the decision rules whether primary signal is present or absent.

The paper is organized as follows: Section 2 reviews spectrum sensing schemes. In section 3, we provide comparison of spectrum sensing schemes. Conclusions are presented in Section 4.

2.Spectrum Sensing Schemes

Several methods have been proposed to perform local spectrum sensing [16], [17], [18], [19]. The following section highlights three of the most relevant methods from the literature [19]: 1) energy detection based spectrum sensing, 2) cyclostationary-based spectrum sensing, and 3) matched filtering. A brief overview of each technique is provided below along with the relative advantages and disadvantages of each.

2.1.Energy Detection Based Spectrum Sensing

Due to its low complexity and computational cost, energy detection based spectrum sensing is the most common spectrum sensing method [16]. It is performed by comparing the received energy of the signal against a predefined energy detection threshold to determine the presence or absence of the user in the frequency band of interest [16], [17], [20]. The energy of the received signal is determined by squaring and integrating the received signal strength (RSS) over the observation time interval [16], [17], [20]. The energy detection threshold is determined using the noise variance of the environment [17]. Thus, small errors in the noise variance estimation can cause significant performance degradation [17]. Energy detection based spectrum sensing is the optimal detection method for zero-mean constellation signals when no information is known in advance about the user occupying the channel [17], [20]. However, energy detection based spectrum sensing cannot distinguish the type of user occupying the frequency band [16], [17]. In addition, under low signal-to-noise ratio (SNR) conditions, energy detection performs poorly [16], [17].

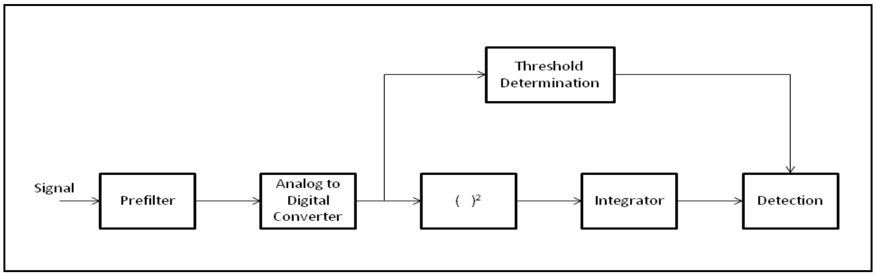

Figure 1: Energy Detector-based Sensing

2.2.Cyclostationary-Based Spectrum Sensing

Given the disadvantages of energy detection based spectrum sensing, cyclostationary-based spectrum sensing offers an attractive alternative [16], [17]. By exploiting the cyclostationary features of the received signal [16], cyclostationary-based spectrum sensing is capable of discriminating which type of user is present [16], [17] and detecting the presence of a user under low SNR conditions [17]. Such benefits come at the cost of additional hardware complexity and a lengthier detection process when compared to energy detection based spectrum sensing [17]. Cyclostationary features are the result of periodicity in the received signal or its statistical properties [16]. As such, detection is accomplished by finding the unique cyclic frequency of the spectral correlation function of the received signal [16], [17]. The spectral correlation function is determined by taking the Fourier transform of the cyclic autocorrelation function.

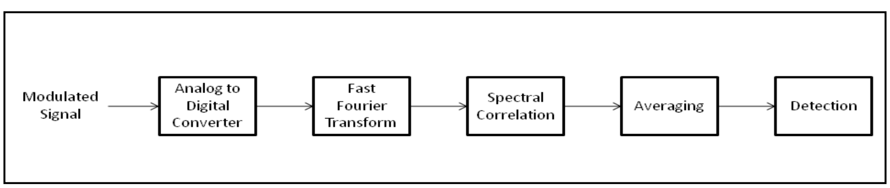

Figure 2: Cyclostationary-based Sensing

2.3.Matched Filter Detection

This method incorporates a filter matched to the primary user's signal at the cognitive radio receiver. Obviously, this method is optimal in the sense that it maximizes the SNR, minimizing the decision errors. However, this method is not practical since it requires the cognitive user to know the primary user's signalling type.

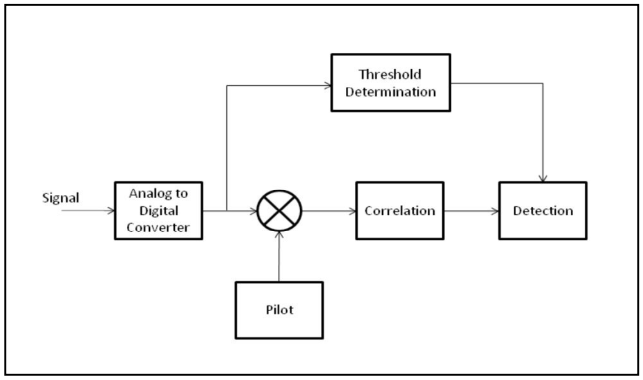

Figure 3: Matched Filtering Method

2.4.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 [25], [26], [28]. This method is only applicable to systems with known signal patterns, and it is termed as waveform-based sensing or coherent sensing. In [25], it is shown that waveform 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.

2.5.Radio Identification Based Sensing

A complete knowledge about the spectrum characteristics can be obtained by identifying the transmission technologies used by primary users. Such identification enables cognitive radio with a higher dimensional knowledge as well as providing higher accuracy [27]. 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 [34]. 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. In radio identification based sensing, several features are extracted from the received signal and they are used for selecting the most probable primary user technology by employing various classification methods. In [21], [35], features obtained by energy detector based methods are used for classification. These features include amount of energy detected and its distribution across the spectrum. Channel bandwidth and its shape are used in [36] as reference features. Channel bandwidth is found to be the most discriminating parameter among others. For classification, radial basis function (RBF) neural network is employed. Operation bandwidth and centre frequency of a received signal are extracted using energy detector based methods in [27]. These two features are fed to a Bayesian classifier for determining the active primary user and for identifying spectrum opportunities. The standard deviation of the instantaneous frequency and the maximum duration of a signal are extracted using time-frequency analysis in [23], [24], [37], [38] and neural networks are used for identification of active transmissions using these features. Cycle frequencies of the incoming signal are used for detection and signal classification in [31]. Signal identification is performed by processing the (cyclostationary) signal features using hidden Markov model (HMM). Another cyclostationarity based method is used in [29], [30] where spectral correlation density (SCD) and spectral coherence function (SCF) are used as features. Neural network are utilized for classification in [30] while statistical tests are used in [29].

3.Comparison of Sensing Schemes

A basic comparison of the sensing methods given in this section is presented in Fig. 4. Waveform-based sensing is more robust than energy detector and cyclostationarity based methods because of the coherent processing that comes from using deterministic signal component [25]. However, there should be a priori information about the primary user's characteristics and primary users should transmit known patterns or pilots.

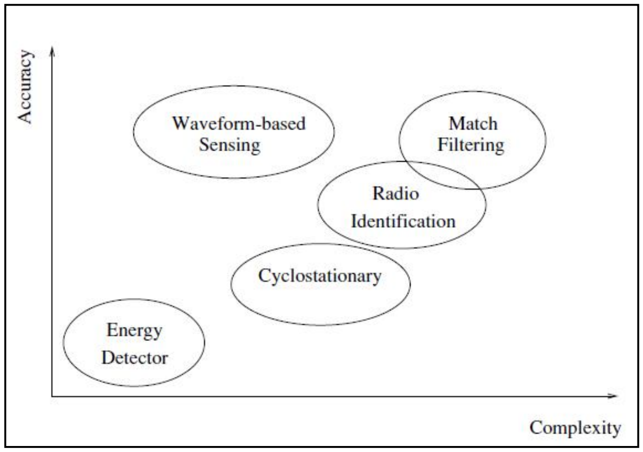

Figure 4: Main sensing methods in terms of their sensing accuracies and complexities.

The performance of energy detector based sensing is limited when two common assumptions do not hold [25]. The noise may not be stationary and its variance may not be known. Other problems with the energy detector include baseband filter effects and spurious tones [28]. It is stated in literature that cyclostationary-based methods perform worse than energy detector based sensing methods when the noise is stationary. However, in the presence of co-channel or adjacent channel interferers, noise becomes non-stationary. Hence, energy detector based schemes fail while cyclostationarity-based algorithms are not affected [33]. On the other hand, cyclostationary features may be completely lost due to channel fading [32], [40]. It is shown in [40] that model uncertainties cause an SNR wall for cyclostationary based feature detectors similar to energy detectors [39]. Furthermore, cyclostationarity based sensing is known to be vulnerable to sampling clock offsets [33].

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 usage, has become an exciting and promising concept. One of the important elements of cognitive radio is sensing the available spectrum opportunities. Several sensing methods are studied.

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