Research Paper Engineering

A Review on Different Spectrum Sensing Methods in Cognitive Radio Networks

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ABSTRACT

With the rapid growth in the number of wireless users, there is a need to utilize the spectrum efficiently. Cognitive radio has been proposed as a solution for the opportunistic usage of wireless spectrum. Spectrum sensing is a key component of cognitive radio which ensures that the unlicensed users access the spectrum without interfering with the licensed users by detecting spectrum holes. In this paper, we discuss various spectrum sensing techniques and their performance comparison. Along with this, a brief overview of cooperative spectrum sensing is also presented. Second section introduces the fundamental concepts of spectrum sensing. Third section discusses different methods of spectrum sensing and their comparison. The cooperative spectrum sensing and its fusion rules are outlined. Finally section concludes the paper.

KEYWORDS Cognitive radio, Spectrum sensing, Blind sensing, Non-blind sensing, Cooperative detection

INTRODUCTION

The electromagnetic spectrum, a valuable resource is under-utilized by the licensed/primary users. Recent studies showed that the spectrum usage varies from 15% to 85% [1] by the primary users. So the spectrum may remain idle for most of the time. The frequency band that remains idle temporarily is termed as a spectrum hole or white space. These spectrum holes can be used by the unlicensed/secondary/cognitive users without disturbing the primary user's transmission. As stated in [2]"A cognitive radio (CR) is a transceiver that dynamically senses the available channels in wireless spectrum and accordingly changes its communication parameters to network and user demands". A CR continuously and intelligently senses the vacant frequency bands in the spectrum and exchanges this information with the network as well as with other cognitive users [3]. The cognitive user relies on this information and decides the frequency band for its transmission.

Spectrum Holes

Spectrum holes can be categorized as: temporal spectrum holes and spatial spectrum holes. A temporal spectral hole is one which is used by CR users when there is no transmission by the primary user in the respective band while sensing. In this type of spectrum holes, the CR users and the primary users are situated in the same coverage area. This facilitates easier sensing if CR users have the same sensitivity requirements as that of primary receivers. On the other hand, a spatial spectrum hole occurs when the allocated frequency band for primary transmission is confined to a particular area, therefore this spectrum hole can be used by the CR users outside this coverage area. Now the CR users can transmit in this frequency band without causing interference to the primary transmission.

This requires the successful detection of nearby primary transmitters and receivers. This is a challenging task as the CR users lie well outside the coverage area of primary transmission.

Functions of CR

The main functions of CR are: spectrum sensing, spectrum decision, spectrum mobility and spectrum sharing [4] as shown in figure 1. Spectrum sensing is the most crucial component of CR. The task of spectrum sensing is to observe the RF spectrum for the detection of spectrum holes and allocate them to the cognitive users. Sensing not only involves the measurement of spectral content or energy, but also incurs the characteristics of spectrum over dimensions like time, frequency, code and space. Spectrum decision is to pick out the suitable frequency band from the available list of channels. Spectrum mobility is the process of performing a proper handoff to the next available vacant frequency band when the actual primary user is detected in the currently utilized frequency band by the cognitive user. As there are multiple CR users sensing the frequency bands simultaneously, there may be a possibility of collision when more than one cognitive user attempts to use the same frequency band. Spectrum sharing is the task of distributing the vacant frequency bands reasonably to the cognitive users, thereby preventing collisions. This paper focuses on various spectrum sensing techniques and their performance comparison. Along with this, a brief overview of cooperative spectrum sensing is also presented. The cooperative spectrum sensing and its fusion rules are also outlined.

SPECTRUM SENSING

The inability to serve the increasing number of wireless gadgets is not due to the physical shortage of the spectrum, but due to the inefficient usage of the spectrum. To utilize the spectrum effectively, the unoccupied frequency bands of the licensed users are to be identified. These vacant frequency bands can be allocated to the unlicensed users with the permission of licensed users. The unlicensed users can continue their transmission without causing hindrance to the actual licensed users. However, the unlicensed users must abandon these frequency bands as soon as the incumbents are detected in the band of interest. This task of detecting the unoccupied frequency bands and allocating them to unlicensed users is termed as spectrum sensing. Broadly, spectrum sensing is classified into: Non-Blind sensing and Blind sensing [5] as shown in figure 1.

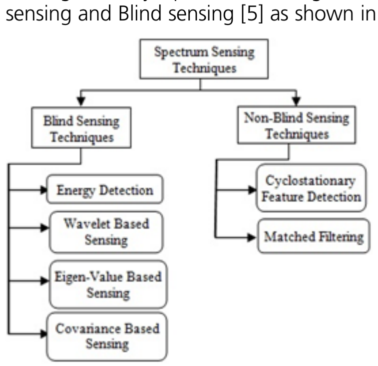

Figure.1: Classification of spectrum sensing techniques

Non-blind sensing technique demands the knowledge of the characteristics of the signal and noise before processing whereas blind sensing techniques do not need any such information.

Spectrum Sensing Model

The first and foremost step in cognitive radio networks is the spectrum sensing. The problem of detection of the primary signal at the secondary user can be modeled as binary hypothesis [6]:

$$H_0: y[n] = w[n] \qquad (1)$$

$$H_1: y[n] = s[n] + w[n] \qquad (2)$$

Where

s[n] are the samples of the primary signal. w[n] are the samples of the additive white Gaussian noise (AWGN) with zero mean and variance . σ_w^2. Y[n] are the received signal samples. Hypothesis H_0 corresponds to the presence of noise signal only i.e., absence of the primary signal. Hypothesis H_1 corresponds to the presence of the primary signal.

SPECTRUM SENSING TECHNIQUES

From figure 1, it is clear that spectrum sensing techniques can be categorized as blind and non-blind sensing techniques. Energy detection, wavelet based sensing, Eigen - value based sensing and covariance based sensing techniques come under blind sensing, as they do not require any prior information about the primary signal. Cyclostationary feature detection and matched filtering methods come under non-blind sensing, which uses the known characteristics of the primary signal. These methods are discussed in detail in the following subsections.

Energy Detection

Energy detection based sensing is the simplest approach of all sensing techniques. It is also one of the widely used methods because of its less number of computations and low implementation complexity. Both analog and digital signals can be conveniently detected using this technique.

The energy detection process is illustrated in figure 2. Here, the received signal y(t) is first passed through an ideal Bandpass filter of bandwidth W. The filtered signal is now converted to discrete samples by using an ADC. These samples are then squared and integrated to obtain the energy of the received signal, which is the actual test statistic, T given as [6]:

$$T = \frac{1}{N}\sum_{n=1}^{N} |[y(n)]^2| \qquad (3)$$

Next to decide the decision threshold, γ noise variance of the signal $\sigma_w 2$ is computed. The test statistic, T is then compared with the threshold, γ. Now the hypothesis H_1 is true if the test statistic, T exceeds the decision threshold, γ. is true if the test statistic, T is less than the decision threshold,.

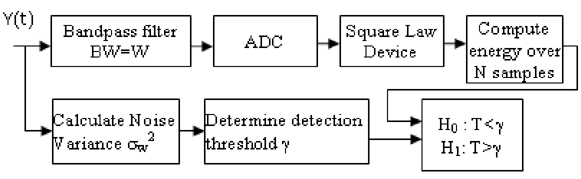

Figure 2 Illustration of energy detection process

The performance of energy detection process can be estimated using two parameters [7]:

(a) P_D Probability of detection It is the probability of detecting the presence of primary signal in the frequency band of interest when it actually exists, given as:

$$P_D: P(T>\gamma|H_1) \qquad (4)$$

(b))P_{FA} Probability of false alarm It is the probability of falsely deciding the presence of primary signal in the frequency band of interest when it actually does not exist, given as:

$$P_{FA}: P(T>\gamma|H_0) \qquad (5)$$

The value of P_D must be as high as possible and P_{FA} must be as low as possible. The complement of P_D is termed as P_{MD}, probability of misdetection. P_{MD} is the probability of falsely rejecting the hypothesis, H_1.

In the paper [6], the primary signal considered was a QPSK modulated signal of bandwidth 4MHZ. results have shown that by considering P_{FA}=0.2, P_D, approaches 0.9 by increasing the number of samples from N=100 to 1000 for SNR=-8dB. . It also shows that does not improve even if the number of samples are increased when SNR<-16dB. . But with P_{FA}=0.2, $P_D \geq 0.9$ was achieved only for SNR≥ - 8dB.

One of the limitations of energy detection technique is uncertainty in threshold due to indefinite nature of noise power. Energy detection fails below SNR wall even if the sample size is made infinite. The key limitation of energy detection is its inability to distinguish between primary user signals and secondary user signals. The performance of energy detection is poor under low SNRs due to shadowing and multipath fading.

Wavelet Based Sensing

Wavelet based sensing technique is employed for detecting wideband signals [5]. This method divides the wide spectrum into smaller sub bands and tries to identify the variations in the power level in these sub bands. This task is accomplished by using wavelet transform which identifies the edges in PSD. Identification of these edges of sub bands helps in determining whether the band is occupied or not. It is a flexible and low cost blind detection technique.

Eigen-Value Based Sensing Technique

In this method, the presence of primary user signal can be known by calculating the eigen values of the covariance matrix of the received signal. A number of algorithms have been proposed based on random matrix theories, such as MME [8], which computes the ratio of maximum eigen value to minimum eigen value and EME [9], which computes the ratio of energy of received signal to minimum eigen value. Using this analysis, the threshold and P_{FA} can be found to detect the primary signal.

In [8], 2000 Monte Carlo simulations were carried out over energy detection with and without noise uncertainty and the proposed MME. The results show that energy detection method performs well without noise uncertainty. However, energy detection method failed to achieve $P_{FA} \leq 0.1$ in the presence of noise uncertainty whereas in this case MME outperforms energy detection at an SNR=-15dB..

Covariance Based Sensing Technique

Covariance based detection uses the correlative nature of the received signal samples in order to clearly distinguish between the primary user samples and noise. A covariance matrix is computed from received signal that decides whether a primary signal is present or not as shown in the figure-3.

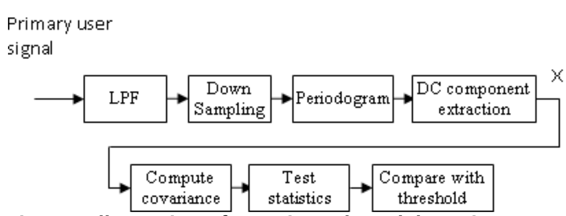

Figure 3 Illustration of covariance based detection process

The primary user signal is filtered with required bandwidth w. by choosing appropriate fs, the signal is down sampled [10]. Next, the periodogram of these samples is computed by applying FFT and squaring them.

$$F_\tau(q) = \frac{1}{N}\left|\sum_{n=0}^{N-1} f(n+\tau N)e^{\frac{-j2\pi nq}{N}}\right|^2 \qquad [6]$$

Where N: number of FFT points
τ:{0,1,2,...,Ns-1}, i index of sensing window
Ns: total number of sensing windows
q:{-N/2,....0,...N/2-1},frequency index

Not all these samples are used to obtain the covariance matrix. So by appropriately choosing the bin, few components are selected and given for processing. Finally, a covariance matrix is calculated to obtain the test statistics [10].

cov =covariance(X) (7)

$$\mathrm{cov} = E_q\left[(X - 1_{N_s}\mu_x)^T(X - 1_{N_s}\mu_x)\right] \qquad (8)$$

Where $\mu_x=[\mu_0,\mu_1,\ldots,\mu_{Ns-1}]$

$1_{Ns}=[1,1,\ldots,1]^T$ is the all one's vector of length

$$E^q[\cdot] = \frac{1}{2Q}\sum_q[\cdot]$$

where
Q = index of low pass filter cutoff frequency $(f_c) = \frac{Nf_c}{f_s}$

f_s =sampling frequency
The covariance matrix obtained will have same diagonal elements with information being carried in off-diagonal elements. The diagonal elements always represent noise and off-diagonal elements represent the signal samples. Further, these elements are used to estimate the noise and signal thresholds Tn and Ts. the ratio of Tn and Ts is used as a measure to sense whether a primary signal is present or not.

If $\frac{T_n}{T_s} = 1$, there is no signal.

If $\frac{T_n}{T_s} > \gamma$, signal is present.

However, autocorrelation can also be used to compute the thresholds in place of covariance. Recently, many covariance detection algorithms have been developed for primary signal detection in cognitive radio networks.

In [11], covariance based algorithms were derived based on autocorrelation of the received signal. The proposed covariance detection method was also compared with energy detection. The simulations have shown that covariance detection method is far better than energy detection scheme. The performance of the algorithm is tested using three different types of signals: narrowband signals, DTV signals and multiple antenna signals. A value of 0.9 was obtained when and Ns = 50,000.

In [10], a spectral covariance sensing algorithm is proposed in frequency domain for detecting ATSC signals. The results were compared with FFT based pilot detection method. Spectral covariance sensing method improved the SNR by 3dB when compared with FFT based method. By increasing the number of dwells, the sensitivity was increased.

As it comes under the category of blind sensing technique, it does not require any previous information of primary signal. It works well for highly correlated signals. If the primary signal tends to be uncorrelated, the performance of covariance based spectrum sensing technique is poor.

Cyclostationary Feature Detection Technique
Cyclostationary feature detection technique performs better than energy detection technique in low SNR regime due to its robustness to noise power uncertainty with an increase in implementation complexity. As it comes under non-blind sensing techniques, it requires some knowledge of primary signal characteristics before processing.Cyclostationarity indicates the presence of periodicity in the statistical parameters of the signal in time. This periodicity may be due to modulation or may be intentionally generated to assist in processing. The periodicity nature in cyclostationary signals causes the parameters like mean and variance to repeat at regular time intervals. This makes clear that there exists correlation between different frequency components of the primary signal which can be identified by calculating the cyclic autocorrelation function (CAF) or cyclic spectral density (CSD) in frequency domain. The cyclic spectral density function, CSD of the received signal is given as [7],

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\infty} R_y^\alpha(\tau)e^{-j2\pi f\tau} \qquad (9)$$

where

$$R_y^\alpha(\tau) = E[y(n+\tau)y^*(n-\tau)e^{j2\pi\alpha n}] \qquad (10)$$

α is the cyclic frequency.

The cyclostationary feature detection process is illustrated in figure-4

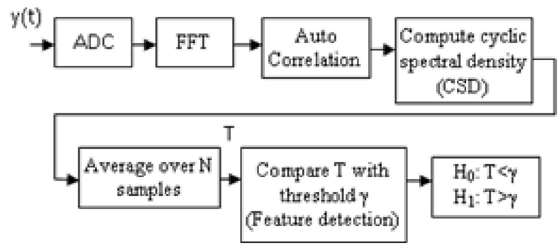

Figure 4 Illustration of cyclostationary feature detection process

In the paper [12], simulation results show that an optimal SNR of -8dB was achieved for detecting a BPSK signal assuming 10% PFA where 90% of PD was achieved, using Kaiser Window function.

In the paper [13], Yue and Zheng proposed a two stage spectrum sensing method by combining both energy detection and cyclostationary feature detection to achieve better results. In the first stage, the energy detection technique was used for coarse detection over the band of interest. Next, it arranges the channels in ascending order according to the power levels of the signal. In the second stage, fine sensing is performed on channels with lowest power using feature detection. The results of this paper indicate that probability of misdetection can be reduced with two stage spectrum sensing method when compared to traditional energy detection technique.

The key feature of cyclostationary feature detection technique is its capability to distinguish primary signal from noise and also between different primary signals. Higher value of PD can be achieved here than that of energy detection process. The main limitation of cyclostationary feature detection technique is its increased implementation complexity, because in addition to normal processing, it requires to extract the cyclic frequencies also. It also requires large sensing time.

Matched Filtering
Like cyclostationary feature detection technique, matched filtering also works well in low SNR region and even with less number of samples and shorter detection time [7], [5]. Matched filter detection technique also requires some specific signature of the primary signal as it belongs to non-blind sensing techniques. This technique needs exact information on the features of the primary signal such as bandwidth, modulation type and order, operating frequency, pulse shaping, frame format etc. For detecting different types of primary user signals, different receiver designs are required, which increases the implementation complexity.

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Comparison of Sensing Techniques

Comparison of different sensing techniques is presented in figure-5. The choice of a spectrum sensing technique can be made with a trade-off between complexity and sensing accuracy. Of all the sensing techniques, energy detection technique is the simplest one in terms of implementation. But the performance of energy detection technique degrades in the presence of shadowing and multipath fading. Energy detection technique also fails when noise variance is not known and also if noise is not stationary [7], [5]. Cyclostationary methods perform better than energy detection technique, which can be used when prior knowledge of the primary signal is available. But when the noise is stationary, cyclostationary feature detection techniques perform worse than energy detection techniques. Matched filtering can be preferred when pilot transmissions or synchronization sequences of primary signal are known. On the other hand, blind sensing techniques based on eigen values or covariance matrix of received signal give high accuracy but with an increase in implementation and computational complexity. During the selection of a particular sensing technique, trade-offs should be considered.

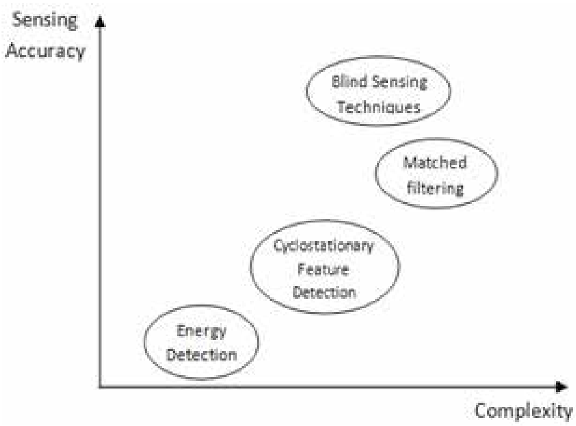

Figure 5 Comparison of spectrum sensing techniques

COOPERATIVE SPECTRUM SENSING TECHNIQUE

The serious problems that the secondary users may suffer during transmitter detection are multipath fading and shadowing. To overcome these limitations and to achieve robustness in spectrum sensing without drastic changes in secondary user's equipment, the cooperative spectrum sensing technique was proposed.

The basic idea of cooperative spectrum sensing technique is to combine the sensing information from multiple secondary users to obtain more reliable output [5], [7]. Here, cooperation is maintained among secondary users or cognitive radios in such a way that they exchange sensing information between them. Based on this information, final decision is made. The location where the final decision is made distinguishes between two types of sensing in cooperative spectrum sensing technique: centralized sensing and decentralized/distributed sensing.

In centralized sensing [14], a central unit called fusion center (FC) collects the sensing information from all the secondary users and based on this information, FC identifies the spectrum hole and the broadcasts this spectrum hole information to all the secondary users or controls the traffic on its own. The central unit is also known as access point (AP). As this information is collected from multiple secondary users, the effects due to multipath fading and shadowing can be mitigated. Centralized sensing is more efficient in terms of bandwidth when compared to distributed sensing for same number of cooperating secondary users. Also, only the secondary users with reliable information can be allowed to report their information to fusion center. This can be accomplished by censoring some sensors by using two threshold values rather than one. The critical point in centralized sensing is that, only one secondary user which works as fusion center is burdened to carry the task of all secondary users.

In distributed sensing, secondary users do not rely on fusion center to make a decision. Here, each secondary user transmits its sensing information to other secondary users in its neighborhood. Each secondary user now makes a decision by combining its data with the information received from other neighboring cognitive radios. Generally, the sensing information shared among cognitive radios will be in binary form. If no spectrum hole is identified, secondary users send their sensing information to other set of neighboring cognitive radios in the next iteration. This process continues until a final decision is made. The advantage of distributed sensing lies in its low implementation cost, because it does not need any extra infrastructure. The key limitation of distributed sensing is the large bandwidth that is required to exchange the sensing information among all secondary users. In cooperative spectrum sensing technique, each cognitive radio can employ any sensing technique to detect the presence of spectrum hole.

CONCLUSION

In this paper, the importance of the utilization of the spectrum is discussed to meet the increasing demand for wireless spectrum. Spectrum sensing, the key component of cognitive radio is presented along with various spectrum sensing methods, their advantages and limitations. Cooperative spectrum sensing technique, which is a solution to the problems like multipath fading and shadowing, is also explained. Comparison of different sensing techniques clearly indicates that future research areas can aim at developing a sensing algorithm which is less complex and implementation friendly, and at the same time robust with minimum sensing time.

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