Spectrum Sensing

Marjan Hadian
Instructor: Professor M. J. Omidi

Abstract—Cognitive Radio have been proposed as a possible solution to improve spectrum utilization via spectrum opportunistic. The fundamental requirement for this and also for working without interference to licensed user is spectrum sensing. Spectrum Sensing enables the cognitive radio to adapt its environment by detecting spectrum holes. Spectrum sensing can be done in two ways, frequency usage and mode identification. In this paper we review some of the spectrum sensing methods, describe some challenges of spectrum sensing.

Index Terms—Cognitive Radio, Spectrum Sensing, primary user, secondary user.

I. INTRODUCTION

A Cognitive Radio can be defined as a communication terminal which can observed external world, gather data and analyze them after that make decision about the action, it must be done. This tasks can be summarized in what Mitola calls cognitive radio cycle: cognitive radio continually observes the environment, orients itself, creates plans, decides, and then acts [1].As we can see, from the time which cognitive radio begins its work, this cycle occurs in a continuous way in order to improve dynamically behavior. So this cycle can be considered as a continuous learning phase. In Fig.1.a representation of a cognitive radio cycle is shown.
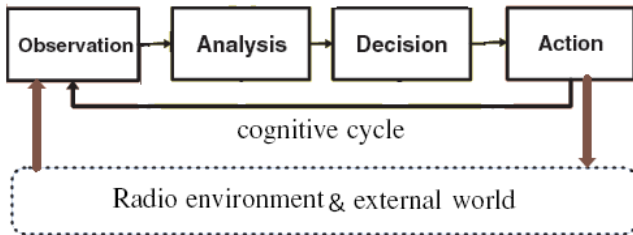

Fig.1. Cognitive Cycle

We can see the two first stages of this cycle are related to spectrum sensing since we define it as follow. Spectrum sensing is analysis of reference band through the collection of information in terms of respectively[1],Frequencies usage and Air interfaces classification(mode identification) the use of frequencies in a particular band have been studied by calculated different parameters such as energy level and interference temperature which will be described later. But by calculating this parameter, we can only qualitatively describe the occupation of a given frequency band. So we use mode identification to provide a quantities description of spectrum. Air interface or mode identification can be defined as the specification of the radio transmission between a transmitter and a receiver. It defines the frequencies or the bandwidth of the radio channels, and the encoding methods used such as FH-CDMA, DS-CDMA, TDMA, MC-CDMA, etc. [1] for further calculation consider a hypothesis test for signal detection:

$$r(t) = hs(t) + w(t) \tag{1}$$

If $h = 0$, under hypothesis H_0, means the absent of signals and if $h = 1$ under hypothesis H_1, means presence of signals. It is assumed that $w(t)$ is AWGN with spectral density σ^2 and $s(t)$ is the detected signal waveform. And also $r[n], s[n], w[n]$ are samples of $r(t), s(t), w(t)$ where $n = 1,2, ..., N$. Generally spectrum sensing can be classified as single detection and cooperative detection and interference based detection as shown in Fig.2. In the following we describe these methods. General scenario in spectrum sensing is that each radio gathers data about spectrum and by means of distributed detection theory estimates which type of air interfaces are present. [1] The rest of the paper is organized as follows. In Section II, we discuss about spectrum sensing implementation. The Interference Temperature model is presented in Section III. Section IV discusses about spectral analysis, Section V describes cooperative detection method and finally Section VI concludes the paper.

II. SPECTRUM SENSING IMPLEMENTATION

In this section we describe three methods of spectrum sensing, which is now implemented in cognitive radios.

A. Energy Detection

The simplest detector, and also the optimal detector when SU doesn't have sufficient information about PU signal, is energy detector. An energy detector can be implemented by using welch periodogram (Fourier Transform) as depicted in figure

Fig.2. Energy Detector

In this architecture the frequency resolution of FFT increases with the number of point's k, which effectively increases the sensing time. A decision statistics for energy detector is:

$$T = \sum_N (r[n])^2 \qquad (2)$$

Also, in [experimental] said that, if the number of samples used in sensing is not limited, an energy detector can meet any desired p_d and p_{fa} simultaneously. The minimum number of samples is a function of the signal to noise ratio($SNR = \sigma_x{}^2 / \sigma_w{}^2$)

$$N = 2[\left(Q^{-1}(p_{fa}) - Q^{-1}(p_d)\right) SNR^{-1} - Q^{-1}(p_d)]^2 \quad (3)$$

Although this method is the simplest one but it has many disadvantages. One of the most important of these problems is which one called SNR wall. This problem comes from uncertainty. Uncertainty is the difference between our assumptions and real world, for example real noise is not perfectly Gaussian, perfectly white, nor perfectly stationary. Also we assume that noise variance is precisely known to the receiver but even if receiver can estimate it precisely, obviously it varies over time due to temperature change and other parameters. These model uncertainties impose fundamental limitations on detection performance in low SNR environment. The limitations cannot be countered by increasing the sensing duration.SNR wall is a minimum SNR below which signal cannot be detected and formula (3) no longer holds. Also in frequency selective fading it is not clear how to set the threshold with respect to channels notches.[2] Since energy detector doesn't differentiate between modulated signals, noise ,interferences, it has lower robustness than other detectors.

B. Matched filter

Te optimal detector for PU signal detection signal, when the information of the PU signal is known to SU, is a matched filter, since it maximizes SNR. For implementation of matched filter cognitive radio has a priori knowledge of modulation type, pulse shaping and etc. Since most wireless network systems have pilot, preambles, synchronization word or spreading codes these can be used for the coherent detection. The main advantage of this filter is that it requires less time to achieve high processing gain because of the coherency [5]. So the equation of this detector can be written as follow

$$A = \sum_{n=0}^{N-1} s[n]r[n] \qquad (4)$$

If γ is the detection threshold, then by comparing A and , the situation H_0 or H_1 is declared .Also number of samples required for optimal detection is

$$N = [\left(Q^{-1}(p_{fa}) - Q^{-1}(p_d)\right)]^2 SNR^{-1} \qquad (5)$$

A significant drawback of a matched filter is that a cognitive radio would need dedicated receiver for every primary user class. [2]

C. cyclostationary feature detector

Modulated signals are in general coupled with sine wave carriers, pulse trains, repeating spreading, hopping sequences, or cyclic prefixes, which result in built-in periodicity. These modulated signals are characterized as cyclostationarity since their mean and autocorrelation exhibit periodicity. These features are detected by analyzing a spectral correlation function. The main advantage of the spectral correlation function is that it differentiates the noise energy from modulated signal energy, which is a result of the fact that the noise is a wide-sense stationary signal with no correlation, while modulated signals are cyclostationary with spectral correlation due to the embedded redundancy of signal periodicity. [5] Therefore, this method is considered than formers, due to its robustness to the uncertainty in noise power.

III. Interference Temperature

Although, interference takes place at the receiver, but FCC try to solve and control it at the transmitter through the radiated power and out of band emission. Due to this FCC suggested that Interference Temperature limit should be used as a metric to estimate and manage the amount of interference present. In this model, as additional interfering signals appear the noise floor increases and then unlicensed devices could use that particular band as long as their energy is under mention noise floor set by FCC. Fig.2. illustrates the Interference Temperature model. There are several equivalent definitions of Interference Temperature but we use the following equation here: [6]

$$T_c(f_c, B_c) = \frac{pi(f_c, B_c)}{kB_c} \qquad (6)$$

Where $T_c(f_c, B_c)$ is the interference temperature for channel$c$, with central frequency f_c and bandwidthB_c. $pi(f_c, B_c)$ is the average interference power in Watts (at the antenna of a receiving or measuring device) centered at frequency f_c and covering the bandwidth B_c (in Hertz). k is Boltzmann's constant (1.38×10^{-23} Joules per Kelvin) .
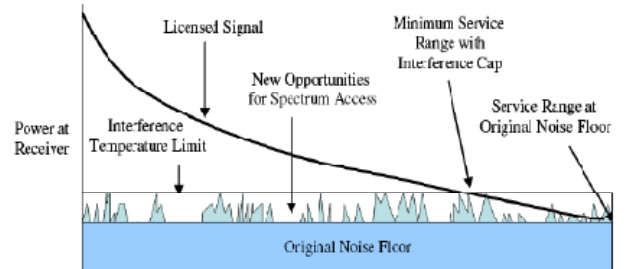

Fig.3. Interference Temperature model [5]

This method considers factors such as the type of unlicensed signal modulation, antennas, ability to detect active licensed channels, power control, activity levels of the licensed and unlicensed users [5]. In order to reliable estimating the power spectrum of Interference Temperature,

Multi-Taper-Method is being suggested but one of the difficulty of this method is that the primary receivers are usually passive devices [5] and SUs cannot be aware of their exact location, so measuring Interference Temperature is actually difficult. Also, if in an area more than one receiver exists, SUs must calculate Interference Temperature in all of them and increasing the number of primary receiver s equal to increasing the probability of the effect of SUs transmission on some of receivers since accurate Interference Temperature measurement may not possible. In [5] suggested that using large number of low cost sensors can be mounted close to the primary receivers which can increase the accuracy of estimation and Interference Temperature measurement.

IV. Spectral Analysis

There exists several methods for spectral estimation which can be mainly divided into two categories. In first one, parametric spectral estimation, the signal $s[n]$ which spectrum is desired, asssumed that have some given parameters.So by using this parameter we estimate the $\hat{s}[n]$ which has the closet autocorrelation with $s[n]$.In fig.33 an example for implementation of this method is shown. where the input $v(n)$ is a white random process with variance of unity, so the parameters a_k and b_k are optimized such that $\hat{s}[n]$ and $s[n]$ have the closet autocorrelation coefficients.

$$\nu(n) \rightarrow H(z) = \frac{\displaystyle\sum_{k=0}^{N-1} b_k z^{-k}}{\displaystyle\sum_{k=0}^{M-1} a_k z^{-k}} \rightarrow \hat{s}(n)$$
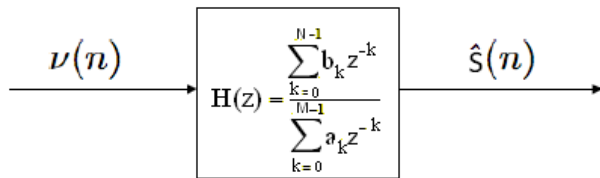
Fig.4. implementation of parametric spectral estimation.

The second class is non-parametric spectral estimation. In this class, an estimate of the Power Spectral Density (PSD) of a random process $s[n]$ is obtained by passing it $s[n]$ through a bank of narrowband bandpass filters and measuring the average output power of these filters [4]. There are different types of non-parametric spectral estimators, which we explain some of them here. The Periodogram (Fourier transform) Spectral Estimator (PSE) method is perhaps the simplest method for doing spectral analysis. The data (multiplied by a window to minimize spectral leakage) are just Fourier transformed. However, this method is not suitable for short and noisy data, because results are not stable with respect to small changes in the input signal. In order to reduce the problem of large side lobes in PSE a window function before filtering can be applied, this method is called Blackman-Tukey Spectral Estimator (BTSE). BTSE computes first the auto covariance of the data, then applies a window, and finally

Fourier-transforms it to compute the spectrum. One of the most important methods in spectral estimation is Multi Taper Method (MTM). This method of spectrum estimation expands a part of the time series in a frequency band f - W to f + W where f is the centered frequency and W the bandwidth, into a special form of sequence known as Slepian Sequence whose property is that its Fourier Transforms have its maximal energy concentration in that bandwidth stated above for a finite number of samples. Furthermore in MTM, each point of the desired PSD is obtained by averaging the signal power at the output of a set of narrowband (known as porlate) filters that have the same pass band, but have been designed to generate a set of independent outputs [4]
This helps in reducing the variance of the spectral estimate and keeping the estimates unbiased.
Recently, Haykin has identified MTM as the best method for channel sensing in CR, because of its near optimal performance. [4].MTM has several advantages such as a high resolution and statistical confidence levels that are independent of the spectral power. In addition, contributions at selected frequencies can be reconstructed.

V. COOPERATIVE DETECTION

In all traditional methods which discusses above, hidden node (terminal) problem exists. This problem has different sources; two of them are shown in Fig2.
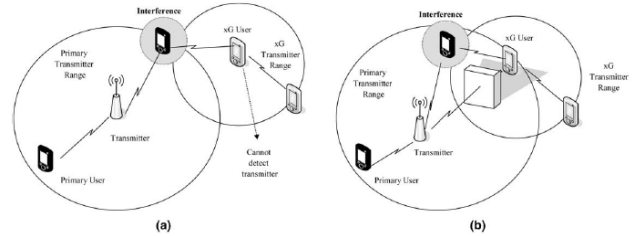

Fig.5. Hidden node problem

In order to prevent the hidden terminal problem the SUs (secondary users) can cooperate to detect the presence of PU(primary user).also Cooperative detection schemes mitigate the multipath fading and shadowing effect which are the most important factors that degrade the performance of traditional methods. In this method, information from multiple SUs are incorporated for primary user detection. Cooperative detection can be implemented either in a centralized or a distributed manner [5]. In cooperative detection each SUs provide its observation to other terminals. This transmission can overlap to the air interfaces already present in the environment, so it can change the nature of observations and make new problems. In order to solve this problem in [5] two distinct networks are deployed separately, i.e. the sensor network for cooperative spectrum sensing and the operational network for data transmission. The sensor network is deployed in the desired target area and sense the spectrum. Of course in this

method central implementation method is used and it processes the spectrum information collected from sensors and makes the spectrum occupancy map for the operational network and the operational network uses this information to determine the available spectrum hole. Also for solving this problem in [1], suggested that each of SUs shares the analysis model with all other devices in a priori way. In this technique, the analysis model is shared in an off-line method when in the environment no SUs is observing the radio scene. This means that the observation y_i of SU i is due to its position x_i and to the state of radio source H_k ,but not to the observation of other SU j and y_i.Thus we assume that, independent measurements for each SUs is presented either in a centralized or distributed manner. Now we review two detection methods: log-likelihood combining and weighted gain combining.

A. log-likelihood combining

Assume that $\underline{y} = (y_1, \dots, y_N)$ is the vector of SUs energy detector output.So a solution to the distributed detection problem is obtained by applying likelihood ratio test(LRT)

$$\Lambda\left(\underline{y}\right) = \frac{p\left(\underline{y}|H_1\right)}{p\left(\underline{y}|H_0\right)} \qquad (7)$$

In this equation if $\Lambda\left(\underline{y}\right) > \lambda$ Then this is H_1 mode else this is H_0.Also due to the independence of y_i we can rewrite above equation:

$$\frac{p\left(\underline{y}|H_1\right)}{p\left(\underline{y}|H_0\right)} = \prod_{n=1}^{N} \frac{p(y_n|H_1)}{p(y_n|H_0)} \qquad (8)$$

For easier calculation LRT can be rewritten with:

$$\Lambda\left(\underline{y}\right) = \sum_{n=1}^{N} \log[\frac{p(y_n|H_1)}{p(y_n|H_0)}] \qquad (9)$$

As we can see, in this technique we need conditional pdf's, but the SNR is not known. So in order to employ the likelihood ratio test an estimate of the SNR can be used to derive the pdf's.

B. weighted gain combining

This technique is usually applied in a centralized manner of cooperative technique. The center weights and combines the measurement values of the N local detector. Because some nodes will have a better location, they are given greater coefficient, thus different weights is given to different nodes.

$$y_{WC} = \sum_{n=1}^{N} w_n y_n \qquad (10)$$

Where w_n is calculated from

$$w_n = \frac{\overline{\gamma_n}}{\sum_{n=1}^{N} \overline{\gamma_n}} \qquad (11)$$

Where γ_n , the mean SNR over the last k measured SNR values of user n ,is defined as [multinode based energy detection]

$$\overline{\gamma_n} = \frac{1}{2k} \sum_{j=i-k}^{i} (y_{n,j} - 2TW) \qquad (12)$$

And $y_{n,j}$ is the non-quantized jth measurement of the SU n. [7]In this analysis , w is the bandwidth which we observe it over time T. This method implies higher weight for nodes with a high SNR than those with a low SNR.

VI. CONCLUSION

In this paper we describe some methods of spectrum sensing implementation, and describe their challenges. Also we describe new method of spectrum sensing, cooperative detection to mitigate hidden node problem.

REFERENCES

[1] Matteo Gandetto, *Member, IEEE,* Carlo Regazzoni, *Senior Member, IEEE* "Spectrum Sensing: A Distributed Approach for Cognitive Terminals," IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS, VOL. 25, NO. 3, APRIL 2007

[2] Danijela Cabric, Shridhar Mubaraq Mishra, Robert W. Brodersen,"Implementation Issues in Spectrum Sensing for Cognitive Radios"Berkeley Wireless Research Center, University of California, Berkeley

[3] Danijela Cabric, Artem Tkachenko and Robert W. Brodersen ,"Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection" Berkeley Wireless Research Center

[4] Behrouz Farhang-Boroujeny and Roland Kempter," Multicarrier Communication Techniques for Spectrum Sensing and Communication in Cognitive Radios" ECE Department, University of Utah, USA

[5] Ian F. Akyildiz, Won-Yeol Lee, Mehmet C. Vuran , Shantidev Mohanty "NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey", science direct

[6] Karama Hamdi and Khaled Ben Letaief, *Fellow, IEEE,*"Cooperative Communications for Cognitive Radio Networks"

[7] Frank E. Visser, Gerard J.M. Janssen, Przemysław Pawełczak," Multinode Spectrum Sensing Based on Energy Detection for Dynamic Spectrum Access".