Comparative analysis of Signal Processing Techniques for Transmitter Detection for spectrum sensing in cognitive radio

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***Abstract*--Today's wireless communication systems follow fixed spectrum assignment policies that leads to overall inefficient spectrum use. Further the scarcity of spectrum is an issue for service providers with emerging mobile services and such a large number of consumer with even higher bandwidth requirement. Spectrum sensing enable secondary user to use frequency spectrum which is provided for primary user without affecting his data. In this paper, we are going to provide various spectrum sensing methods in cognitive radio (CR).**

***Keywords*–Spectrum sensing methods, signal processing in cognitive radio (CR), cognitive radio networks primary user (PU).**

I. INTRODUCTION

Most of the radio frequency spectrum is allocated, although much of it is unused. The main aim of spectrum sensing can be divided in two categories, first is dynamically identify unused spectrum and avoids primary system (PS) interference is essential for efficient utilization of the spectrum. Spectrum sensing should also supervise the activation of primary users and order the secondary users to vacate the occupied spectrum sections. However, it is difficult for a cognitive radio to catch such information instantaneously due to the absence of cooperation between the primary and secondary users. Thus, recent research attempts on spectrum sensing have focused on the detection of on-going primary transmissions by CR devices.

Moreover, the spectrum sharing by Cognitive Radio users in given spectrum band can be categorized in Horizontal sharing and Vertical sharing as shown in Fig. 1.

- Horizontal sharing, where Cognitive Radio users and primary users have equal chances to access the spectrum such as in wireless LAN operating in ISM band at 2.4GHz, and in order to improve the overall system functioning, CR users can choose the channels which have less number of users or less traffics. In this approach CR users and primary users co-exist in the system and use the bands simultaneously.
- Vertical sharing, where Cognitive Radio users have less preference over the PU's spectrum , and thus CR user must vacate the spectrum as fast as possible when the licensed primary user are detected in the band. Even so, CR users can use the spectrum with potential whenever they detect the idle spectrum band. Moreover, in vertical sharing, Cognitive Radio system needs operator's help.

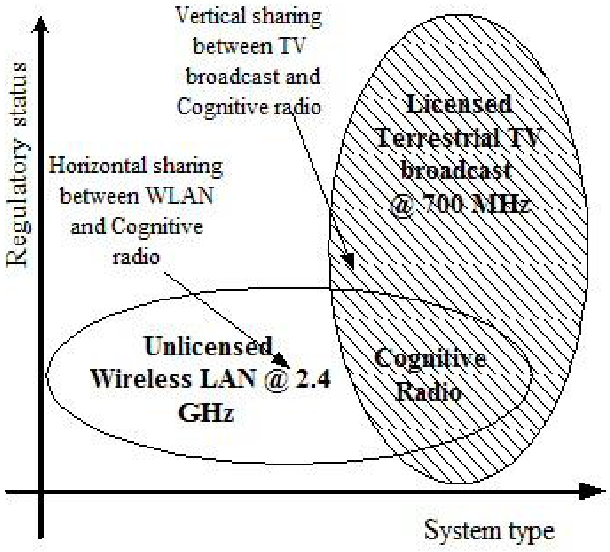


Fig. 1 Horizontal and Vertical spectrum sharing

However, the two individual phases cannot be designed and optimized individually , since they affect each other [2]. To be sure, when an available spectrum hole is not sensed by the cognitive source during a certain time duration, the spectrum hole utilization efficiency will be spoilt. Unutilized spectrum that is called spectrum hole is shown in Fig. 2.

We may increase the time duration of spectrum sensing phase to relieve the problem of misdetection of spectrum holes, which, however, comes at the expense of a transmission performance reduction since less time is now available for the data transmission phase .

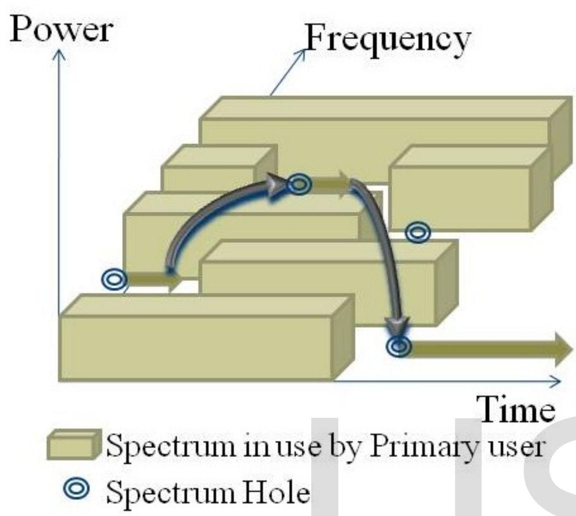


Fig. 2 Spectrum hole

We may increase the time duration of spectrum sensing phase to relieve the problem of misdetection of spectrum holes, which, however, comes at the expense of a transmission performance reduction since less time is now available for the data transmission phase .

The detection problem may be formulated as a binary hypothesis test

$$H0 : r(t) = n(t), \qquad H1 : r(t) = s(t) + n(t) \qquad \text{........ (1)}$$

where r(t) and n(t) denote the received signal and the noise, respectively, and s(t) denotes the signal to be detected. In a binary hypothesis test there are two types of errors that can be made.

These errors are called type 1 and type 2 errors, respectively. A type 1 error is made if H1 is accepted when H0 is true. The probability of making a type 1 error is often called the probability of false alarm. In spectrum sensing the probability of false alarm of a detector is an important design parameter since false alarms lead to overlooking spectral chances . A type 2 error is made if H0 is accepted when H1 is true. Type 2 error is if a missed detection and hence lead to collisions with primary transmissions and decreased rate for both the primary system and the secondary system.

Generally , a cognitive radio system should satisfy restraints on both the probability of false alarm and the probability of miss detection. Contriving a detection rule presents a trade-off between these two probabilities. However, given that the detector behaves averagely, in other words the probability of error reduces when the number of samples increases, both restraints may be satisfied by choosing the number of samples to be large enough. From the execution point of view it is desirable to have algorithms which threshold may be set analytically and which performance may be analyzed analytically[1]. Even so, in practice especially the probability of detection and the number of samples required to achieve a given probability of detection will most likely have to be determined experimentally due to the large number of variables, such as the synchronization errors, fading channel, noise power uncertainty, etc. Affecting their values.

II. TRANSMITTER DETECTION

In this method we detect the primary user’s signal by his signal which is received at Cognitive Radio user’s receiver. This approach includes.

Energy Detection.

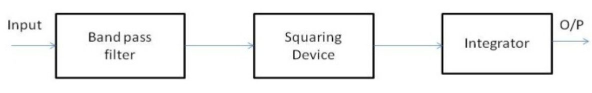
Matched Filter Detection.

Waveform-Based Detection.

Cyclostationary Feature Detection

A. Energy Detection

Energy detection is the most popular signal detection method due to its simple circuit in practical implementation. The principle of energy detector is finding the energy of the received signal and compares that with the threshold [2].



Energy detector

Fig.3 Blok digram of energy detection

For the energy detector, a popular decision statistic is given by

$$D=\sum_{n=1}^{N}\chi(n)^{2} \quad ....(2)$$

Under hypothesis H0(given in equation 1),the test statistic D is a random variable whose probability density function is a chi-square distribution with 2*N* degrees of freedom for a complex-valued case or with *N* degrees of freedom for a real-valued case.

Energy detection is a simple general approach as it requires minimum information of the PUs[3,4,5] . This method is legal only if the energy detected is above a certain threshold; in addition, it works ineffectively for signals whose power has been spread over a wideband. Threshold selection is difficult, as it is subject to the changing background interference level and noise .

B. Matched Filter Detection.

This technique increases Signal to Noise Ratio of received signal that helps in better detection [6],[7]. We consider that Matched filter is the optimal detector of a known signal in the presence of additive Gaussian noise. It has analytic knowledge of the primary signal, coherency makes sure that only O(1=SNR) samples are required for effective detection, thereby making detection faster so that an idle channel can be quickly occupied without any delay. It is the linear filter that maximizes the Signal to Noise Ratio of the output. On the bare side, knowledge of the primary signal might not be available. Furthermore, in case there are a lot of PUs, the radio receiver would have to have a dedicated matched filter for each different one of them. The Fig. 4 of matched filter detection is given below

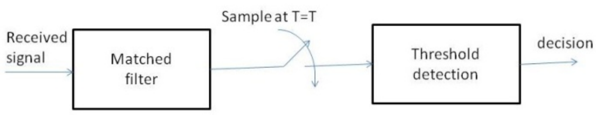


Fig. 4 block diagram of matched filter detection

The output of the matched filter is given by

$$x= s^{H}\sum_{n}^{-1} y$$

where y is the observation vector, s is the known deterministic signal to be detected, and $\sum_{n}$ is the noise covariance matrix.

Let us that the noise is Gaussian it follows that the output x is Gaussian as well since it is a linear transformation of a Gaussian random vector. The mean of x is zero under H0 and $s^{H}\sum_{n}^{-1}$ Under $H_{1.}$ Experimental measurements of matched filter pilot detection performance with synchronization errors have been provided in [8],[9]. In [10], an entropy-based matched filter method is given. The proposed detector compares the approximated entropy of the matched filter output to a threshold.

C. Waveform-Based Detection

It is another approach for primary signal detection. In this approach, the patterns corresponding to the signal, such as midambles, preambles, spreading sequences, regularly transmitted pilot patterns, etc detection [11], are usually utilized in wireless systems to serve synchronization or detect the presence of signal. When a known pattern of the signal is present, the detection method can be applied by correlating the received signal with a known reference of itself [11] can be performed and the method is known as waveform based detection. Tang in [11] has shown that waveform-based detection is better than energy based detection in terms of reliability and convergence time, and also has shown that the performance of the algorithm increase with length of the known signal pattern increase.

In order to perform waveform-based signal detection, we consider the received signal in (4) and calculate the detection metric as [11].

$$P= \mathrm{Re}\left[\sum_{n=1}^{N} x(n)y^{*}(n)\right]$$

$$=\sum_{n=1}^{N} y^{2}(n) + \mathrm{Re}\left[\sum w(n)y^{*}(n)\right] \quad ....(3)$$

Where *N* is length of known pattern. The detection metric M for waveform-based detection in equation (2) consists of two terms: the first term $\sum_{n=1}^{N} y(n)$ in second equality is related to signal and the second term Re[$\sum w(n)y^{*}(n)$]of second equality consist of noise component. Therefore we can conclude that when the primary user is idle (i.e.y(n)=0)

$P_T = P_r\ (M>\lambda|H_1)$, $P_F = P_r\ (M>\lambda|H_0)$ …….(4)

where P_T = the probability of true detection, that is, when signal is present in the frequency band and the detection is successful P_F is the probability of false alarm, that is, the detection algorithm shows that the frequency is occupied even so actually it is not. We want to reduce probability of false alarm P_F. We find that the value of threshold λ have important role in this access and can be measure based on noise variance. We also see that measurement results presented by Cabric, et al. in [12] shows that waveform-based detection requires less measurements time, however, it is capable to synchronization errors.

D. Cyclostationary Feature Detection

Man-made modulated signals are, in general, coupled with cosine wave carriers, coding, pulse spreading, cyclic prefixes, or hopping sequences, or resulting in built in periodicity. These modulated signals are characterized by second-order cyclostationarity if their mean and autocorrelation display periodicity. For static signals, non overlapping frequency bands are typically uncorrelated. However, the inherent periodicities of cyclostationarity signals mean some spectral redundancy, which results in correlation between those non overlapping spectral components classed by some multiple of the cycles [14]. In the time domain, a second-order cyclostationarity process is a random process for which its mean and autocorrelation periodically change as functions of time, with period *T* [14].

$E[x(t)] = E[x(t + T)]$

$E[x(t)x(t + \Omega)] = E[x(t + T)x(t + T + \Omega)]$ .... (5)

For all t and Ω

Man-made signals such as wireless radar signals and communication typically so cyclostationarity at various cyclic frequencies that may be related to the carrier frequency, symbol, chip, carrier frequency, hop rates ,or code, as well as their harmonics, sums, differences. The cycle (or conjugate cycle) frequencies of conventional modulated signals are tabulated in [13]. Overworking these periodicities allows designing powerful feature detectors that possess very attractive properties.

III. COMPARISION

The comparison between four methods which have been discussed in this paper is given below in tabular form. We can conclude from the table that these methods are suitable in different situation as per requirement of the parameter.

Spectrum Sensing Techniques	Advantages	Disadvantages
Matched Filter	Does not need a priori information, simple and low computational cost.	Probability of false alarm detection increases at low SNR.
Energy Detection	Optimal detection performance, low computational cost.	Requires a priori knowledge of primary user signal
Waveform-Based Detection	Better reliability and in convergence time.	Requires partial information of the primary user signal,
Cyclostati-onarity Detection	Robust in low SNR, robust to interference.	Requires partial information of the primary user signal, high computational cost.

IV. CONCLUSION

Spectrum is a very valuable resource in wireless communication systems. Cognitive radio is one of the efforts to utilize the available spectrum more efficiently through opportunistic spectrum usage. One of the important elements of cognitive radio is sensing the available spectrum opportunities. We enhance the CR's capability to differentiate signals from various sensing dimensions by utilizing change detection and fusion process to combine sensing results in different dimensions based on geographical information.

REFERENCES

[1] Teknillinen korkeakoulu Signaalinkäsittelyn ja akustiikan laitos-Helsinki University of Technology Department of Signal Processing and Acoustics Espoo 2009

[2] Y. Zou, Y.-D. Yao, and B. Zheng, "Outage probability analysis of cognitive transmissions: the impact of spectrum sensing overhead," IEEE Trans. Wireless Commun., vol. 9, no. 8, pp. 2676-2688, Aug. 2010.

[3] H. Urkowitz, ―Energy Detection of Unknown Deterministic Signals,‖ in Proceedings of the IEEE, vol. 55, Apr. 1967, pp. 523—531.

[4] Y. Zhuan, G. Memik, and J. Grosspietsch, ―PHY 28-1 - Energy Detection Using Estimated Noise Variance for Spectrum Sensing in Cognitive Radio Networks,‖ in IEEE Wireless Communications and Networking Conference, 2008. WCNC 2008, Apr. 2008, pp. 711–716.

[5] P. De and Y.-C. Liang, ―Blind Sensing Algorithms for Cognitive Radio,‖ in IEEE Radio and Wireless Symposium, 2007, Jan. 2007, pp. 201–204.

[6] Cabric, S. M. Mishra, and R. W. Brodersen, "Imple-mentation Issues in Spectrum Sensing for Cognitive Radios," Proc. Asilomar Conf. Signals, Systems, and Computers, Nov. 2004, pp. 772–76.

[7] A. Sonnenschein and P. M. Fishman, "Radiometric Detection of Spread-Spectrum Signals in Noise," IEEE Trans. Aerospace Elect. Sys., vol. 28, no. 3, Jul. 1992,pp. 654–60

[8] D. Cabric, A. Tkachenko, and R. Brodersen, "Spectrum sensing measurements of pilot, energy, and collaborative detection," in Proc. of the Military Communications Conference (MILCOM), Oct. 23–25 2006, pp. 1–7.

[9] D. Cabric, "Addressing the feasibility of cognitive radios," IEEE Signal Processing Magazine, vol. 25, no. 6, pp. 85–93, Nov. 2008.

[10] S. V. Nagaraj, "Entropy-based spectrum sensing in cognitive radio," Signal Processing, vol. 89, no. 2, pp. 174–180, Feb. 2009.

[11] H. Tang, ―Some Physical Layer Issues of Wide-band Cognitive Radio Systems,‖ in IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks, Baltimore, MD, Jun. 2005, pp. 151—159.

[12] W. A. Gardner, Statistical Spectral Analysis: An Nonprobabilistic Theory. Englewood Cliffs, NJ: Prentice-Hall, 1987.

[13] B. G. Agee, S. V. Schell, and W. A. Gardner, "Spectral self-coherent restoral: A new approach to blind adaptive signal extraction using antenna arrays," Proc. IEEE, vol. 78, no. 4, pp. 753–767, Apr. 1990.

[14] P. Pawełczak, "Cognitive Radio: Ten Years of Experimentation and Development," IEEE Communications Magazine, vol. 49, no. 3, pp. 90-100, Mar. 2011. IEEE DOI: