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Analysis of Various Quality of Service (QoS) provisioning techniques in Cognitive Radios Networks

Manwinder Singh*, Dr. Manoj Kumar** and Dr. Jyoteesh Malhotra***
**Ph.D. Research Scholar PTU Jalandhar, (PB), INDIA*
***Group Director- CT Group of institutes, Jalandhar, (PB), INDIA*
****HOD CSE/ECE GNDU Regional Campus Jalandhar, (PB), INDIA*

(Corresponding author: Manwinder Singh)
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ABSTRACT: The rapid growing of wireless multimedia applications increases the needs of spectrum resources, but today's spectrum resources have become more and more scarce and large part of the assigned spectrum is in an inefficiency usage. Cognitive Radio (CR) technologies are proposed to solve current spectrum inefficiency problems and offer users a ubiquitous wireless accessing environment, relying on dynamic spectrum allocation.
Spectrum sensing, that is, detecting the presence of the primary users in a licensed spectrum, is a fundamental problem for cognitive radio. As a result, spectrum sensing has reborn as a very active research area in recent years despite its long history. In this paper, firstly analysis of Cyclostationary and energy detection sensing is discussed, Cyclostationary feature can be used for spectrum sensing in a very low SNR environment (less than -20 dB). We also develop the hybrid spectrum sensing based resource allocation scheme for the ROC constrained CRNs. Finally we compare the results of hybrid sensing technique with Cyclostationary and ED sensing methods.

Key Words: Cognitive radio networks, Dynamic spectrum allocation, Quality of service, Spectrum sensing, Energy detector, Detection features, Hybrid Sensing detector (HSD).

I. INTRODUCTION

Currently, the radio spectrum is divided into licensed and unlicensed frequencies. The licensed spectrum is for the exclusive use of designated users. For instance, it includes the UHF/VHF TV frequency bands. The unlicensed spectrum can be freely accessed by any user, following certain rules (e.g., not exceeding a defined limit for transmission power) [1-4]. It includes, for instance, the ISM (Industrial, Scientific and Medical) and U-NII (Unlicensed National Information Infrastructure) frequency bands. ISM is shared by technologies such as high speed wireless local area networks and cordless phones. It is used by technologies such as IEEE (Institute of Electrical and Electronics Engineers) 802.11 and IEEE 802.11 g. U-NII includes frequency bands that are used by the IEEE 802.11 a technology and by internet service providers (ISPs). Therefore, many wireless technologies operate and must coexist in the same frequency bands, and devices must compete with neighbours for the same spectrum resources.
Appropriate dynamic frequency selection mechanisms have already been proposed to enable license-free wireless devices to make an efficient use of the unlicensed spectrum. However, the number of non-overlapping frequency bands in the unlicensed spectrum is limited, and increasing performance degradation cannot be avoided as it becomes more crowded, especially in densely populated areas.

II. SPECTRUM SENSING METHODS

The current work of development in spectrum sensing methods are still in early stages. There are different approaches are recommended for detecting signal presence in the transmissions system. In some of the methodologies and the features of recognized transmission detected to identifying the signal type and also deciding signal transmission [5-9]. This section explains various models of spectrum sensing techniques used in cognitive radio system and all these are described in Fig. 1.

A. Cyclostationary-Based Sensing
Cyclostationary sensing can be explained analytically as follows

$$C= \frac{1}{N}\sum_{n=L-1}^{N-1}(Y[n]y^{H}[n]) \quad \ldots(1)$$

Signals exhibit periodicities in its Statistics are called Cyclostationary signals [3-4]. Then periodicity of a random signal can be utilized for detection with specific modulation type used in related modulated signals and noise.

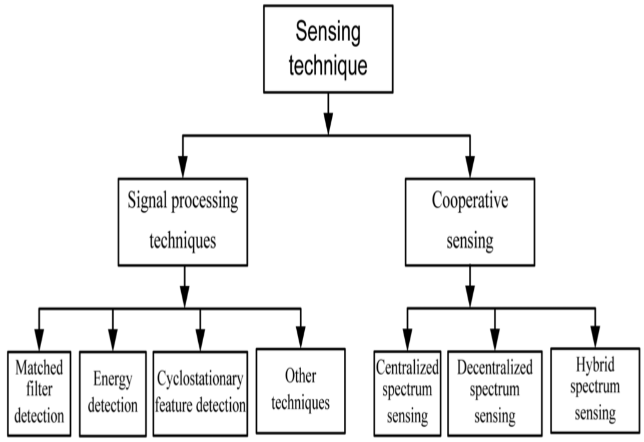

Fig. 1. Various Spectrum Sensing techniques.

Cyclostationary detection. This can be achieved from two dimensional spectrum correlation function or cyclic autocorrelation function, these two are under received signal.

Cyclostationarity feature detection is another method used in spectrum sensing. This method used for identifying transmissions of primary user. This method used to detect signals present spectrum. This is done by using cyclic correlation function by replacing power spectral density (PSD).

Important thing in wide sense stationary (WSS) is no other correlation happen when modulated received signals. If cyclostationary is facing a problem of spectral correlation problem means it is due to signal periodicities redundant. Cyclostationary features happen in Transmitted signals to and it causes an autocorrelation of the signal or periodicity of the signal or statistics of mean and its cyclostationary detector will abuses features to detect either primary user is present or not.

Spectral correlation function (SCF) is used by replacing the PSD in cyclostationary detector (CSD). Then SCF will detects the occurrence of a signal based on transmission periodicity. Normally in wide sense stationary (WSS) there is no noise present and it specifies no periodicity. Therefore the CSD easily separate noise pattern. Transmitter information need for Matched detector, but CSD do not require any transmitter information. Under low SNR and noise powers it can execute better than energy detector. Received signal cyclic spectral density function written as

$$R_y^{\alpha}(\tau) = E[y(n+\tau)y*((n-\tau)e^{j2\pi\alpha n}] \quad ...(2)$$

Cyclic autocorrelation function (CAF) is expressed in above equation. Cyclic frequency denoted as α. Fundamental frequencies signal while in transmission denoted as x(n). CF used for effective signal mechanism. Signal features are increased to improve the multipath fading. The increased overhead and loss of bandwidth causes more expanse.

B. Energy Detector Based Spectrum Sensing

Energy detector method also called as period gram [3], for finding spectrum sensing this will and basic approach because of its implementation complexities and low computational and also more generic compare to other methods. Main principle of energy detector is finding the received signal energy and compares with the threshold. These signals are sensed by comparing the energy detector output and also noise floor.

Threshold values are depends on noise level. Energy detector based sensing also facing some challenges those are failure to differentiate the interference from noise and primary users, detecting primary users with appropriate threshold, and also performance is poor due to low signal-to-noise ratio (SNR) values. For detecting spread spectrum signals energy detectors do not work powerfully [7-12].

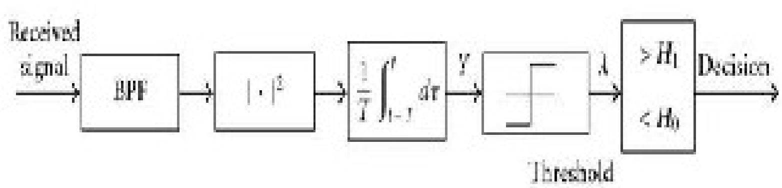

Fig. 2. Energy Detection based Spectrum Sensing.

This method optimal for identifying identical signal distribute with high SNR rate, but it is not suitable while going to correlated signal to detecting. Received signal of energy detector is

$$w(n)+ s(n) = y(n) \qquad \ldots(3)$$

By matching the decision metric M opposite to fixed threshold λE can obtain by choice of occupancy band. It is equal to examining two hypotheses give below

$$Y(n) = s(n) + w(n){:}\ H1, \ldots(4)$$
$$Y(n) = w(n) {:}H0,$$

Probability of incorrectly test decides that signal is not occupied actually and noted PF. This can be expressed as [4]

$$PF= Pr\ (M >, \lambda E\ |H0) \qquad \ldots(5)$$

Probability of detecting a signal when it truly is present in spectrum is noted as PD. Then large probability detection can be expressed as

$$PD = Pr\ (M>, \lambda E\ |H1) \qquad \ldots(6)$$

Incomplete gamma function is denoted as r (a, x) and Decision threshold can be denoted as, λE [4]. Region of convergence (ROC) curves for different SNR shown in below fig below [4].

III. HYBRID SENSING

The hybrid architecture, which is presented in Fig. 3 is an iteratively adaptative architecture as it is explained in [1].

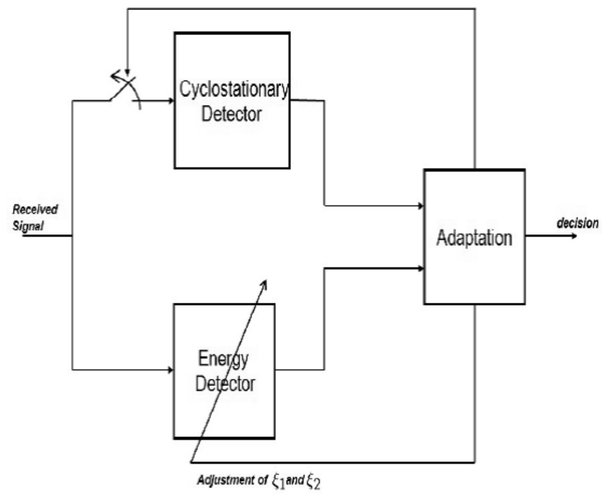

Fig 3. Hybrid Spectrum sensing Detector (HSD) architecture.

In the next section we introduce the M-HSD algorithm, which is the same as the HSD proposed in [1] but this time we added $buffer_1$ and $buffer_2$ in order to take soft decisions over the modifications of the thresholds ξ_1 and ξ_2. The benefit of using buffers gives stability for operating at low SNRs

A. Decision Rule of the M-HSD Algorithm

We first assume that N_0 is constant with respect to time. Let X_i be the energy of the received signal x(t) during an observation time T after the iteration i, B the bandwidth of the tested band, ξ_1 and ξ_2 two thresholds that are first initialized at 0 and +1 respectively. ξ_G, which is the threshold of the cyclostationary block that is defined in order to respect the desired P_{fa}; d_{es}, is fixed using the central X^2 table as described in [13].

At the beginning of the sensing, the energy detector calculates the energy X of the received signal after an observation time T. Then if X falls inside the interval [ξ_1; ξ_2], the energy detector cannot make a direct decision of type signal present or signal absent. In that case, the adaptation stage presented in Fig. 4 will call the cyclostationary block (which a priori knows the cyclic frequency of the signal of interest) to make the decision. After the decision of the cyclic test is taken, if it is of the type signal present (resp. signal absent), the calculated value X is then saved in a buffer called $buffer_2$ of size N_2,(resp. $buffer_1$ of size N_1).

The algorithm continues in the same way except when $buffer_2$ (resp. $buffer_1$) is full. In this case, the adaptation stage starts to modify the value of the threshold ξ_2 (resp. ξ_1) according to the average of $buffer_2$, (resp. $buffer_1$) and then the oldest value in the buffer will be replaced by the new calculated one (X_i after the iteration i). At any time, if the calculated value X is outside the interval [ξ_1; ξ_2], the adaptation stage will take automatic decision of type signal absent (resp. signal present) depending on whether X is less than ξ_1 (resp. greater than ξ_2) avoiding the use of the cyclic test. The process is repeated making the interval [ξ_1; ξ_2], smaller and smaller. Two cases, high and low SNR, need to be studied in order to analyze the M-HSD architecture limits, which will be explained in the next paragraph. Figure 4 shows the algorithm of the M-HSD method.

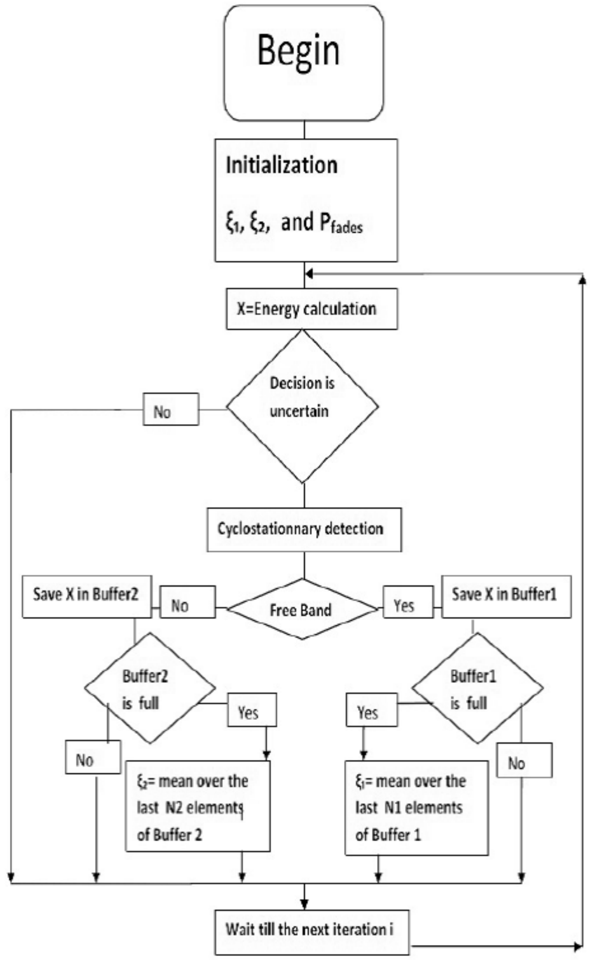

Fig. 4. Modified version of the HSD algorithm (M-HSD)

IV. SIMULATION RESULTS AND DISCUSSION

Simulation is done using NS2 where 20 users are taken into account out of which 10 users are PU's and rest 10 Users are SU. In the simulations, we used a 4-PSK modulation at 20 Khz where $\alpha = 1/T_s$ is the cyclic frequency used in the cyclostationary detector a priori known, and Ts refers to the symbol period of the 16-PSK. We set N_1 and N_2 equal to 30 in the simulation of the M-HSD algorithm.

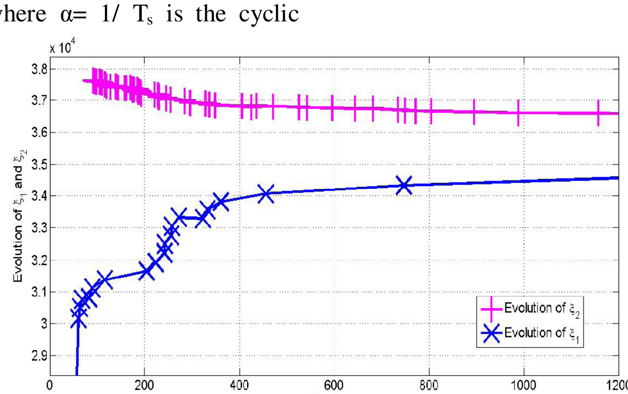

Fig. 5. The variation of ξ_1 and ξ_2 at -5 dB using M-HSD algorithm, with γ= 1, N1 = 30, and N2 = 30. Each mark on the curves indicates a modification of ξ_1 and ξ_2.

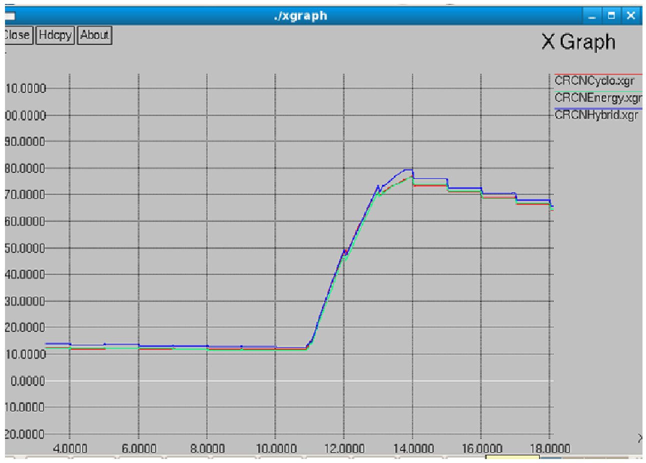

Fig. 6. Probability of detection (P_D) Vs Sensing Time.

The time bandwidth product BT is equal to 4500 and an equiprobabilist environment ($\gamma = 1$) was used, unless otherwise stated while simulating the different architectures. P_D probability of detection vs Sensing Time is drawn in fig 6. Given results clearly depict that P_D has significant improvement with the help of Hybrid detector as compare to convention detectors like Cyclostationary as well as Energy detector.

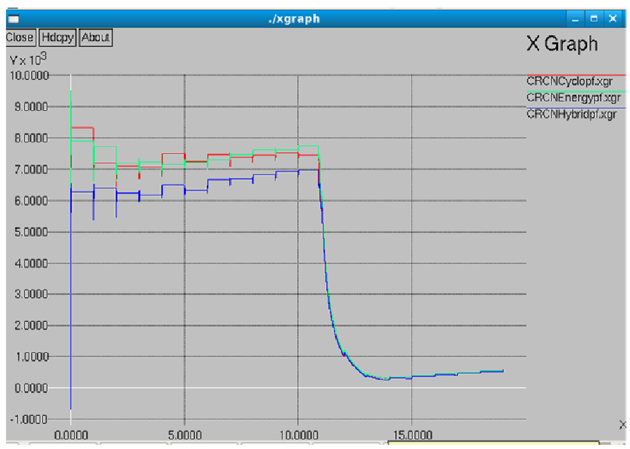

Fig. 7. Probability of False Alarm (P_{FA}) Vs Sensing Time.

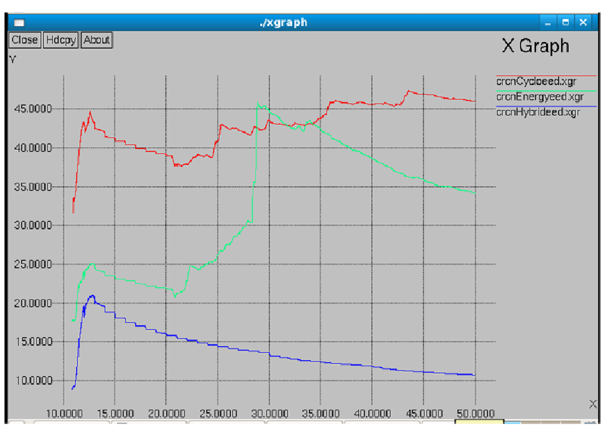

Fig. 8. End to End delay Vs sensing time.

Fig. 7. shows Probability of False Alarm (P_{FA}) Vs Sensing Time which clearly shows significant improvement in case of M-HSD as compare to convention detectors like Cyclostationary as well as Energy detector. Fig. 8. shows End to End delay Vs sensing time which clearly shows significant low end to end delay in case of M-HSD as compare to convention detectors like Cyclostationary as well as Energy detector.

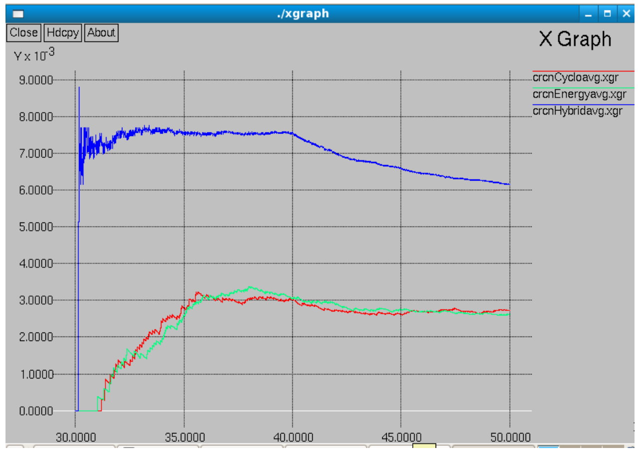

Fig. 9. Average residual energy vs sensing time.

Fig. 9. Depicts Average residual energy vs sensing time which clearly shows significant large residual energy preserved in case of M-HSD as compare to convention detectors like Cyclostationary as well as Energy detector.

V. CONCLUSION

Spectrum sensing is subject to time constraints. For this reason, we have proposed adaptive architectures, which combine two systems. The first system is a low complexity detector, but it is very sensitive to a bad estimation of the noise level N_0. As for the second, it is a more complex system based on cyclostationary detection, but it is insensitive to a poor estimation of N_0. These new adaptive architectures allow the sensing at lower SNR and with a decreasing algorithmic complexity. In a Gaussian noise environment obtained results are promising as it was shown by the performed simulations. Future work will include the study of different channel types with a variable N_0. A study of the spectrum assignment and power consumption/control techniques of the proposed architectures are still under investigation.

REFERENCES

[1]. Mitola J, Maguire GQ (1999). Cognitive radio: making software radios more personal. *IEEE Pers Commun* **6**(4): 13–18.

[2]. J. Mitola, (2000). Cognitive Radio An Integrated Agent Architecture for Software Defined Radio, Ph.D. thesis, Royal Institute of Technology (KTH), May 2000.

[3]. Spectrum Efficiency Working Group. (2002). Report of the Spectrum Efficiency Working Group. *Technical report,* FCC, November 2002.

[4]. Y. Zeng, Y. Liang, A. T. Hoang, and R. Zhang, (2009). A Review on Spectrum Sensing for Cognitive Radio: Challenges and Solutions, *EURASIP Journal on Advances in Signal Processing*, Volume **2010**, Article ID 381465, October 2009.

[5]. S. M. Kay, (1998). Fundamentals of Statistical Signal Processing: *Detection Theory*, vol. **2**, Prentice Hall, Upper Saddle River, NJ, USA, 1998.

[6]. P.M. Fishman, (1992). Radiometric detection of spread-spectrum signals in noise of uncertain power, *IEEE Transactions on Aerospace and Electronic Systems*, vol. **28**, pp. 654-660, July 1992.

[7]. H. Urkowitz, (1967). Energy detection of unknown deterministic signals, *Proceedings of the IEEE*, vol. **55**, no. 4, pp. 523-531, 1967.

[8]. H. S. Chen, W. Gao, and D. G. Daut, (2007). Signature based spectrum sensing algorithms for IEEE 802.22 WRAN, in *Proceedings of the IEEE International Conference on Communications (ICC 07),* pp. 6487-6492, Glasgow, Scotland, June 2007.

[9]. M. Ghozzi, (2008). Cyclostationary detection of free frequency bands. Ph.D. thesis, 2008.

[10]. W.A. Gardner and C.M. Spooner, Signal interception: Performance advantages of cyclic feature detectors, *IEEE Transaction on Communications*, vol. **40**, January 1992.

[11]. W.A. Gardner and G. Zivanovic, (1991). Degrees of cyclostationary and their application to signal detection and estimation, *Signal processing*, vol. **22**, March 1991.

[12]. W. A. Gardner, (1991). Exploitation of spectral redundancy in Cyclostationary signals, *IEEE Signal Processing Magazine*, vol. **8**, no. 2, pp. 14-36, 1991.

[13]. A.V. Dandawate and G.B. Giannakis, (1994). Statistical tests for presence of cyslostationarity, *IEEE Transactions on Information Theory*, vol. **42**, pp. 2355-2369, September 1994.