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Wavelet Based Spectrum Sensing Techniques in Cognitive Radio

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Abstract

For cognitive radio the main issue is to sense and identify all spectrum holes present in the environment. In this paper we are proposing a wavelet approach for spectrum sensing and spectrum hole identification. We will apply wavelet transform on the sub-divided signal to detect the edges and holes over a wide frequency band. The proposed sensing techniques provide an effective radio sensing architecture to identify and locate spectrum holes in the signal spectrum

Keywords- wavelets; sensing technique; CWT; PSD.

1. Introduction

Cognitive Radio (CR) is emerging as one of the key technologies to solve the problem of spectrum scarcity faced by current wireless systems. It helps in efficient utilization of available spectrum and removes the problem of spectrum scarcity. A cognitive radio network aims to support highly reconfigurable devices that are capable of sensing the current environment, and adapting the transmission parameters to the specific scenarios, also based on the Quality of Service (QoS) requirements of the applications [1-3]. The potential deployment of cognitive radio networks has been further augmented through various standardization activities supported by the IEEE and directives of spectrum regulatory agencies. These efforts have opened portions of the spectrum for opportunistic spectrum access and laid down rules for sharing the spectrum so that general purpose networks as well as communication in critical scenarios, like vehicular networks, public safety networks, emergency networks are supported. However, to fully realize the potential of cognitive radio networks, there is a need to draw the attention of the research community for developing advanced, context-based and innovative methodologies, techniques and algorithms possibly inspired by multi-disciplinary research fields, including current results from inter-

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disciplinary research. Hence, the first and very important task in a cognitive radio is the spectrum sensing. The energy detection techniques can be broadly classified as “Transmitter Detection” and “Receiver Detection”. In the first category, the primary user (PU) is assumed to be transmitting and in the latter, the PU is receiving.

In this paper we have emphasized on transmitter detection. There exist several different approaches for transmitter detection which may be used in different sensing scenarios. The most well-known methods are perhaps energy detection, cyclostationary detection and matched filter (MF) detection, which is discussed in detail in [4-15]. Furthermore, the spectrum sensing can be performed by a single unit or it can be collaborative in which case measurements from several sensors are combined in a fusion centre to obtain a more reliable decision. On this manner cooperative spectrum sensing [4] offers increased detection performance by spatial diversity of the sensors. The least demanding approach is energy detection. An energy detector measures the energy in a radio resource and compares the value against a threshold. In general, if the measured energy is below the threshold, the radio resource is declared as not occupied means it is available for opportunistic use. The energy detection is a non-specific detection method in the sense that no particular knowledge of the signal properties is used. In this sense, energy detection can be used for declaring whether a resource is occupied or not, but it cannot be used to identify the type of system or user that is occupying the channel. Also, an energy detector needs to have an idea of the noise level to adjust the detection threshold [5]. In the matched filter detection, which provides an optimal detection performance, but requires prior knowledge of primary signal; has lower accuracy. This technique is used when the xG user knows the information (various parameters) of the primary user signal. The optimal detector in stationary Gaussian noise is the matched filter since it maximizes the received signal-to-noise ratio (SNR) [13]. While the main advantage of the matched filter detector is that it requires less time to achieve high processing gain due to coherency. It requires a prior knowledge of the primary user signal such as the modulation type and order, the pulse shape, and the packet format. Alternately, if this information is not accurate, then the matched filter performs poorly. The Cyclostationary method is more accurate, but has increased complexity. Cyclostationary detection is typically a statistical test based on the estimated autocorrelation function of one or several known cyclic frequencies. The advantage being that the autocorrelation is periodic, which enables detection under very low SNR. It also requires partial knowledge of primary signal with high computational cost. 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.

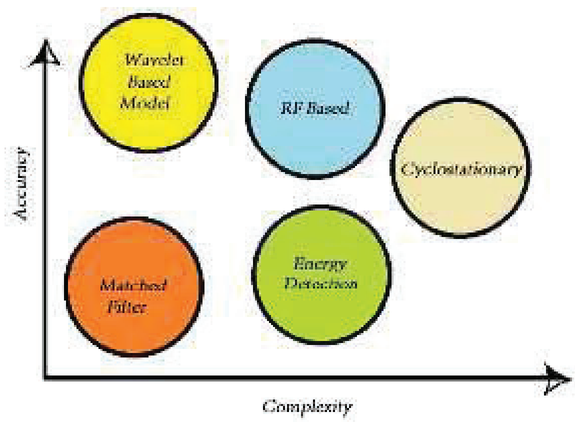


Fig. 1: Plot of complexity verses accuracy for various spectrum sensing techniques.

These modulated signals are characterized as cyclostationarity since their mean and autocorrelation exhibit periodicity. 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. Therefore, a cyclostationary feature detector can perform better than the energy detector in discriminating against noise due to its robustness to the uncertainty in noise power [14, 15]. 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 [16]. These features include amount of energy detected and its distribution across the spectrum. Channel bandwidth and its shape are used in 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 canter frequency of a received signal are extracted using energy detector based methods in .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 and neural networks are used for identification of active transmissions using these features. Comparing all the detection techniques mentioned above, we proved that wavelet based sensing technique is more accurate and less complex in specific as indicated in Fig 1.

2 SPECTRUM SENSING TECHNIQUES

2.1. Original Sensing Method

In [4], the spectrum sensing has been treated as edge detection problem. In this edge detection technique has been implemented to find the spectrum hole. Let us assume a frequency band of interest as shown in Fig. 2, which is further divided into *N* sub-bands consecutively with their frequency boundaries located at $f_0 < f_1 < f_n$. The idea is to locate any vacant spaces between the two adjacent sub bands so that a secondary user can utilize it without any interference to the primary user. The normalized power spectral density (PSD), in each sub-band, in the absence of noise, is [19]:

$$\int_{F_{i-1}}^{F_i} S_i(f)\, df = F_i - F_{i-1} \tag{1}$$

Power spectral density of the observed signal r (t):

$$S_r(f) = \sum_{n=1}^{N} \alpha_n^2 S_n(f) + S_w(f), \qquad f \in [f_0, f_n] \tag{2}$$

where α_n^2 indicates the signal power density within the n^{th} band and S_n (f) is PSD of each sub-band.

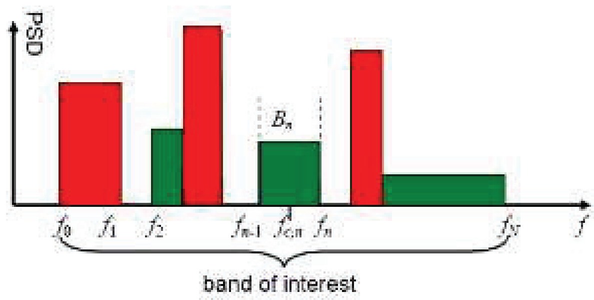


Figure 2: The PSD inside each sub-band PSD inside each sub-band is estimated as [15]:

$$B_i = \frac{1}{F_i - F_{i-1}} \int_{F_{i-1}}^{F_i} S_r(f)\,df \tag{3}$$

The identification of the frequency boundaries between successive sub-bands is done using properties of the wavelet transform [17]. The dilatation of the wavelet functions $\psi(s)$ by one scale is:

$$\psi_s(f) = \frac{1}{s} \quad \psi\left(\frac{f}{s}\right) \tag{4}$$

The continuous wavelet transform is defined as:

$$W_s S_r(f) = S_r \quad \psi_s(f) \tag{5}$$

At fine scales, it provides localized information of $S_r(f)$, to find the edges and irregularities in it we have to find its first and second derivatives. The first derivative is:

$$W_s^1 S_r(f) = s\frac{d}{df}(S_r \quad \psi_s)(f) \tag{6}$$

The second derivative is:

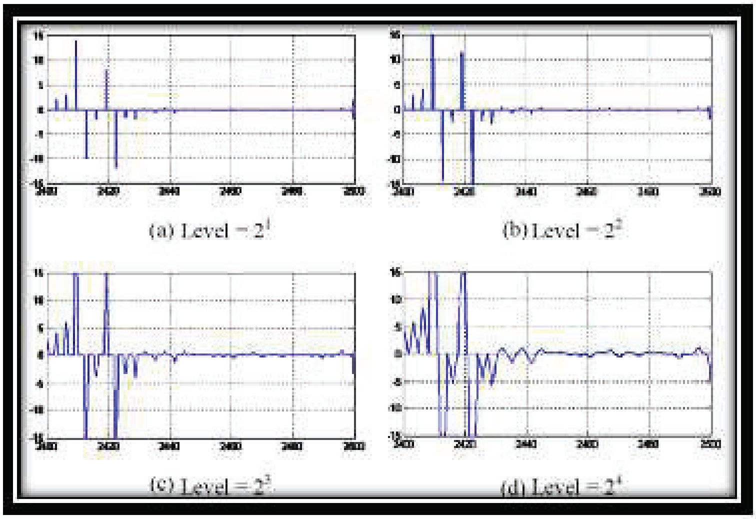
$$W_s^2 S_r(f) = s^2\frac{d^2}{df^2}(S_r \quad \psi_s)(f) \tag{7}$$

Edges and discontinuities propagate to different scales s. In [18], the CWT is obtained with dyadic scales $s=2^j$, i=1, 2, 3…, j. In order to track de propagation of edges and discontinuities in multiple scales, the multi scale product of the J CWT gradients is done [19].

$$U_j S_r(f) = \prod_{j=1}^{j} W_{s=s_j}^1 S_r(f) \tag{8}$$

2.2. Problems

If the value of 'j' is very large as in Fig. 3(d) smaller peaks are dissolved among larger ones as shown in Fig. 3. This is an efficient method to remove noise. In other cases, where the borders S_r (f) are not so abrupt or in less noisy environments, this method is quite inefficient since some of spectrum holes would be ignored.



(a) Level = 2^1 (b) Level = 2^2

(c) Level = 2^3 (d) Level = 2^4

Figure 3: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4

Value of 'S_j' denotes the scale, as we increase the scale, frequency span widens, hence while calculating the product. We cannot correlate the boundaries of every peak. Thus, boundaries may not be detected with a good precision.

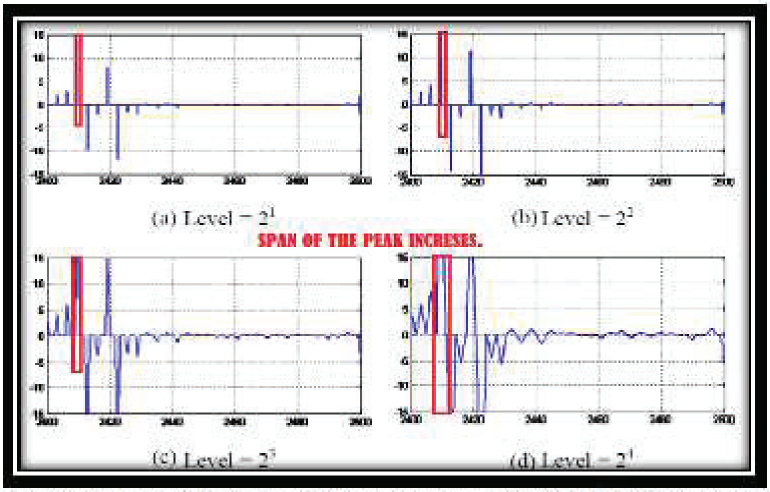


Figure 4: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4.

2. SOLUTION AND THE PROPOSED MODEL

- Value of 'j' can be a little large than required Fig. 4 and Fig. 5, so that smaller peaks are dissolved among larger ones, which removes the noise. In other cases, where the borders S_r (f) are not so abrupt or in less noisy environments, j value should not exceed 4.

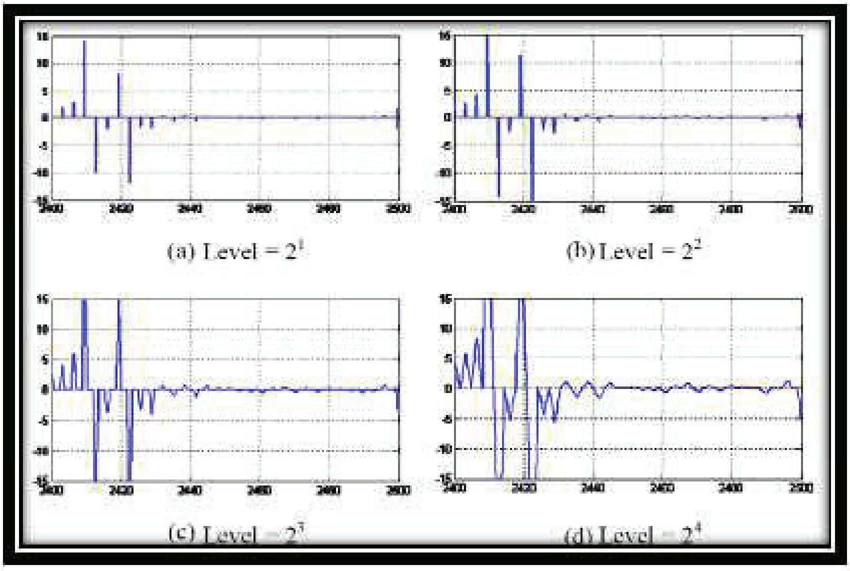


Figure 5: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4

- Value of ‘S_{jk}’ would denote the scale corresponding to each peak as shown in Fig. 6. As we increase the scale, frequency span widens but the reference no. ‘k’ would keep the track of the peak. Thus, we know which peak’s product we are calculating.

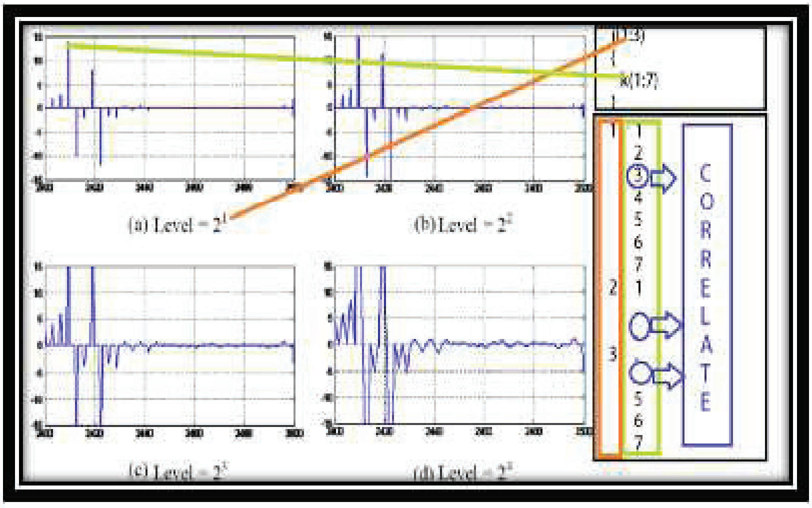


Figure 6: Showing the CWT coefficients with different values of j (a) j=1 (b) j=2 (c) j=3 (d) j=4.

4. SIMULATION

Using matlab R2008a, we have simulated the above mentioned algorithm. The program has been designed with a flexible spectrum creation such that we can create a dummy spectrum by inputting the probability of spectrum utilized at a certain instant of time. For example, if we input 25% as percentage of occupancy, the spectrum will be 75% vacant and hence our aim would be to detect those frequencies. Next, we compute the power spectral density. Obviously, psd of the free spectrum value is far below than the values of allocated bands and hence by virtue of their proportion, we find out a threshold value. Based on this threshold, values below it are considered to be frequencies that are free and can be allocated to secondary users while the others are being used by primary or the licensed users.

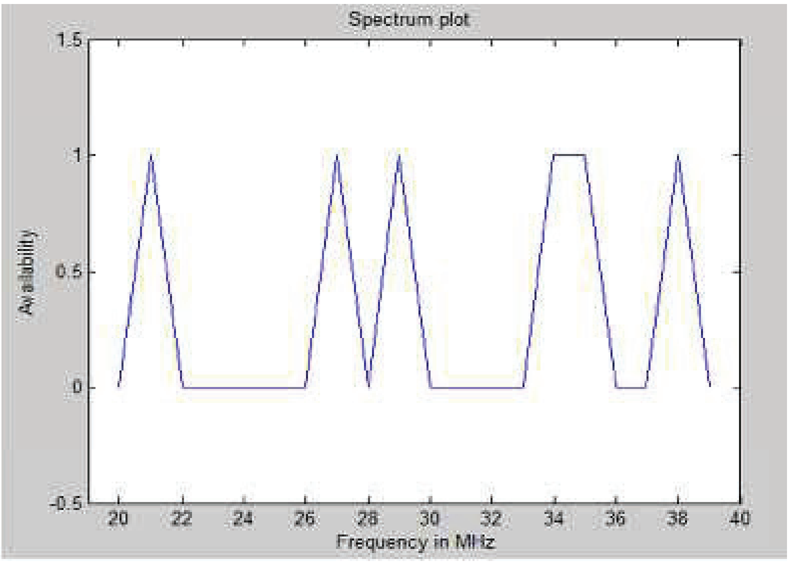


Figure 7: Creating a dummy spectrum in matlab to run the code to find spectrum hole in the spectrum.

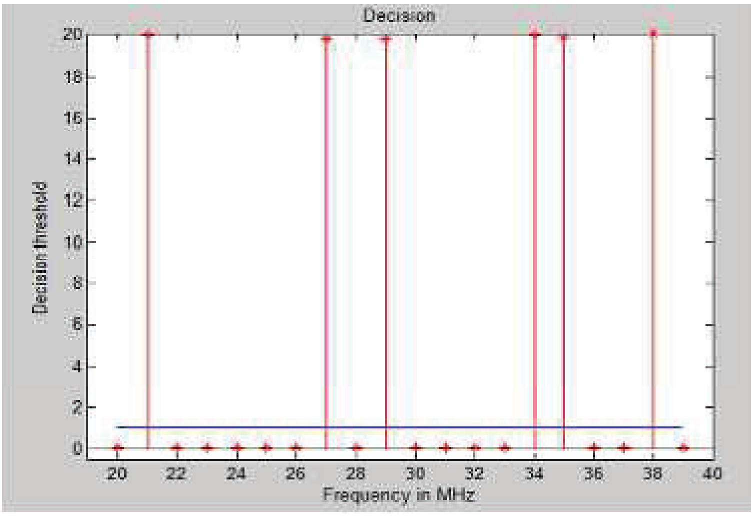


Figure 8: Plot of psd to the frequency. Comparing it with Fig 7, we can clearly define spectrum holes.

Fig. 8 gives a plot in which value 1 signifies that the spectrum is already occupied and 0 indicates free values. Again, since it was difficult to obtain actual spectrum plot on any analyzer, we created a dummy spectrum to see how our code works on the spectrum. This is the input data that is fed to the algorithm mentioned above and it gives the result as Fig. 8 which shows values below the threshold are vacant and can be allocated. The other simulation we had was simulation of cognitive radio, and performing the most important operation of spectrum sensing, allocating and de-allocating the spectrum at run time. In the program, we first have certain vacant spaces in a particular spectral band and we allocate them to the primary users first, once they had been allocated to the primary users, we allocate the vacant spaces to the secondary users, once the spectrum is completely filled and we can find a slot and allocate it to another user. Then we have minor functionalities of adding noise or changing amplitude of the signal. This is totally a user dependent program and hence gives the output on users will one iteration of this running code has been explained here.

5. CONCLUSION

In this paper, we have pointed out the problems in the original model and also suggested the improvement we can do. We have also simulated major feature of cognitive radio of spectrum sensing and tried to allocate and de-allocate spectrum at run time with minimal computation time. The computation time of our algorithm comes out to be 0.000167 seconds (on an average), however, we run the same code on a number of systems and realized that this was the CPU time which depends on the strength of CPU. In future we would be simulating the proposed idea for better and more functional and realistic cognitive radio and try to produce precise experimental results. The time obtained in sensing the spectrum is apt since it is expected to be in microseconds .This is because of the fact that time should not be too long so that by the time we allocate the spectrum after sensing, again a primary user starts to use it. This would not solve the purpose. We would also try to run the code for an actual spectrum data rather than using dummy self constructed spectrum plot. This second segment of simulation of a cognitive radio system has no boundaries and can be extended up to any level with more and more features and functionalities.

References

[1] J. Mitola III and G.Q. Maguire Jr., *Cognitive Radio: Making software Radios More Personal*, IEEE Personal Communication,vol.6,no.4,pp 13-18,August1999 .

[2] S. Haykin, Cognitive Dynamic Systems, Proceedings of the IEEE, vol. 94, no. 11, pp. 1910-1911, November 2006.

[3] I. F. Akyildiz, W.-Y. Lee, M.C. Vuran, S. Mohanty, *NeXt generation/dynamic spectrum access/cognitive radio wirelessnetworks: a survey*, Computer Networks, vol. 50, no. 13, pp. 2127-2159 , September 2006.

[4] A. Taherpour, S. Gazor, and M. Nasiri-Kenari, "Wideband spectrum sensing in unknown white Gaussian noise", IET Communications, vol. 2, no. 6, pp. 763-771, July 2008.

[5] M. Agarwal, J. Rajpurohit, P.Aluru, S. V. R. K. Rao and G. Singh,"Performance evaluation of cognitive radio with emphasis on uplink and downlink", International conference on Advances in Recent Technologies in Communication and Computing (ARTCom), Oct2010, India, pp 440-442.

[6] P.Aluru , J. Rajpurohit , M.Agarwal ,S.V.R.K.Rao and G.Singh,"Improvement in total sensing time of the receiver in the cognitive Radio", International conference on Advances in Recent Technologies in Communication and Computing (ARTCom), Oct2010, India, pp. 437-439,

[7] Z. Quan, S. Cui, A.H. Sayed, and H.V. Poor, "Wideband spectrum sensing in cognitive radio networks," IEEE International Conference on Communications, 2008. (ICC'08), May 2008, Canada,pp. 901-906.

[8] Z. Tian, Giannakis and B.Georgios, "A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios", Proc. 1st International Conference on Cognitive Radio Oriented Wireless Networks and Communications, June 2006, Mykonos Island pp. 1-5.

[9] S.Kapoor , S.V.R.K.Rao and G.Singh, "International Conference on Communication Systems and Network, Technologies" pp. 580-583,June2011

[10] S. Mallat e W. L. Hwang, *Singularity Detection and processing with Wavelets,* IEEE Transactions on, Information Theory , vol. 38, pp. 617-643, March 1992.

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

[12] A. V. Dandawate and G. B. Giannakis, *Statistical tests for presence of cyclostationarity*, IEEE Transactions on SignalProcessing, vol. 42, no.9, pp. 2355-2369, September1994.

[13] A. Sahai, N. Hoven and R. Tandra, "Some fundamental limits in cognitive radio," Allerton Conf. on Commun, Control and Computing 2004, October 2004, pp. ??.

[14] T.X. Brown, "An analysis of unlicensed device operation in licensed broadcast service bands,": Proc. IEEE DySPAN 2005, November 2005, pp. 11–29.

[15] A. Huttunen, J. Pihlaja, V. Koivunen, J. Junell, and K. Kalliojärvi "Collaborative, distributed spectrum sensing for cognitive radio," in Wireless World Research Forum Meeting 20, Ottawa,Canada,22–24 April,2008.

[16] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio applications", Proc. of IEEE Communication Surveys and Tutorials, vol-2, no 1, pp. 116-130, 2009.

[17] Y. Hur, J. Park, W. Woo, K. Lim, C.-H. Lee, H. S. Kim, and J. Laskar,"A wideband analog multi-resolution spectrum sensing technique forcognitive radio systems," IEEE International Symposium on Circuits and Systems (ISCAS'06), pp. 4090-4093, May 2006.

[18] Shipra Kapoor and G. Singh ," Non-Cooperative Spectrum Sensing: A Hybrid Model Approach," International Conference on devices and Communications (IC DeCom),pp 1-5,Feb 2011.

[20] H. Poor, *An Introduction to Signal Detection and Estimation, 2nd ed.*New York: Springer-Verlag, 1998.]

[21] Y. Hur, J. Park, W. Woo, K. Lim, C.-H. Lee, H. S. Kim, and J. Laskar, "A wideband analog multi-resolution spectrum sensing technique for cognitive radio systems," in *IEEE International Symposium on Circuits and Systems*, Island of Kos, Greece, May 2006.

[22] C. Han Lee and W. Wolf, "Multiple access-inspired cooperative spectrum sensing for cognitive radio," in *IEEE Military Communications Conference*, Orlando, FL, October 2007.

[23] S. Enserik and D. Cochran, "A cyclostationary feature detector," in *28th Asilomar Conf on Signals, Systems and Computers*, CA, Oct 1994.

[24] T. C. Aysal, S. Kandeepan, and R. Piesiewicz, "Cooperative spectrum sensing over imperfect channels," in *Proc of BWA Workshop at the IEEE Conf on GLOBECOM*, 30 Nov - 3 Dec 2008.