Journal of Theoretical and Applied Information Technology
10th April 2014. Vol. 62 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MATCHED FILTER BASED SPECTRUM SENSING FOR COGNITIVE RADIO AT LOW SIGNAL TO NOISE RATIO

[1]R. VADIVELU, [2]K. SANKARANARAYANAN, [3]V. VIJAYAKUMARI

[1]Assistant Professor, Department of Electronics and Communication Engineering,
Sri Krishna College of Technology, Coimbatore, India
[2]Dean, PG Studies, Department of Computer Science and Engineering
Sri Ramakrishna Institute of Technology, Coimbatore, India
[3]Associate Professor, Department of Electronics and Communication Engineering
Sri Krishna College of Technology, Coimbatore, India
E-mail: [1]vadiveluece@gmail.com, [2]kkdcbesankar@gmail.com, [3]ebinviji@gmail.com

ABSTRACT

Custom usage of a Cognitive Radio is administrated by the essential utilization aspect of the radio spectrum the natural resource. Cognitive radio trying to resourcefully share the radio spectrum along with potential primary users in the spectrum that must be identified in order to evade causing harmful interference with other users on the spectrum. The vibrant usage of spectrum belongs to the white space assessment and how accurately it can be utilized. In this paper we put forward an open situation of channel estimation at low signal to noise ratio. A Matched Filter based system is well-thought-out to make the spectrum sensing resolution based on the observed signal to noise ratio from the Cognitive Users. With the existing knowledge of the regulated system parameters, the fusion Centre can make a global sensing decision consistently without any additional requirements such as channel state information, prior information and prior prospects about the primary user's signal. Numerical results in terms of receiver operating characteristics show that the sensing performance of the proposed Matched filter based system outperforms the performance of the adaptive Takagi and Sugeno's fuzzy energy based system model at low Signal to Noise Ratio and one order Cyclostationary detection based on estimated signal to noise ratio.

Keywords: *Cognitive Radio, Spectrum Hole, Signal to Noise Ratio, Matched Filter, Spectrum Sensing, Channel State Information, Receiver Operating Characteristics*

1. INTRODUCTION

Current and Innovative wireless communication devices are proficient to offer higher data rates and innovative services to end users, extensive radio spectrum is available for several wireless communication services. On the other hand with the exponential growth in wireless communication devices and their usage, the radio spectrum is becoming a scarce resource [1][2]. Cognitive Radio (CR) has been identified as a new design technique wishes to enrich the proficient utilization of electromagnetic radio spectrum by empowering dynamic spectrum access (DSA) for the current and next-generation wireless communication technology. The stimulus for the design of CR communication system arises from the fact that the ample portions of the authorized or licensed radio spectrum are underutilized by the primary users or licensed users. As per Federal Communications Committee (FCC) about 15 - 85 % of the spectrum is assessed to be underutilized [3]. This lays the strong foundation for the secondary user or CR user (CU) permitted to access a spectrum band that is unoccupied by the primary user at a specific time and geographic location [4]. The spectrum hole or white space is the frequency band that has been allocated to a PU who is not using the spectrum at the specified allotted time. Opportunistic Spectrum Access (OSA) by the CU depends on how efficiently and reliably the spectrum is sensed and utilized by the CU. Moreover, a periodic spectrum sensing is the basic requirement that a CU to transmit data over the spectrum, to overcome the interference with the PU [5].

Spectrum can be sensed by various techniques i.e., matched filter, energy detection, Cyclostationary feature detection and stochastic process techniques to detect the presence of the PU signal in the channel or sub channel. Cooperative spectrum sensing used to estimate the optimal number of CU's involved in spectrum sensing. An energy efficient technique for minimizing the number of CU's subject to the constraints on the probability of false alarm (PF) and probability of detection (PD) are dealt in [6]. In [7] a new cooperative spectrum sens-

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ing algorithm was proposed to improve the bandwidth problem of reporting channels, only the cognitive users with reliable information are allowed to report their sensing results. Under user less reliability condition, the cognitive user with highest reputation will report its sensing result to the fusion center. In Data throughput optimization scenario, the throughput of the CU's network is maximized subject to a constraint on the global probability of detection (PD) in order to determine the optimal number of CU's dealt in [8]. To avoid interference to the licensed user by the CU, spectrum sensing process or algorithms must be more accurate and should be highly reliable.

The firmness on whether the signal is present or absent on the channel can be expedited if we pass the signal through a filter that will accentuate the useful signal and suppress the noise signal. A Matched Filter will peak out the signal component at some instant of time and suppress the noise amplitude at the same time. If Signal is present on the channel, a large peak at this instant will occur and if the signal is absent, no such peak will appear. This prearrangement will make it possible to decide whether the signal is present or not in the channel. A matched filter detection technique is the optimal linear filter used to maximize the signal to noise ratio (SNR) in the presence of additive white Gaussian noise. Cooperation among CUs are established to estimate the PU's presence or absence, fusion Centre (FC) is used to take the overall resolution about the PU's.

In [9], Quan et al. projected an optimal linear collaboration framework for sensing the spectrum in order to exactly detect the weak primary user signal in the spectrum band or sub band. However, the weakness of algorithm implementation in [9] is the overall knowledge of signal to noise ratio (SNR) and the noise variance of the PU signal should be known at the FC during the spectrum sensing process. In [10] a fuzzy inference system was proposed by Kieu-Xuan et al., assuming the SNR of the PU is known to the CU which provides an advantage of local soft spectrum sensing decision made at CUs terminal. Results in [10] shows that the sensing performance of the proposed scheme is comparable with the sensing performance of the maximal-ratio combination (MRC) based scheme which does not require SNR of the PU signal from CUs to the FC.

In real time it is very challenging for a CU to precisely estimate SNR of the PU in a given spectrum band or sub band in a non-cooperative environment. It is apparent that most of the contemporary cooperative spectrum sensing schemes makes a speculation that the SNR of the PU signal at the CU is perfectly known. Moreover, the CUs can estimate these parameters well but it is very difficult to communicate them along with local observations to the FC. In [11] Kieu-Xuan et al. assumed each CU in the CR network estimated the energy of the received signal in the given band or sub band of interest and then transmitted the experimental parameters to the FC. Data fusion at the FC is accomplished by using an adaptive Takagi and Sugeno's fuzzy system where fuzzification parameters are adapted from received data through a Kalman filter. In this paper we first estimated the SNR of each CU in the CR network and then it is transmitted along with the parameters of the received signal in the given band or sub band of interest to the FC. Data fusion is performed at the FC by an adaptive Bayesian system where SNR are adapted from received data through a Kalman filter. It means that the detection problem and the estimation problem are solved at the FC concurrently and cooperatively. Therefore, the FC can make a global decision based on local observed SNR in an additive white Gaussian noise environment of PU signal at CUs. In [12] Waleed Ejaz et.al proposed one order Cyclostationary detection with estimated SNR in terms of reduced detection time.

The rest of the paper is organized as: Section 2 describes the system model for adaptive cooperative spectrum sensing problem. A matched filter detection overview is dealt in Section 3. Section 4 derives Detection of primary user signal in additive white Gaussian channel. Numerical result analysis is presented in Section 5. Finally Section 6 concludes the paper.

2. SYSTEM MODEL FOR COOPERATIVE SPECTRUM SENSING

The basic problem of existence based spectrum sensing is to differentiate between two postulates i.e., based on presence or absence of the primary user: that the possibly faded primary user signal is present at a sufficiently high power level or it is absent. The detector that it can reliably detect the weakest signal present over the channel is its sensitivity. The spectrum sensing problem can be formulated based upon the appearance or non-appearance of PU in the concerned band or sub band based on binary hypothesis testing model [13] as

$$\begin{aligned} &H_0 \; \Pr\text{imaryUserAbsent} \\ &H_1 \; \Pr\text{imaryUser}\Pr\text{esent} \end{aligned} \qquad (1)$$

Any detection scheme can be written as a possibly random function F: RN → {0, 1}, where F maps

Journal of Theoretical and Applied Information Technology
10th April 2014. Vol. 62 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the N dimensional received vector y = (y[1], y[2],y[3],• • •, y[N]) onto the set {0, 1}. Here '0' stands for the decision that the received signal is only noise and '1' stands for the decision that the received signal is signal plus noise. Considering a single FC with N number of CUs scattered across a given CR network. The received signal at each CU based on the appearance or non-appearance of PU is given by

$$\begin{aligned} y_i(t) &= H_0 : n_i(t) \\ y_i(t) &= H_1 : h_i(t)x_i(t) + n_i(t) \end{aligned} \tag{2}$$

Where the received signal at the i^{th} CU is represented by $y_i(t)$ and gain of the channel between the PU and the i^{th} CU represented by hi(t). The signal transferred by the PU is represented by $x_i(t)$ and the additive white Gaussian noise (AWGN) at the i^{th} CU represented by $n_i(t)$. In addition to above considerations we assume that the channels corresponding to different CUs are assumed to be independent and identically distributed, and the CUs and the PU share a common spectrum of concerned band or sub band.

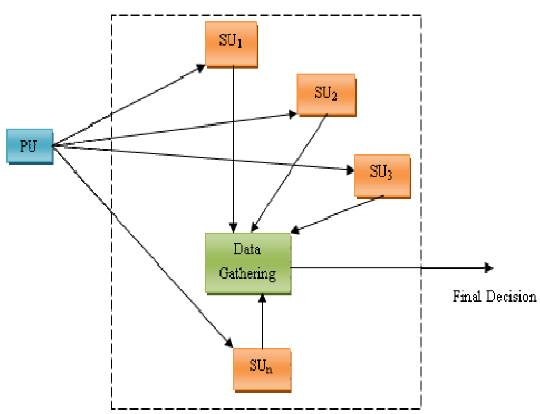

Figure 1: Sensing in Cooperative Environment

Cooperative spectrum sensing environment is shown in Figure 1. For a given sequence of sensing, the CU estimates the SNR of its received signal in the AWGN channel. The SNR observed from the CUs are then communicated to the overall FC through the control channel for final decision. Finally, the FC coordinates with the observations of all the CUs and their observed SNR to make a final decision about the appearance or non-appearance of the PU signal.

Our primary goal is to detect the PU signal in the given AWGN channel and that is never seamlessly known in the real time spectrum sensing, hence we assumed that the PU signal is present in the AWGN channel and by maximizing the SNR we detect the presence or absence of PU signal using optimal filter based on fixed threshold [14].

3. MATCHED FILTER DETECTION

To enrich the SNR a matched filter is often used at the receiver front end. Matched filter coefficients are basically given by the complex conjugated reversed signal samples in terms of discrete signals. Two types of coherent or non-coherent receivers are used based on signal analysis either as complex signals or noises. If the amplitude and phase of the received signal are known coherent receivers are used results in a perfect match between the matched filter coefficients and the signals. In case of a noncoherent receiver, the received signal is modeled as a replica of the original signal with a random phase error. With a noncoherent receiver the detection after the matched filter is generally based on the power or magnitude of the signal since we need both real and imaginary parts to define the signal entirely [15].

Power Spectral Density (PSD) of the AWGN signals is given

$$PSD_{AWGN}(f) = \frac{N_0}{2} \tag{3}$$

Where N_0 is the noise signal and AWGN channel Signal to Noise Power measured at the output of the matched filter is given by

$$SNR = \frac{|S(t)|^2}{|N(t)|^2} \tag{4}$$

The output noise power P_n calculated of the n^{th} primary user is found to be [16]

$$P_n = \frac{N_0}{2} \int_{-\infty}^{+\infty} |H_n(f)|^2 \, df \tag{5}$$

The output signal power P_s calculated of the n^{th} primary user is found to be

$$P_s = \int_{-\infty}^{+\infty} \left| H_n(f) S_i(f)^{ej2\pi ft} \, df \right|^2 \tag{6}$$

Output signal power P_s is decomposed in terms of input signal power S_i using Schwartz inequality

$$P_s = \int_{-\infty}^{+\infty} |H_n(f) df|^2 P_{is} \tag{7}$$

Now the SNR of the primary user is simplified to SNR_o

$$SNR_o = \frac{2P_{is}}{N_0} \tag{8}$$

The above equation represents the PU signal over the noise.

Journal of Theoretical and Applied Information Technology
10th April 2014. Vol. 62 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4. DETECTION OF PRIMARY USER SIGNAL IN ADDITIVE WHITE GAUSSIAN NOISE CHANNEL

The reason behind introducing Matched Filter implementation is to model the evolution of PU signal in the spectrum band considered over time by measurements using CR. In this section, we consider the basic functional model of linear matched filter. Primarily matched filter implementation is best suitable for radar, sonar, wireless communication systems, Intelligent Radio Systems and binary detection of AWGN channel as shown in Figure 2.

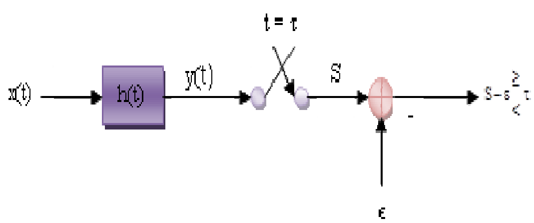

Figure 2: Implementation of Matched Filter

Binary detection problem is used to identify the state of PU signal presence or absence in AWGN channel in the time interval of $0 \le t \le T$. The binary hypothesis specified by H_1 and H_0 indicates the presence and absence of PU signal [17] in the channel considered.

$$\begin{aligned} H_0 &: Y(t) = N(t) \\ H_1 &: Y(t) = s(t) + N(t) \end{aligned} \qquad (9)$$

Here N(t) is the AWGN with zero mean and covariance of $\sigma^2\ \delta(t\text{-}s)$, where σ^2 is the power density of intensity of the AWGN signal. In order to detect the PU signal an orthonormal basis function in signal space $\{\Phi_i(t), i \in I\}$ of space $S_2\,[0,T]$ integrable over the function [0,T]. As the first element of the basis, we select the function as

$$\Phi_1(t) = \frac{s(t)}{E^{\frac{1}{2}}} \qquad (10)$$

Where

$$E = \left\| s^2 \right\| = \int_0^T s^2\,dt \qquad (11)$$

If we identified orthonormal basis $\{\Phi_i(t), i \in I\}$, using Karhunen-Loeve decomposition [18] AWGN noise N(t) decomposed to

$$N_i = \int_0^T N(t)\Phi_i(t)dt \qquad (12)$$

Similarly the received signal Y(t) can be decomposed to

$$Y_i = \int_0^T Y(t)\Phi_i(t)dt \qquad (13)$$

Under signal space domain, the detection problem reduces to one dimensional problem as

$$\begin{aligned} H_0 &: Y_1 = N_1 \\ H_1 &: Y_1 = E^{\frac{1}{2}} + N_1 \end{aligned} \qquad (14)$$

Now the Binary Hypothesis theory in terms of Generalized Likelihood Ratio Test (GLRT) [19] statistics established as

$$L(y_1) = \frac{\exp\left(-\frac{1}{2\sigma^2}(y_1 - E^{\frac{1}{2}})^2\right)}{\exp\left(-\frac{1}{2\sigma^2}y_1^2\right)} \underset{H_0}{\overset{H_1}{\gtrless}} \tau \qquad (15)$$

Where τ denotes the threshold and taking logarithms and reorganizing the resulting identity gives

$$Y_1 \underset{H_0}{\overset{H_1}{\gtrless}} \Omega \quad \frac{E^{\frac{1}{2}}}{2} + \frac{\sigma^2}{E^{\frac{1}{2}}}\ln(\tau) \qquad (16)$$

Hence the optimum filter expressed in terms of sufficient statistics S as

$$S = \frac{1}{E^{\frac{1}{2}}}\int_0^T Y(t)s(t)dt \qquad (17)$$

Under binary hypothesis it is observed that Y1~N(0, σ2) based on H0 and Y1~N(E1/2, σ2) based on H1. If r denotes the distance between the two hypotheses measured in terms of noise standard deviation.

Different types of responses based on old stimulus to a correct response, called detection whereas a yes response to a new stimulus is a miss, called a false alarm (FA). A No response given to a new stimulus is a true response, called a Correct Rejection whereas a No response to an old stimulus is a false response called a Miss or a false alarm (FA). These four types of reaction can be organized as shown in Table 1.

Journal of Theoretical and Applied Information Technology
10th April 2014. Vol. 62 No.1

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: The four possible types of reaction

	Decisions (Reactions)	
Reality	Yes	No
Signal present	Detection	Miss Detection
Signal absent	False Alarm	Rejection

It is shown that the probability of detection PD and Probability of false alarm PF for the test are given by

$$P_D = 1 - Q\left(\frac{r}{2} - \frac{\ln(\tau)}{r}\right) \tag{18}$$

$$P_F = Q\left(\frac{r}{2} - \frac{\ln(\tau)}{r}\right) \tag{19}$$

By using Neyman-Pearson (NP) test and eliminating the threshold τ from the above identities we achieve

$$P_D = 1 - Q(r - Q^{-1}(P_F)) \tag{20}$$

Using unnormalised statics we obtain the sufficient static S as

$$S \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \quad \frac{E}{2} + \sigma^2 \ln(\tau) \tag{21}$$

5. RESULT AND DISCUSSION

In order to increase the performance of spectrum sensing, we allow various SU to cooperate by sharing their information and to reduce the communication overheads, users share their decision statistics based on the binary hypothesis testing. In signal estimation theory, a receiver operating characteristic (ROC) curve is a graphical plot which demonstrates the performance of a binary classifier system as with threshold variation. It is created by plotting the probability of detection (PD) vs. Probability of False alarm (PF), at various threshold values. In general, if both of the probability distributions for detection and false alarm are known, the ROC curve can be generated by plotting the Cumulative Distribution Function of the detection probability in the y-axis versus the Cumulative Distribution Function of the false alarm probability in x-axis. The sensing performance of the proposed scheme, in terms of its ROC curve is evaluated using Monte-Carlo simulations.

It is assumed that the PU signal is likely-equally Binary Phase Shift Keying (BPSK) signal [19] with prior probabilities Pr {H0} = Pr {H1} = 0.5 and the noises at CUs are AWGN with zero mean and unit variance.

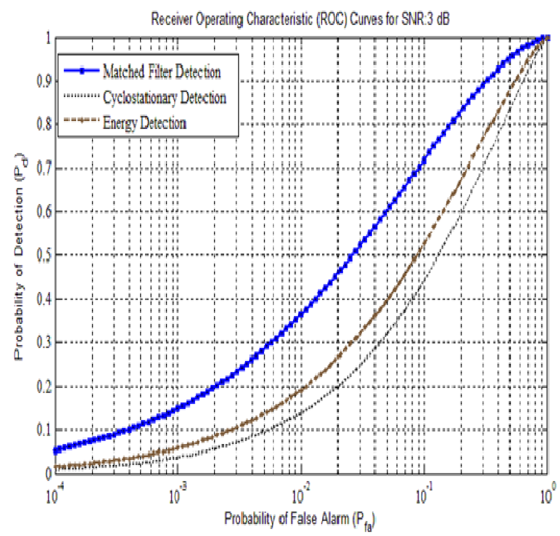

Figure 3: Receiver Operating Characteristics Curve For 3 Db SNR

Under the above assumptions the ROC curve of the proposed scheme is compared with [11], namely the Kalman filter based adaptive fuzzy system scheme and with [12] one order Cyclostationary detection based on estimated signal to noise ratio. A comparison of these results is presented in Figure 3 and Figure 4 for different values of lower SNRs. The proposed scheme outperforms the Kalman filter based adaptive fuzzy system scheme and one order Cyclostationary detection scheme. To implement the proposed scheme, the SNR at reduced rate is considered normally at 3 dB and 6 dB and also in the proposed scheme each CU must send the SNR of the PU signal to the FC.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

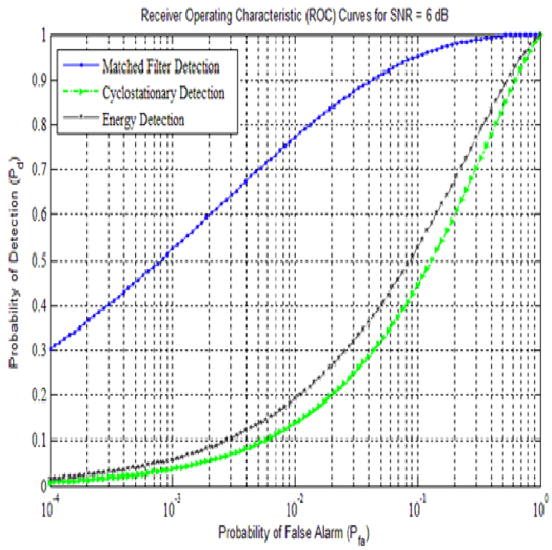

Figure 4: Receiver Operating Characteristics Curve For 6 Db SNR

6. CONCLUSSION

In order to sense the spectrum holes consistently and resourcefully, in this paper we propose a matched filter based cooperative spectrum sensing in CR networks. The advantage of the proposed scheme comes from the fact that it can work with very low SNR with the knowledge of the PU signal, the prior probability of the PU activity, and SNRs of the PU signal at cognitive radio terminals. Monte-Carlo simulation results based on ROC curve show that the sensing performance of the proposed scheme outperforms the performance of Kalman filter based adaptive fuzzy system scheme and one order Cyclostationary detection scheme.

The only limitation of the proposed scheme is we should have the prior knowledge about the PU signal before sensing the channel. The choice of matched filter detection technique proposed here to estimate the channel in the lower SNR regime. Consequently, finding lower bound of min τ (Threshold) and upper bound of max τ is still an open issue. Future work is in progress in this direction.

REFRENCES:

[1] S. Haykin, "Cognitive Radio: Brain-Empowered Wireless Communications", *IEEE Journal on Selected Areas in Communications*, vol. 23, 2005, pp. 201-220.

[2] K. Yau, P. Komisarczuk and P.D. Teal, "Cognitive Radio-based Wireless Sensor Networks: Conceptual Design and Open Issues", *IEEE 34th Conference on Local Computer Network*, 2009, pp. 955-962.

[3] Federal Communications Commission (FCC), *Spectrum Policy Task Force*, ET Docket no.2, 2002, pp. 1-135.

[4] R.W. Broderson, A. Wolisz, D. Cabric, S.M. Mishra and D. Willkomm, "CORVUS: A Cognitive Radio Approach for Usage of Virtual Unlicensed Spectrum", *White Paper, University of California, Berkeley*, Technical Report, 2004.

[5] A. Ghasemi and E.S. Sousa, "Collaborative Spectrum Sensing for Opportunistic Access in Fading Environments", *1st IEEE Symposium on New Frontiers in Dynamic Spectrum Access Network*, 2005, pp. 131-136.

[6] F. F. Digham, M.S. Alouini and M.K. Simon, "On the Energy Detection of Unknown Signals Over Fading Channels", *IEEE International Conference on Communications*, vol. 5, 2003, pp. 3575-3579.

[7] Lei Zhang and Shuquan Xia, "A New Cooperative Spectrum Sensing Algorithm for Cognitive Radio Networks", *Proceedings of ISECS International Colloquium on Computing, Communication, Control, and Management*, vol. 1, 2009, pp. 107-110.

[8] Sina Maleki, Sundeep Prabhakar Chepuri and Geert Leus, "Energy and Throughput Efficient Strategies for Cooperative Spectrum Sensing in Cognitive Radios", *IEEE 12th International Workshop on Signal Processing Advances in Wireless Communications*, 2011, pp. 71-75.

[9] Z. Quan, S. Cui and A.H. Sayed, "Optimal Linear Cooperation for Spectrum Sensing in Cognitive Radio Networks", *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, 2008, pp. 28-45.

[10] T. Kieu-Xuan and I. Koo, "A Cooperative Spectrum Sensing Using Fuzzy Logic for Cognitive Radio Networks", *KSII Transactions on Internet and Information Systems*, vol. 4, 2010, pp. 289-304.

[11] T. Kieu-Xuan and I. Koo, "Cooperative Spectrum Sensing using Kalman Filter based Adaptive Fuzzy System for Cognitive Radio Networks", *KSII Transactions on Internet and Information Systems*, vol. 6, 2012, pp. 287-304.

[12] Waleed Ejaz, Najam Ul Hasan and Hyung Seok Kim, "SNR Based Adaptive Spectrum Sensing for Cognitive Radio Networks", *International Journal of Innovative Computing, Information and Control*, vol. 8, 2012, pp. 6095-6105.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[13] Rahul Tandra and Anant Sahai, "SNR Walls for Signal Detection", *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, 2008, pp. 4-17.

[14] Pu Wang, Hongbin Li and Braham Himed, "Bayesian Parametric Approach for Multichannel Adaptive Signal Detection", *IEEE Radar Conference*, Washington DC, 2010, pp. 838-841.

[15] A. Eftekhari, A. J. Romberg and M.B. Wakin, "Matched Filtering from Limited Frequency Samples", *IEEE Transactions on Information Theory*, vol. 59, 2013, pp. 3475-3496.

[16] F. Chaillan, C. Fraschini and P. Courmontagne, "Stochastic Matched Filtering Method Applied to SAS Imagery", *Proceedings of OCEANS'05*, vol. 1, 2005, pp. 233-238.

[17] Rongfei Fan and Hai Jiang, "Optimal Multi Channel Cooperative Sensing in Cognitive Radio Networks", *IEEE Transactions on Wireless Communications*, vol. 9, 2010, pp. 1128-1138.

[18] P. A. Regalia, "An Adaptive Unit Norm Filter with Applications to Signal Analysis and Karhunen-Loeve Transformations", *IEEE Transactions on Circuits and Systems*, vol. 37, 1990, pp. 646-649.

[19] John Proakis and Masoud Salehi, *Digital Communications*, McGraw-Hill, 2007.

[20] Peter J. Schreier, Louis L. Scharf and Alfred Hanssen, "A Generalized Likelihood Ratio Test for Impropriety of Complex Signals", *IEEE Signal Processing Letters*, vol. 13, 2006, pp. 433-436.