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ENHANCED ENERGY DETECTORS UTILIZING WAVELET AND RLS DE-NOISING FILTERS IN COGNITIVE RADIO

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***Abstract*— Spectrum resources are limited due to the fast developing technology in wireless communications. Various techniques, for instance, tackled this problem by giving permissions to unlicensed users to utilize the various licensed bands. Spectrum sensing is one of the most utilized technique in cognitive radio system, which has a reliable technique called energy detection. It has reduced the computational and complexities of usage. In order to differentiate between the primary and secondary users in low signal-to-noise ratio (SNR), noise interference is eliminated using de-noising filters. In this paper, a new energy detection technique for spectrum sensing is developed. Besides that, a comparison between common de-noising filters is introduced, which are Recursive Least Square (RLS), 1-D and 2-D wavelet de-noising filters. The performance of the wavelet packet transform algorithm is analyzed under many Signal to Noise Ratios, different number of samples, probability of false alarm levels, and number of samples. Moreover, the technique is analyzed for different level of decomposition and different wavelet families. Simulation results revealed that utilizing RLS de-noising filter outperforms the technique used by wavelet de-noising filters under all analyzed circumstances.**

***Keywords*— Cognitive radio (CR), Compressive Sensing, De-noising filters, Genetic Algorithm (GA), Spectrum sensing (SS)**

1. INTRODUCTION

A huge demand on high wireless communications with high data rates over spectrum-based communications is increasing every day. Utilization of the specified frequency spectrum and unlicensed bands should be implemented without making any interference. Cognitive radio system appeared to be anew reliable technique to utilize the unlicensed frequency bands and this is done by Spectrum Sensing (SS). SS permit the Secondary Users (SU) an access to these free bands without making an interference with the Primary Users (PU).

Because of ED's low computational and implementation difficulties, it is the most widely used technique for spectrum sensing as mentioned in [1]. The drawback of energy detection

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technique application is, when noise is higher than certain limit, the performance of the energy detector will ebb dramatically as mentioned in [2].

Moreover, De-noising filters which use Recursive Lease Square (RLS) and Wavelet as a de-noising filters are utilized to increase SNR of the received signal. Simulation results show that utilization of de-noising filters are significantly enhanced besides the enhancement of the Receiver Operating Characteristics (ROC) curves of the CR system. This paper is organized as follows. In section 2, the block diagram of energy detector is description of its components and functions are introduced. The de-noising filters are described in section 3. The proposed spectrum sensing technique is introduced in section 4. Finally, simulation results are discussed in section 5.

2. SPECTRUM SENSING AND ENERGY DETECTOR

This part introduces a brief background on ED. To begin, a primary signal is considered as $s(n)$. The primary signal has a carrier frequency f_c with a bandwidth of B_w Hz, which can be detected by a secondary users' receiver. Then, the signal received at the receiver can be expressed as in [15]:

$$Y_{ED}\ (n) = X(n) + U_n(n) \tag{1}$$

where $X(n)$ denotes the detected signal, $U_n(n)$ is the Additive White Gaussian Noise (AWGN). AWGN has a mean of $\mu_u = 0$ and variance σ_u^2, and n is the sample index. The primary user is detected between a two hypotheses. The first hypothesis assumes that there is no primary user and denoted as H_o, while the other hypothesis which assumes that the primary user is actually exist is denoted as H_1.

The two mathematical hypotheses are expressed in the following equations:

$$H_o: \quad Y_{ED}\ (n) = U(n) \tag{2}$$

$$H_1: \quad Y_{ED}\ (n) = X(n) + U_n(n) \tag{3}$$

Energy in primary signal is measured through ED. The differentiation between the above two hypotheses is calculated through a decision metric equation expressed as:

$$D(y) = \frac{1}{N} \sum_{n=1}^{N} |Y_{ED}(n)|^2 \tag{4}$$

By assuming τ to be sensing time and N is a total number of samples, the relation between them is expressed by the following equation:

$$N = \tau f_s \tag{5}$$

The decision metric $D(y)$ is a random variable which has a Probability Density Function (PDF). For a large number of samples N according to [4], usually $N \geq 250$, a Gaussian approximation is used to the PDF of test statistics $D(y)$ under either hypothesis: Ho noise alone, or H_1 signal with noise. This is done by using Central Limit Theorem (CLT) [3].

The probability of an algorithm correctly detects the presence of a primary signal is called probability of detection (P_d), and the probability of an algorithm falsely declares the presence of a primary signal is called probability of false alarm (P_f) under hypothesis H_1 and H_o respectively [4]. The probability of false alarm is given by:

$$P_f(\epsilon_{TH}, \tau) = Q\left(\left(\frac{\epsilon_{TH}}{\sigma_u^2} - 1\right)\sqrt{\tau f_s}\right) \tag{6}$$

According to [9], Probability of detection can be approximated by:

$$P_d(\epsilon_{TH}, \tau) = Q\left(\left(\frac{\epsilon_{TH}}{\sigma_u^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma+1}}\right) \quad (7)$$

where $Q(\cdot)$ is the complementary distribution function of the standard Gaussian, according to [5] *i.e.*,

$$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty exp\left(-\frac{t^2}{2}\right) dt \quad (8)$$

$$\gamma = \frac{\sigma_s^2}{\sigma_u^2} \quad (9)$$

where σ_s^2 is signal variance and γ is SNR. The probability of missed detection can be written as:

$$P_{md} = 1 - P_d \quad (10)$$

From equation (6), detection threshold ϵ is related to the probability of false alarm as follows [9]:

$$\epsilon_{TH} = \left(\frac{Q^{-1}(P_f)}{\sqrt{\tau f_s}} + 1\right)\sigma_u^2 \quad (11)$$

As shown in Fig. 1, the energy detector is divided into three parts. The first part is the noise pre-filter which is used to limit noise bandwidth. The second part is squaring device which is used to calculate the energy of the filtered signal. Finally, the third part is an integrator which determines the energy of the filtered received signal over the sensing time interval τ. The integrator output is considered to be the test statistic of the two hypothesis H_o and H_1.

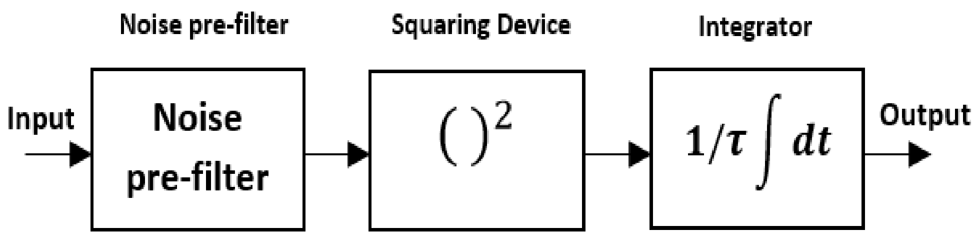

Fig. 1 Energy Detector Simplified Model [9].

3. DE-NOISING FILTERS

In this section, two powerful de-noising filters are briefly introduced to reduce the effect of the noise on the received signal. A modified energy detection technique for spectrum sensing is introduced. The proposed technique is based on adding two de-noising filters which are Recursive Least Square (RLS) and wavelet filter. Both of the two filter are added separately to the energy detector after the noise pre-filter.

A. Recursive Least Square Filter

One of the most popular adaptive filters which are widely used recently is Recursive Least Square (RLS) filter. Its frequency response is adjustable to enhance its performance according to some criterion. Because of this advantage, RLS can adapt and change its coefficients. RLS filter has two operation phases: the first phase is a digital filter with coefficients which are adjustable. The second operation phase is the adaptive algorithm, which has the ability to modify filter coefficients [12, 13]. RLS can be briefly modeled as in Fig. 2 [12].

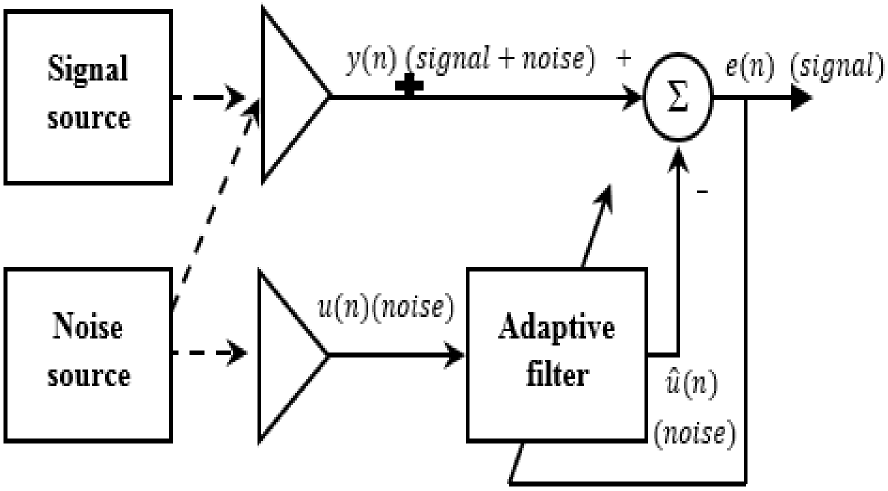

Fig. 2 RLS Filter Model [12]

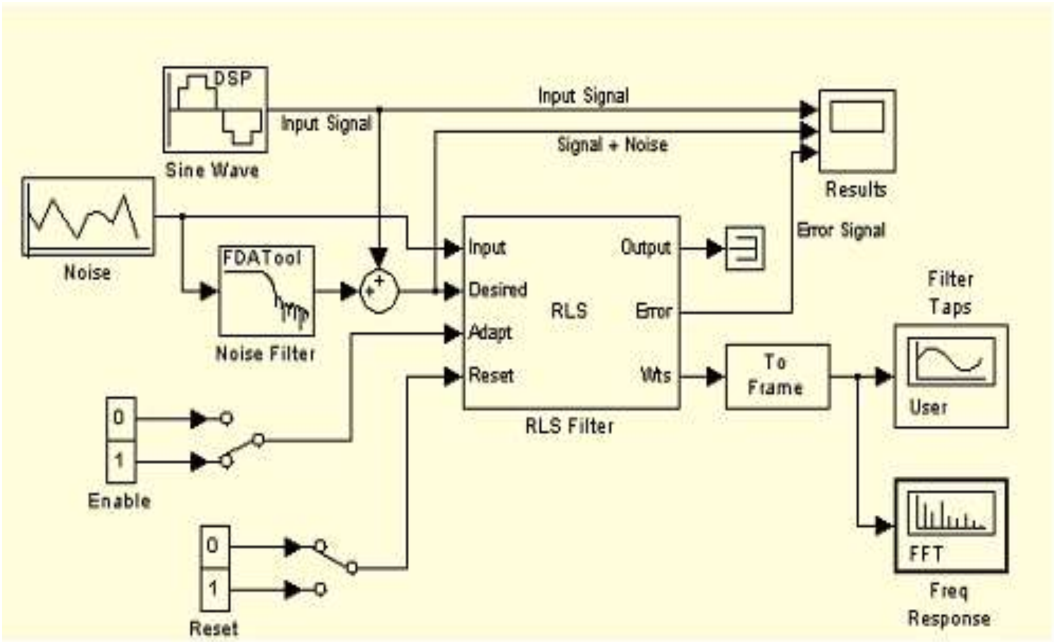

Fig. 3 RLS filter Simulink Model [6]

From Fig. 2, two input signals $Y_{ED}(n)$ and $U_n(n)$ are applied simultaneously to an adaptive filter where, $Y_{ED}(n)$ is a contaminated signal containing both uncorrelated desired signal $s(n)$ and noise $u(n)$. The main objective of the adaptive algorithm is to produce an optimum estimation of noise $\hat{u}(n)$in the contaminated signal. This can be achieved by using a suitable adaptive algorithm to minimize noise [13]. A simple equation of the RLS filter can be expressed in [12] as:

$$ER(n) = Y_{ED}(n) - \widehat{U}(n) = X(n) + U(n) - \widehat{U} \tag{12}$$

Where $ER(\mathrm{n})$ is the Error Signal, which has two purposes; the first one is to estimate the desired signal and the second is to adjust filter coefficients.

The disadvantage of implementing RLS algorithm is usually associated with high computational complexity and poor numerical properties as mentioned in [5].

B. Wavelet De-Noising Filter

Wavelet is defined as wave-like oscillation with amplitude starts out at zero, increase, and then decreases back to zero. Regression model is utilized in order to recover the underlying function from the noisy signal statistically. This method is called Wavelet de-noising by Thresholding [11]. Suppose that there is a number of n noisy samples of a function s.

$$Y_{EDi} = X(t_i) + \sigma U(n), \; i = 1 \ldots n \tag{13}$$

where Y_{EDi} is the noisy data, $Y_{EDi} = (Y_{ED1}, \ldots, y_{EDn})$, and $U(n)$ is AWGN, N $(0\,,\sigma_{\mathrm{u}}^2)$ and the noise level σ is unknown according to [17]. The main goal is to recover function s from the noisy data y_i that satisfies the following equation from [17]:

$$\hat{s} = \min_{\hat{s}} \|\hat{s} - s\|_2 \tag{14}$$

where $\hat{s} = \hat{s}(Y_{EDi})$. The thresholding of the wavelet coefficients is usually applied only to the detail coefficients of y rather than the approximation coefficients. Because the approximation coefficients always contain the most important components of the signal, and are less affected by noise. Thresholding will set significant coefficients, whose values will be below a certain threshold level λ, to zero [17].

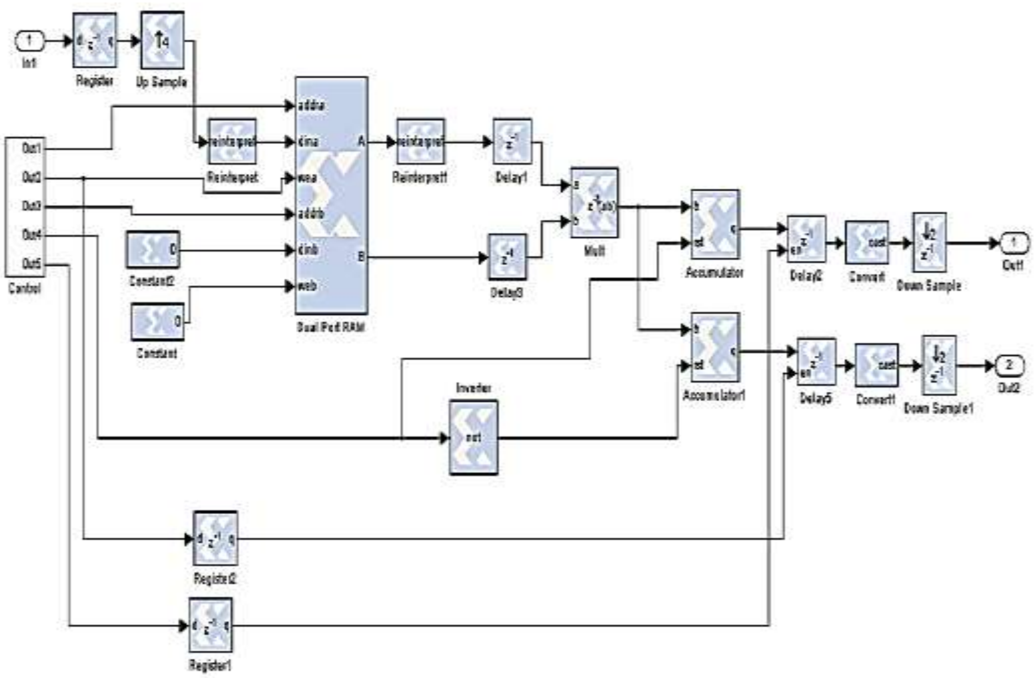

Fig. 4 Wavelet implementation in FPGA as mentioned in [6]

C. Comparison of Performance Parameters Between RLS and Wavelet De-Noising Filters

Form the analysis of the paper in [7], is concluded that for real time de-noising operation (for example, live broadcasting of speech) of voice signal DWT is preferable (from CPU time).But for non-real time case (for example, de-noising of an old song from a gramophone) RLS is preferable for precise de-noising (from mean square error) as shown in Table I.

Table I. Comparison of performance parameters between RLS and Wavelet de-noising filters [6].

Parameters	**Wavelet**	**RLS**
Mean Error	0.0339	0.0247
Maximum Error	0.5608	0.8661
Variance	0.0043	0.0083
CPU time	0.9844	28.1719
Practical Implementation	Complex	Simple

4. PROPOSED SPECTRUM SENSING TECHNIQUE

In this section, an efficient spectrum sensing technique based on de-noising filters is introduced. Fig. 5 shows the block diagram of the proposed technique.

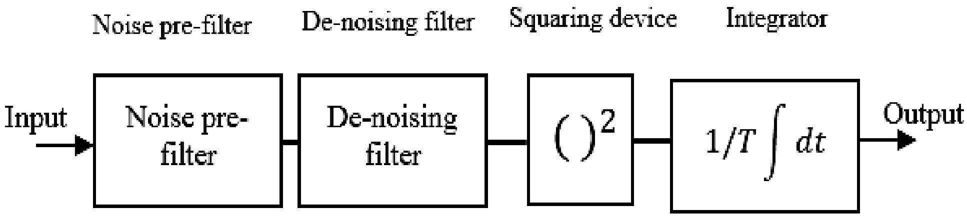

Fig. 5 Block diagram of the proposed spectrum sensing technique.

First the input signal is passed through a noise pre-filter. Then the signal is applied to Noise pre-filter. De-noising filter will minimize the added noise of the received signal which leads achieving SNR gain and variance reduction. Hence, the detection threshold will be enhanced dramatically which leads to an improvement with the ROC curves of the energy detector. Enhancing ROC curves is because of the increment in probability of detection P_d and the decrement in probability of false alarm P_f and probability of missed detection P_{md}.

5. SIMULATION RESULTS

In this section, a performance comparison between the proposed spectrum sensing technique and the traditional energy detector is presented. Simulations are performed using MATLAB R2014a. A frame of 8 bits is sent using BPSK modulation with bandwidth of 2 MHz. AWGN is added to a modulated signal. In order to compare the results, SNR should be in the range of -10 dB to 0 dB. Meyer wavelet family is used in the wavelet filter with two-stage wavelet packet decomposition. A comparison is made in the last case between different wavelet families Analysis.

Case A: Performance analysis of the proposed algorithm.

In this part, both RLS and wavelet De-noising filters are applied on the received signal. The number of samples N is 500. The P_f is taken at 0.01. The result is shown in Fig. 6, Fig. 7 and Fig. 8.

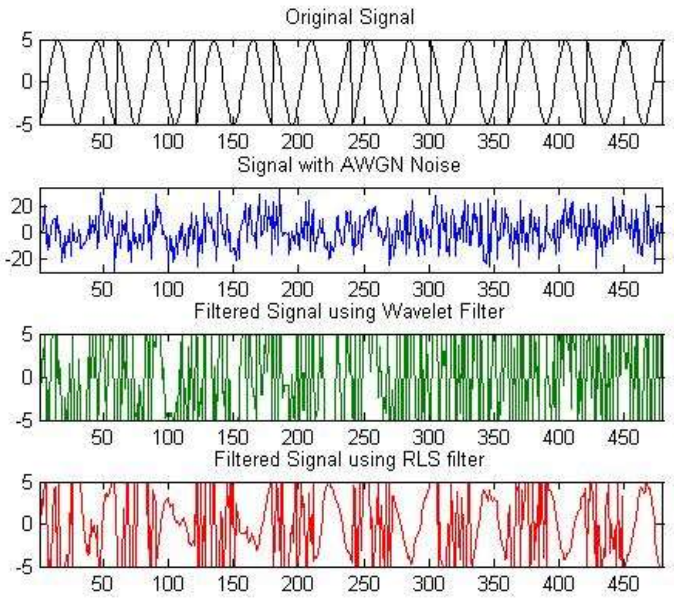

Fig. 6 Shapes of Noisy Signal Compared to Filtered Signals

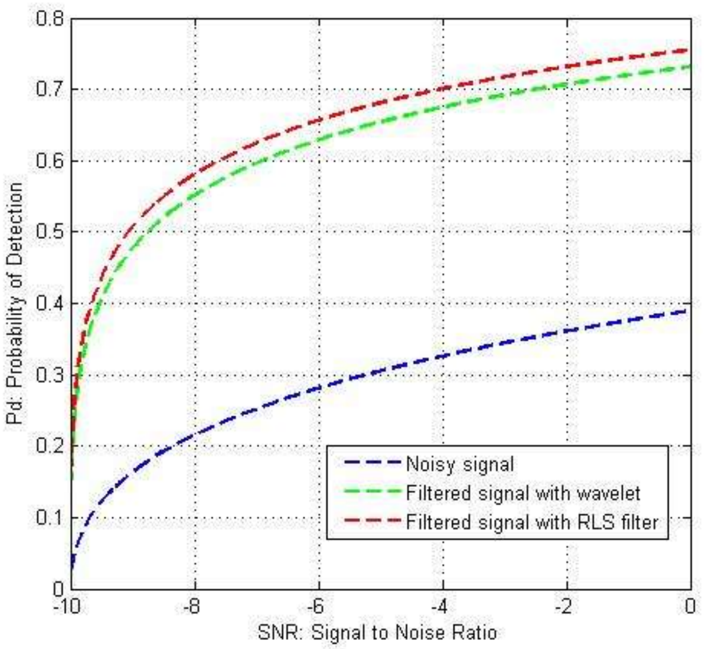

Fig. 7 Comparison between the Probability of Detection and SNR

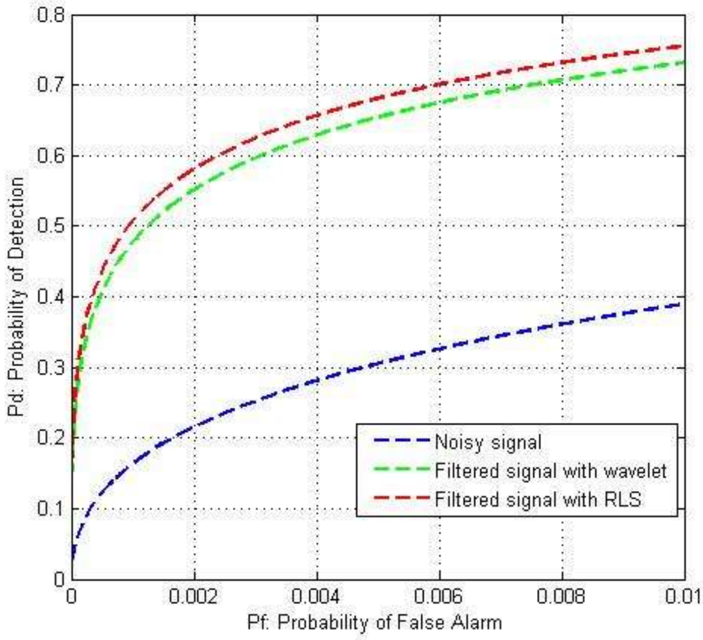

Fig. 8 Comparison between the probability of false alarm and probability of detection.

P_d values are taken and compared. SNR varies from -10 dB to 0 dB. After analysis, it is found that P_d of utilizing RLS de-noising filter outperforms utilization of wavelet de-noising filter.

Case B: The effect of varying level of Decomposition.

The level of decomposition is varied from two to three. Other parameters are not changed. The results are shown in Fig. 9 and Fig. 10.

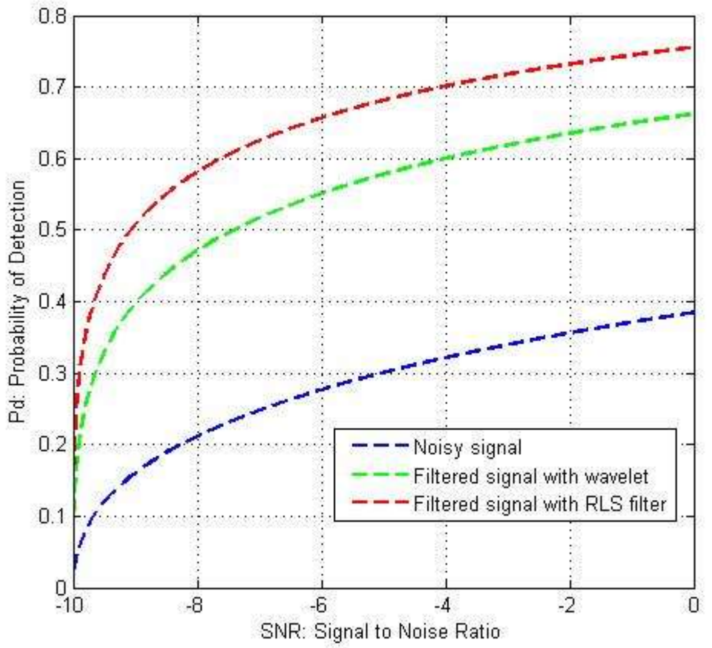

Fig. 9 Comparison between the probability of detection and SNR

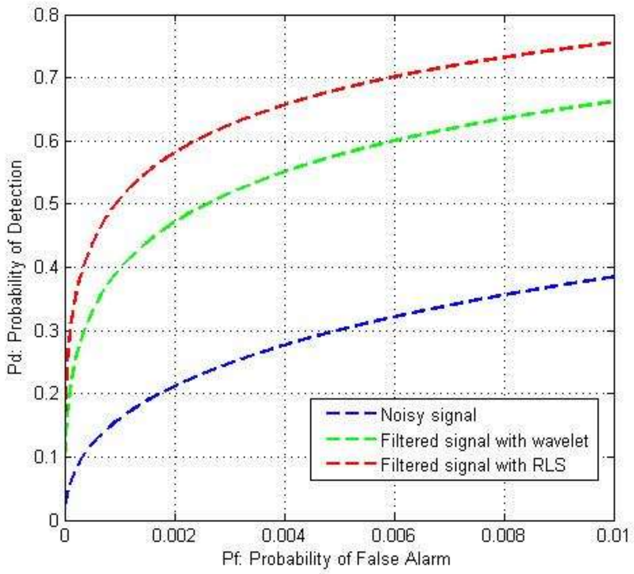

Fig. 10 Comparison between the probability of false alarm and probability of detection

Analysis: The decision threshold and probability of detection P_d are considered and compared. The values are taken for different SNRs and Dmey wavelet family is chosen. After comparison, it is found that P_d does not change with the increase in the decomposition level. Besides that, RLS de-noising filter still outperforms the wavelet three-level decomposition de-noising filter.

Case C: Effect of Varying Number of Samples.

The number of samples is varied into 250,500 and 1000. P_f is chosen to be 0.01. P_d is calculated for each case and compared to both SNR and P_f. The results are shown on Fig. 11 through Fig. 16.

First: choose N=250 samples

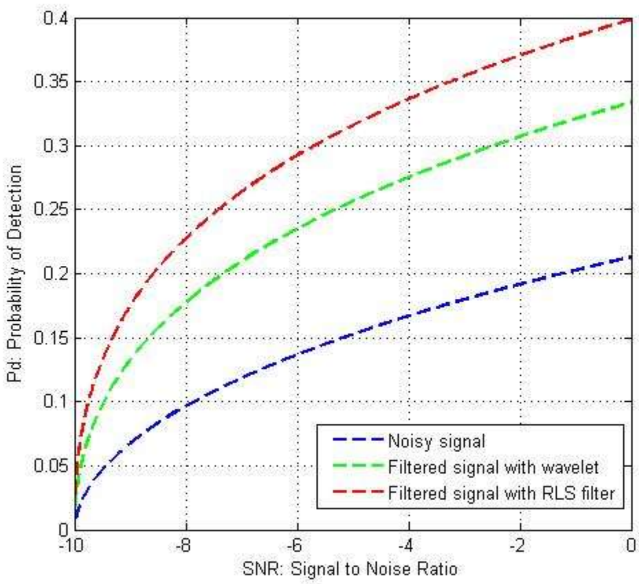

Fig. 11 Comparison between the probability of detection and SNR for N=250 samples

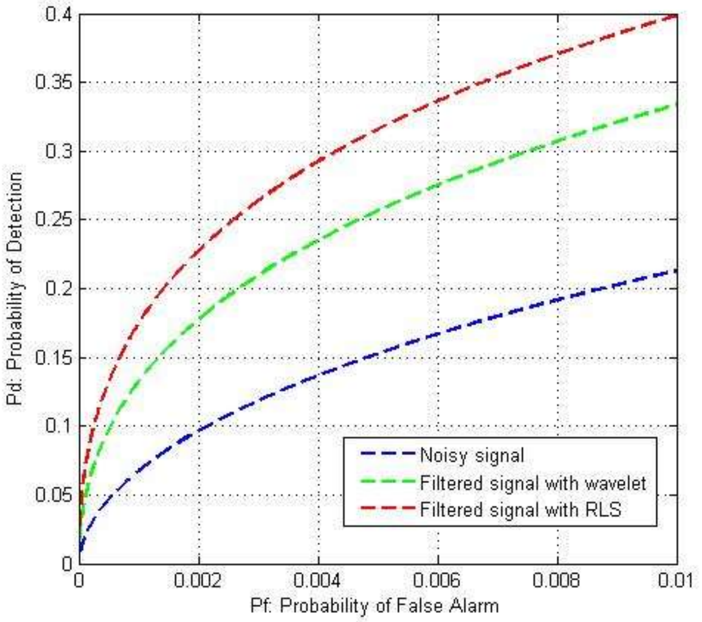

Fig. 12 Comparison between the probability of false alarm and probability of detection for N=250 samples

Second: choose N=500 samples, i.e. number of samples is doubled.

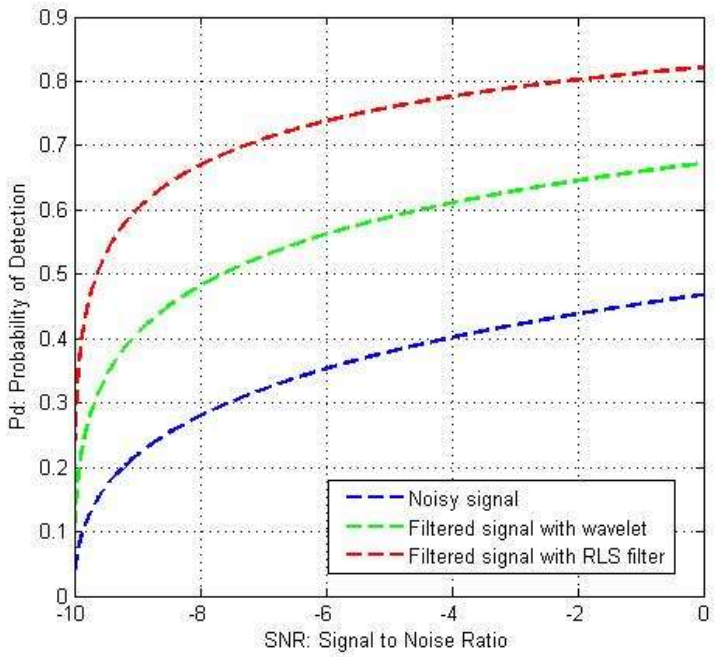

Fig. 13 Comparison between the probability of detection and SNR for N=500 samples

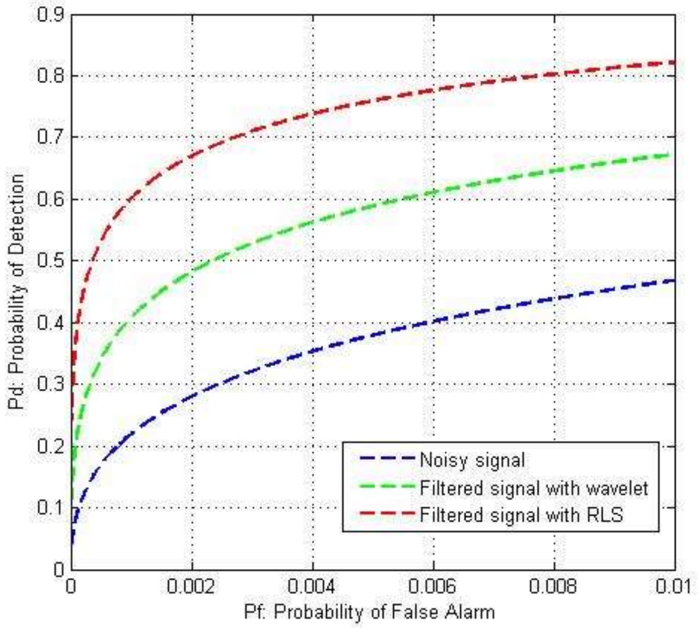

Fig. 14 Comparison between the probability of false alarm and probability of detection for N=500 samples.

Third: choose N=1000 samples, the number of samples is doubled again.

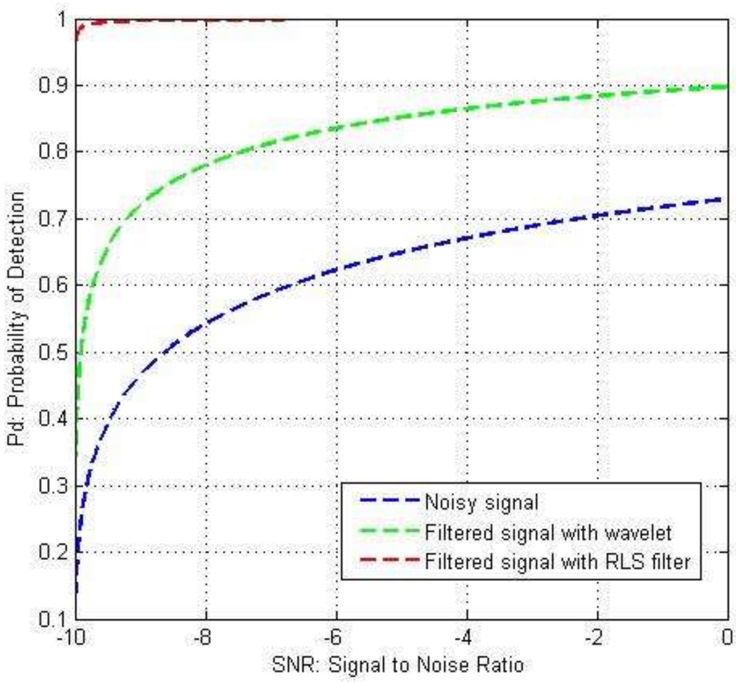

Fig. 15 Comparison between the probability of detection and SNR for N=1000 samples

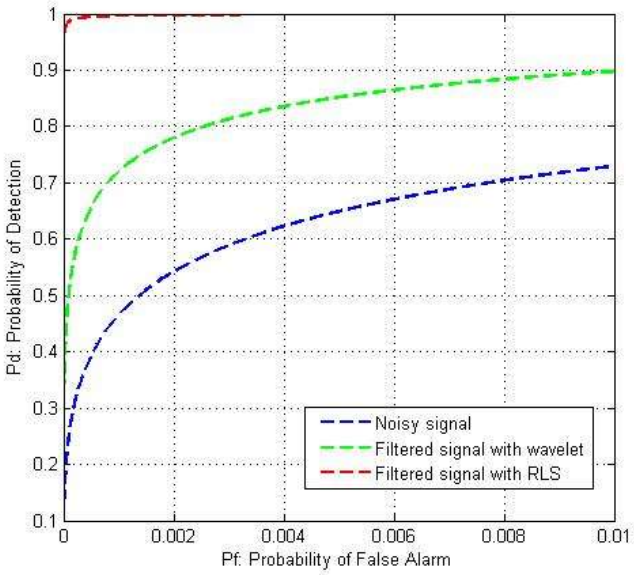

Fig. 16 Comparison between the probability of false alarm and probability of detection for N=1000 samples.

Analysis: The P_d values are taken and compared. The values are taken at SNR varying from -10 dB to 0 dB and Dmey wavelet family is chosen. After comparison, it is found that P_d increased when the number of samples increased. Again, RLS de-noising filter still outperforms the wavelet de-noising filter.

Case D: Effect of varying probability of false alarm$\mathbf{P_f = 0.001}$.

The number of samples is chosen 500. Wavelet decomposition level is two and P_f is changed to 0.1, 0.01 and 0.001. Dmey wavelet family is utilized for wavelet transform. The results are shown in Fig. 17 through Fig. 21.

First choose $P_f = 0.001$.

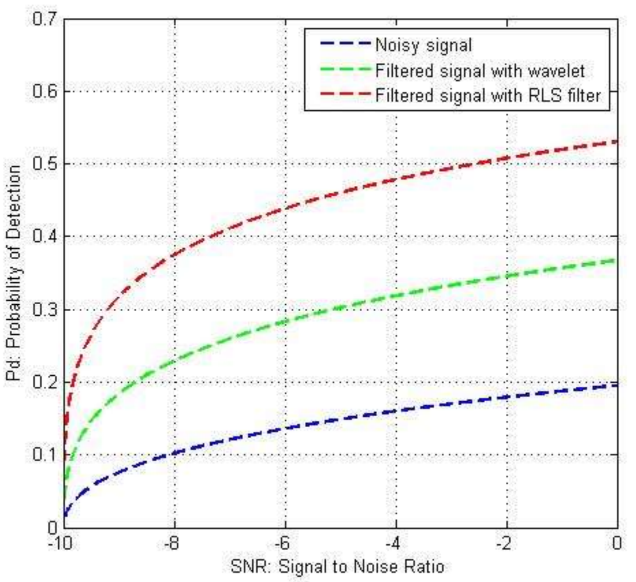

Fig. 17 Comparison between the probability of detection and SNR for $P_f = 0.001$

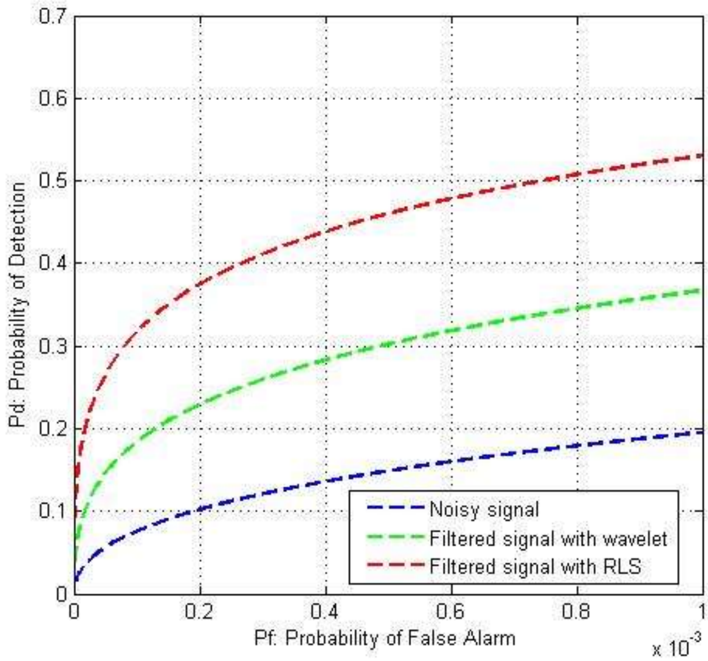

Fig. 18 Comparison between the probability of false alarm and probability of detection for $P_f = 0.001$

Second choose $P_f = 0.01$.

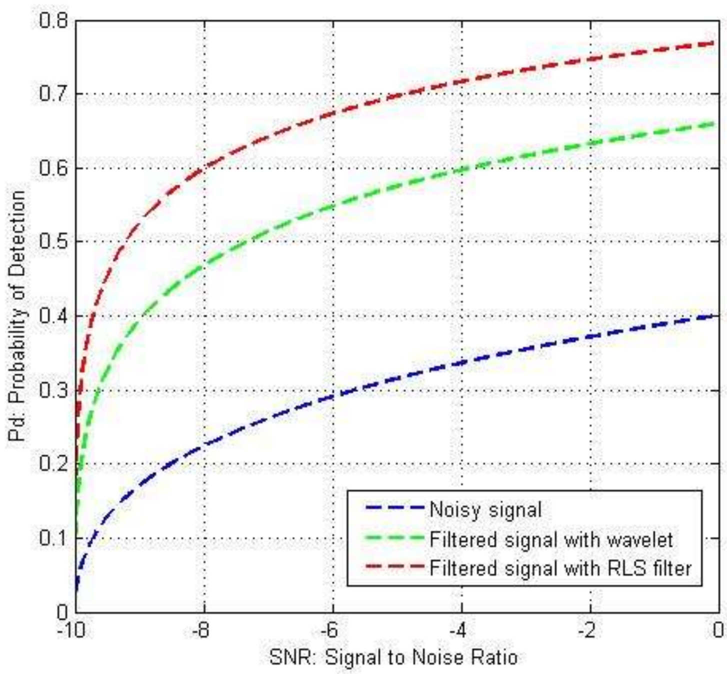

Fig. 19 Comparison between the probability of detection and SNR for $P_f = 0.01$

Third choose $P_f = 0.1$.

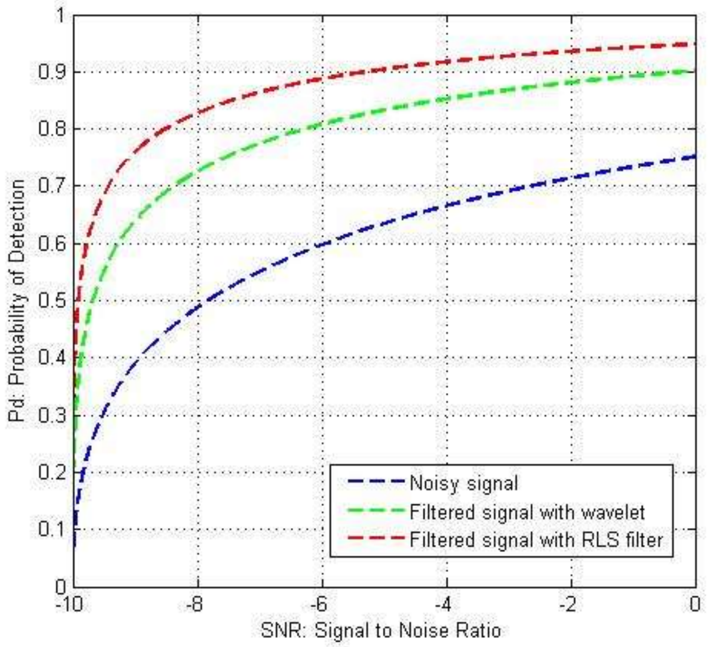

Fig. 20 Comparison between the probability of detection and SNR for $P_f = 0.01$

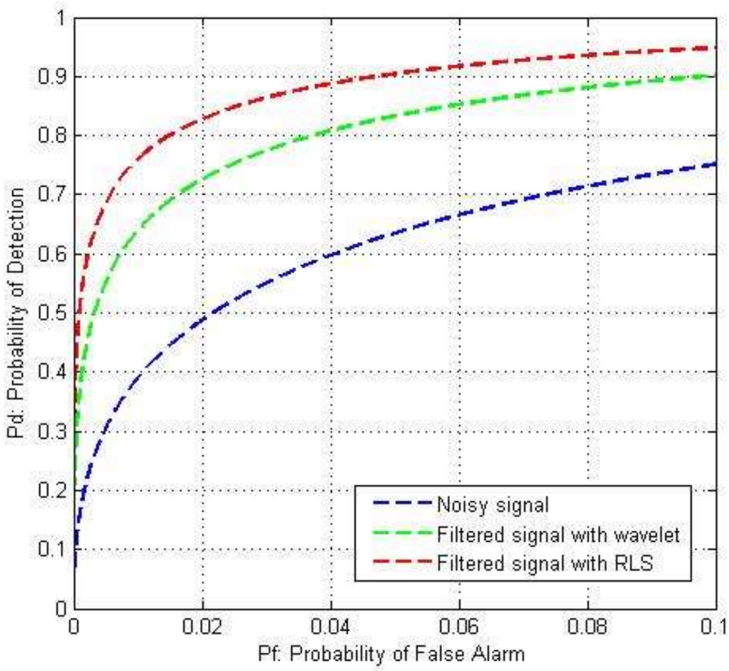

Fig. 21 Comparison between the probability of false alarm and probability of detection for $P_f = 0.1$

Analysis: The P_d values are chosen and compared. The values are taken at SNR varying from -10 dB to 0 dB. After comparison, it is found that P_d increased with the degradation of

P_f.On the other hand, the variation is very small. Thus, change in P_f has a minor effect on P_d .

6. CONCLUSIONS

In this paper, efficient spectrum sensing technique based on energy detection and de-noising filters is introduced. There has been a comparison which is introduced breifly between the two de-noising filters. The simulation results revealed RLS de-noising filter provides much higher performance more than both: the energy detector based on Wavelet de-noising filter and the traditional energy detector. The comparison revealed that:

A. The energy detection algorithm based on RLS is much better than wavelet based algorithm. Simulation results suggest that the presented algorithm is robust to AWGN noise.

B. The probability of detection P_d does not affected by the change in the level of wavelet packet decomposition. Therefore, higher number of coefficients are obtained at the same probability of detection by increasing the level if decomposition. In other words, RLS de-noising filter still outperforms the increased decomposition level of Wavelet filter.

C. The probability of detection P_d increased with the increment of number of samples. For a better PU detection, higher number of samples should be utilized for both RLS and Wavelet de-noising techniques.

D. The probability of detection P_d increased with the decrease of probability of false alarmP_f. However, the enhancement is very low comparing to the decrement in probability of false alarm P_f.

REFERENCES

[1] P. Semba Yawada, An Jian Wei and M. Mbyamm Kiki, "Performance evaluation of energy detection based on non-cooperative spectrum sensing in cognitive radio network," 2015 4th International Conference on Computer Science and Network Technology (ICCSNT), Harbin, China, 2015.

[2] Performance of Spectrum Sensing in Cognitive Radio", I.J. Information Technology and Computer Science, 2012, 11, 11-17.

[3] Emmanuel Candes and Justin Romberg, "Practical signal recovery from random projections", SPIE Symposium on Electronic Imaging, 2005.

[4] Al-Hmood H. and Al-Raweshidy H. S., "Energy detection performance enhancement for cognitive radio using noise processing approach," Global Information Infrastructure Symposium - GIIS 2013, Trento, pp. 1-6, 2013.

[5] Gavrincea Ciprian, Tisan Alin, Oniga Stefan, Buchman Attila , FPGA-based discrete wavelet transforms design using MatLab/Simulink , International Symposium for Design and Technology of Electronic Packages 13th Edition, Baia Mare, Romania

[6] Mahbubul Alam, Md. Imdadul Islam, and M. R. Amin , Performance Comparison of STFT, WT, LMS and RLS Adaptive Algorithms in Denoising of Speech Signal 'IACSIT International Journal of Engineering and Technology, Vol.3, No.3, June 2011.

[7] T. E. Bogale, L. Vandendorpe and L. B. Le, "Sensing throughput tradeoff for cognitive radio networks with noise variance uncertainty,"2014 9th International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM), Oulu, 2014.

[8] "IEEE Standard of Information Technology" Part 22: Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications: Policies and Procedures for Operation in the TV Bands, 1 July 2011.

[9] Hussein Al-Mood, H. S. Al-Raweshidy," Energy Detection Performance Enhancement for Cognitive Radio Using Noise Processing, Approach", IEEE, 2013.

[10] P. Semba Yawada, An Jian Wei and M. Mbyamm Kiki, "Performance evaluation of energy detection based on non-cooperative spectrum sensing in cognitive radio network," 2015 4th International Conference on Computer Science and Network Technology (ICCSNT), Harbin, China, 2015.

[11] Emmanuel Candes and Justin Romberg, "Practical signal recovery from random projections", SPIE Symposium on Electronic Imaging, 2005.

[12] Guto Quan Xiang, YuXia Zhang, ”Analysis of RLS Adaptive Filter in Signal De-noising”, IEEE, 978-1-4244-8165-1/11, 2011.
[13] Emmanuel C. Ifeachor, Barrie W. Jervis,”Digital Signal Processing, A Practical Approach”, second edition, Ch. (10), 2002.
[14] Z. Tian and G. B. Giannakis, “Compressed sensing for wideband cognitive radio”, in ICASSP, vol. 4, pp.1357-1360, April 2007.
[15] Z. Tian and G. B. Giannakis Peh, E.C.Y.;Anh Tuan Hoang, “Sensing-Throughput Tradeoff for Cognitive Radio Networks ”, Wireless Communications, IEEE Transactions on, vol.7, no.4, pp.1326,1337, April 2008.
[16] Ghido, I. Tabus, “Sparse Modeling for Lossless Audio Compres- sion,”,IEEE Trans. on Audio, Speech, and Language Processing, vol.21, no.1, pp.14,28, 2013.
[17] Rami Cohen,” Signal Denoising Using Wavelets”, Project Rebort, February 2014.