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A Wavelet and Advanced Wavelet Analysis for Wavelet Domain Communication System (WDCS)

(A Way to Designing Communication System for Cognitive Radio)

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Abstract: **Wavelet analysis is an exciting new method for solving difficult problems in mathematics, physics, and engineering, with modern applications. Wavelet transform of a function is the improved version of Fourier transform. In conventional Fourier transform, we use sinusoids for basis functions. It can only provide the frequency information. Temporal information is lost in this transformation process. In some applications, we need to know the frequency and temporal information at the same time The time and frequency analysis made possible by the wavelet transform provides insight into the character of transient signals through time-frequency maps of the time variant spectral decomposition that traditional approaches miss. Wavelet transform is one of a best tool for us to determine where the low frequency area and high frequency area is. In this paper, our main goal is to categorise the wavelet and advanced wavelet transform approach because the original WDCS implementation (Wavelet domain communication system) uses a linear Wavelet-based transform approach to overcome TDCS(Transform domain communication system) shortcomings in the way of cognitive radio designing**.

Keywords: Fourier Transform, TDCS, WDCS, Wavelet Transform, Cognitive Radio

I. WAVELET

Wavelets[1][2] are mathematical functions with oscillatory nature similar to sinusoidal waves with the difference being that they are of "finite oscillatory nature". Essentially a finite length, decaying waveform, when scaled and translated results in what is called a "daughter wavelet" of the original "mother wavelet". Hence different scaling and translation variables result in a different daughter wavelet from a single mother wavelet. Wavelet transforms are classified as Continuous wavelet transforms (CWT) and Discrete wavelet transforms (DWT). The finite oscillatory nature of the wavelets makes them extremely useful in real life situations in which signals are not stationary. While Fourier transform of a signal only offers frequency resolution, wavelet transforms offer "variable time frequency" resolution which is the hallmark of wavelet transforms.
The first use of wavelets was by Haar in 1909. He was keen in finding a basis on a dynamic space same as Fourier's basis in frequency space. In physics, wavelets were used in the characterization of Brownian motion. This work led to some of the opinion used to construct wavelet bases. If the features of the signal in question do not change over time, i.e, the signal is stationary then Fourier transform is substantial, for the analysis of the signal. Nevertheless, in many applications it is the variable or non-stationary phase of the signal (that is sudden changes) that is of maximum interest. In some cases, Fourier analysis is unable to find out when/where such events take place and is therefore not appropriate to depict or represent them. In order to conquer this limitation of Fourier to gain data in time and frequency domain, a different kind of transform, called wavelet transform can be used. Wavelet. Transform[3][4] can be sighted as a trade-off between frequency and time domains. Fourier transforms a signal between time and frequency domains, while wavelet transform emphasizes on scales and locations (in place of frequency).

II. WAVELET TRANSFORM

The Wavelet Transform (WT) [3][4]is a method for analyzing signals. It was developed as a replacement to the short time Fourier Transform (STFT) to conquer problems related to its frequency and time resolution characteristics. unlike the Short Time Fourier Transform that gives uniform time resolution for all Frequencies the Discrete Wavelet Transform gives high time resolution and low frequency resolution for high frequencies only and high level frequency resolution and low time resolution for low level frequencies. In that respect it is similar to the ear of a human which reveal similar time-frequency resolution properties. The Discrete Wavelet Transform (DWT) is a unique case of the

Wavelet Transform (WT) form that gives a tight characterization of a signal in frequency and time that can be evaluated efficiently.

A wavelet transform[5][6] decomposes a signal into basis functions which are known as wavelets. Wavelet transform is calculated separately for different segments of the time-domain signal at different frequencies resulting in Multi-resolution analysis or MRA. It is designed in such a way that the product of time resolution and frequency resolution is constant. Therefore it gives good time resolution and poor frequency resolution at high frequencies whereas good frequency resolution and poor time resolution at low frequencies. This feature of MRA makes it excellent for signals having high frequency components for short durations and low frequency components for long duration .e.g. noise in signals, images , video frames etc.

III. ROLE OF WAVELET TRANSFORM FOR COGNITIVE RADIO

Rapid development of new and ever expanding wireless applications and services, spectrum resources are facing huge demands. Currently, spectrum allotment is done by giving each new service with its own fixed frequency block. As more and more technologies are moving towards fully wireless, demand for spectrum is enhancing. In this context, a new technology, cognitive radio (CR) has been come out to solve this spectrum scarcity problem. In the Area of cognitive radio(CR) ,Several modulation techniques have been disseminated to reduce interference effects. Two developmental communication systems pointing interference avoidance capabilities are Transform Domain Communication System (TDCS) and the Wavelet Domain Communication System (WDCS)[7][8]. The TDCS and WDCS are particularly designed to operate successfully in an environment consisting hostile, unintentional interference. TDCS implementation used a Fourier transform approach.but WDCS implementation used a lineal wavelet-based transform approach. The WDCS architecture exclusively fungibled the Fourier based spectral estimation processes with a lineal wavelet transform. And,the inverse Wavelet transform block replaced the inverse Fourier transform block. After scaling and translation we can achieve a two-dimensional mother wavelet.WDCS reduced the shortcoming of TDCS. The Fourier-based estimator instinctively dilates interference energy into proximate spectral domains not containing interference energy, an inefficiency probably resulting in less performance. The TDCS is unable to efficiently estimate the spectral type of non-stationary interference.

*A. **WDCS(wavelet Domain Communication System)-***

The Original WDCS[9][10] implementation used a traditional wavelet-based approach to perform to estimate a spectrum and was developed to overcome some major TDCS deficiencies, these are:

1) The Fourier-based estimator instinctively extends interference energy into adjacent regions of spectrum not containing interference, an inaptness resulting in demoted performance, and

2) The TDCS fails to estimate the spectral characteristics of non-stationary interference effectively.

The original Wavelet Domain Communication System (WDCS) simply taked place the Fourier based spectral estimation processes with a traditional wavelet approach. of necessity, the inverse wavelet transform taked place the inverse Fourier transform. In WDCS the mother wavelet is the fundamental waveform that is translated and scaled to achieve time and frequency characterization of a signal. A smart supported waveform contains a particular amount of energy concentrated in time, permitting analysis of non-stationary signals. Spectral estimation in the WDCS is fulfill by filtering andsampling or decimating the samples of the electromagnetic environment. In this case, the filter coefficients are computed using the various wavelet approaches.The phase code is a pseudorandom (PR) sequence produced from a linear feedback shift register (LFSR). The LFSR of n-stages produces an m-sequence of period, or length of $2^n - 1$. The LFSR output sequence replicate every $2^n - 1$ clock cycles.The original WDCS implementation only uses binary modulation.The basic idea for WDCS is to synthesize an sharp adaptive waveform in the wavelet region at both the transmitter and receiver to avoid spectral densed regions. this wavelet approach offers better bit error(BER) performance in contrast to other conventional interference suppression mechanism that process the signal at the receiver side only. Moreover, since this smart adaptive waveform is able to search “spectrum hole” and adapt to EM(Electromagnetic environment), it could be a powerful candidate in Cognitive Radio(CR) technology.

IV. DWT AND CWT

A Discrete wavelet transform

A wavelet transform [11][12] in which the wavelets are discretely sampled are known as *discrete wavelet transform*. The DWT gives a multi-resolution description of a signal which is very useful in analyzing "real-world" signals. Essentially, a discrete multi-resolution description of a continuous-time signal is obtained by a DWT. It converts a series a0, a1, a2……. am into one low pass coefficient series known as “approximation” and one high pass coefficient series known as “detail”. Length of each series is m/2.In real life situations, such transformation is applied recursively on the low-pass series until the desired number of iterations is reached. Some examples of discrete wavelets are the Haar wavelets, Daubechies wavelets, symmlets etc. For any input comprising of 2n numbers, the Haar wavelet transform simply pairs up input values, storing the difference and passing the sum. This process is recursive, pairing up the sums to provide the next scale: finally resulting in $2n - 1$ differences and one final sum and this is done in O(n) time i.e. linear time.

Discrete Wavelet Transform[13][14] is more informative and flexible than the other. It is a transform that breaks the data into frequency component or sub bands. Fourier involves the decomposition of a signal into sin waves of several frequencies. The advantage of the wavelet over Fourier is in analyzing physical situation that the sinusoid do not have a limited duration but instead extend from minus to plus infinity. In Fourier transform domain we completely lose information about the audio signal. A wavelet expansion coefficient refers a component that is local and easier to interpret. Wavelets are adjustable and adaptable and designed for adaptive systems whereas Fourier transform is suitable if the signal consists of few stationary components.

B. Continuous Wavelet Transform

In order to examine signals of very distinct sizes, it is necessary to use time-frequency atoms with different time pillars. The wavelet transform divided signals over extended and translated functions called wavelets, which transform a continuous function(CW) [12] [13]into a highly unnecessary function . A wavelet is a function with zero average formulated as follows-

$$\int_{-\infty}^{\infty} \varphi(t)dt=0 \qquad (1)$$

Different types of wavelets have evolved with each one having different property and usage in different areas.

V. CLASSIFICATION OF WAVELETS

Various different types of Wavelets and associated transform used are discussed as follows:

A . Haar wavelet and Haar transform

In mathematics, the Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis. The Haar wavelet is also the simplest possible wavelet. The technical disadvantage of the Haar wavelet is that it is not continuous, and therefore not differentiable.. The Haar sequence was proposed in 1909 by Alfréd Haar. Haar used these functions to give an example of an orthonormal system for the space of square-integrable functions on the unit interval [0, 1] And The Haar transform [15] is the easiest of the wavelet transform. With the use of various stretches and shifts this transform slant multiplication non a particular function against Haar Wavelet. It is same as the Fourier transform cross multiplied as a function against a sin wave with two phases and many stretches. Haartransform is found to be more effective in applications such as signal and image compression in electrical and computer engineering as it gives a simple and computationally efficient advance approach for analyzing the local aspects of a signal. Haar transform[16][17] is formulated as-

$$y_n = H_n x_n \qquad (2)$$

And the inverse formula is

$$x_n = H_n^T y_n \qquad (3)$$

Where H_n^T is the transpose Haar matrix.

A Haar transform decompose each signal into two components one is called average(approximation) & other is known as difference(detail). The formula for the average sub signal is as follows:

$$a_n = (.f_{2n-1}+f_{2n})/\sqrt{2} \qquad (4)$$

where n-=1,2,3………N/2

And the detail sub-signal part is given by:

$$a_n = (.f_{2n-1}-f_{2n})/\sqrt{2} \qquad (5)$$

where n-=1,2,3………N/2

Some properties of Haar transform are as follows-

a) *No need for multiplications. It requires only additions and there are many elements with zero value in the Haar matrix, so the computation time is short. It is faster than Walsh transform, whose matrix is composed of +1 and -1.*

b) *Input and output lengths are the same. However, the length should be a power of 2.*

c) *It can be used to analyze the localized feature of signals. Due to the orthogonal property of Haar function, the frequency components of input signal can be analyzed.*

B. Gauss wavelet and Gaussian Transform

Fourier transformation The correct selection of the analyzing wavelet with different properties is of critical importance for enhancing the fault features in the wavelet analysis. Various wavelets are available for wavelet applications. Some of them have a
good time–frequency localization property which is a desirable attribute for fault detection applications Gaussian wavelet were initially examined for their performance in detecting fault conditions in the steam turbine. Gaussian wavelet[18][19] also generated good results for the analysis.

The direct Gaussian Transform G in wavelet theory is defined as the operator which transforms or changes p(x) function into $G(\sigma^2)$, and the Inverse Gaussian Transform G^{-1} is opposite of G defined as the operator which maps $G(\sigma^2)$to p(x):

$$\int_0^{\infty} G(\sigma^2)\, N(x|\sigma^2) d\sigma^2 = p(x) \quad (6)$$

Where,$N(x|\sigma^2)$is the gaussian distribution(Zero-mean) and it is formulated as

$$N(x|\sigma^2) = (1 / \sqrt{2\pi\sigma^2})\, e^{x^2/2\sigma^2} \quad (7)$$

Where $G(\sigma^2)$ is the mixture of functions for to reproduce p(x).Properties of gauss transform is Final value theorem means transform is 0 when $\sigma^2$is tend to infinity.

C. Daubachies Wavelet

The Daubechies Wavelet is the group of the wavelets (orthogonal) denoting a Discrete Wavelet Transform(DWT). With every wavelet of this kind, there is a scale function or the father wavelet. Daubechies (DB) wavelets are basically used in solving a broad range of problems, as fractal problems, self-resemble properties of a signal etc.
Daubechies wavelets[20][21] are families of wavelets whose inverse wavelet transforms are adjoint of the wavelet transform i.e. they are orthogonal. They have maximal number of vanishing moments and hence they can represent higher degree polynomial functions. With each wavelet type of this class, there is a scaling function known as “father wavelet” that generates an orthogonal multi-resolution analysis .Daubechies orthogonal wavelets D2-D20 (even index numbers only) are commonly used. The numbers associated with the name refers to the number ‘N’ of coefficients. Each wavelet has vanishing moments equal to half the number of coefficients. For example, D2 which is the Haar wavelet has one vanishing moment, D4 has two, etc. The number of vanishing moments is what decides the wavelet's ability to represent a signal. For example, D2, with one moment, easily encodes polynomials of one coefficient, or constant signal components. D4 encodes polynomials with two coefficients, i.e. constant and linear signal components etc. The wavelet transform using Daubechies wavelets result in progressively finer discrete samplings using recurrence relations. Every resolution scale is double that of the previous scale. Daubechies derived a family of wavelets, the first of which is the Haar wavelet. Since then interest in this field has shot up and many variations of Daubechies original wavelets have been developed. The discrete wavelet transform has applications ranging from data compression to signal coding. In our research work, Daubechies wavelet was used to filter a noisy signal to extract information from the signal.

VI. ADVANCE APPROACH OF WAVELETS

In order to examine signals of very distinct sizes, it is necessary to use time-frequency atoms with different time pillars. The wavelet transform divided signals over extended and translated functions called wavelets, which transform a continuous function (CW) into a highly unnecessary function.

In1946, physicist Dennis Gabor, applying ideas from quantum physics, introduced the use of Gaussian-windowed sinusoids for time-frequency decomposition, which he referred to as *atoms*, and which provide the best trade-off between spatial and frequency resolution. These are used in the Gabor transform, a type of short-time Fourier transform. In 1984, Jean Morlet introduced Gabor's work to the seismology community and, with Goupillaud and Grossmann, modified it to keep the same wavelet shape over equal octave intervals, resulting in the first formalization of the continuous wavelet transform.
Some continuous wavelet examples are as follows.

A. Morlet Wavelet

The commonly used Continuous Wavelet is the Morlet wavelet [22][23] .it is defined as following in time and frequency domains-

$$\varphi(t) = e^{imt}\, e^{-t^2/2} \pi^{-1/4} \quad (8)$$

$$\varphi(\omega) = U(\omega)\ e^{-(\omega-m)^2/2}\pi^{-1/4} \quad (9)$$

where, m is an adjustable variable of wave number and U is the step function that allows for correct signal reconstruction.

The Morlet Wavelet Transform method presented offers an intuitive bridge between frequency and time information which can clarify interpretation of complex head trauma spectra obtained with Fourier Transform. The Morlet Wavelet Transform, however, is not intended as a replacement for the Fourier Transform, but rather a supplement that allows qualitative access to time related changes and takes advantage of the multiple dimensions available in a free induction decay analysis.

B. Maxican Hat Wavalet

Klein adduced that WDCS It is a special case of the family of continuous wavelets (wavelets used in a continuous wavelet transform) known as Hermitian wavelets. It is usually only referred to as the "Mexican hat" in the Americas, due to cultural association; see "sombrero". The Ricker Wavelet is frequently employed to model seismic data, and as a broad spectrum source term in computational electrodynamics.

The Mexican hat wavelet [24][25] is known as the second derivative of the Gaussian function g(t).

$$g(t)=1/\sqrt{2\pi}\sigma(e^{-t^2/2\sigma^2}) \quad (10)$$

and second derivative is

$$1/\sqrt{2\pi}\sigma^3\{ (e^{-t^2/2\sigma^2})\,(t^2\ /\sigma^2 -1)\}$$

C. Meyer Wavelet

Yves Meyer [26][27] constructed a smooth orthonormal wavelet basis as follows. First of all define the fourier transform $\emptyset(\omega)$ of a scaling function $\emptyset(t)$ as:

$$\emptyset(\omega) = 1 \qquad \text{if } |\omega| <= 2\pi/3$$
$$\cos\{\tfrac{\pi}{2}\, v(\tfrac{3}{4\pi}\,|\omega|\ -1)\} \qquad \text{if } 2\pi/3 <= |\omega| <= 4/3$$
$$0 \qquad \text{otherwise}$$

Where v is a smooth function satisfying the following condition:

$$v(t) = \ 0 \qquad \text{if } \ t<=0$$
$$1 \qquad \text{if } \ t>=1$$

With the additional property

$$v(t) + v(1-t) = 1 \quad (11)$$

In this case the wavelet function φ can be found easily from $\emptyset$. First we find the fourier transform of φ.

$$\varphi(\omega) = e^{j\omega/2}\ \sum_{l\in Z}\varphi(\ \omega + 2\pi(\ 2l+1)\ \varphi(\omega/2) \quad (12)$$

Which is ,

$$e^{j\omega/2}\{\ \ \varphi(\omega+2\pi) + \varphi(\omega-2\pi)\ \}\ \varphi(\omega/2)$$

Now since φ is compactly supported and $\varphi \in c_k$ where k is arbitrary and may be ∞ .

D. Battle Lamare Wavelet

The Battle-Lemarie wavelet[28] is characterized by its Fourier transform

$$\varphi(\omega) = e^{-i(\frac{\omega}{2})}\ \sqrt{\Sigma_g\left(\tfrac{\omega}{2}+\pi\right)}\ /\ \omega^4\ \sqrt{\Sigma_g(\omega\,)\,\Sigma_g(\tfrac{\omega}{2})} \quad (13)$$

Where , $\Sigma_g = \ N_1\,(\omega) + N_2\,(\omega)\ /\ 105\ (\sin\omega/2)^8$ (14)

With, N_1 =5+ 30 $(\cos\omega/2)^2$ +30 $(\sin\omega/2)^2\ (\cos\omega/2)^2$ (15)

and N_2 = 2 $(\sin\omega/2)^4(\cos\omega/2)^2$ +70$(\cos\omega/2)^4 + 2/3(\sin\omega/2)^6$ (16)

VII. MATLAB SIMULATIONS

For Matlab simulation of different wavelets Haar,Db3,Db5 we choose some Discrete and Continuous data by applying wavelet transform on these signal we can get coefficient of approximation and coefficient of detail.

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We can observe that the signal is decompose into two coefficients the approximation, or scaling, coefficients which are the lowpass representation of the signal(Discrete or Continuous) and the details are the wavelet coefficients.
The Approximate and Detail coefficients can be used to reconstruct the signal perfectly when run through the reconstruction filters.

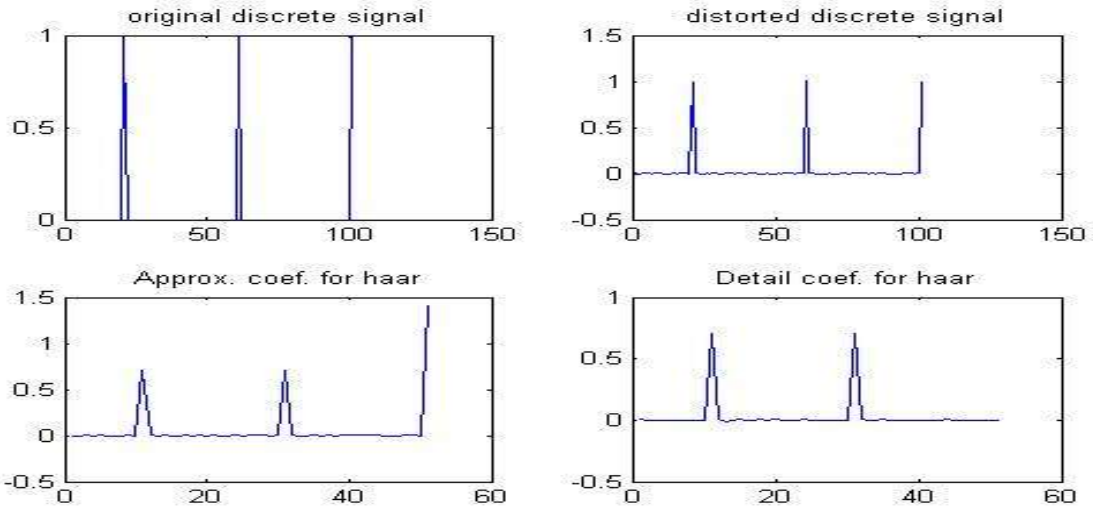

Fig.1: Haar wavelet approximate and detail coefficient analysis for digital data

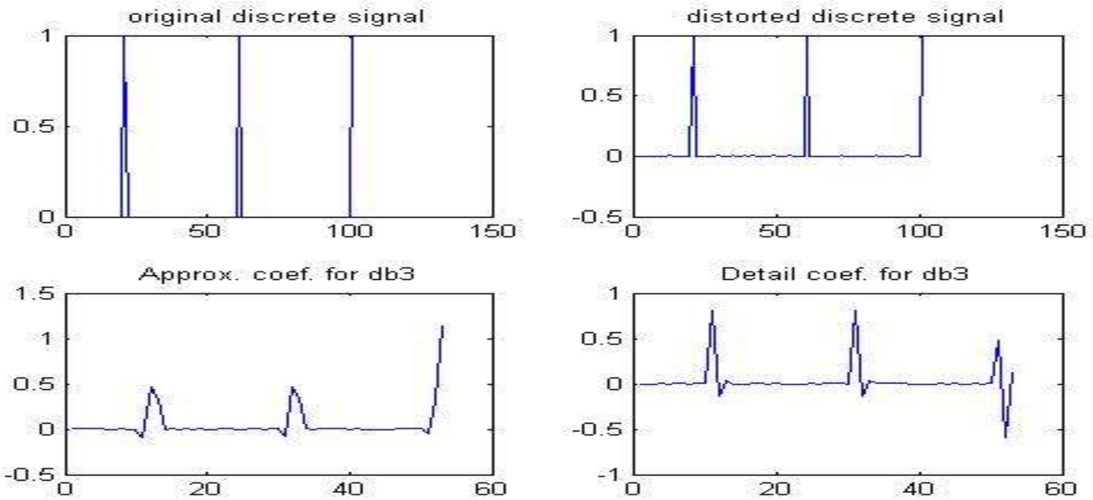

Fig.2: DB3 wavelet approximate and detail coefficient analysis for digital data

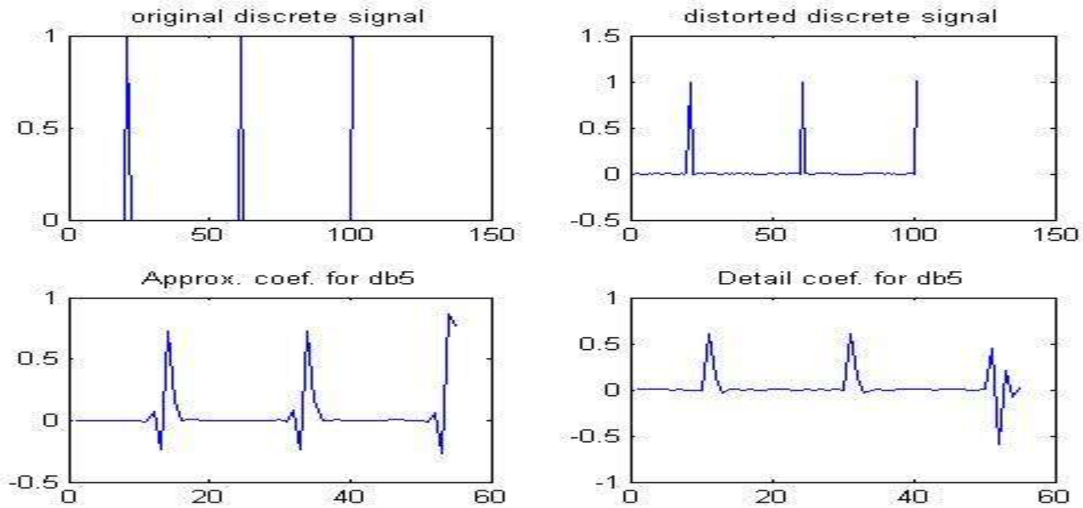

Fig 3: DB5 wavelet approximate and detail coefficient analysis for digital data

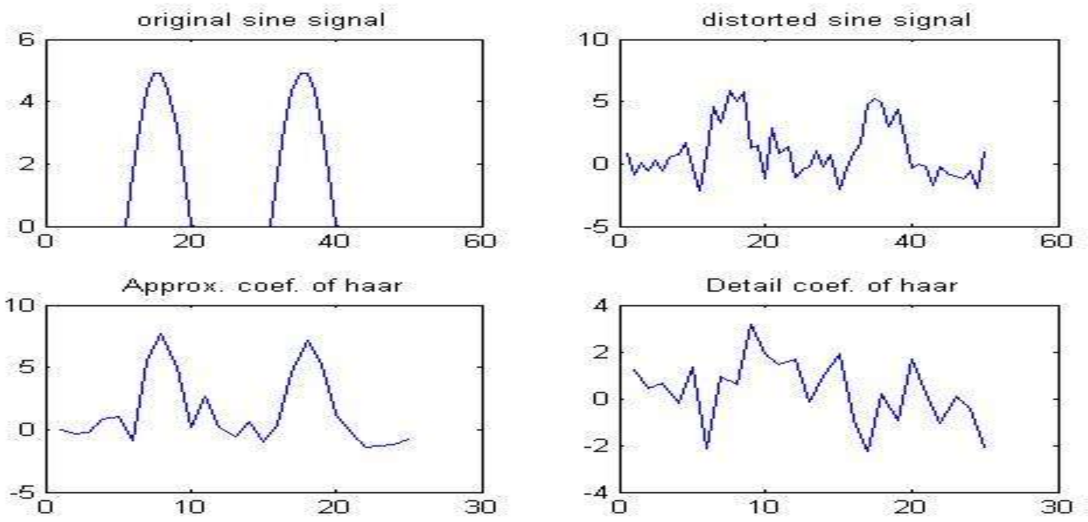

Fig.4: Haar wavelet approximate and detail coefficient analysis for continuous signal

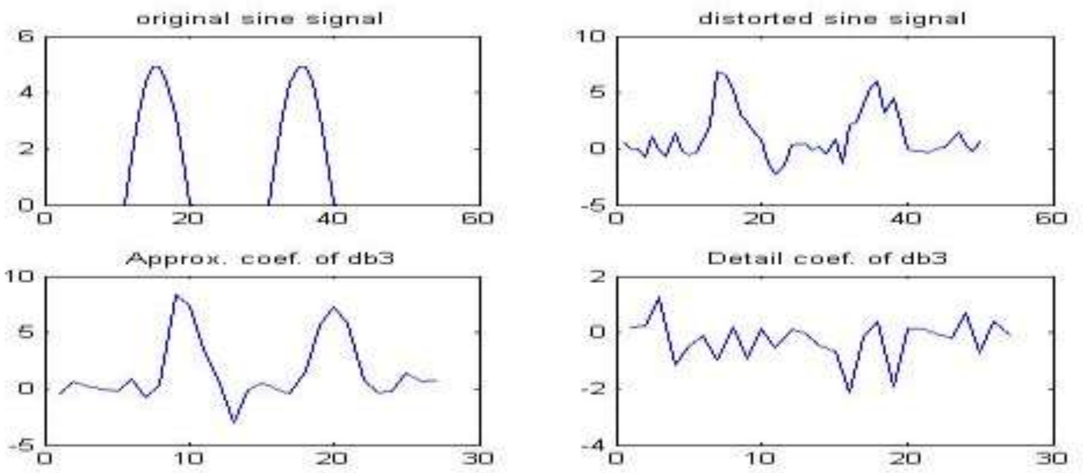

Fig.5: Db3 wavelet approximate and detail coefficient analysis for continuous signal

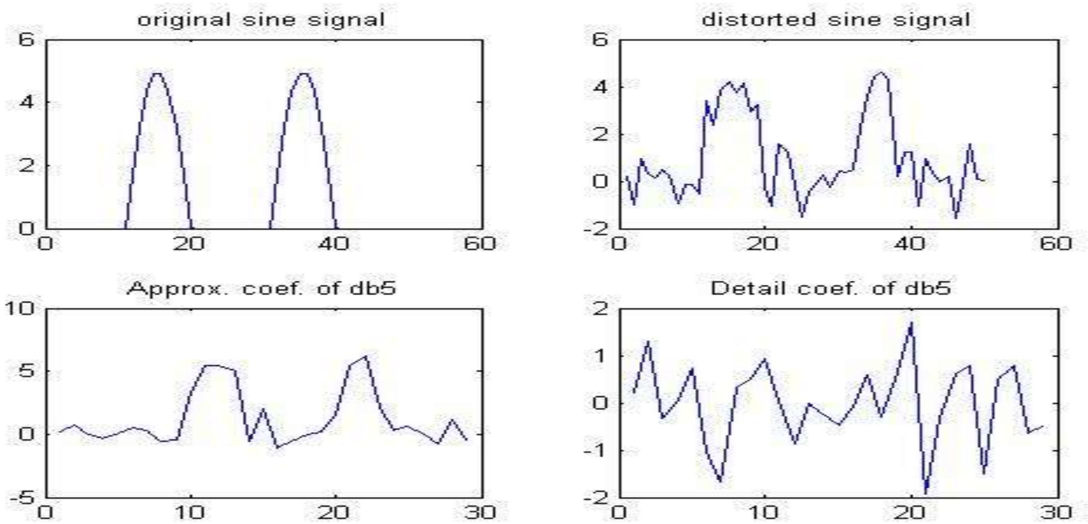

Fig.6: Db5 wavelet approximate and detail coefficient analysis for continuous signal

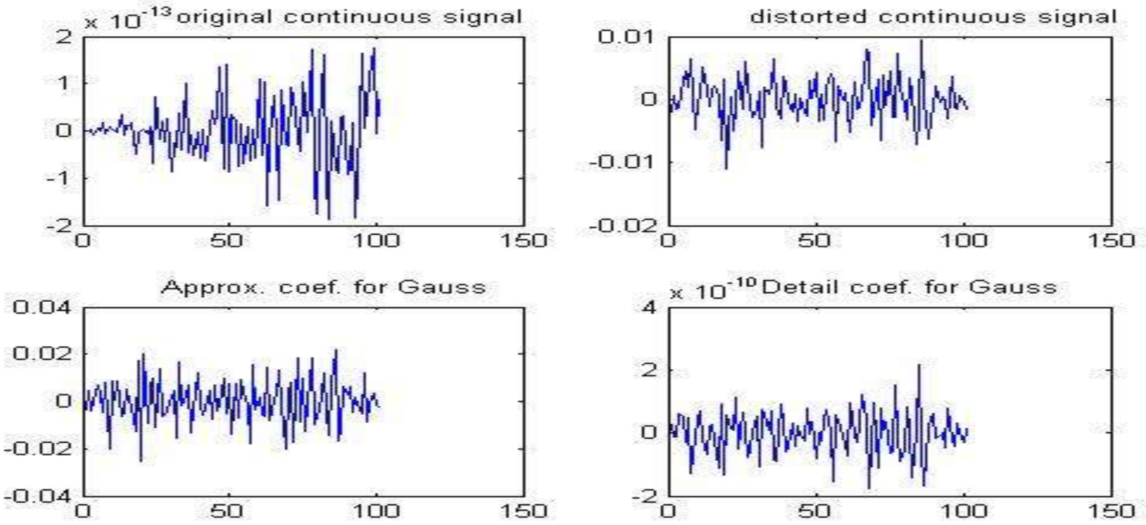

Fig.7: Gauss wavelet approximate and detail coefficient analysis for continuous signal

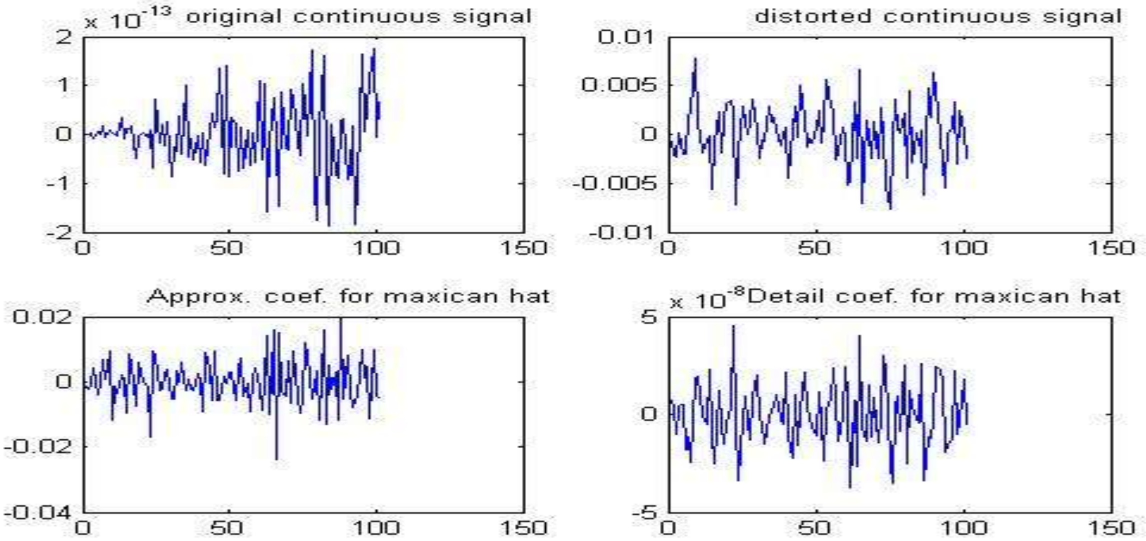

Fig. 8: Maxican Hat wavelet approximate and detail coefficient analysis for continuous signal

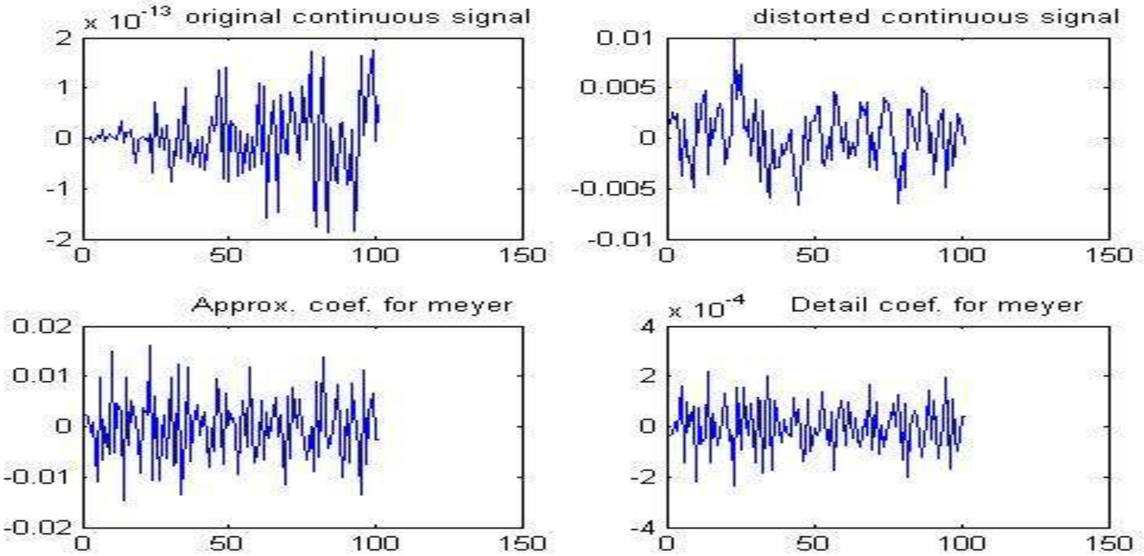

Fig. 9: Meyer wavelet approximate and detail coefficient Analysis for continuous signal

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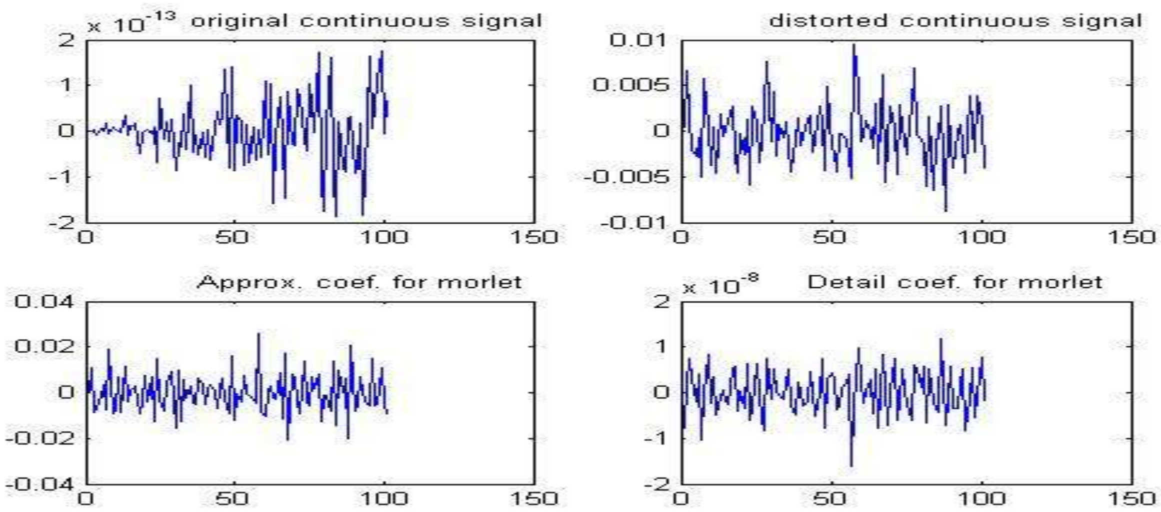

Fig.10: Morlet wavelet approximate and detail coefficient analysis for continuous signal

Here, it is clear that Wavelet transforms basically used for performing signal analysis. For certain classes of signals wavelet analysis provides more precise information about signal data than other signal analysis techniques. For wavelet analysis in communication system it is necessary to know about the suitability of transforms with the digital data. To calculate error plot to know that which wavelet transform is more suitable for the Digital Data transmission .

For to see the performance of Haar and Db3 wavelet transform for Digital signal we simulate the Error Plot in Matlab Simulations.

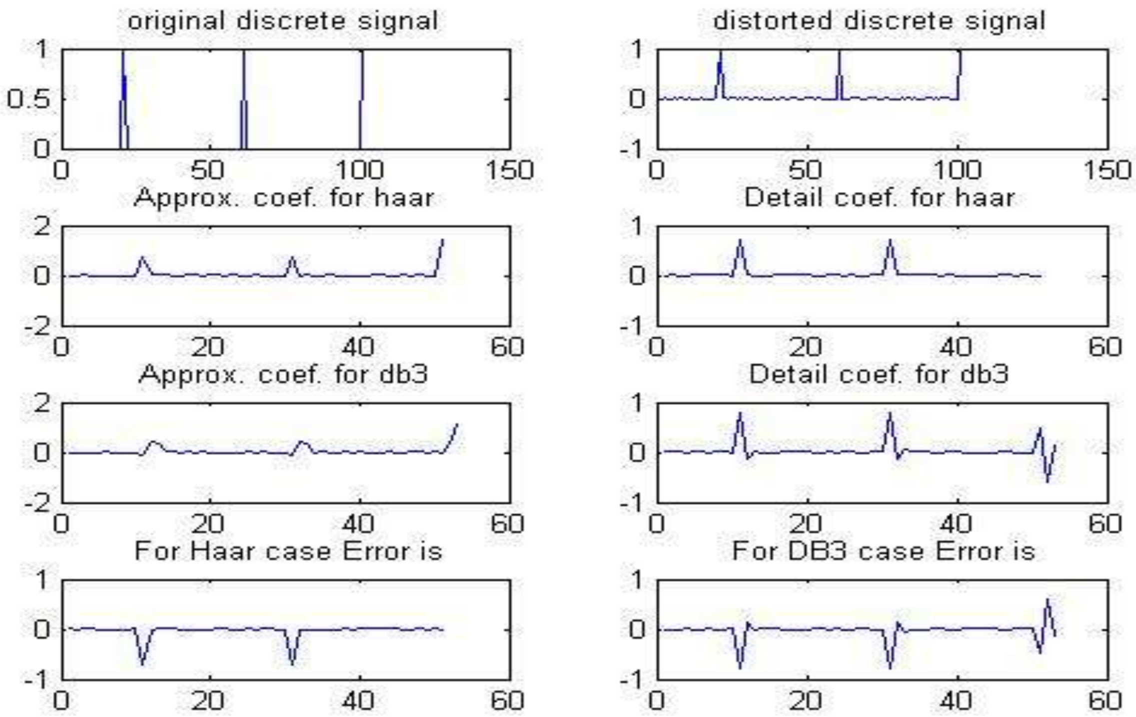

Fig.11: Haar and DB3 Error analysis for Digital data

Here by doing the Db3 and Haar analysis by MATLAB simulation we can conclude that the haar wavelet transform is more effective for the digital signals than the Db3 or others wavelet transform approaches. Haar suitability with Digital Comunication System makes it to use in the Wavelet Edge Detection in Cognitive Radio.
The Wavelet Edge Detection is one of the most widely used Spectrum Sensing techniques. This technique observes the spatial distribution of spectral data at multiple resolutions. However, the success of this technique is dependent on the

Wavelet system choosen. Sparse spectra with conspicuous peaks utilize Haar wavelet system only. Hence it is clear that Haar transform plays a significant role for the Spectrum sensing in Cognitive Radio.

VIII. CONCLUSION

In this paper, it is clear that the experimental results from different wavelet shows that the wavelet transform based approach gives more information than the existing minutiae based method and we can say that wavelet transform is a reliable and better technique than that of Fourier transform technique. Continuous Wavelet transform can also be discretized. It is basically based on continuous wavelet transform. Then we studied the various wavelets concepts and advance wavelet concepts. Nowadays, discrete wavelet transform has become the most useful tool for signal processing and it still has many potentialities. For this reason, we should continue on developing more powerful tool or efficient algorithm in this area.

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