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Chapter

Wavelet Theory and Application in Communication and Signal Processing

Nizar Al Bassam, Vidhyalavanya Ramachandran and Sumesh Eratt Parameswaran

Abstract

Wavelet analysis is the recent development in applied mathematics. For several applications, Fourier analysis fails to provide tangible results due to non-stationary behavior of signals. In such situation, wavelet transforms can be used as a potential alternative. The book chapter starts with the description about importance of frequency domain representation with the concept of Fourier series and Fourier transform for periodic, aperiodic signals in continuous and discrete domain followed by shortcoming of Fourier transform. Further, Short Time Fourier Transform (STFT) will be discussed to induce the concept of time frequency analysis. Explanation of Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) will be provided with the help of theoretical approach involving mathematical equations. Decomposition of 1D and 2D signals will be discussed suitable examples, leading to application concept. Wavelet based communication systems are becoming popular due to growing multimedia applications. Wavelet based Orthogonal Frequency Division Multiplexing (OFDM) technique and its merit also presented. Biomedical signal processing is an emerging field where wavelet provides considerable improvement in performance ranging from extraction of abnormal areas and improved feature extraction scheme for further processing. Advancement in multimedia systems together with the developments in wireless technologies demands effective data compression schemes. Wavelet transform along with EZW, SPIHT algorithms are discussed. The chapter will be a useful guide to undergraduate and post graduate who would like to conduct a research study that include wavelet transform and its usage.

Keywords: 1-D and 2-D signals, continuous wavelet transform (CWT), discrete wavelet transform (DWT), orthogonal frequency division multiplexing (OFDM), image compression, cough detection

1. Introduction

We are familiar with real world signals such as speech signal, temperature of a patient in every hour etc. Generally, signals are visualized as a time domain graph. In literature, it is possible to express same information in many different languages; in a similar fashion signals can be represented in frequency domain to convey the message [1]. These signals can be processed to achieve desired outputs or to carry out certain actions according to the application.

2. Concept of frequency and time domain analysis

2.1 Frequency domain

Figure 1 represents a sinusoidal signal expressed in time and frequency domain. The representation in frequency domain shows there is only one frequency component in the waveform. This representation is simple to extract behavior of signal compared to that in time domain in majority of real-world applications.

In real world, not the signals are processed in frequency domain to arrive at desired output, since they simplify the analysis mathematically [2]. In applications like control engineering, differential equations are used to represent systems. Frequency domain analysis converts the differential equations to algebraic equations which are relatively easy to solve. Applications related to speech, image and video also gets simplified with the use of frequency domain approach since the sensory organs interprets the signal in frequency domain.

2.2 Fourier analysis - the tool used to convert to frequency domain

Any signal which satisfy Dirichlet conditions (signals with finite number of discontinuity, finite maximum or minimum magnitude) can be converted to frequency domain by Fourier analysis. For analog signals Fourier series or Fourier transform if signal is periodic or aperiodic, respectively. The corresponding counterparts for discrete signals are Discrete Fourier series and Discrete Fourier transform [1]. Fourier analysis can be visualized as inner product of a kernel function with the signal. For example, to find the coefficient corresponding to 100 Hz, find the inner product of signal with a kernel which is a unit sine wave of 100 Hz.
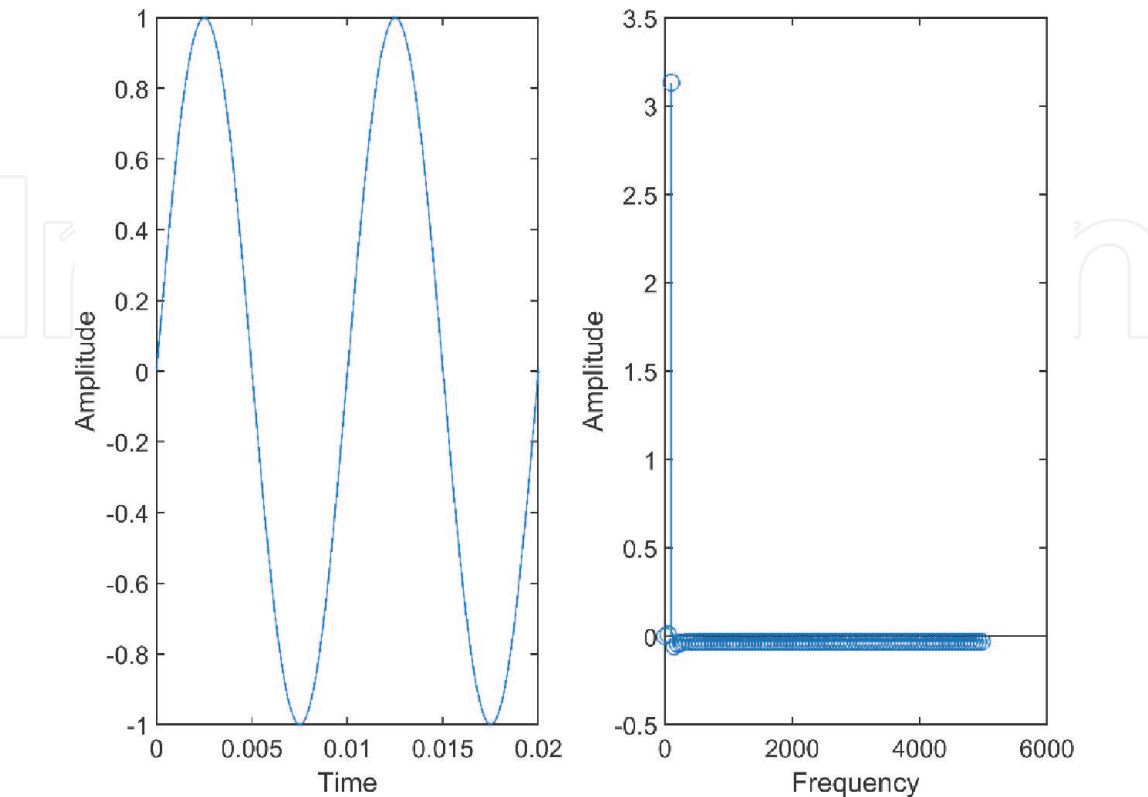

Figure 1.
Representation of a 100 Hz sinusoidal signal in time and frequency domain.

2.2.1 Time frequency analysis - short time Fourier transform

Fourier transforms (FT) assumes periodicity if waveform is known for a finite duration of time and it works only for stationary signals. For non-stationary signals it fails to provide complete behavior of signal. As an example, consider the waveform given in **Figure 2**. The signal has constantly changing frequency. But Fourier
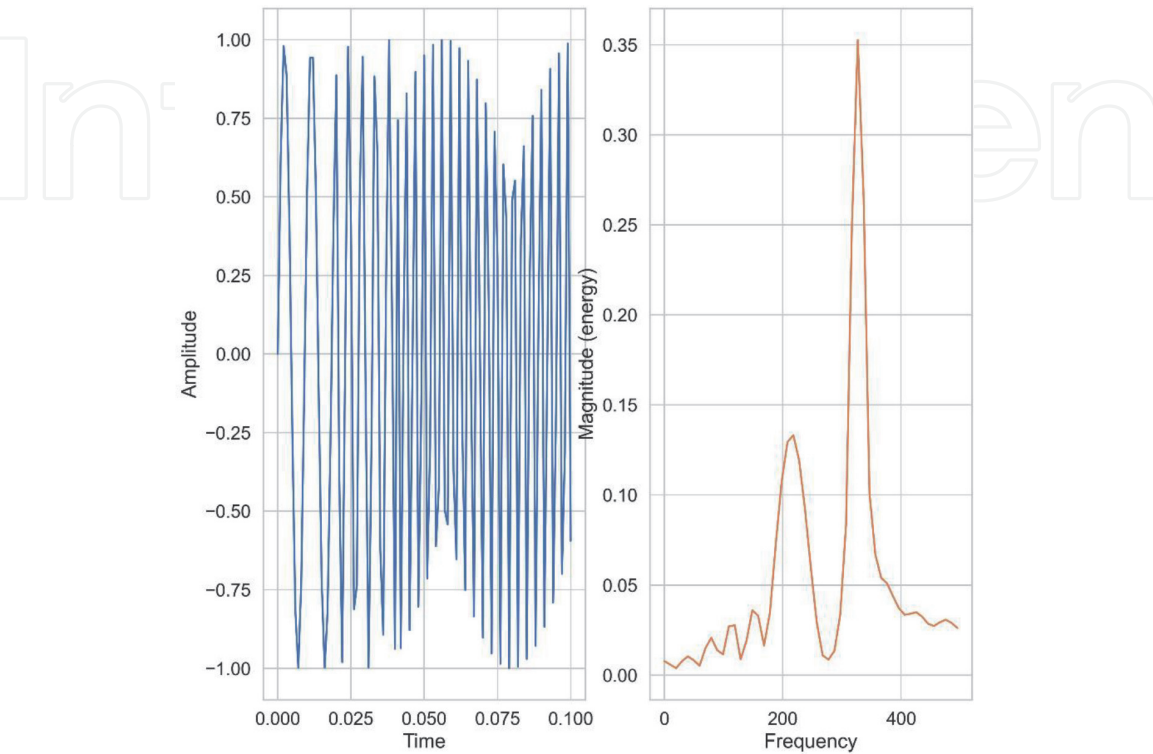
Figure 2.
Non-stationary sinusoidal signal of varying frequency in time and frequency domain.
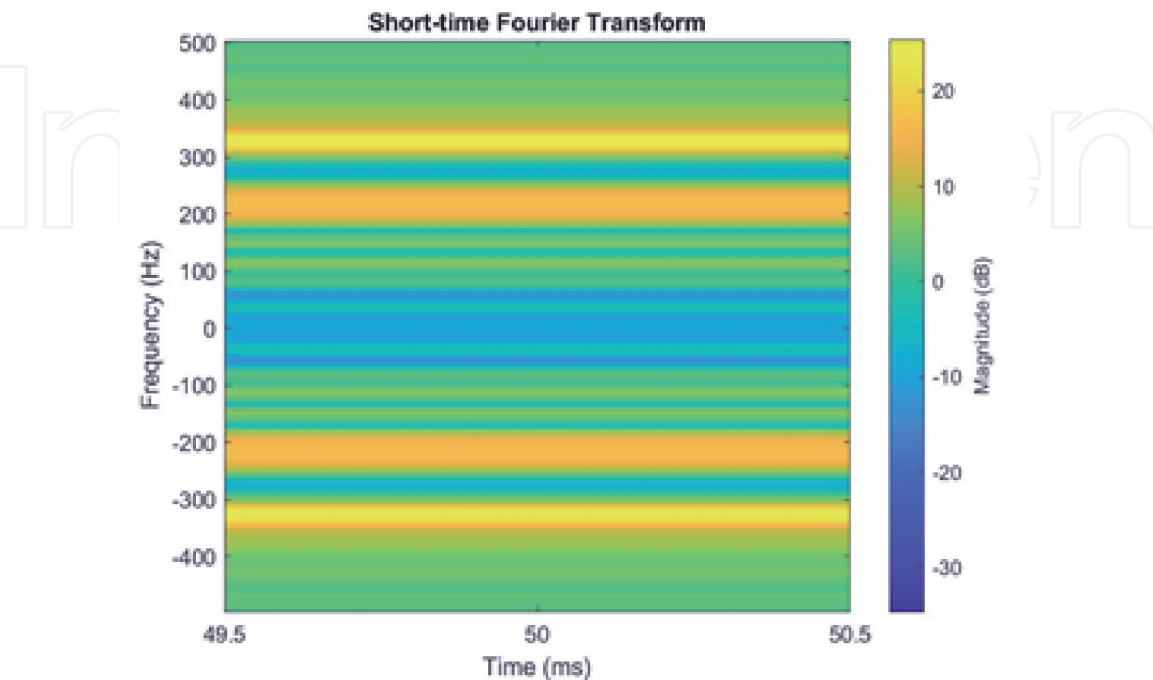
Figure 3.
STFT of chirp signal.

analysis represents it as a combination of 1 Hz and 2 Hz present all the time. If the application demands to initiate some operations when the frequency starts to change, Fourier analysis cannot be used for the application. In order to tackle these difficulties Short Time Fourier Transform (STFT) is used.

In STFT signal is divided into small sub intervals or windows and FT is calculated for each sub interval separately. The problem of STFT is the choice of time windows; low frequencies require large time windows and high frequencies need a short time windows to provide required resolution in time and frequency. This resolution issue is similar to the Heisenberg uncertainty principle relating position and speed which are analogous to time and frequency respectively [3]. **Figure 3** shows STFT of the chirp signal given in **Figure 2**. It is evident that the time localization of frequency is not clearly defined in STFT output. Frequency values corresponding to the 200 Hz and 300 Hz are present across the time interval 49.5 to 50 ms. But **Figure 2** indicated only 300 Hz was present between time 49.5 to 50 ms.

3. Wavelets

As discussed in Section 1.2 the kernel of FT is not time limited (exists for all time values) and this is the bottleneck for analyzing a non-stationary signal. Wavelets are waveforms which are time limited or exists only for a given time period only. Wavelets are useful for examining aperiodic, noisy signal in both time and frequency domain simultaneously. The word "wavelet" means a "small wave". There are variety of wavelets available which are selected according to the application. The short duration wavelet is superimposed to the signal under consideration for a short duration of time and decompose them to useful form. This process is called wavelet transform. The method of transforming the decomposed signal to original wave is called inverse wavelet transform.

There are the two ways the wavelets are manipulated. The transform of the entire signal is done by translating the wavelet to the next instance of time called as translation. If the signal is of different frequency the mother wavelet is expanded or contracted. This method is called as dilation.

3.1 Continuous wavelet transform (CWT)

Mathematical expression for wavelet function is

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) \tag{1}$$

where a represents the scaling parameter for dilation and 'b' represents the moving parameter for translation for the entire signal location [4].

Continuous wavelet transform follows two properties.

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{2}$$

$$\int_{-\infty}^{\infty} |\psi(t)|^2 = 0 \tag{3}$$

For the CWT the mathematical expression C(a, b) obtained by integrating the input function with the wavelet is

$$C(a,b) = \int_t f(t)\frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)dt \qquad (4)$$

Figures 4 and **5** represent the translation and dilation of wavelets respectively.

3.2 Discrete Wavelet Transform (DWT)

Eq. 1 represents the CWT, on substituting $a = 2^{-j}$ and $b = k2^{-j}$ the equation will become as $D(a,b) = \int_t f(t)2^{-j}\psi(2^j t - k)dt$, where j refer to the scale.

Haar scaling and wavelet functions are given as

$$\phi(t) = \begin{cases} 1, & 0 \leq t < 1 \\ 0 & otherwise \end{cases} \qquad (5)$$

$$\psi(t) = \begin{cases} 1, & 0 \leq t < 1/2 \\ -1 & 1/2 \leq t < 1 \end{cases} \qquad (6)$$

The scaling coefficients are [h(0), h(1)]= [1, 1] and wavelet coefficients are [g(0), g(1)] = [1, −1]. The scaling and the wavelet functions shown in **Figure 6** are orthogonal with each other. The decomposition of coefficients done by scaling function is done by the low pass filter and wavelet function is by the high pass filter [5].

For eg. Let us consider a signal having function f(t) as

$$f(t) = \begin{cases} 2, & 0 < t \leq 1 \\ 4, & 2 < t \leq 3 \\ 3, & 4 < t \leq 5 \end{cases} \qquad (7)$$

If the signal is decomposed by Haar scaling, the function will be

$$f(t) = 2\phi(t) + 4\phi(t-1) + 4\phi(t-2) + 3\phi(t-3) + 3\phi(t-4) \qquad (8)$$

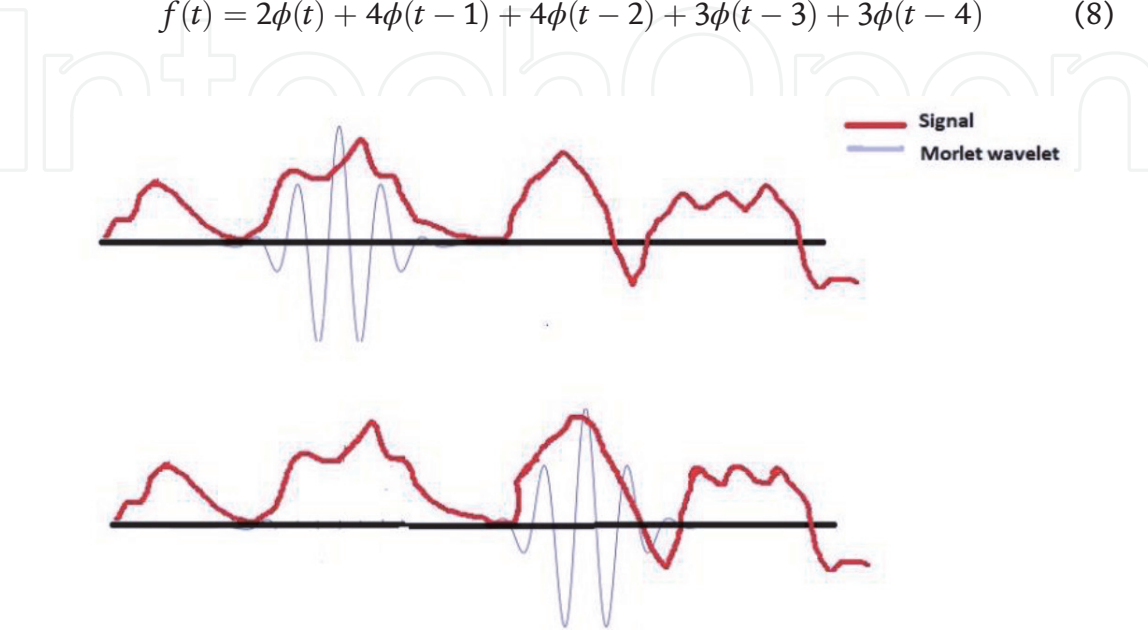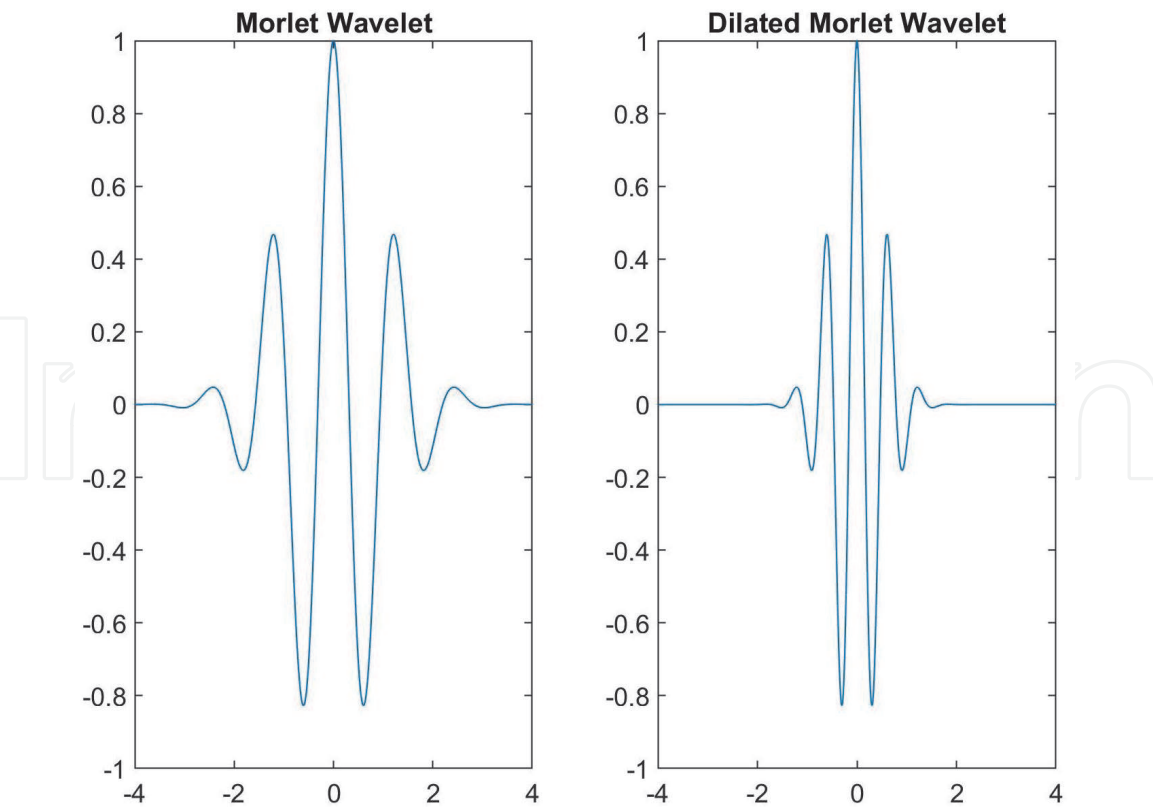**Figure 4.**
Signal with the translated Morlet wavelet [5].
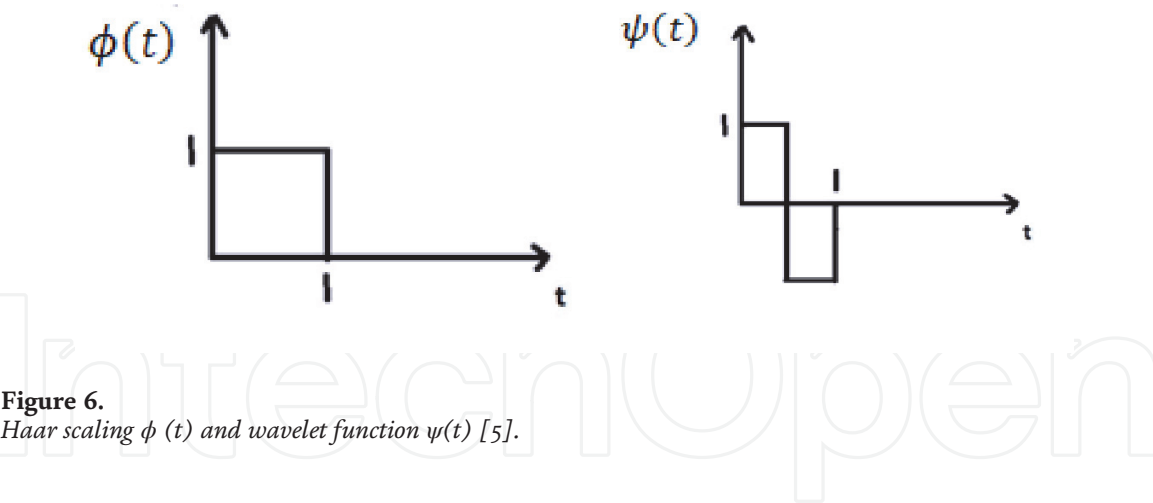
Figure 5.
Dilated Morlet wavelet [5].

Figure 6.
Haar scaling ϕ (t) and wavelet function ψ(t) [5].

3.3 Properties of the scaling and wavelet functions

1. The scaling and wavelet functions are orthogonal to each other

2. The scaling function and translates are orthogonal to each other.

3. The area of the scaling function is equal to one.

4. The scaling function and translates of wavelet function are orthonormal to each other.

All the above conditions are satisfied by all the scaling and wavelet coefficients. Nonlinear equations are derived using the numerical values of the coefficients [5].

4. Analysis and synthesis of signals

As discussed in Section 2, h(n) and g(n) are the dilation coefficients. The refinement relation can be written as

$$\phi(t) = \sum_{n=0}^{N-1} h(n)\sqrt{2}\phi(2t-n) \tag{9}$$

$$\psi(t) = \sum_{n=0}^{N-1} g(n)\sqrt{2}\phi(2t-n) \tag{10}$$

where h(n) and g(n) are the scaling and wavelet coefficients, N is the support of wavelet [4].

4.1 Decomposition of signal

The analysis of the signal or the decomposition of the signal can be represented in a block diagram as decomposing input into low frequency and high frequency samples.

Let us consider a signal having function f(t) as

$$f(t) = \begin{cases} 2, & 0 < t \leq 1 \\ 4, & 2 < t \leq 3 \\ 3, & 4 < t \leq 5 \end{cases} \tag{11}$$

If the signal is decomposed by Haar scaling, the function will be

$$f(t) = 2\phi(t) + 4\phi(t-1) + 4\phi(t-2) + 3\phi(t-3) + 3\phi(t-4) \tag{12}$$

The decomposed output of the low pass filter shown in **Figure 7** can be visualized as the average of the immediate signals.

Figure 7 represents the decomposition and reconstruction of one level of the signal. Let us consider the vector space of the input function f(t) is V_2. After decomposition the samples are decomposed as f1(t) of low frequency samples spanning the vector space of V_1 and high frequency samples g1(t) of high frequency spanning the vector space of W_1.
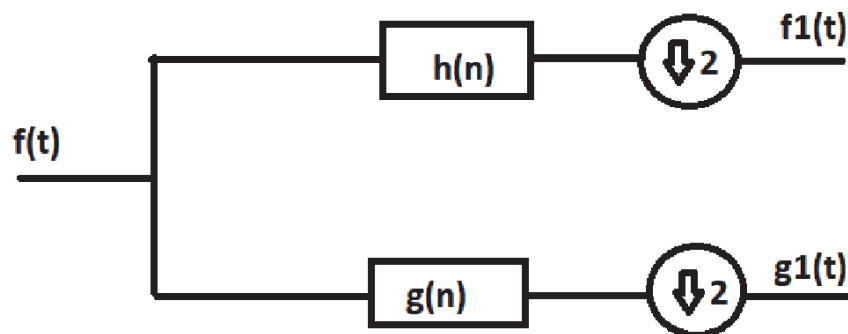

Figure 7.
Block diagram of one level of decomposition of signal.

If the signal f1(t) is again decomposed (second level of decomposition), then they are still split up as low frequency samples say f2(t) spanning the vector space V_0 and the high frequency samples say g2(t) spanning the vector space W_0. Like this, the signal can be decomposed for any level there by splitting the signal with the cut off frequency as per the coefficients of the filter h(n) and g(n).

For V_2 space the vector space can be written as

$$V_2 = V_1 \oplus W_1$$

$$V_2 = V_0 \oplus W_0 \oplus W_1 \qquad (13)$$

Frequency band split and the vector space is shown in the **Figure 8**.

Thus, decomposition is the process in which the signal of high resolution is converted to signal of two orthogonal signal of low resolution [5].

4.2 Reconstruction of signal

The synthesis or the reconstruction of the signal can be represented in a block diagram (**Figure 9**) combining input low frequency and high frequency samples.

For a perfectly matched filter the signal f(t) given as input in the analysis filter and the output of the reconstruction filter r(t) will be equal.

Any signal resolution in the present level and previous level are orthogonal. This property was useful for the wavelets to be used for Multiresolution Analysis (MRA) [4].
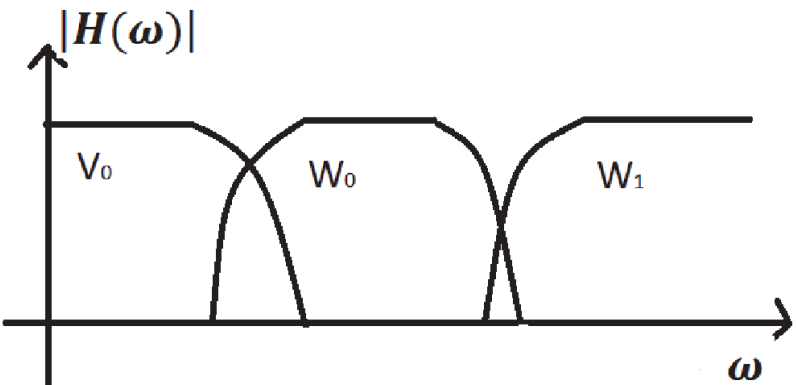

Figure 8.
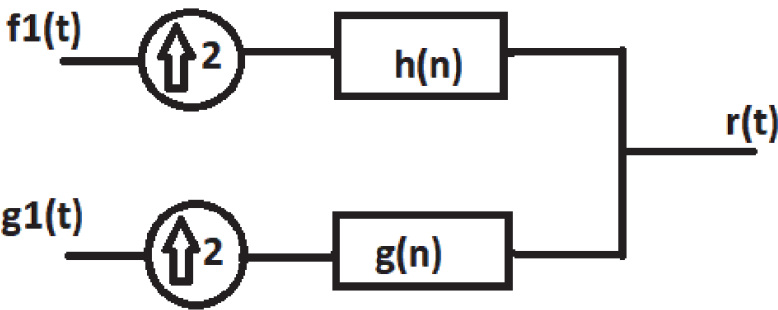*Frequency split for a two-level decomposition.*

Figure 9.
Block diagram of one level of reconstruction of signal.

4.3 Decomposition of 2-D signal

Two-dimensional signal is an image that has row and column pixel or samples. Wavelet decomposition of the image can be done by scanning the pixel values in a regular fashion and given as input to the decomposition block as explained in Section 3.1. Two types of scanning methods are used for reading the row-column pixel values thereby converting the 2-D signal to 1-D. They are raster scanning and Morton scanning.

Figure 10 shows the scanning of pixel values in the horizontal direction. Once the samples are decomposed by sending it to the block in **Figure 7**, then the pixels are then scanned vertically and again decomposed. This completes one level of decomposition of 2-D signal. After horizontal decompose, the image will be separated as Low pass and high pass pixels in horizontal fashion. Once the vertical decompose is done followed by horizontal the image is divided into two rows and two columns named as LL, LH, HL, HH as shown in **Figure 11**.

For a second level of decomposition the scanning process is done to the LL band of the first level and LL band is again decomposed as LL1, LH1, HL1, HH1. Thus, the high-resolution signal is transformed to Low frequency and high frequency bands. For higher levels, the process is repeated for the LL bands leading to the coarser resolutions [5].

4.4 Reconstruction of 2-D signal

The decomposed signal after processing can be reconstructed by up sample the data by two and then convoluted with the filter of low and high frequency coefficients. This need to be done for all the sub bands and the values are summed up to move from the coarser scale to high resolution scale. This process is repeated to reach the final image is reached [5].
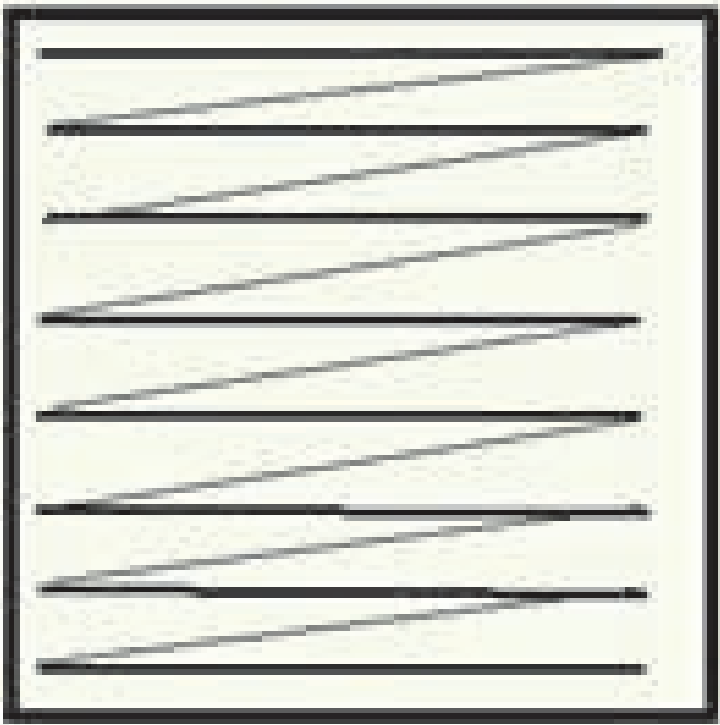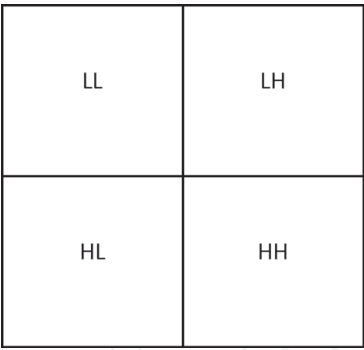

Figure 10.
Scanning of pixels.

Figure 11.
Bands of 2-D after one level of decomposition.

5. Applications

5.1 Wavelets in communication system

Wavelets are suited for communication systems due to its potential to handle non stationary behavior and to segregate information into uncorrelated segments. This section provides a brief about various methodologies to extract benefits of wavelets into communication systems.

5.1.1 OFDM systems using wavelets

Orthogonal Frequency Division Multiplexing (OFDM) uses multicarrier technique by dividing the spectrum into many subcarriers and each subcarrier gets modulated by low data rate. If M symbols are required to be transmitted, M orthogonal subcarriers are used to modulate each symbols.

Wavelet packet transforms can be effectively used in OFDM systems **Figure 4**.1 shows a wavelet packet based system.

In **Figure 12**, M band IDWT is used to split the signal to smaller sub bands while the M band DWT is used to combine the sub bands. The wavelet packet transform structure is given in **Figure 13**. Here sub band division is done in both approximation and detail coefficients compared with a discrete wavelet transform.

Wavelet based OFDM systems provides improved Bit Error Rate (BER) and peak-to-average-power ratio (PAPR) performance compared to conventional OFDM system using FFT. Due to large number of sub band carriers, OFDM has high PAPR and makes it sensitive to nonlinear effects. Wavelet based system controls the PAPR ratio and results in improved performance compared to FFT based
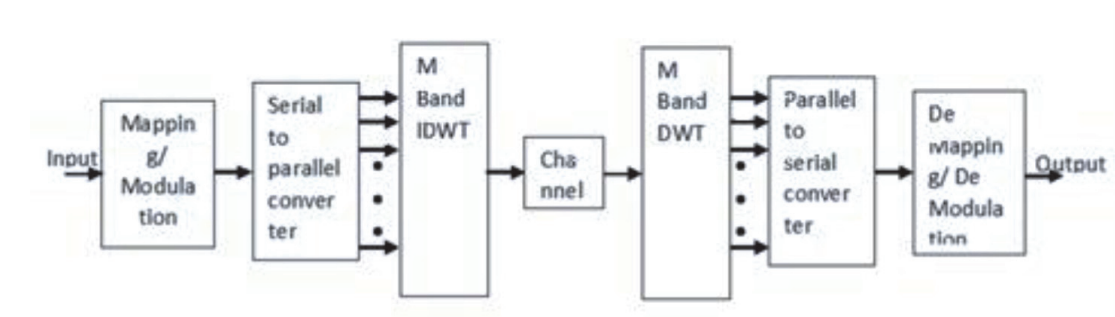

Figure 12.
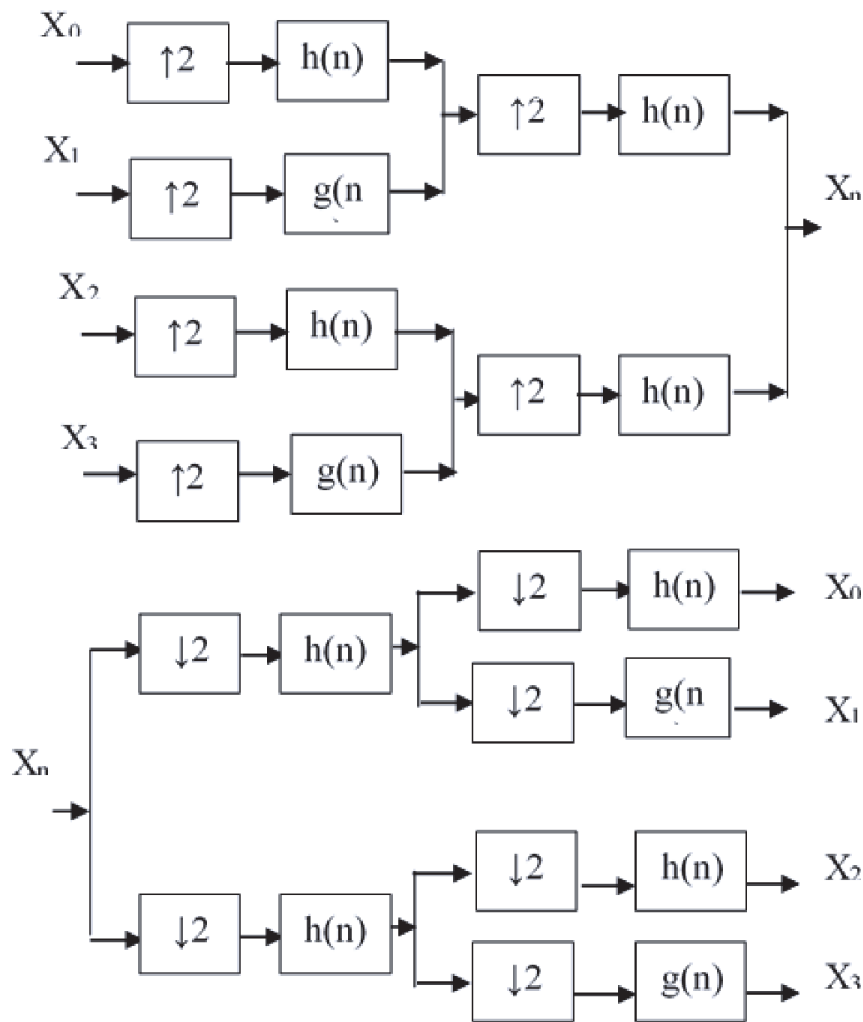*Wavelet based OFDM system [6].*

Figure 13.
Wavelet packet based combining or splitting into sub bands in OFDM system.

systems. Applications of Wavelets in 4G, 5G and beyond was reported in literature [6–8]. Selection of wavelet and level plays an important role and is promising field for future research.

5.2 Wavelets in biomedical applications

Bio medical signal processing is a promising field for future research. Wavelet transform can be used effectively in combination with artificial intelligence to provide solution to many problems. Bio medical signals are generally one dimensional time series data (Electro Cardiogram- ECG, electroencephalogram -EEG) or an image (X ray, ultrasound scan, MRI). Accordingly a 1D or 2D wavelet transform can be used to process the signal. Wavelet transform helps to divide the signal to uncorrelated sub bands due to orthogonality property. The transform coefficients or a part of it (say certain level coefficients) are used as feature for classifying the signal is a common methodology that can be adopted for a variety of applications. Recent advancement in neural networks like CNN with wavelet coefficients as input features opens up stage for a wide variety of research solutions. Another promising category of application is in signal preprocessing to remove unwanted information in biomedical signals [9] with thresholding techniques. A complete list of applications is beyond the scope of this book chapter, a few applications of wavelets are described briefly in coming sections.

5.2.1 Wavelets in EEG signal processing

Wavelet transform with suitable mother wavelet and appropriate level of transform has to be selected to extract maximum performance for a given application. **Figure 14** gives a general block level representation for an EEG signal classification system to detect abnormality type.

EEG signal after required preprocessing steps to remove noise is passed through a DWT step to divide it to different sub bands. The required sub bands are further passed through a thresholding step (optional) to remove certain features that do not contribute to abnormalities. The DWT coefficients are fed as input to a neural network classifier to classify the signal to different categories based on the abnormality. The challenges in these signal processing is selection of wavelets, level of transform, threshold calculations, selection of neural network of appropriate level and availability of data to train the network to achieve a desired accuracy [10]. In [11] EEG classification system 5 level decomposition with Db4 wavelet is used to extract features for a neural network classifier is described to arrive at success rate of 94% to identify healthy, epilepsy syndrome and seizure cases with 250 and 50 training and testing samples of EEG respectively. Similar kind of systems can be used to classify ECG signals as well. In [12] Haar wavelet transform was used to identify characteristics of ECG wave. QRS complex detection sensitivity above 99% was reported. Here wavelet packet transform for 20 levels are done and D20 coefficient was used to detect R wave of ECG signal.

5.2.2 Wavelets in cancer detection

Wavelets can be effectively used for abnormality detection in biomedical images. In [13] wavelet decomposition coefficients are used to extract features by calculating 2 level Haar wavelet transform and extract mean, standard deviation and energy of the transform coefficients as features for extraction of abnormal areas in image.

Figure 15 shows the block schematics of the system described in [13].

5.2.3 Research scope for wavelets in COVID 19

Cough detection is one of the important application in monitoring of public places and to monitor people in isolation or quarantine. Ability of wavelet to model nonstationary signal is a potential strength here since cough signals (audio) are non stationary time series signal. Currently Arduino based cough detection systems are being developed as low cost cough detection system. In these system Mel Frequency Cepstral Coefficient (MFCC) are used to extract feature from cough signals to train neural network model like Convolutional Neural Networks (CNN) [14]. Wavelets can be used instead of MFCC for feature extraction to improve system accuracy. This require further research to arrive at optimized set of wavelets and appropriate level of transform.
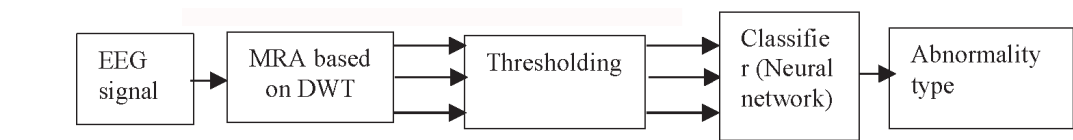

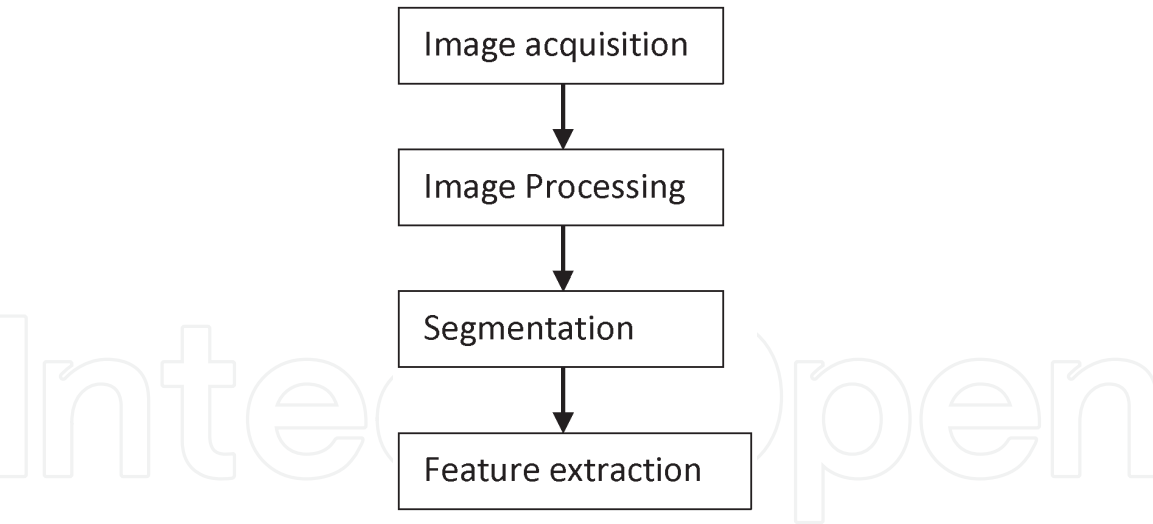**Figure 14.**
Wavelet based EEG signal classification system.

Figure 15.
Block diagram of breast cancer diagnosis system [13].

5.3 Image compression

In today's world handling of huge amount of data is complex. Conversion of large data files into smaller one is important for storing and transmission. This conversion process is called as data compression. This is important in this digital era. The reverse process is called as decompression. Several algorithms are proposed for efficient conversion process. Lossy and Lossless compression techniques are used in different applications. JPEG image compression technique is the standard technique used. It uses Discrete Cosine Transform (DCT) for the frequency domain conversion followed by Huffman coding [5].

5.3.1 EZW (embedded zero tree) coder

EZW algorithm was proposed by Shapiro. After applying Wavelet transform on an image the pixels will be converted to four bands of pixels as explained in Section 3.3. then the wavelet coefficients are passed to the EZW encoder. It is a progressive encoding which is embedded encoding with high accuracy. EZW is a lossless compressor which can be applied for any level of decomposition [15].

EZW takes care of coding both time and space. After decomposition, the pixels are represented as trees. One coefficient in the lower sub band will have four children. Each of the children will have four more grandchildren in the next higher sub band. **Figure 16** represents the relationship between the coefficients of lower sub bands with the higher sub bands.

Each tree is coded with a symbol as P, N, T, Z. For every decomposition levels, the pixels are categorized to two passes as Dominant pass and Subordinate pass. Dominant pass will find the pixel values which are above the threshold value and subordinate pass quantize all the pixel values in the present pass and the previous dominant pass. The threshold value is calculated using the equation

$$T_0 = 2^{\lfloor log_2(Max(|C(x,y)|)) \rfloor} \tag{14}$$

where (x, y) are the coordinates of the image and C (x, y) represent the pixel coefficient. The main advantage of the EZW coder is that the output can be coded for the desired size. The eliminated pixels are least significant bits and the low frequency pixel are not eliminated entirely.
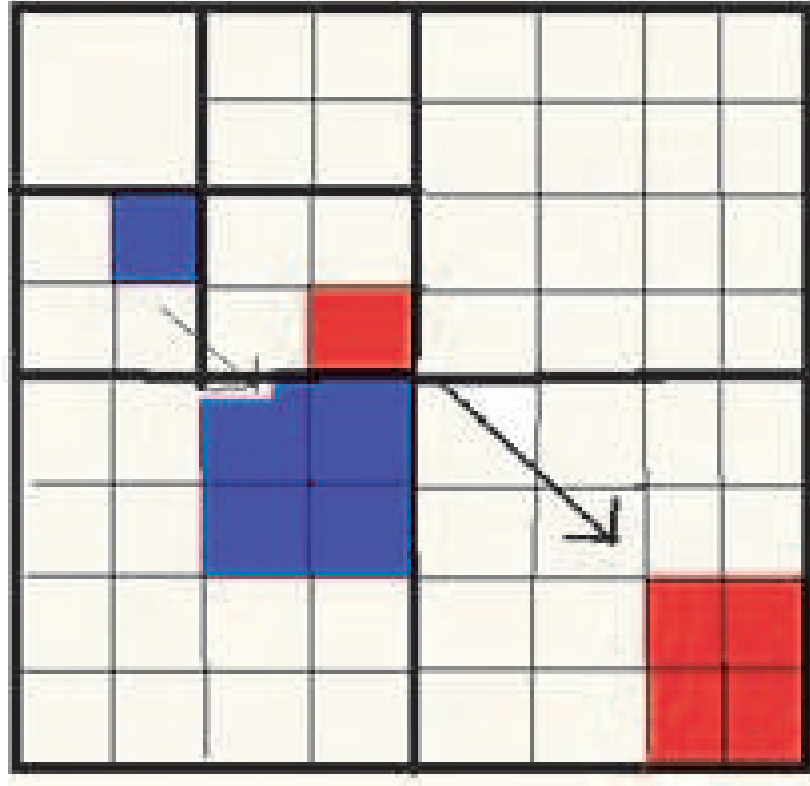
Figure 16.
Wavelet coefficients and their relationships with sub bands.

5.3.2 SPIHT Coder:

SPIHT algorithm was designed by Said and Pearlman. This algorithm has a spatial relationship with the children and grandchildren of the pixels. As in EZW algorithm SPHIT algorithm has two passes, sorting and refinement pass. In the sorting pass, the List of Insignificant Pixel (LIP) is updated comparing with the threshold value. Then the List of Insignificant Set (LIS) is updated. The sorting of LIS is to have a single zero for the set of coefficients and zero trees. In the refinement pass, the List of significant Pixel (LSP) is used to refine the coefficients with the current threshold. For the next level the threshold will be halved [16].

5.3.3 Performance analysis.

The performance of the compressor algorithms is evaluated by PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error)

$$PSNR(db) = 10 \, log_{10} \left(\frac{255^2}{MSE} \right) \tag{15}$$

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[(I(i,j) - K(i,j))^2 \right]$$

where m and n are the number of rows and columns.
where $I(i,j)$ is the coefficients of the original image and $K(i,j)$ is the coefficients of the decompressed image. When the original image and the decompressed image are same, they subtracts each other and the value of MSE is equal to zero. So lesser the value of MSE the better the compression by the coder. The performance of SPHIT algorithm and EZW algorithm outperforms the JPEG standard compression algorithm.

6. Conclusion

Frequency domain approach is a powerful tool in signal processing since many of the natural system like human auditory system works based on frequency content of audio signals. Fourier transform is a conventional tool to convert the signal from time to frequency domain. However, FT fails for non-stationary signals. In such a situation wavelet transforms are primarily useful for processing non stationary signals. Applications demanding time and frequency information simultaneously wavelets are considered as a potential tool to provide tangible results. Ability of wavelet transform to split signals into orthogonal bands makes them suitable in communication systems. Improved BER and PAPR performance is highlight of wavelet based system. Biomedical signals like speech, scan images etc. can be processed effectively with wavelet transform in conjunction with techniques like neural network classifier can be thought as an efficient method to solve a multitude of problems. Compression and preprocessing of signal are other categories of wavelet applications. Artificial Intelligence techniques are considered as a hot research topic in recent technology. A combination of wavelet based feature extraction and AI techniques can be applied to problems demanding processing of big data.

Acknowledgements

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