DISCRETE WAVELET MATHEMATICAL TRANSFORMATION METHOD FOR NON-STATIONARY HEART SOUNDS SIGNAL ANALYSIS

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ABSTRACT

Wavelet mathematical transformation and heart sound signal processing have recently been attracting a significant amount of attention in the research community. Why is this new priority being given to improved approach to heart sound signal analysis for accurate pattern recognition using the wavelet transform technique? This article provides an overview of this emerging field of digital bio-signal processing, clarifying how wavelet transformation is superior to other signal processing techniques such as Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT). The article presents an overview of mathematical and theoretical background for Discrete Wavelet Transform (DWT). It discusses the application of a new DWT algorithm to the analysis and characterisation of heart sounds for diagnostic purpose and charts a course for future research direction in the field of knowledge discovery in databases (KDD).

Keywords: heart sound, mathematical transformation, digital signal processing, non-stationary, uncertainty principle, time-frequency representation, phonocardiogram.

1. INTRODUCTION

Efficient analysis of the observed information derived from the processes of a physical system determines the extent of the understanding gained on the events and behaviour of the system. Furthermore, the observed information is dependent on the complexity of the activities of the system from which it was derived. In the real world, physical processes are complex. Consequently, the capability to correctly analyze and interpret observed information based on the events of a complex system has become priority. Information is acquired as continuous or a real time of events known as signal. With the application of mathematical procedures on measured information to better understand the mechanism of a complex physical system, this is known as Signal Processing. These procedures essentially rely on various transformations that are mathematically based and which are implemented using digital techniques. By these techniques, it is possible to characterize a system process in a quantified way. The objective of this quantification is to reveal hidden information about the process and accounts for the system behaviour. The complexity of physical processes (such as cardiovascular processes) is unlimited - and being able to characterize them in a quantified way relies on the use of physical 'laws' or other 'models' usually phrased within the language of mathematics (Kihong and Hammon, 2008).

Signal processing is the extraction of information from a signal (such as heart sound), especially when it is difficult to obtain from direct observation (Kihong *et al.*, 2008). The methodology of extracting information from a signal has three key stages: (i) acquisition, (ii) processing (iii) characterization.

The development of Wavelet transform (DWT) method for signal processing of heart sound is to address the problem of mapping heart sound data which in their raw state do not make any clinical diagnostic sense into other useful form that might be a descriptive and predictive model for estimating the clinical condition of observed cardiovascular system. This process essentially revolves around the application of wavelet mathematical transformation for pattern discovery and characterization. This article begins with an overview of signal processing and historical trends in heart sound analysis. The mathematical and theoretical background for Discrete Wavelet Transform (DWT) is presented. It discusses the application of DWT algorithm to the analysis and characterisation of heart sounds for diagnostic purpose and charts a course for future research direction in the field.

1.1 Overview of heart sound analysis

In the studies carried out by Gabarda *et al*. (2006) and Yuenyong, *et al*., (2011), it was observed that, mechanical processes in the body produce sounds which indicate health status of an individual and this information is valuable in the diagnosis of patients with cardiovascular conditions. Martinez-Alajarin *et al*. (2005) and Amin *et al*. (2008) noted that the auscultation of the heart, that is listening to the heart sound is still the basic analysis tool used to evaluate the functional state of the heart. However, Amin *et al*. (2008) further argued that heart sound analysis by auscultation is grossly insufficient as it does not allow for qualitative and quantitative characteristics of heart sound signal. The reasons for the insufficiency of auscultation technique were reported by Avendano-Valencia *et al*. (2008) as being due to its inherent restrictions namely: human ear limitations; subjectivity of the analyst and the discriminatory skills that can take years to acquire.

Research on signal processing and characterisation of heart sound signals for diagnostic applications has been extensive (Clifford, 2002, Ahlstrom *et al*., 2006, Amin *et al*., 2008, Yuenyong *et al*., 2011). According to Amin *et al*. (2008) the characteristics of the heart sounds such as first and second heart sounds (S1 and S2) locations as well as extra sounds such as S3 and S4;

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their frequency content; and their time interval (or split S2), all can be measured more accurately by digital signal processing techniques. Discovering such kind of diagnostic information through a suitable device requires special techniques, in order to determine the functional condition of the heart. Hence, recording of the heart sound in the form of the waveform display called Phonocardiogram (PCG) has been developed over the years to visually inspect the heart sound for the purpose of clinical diagnosis (Balasubramaniam *et al*., 2010).

2. MATHEMATICAL TRANSFORMATION METHODS

There are many techniques for signal processing, the prevalent ones are the Fourier and wavelet transforms. The Fourier and wavelet transforms techniques are applied to a signal to obtained further information contained in the signal that is not readily available in the raw signal or otherwise called time domain.

2.1 The concept and application of the Fourier transformation

The Fourier methods relate to temporal characteristic of signal with its frequency spectrums by representing the signal as an infinite summation of weighted sine and cosine waves of multiple fundamental frequencies. This allows Fourier mathematical transform to alter the domain of representation from time domain to the frequency domain as well as allow the reverse to move back and forth between two domains. This change of domains is used to simplify and understand the information. Considering a signal in the time domain, it is overwhelming to initially describe the characteristics. However, when signal is transform into frequency domain, information about the frequency content is revealed. It should be noted that, there is no frequency information that is available in the time domain of the signal and there is no time information that is available in the Fourier transformed signal (Polikar, 1999). Although the Fourier transforms tells us how much its frequency exists in a signal, it does not tell us when in time these frequency components occur. This information is not required when the signal is stationary. A stationary signal is the one that the frequency information of the signal does not change in time and it is said to be periodic.

In the real world, the signals are not stationary. The frequency changes in time. For example, in the cardiovascular system, the heart chambers do not all contract at once, there is latency involved which works as a system to move the blood appropriately around the circulatory system. All these signals are non-stationary and are called transient signals. So what happen to a non-stationary signal when it is processed, to view it in a frequency domain? It starts to become distorted adding noise where it should not be. This is because of the underlying assumption of the Fourier transform. It models the periodic nature of a signal. However, there is nothing periodic of a non-stationary signal. This was one of the major problems with signal processing using Fourier transform techniques.

2.2 Short time Fourier transform (STFT)

In order to deal with the limitation of Fourier Transform's periodicity assumption, further mathematical analysis procedures are required. That is, if the signal is properly windowed or cut in segments to a place in time, the signal can become stationary. Then we can use the Fourier transform method because the signal, sectioned into segments has been forced to be periodic. This usage of windowing with the Fourier Transform is called the Short Time Fourier Transform, (STFT). The problem with this is that adequate understanding of the contents of the signal is required to make appropriate windowing. This is hardly ever the case and many times, these assumptions lead to problems. This became an important concept because of the limitation of the Heisenberg's uncertainty principle imposed on data analysis. The uncertainty principle deals with the concept of time-frequency resolution. The principle states that with high time resolution, a poor frequency resolution and with high frequency resolution, a low time resolution occurs. So when using STFT, once the window size has been chosen, the time frequency resolution is fixed. Thus a window could be analyzed with good time resolution or frequency resolution but not both.

2.3 Wavelet transform

In order to deal with the limitations of Short Time Fourier Transform, trade-offs between the time and frequency has to be explored. That is, the window size must be varied at several different values thus, achieving a multi-resolution analysis. The Heisenberg's principle is still satisfied but the time resolution enhances at high frequencies while the frequency resolution enhances at low frequencies. This is the logical reason for the concept of wavelet transformation technique which provides for time-frequency multi-resolution analysis.

3. MATHEMATICAL METHODS

According to Sripathi (2003) the transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of a signal. That is, it posses the functionality to analyse signal in time and frequency concurrently (Hedayioglu, 2009). It was developed to overcome the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions (Sripathi, 2003). The wavelet transform is a powerful mathematical technique with the capability of filtering and analyzing non-stationary signals (Hedayioglu, 2009). It uses wavelets (localized waves) of finite energy to analyze signals.

The first step in the procedures of a wavelet transformation is to determine a mother wavelet. There are many types of mother wavelet and each one has its applications. Once a mother wavelet is decided, it is translated through the signal using the convolution. The windowing technique is used by changing the scale of the wavelet, hence, the dilation and compression of the wavelet. The idea behind dilation and compression is that if the wavelet is compressed it represents high frequency and if it is dilated, it has a slow rate of change that is low frequency. As wavelet is translated and dilated multiple times through the signal, the wavelet quantifies how well it correlates to the topology of the signal. The correlation of the signal receives a value of how well it matches the signal. If there is a high correlation, the transform reports high value at a particular scale and position in time. If there is no correlation you see the low index value of correlation. Eventually, after receiving all these index values in terms of time and scale, it develops a 3-dimensional image. But in most cases, it is expressed in 2-dimensions with a 3rd dimension expressed in contours using a colour scheme where colours represent the amplitude.

3.1 The continuous wavelet transform and the wavelet series

The mathematical representation of the Continuous Wavelet Transform (CWT) is provided by equation (1), where f (t) is the signal to be analyzed. φ (t) Is the mother wavelet or the basis function. All the wavelet functions used in the transformation are derived from the mother wavelet through translation (shifting) and scaling (dilation or compression).

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int f(t).\varphi^{*}\left(\frac{t-\tau}{s}\right) dt \qquad (3.1)$$

The mother wavelet used to generate all the basis functions for the analysis of signal f (t) is designed based on some desired characteristics associated with f (t). The translation parameter τ relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the Wavelet Transform. The scale parameter *s* is defined as |1/frequency| and corresponds to frequency information. Scaling either dilates (expands) or compresses a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal. Notice that the Wavelet Transform merely performs the convolution operation of the signal and the basis function.

3.2 Wavelet families

Haar wavelet is one of the oldest and simplest wavelet. Daubechies wavelets are the most popular wavelets. They represent the foundations of wavelet signal processing and are used in numerous applications (Polikar, 1999; Sripathi, 2003). These are also called Maxflat wavelets as their frequency responses have maximum flatness at frequencies 0 and π. This is a very desirable property in some applications. The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets along with Meyer wavelets are capable of perfect reconstruction. The Meyer, Morlet and Mexican Hat wavelets are symmetric in shape. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application (Misiti *et al*., 1997).

There are a number of basis functions that can be used as the mother wavelet for Wavelet Transformation. Since the mother wavelet produces all wavelet functions used in the transformation through translation and scaling, it determines the characteristics of the resulting Wavelet Transform. Therefore, the details of the particular application should be taken into account and the appropriate mother wavelet should be chosen in order to use the Wavelet Transform effectively. According to Hedayioglu (2009) the wavelet function $\psi(t)$ has to satisfy certain mathematical conditions, such as:

a) It must have finite energy:

$$E = \int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \qquad (2)$$

b) It must have no zero frequency component $(\hat{\psi}(0) = 0)$, or in other words, if $(\hat{\psi}(t))$ is the Fourier Transform of $(\psi(t))$:

$$(\hat{\psi}(0) = \int_{-\infty}^{\infty} \psi(t)\, e^{(-i(2\pi f t))}\, dt = 0) \qquad (3)$$

c) It must hold the following condition:

$$C_g = \int_0^{\infty} \frac{|\psi(f)|^2}{f} df = \infty \qquad (4)$$

The above equation is known as admissibility condition and C_g is known as admissibility constant and is dependent on chosen wavelet.

d) An extra criterion, on complex wavelets, is that the Fourier transform must vanish for negative frequencies and also must be real.

3.3 Theory of wavelets

This section describes the concept of signal analysis method based on the wavelet approach. As noted by Polikar (2001), the transformation defined by Fourier uses basis functions to analyse and reconstruct a function. Every vector in a vector space can be written as a linear combination of the basis vectors in that vector space. That is, by multiplying the vectors by some constant numbers, and then taking the summation of the products. The analysis of the signal involves the estimation of these constant numbers (transform coefficient or wavelet

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coefficient). The wavelet analysis is a measure of similarity between the basis functions (wavelets) and the signal itself. As earlier noted, the wavelet transform provides a time-frequency representation of a signal. It helps to address the problem of localization of frequency contents of a signal. That is, to determine at what point in time did a specific (low or high) frequency components exist in the signal waveform. This is to the intents that an improved signal localization characteristic is achieved (Sengupta, 2007). Here, we develop a wavelet theory with one-dimensional signal and extend it logically to two-dimensional signal. Suppose, we have a function;

$$f(t) = \sum_k \alpha_k \varphi_k(t) \tag{5}$$

This is a series summation of some coefficients α_k multiplying a set of function $\varphi_k(t)$. k is the index of summation. The number of terms in the series summation will be determined by how close the approximation of the signal $f(t)$ is going to be. The set of function $\varphi_k(t)$ will be realised using a scaled and shifted versions of some basis functions. $\varphi_k(t)$ Will have two basis parameters (r, s) associated with it. That is,

i) To what extent $\varphi_k(t)$ is scaled
ii) To what extent $\varphi_k(t)$ is shifted

This set of function is given $\varphi_{r,s}(t)$. Where r = scaling parameter, s = shift parameter and r, s belong to integer space Z, (r, s $\in$ Z). Therefore,

$$\varphi_{r,s}(t) = 2^{\frac{r}{2}}\, \varphi(2^r t - s) \tag{6}$$

At the starting point, r = 0, s = 0. Then, $\varphi_{0,0}(t) = \varphi(t)$. At r = 1, s = 0, we have, $\varphi_{1,0} = \sqrt{2}\varphi(2t)$. That is, $\varphi(t)$ now has amplitude of $\sqrt{2}$ and it is now scaled by 2*t* (compressed by a factor of 2). This obtained a scaled and shifted version of the basis function $\varphi_{0,0}(t)$. This set of function is given $\varphi_{r,s}(t)$ can be derived from different values of r and s and it is referred to as scaling functions. If we choose a function such that with all values of r and s, it is possible for us to cover the square integrable real space, $L^2(R)$. It follows therefore that the higher scaled versions of $\varphi_{r,s}(t)$ can be used to reconstruct $\varphi_{0,0}(t)$. In general,

$$\varphi(t) = \sum_n \mathbf{h}_\varphi \sqrt{2}\boldsymbol{\varphi}(2t - n) \tag{7}$$

Where $\varphi(t)$ is the series summation of shifted versions of higher order wavelets? $\mathbf{h}_\varphi$ is the weight or the coefficients associated with the shifted versions of $\varphi(2t - n)$ and n is the shift parameter.

The class of function, $\Psi_{r,s}(t)$ which is referred to as the wavelet function is given by:

$$\Psi_{r,s}(t) = 2^{\frac{r}{2}}\, \Psi(2^r t - s) \tag{8}$$

This function is used to cover the difference subspace of the shifted versions of a non-stationary signal to determine the localization properties of its frequency components. The shifted versions of this function must be orthogonal with respect to each other. The relationship between the scaling function, $\varphi_{r,s}(t)$ and the wavelet function, $\Psi_{r,s}(t)$ is given by:

$$\Psi(t) = \sum_i \mathbf{h}_\Psi(\mathbf{i})\sqrt{2}\boldsymbol{\varphi}(2t - i) \tag{9}$$

This means that the wavelet function can be realized from the series summation of the shifted versions of the scaling functions. Putting forward the condition of orthogonality, it is possible to extract a relationship between $\mathbf{h}_\Psi$ and $\mathbf{h}_\varphi$.

3.4 The wavelet series

In reality, signal processing procedures are carried out by digital computers and therefore we work with samples of continuous signals. Sampled signal means that it is only defined at some discrete points. The wavelet series represent the discretised continuous wavelet transform to enable the computation of the transform by digital computers. However, it produces highly redundant information which requires a significant amount of computational time and resources. The discrete wavelet transform (DWT) provides sufficient information both for analysis and synthesis of the original signal with a significant reduction in computational time.

For a function, $f(t)$ given that $f(t) \in L^2$ (R)

$$f(t) = \sum_s \mathbf{a}_{r_0,s}\boldsymbol{\varphi}_{r_0,s}(t) \tag{10}$$

Where $\mathbf{a}_{r_0,s}$ are corresponding coefficients associated with $\varphi_{r_0,s}(t)$. To approximate the function $f(t)$ fully, we consider the difference subspaces in the next higher order. This will include a second term $\Psi_{r,s}(t)$ in the series.

So that,

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$$f(t) = \sum_{s} \mathbf{a}_{r_0,s} \boldsymbol{\varphi}_{r_0,s}(t) + \sum_{r_0}^{\infty} \sum_{s} \mathbf{b}_{r,s}\, \Psi_{r,s}(t) \tag{11}$$

This is the series summation of $f(t)$. The set of functions $\varphi_{r,s}(t)$ and $\Psi_{r,s}(t)$ are the basis functions. To obtain the coefficients $\mathbf{a}_{r_0,s}$ and $\mathbf{b}_{r,s}$:

$$\mathbf{a}_{r_0,s} = \int f(t) \boldsymbol{\varphi}_{r_0,s}(t) dt \tag{12}$$

$$\mathbf{b}_{r,s} = \int f(t)\, \Psi_{r,s}(t) dt \tag{13}$$

3.5 Discrete wavelet transform (DWT)

As previously noted, the Wavelet Series is just a sampled version of CWT and its computation may consume significant amount of time and resources, depending on the resolution required. The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required.

The foundations of DWT go back to 1976 when techniques to decompose discrete time signals were devised (Sripathi, 2003). Similar work was done in speech signal coding which was named as sub-band coding. In 1983, a technique similar to sub-band coding was developed which was named pyramidal coding. Later many improvements were made to these coding schemes which resulted in efficient multi-resolution analysis schemes (Sripathi, 2003).

In CWT, the signals are analyzed using a set of basis functions which relate to each other by simple scaling and translation. In the case of DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with different cutoff frequencies at different scales. For a discrete time signal (sequence) x (n), where integer n = 0, 1, 2 ... m-1. There are m numbers of samples in the sequence.

The scaling function $w_{\phi}(j_o, k)$ and wavelet function $w_{\Psi}(j, k)$ are given by

$$w_{\varphi}(j_o, k) = \frac{1}{\sqrt{m}} \sum_{n} x(n) \varphi_{j_o,k}(n) \tag{14}$$

$$w_{\Psi}(j, k) = \frac{1}{\sqrt{m}} \sum_{n} x(n) \Psi_{j,k}(n) \tag{15}$$

Note that $\frac{1}{\sqrt{m}}$ is a normalizing term. This is to ensure that the energy of the signal in the two transformation domain remains the same. Therefore,

$$x(n) = \frac{1}{\sqrt{m}} \sum_{k} w_{\varphi}(j_o, k) \varphi_{j_o,k}(n) + \sum_{j=j_o}^{\infty} \sum_{k} w_{\Psi}(j, k) \Psi_{j,k}(n) \tag{16}$$

Equations (14) and (15) can be called forward discrete wavelet transform while equation (16) is the inverse discrete wavelet transform. Every mathematical transformation involves the original signal; the transformed signal and the transformation kernel. In this case, the transformation kernels are $w_{\phi}(j_o, k)$ and $w_{\Psi}(j, k)$.

3.6 Multi-resolution analysis using filter banks

Filters are one of the most widely used signal processing functions. Wavelets can be realized by iteration of filters with rescaling. The resolution of the signal, which is a measure of the amount of detail information in the signal, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operations (Sengupta, 2007). The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in Figure-1. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time mutiresolution to discrete-time filters. In Figure-1, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G_0 while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information; d [n], while the low pass filter associated with scaling function produces coarse approximations, a [n].

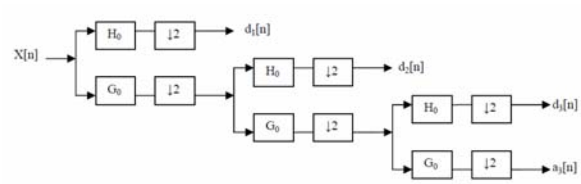

Figure-1. Three-level wavelet decomposition tree.

At each decomposition level, the half band filters produce signals spanning only half the frequency band. This doubles the frequency resolution as the uncertainity in frequency is reduced by half. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire signal is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2, doubles the scale.

With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The filtering and decimation process is continued until the desired level is reached. The maximum number of levels depends on the length of the signal. The DWT of the original signal is then obtained by concatenating all the coefficients, a [n] and d [n], starting from the last level of decomposition.

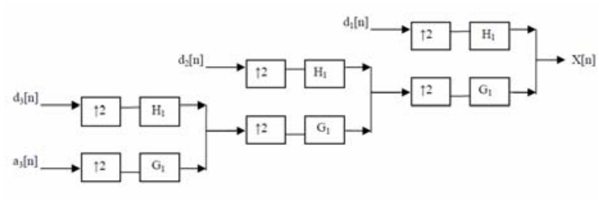

Figure-2. Three-level wavelet reconstruction tree.

Figure-2 shows the reconstruction of the original signal from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are up sampled by two, passed through the low pass and high pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain the original signal. The Mallat algorithm works equally well if the analysis filters, G_0 and H_0, are exchanged with the synthesis filters, G_1 and H_1. In most Wavelet Transform applications, it is required that the original signal be synthesized from the wavelet coefficients whereas some applications like pattern recognition do not require signal reconstruction.

4. PROPOSED DWT ALGORITHM FOR HEART SOUND SIGNAL PROCESSING

The basic task for the diagnosis of heart sound signal for pathologies is to detect the events such as normal and abnormal sounds as well as murmurs, present in the cardiac cycle. This procedure for the analysis and interpretation of PCG signal using DWT is similar to the procedure used by physician during cardiac auscultation.

First, PCG signal is acquired using suitable device such as electronic stethoscope and segmented into cardiac cycles from which an envelope signal is derived for analysis. Peaks in the envelope signal which correspond to the fundamental heart sounds (FHS) and are easily detected using thresholds. Based on the assumption that systole is shorter than diastole, it is easy to identify systole as the shorter interval; thus, S1 must be the peak to the left of systole, or equivalently, S2 must be to the right. Identifying one peak allows all other peaks to be identified by noting that S1 and S2 must alternate. Boundaries of cardiac cycles are then formed by the S1-S1 intervals and segmentation is completed. However, segmentation is not straight forward in unhealthy heart sounds as extra peaks such as S3 and S4 may be introduced (Yuenyong *et al.*, 2011). Consequently, this results in the problem of false peak detection. Segmentation is even more challenging in the events of murmurs. Hence, the problem of signal corruption and uncertain localization where normal heart sounds are submerged in murmurs. The threshold parameter is very important for analysis results. A low threshold provides many correct detections but also a lot of false detections, while a high threshold might miss many heart sound occurrences. In this condition, efficient segmentation will require the need to eliminate extra peaks and disturbances while preserving the integrity of normal heart sounds. After the transformation, a threshold is applied to locate the heart sounds. Heart sound localization and segmentation in the proposed DWT algorithm emphasize heart sound occurrences in time and this entail signal filtering, conditioning and thresholding. The DWT algorithm for decomposing heart sound with peak threshold identification is described as follows:

a. The acquired heart sound as PCG signal will be segmented into cardiac cycles.
b. The PCG signal will be decomposed by discrete wavelet transforms (DWT) using db6 as the mother wavelet.
c. Signal peaks will be detected and characterized using the Eigen value spectrum method
d. Peaks of S1 and S2 sounds as well as their durations will be computed. This will be accomplished by employing the mean square error criterion as the stopping criterion using iteratively finding-threshold. These thresholds are multiplied with the wavelet coefficients. The outcomes of these multiplications consist of the WT coefficients that are related to S1 and S2 sound waveform and the WT coefficients that are related to the presence of murmur.
e. Similarly, peaks of S3 and S4 sounds, if present, as well as their durations will be computed. This will be accomplished by employing the mean square error criterion as the stopping criterion using iteratively finding-threshold.
f. The wavelet coefficients related to heart sounds and murmurs will be reconstructed.
g. The reconstructed heart sounds and murmur signals will be characterized.
h. Heart sounds and murmurs will be classified for healthy or pathologic condition.

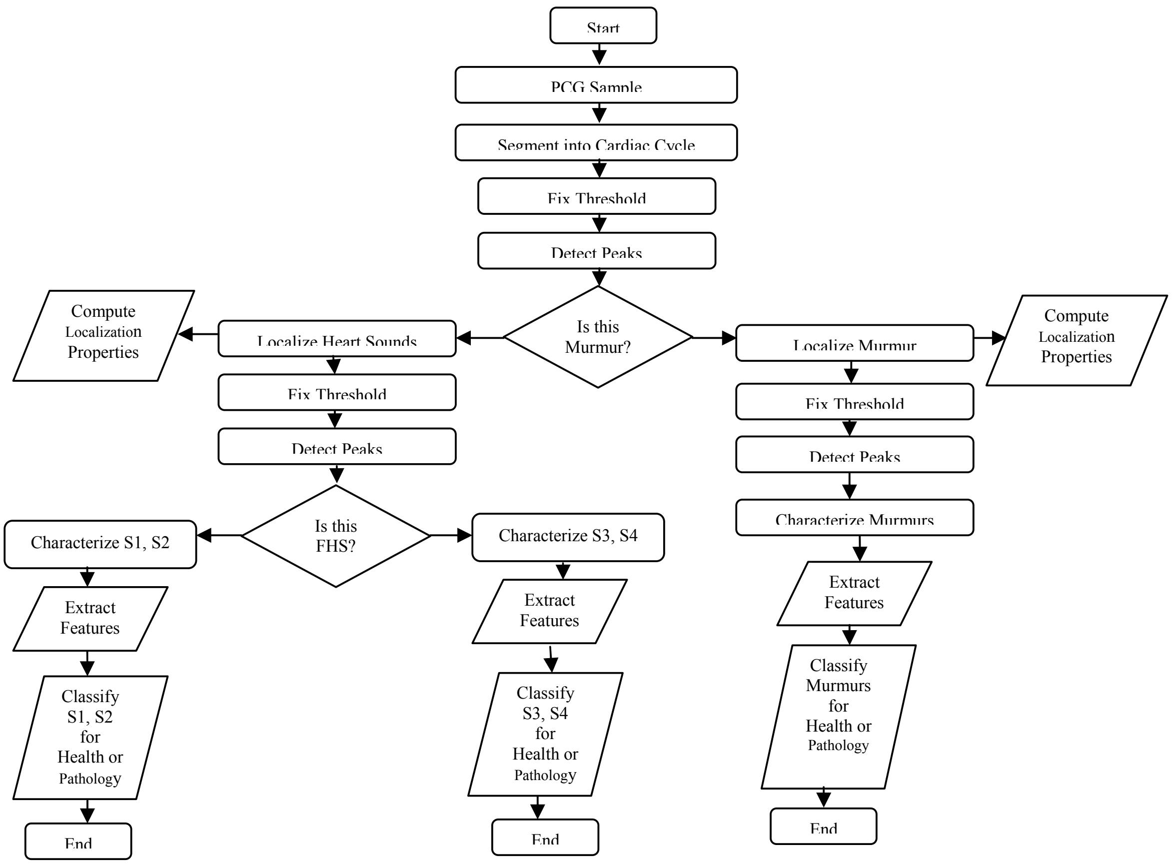

Figure-3. DWT Algorithm for segmentation, localization, characterization and classification of heart sounds and murmurs.

5. CONCLUSIONS

There is a wide range of applications for Wavelet Transforms. They are applied in different fields ranging from image compression to signal processing of bio-signals such as heart sound signals, and the list is still growing. In practice, the most prominent information in a transformed signal appears in high amplitudes and the less prominent information appears in very low amplitudes. Bio-signal pattern recognition is one of such possible DWT application. Wavelets are used in biomedical applications. For example, the PCG signals, measured from the heart beats, can be analyzed using wavelets transform. The popularity of Wavelet Transform is growing because of its ability to reduce distortion in the reconstructed signal while retaining all the significant features present in the signal.

Using the wavelet transform techniques, it is possible to apply the scaling and wavelet functions to carry out filtering operations on a signal. This article is of the position that the proposed discrete wavelet transform algorithm can be used to carry out time-frequency localization analysis of heart sound signals in clinical diagnosis. That is, it is possible to determine the pattern and at what point in time a specific frequency components such as the fundamental heart sounds and murmurs exist in the heart signal which could be characterized to determine the state of health or pathology. This is essentially to improve the auscultation procedures of the clinicians.

5.1 Future research direction

Considering the rate at which bio-data is increasingly being collected for diagnostic analysis, there is an urgent need for a new approach to biological signal processing to assist physicians in extracting useful diagnostic information from the available high volume of measured clinical data. This approach is to be developed using the emerging field of knowledge discovery in databases (KDD) which is concerned with techniques for making diagnostic sense from a wide spectrum of measured clinical data for pattern discovery and extraction. This is the proposal of this article as future research direction in PCG signal analysis.

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