Application of Wavelet Analysis in Detection of Fault Diagnosis of Heart

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Abstract

The ECG waveform is a non-stationary signal, and its variation can contain indicators of current disease or warnings about impending cardiac diseases. In this paper, we have evaluated wavelet transform (WT) based detector of ECG. Dyadic wavelet transform (DyWT) was used as prototype wavelet, which is robust to time varying & noise. It includes noise purification, sample design of digital ECG. This method can implement ECG report in real time and provide exact explanation for diagnostic decision obtained. We exemplify the performance of the DyWT based detector by considering problematic ECG signal from MIT-BIH database. From the results we observed that DyWT based detector exhibited superior performance compared to standard techniques. The paper deals with the classification of cardiac rhythms using an artificial neural network (ANN) for the use of fault diagnosis of heart.

1. Introduction

The automatic detection of ECG waves is important to cardiac disease diagnosis. A good performance of an automatic ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified, a more detailed examination of ECG signal, including the heart rate, the ST segment, etc., can be performed.

In order to tackle the problem of non-stationarity, wavelets (WT) have been utilized because they can produce a good local representation of the signal in both time and frequency domains [1]. Moreover, the wavelet decomposition, as a multiscale analysis tool, can be used to unfold inner load characteristics, which are useful for more precise detection. In this paper, the effectiveness of detection strategies that exploit multiresolutions representation via wavelet transform is investigated. The goal is to identify different sources of useful information embedded in a ECG data.

The MultiResolution Analysis (MRA) approach for tackling feature extraction problems splits up the ECG data into one low-frequency and some high-frequency sub series in the wavelet domain. Using this new representation of the original ECG signal, two different alternatives are investigated. The first one consists of creating a model for forecasting each input are based on information from the original ECG signal and from wavelet domain subseries. The second alternative predicts the disease by independently forecasting each subseries in the wavelet domain.

This feature can be used to distinguish ECG waves from serious noise, artifacts and baseline drift. In this paper, an algorithm based on the WT for detecting QRS complex, P and T wave is proposed.

A dyadic wavelet transform is used for extracting ECG characteristic points. The local maxima of the WT modulus at different scales can be used to locate the sharp variation points of ECG signals. The algorithm first detects the QRS complex, then the P & T wave, and final.

The feasibility of aforementioned approaches for forecasting is verified using MIT-BIH data from internet. This paper is divided as follows: section II deals with some theoretical aspects of the wavelet transform (WT) and MRA. In section III, the proposed model for features extraction is described. In section IV, fault diagnosis of the heart is described. Finally, Section V presents the main conclusions of this work.

2. Wavelet Transform

Wavelets can be described as a pulse of short duration with finite energy that can integrates to zero. The basic
fact about them is that they are located in time (or space), unlike trigonometric functions. This characteristic enables them to analyze a great deal on nonstationary signal[2].

A. Motivation for Using Wavelet Transforms

When using Fourier transforms for analyzing a signal, it is very hard to say when a particular event took place because the basis functions used in Fourier analysis are precisely located in frequency but are applied all the time. This drawback implies that the conventional Fourier analysis is suited for dealing with frequencies that do not evolve with time i.e. stationary signals. The short-time Fourier transform (STFT), which takes into account short date windows, has been tried in order to deal with nonstationary signals. However, low frequency estimates require long windows, while the high frequency ones need small windows.

On the other hand, it is very well known that ECG series contain several nonstationary features P,QRS, T, changes in level and slope to name few. These features are often the most important and challenging parts of the load signal and must be taken into account when dealing with nonstationarity. Hence, it is plain to note that ECG characteristics challenge the traditional Fourier analysis.

Wavelet analysis overcomes the limitations of the Fourier methods by using functions that retain a useful compromise between time location and frequency information. Implicitly, wavelets have a window that automatically adapts itself to give the appropriate resolutions.

B. Continuous and Discrete Wavelet Transform

Wavelet analysis employs a prototype functions called mother wavelet \( \psi(t) \) with most of the energy in concentrated in localized region. This function has null mean and sharply drops in an oscillatory way. Data are represented via superposition of scaled and translated versions of the prespecified mother wavelet. The Continuous Wavelet Transform (CWT) of a given signal \( f(t) \), with respect to \( \psi(t) \), is defined in (1), where \( s \) and \( \tau \) are the scale and transformation factors, respectively.

\[
\text{CWT}(s, \tau) = \int f(t) \psi^*_s(t-\tau)/s dt
\]

where \( \psi^*_s(t-\tau)/s \) is the \( s \) and \( \tau \) that correspond to the peaks in A3. This method repeats the process until it reaches the finest scale in a particular signal \( f(t) \), is wavelet representation of the signal with respect to the mother wavelet \( \psi(t) \).

Since the CWT is achieved by continuously scaling and translating the mother wavelet, substantial redundant information is generated. Therefore, instead of doing that, the mother wavelet can be scaled and translated using certain scales and positions based on powers of two. This scheme is more efficient than and just as accurate as the CWT. It is known as discrete Wavelet Transform (DWT). If the scale parameter is the set of integral powers of 2, i.e., \( a = 2^j \) (\( j \in \mathbb{Z}, Z \) is Integer set), then the wavelet is called a dyadic wavelet and defined as

\[
Wf(2^j, \tau) = 1/\sqrt{2^j} \int f(t) \psi^*(t-\tau)/2^j dt
\]

In this work, the feasibility of the Daubechies wavelets of the order of 2-4 has been evaluated.

It is advisable to select a suitable number of decomposition levels based on the nature of the signal. In this paper, based on features of typical ECG, three, four, and five levels of decomposition have been considered. It has been found out that three levels of decomposition is the most promising choice, because it has described the ECG series in a more thorough and meaningful way than the others. This conclusion is mainly due to the low-frequency band (approximation), which is the most significant part of an ECG signal. The three-level decomposition scheme emphasizes the regular behavior of a load series. It reveals hidden parameters that cannot be seen with higher resolutions. Periodic details provide different sources of useful information. However, high-frequency details associated to higher resolutions are mainly superfluous noise.

The signal can be represented using the following equation:

\[
\text{Signal} = A1 + D1 = A2 + D2 + D1 = ... = A5 + D5 + D4 + D3 + D2 + D1
\]

Where A denotes the approximation coefficients and D denotes the detail coefficients. After applying the decomposition to the signal, the wavelet-based peak detection method first checks D5 for zero crossings, which correspond to the peaks in A4. Then, this method checks D4 for zero crossings. More zero crossings might exist in D4 than in D5 due to higher-frequency components or noise, so this method selects the zero-crossing points that are nearest to those in D5, which correspond to the peaks in A3. This method repeats the process until it reaches the finest scale in
Fig. 1 Multiresolution process of wavelet-based peak detection

D1. The above Fig. 1 shows the refinement process of the first detected peak.

3. Models for Features Extractions of ECG

QRS Complex detection:

The detection of the QRS complex is based on modulus maxima of the wavelet transform, defined as any point \( W_f(2^j, \tau_0) \) such that

\[
|W_f(2^j, \tau)| < |W_f(2^j, \tau_0)|,
\]

when \( \tau \) belongs to either the left or right neighborhood of \( \tau_0 \), and

\[
|W_f(2^j, \tau)| \leq |W_f(2^j, \tau_0)|
\]

when \( \tau \) belongs to the other side of the neighborhood of \( \tau_0 \). This is because modulus maxima and zero crossings of the wavelet transform correspond to the sharp edges in the signal. The QRS complex produces two modulus maxima with opposite signs of \( W_f(2^j, \tau) \), with a zero crossing between them. Therefore, it is determined by applying detection rules (thresholds) to the wavelet transform of the ECG signal.

Most of the energy of the QRS complex lies between 3 Hz and 40 Hz. The 3-dB frequencies of the Fourier transform of the wavelets indicate that most of the energy of the QRS complex lies between scales of \( 2^3 \) and \( 2^4 \), with the largest at \( 2^4 \). The energy decreases if the scale is larger than \( 2^4 \). The energy of motion artifacts and baseline wander (i.e., noise) increases for scales greater than \( 2^4 \). Therefore, we chose to use characteristic scales of \( 2^1 \) to \( 2^4 \) for the wavelet.
Fig. 2, ECG signal, its wavelet transforms at scale $2^4, 2^5, 2^6, 2^7$, maxima; minima; and zero crossing of wavelet transform at scale 24. The vertical lines above the ECG signal indicate the position of the QRS complex, as detected by the algorithm.

**R Peak Detection:**

The QRS complex corresponds to two modulus maxima with opposite signs of the wavelet transform. (Fig. 2), i.e., a biphasic shape. The modulus maxima that correspond to the R-wave are determined by the following steps:

Step 1: The modulus maxima at the largest scale, $2^4$, that cross threshold $Th4$ are determined ($Thj$ is the threshold for wavelet transform at scale $2^j$) and their positions \{nk4 I k = 1.. N\} are marked.

Step 2: The modulus maxima in the neighborhood of nk4 at scale $2^3$ is determined and its location is marked as nk3. If several modulus maxima exist, then the largest one is selected. If no modulus maxima exist, then nk1, nk2, nk3 are set to zero.

Step 3: Similarly, the location set of modulus maxima \{nk4,nk3, nk2, nk1 I k=0..N\} at remaining scales are determined.

In the above steps, the search for modulus maxima is made first at larger scales (i.e., $2^4$) and then at finer scales (i.e., $2^3$, $2^2$, and $2^1$). This strategy reduces the affect of high-frequency noise, which is present more in the lower scales, and also there is a smaller number of modulus maxima in larger scales. Following this procedure, appropriate thresholds are applied to modulus maxima at the large scale to detect the modulus maxima corresponding to the QRS complex.

Usually, a given R-wave corresponds to a modulus maxima pair with opposite signs (i.e., a maxima and a minima) of wavelet transform. But in some ectopic beats or in the presence of noise, two or more modulus
maxima can occur, of which only one is useful. If two negative minima MIN1 and MIN2 are near a positive maxima, with A1 and A2 as their absolute values, and L1 and L2 as their respective distances from the maxima, then the rule for judging which minima is extraneous is:
1. If A1L1 > 1.2 A2L2, MIN2 is redundant
2. If A2L2 > 1.2 A1L1, MIN1s is redundant
3. If MIN1 and MIN2 are on the same side of the maxima, then the minum at the greater distance from the maxima is redundant. This is true even if the most-distant minima is larger than the peak of the closest minima, due to the fact that maxima and minima produced by rising and falling edge of the QRS complex will be adjacent. This same procedure can be applied to one negative minimum and two positive minima.

The R-wave corresponds to positive maxima and a negative minima pair at each scale, and the interval between two modulus maxima at scale 2^j is slightly less than the QRS width. If this interval is greater than a certain time limit, then the modulus maxima is an isolated one and should be eliminated from the set of true modulus maxima. This interval should be less then the widest possible QRS complex (150 ms [6]). Here, the value of this interval is taken as 120 ms. According to the relation of a signal and its wavelet transform, the horizontal axis is scaled, and the zero crossings at scale 2^j correspond to the R-peak. If all redundant and isolated modulus maxima are eliminated, then the remaining modulus maxima pairs correspond to the QRS complex. The thresholds used are Th1, Th2, Th3, and Th4, for scales 2^1, 2^2, 2^3, and 2^4, respectively. These thresholds adapt to the signal in order to track the signal variations.

If a very sharp noise peak occurs, then the value of the peak modulus maxima will be large. In order to avoid errors, the parameter Ajm+1 (estimated modulus maxima for calculation of threshold for the next QRS complex) is kept the same (equal to the previous estimate, Ajm) if the modulus maxima |
\[ |Wf(2^j, n_j^k)| \]

is greater then twice the Ajm

If

\[ |Wf(2^j, n_j^k)| >= 2 A_jm \]

Then

\[ A_{j+1} = A_jm \]

Otherwise:

\[ A_{j+1} = (7/8) A_jm + (1/8) |Wf(2^j, n_j^k)| \]

\[ Th_j = 0.3, \quad \text{for} \quad j=1,2,3,4 \]

Where Thj is the threshold at scale 2^j.

To further improve the detection accuracy, the following standard precautions are observed:
1. As no two QRS complexes can occur in less then 200 ms [10], 200 ms refractory period is used.
2. If a QRS complex is not found within a certain limit, then a search back is made with lower thresholds (OSThj). During the forward search, the positions of modulus maxima pairs, which cross either the full thresholds or the lower thresholds and satisfy the conditions for a QRS complex, are noted. During the search back, we already have the position of QRS complexes that have been missed by larger thresholds. Therefore, in search back, no extra processing time is required, and the system remains on-line. Figure shows the ECG waveform and the vertical lines above the ECG signal indicate the position of the QRS complex the wavelet transforms at various scales.

Onset, Offset and Width of QRS complex:

QRS width is calculated from the onset and offset of the QRS complex. The onset is the beginning of the Q-wave (or R-wave if the Q-wave is missing) and the offset is the ending of the S-wave (or R-wave if the S-wave is missing). Normally, the onset of the QRS complex contains the high-frequency components, which are detected at finer scales. The onset is the beginning and the offset is the ending of the first modulus maxima pair.

P and T W avea Peak Detection:

The P- and T-wave power spectra lie in the range of 0.5 Hz to 10 Hz, while baseline and motion artifacts have a frequency of 0.5 Hz to 7 Hz [6]. In order to avoid errors in detecting the onset and offset of these waves due to baseline drift and motion artifact, the 2^3 scale is selected. The P-wave generally consists of a modulus maxima pair with opposite signs, and its onset and offset correspond to the onset and offset of this pair. This pair of modulus maxima is searched for within a window prior to the onset of the QRS complex. The search window starts at 200 ms before the onset of the QRS complex and ends with the onset of the QRS complex. The peak and width of the P-wave are found with the following steps:
1. The modulus maxima is a point where the \(|Wf(2^3, T)|\) is at a maximum (the slope of \(-f(2^3, q)\) will equal zero).
2. The zero crossing between the modulus maxima pair corresponds to the peak of the P-wave.

Onset, Offset, and Width of P and T Waves:

To find the onset, a backward search is made from the point of modulus maxima that is on the left of the zero crossing, to the start of the search window, until a point is reached where the \(|Wf(2^3, T)|\) becomes equal to or less then 5% of the modulus maximum. This point is marked as the onset of the P-wave. Empirically, it has
been found that this 5% criteria best approximates the onset and offset of the P-and the T-waves. To find the offset, a forward search is made from the point of modulus maxima that is on the right of the zero crossing, to the end of search window, until a point is reached where the $|Wf(2',~)|$ becomes equal to or less than 5% of the modulus maximum (modulus minimum). This point is marked as the offset of the P-wave. The T-wave has characteristics similar to the P-wave. The detection procedure is the same as that for the P-wave, except that the search window follows the QRS complex. The T-wave onset is considered to be same as the offset of proceeding QRS complex.

**PR Interval, ST Interval, and QT Interval:**

The PR interval is defined as the interval between the onset of the P-wave and the onset of the R-wave. The ST interval is the interval between the offset of the S-wave and offset of the T-wave. The QT interval is calculated by finding the difference between the onset of the Q-wave and the offset of T-wave.

**4. Fault Diagnosis**

This paper emphasis on analysis & interpretation of the ECG by using Artificial Neural Network (ANN). ECG analysis using ANN is an important tool in which two or more successive ECG recordings from the same patients are compared in order to find changes due to disorders in cardiac. Reliable detection of the QRS complex in either a normal or an abnormal ECG and its analysis is the first and foremost task in almost every ECG signal analysis system aimed at the diagnostic interpretation of ECG. DyWT based PQRST detector by considering problematic ECG signal from MIT-BIH database and given to the neural network as input. Neural network is designed and training & testing sets are prepared in such away that it analyses ECG and gives output as normal or abnormal ECG. The result indicate ANN, if properly trained and validated will be a useful aid in the attempt to improve the diagnosis yield of the ECG.

**5. Conclusion**

In this paper, ECG PQRST key feature elements detection algorithm based on DyWT was proposed. The performance of the DyWT based detector was thoroughly examined by testing the algorithm on data standardized MIT-BIH database. The DyWT based QRS detector performs well with standard techniques. Thus, the primary advantages of the DyWT over existing techniques are 1) its robust noise performance and 2) flexibility in analyzing the time varying morphology of ECG data. This method is explicit, highly efficient, highly accurate and reliable. It can run in real time and can offer a clear and explicit explanation for the Cardiologist diagnosis (fault diagnosis) by using any standard classification method like fuzzy, neural network etc. This study has shown large evidence in favour of using neural nets to improve the exercise ECG as a non-invasive technique for detecting heart diseases.

**6. References**


