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Cross Wavelet Transform Based Analysis of Electrocardiogram Signals

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ABSTRACT: This paper presents a method for analysis of ECG patterns using Cross Wavelet Transform (XWT) and Wavelet Coherence (WCOH) techniques. The cross-correlation is the measure of similarity between two waveforms. The application of the Continuous Wavelet Transform to two time series and the cross examination of the two decomposition reveals localized similarities in time and scale. Morlet wavelet is used as the mother wavelet. A pathologically varying pattern in QT zone of inferior lead III shows the presence of Inferior Myocardial Infarction (IMI). The Cross Wavelet Transform and Wavelet Coherence is used for the cross examination of normal and abnormal (IMI) beats. A normal beat template is selected as the absolute normal pattern and the coherence between various other normal and abnormal is computed. The Wavelet cross spectrum and Wavelet coherence of various ECG patterns shows distinguishing characteristics over two specific regions R1 and R2, where R1 is the QRS complex area and R2 is the T wave region. These obtained results further opens scopes for extraction of appropriate parameter(s) for classification of normal and abnormal data.

Keywords: Cross wavelet transform, Wavelet Coherence, Myocardial Infarction, interpolation, Fiducial point.

I. INTRODUCTION

Coronary heart disease, also called coronary artery disease is one of the predominant health concerns all over the world. Electrocardiogram is the interpretation of the electrical activity of the heart over a period of time [1], which is an effective low cost diagnostic tool for screening of cardiac abnormalities. Good performance of any automatic ECG analysing system depends upon the reliable and accurate detection of the basic features. QRS detection is necessary to determine the heart rate and is used as reference for beat alignment. The automatic delineation of the ECG is widely studied and algorithms are developed for QRS complex and T wave detection [2]-[4]. Wavelet transforms have been applied to ECG signals for enhancing late potentials [5], reducing noise [6], QRS detection [7], normal and abnormal beat recognition [8] and delineation of ECG characteristic features [11]. The developed methods in these studies explored discreet wavelet transform [9], multiresolution analysis [8, 9] and dyadic wavelet transform [10]. Many classification methods each having distinguishing characteristics have been developed using neuro - fuzzy [12, 13] and self organizing maps [14, 15, 16]. A rule mining based method is developed in [17], where ischemic beats are identified by extraction of features followed by feature discretization and rule mining. ECG features are also extracted using linear predictive coding in [18]. In addition, the wavelet analysis has been used with success on many other signals such as EEG signals [21] and also on geophysical time series [22].

In this work a method for analysis of ECG data by the method of cross-wavelet transform (XWT) is proposed. Before any form of analysis the signal is denoised and R peaks are registered. The heart rate is computed and then beats are segmented for analysis. Each of the segmented beats is time normalized before analysis because the heart rate varies from subject to subject. For this study only Inferior MI (IMI) and normal class is considered. IMI is identifiable from the inferior leads II, III, aVF, of which lead III is selected for analysis in this paper. All the input data for this method has been selected from Physikalisch-Technische Bundesanstalt diagnostic ECG database (ptb-db) [24] with a sampling frequency of 1 KHz. A pathologically normal patient is selected as standard normal and an extracted beat is labeled, as the standard normal template beat. Normal and abnormal ECG patterns are analyzed by subjecting them to XWT. Because of the morphological similarity with that of the QRS complex, morlet is used as the mother wavelet. The wavelet cross spectrum and wavelet coherence reveals various distinguishing characteristics in the regions R1 and R2 when compared to normal and abnormal ECG data. Where R1 is the QRS Complex region and R2 is the T wave region. Once extracted, these characteristics can be used for further classification of normal and abnormal ECG data.

II. WAVELET TRANSFORM

Wavelet transform is a linear transform, which decomposes a signal into components that appears at different scales (or resolution).Time localization of spectral components can be obtained by multiresolution wavelet analysis, as this provides the time-frequency representation of the signal.

A. Continuous wavelet transform(CWT)

The continuous wavelet transform involves decomposing a signal *f(t),* into a number of translated and dilated wavelets. The main idea behind this is to take a *mother* wavelet $\psi(t)$, translate and dilate it, convolve it with the function of interest, and map out the coefficients in *wavelet space*, spanned by translation and dilation. Periodic behavior, then shows up as a pattern spanning all translations at a given dilation, and this redundancy in the wavelet space makes detection of periodic behavior rather easy. The wavelet transform preserves temporal locality which is an advantage over Fourier analysis.

B. Cross Wavelet transform (XWT) and wavelet coherence (WCOH)

The cross wavelet transform (XWT) of two time series x_n and y_n , is defined as

$$W^{XY} = W^{X} W^{Y*} \qquad \ldots(1)$$

Where * denotes complex conjugation. We further define the cross wavelet power as $|W^{XY}|$. The complex argument $\arg(W^{XY})$ can be interpreted as the local relative phase between x_n and y_n in time frequency space. The theoretical distribution of the cross wavelet power of two time series with background power spectra P_k^X and P_k^Y is given by Torrence and compo in [23, 24]. Another useful measure is how coherent the cross wavelet transform is in time frequency space. Following, Torrence and Webster [24], the wavelet coherence of two time series is defined as:

$$R_n^2(s) = \frac{\left|S(s^{-1}W_n^{XY}(s)\right|^2}{S(s^{-1}\left|W_n^X(s)\right|^2).S(s^{-1}\left|W_n^Y(s)\right|^2)} \qquad \ldots(2)$$

Where, S is a smoothing operator. And wavelet coherence can be thought of as a localized correlation coefficient in time frequency space.

III. MATERIAL AND METHODS

The proposed methodology consists of denoising of ECG data followed by R peak registration and beat segmentation. R peak detection is essential for accurate time alignment of different segments. The heart rate is a variable quantity and accordingly the beat duration changes. So, each of the segmented beat is time normalized. These beats are subjected to further analysis. The cross wavelet analysis of the ECG beats reveals many significant characteristics. The detailed description of the method is illustrated by Fig. 1.

A. Data

For the analysis all the ECG data is taken from ptb-db diagnostic database. One cardiac beat from a 25 year old, pathologically normal, male subject with a heart rate of 72 beats/min, is considered as the standard normal template for analysis. Notable, morphological differences exist for normal Inferior MI subjects in the QT zone of the inferior leads. Inferior lead III is used to show the results of the analysis.

B. R Peak Registration

Denoising of ECG data is an essential step before any form of analysis as this increases the efficiency of the algorithm. Present work uses DWT based decomposition and selective reconstructions of wavelet coefficients for denoising and QRS detection. The denoising and basic feature extraction technique used for this work is the method developed in [11].

C. Time normalization of cardiac cycles

Once the R peaks are registered, the R-R interval is computed and divided into 1:2 ratios (Say, x: 2x points). One cardiac cycle gives the details of the pathological condition of the patient and hence each beat needs to be segmented before subjecting it to cross-wavelet analysis. Considering x points to the left and 2x points to the right of R index one cardiac beat is extracted. FFT based interpolation technique [19] is used for time normalization of each beat segment as the heart rate varies for each subjects. In this study all beats are normalized to 800 samples. The time normalization is important for comparability of two different patterns and finding out notable differences and variations in the same time scale.

C. Cross wavelet transform (XWT) and Wavelet Coherence (WC) analysis of ECG beats

The cross correlation is the measure of similarity between two waveforms. The application of CWT to two time series and the cross examination of the two decompositions reveals localized similarities in time and scale (scale being inverse of frequency). The XWT and WCOH are used for cross examination of a single normal and abnormal (IMI) beat with that of a standard normal template beat. Because of the morphological similarity with that of the QRS complex db4 is selected as the mother wavelet for analysis. The XWT and WCOH give a relationship between the two signals in time scale space.

The resultant Wavelet Cross spectrum (WCS) shows the spectral components of interest. In this analysis 512 scales are used and the Wavelet Coherence (WCOH) is used for the purpose of analysis.

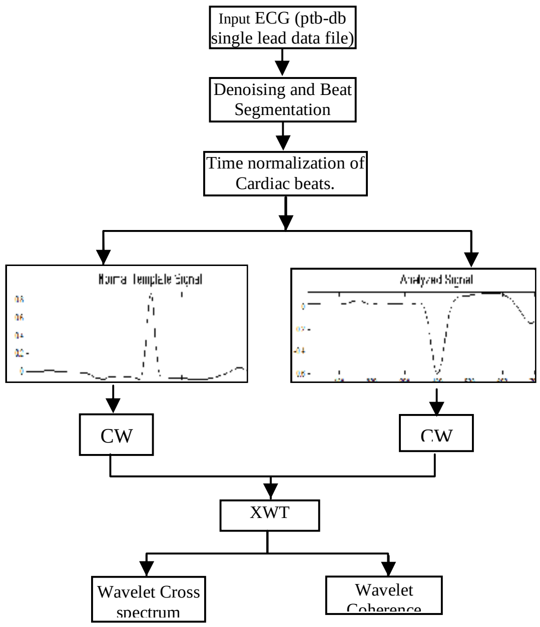


Fig. 1. Schematic representation of the method.

IV. RESULTS

All the input data for this method has been selected from ptb-db of Physionet [23], which contains 549 records from 290 subjects with 52 healthy controls and 148 Myocardiac infarction patients. A normal non smoker male subject of 25 years old, is selected as the normal template for analysis, the patient id is: ptbdb/patient150/s0287lre.

A. The CWT of Signals

The Continuous wavelet transform of two signals is presented in Fig. 2.

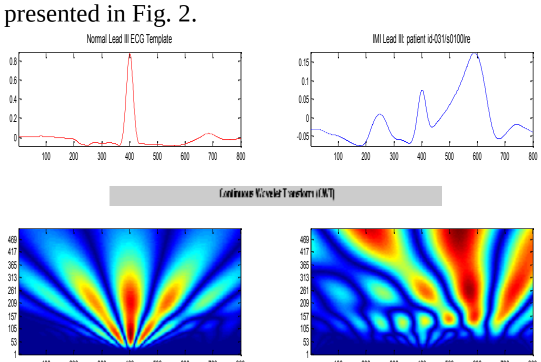
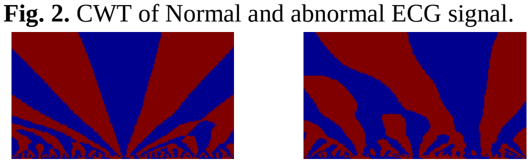


Fig. 2. CWT of Normal and abnormal ECG signal.



B. Analysis of morphologically varying ECG data by WCS and WCOH

Notable differences in WCS and WCOH are revealed in fig.3, fig4 and fig.5 when normal-normal and normal-abnormal pairs are subjected to XWT analysis. Two major region of difference is marked as R1 and R2. Where R1 is the QRS Complex region and R2 is the T wave region. The fig. 3, 4 and 5 shows, Type 1, IMI (non Q type, with ST elevation and attenuated QRS complex), a normal and a Type 2, IMI (Q type MI with deep Q and inverted T). From the colour coded spectrogram for WCS and WCOH it is evident that spectral and coherence variations exist in region R1 and R2. These obtained results further opens scopes for extraction of appropriate parameter(s) for classification of normal and abnormal ECG data. For concise presentation of data and due to space constrains limited number of analysis is shown.

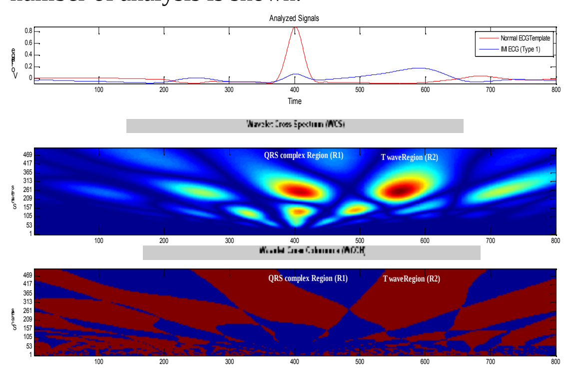


Fig.3. WCS and WC between the standard normal template and an abnormal ECG (IMI –Type1).

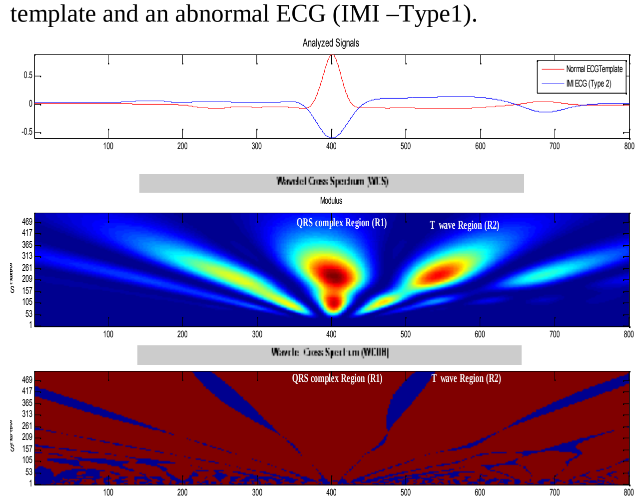


Fig. 4. WCS and WC between the standard normal template and an abnormal ECG (IMI –Type2).

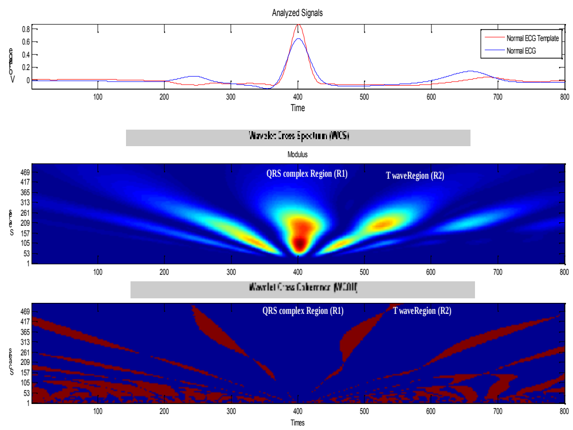


Fig. 5. WCS and WC between the standard normal template and a normal ECG data.

V. CONCLUSION

This paper presents a method for analysis of ECG patterns using Cross Wavelet Transform (XWT) and Wavelet Coherence (WCOH) techniques. The cross-correlation is the measure of similarity between two waveforms. The application of the Continuous Wavelet Transform to two time series and the cross examination of the two decomposition reveals localized similarities in time and scale. Morlet wavelet is used as the mother wavelet. From, the analysis it was found that wavelet coherence reveals great insight into the dissimilarities of the signals under analysis. Region based differences are visible in WCS and WCOH of normal-normal and normal-abnormal pairs. This revealed result further opens scopes for extraction of appropriate parameter(s) for classification of normal and abnormal data.

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