Heart Rate Variability Analysis in IMI Patient

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***Abstract*— Heart Rate Variability (HRV) analysis is the ability to assess overall cardiac health and the state of the autonomic nervous system (ANS), responsible for regulating cardiac activity. Reduced HRV has been shown to be a predictor of mortality after myocardial infarction although others have shown that the information in HRV relevant to acute myocardial infarction survival is fully contained in the mean heart rate. HRV analysis has become an important tool in cardiology, because its measurements are non-invasive and easy to perform, have relatively good reproducibility and provide prognostic information on patients with heart disease. Here paper for the analysis of HRV for different ischemic Patient's signals, a threshold value is calculated. The presented work mostly focused on the efficient way of detection of R-peak and the HR calculation for ischemic signals. We use cross wavelet transform (XWT) for the analysis and classification of electrocardiogram (ECG) signals. The cross-correlation between two time-domain signals gives a measure of similarity between two waveforms. The application of the continuous wavelet transform to two time series and the cross examination of the two decompositions reveal localized similarities in time and frequency. Application of the XWT to a pair of data yields wavelet cross spectrum (WCS) and wavelet coherence (WCOH). The Physikalisch-Technische Bundesanstalt diagnostic ECG database is used for evaluation of the methods. A heuristically determined mathematical formula extracts the parameter(s) from the WCS and WCOH. Empirical tests establish that the parameter(s) are relevant for classification of normal and abnormal cardiac patterns.**

Keywords*— *Denoising and beat segmentation, wavelet cross spectrum (WCS) and wavelet coherence (WCOH), cross wavelet transform (XWT), R Peak detection.

1 . INTRODUCTION

EACH individual heartbeat in the cardiac cycle of the recorded electrocardiogram (ECG) waveform shows the time evolution of the heart's electrical activity, which is made of distinct electrical depolarization–repolarization patterns of the heart. Any disorder of heart rate or rhythm, or change in the morphological pattern, is an indication of some underlying pathology, which could be detected by the analysis of the recorded ECG waveform [1], [2]. Coronary heart disease is one of the dominant health concerns all over the world. The analysis of individual ECG beat's characteristic shape, morphological features, and spectral properties can give significantly correlated clinical information for automatic detection of the ECG pattern. However, automated classification of ECG beats is a challenging problem because the morphological and temporal characteristics of ECG signals show significant variation for different patients under different physical conditions.

Biomedical signals are intrinsically nonstationary because their underlying statistical properties change with time. This source of nonstationarity is intrinsic in the sense that the origins are physiological in nature. Coronary heart disease (CHD), also called coronary artery disease, is a condition in which plaque (plak) builds up inside the coronary arteries.These arteries supply oxygen-rich blood to the heart muscle. A heart attack occurs if the flow of oxygen-rich blood to a section of heart muscle suddenly becomes blocked. If blood flow isn't restored quickly, the section of heart muscle begins to die. The CHD remains the main cause of mortality in many region of the world, and several studies reveals the importance of reducing the time delay for treatment to improve the clinical outcome of the patients in case of acute coronary syndromes[3] . Good performance of an 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 detection and wave detection [4]-[6]. Wavelet transforms have been applied to ECG signals for enhancing late potentials [7], reducing noise [8], QRS detection [9], normal and abnormal beat recognition [10] and delineation of ECG characteristic features [11]. 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. A pathologically normal patient is selected as standard normal and an extracted beat is labeled, as the standard normal template beat. Other normal and abnormal ECG patterns are analyzed by subjecting them to XWT. Because of the morphological similarity with that of the QRS complex, db4 is selected as the mother wavelet. The application of CWT to two time series and the cross examination of the two decompositions reveals localized similarities in time and scale. The XWT and WC are used for cross examination of a single normal and abnormal (I MI) beat with that of a standard normal template beat. The summation of the coherence value over the QT zone is the distinguishing parameter established for classification. In this method we have used wavelet coherence because of its ability of good

Heart Rate Variability (HRV) is the physiological phenomenon of variation in the time interval between heart beats. It is measured by the variation in the beat-to-beat interval i.e. "cycle length variability", "RR variability" and "heart period variability" Reduced HRV has been shown to be a predictor of mortality after myocardial infarction [12, 13] although others have shown that the information in HRV relevant to acute myocardial infarction survival is fully contained in the mean heart rate [14]. The presented work mostly focused on the efficient way of detection of R-peak by this method and the HR calculation for ischemic signals.

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 ψ(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. For instance, power associated with irregular sampling does not contribute to the coefficients as in Fourier analysis, which is extremely helpful when using poorly sampled data.

B) Cross Wavelet transform (XWT)

The cross wavelet transform (XWT) of two time series *xn* and *yn* , is defined as

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

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 powerspectra P_k^X and P_k^Y is given by torrence and compo in [15].

C) Wavelet Coherence (WC)

Another useful measure is how coherent the cross wavelet transform is in time frequence space. Following, Torrence and Webster [16], the wavelet coherence of two time series is defined as

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

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

III. PROPOSED METHOD

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, a time normalization of each of the segmented beat is done. The cross wavelet analysis of the ECG beats reveals many significant characteristics. Heart rate can be calculated by accurately detecting the R peaks in the denoised signal using a threshold value.The following subsections illustrate the proposed technique. The block schematic in Fig. 1 shows the stepwise procedure.

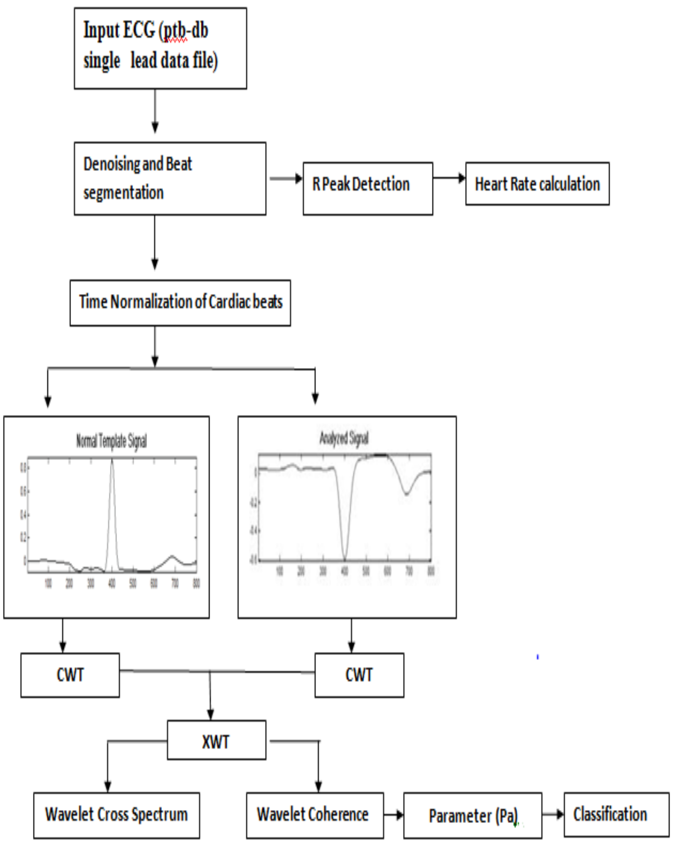

Fig1: Schematic representation of the method

1) Data

All the ECG data in this paper have been selected from the Physikalisch-Technische Bundesanstalt diagnostic 12-lead ECG database (ptbdb) of Physionet [17]. The ptbdb ECG diagnostic database contains 549 records from 290 subjects. with 52 healthy controls and 148 MI patients. The dataset is sampled at 1 kHz. The reason for choosing the ptbdb
is that this database has abundant and well-classified ECG recordings related to MI, and our main task in this paper is to detect MI from ECGs. In ptb-db, conventional simultaneously measured 12-lead data are presented. The inferior wall of the left ventricular cone is oriented to the standard leads II, III, and AVF. IMI will therefore be

reflected by the appearance of the classic features of hyperacute, fully evolved, and chronic stabilized phases in these leads. In the fully evolved phase, the standard lead III commonly reflects a QS complex and the standard leads II and AVF reflect QR complexes. Deviations of the ST segment and the T wave from normal pattern are also clinically significant.

Selection of a Standard Normal Template: A cardiac beat from a 25-year-old pathologically normal nonsmoking male subject with a heart rate of 72 beats/min is considered as the normal template for analysis. A beat ensemble from patient id: ptbdb/patient150/s0287lre is considered as the normal template. This normal template is validated using standard textbooks [18], [19] and also by visual inspection by doctors. *2) Denoising and beat segmentation*

The automatic delineation of the ECG is widely studied and algorithms are developed for QRS detection and wave detection. ECG signal is normally corrupted with several noises, some of which are of physiological origin and others external. These are power line frequency interference, baseline drift, electrode contact noise, polarization noise, muscle noise, electrosurgical noise and the internal amplifier noise. So, denoising of the signal is a pre requisite to the accurate analysis. The wavelet transform (WT) provides a description of a signal, decomposing it at different time–frequency resolution. WT is a well suited tool for analysis of non-stationary signals like ECG. The different wave components of ECG having separate frequencies, becomes clearly visible when subjected to multiresolution analysis. Moreover the various noise levels, which appear at different frequency bands and their contribution towards distortion of the signal, can be clearly identified .It is a decomposition of signal using a combination of a set of basis functions, obtained by means of dialation (scaling) and translation of a single prototype wavelet. The greater the scale factor, wider is the basis function and consequently, the corresponding components give the low frequency component of the signal and vice versa. In this way the temporal resolution is higher at high frequencies than at low frequencies.

The DWT analyses the signal at different resolution (hence, multiresolution) through the decomposition of the signal into several successive frequency bands. The DWT utilizes two set of functions ϕ (t) and φ(t), each associated with the low pass and the high pass filters respectively. These functions have a property that they can be obtained as the weighted sum of the scaled (dilated) and shifted version of the scaling function itself. Different scale and translation of these functions allows one to obtain different frequency and time localization of the signal. Decomposition of the signal into different frequency bands is therefore accomplished by successive low pass and high pass filtering of the time domain signal. The original time domain signal x(t) sampled at 1000 samples/s forms a discrete time signal x[n], which is first passed through a half-band high pass filter g[n], and a low pass filter h[n] along with down sampling by a factor of 2. Filtering followed by sub-sampling constitutes one level of decomposition, and it can be expressed as follows:

$$D1[k]=y_{high}[k]=\sum_n x[n]g[2k-n] \qquad (3)$$

$$A1[k]=y_{low}[k]=\sum_n x[n]h[2k-n] \qquad (4)$$

The DWT decomposition tree for a signal with 1 kHz of sampling frequency is shown in Fig. 2 The detail coefficients are designated as Dn and approximation coefficients as An, where n = 1–10

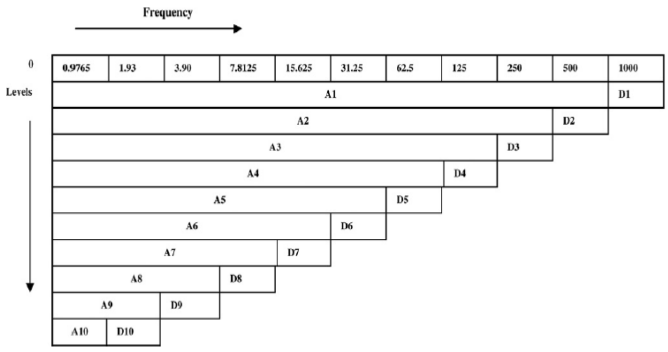

Fig 2 DWT decomposition structure.

In this stage the noise frequency identification and their elimination is carried out in two basic steps,(A) high frequency noise removal, (B) baseline wander correction and power line interference removal

3) High frequency noise removal

Electrosurgical noise and muscle contraction noise are high frequency noise. Electrosurgical noise completely destroys he ECG and without its removal an accurate feature extraction cannot be accomplished. The frequency content of this noise is 100 kHz–10 MHz. The muscle contraction noise has a frequency range from dc-10 kHz. These two noises are eliminated by discarding the detail coefficients D1, D2. After removal of these noises the remaining ECG signal ranges from 0 to 125 Hz.

4) Baseline correction and power line interference removal

The drift of the baseline is caused due to respiration and is likely to be as a nearly sinusoidal component and the frequency of respiration gets added to the ECG during its acquisition. The baseline variation frequency is 0.15– 0.8 Hz. Motion artifacts are transient baseline changes caused by change in the electrode skin impedance with electrode motion. The baseline disturbances caused by motion artifact can be assumed as a signal resembling one cycle of a sine wave and is within the frequency range of baseline drift. These two type of noises stated above can be eliminated by removal of the lowest frequency component, after decomposition of the ECG signal, coefficient A10 contains this frequency along with the DC component of the ECG. Discarding A10 frequency band and reconstructing the signal eliminates these two noises.

For, identification of the QRS frequency band, the detail coefficients D4 and D5 are selected, as together they contain most of the QRS information. A detailed description of this method can be found in [20], which is used as the basic
feature extraction technique for this work.

5) 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 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 1000 samples. The time normalization is important for comparability of two different patterns and finding out notable differences and variations.

6) XWT on ECG Beats

Cross-correlation is a measure of similarity between two waveforms. Application of CWT to two time series and the cross examination of the two decompositions reveals localized similarities in time and scale (scale being nearly inverse of frequency) and divulge various characteristic information of the signal under study. As shown in Fig. 3 and 4, the result of XWT of two signals generates the WCS and WCOH. WCS and WCOH are used for cross examination of a single normal and abnormal (IMI) beat with a standard normal template beat. The resultant Wavelet Cross spectrum (WCS) shows the spectral components of interest. The Wavelet Coherence (WC) is used for the purpose of analysis.

7) Parameter Extraction for Classification

The WC is a matrix containing the coherence between two signals. A classification parameter for grouping of normal and abnormal subjects is obtained from this matrix. The QT zone being the pathological region is selected for parameter extraction. A span of 80 points from the left of the R peak and 200 points right to the R peak is the QT zone. Let

WCOH be the matrix containing the coherence and t1 to t2 is the start and end of QT zone respectively. It has been empirically determined that significant features, dominating the analysis is prominent in the scale range of s1=250 to s2=400. So the parameter pa is given by,

$$\text{Pa} = \sum_{s1}^{s2} \sum_{t2}^{t1} WCOH \qquad (5)$$

The scatter plot for Pa value of several samples gives a discriminating threshold value (TH), used for distinction between two classes. Any value of pa, greater than TH signifies normal else is classified as abnormal.

IV. HEART RATE MEASUREMENT

The proposed thresholding based beat counting is simple and efficient algorithm which is briefly described below:

Algorithm: Step 1: Determining the threshold value (T) of the ECG signal:

$$\frac{\text{Max}-\text{Mean}}{2} \text{ of the ECG Signal.}$$

Step2: R-Peak detection of ECG signal: (Let, x= sample value of R-peak) Then, detect x, if

$$X\text{-}1<x>x+1 \ \& x>Th$$

Step 3: Heart Rate Calculation:

HR or BPM= No. of R-Peaks Detected/Duration

V. CONCLUSION

In this paper, methods for classification of ECG pattern and its heart rate measurement are proposed. The application of CWT to two time series and cross examination (XWT and WC) of two decompositions reveals localized similarities in time and scale. From, the analysis it was found that wavelet coherence reveals great insight into the dissimilarities of data, it is being presentedwith. The extracted parameter *pa* obtained from the summation of coherence over the significant scale range of gives a distinguishing threshold value. This threshold value is used for classification of normal and MI subjects .The developed algorithm(using threshold) has been showing promising results in detecting R-peak & calculating the Heart rate from normal and ischemic patient's data

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