IARJSET

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
National Conference on Emerging Trends in Engineering and Technology (NCETET'16)
Lourdes Matha College of Science & Technology, Thiruvananthapuram
Vol. 3, Special Issue 3, August 2016

Adaptive Hierarchical Clustering Based ECG Pattern Classification

Mebby Jasmin Benny[1], Divya Subhash[2]

PG Student, Department of Electronics, Applied Electronics and Instrumentation, Lourdes Matha College of Science and Technology, Kerala, India [1]

Department of Electronics, Faculty of Biomedical Engineering, Lourdes Matha College of Science and Technology, Kerala, India [2]

Abstract: This paper gives a review of ECG analysis using cross wavelet transform method. 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 algorithm analyzes ECG data utilizing XWT and explores the resulting spectral differences. Hierarchical clustering 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. The accuracy is higher than normal wavelet denoising and threshold based classification

Keywords: Hierarchical clustering, wavelet cross spectrum, wavelet coherence,

I. 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. 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. Good performance of any automatic ECG analyzing system depends upon the reliable and accurate detection of the basic characteristic features of the signal under study. QRS detection is necessary to determine the heart rate and is used as the reference point for beat alignment. Automatic delineation of the ECG has been widely studied, and many algorithms have been developed for QRS detection and fiducial point identification. ECG analysis algorithms operate on ECG data samples and generate automatic outputs, including morphology, time-interval measurements, and rhythm analysis. ECG signals are intrinsically non stationary in nature. This makes wavelet transforms an effective tool for the analysis of ECG signals. Wavelet transforms have been applied to ECG signals for enhancing late potentials, reducing noise, QRS detection; normal and abnormal beat recognition, and delineation of ECG characteristic features. The methods used in these studies were conducted through continuous wavelet transform (CWT), multi resolution analysis, and dyadic wavelet transform. Classification of ECG beats is a challenging problem because the morphological and temporal characteristics of ECG signals show significant variations for different patients. Many classification methods with distinguishing characteristics have been developed using neuro-fuzzy and self-organizing maps. Classification problems specific to myocardial infarction and ischemia are addressed, where the time plane characteristics of the signal are employed for classification. A PC-based virtual instrument was used as a testing plat-form for acquiring, processing, presenting, and distributing ECG data. A very large scale integration implementation of a linear-phase digital filter for ECG signal processing has been designed, and the developed circuit is said to have very low computational complexity. A model based on the hid-den Markov tree for ECG delineation technique is developed. An approach for human identification using standard 12-lead ECG recorded during rest is investigated. Most of the classification methods use explicit time-plane features such as ST segment, R height, T height, etc. Apart from the measurement accuracy issues of the extracted features, a large feature set is obtained when time-plane features are used for classification. As a result, rule mining techniques are employed for feature set reduction, which increases the computational

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
National Conference on Emerging Trends in Engineering and Technology (NCETET'16)
Lourdes Matha College of Science & Technology, Thiruvananthapuram
Vol. 3, Special Issue 3, August 2016

II. WAVELET TRANSFORM

The wavelet transform or wavelet analysis is probably the most recent solution to overcome the shortcomings of the Fourier transform. In wavelet analysis the use of a fully scalable modulated window solves the signal-cutting problem. The window is shifted along the signal and for every position the spectrum is calculated. Then this process is repeated many times with a slightly shorter (or longer) window for every new cycle. In the end the result will be a collection of time-frequency representations of the signal, all with different resolutions.

The fundamental idea of wavelet transforms is that the transformation should allow only changes in time extension, but not shape. This is effected by choosing suitable basis functions that allow for this. Changes in the time extension are expected to conform to the corresponding analysis frequency of the basis function. Based on the uncertainty principle of signal processing,

$$\Delta t \Delta \omega \geqq \frac{1}{2}$$

where t represents time and ω angular frequency (ω = 2πf, where f is temporal frequency).

The higher the required resolution in time, the lower the resolution in frequency has to be. The larger the extension of the analysis windows is chosen, the larger is the value of Δt.

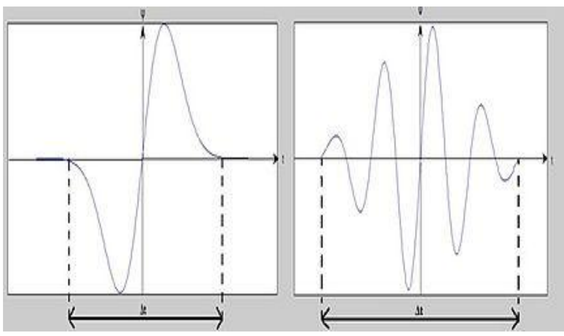
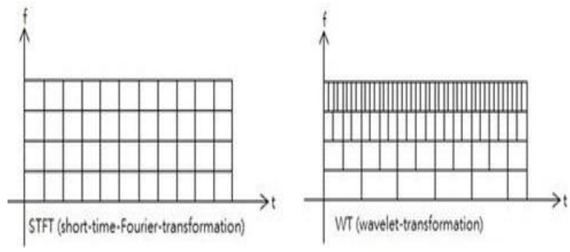


Fig.1. Diagram of proposed scheme. (a) Basic function with compression factor

When Δt is large,
Bad time resolution
1. Good frequency resolution
2. Low frequency, large scaling factor

When Δt is small
1. Good time resolution
2. Bad frequency resolution
3. High frequency, small scaling factor

In other words, the basis function Ψ can be regarded as an impulse response of a system with which the function x(t) has been filtered. The transformed signal provides information about the time and the frequency. Therefore, wavelet-transformation contains information similar to the short-time-Fourier-transformation, but with additional special properties of the wavelets, which show up at the resolution in time at higher analysis frequencies of the basis function. The difference in time resolution at ascending frequencies for the Fourier transform and the wavelet transform is shown below.



This shows that wavelet transformation is good in time resolution of high frequencies, while for slowly varying functions, the frequency resolution is remarkable.

III. PROPOSED SYSTEM

The most widely used signal in clinical practice is the ECG. ECG conveys information regarding the electrical function of the heart, by altering the shape of its constituent waves, namely the P, QRS, and T waves. Thus, the required tasks of ECG processing are the reliable recognition of these waves, and the accurate measurement of clinically important parameters measured from the temporal distribution of the ECG constituent waves. In this paper a new hierarchical Clustering strategy with adequate robustness against noise, artifacts and arrhythmic outliers is proposed. Also this work deals with problems of power line interference reduction using Power line interference filter.

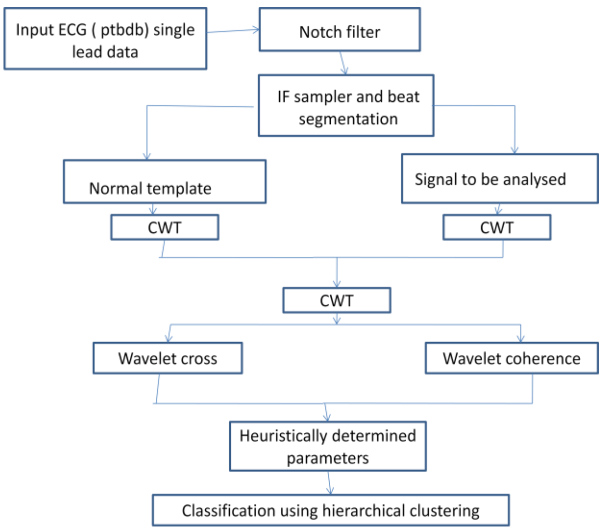


Figure 2: Flow chart for analysis

A. Material and developed method

All the ECG data in this paper have been selected from the Physikalisch-Technische Bundesanstalt diagnostic 12-lead

IARJSET

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
National Conference on Emerging Trends in Engineering and Technology (NCETET'16)
Lourdes Matha College of Science & Technology, Thiruvananthapuram
Vol. 3, Special Issue 3, August 2016

ECG database (ptbdb) of Physionet [7]. The ptbdb ECG diagnostic database contains 549 records from 290 subjects accomplished 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.

B. Denoising and R-Peak Registration

Denoising of ECG data is an essential step before any form of analysis because this increases the efficiency of the algorithm. Signal processors use analog to digital converters (ADC) to represent a given signal using uniform sampling, which relies on a worst case condition, i.e., Nyquist criterion to represent a band limited signal. However, this type of sampling also referred to as redundant sampling is not efficient in applications, where only specific regions are of interest. For example, in biomedical signals such as ECG the regions of interest are P,Q,R, S, and T. waves only, and hence a sampler tuned to these specific regions is desirable. The input dependent samplers concentrate on the high amplitude regions of interest in the signal and under represent the relatively lower amplitude noisy background, thereby reducing the overall bandwidth to sub-Nyquist rate.

The IF model is inspired by a simplified biological neuron operation from computational neuroscience. Time encoding models based on IF have been proposed in the past [1], [2] especially with regard to discrete, continuous time asynchronous sigma-delta modulators. Recent research has shown that the IF model can be considered a sampler [3]–[6], with its output codifying the variation of the integral of the signal. Information in an IF encoded signal is in the timing between events referred to as pulses. The block level schematic of the IF sampler is shown in Fig. 3.

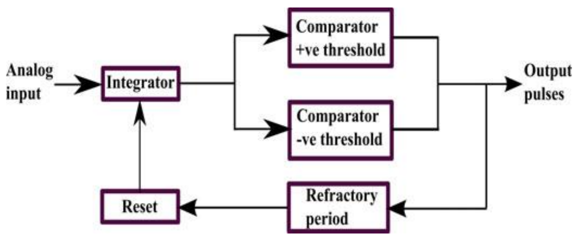
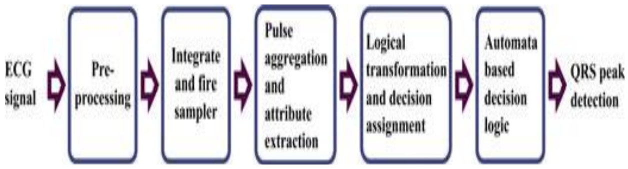


Fig. 3 Block level schematic of IF sampler

The block diagram of the proposed QRS detection algorithm is shown in Fig. 4. The preprocessed ECG signal is converted into a train of pulses using the IF sampler. The pulse train is aggregated online into different pulse segments and each segment is represented by a set of attributes which serve as descriptors of the pulse train. The proposed decision logic is based on morphological checking. The attributes of the pulse segment are transformed into a set of logical values. Based on the logical values, different automata-based decision rules are executed and QRS complexes are detected.



. Fig. 4 QRS detection block diagram

C. Wavelet transform and hierarchical clustering

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. 2, 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. Because of the morphological similarity with that of the RS complex, the Mor let wavelet is selected as the mother wavelet for analysis. XWT gives a relationship between the two signals in timescale space. In this analysis, 512 scales are considered. The resultant WCS shows the spectral components of interest. Figs. 5–6 show the distinguishing regions R1, the RS complex region, and R2, the T-wave region. It is evident from the color-coded plots that there exist distinct variations in the spectral and coherence components, revealing the nature of the analyzed signals. After analysis, parameter extraction formulas are developed for classification of normal and abnormal cardiac patterns.

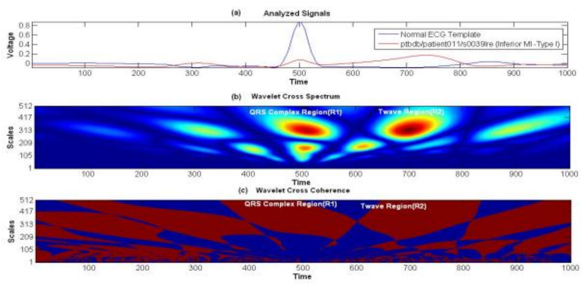


Fig. 5 WCS and WCOH between the standard normal template and an abnormal ECG (IMI–Type1)

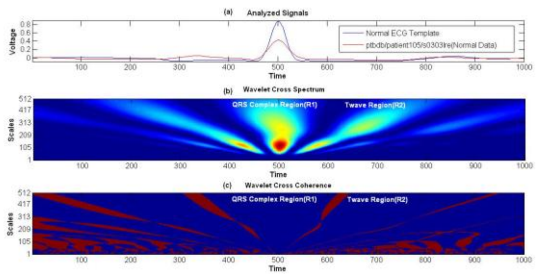


Fig.6. WCS and WCOH between the standard normal template and normal ECG data

Hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. Strategies for hierarchical clustering generally fall into two types:

- Agglomerative: This is a "bottom up" approach: each observation starts in its own cluster, and pairs of clusters are merged as one moves up the hierarchy.
- Divisive: This is a "top down" approach: all observations start in one cluster, and splits are performed recursively as one moves down the hierarchy.

In general, the merges and splits are determined in a greedy manner. The results of hierarchical clustering are usually presented in a dendrogram. In the general case, the complexity of agglomerative clusters which makes them too slow for large data sets. Divisive clustering with an exhaustive search which is even worse

Cluster dissimilarity

In order to decide which clusters should be combined (for agglomerative), or where a cluster should be split (for divisive), a measure of dissimilarity between sets of observations is required. In most methods of hierarchical clustering, this is achieved by use of an appropriate metric (a measure of distance between pairs of observations), and a linkage criterion which specifies the dissimilarity of sets as a function of the pairwise distances of observations in the sets.

IV.CONCLUSIONS AND FUTURE WORK

The method presented in this paper subjects the ECG beat patterns to wavelet transform and then explores the existing spectral variations between two signals. The ECG datasets are preprocessed for the removal of artifacts and other noise before subjecting them to XWT-based analysis. If noisy beats are used as input to the system, the power line interference is removed by using a notch filter. However, other noises will not affect the system because after CWT decomposition they will reside in a different scale range. Unlike other existing methods, this algorithm does not require extraction of explicit time-plane features. The classification is based hierarchical method and time required to compute it reduces significantly The work reported here may be extended for 12-lead ECG data classification for differentiating different types of MI by examining various lead groups. Some preliminary investigations have shown that the parameter values pp and pa obtained from regions R1 and R2 can be used for ST-type and Q-type MI. We also propose to cover the arrhythmic disease class through our system. This also provides scope for further research work on these issues.

REFERENCES

[1] A. A. Lazar, “Time encoding with an integrate and fire neuron with a refractory period,” Neurocomputing, vol. 58–60, pp. 53–58, Jun. 2004.
[2] A. A. Lazar, E. A. Pnevmatikakis, and Y. Zhou, Encoding natural scenes with neural circuits with random thresholds,” Vision Res., vol. 50, no. 22, pp. 2200–2212, Oct. 2010, (special Issue on Mathematical Models of Visual coding).
[3] H. Feichtinger, J. Principe, J. Romero, A. Alvarado, and G. Velasco, “Approximate reconstruction of bandlimited functions for the integrate and fire sampler,” Adv. Comput. Math., vol. 36, pp. 67–78, 2012.
[4] A. Alvarado, J. Principe, and J. Harris, “Stimulus reconstruction from the biphasic integrate-and-fire sampler,” in Proc. 4th Int. IEEE/EMBS Conf Neural Eng., May 2009, pp. 415–418.
[5] A. Alvarado, C. Lakshminarayan, and J. Principe, “Time-based compression and classification of heartbeats,” IEEE Trans. Biomed. Eng., vol. 59, no. 6, pp. 1641–1648, Jun. 2012.
[6] M. Rastogi, A. S. Alvarado, J. G. Harris, and J. C. principe,“Integrate and fire circuit as an ADC replacement,” in Proc. IEEE Int. Sym. Circuits Syst., May 2011, pp. 2421–2424.
[7] (2012). PTB Diagnostic ECG Database Directory, physiobank Archive Index, PTB Diagnostic ECG Database [Online]. Available: <http://physionet.org/physiobank/database>

BIOGRAPHHY

Mebby Jasmin Benny has completed her Bachelor's degree in engineering in Applied Electronics and Instrumentation from Saintgits College of Engineering, Kottayam Kerala, India (2014) and presently pursuing Master of Technology in the department of Applied Electronics and Instrumentation Engineering in Lourdes Matha College of Science and Technology, Kerala, India.