ISSN: 2347-6540

International Journal of Latest Research In Engineering and Computing (IJLREC)
Volume 3, Issue 2 , Page No. 1-6 March-April 2015
www.ijlrec.com

DETECTION OF CARDIAC ARRHYTHMIA THROUGH CONTINUOUS WAVELET TRANSFORM

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ABSTRACT

Biomedical signals like heart wave tend to be non stationary. To analyze this kind of signals wavelet are a powerful tool. Automatic detection of arrhythmias is importantfor diagnosis of heart problems. However, inElectrocardiogram(ECG) signals, there is significant variation of waveformsin both normal and abnormal beats. It is this phenomenon,which makes it difficult to analyze ECG signals.The aim of developing methodology is to distinguishbetween normal beats and abnormal beats in an ECGsignal.In this paper we make use of wavelets to filter and analyze noisy ECG signals.With our proposed methods, the normal beatsand abnormal beats formed different clusters of vectorpoints. By eliminating normal beats which occur beforeand after the abnormal beats, the clusters of differenttypes of beats showed more apparent separation.The combination of wavelet decomposition the classification using feature vectors of thebeats in ECG signals separate abnormal beats fromnormal beats. The elimination of the normal beatswhich occur before and after the abnormal beats succeededin minimizing the size of normal beats cluster.

Keywords: ECG, wavelet transform

I. INTRODUCTION

The electrocardiogram (ECG) is the record of the electrical activity of the heart and provides fundamental information about its electrical instability being the most significant bio signal used by cardiologists for diagnostic purposes. A trial fibrillation (AF) is perhaps the most common arrhythmia encountered in clinical practice, affecting about 0.5-1% of the general population. AF is not only related to frequent symptoms and reduced quality of life but also constitutes a major risk factor for stroke and mortality from cardiovascular and all other causes [1].

A Fpathology is usually diagnosed based on ECG analysis. Normally continuous monitoring over an extended period of time is required in order to increase the understanding of patients' cardiac abnormalities. Such situations require continuous monitoring by the physicians or alternatively the aid of automated arrhythmia detection equipment, which can be able to identify different types of arrhythmias. This problem of cardiac arrhythmia detection can be viewed as a pattern recognition problem, since it is possible to identify a finite number of different patterns(arrhythmias).Hidden Markov Models have been successfully applied to pattern recognition problems in applications spanning automatic speech recognition [2], image segmentation [3],ECG modelling [4] and cardiac arrhythmia analysis [5]. The most common approach regarding HMM training is finding the stochastic distribution that best fits the data. Usually this data is derived from the waveform from some type of signal processing usually known as feature extraction method.

The most classical technique for feature extraction in the HMM framework is perhaps the linear segmentation where the ECG is segmented in straight line segments. More recently advanced signal processing techniques as Fourier Transform, Linear Predictive Analysis, Lyapunov Functions[6] and Multivariate Analysis (MA) have been used in order to overcome some limitations of the linear segmentation. Multivariate Analysis allows observing the signal at various scales emphasizing some hidden particularities not viewed at other scales. Wavelet Analysis is perhaps the most common form of multivariate analysis. Recently Wavelet Analysis was been successfully combined with Hidden Markov Models (HMMs) especially regarding ECG segmentation [7].

This paper reports the performance of two types of extraction feature methods evaluated under the conventional HMMs framework. The considered feature extraction methods are the classical linear segmentation [4],[8] where the ECG signal is linearized in order to discard some linear redundancy and the wavelet transform where the signal is simultaneously viewed at different scales. The wavelet transform has the advantage over conventional techniques that time/frequency representation can be more accurately modelled by decomposing the signal in the corresponding scales. When the composition level decreases in the time domain it increases in the frequency domain providing zooming capabilities and instantaneous characterization of the signal [9]. This time/frequency
Representation which preserves both global and local information seems to be more adequate than linear segmentation for local characterization of the signal. In this paper, the combined technique of wavelet decomposition and feature

extraction was applied to an ECG signal. This method has previously been applied successfully to classify other signals [10].Abnormal cardiac activities are reflected on an ECG signal as abnormal beats. However, it is thought that even normal beats may be influenced by these abnormal activities. Therefore by eliminating those normal beats which occur before and after the abnormal beats from the collection of normal beats, separation between normal and abnormal beats can be shown more clearly.

The aim of developing methodology is to distinguish between normal beats and abnormal beats in an ECG signal. In ECG signals, there is significant variation of waveforms in both normal and abnormal beats. It is this phenomenon, which makes it difficult to analyse ECG signals. Figure 1.1 shows the ECG signal analysis flow. The signal processing technique presented in this paper consists of two stages: the wavelet decomposition stage and the feature extraction stage. The details of each stage are described next.

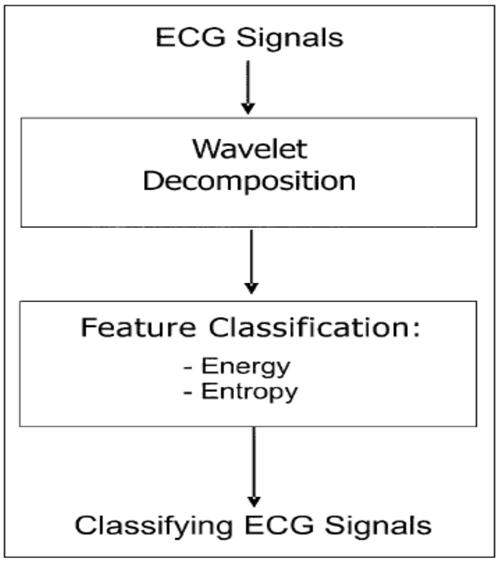


Fig 1.1.ECG Signal analysis flow

II. ANALYSIS METHOD

A) Wavelet Decomposition

The first step of wavelet decomposition is to select an appropriate wavelet for the signal to be analysed. Appropriate wavelets should have a wave shape, which is close to the signal to be analysed or filtered.

Convolving the wavelet function with the original signal produces the equivalent of a high-pass filter (or a low-pass filter), resulting in the details (or the approximation) of the signal [11], see Figure 2.1.Abnormal ECG signals were obtained from the Physio net Database [12]. A set of programs from the Physio net was used to import ECG records each of which consists of data file, attribute file and header file to Matlab and its Wavelet toolbox were used for ECG signal processing and analysis. Using wavelet packet decomposition command, ‘wpdec’ in Matlab [13], each signal above was decomposed to Level 4.The wavelet ‘bior5.5’ was selected because of the similarity its wave-form to ECG signals. The start ofthe QRS complex was defined as the beginning of the each beat. This information was extracted from the attribute file of the record.

B) Feature Extraction

The purpose of feature extraction is to select and retain relevant information from the original signals. Normalized energy and entropy are selected as the features of signals because these features have been shown to distinguish normal signals from abnormal signals in other applications [12].

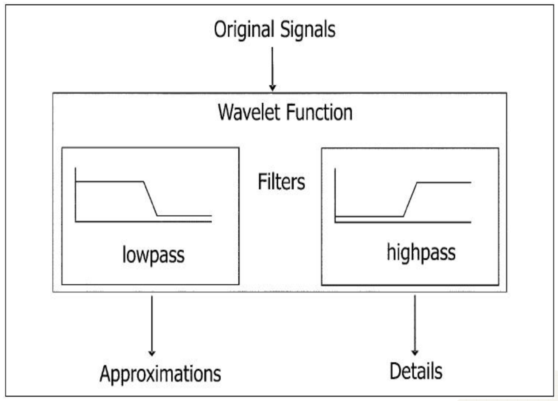


Fig. 2.1 Wavelet Decomposition

(i) ***Normalized Energy:***

The normalized energy at decomposition level*n* for each beat was calculated as follows:

$$E(j)_n = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - m)^2 \qquad (1)$$

(j: beat number, N: number of samples in one beat, i: sample number, n: decomposition level, m: sample mean)The energy of each beat, $E(j)_n$, was then normalized across the decomposition levels, which allows comparison between the decomposed signals in different levels. The normalized energy $E(j)_{norm_n}$of the beat j at decomposition level n is defined as:

$$E(j)_{norm_n} = \frac{E(j)_n}{\sqrt{E(j)_1^2 + E(j)_2^2 + E(j)_3^2}} \quad (2)$$

(j: beat number,n: decomposition level)

(ii)*Entropy:*

The entropy of a signal is a measure of the randomness of the signal. In other words, it can be viewed as a measure of uncertainty[15]. Entropy has been shown to be effective in dealing with complex biological signals, such as electroencephalogram (EEG) [14].The classical log energy entropy was used in this study. The entropy $Ent(j)_{log_n}$ofthe beat *j* at decomposition level *n* was obtainedas follows :

$$Ent(j)_{\log\_n} = \sum_{i=1}^{N} \log(x_i^2) \qquad (3)$$

(j: beat number,n: decomposition level, N:sample size, i:sample number)

(iii) Normalization:

Those normal beats which do not occur before or after the abnormal beats are defined as ‘pure’ normal beats. The wave shapes ofthese ‘pure’ normal beats are thought tohave no effect of the abnormal beats. The average values of normalized energy $E_{NB}$and entropy $Ent_{NB}$of normal beats (*NB* =normal beat) were calculated using the collection of the ‘pure’ normal beats.The values of both normalized energy and entropy were divided by the average values of the ‘pure’ normal beats obtained above (see formulas below).

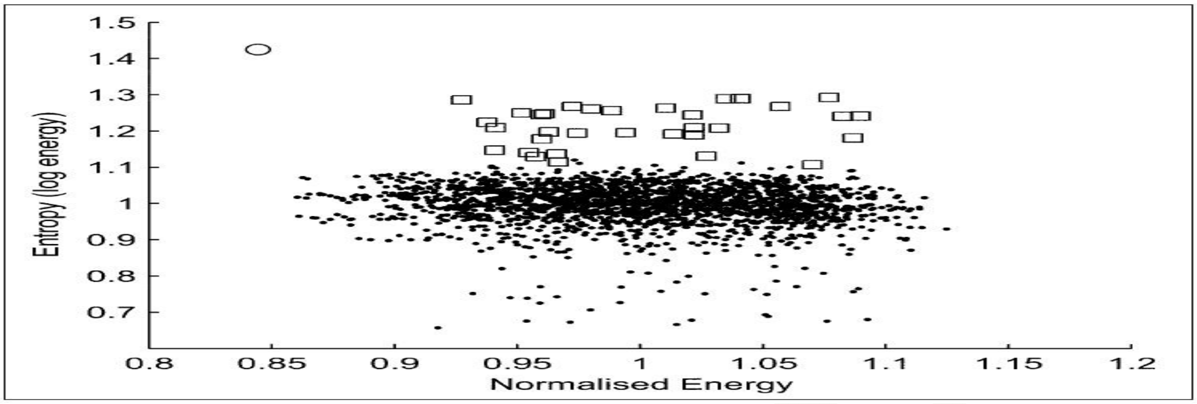
$$E_{ratio}(j)_n = \frac{E(j)_{norm\_n}}{E_{NB}} \qquad (4)$$

$$Ent_{ratio}(j)_n = \frac{Ent(j)_{\log\_n}}{Ent_{NB}} \qquad (5)$$

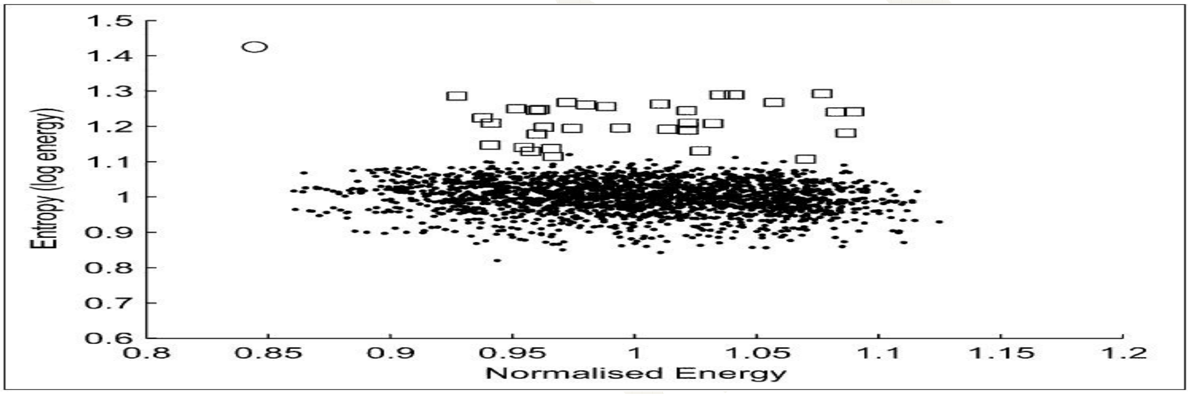
Each beat of the decomposed signals at each decomposition level now has two features: normalized energy: $E_{ratio}(j)_n$and entropy:$Ent_{ratio}(j)n$By plotting the feature vectors of different types of known beats of a signal, groups of vector points, known as clusters can be obtained. It was expected that a trial premature form a different cluster to normalbeats.

III. SIMULATION RESULTS

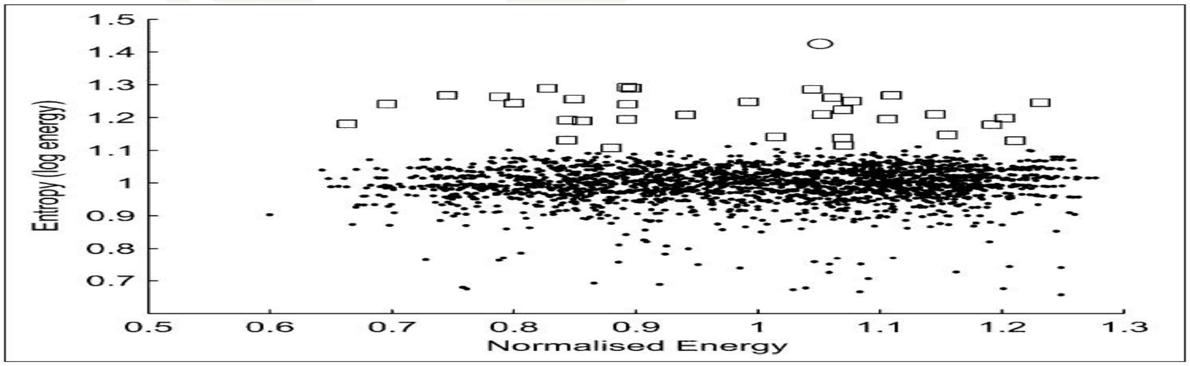
The approximate information of the ECG signals is used to investigate if there is any difference in the two methods: Method 1 – using all normal beats – and Method 2 – with the elimination of normal beats which occur before and after the abnormal beats. Figures 3.1 and 3.2 are the signal processing results of the record number db/100, at the decomposition level 1. Figures 3.3 and 3.4 are the results of the same record, but at the decomposition level 3. All results show the clear separation in the clusters of normal and atrial premature beats. Table 3.1-3.4 records all the simulation results for various decomposition level.



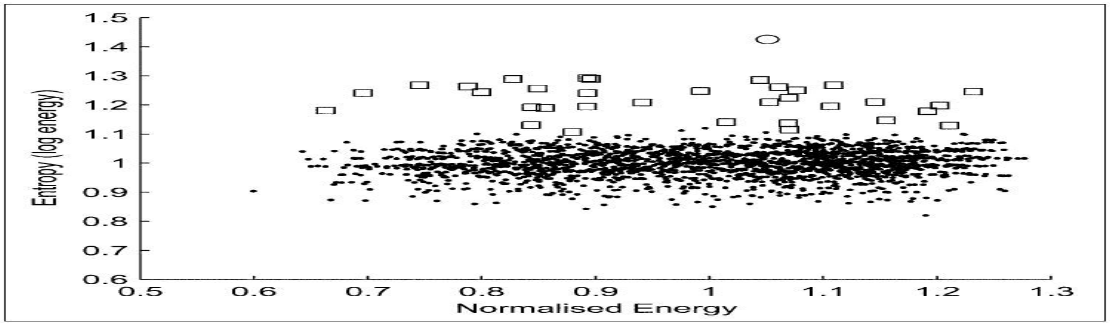
●normal beats, □ atrial premature beats,
○: premature ventricular contractions
Fig.3.1 bior4.6, decomposition level:1 with Method 1



●normal beats, □ atrial premature beats,
○: premature ventricular contractions
Fig.3.2 bior4.6, decomposition level:1 with Method 2



●normal beats, □ atrial premature beats,
○: premature ventricular contractions
Fig.3.3 bior4.6, decomposition level:3 with Method



●normal beats, □ atrial premature beats,
○: premature ventricular contractions
Fig.3.4 bior4.6, decomposition level:3 with Method 2

Entropy is an intuitive parameter in the sense that one can visually distinguish a regular signal from an irregular one. Entropy describes the irregularity or complexity or unpredictability characteristics of a signal.10 An ECG signal which is regular, both in rate and amplitude (voltage) has an entropy value of near zero whereas an irregularly irregular ECG trading has a very high entropy value and the entropy value of a regularly irregular ECG wave form falling in between. The wave forms of entropy value of zero or near zero are predictable and those with very high entropy value (for eg.100) are totally unpredictable.

Table:3.1Normalized Entropy Vs Energy –Wavelet Decomposition Level-1(Method-1)

Sr. No.	ECG Signal	No. of Samples	Entropy	Energy
1	Normal Beats	50	0.9 – 1.1	0.5 – 1.3
2	Atrial premature beats	50	1.2 – 1.3	0.5 – 1.3
3	Premature Ventricular Contractions	50	1.4 – 1.5	0.5 – 1.3

Table:3.2Normalized Entropy Vs Energy –Wavelet Decomposition Level-1(Method-2)

Sr. No.	ECG Signal	No. of Samples	Entropy	Energy
1	Normal Beats	50	0.85 – 1.1	0.5 – 1.3
2	Atrial premature beats	50	1.1 – 1.3	0.5 – 1.3
3	Premature Ventricular Contractions	50	1.3 – 1.5	0.5 – 1.3

Table:3.3Normalized Entropy Vs Energy –Wavelet Decomposition Level-3(Method-1)

Sr. No.	ECG Signal	No. of Samples	Entropy	Energy
1	Normal Beats	50	0.85 – 1.1	0.5 – 1.3
2	Atrial premature beats	50	1.1 – 1.3	0.5 – 1.3
3	Premature Ventricular Contractions	50	1.3 – 1.5	0.5 – 1.3

Table:3.4Normalized Entropy Vs Energy –Wavelet Decomposition Level-3(Method-2)

Sr. No.	ECG Signal	No. of Samples	Entropy	Energy
1	Normal Beats	50	0.9 – 1.1	0.5 – 1.3
2	Atrial premature beats	50	1.2 – 1.3	0.5 – 1.3
3	Premature Ventricular	50	1.4 – 1.5	0.5 – 1.3

IV CONCLUSION

The wavelet entropy computed from the wavelet transform has been applied to the ECG. Entropy is related to the degree of irregularity of a signal. A signal with regular patterns has a low entropy value but a disordered signal shows a high entropy value. The combination of wavelet decomposition and the classification using feature vectors of the beats in ECG signals distinguishes abnormal beats and normal beats. The elimination of the normal beats which occur before and after the abnormal beats can minimize the size of normal beats cluster, which is useful for the accurate classification. In a normal heart, propagation of the energy can travel through the myocardium easily and homogeneously, thus resulting in the high energy. In a damaged heart, the energy cannot be transferred within the myocardium easily, thus the low energy is produced. Results of the Continuous Wave Transform (CWT) energy showed that the patient with Ventricular Late Potentials would appear to have lower energy within the terminal QRS complex than the patient without.

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