ECG - QRS detection method adopting wavelet parallel filter banks

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Abstract: - Due to the possibility to have temporal and spectral informations simultaneously adopting wavelet transforms, wavelet filter banks are frequently used in signal processing and communication systems. The inherently sequential structure of wavelet theory does not merge efficiently with modern techniques such as parallel processing, concurrent programming and implementation in design tools. In this paper a real-time signal processing technique adopting a fast parallelized algorithm for QRS complex locations is presented. The obtained performance shows the method validity as results with minimum interferences from noise and artefacts have been obtained.

Key-Words: - ECG, QRS, wavelet transform, parallel filter bank, signal processing, parallel computing

1 Introduction

The Electrocardiogram (ECG) is obtained by recording the potential difference between two electrodes placed on the surface of the skin. Therefore it is a non invasive technique that allows the visualization of the heart electrical activity. ECG is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax. The ECG signal analysis is widely used for the cardiac disease diagnostic [1] and consequently for urgent treatments of ill patients.

The QRS detection is the most important task in ECG signal analysis systems. In fact after the QRS identification, the heart rate may be calculated and other parameters can be examined to avoid serious pathologies such as ischemia.

The used ECG detectors generally include a bandpass filter with a centre frequency in the range of 10-17 KHz [2], [3], [4]. After passing through the bandpass the signal may be squared. A short time energy estimate is obtained by smoothing the resulting signal with a moving window integration. The duration of the window and the choice of the bandwidth of the filter is a difficult task. In fact, the choice of a suitable bandwidth is a trade off between noise reduction and high frequency details: adopting a too large bandwidth, noise reduction suffers while with too narrow band high frequency QRS details are lost. The duration of the sliding window is a trade off between false and missed detections.

This technique mainly suffers from two problems:

- the signal frequency band of the QRS complex is different for different subjects and even for different beats of the same subject;
- noise and QRS complex pass bands overlap.

Due to the non linear behaviour of the human body, all processing methods should change their state during measurement. The design of an optimal matched filter could increase the SNR ratio but the non stationary behaviour of ECG signal and noise represent a limit to its applicability.

Within the last decade many new approaches to QRS detection have been proposed; for example genetic algorithms, procedures adopting artificial neural networks, filter banks, heuristic methods based on nonlinear transforms and wavelet transforms [4], [5], [6], [7].

In this paper an improved signal processing technique able to provide an easy implementation in design tools is presented. It adopts the wavelet transform for R characteristic point detection. Moreover, for parallel computing and for implementation in design tool, parallel filter banks have used in the adopted technique. Experimental results show the method validity and its high sensitivity and predictivity parameters. In fact, results with minimum interferences from noise and artifacts have been obtained.

2 ECG Technique

A single normal cycle of the ECG represents the successive atrial depolarization/repolarization and ventricular depolarization/repolarization which occurs with every heartbeat.

Each beat of the hearth produces a series of deflections away from the baseline on the ECG heartbeat produces a single normal cycle of the ECG that is indicated with the letters P, Q, R, S and T (fig.1) [8].

The ECG signal can be divided into the following sections:

- P wave: it represents the atria activation (depolarization). The first half of the P wave is the activation of the right atrium, whereas the second half is the activation of the atria septum and the left atrium. The normal shape of the P wave does not include any notches or peaks and its duration can vary between 0.08 and 0.11 sec. in normal adults.
- PQ interval: it represents the time between the beginning of atrial depolarization and the beginning of ventricular depolarization
- The QRS complex is a general term representing activation in the ventricles and is a result of the depolarization of the ventricles.. The Q and S waves represent negative (downward) deflections on the plot of the lead, and the R wave represents positive (upward) deflection. The duration is normally less than 100ms a higher value can reflect an abnormality due to intraventricular conduction.
- The T wave results from ventricular repolarization, whereby the cardiac muscle is prepared for the next cycle of the ECG. The normal morphology of the T wave is rounded and asymmetrical
- The S–T segment is measured from the end of QRS complex to the onset of the T wave. This segment represents the early stage of ventricular repolarization and under normal conditions is isoelectric (constant potential). A marked displacement of the S–T segment signifies coronary artery disease
- The P–R interval represents the atrioventricular (AV) conduction time, i.e. the time required for the electrical impulse to propagate from the sinus node through the atrium and the AV node to the ventricles (which results in ventricular depolarization). The normal range of the P–R interval is 120ms to 200ms. This interval can vary with heart rate.
- The Q–T interval reflects the total duration of ventricular systole, and is measured from the onset of the QRS complex to the end of the T wave. Normally the Q–T interval is less than half the preceding R–R interval. A long QT interval can be associated with heart failure, ischaemic heart disease, bradycardia, some electrolyte disorders (e.g. hypocalcaemia) and can be consequence of different drugs taking.

signal. These deflections represents the time evolution of the heart electrical activity. One

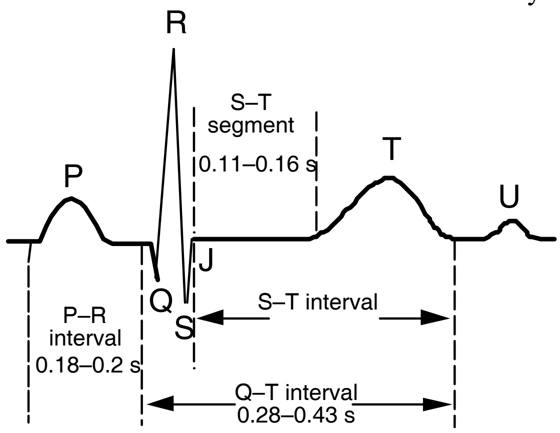

Fig.1 ECG characteristic shape

Frequently the ECG signal is corrupted by noise. Baseline wander and 50Hz power line are predominant interference sources. Baseline wander is mainly caused by patient breathing, movement, bad electrodes, improper electrode site preparation, etc; The frequency range of baseline wander is usually below 0.5Hz, which is close to the frequency range of ST segments. For this reason, this type of noise can easily lead to false diagnosis. Eliminating the baseline wander and the power line interference in ECG signals are usually the necessary preprocessing step to enhance the signal characteristics for diagnosis [9].

3 Wavelet Transform Principles

Wavelet transform provides temporal and spectral information simultaneously, so it is suited for determining characteristic points of non stationary and fast transient signals, such as ECG signals. This feature is suitable to distinguish the ECG signal from noise and interferences.

The wavelet method decomposes a time variant signal into several components having various scales or resolutions. A suitable time and frequency limited wavelet is chosen as the “mother”. Scaling and shifting the mother wavelet, a family of functions called “daughter” wavelets is generated. For small value of the scale factor, wavelet is constructed in the time domain and gives information about fine details of signals. Therefore a global view of the signal is obtained by the scale factor large value. The wavelet transform of a time signal at any scale is the convolution of the signal and a time-scaled daughter wavelet.

There are essentially two types of wavelet decompositions: the redundant ones (continuous wavelet transform)), and the nonredundant ones

(orthogonal, semi-orthogonal, or biorthogonal wavelet bases) [10]. The first type is preferable for feature extraction because it provides for a description that is truly shift-invariant. The second type is preferable for data reduction, or when the orthogonality of the representation is an important factor. However, the choice between these types of decompositions has to take into account computational considerations, too. A decomposition in terms of wavelet bases using Mallat fast algorithm is typically orders of magnitude faster than a redundant analysis, even if the fastest available algorithms are used [11], [12].
As the aim of this paper is the implementation of a fast parallelized algorithm based on nonredundant wavelet decompositions. To determine the best wavelet function to be used, the ECG signal properties have been studied, such as the shape and the time localization of events. Temporal signal shape is an important parameter, so orthogonal wavelets are unsuitable to be used. In fact they are unable to provide symmetry in the time domain and they introduce non-linear phase shift. The signal shape is maintained if the phase shift is linear. Thus the wavelet to be adopted should be a symmetrical function [13]. Spline wavelets have properties satisfying the previous requirements. The higher order of the Spline wavelet results in the sharper frequency response of the equivalent FIR filter, that is always desirable. But the FIR equivalent filter of the higher order Spline wavelet has longer coefficient series leading to more computational time consumption. Therefore, the cubic spline wavelet is assumed to have an order high enough for this application.
Traditional wavelet theory [14] considers a decomposition algorithm with an iterative structure (in particular an asymmetrical tree structure) that does not efficiently merge with the novel computational techniques, such as parallel processing, concurrent programming and design tools. In this study the a' trous and the Mallat algorithms for parallelized filter bank design have been used [15]. The algorithm generates a set of parallelized perfect-reconstruction filter banks for an arbitrary number of end-nodes of a traditional tree structure [16].

4 Procedure Description

The evaluation of the proposed detection methodology are carried out using recorded data from the standard MIT-BIH Arrhythmia database [17].

For the method implementation, called R_POINT_DETECTOR, no external trigger source is necessary; therefore the ECG signal is the only input.
Fig.2 shows the adopted algorithm model in which the obtained results are indicated as:
- ***'R _Number'*** that evaluates the number of R points present in the frame under test;
- ***'R_Indices'*** that indicates the time position of the located singularities

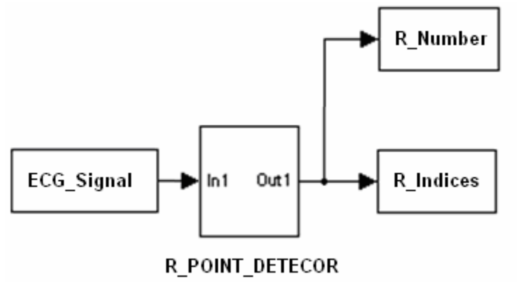

Fig.2 : Algorithm model realized with the software tool MATLAB Simulink®

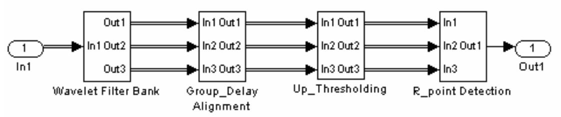

Fig.3: 'R_POINT_DETECTOR' System model.

A suitable mother wavelet is basic for high performance of the proposed QRS detection technique. A wide variety of functions can be chosen as mother wavelets but wavelet bior 3.3 has been adopted because it allows the perfect signal reconstruction keeping phase shift linear. Wavelet bior 3.3 is a cubic spline (fig.4)

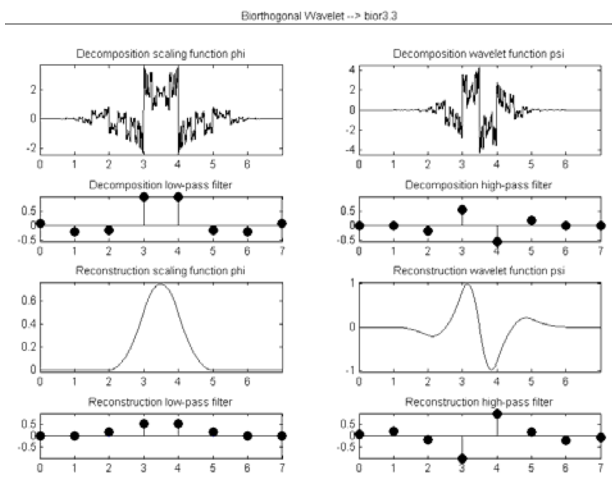

Fig.4: Wavelet 'bior3.3'

To locate R points and consequently the QRS complexes, the method decomposes the ECG signal into six dyadic scales so to reduce noise sensitivity significantly (fig.5). Signal lower frequency components are in high degree scales while higher frequency components are in low degree scales.

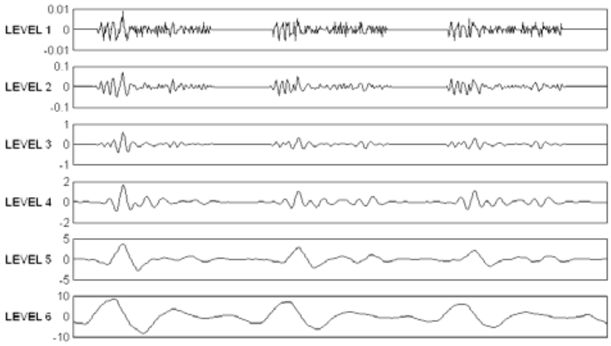

Fig.5: Decomposition of ICG signal over six diadic scales using a' trous algorithm.

According to the power spectra of ECG signal, noise and artefacts, it is evident that the larger contribute of the true signal is located in scales 4, 5 and 6, while scales 1, 2 and 3 are mostly affected by noise [18].
For searching characteristic points, processing of noise free scales only, such as scales 4-5-6, is sufficient.
The method uses an evolution of the classical Mallat decomposition, called a' trous algorithm. The a' trous algorithm for non-ortogonal wavelets uses the same filter bank structure as the Mallat algorithm [19], but differs for high pass and low pass FIR filters. It has been demonstrated that after the application of wavelet filters for j-times, the precision of a' trous algorithm is 2j time higher then Mallat algorithm [20] (Tab.1).

Resolution	**1**	**2**	**……**	**j**
Algorithm	***Precision***	***Precision***	**……**	***Precision***
Mallat	1/512	1/256	……	2^j/1024
a' trous	1/1024	1/1024	……	1/1024

Tab 1: Precision of the Mallat and the a' trous algorithms varying decomposition levels

Usually, wavelet decomposition algorithms make use of filters in a tree structure. This is unsuitable for both the parallel computing and the implementation by design tools. To overcome these limits, equivalent parallel filter banks are used. However, the output signal realignment is necessary to equalize the delay introduced by each filter. This structure makes the algorithm attractive for a hardware implementation.

Adopting a parallel algorithm, the proposed method looks for local maximum points inside scale 4, scale 5 and scale 6 using a thresholding technique: only maximum points higher than the adopted threshold value are taken into account.
Each processed scale gives information about the same signal, so points located inside each scale are related to each others. For this reason, the method executes a tracing across scales to locate overlapping singular points. The method defines as valid peaks, those that are present in two out of three scales at least.
In conclusion, the following steps characterize the new method:

1. signal processing in PARALLEL filter banks for wavelet decomposition;
2. PARALLEL searching for local maximum points inside scales which contain the widest noise free signal contribute;
3. validation of peak points for each scale with respect to peak position in other scales;
4. R-point localizations adopting a simple decisional algorithm.

5 Results and Discussion

Software detection algorithms for medical applications require the evaluation of the detection performance according to ANSI/AAMI standard. Two parameters are used to evaluate algorithms:

Sensitivity:

$$Se = \frac{TP}{TP + FN} \tag{1}$$

Positive Prediction:

$$P = \frac{TP}{TP + Fp} \tag{2}$$

where:

- TP is the number of true positive detections;
- FN (the number of false negatives) is the number of R points present in the signal that the algorithm is not able to detect;
- FP (the number of false positives) is the number of R points detected by the algorithm but really not present in the signal.

Different real ECG frames have been tested to verify the algorithm validity. Therefore they contains the typical noise sources: electromyographic interferences, powerline interference, baseline drift due to respiration and electrode motion artefacts.

Considering frames n.100 and 101 taking from the MIT-BIH Arrhythmia database, simulations show that threshold values inside the range [0.55R*; 0.65R*], denoting with R* the R point average value, are suitable. In this situation Se and P values of about 100% are obtained, respectively (fig.6). For threshold values out of the previous range, the above mentioned parameters decrease in dependence on the chosen threshold value. In fact, values lower than 0.55R* make performance worse because determine the increase of the F_P parameter while values higher than 0.65R* produces the growth of F_N.

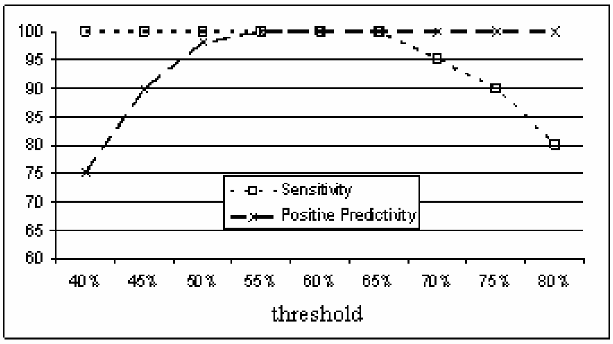

Fig.6 Se and P vs. threshold

6 Conclusion

In this paper, a real-time method has been developed for the analysis of the ECG signal. The wavelet transform is used to detect the R points of the QRS complex. The adopted algorithm optimize the computational time as it processes the ECG signal with a parallel procedure. This technique presents high sensitivity and predictivity parameters in fact values of about 100% are obtained with a suitable threshold value. The adopted procedure is independent of the signal shape therefore can be used all those biological signals requiring a precise peak localization in presence of noise and artefacts.

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