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Automatic detection of QRS complexes in ECG signals collected from patients after cardiac surgery

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Abstract - **A novel automatic QRS detection algorithm that is based on a wavelet pre-filter and an adaptive threshold technique is presented. The algorithm utilizes a bi-orthogonal wavelet filter to de-noise the ECG signal. The QRS complexes are then identified by computing the first derivative of the signal and applying a set of adaptive thresholds that are not limited to a strict range. QRS complexes are identified in multiple ECG channels of a 5-lead configuration and an inter-channel comparison is performed to verify QRS locations. The algorithm was initially developed using ECG signals from Physionet website, but was later refined using ECG data collected from post cardiac surgery patients in the intensive care units. The proposed algorithm was able to detect QRS complexes with high sensitivity (>99%) and specificity (>99%) when compared to the algorithm used in Physionet ECG database. Additionally, the new algorithm can be implemented in real-time and can successfully detect QRS complexes for a wide variety of ECG shapes and characteristics often encountered in cardiac patients.**

Index Terms – **5-lead ECG, ECG database, noise removal, QRS detection, wavelet analysis**

I. INTRODUCTION

THE correct identification of QRS complexes is the fundamental step in analyzing the ECG. This basic step allows segmenting the ECG into individual beats. Detection of QRS complexes not only helps in identifying ECG characteristics such as P and T waves but also aid in detecting ectopic beats and arrhythmias. Additionally, it also forms the first step in computing derived parameters such as heart rate.

Though several QRS detection algorithms are described in the literature [1]-[4], most of them were developed and verified using the same commonly available ECG databases such as MIT-BIH (the Physionet), AHA (American Heart Association), or CSE (Common Standards for Electrocardiography). This may have resulted in a fair amount of "bias" in the reported accuracies of these algorithms. Additionally, their performance in detecting QRS complexes in cardiac patients in a CVICU (Cardio-Vascular Intensive Care Unit) environment where the ECG signals present a wide variety of characteristics associated with differing cardiac abnormality, is either not clear or not tested. Moreover, many of the developed algorithms are not suited for real-time implementation thus limiting their practical application.

In this paper we describe the development of a QRS detection algorithm that is suitable for real-time application in a CVICU environment where patients are generally monitored through a standard 5-lead ECG configuration. However, occasionally based on type of surgery or specialized patient position, alternate 5-lead placements are adopted. The algorithm uses a wavelet pre-filter that removes noise and artifacts commonly encountered in such an environment. The wavelet analysis offers better results than Fourier analysis when used for non-stationary signals as ECG. The noise-free ECG is further processed and adaptive thresholds are applied to detect QRS complexes for ECG signals that are not only non-stationary but also present significant inter-patient variability.

II. METHODS

The proposed QRS detection algorithm comprises of two main steps: 1) a preprocessing stage and 2) a decision-making stage. The main goal of the pre-processing stage is to prepare the ECG signal by eliminating noise so that the subsequent decision-making stage can process and decide on QRS locations accurately. From the 5-lead ECG signals, we used for QRS detection algorithm only two leads, lead II signal and a non-zero and noise-free signal from one of lead I, III or V.

A. Pre-processing stage

The primary component of the pre-processing stage is a bandpass wavelet filter. The purpose of the wavelet filter is to reduce or eliminate movement artifact, electromagnetic interference, EMG interference and baseline wander encountered in a CVICU environment. In the ECG de-noising process, we used a bi-orthogonal wavelet, "bior6.8". Specifically, a pair of compactly supported bi-orthogonal spline wavelets for which symmetry and exact reconstruction are possible, was used. Since, the general shape of QRS complexes and bi-orthogonal wavelet functions are similar,

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the QRS complexes could be reproduced only by a few wavelet coefficients such that the computation time and memory requirements are reduced. The pre-filter assumed that the frequency components of QRS complexes range from 3-40 Hz [3], [4] and that the P wave frequency components are found in the range 0.5-10 Hz. The noise frequency components are assumed to extend over the range 0.5 Hz to 7 Hz as suggested by Li and Sahambi in [3], [4]. It also assumed that the ECG signal, being a biological signal, is non-stationary in nature.

For the removing noise from the ECG signal we used the method proposed by Donoho [5]. The idea behind this process is to decompose the input signal, in our case the ECG, into detail and approximation coefficients over different levels. In the levels associated with the noise frequency, all of the detail coefficients are compared with threshold values established by a soft threshold method, equation (1), resulting estimated detail coefficient - $\tilde{x}$. This is performed in order to eliminate discontinuities where the signal, x, equals the threshold value, T:

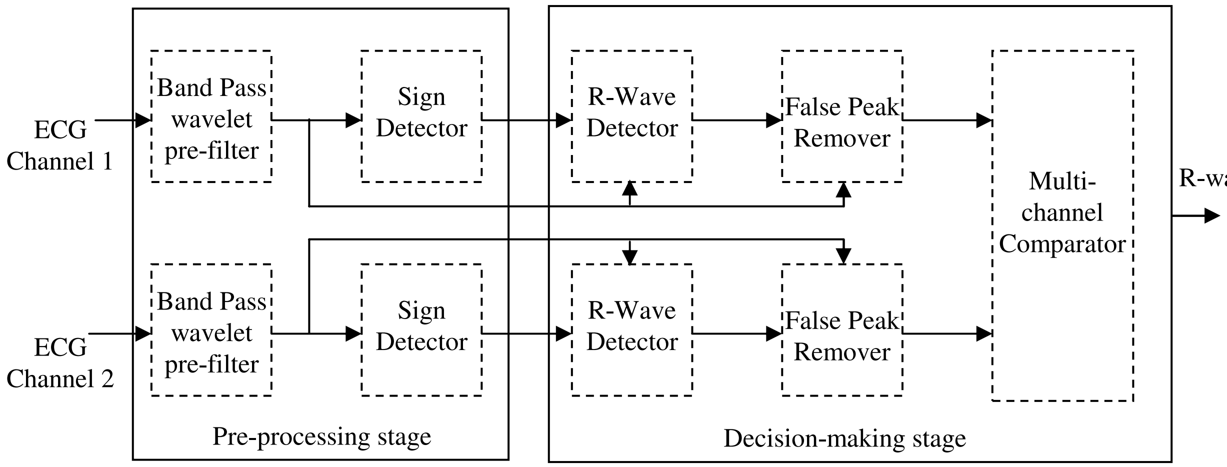

Figure 1 – Flow diagram of QRS detection

$$\tilde{x} = \begin{cases} sign\ (x)(|x| - T), |x| > T \\ 0, |x| \le T \end{cases} \quad (1)$$

Since the noise components are unknown and variable over the ECG registration, sometimes components of the ECG signal may lie within the noise range. Signal to noise ratio (SNR) could provide a measure of noise, but needs an extra computation time. To circumvent this disadvantage, we used a soft threshold computation method, using the “minimax” principle. This method requires only knowledge of the prior range, where the signal is guaranteed to be. The threshold was chosen such that it minimizes the maximum risk of the estimation expressed as a square of the Euclidian norm or mean square error (MSE). In order to ensure a good separation of signal and noise, we computed a threshold value for all of the analyzed levels. The standard deviation of wavelet coefficients for each level is robustly estimated by a median, absolute deviation, estimator. The use of this estimator is justified by two reasons: 1) avoidance of the signal boundary effects that are artifacts due to boundary computation and 2) representation of signal details by a very small number of coefficients. The process is applicable for non-white noise elimination. For ECG signal, since the frequency components are unknown, the above process is very suitable for separating the ECG signal and noise. To determine the number of levels required for analysis, the center pseudo-frequency for each level was computed. The minimum level that produced a center pseudo-frequency that is greater than the noise frequency range (0.5-7 Hz) was chosen as the maximum level for analysis. In our case level 5 was determined to be the maximum required level.

The de-noising process was realized using a MATLAB (The MathWork, Inc., Natick, MA) subroutine. The effect of de-noising a 256-sample ECG segment is presented in the Figure 2. It can be seen that the reconstructed ECG signal (dash thick line) is comparatively noise free when compared with the original signal (continuous light line). After the signal is de-noised, the direction of R-wave deflection is determined. In general during post-surgical recovery periods a standard 5-lead ECG configuration is commonly adopted. However, depending on surgical type and any related specialized patient position, alternate 5-lead placements might have to be adopted leading to differing QRS complex shapes and deflections. The R-wave could have a positive or a negative deflection based on electrode placement, heart position and orientation. A 40-second length of the ECG signal was selected with a SNR (signal to noise ratio) of more than 60 dB. The SNR is estimated as a simple ratio of average value to standard deviation value of the signal over the considered interval. From this segment the largest three extreme values and the 40 ms of ECG signal that surrounded these extreme values were eliminated considering them as being artifacts. The first derivative of the ECG signal in this “cleaned” 40 second segment was computed and the extreme values of the ECG signal were searched around points that corresponded to peaks in the first derivative of the ECG.

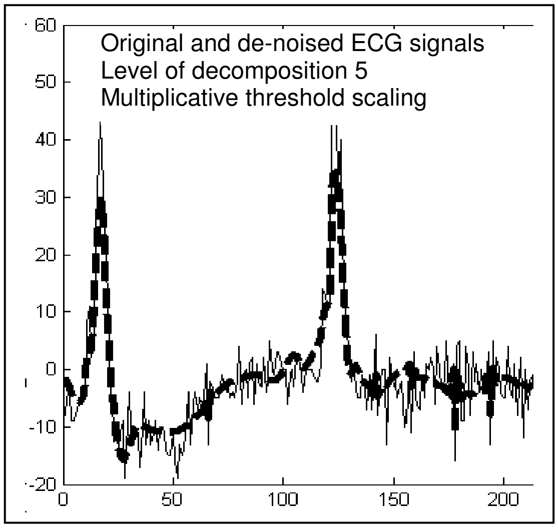

Figure 2 – "bior6.8" de-noising a 256-sample ECG

These ECG signal extreme points were compared in relation to the average value (DC value) of the entire segment. If the number of times the absolute difference between the peaks (extrema-maximum) and the DC value was greater than the absolute difference between the adjacent valleys (extrema-minimum) and the DC value, then the sign of R-wave deflection was decided as positive. Otherwise, the sign was established as negative. Based on the direction of R-wave, the ECG signal was either left unchanged (if the sign was positive) or modified to be the negative image (if the sign was negative). The de-noised and sign adjusted ECG signal is submitted as input to the decision making stage.

B. Decision Making Stage

To identify the position of the R-wave, the first derivative of the ECG signal was computed for two of the ECG signal channels. This was done to amplify the R-wave deflection such that it can be detected easily. Extrema points in the derivative signal were selected using an amplitude threshold algorithm. The searching threshold was established by focusing on the first 15 seconds of the ECG signal. In this segment the largest 7 peaks were eliminated to discriminate noise and the average amplitude (DP_{avg}) of the rest of the peaks was determined. The maximum and minimum thresholds were defined as $20*DP_{avg}$ and $0.55*DP_{avg}$. The multipliers were arrived upon by trial and error. The subsequent derivative signal was scanned using a moving window of 2.5 seconds. Within this window, all points that fall within the maximum and minimum threshold were selected and the average (DS) of the selected values was found. Peaks in the derivative signal were determined using 0.95*DS as the lower threshold. Based on the locations of these extreme points determined on the derivative signal, a refined search was performed on the actual ECG to find the exact maximum (or minimum) that corresponds to the R-wave.

The next step in the decision making stage was to remove any falsely marked R-waves. Based on the periodicity of cardiac electrical activity, a moving average of the amplitude of R-waves was found. An R-wave threshold amplitude limit was established at 10 times the median value of all the peaks detected within a moving window of 10 seconds. Any peak over this limit was discarded as a false peak. In addition, if an RR-interval within this window was found to be less or greater than 500 ms of the average RR-intervals, it was confirmed that the two R-waves of the RR segment have amplitudes greater than half the median R-wave amplitude. Any R-wave that did not satisfy the above condition was also considered as a false peak. The false R-waves were eliminated from further analysis.

As the last step in QRS identification an inter-channel comparison was performed to confirm the presence of valid R-waves. All of the above steps in signal pre-processing and detecting R-wave locations were accomplished for two channels of ECG signals. The detected R-waves were compared between channels and only those R-waves that have similar positions on both channels of registration were selected. Two corresponding R-waves in the two channels were assumed to be similarly placed if their locations were within 20 samples (167 ms) of each other.

The above algorithm was initially developed using a training ECG dataset (sampling rate: 128/sec) obtained from the Physionet database [6]. However, the threshold constants of the algorithm were later refined using signals acquired from post-cardiac surgery patients in the CVICU at the Cleveland Clinic. The ECG signals in the CVICU, sampled at 120/sec, were acquired from the patient monitor using an ECG data collection and analysis computer station (MARS workstation, GE Medical Systems, Milwaukee, WI).

III. RESULTS

The sensitivity and specificity of the developed algorithm were evaluated using a set of testing ECG dataset from the Physionet database. Specifically, the selected ECG signals comprised of 200 ECG signal files that were originally prepared by Computers in Cardiology (CIC) for a contest to predict atrial fibrillation. Along with the ECG data files, QRS annotation files are also made available by Physionet. These annotation files were generated by an automatic algorithm developed by MIT (Massachusetts Institute of Technology, Cambridge, MA). The accuracy of our QRS detection algorithm (termed CCF algorithm) was assessed by comparing the QRS annotations marked by CCF algorithm with those generated by the MIT algorithm.

The verification process was performed using a custom made comparison program that allows us to measure the QRS annotation differences quantitatively and qualitatively. In the total of 200 ECG signal files used for verification a total of 434361 R-waves (or QRS complexes) were annotated by the MIT algorithm. Additionally, the annotation spanned a total of 100 hours of ECG registration. Considering the MIT annotations as the "gold standard", the comparison program was used to compare them against the R-waves marked by the CCF algorithm. It was found that the CCF algorithm detected R-waves with an overall accuracy of

99.77% and a specificity of 99.87%, detecting 433945 R-waves. In 75 of the 200 files the R-wave annotations were exactly similar between the algorithms, while for 32 files the difference was only in one annotation. There were differences in QRS annotations between the two algorithms for the rest of the ECG files. Upon further exploration it was evident that the "gold standard" MIT annotation unfortunately had some wrongly marked as well as unmarked R-waves for certain ECG files. Under this circumstance, the CCF algorithm was able to perform better, with R-waves correctly identified. Some examples that demonstrate the superior performance of the CCF algorithm is shown in Figure 3. In Figure 3, CCF annotation is shown by white squares in the bottom part of the 1st channel while MIT annotation is represented by white circles in the top part of the 2nd ECG channel.

A reason for the differences between the MIT and CCF annotations could be that the MIT algorithm uses only one ECG data channel to detect R-waves while the CCF algorithm uses two channels. The CCF R-wave detection algorithm is based on the existence of R-wave in both the channels to validate the R-waves. Also the CCF algorithm has the flexibility to adjust some of the parameters used in R-wave detection algorithm and customize them to suit a particular data set. The default parameter values used in the algorithm have been arrived upon experimentally such that these values are able to detect R-waves in for a variety of ECG shapes and characteristics.

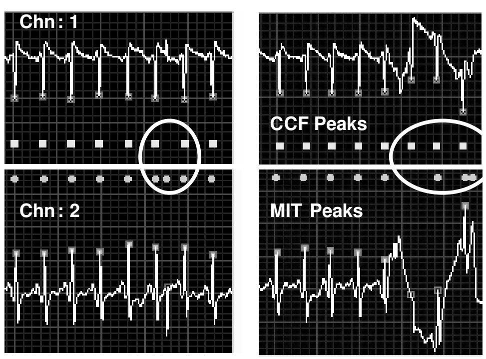

Figure 3 – QRS annotations – a comparison between CCF and MIT algorithms

In addition to the verification of CCF algorithm with respect to the MIT algorithm, we have also applied the algorithm to detect R-waves in ECG signals acquired from CVICU patients. Specifically, the algorithm has been applied on ECG data collected from over 100 patients during their stay in the CVICU. The duration of the ECG signals ranged from 4-28 hours. Though a thorough quantitative analysis of the sensitivity and specificity of the CCF algorithm when applied on CVICU patients is still being completed, a preliminary qualitative analysis has revealed that the algorithm is able to consistently and accurately mark QRS complexes in ECG signals that could vary between patients and also over the time of data collection.

IV. CONCLUSIONS

In conclusion, we have developed a QRS detection algorithm suitable for automatically annotating QRS complexes in 5-lead configuration ECG signals collected from cardiac surgical patients in the CVICU. The developed algorithm uses a wavelet de-noising filter to remove noise and artifacts commonly encountered in a CVICU environment. The filtered signal is differentiated and a set of adaptive defaults are applied to detect R-waves. The adaptive thresholds used in the algorithm enable the algorithm to be applied to detect a wide variety of QRS complex shapes that are commonly encountered in post cardio-vascular surgery patients. A multi-channel comparison of R-wave annotation is also performed to confirm the detected QRS locations and to eliminate false peaks wrongly identified as QRS complexes. A comparison of our algorithm (CCF algorithm) with the MIT algorithm revealed that the CCF algorithm not only detected QRS complexes with high sensitivity and specificity, but also outperformed the MIT algorithm in several instances. Preliminary validation of the algorithm on ECG data collected from CVICU patients show promising results. The CCF algorithm can be applied in real-time thus enhancing its utility for a variety of practical applications.

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