SIGNAL TO NOISE RATIO EVALUATION IN SIGNAL AVERAGED ECG BY DERIVATIVE DYNAMIC TIME WARPING AND PIECEWISE LINEAR APPROXIMATION

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Abstract: Signal Averaged Electrocardiography (SAECG) is a technique widely used as an alternative to improve signal to noise ratio (SNR), but sometimes patient's physiology may alter the characteristics of quasi-steady heartbeats that are assumed in the averaging. This paper evaluates the noise as a parameter for measuring the alignment heartbeats by Derivative Dynamic Time Warping (DDTW) and using Piecewise Linear Approximation (PLA) as well. The records were taken from a group of healthy individuals and the results show that the number of heartbeats averaged necessary to improve the SNR is less than the traditional method.

1 INTRODUCTION

The High Resolution Electrocardiography (HRECG) gives us important information about the normal and abnormal electrical activity of the heart, such as Ventricular Late Potentials (VLP). Often, these VLP occur in people who survive to a heart attack (M.E. Tagluk et al, 1998). Many studies focus the VLP detection on the QRS complex by means of the quantification of its duration (A. Illanes et al, 2008; Z.E. Hadj, 2005 and 2006; T. Bragge et al, 2004). When HRECG are been recorded, it is very common that noise masks signals of interest like VLP. To improve the quality of records, it can be used multiple techniques such as the well known Signal-Averaged ECG (SAECG), a widely used technique in noise reduction for VLPs studies. SAECG assume that the noise is completely a random signal and both the signal of interest (i.e., HRECG) and its VLP pattern (if exists) are quasi-stationary processes, which are repeating heartbeat to heartbeat at the end of the QRS complex or at the beginning of ST segment (G. Breithard, 1991). The noise level is reduced proportionately as long as more and more heartbeats are taken into an ensemble. In the results presented in this paper, the heartbeats had complied with a correlation coefficient higher than 0.9 compared with a reference or template (G. Breithard et al, 1993). Alignment of heartbeats is an important part of the signal averaging, because the physiological nature of electrocardiographic signals. This nature alters the behaviour from heartbeat to heartbeat in lag, in duration, and amplitude. Variations in time are due to both the heart rate variability and the elongation in duration. Variations in amplitude are due to attenuations or amplifications on the wave forms. It makes the heartbeats look lagged, shorter or longer in duration, and higher or lower in amplitude. This would cause that the ensemble rejects those heartbeats which do not reach the minimal correlation coefficient criterion (i.e., 0.9). An alignment technique firstly used in speech recognition was called dynamic programming, and now commonly known as "Dynamic Time Warping" (H. Sakoe et al, 1978). It has been used in making decisions on segmentation of ECG signals, showing good results (A. Zifan et al, 2007).

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In this paper, we recorded 30 HRECG each of them including 350 heartbeats taken from 30 healthy subjects. A method on dynamic programming and heartbeats segmentation, based on Piecewise Linear Approximation (PLA) (H.J.L.M. Vullings et al, 1997) was used for heartbeats alignment. Results show that using PLA it is possible to reach similar noise levels by mean of the added of less heartbeat in the ensemble than in conventional method (G. Breithard, 1991).

2 MATERIALS AND METHODS

A CARDIAX PC-ECG system was used at 500 Hz sampling rate for electrocardiography tracings. Interpolation to a rate of 2 was applied achieving a double sampling frequency. Simple smoothing was applied to remove the high frequency noise. Each of the obtained curves was separated into heartbeats using a conventional method for R peak detection. Those, that meet a correlation higher than 0.9, i.e. 100 to 350 beats were selected and averaged. Then the level of the noise in the ST segment (G. Breithard, 1991) was assessed and the beats were approximated by straight lines using the method of Piecewise Linear Approximation (PLA) from which alignments will be compared with the same heartbeat reference using dynamic programming (DTW), and then perform the averaging of the heartbeats and re-evaluate the noise level in the ST segment.

2.1 Preprocessing

A moving average band pass Butterworth filter (1 to 100 Hz) of order 5 was applied first removing the high frequency noise like interspersions and muscle noise. Next, a previous segmentation was done by selecting QRS complex with the classical Pan and Tompkins algorithm (J. Pan et al, 1985), after that we selected a region around the R-peak, 150 samples before and 250 samples after the R-peak. Then the region around the R-peak, 150 samples before and 250 samples after the R-peak were selected and the template beat is decomposed in three different parts: a) before the QRS complex (P wave and PQ segment); b) the QRS complex part and c) after the QRS complex (ST segment and T wave).

2.2 Piecewise Linear Approximation

The PLA algorithm was used to represent adaptively any signal trough straight lines. We propose to approximate the ECG with a series of line segments. The ECG is regarded as a vector $x = [x(1),......x(n)]$, where $x(i)$ $(1 \le i \le n)$ is the voltage of the ECG at time i. The first proposed segment consist of the first samples of x. We approximate this segment with a straight line connecting the first and the last sample. As long as this line approximates the original segment with an acceptable error e, s more samples are added to the segment. To calculate the error consider figure 1, where j samples are approximated by the straight line $y(i) = ai + b$. The error $e(i)$ for sample $i(1 \le i \le j)$ should never exceed an empirical determined threshold calculated as:

$$e(i) = \frac{|x(i) - y(i)|}{\sqrt{a^2 + 1}} < \in \qquad (1)$$

We add s more samples to the segment, until (1) does not hold. Then, we start shrinking the segment in order to obtain a segment which does not exceed $\in$. The new end-point of the segment is the point i for which $e(i)$ is maximal. If the error on the new segment remains below $\in$, the line segment to approximate a part of the ECG is found. The new segment will start at the end-point of the previous segment. However, if the error is still not below $\in$, we shrink the segment again and again, until (1) holds.

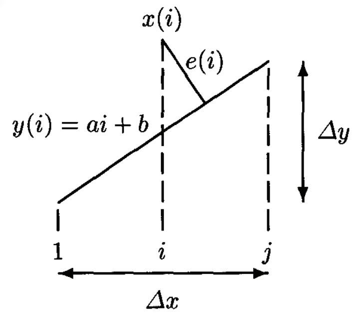

Figure 1: The error $e(i)$ for a segment.

A complete heartbeat consists of a sequence of lines which can be displayed in string format. One line can be represented as a combination of slope and a horizontal length $(a, \Delta x)$, which enable us to describe the heartbeat in terms of segment lines as illustrated in figure 2, where template heartbeat is represented using PLA i.e. using lines defined by a slope and number of samples taken in account by these lines.

Since alignment is an important part of SAECG, a method to perform it is described as follow.

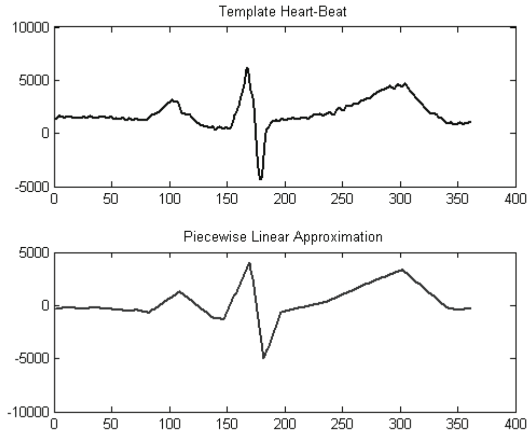

Figure 2: PLA of a heartbeat taken as template.

2.3 Derivative Dynamic Time Warping

In order to overcome some limitations of the classic DTW algorithm the Derivative Dynamic Time Warping algorithm (DDTW) was applied. To find the similarity between two sequences, DTW looks for the best alignment, which is generally referred to as Warp-Path, and thus warps the time axis of one of the series and calculates the distance between the two sequences. In some cases it can produce some misalignments, for instance when multiple points on one time series correspond to only one point in the matching time series, or when the two sequences strongly vary in the Y-axis. Figure 3 shows the limitations of DTW (S. Chu. et al, 2002).

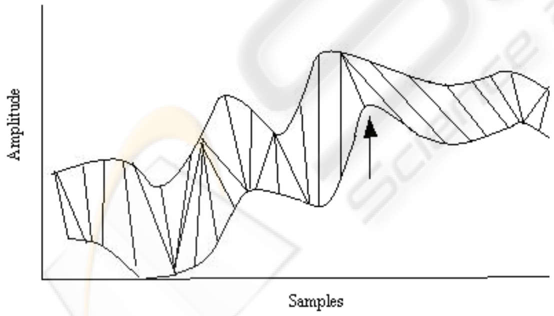

Figure 3: Alignment produced by DTW. Alignment fails because of differences in the "y" axis.

In the present case, each input signal is considered as a sequence of n samples $x=[x(1),x(2).......x(n)]$, and the template is a sequence of m samples $y=[y(1),y(2),......y(m)]$. DTW builds a matrix $D[n \times m]$ in which each element represents the distance between the $i-th$ element of $x(i)$ and the $j-th$ element of $y(j)$. Then, a new matrix θ is introduced, with:

$$\theta(j,i)=d(j,i)+\min[\theta(j-1,i-1),\theta(j,i-1),\theta(j-1,i)] \quad (2)$$

So, that each element is the sum between the local distance $d(j,i)$ and the minimum of the total distances of the neighbor elements.

The warping path W, is a contiguous set of matrix elements that defines a mapping between x and y. The $k-element$ of W is defined as $W_k=(i,j)_k$:

$$W=w_1,w_2,....w_k \quad \max(n,m)<k<n+m-1 \quad (3)$$

The warping path generally undergoes to several constraints: among them, the requirement for the warping path to start and finish in diagonally opposite corner cells of the matrix, restriction to the number of allowable steps in the warping path to adjacent cells and monotonicity in time.

Among all the warping paths that satisfy the above conditions, for recognition/classification purposes of interest is in the path that minimizes the warping cost:

$$DTW(x,y)=\min\left\{\frac{1}{K}\sqrt{\sum_{i=1}^{k}w_k}\right\} \quad (4)$$

DDTW differs from DTW by considering the square of the difference of the estimated derivatives of x_i

$$D(x)=\frac{(x_i-x_{i-1})+(x_{i+1}-x_{i-1})/2}{2}, 1<i<n \quad (5)$$

and y_i instead of the original time series:

A simple representative block diagram of procedure is shown in Figure 4. It is very important to say that averaging has not been made with heartbeat-segmented, but with heartbeat-aligned, and SNR evaluation has been made in the ST segment only.

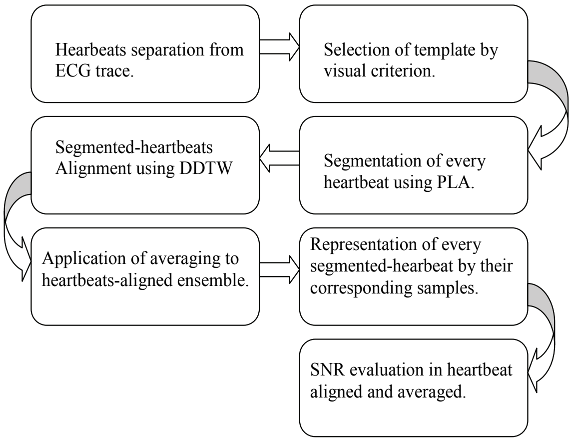

Figure 4: Method used representation by a simple block diagram.

3 RESULTS

Each heartbeat to be segmented has a distance matrix alignment much smaller than if it were made with all samples of the signals, as shown in Figure 5.

Derivative Time Warping alignment technique produces an alignment based on the slopes of the lines generated and amplitude values no matter.

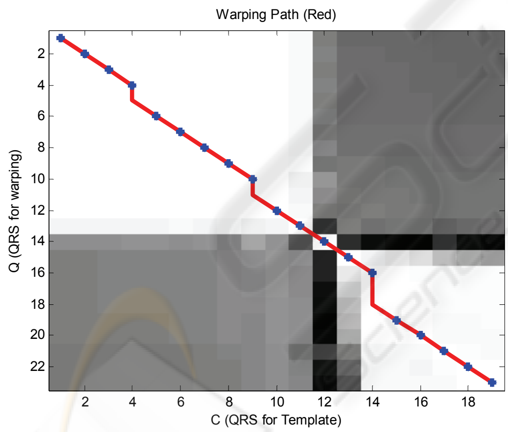

Figure 5: The segmentation produces a smaller matrix alignment.

For instance two heartbeats with high difference in amplitude can be aligned almost completely, as shown in Figure 6.

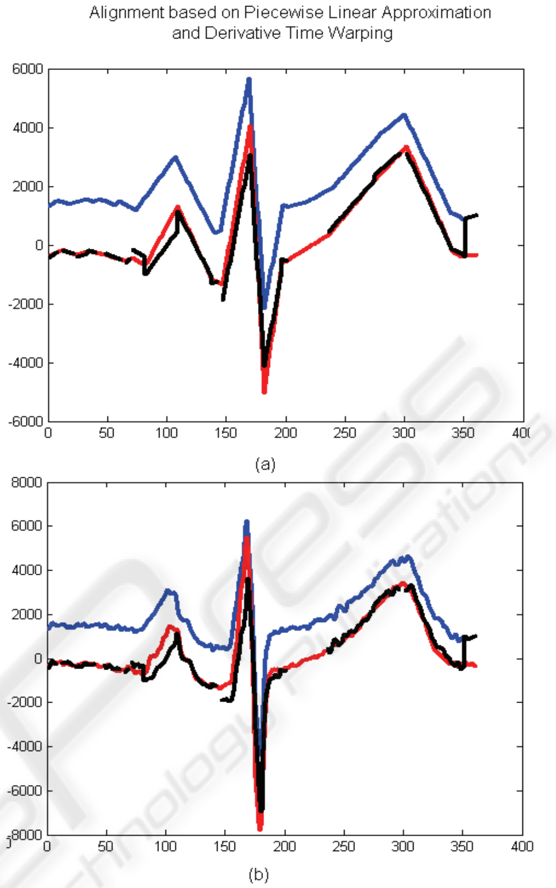

Figure 6: Alignment produced by DDTW (a) Aligning segments P, QRS and T, (b) Heartbeats aligned according to segment slope. Template reference (red), heartbeat to align (blue) and heartbeat aligned (black).

Making signal average with no alignment heartbeats (just those which present high correlation) and aligning with DDTW and PLA noise level could be computed using ST segment variance or n_{RMS} where R is the number of heartbeat taken in account to be averaged (G. Breithard et al, 1993).

$$n_{RMS} = \sqrt{\sum_{i=1}^{R}(x_i-\mu_i)^2 / R - \left(\sum_{i=1}^{R}(x_i-\mu_i)/R\right)^2} \qquad (6)$$

A graphical representation is shown in figure 7, where four individuals ECG records were noise measured.

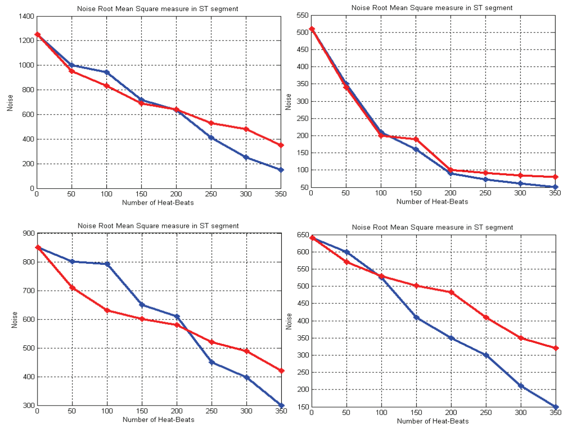

Figure 7: Four patients ECG noise measured in typical SAECG (Blue) and using DDTW and PLA (Red).

4 CONCLUSIONS

The alignment algorithm developed based on DDTW and PLA provides similar results in noise reduction compared with traditional method based on high correlation for same number of heartbeats. For less number of heartbeats however, it reaches lower noise levels excluding thus the need to reject as much as traditional method.

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