Comparison of Alignment Algorithms for P-Wave Coherent Averaging

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Abstract

Aim of this paper was to evaluate the performances of 4 alignment algorithms for P-wave coherent averaging. The first algorithm is based on the maximum of the cross-correlation function (CCF) between the current averaged wave and the incoming wave. The second algorithm computes the minimum square error (MSE) between each incoming wave and the current averaged wave. The third algorithm minimizes the difference between the areas of two rectangular window selected on the current averaged wave and the incoming wave (two-windows minimization, TWM).The fourth algorithm finds the local best alignment using the Dynamic Time Warping (DTW). The best alignment algorithm in terms of both shift error and template error resulted to be MSE, for SNR lower than 20 dB. For higher SNR values, MSE, CCF and TWM algorithms showed similar performances. TWM suffers from the necessity to select the two rectangular windows.

1. Introduction

When normal cardiac impulse travels through atrial myocardium, surface ECG recordings show the P-wave. If the atrial depolarization patterns are different from the normal, P-wave may appear prolonged and highly variable. Abnormal P-waves have been observed in patients prone to atrial fibrillation (AF) [1][2]. Many investigations have been focused on the analysis of P-wave to detect patients prone to AF [1]. The analysis of the P-wave requires a pre-processing step. Acquired ECG signals are usually affected by noise, such as main interference or motion or respiratory artifacts, skin-electrode interface that introduce undesired offsets, waveform fluctuations and baseline instability. To improve the signal-to-noise ratio, averaging algorithms are usually performed. The main issue in P-wave signal averaging is the correct alignment of the signals to sum. P-waves are usually extracted considering windows triggered on QRS complexes, that in a way act as reference points for the application of the stimuli to the system under observation. The response is a set of P-waves that can be averaged to extract a template. This QRS-triggered method is valid in the circumstance that the response delay between the stimulus and the signal is constant. If random fluctuations in the stimulus-response time occur the resulting averaged waveform can be smoothed. For P-waves this latency fluctuation can be due to variations in PR interval or inaccuracy in R wave detection. This "trigger jitter" phenomenon will smooth the shape of the resulting P-wave template [5]. Several alignment methods have therefore been proposed in literature to refine and optimise the P-wave signal-averaging algorithm [6-9]. The aim of this paper was to evaluate four alignment algorithms, on both simulated and real data. Simulated data were chosen in order to mimic monophasic, biphasic and triphasic waves, with random shift and added random noise. Real data were 100 averaged P-waves, extracted from 10 subjects. Analysis has been performed for SNR equal to 10, 15, 20, 25 and 30 dB and by averaging 100 and 200 waves. Three of these methods will be presented and compared in the next paragraphs, together with a fourth alignment algorithm (Dynamic Time Warping, DTW) never applied in P-waves analysis so far.

2. Methods

Cross-correlation function-based algorithm

This algorithm is based on the maximum of the cross-correlation function (CCF) between the current averaged wave and the incoming wave (coherent averaging) [5]: the waveforms to average are aligned according to the information obtained by a cross-correlation matching. A cross-correlation function φ_{xy} between the current averaged wave (i.e. the current template) x(n) and the incoming wave y(n) is computed:

$$\Phi_{xy}(m) = \frac{1}{N}\sum_{n=0}^{N-1} x(n-m)y(n)$$

where x(i)=0 for i<0 or i>N-1 and –N<m<N. If m is the lag at which the CCF shows its maximum, the incoming wave is shifted along the time axis for m samples. The two aligned waveforms are then summed up and the procedure is repeated for the following waves.

Minimum square error-based algorithm

This algorithm is based on the computation of the minimum square error (MSE) between each incoming wave and the corrent averaged wave. The sample at which the MSE is minimum indicates the time of maximum agreement between waves, and the incoming wave is shifted accordingly. The method can be further improved by a quadratic polynomial interpolation applied to the sample corresponding to the minimal error and the neighbouring samples. This procedure leads to an accuracy one order of magnitude greater than the sample time [10].

Two windows minimizazion-based algorithm

This alignment algorithm minimizes the difference between the areas of two rectangular windows, having different mean slopes and selected on the current averaged wave, and the incoming wave (two windows minimization, TWM). In this algorithm a two-step procedure is performed [11]. In the pre-running phase two rectangular windows having different mean slope are selected on the reference wave (i.e. the current template) by means of four cursors (figure 1). Height and width for both rectangular windows (Hr1,Wr1; Hr2,Wr2) and the difference between the areas of the two rectangles (ΔAr) are determined as parameters for the subsequent comparisons.

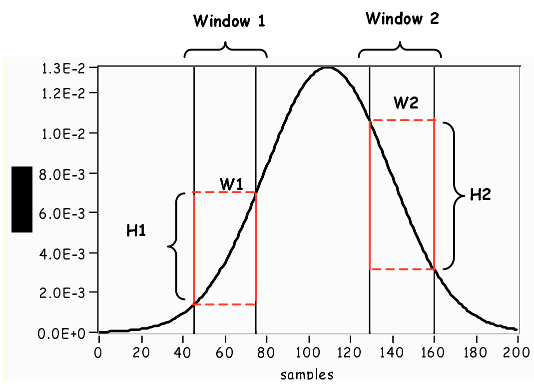

Figure 1. Rectangular windows on the reference wave.

In the running phase the same parameters are extracted from the incoming wave (H1,W1; H2,W2; ΔA), by shifting the fixed two window interval on the new signal. Two functions are determined: an *enable binary function*, which is equal to 0 if both the relative differences between the heights of corresponding rectangles on the template and the signal (i.e. (Hr1-H1)/Hr1 and (Hr2-H2)/Hr2) are lower than a pre-determined threshold and 1 otherwise; an *alignment error function*, given by the absolute difference between the two areas ΔAr-ΔA. The best alignment is thus found considering the signal shift that achieves the minimal error where the enable function is zero.

Dynamic Time Warping

This algorithm finds the local best alignment between samples of the current template (series X, N samples) wave and the incoming wave (series Y, M samples) [12,13]. All the algorithms previously mentioned do not count for possible local misalignments due to beat by beat phase changes in the electrical events that generate the P wave. All the samples of the incoming wave are thus shifted for the same quantity before performing the averaging with the current template. The DTW algorithm finds the local best alignment between samples of two different signals: each sample of the incoming wave (y_i) can be shifted for a different quantity. First a cost function is computed as a matrix estimating the distance between x_i and y_j (i=1,...,N, j=1,...,M) Second, the warping function can be easily extracted, defining the succession of samples (i, j) to be averaged to obtain the new template. The warping function defines a path representing the best alignment (lowest cost) between X and Y.

Simulated data

Simulated data were designed in order to mimic monophasic, biphasic and triphasic P-wave (figure 2), consisting of 400 samples (miming a sampling frequency of 2 KHz, the same used for real data acquisition). To reproduce the fluctuations of the PR interval as well as the inaccuracy in R wave detection, random shifts were simulated on each wave to be averaged. Random shifts were generated as random noises, ranging between –10 and 10 samples. Finally, random noise was added to each wave, for SNR of 10, 15, 20, 25 and 30 dB. On simulated data, 3 algorithms (CCF, MSE and TWM) have been evaluated by estimating the mean absolute value of the difference between the actual and the estimated wave shifts (shift error); for all the four algorithms the power (variance) of the difference signal between the resulted averaged wave and the original sinthetic wave (template error) has been computed and compared.

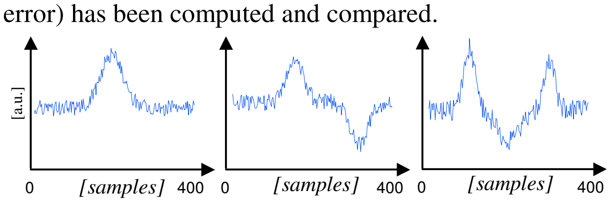

Figure 2. Simulated monophasic, biphasic and triphasic wave for a 10dB SNR (similar to that typically found in experimental data).

Experimental data

Experimental data consisted of 100 P-waves extracted from 10 subjects (sampling frequency 2048 Hz, 24 bit resolution). On these data, the algorithms' performances have been evaluated by estimating the power of the residual noise of the average P-wave estimated on the isoelectric TP track.

3. Results

Table 1 shows the shift errors (estimated in samples as the mean of the absolute value of the difference between the actual and the estimated wave shifts), for the monophasic, biphasic and triphasic simulated P-waves, for 100 (left) and to 200 (right) P-waves, at decreasing levels of added random noise are shown.

Table. 1 Absolute average shift errors (in samples) for the monophasic, biphasic and triphasic simulated P-waves, for 100 (left) and 200 (right) averaged P-waves. Results obtained for different level of added random noise are shown.

	Number of averaged waves=100			Number of averaged waves=200		
			Monophasic simulated P-wave			
SNR	**CCF**	**MSE**	**TWM**	**CCF**	**MSE**	**TWM**
10	0.67	0.46	0.45	0.60	0.58	0.55
15	0.83	0.07	0.08	0.17	0.08	0.21
20	0.00	0.00	0.03	0.00	0.00	0.01
25	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00
			Biphasic simulated P-wave			
SNR	**CCF**	**MSE**	**TWM**	**CCF**	**MSE**	**TWM**
10	0.53	0.39	2.27	0.43	0.68	2.66
15	0.69	0.11	0.99	0.95	0.02	0.86
20	0.00	0.00	0.51	0.00	0.00	0.46
25	0.00	0.00	0.06	0.00	0.00	0.18
30	0.00	0.00	0.00	0.00	0.00	0.02
			Triphasic simulated P-wave			
SNR	**CCF**	**MSE**	**TWM**	**CCF**	**MSE**	**TWM**
10	0.09	0.08	0.72	0.04	0.04	3.24
15	0.00	0.00	0.00	0.00	0.00	0.02
20	0.00	0.00	0.00	0.00	0.00	0.00
25	0.00	0.00	0.00	0.00	0.00	0.00
30	0.00	0.00	0.00	0.00	0.00	0.00

Figure 3 shows the percentage template error estimated as the percentage error between the real waveform and the estimated template obtained averaging 100 (left) and to 200 (right) monophasic, biphasic and triphasic simulated P-waves. Results obtained for different levels of added random noise are shown. Best alignment algorithm in terms of both shift error and template error resulted to be MSE for SNR lower than 20 dB. For higher SNR values, MSE, CCF and TWM algorithms showed similar performances (shift error equal to zero and power of template error as low as –100 dB). Similar results have been obtained for real data: MSE and CCF guaranteed a residual noise always lower than 2μV. DTW gave results comparable to MSE and CCF for SNR higher than 15dB, but it turn out to be the most computationally complex.

4. Discussion and conclusions

Since acquired ECG signals are usually affected with noise, the analysis of the P wave requires a pre-processing step, based on averaging algorithms, to improve P-wave detection and signal-to-noise ratio (SNR). The main issue in P-wave signal averaging is the correct alignment of the signals to sum. P-waves are usually extracted from windows triggered on QRS complexes. Since random fluctuations of PR interval or inaccuracy in R wave detection can occur, alignment methods are needed to refine and optimise the P-wave signal-averaging algorithm. Indeed, percentage template error is higher without an alignment procedure than using any alignment algorithm. However, for monophasic wave template percentage error is always lower than 1%; for biphasic and triphasic waves, alignment resulted to reduce the template percentage error down to 4% and 5% respectively. In conclusion, best alignment algorithms resulted to be MSE and CCF in terms of shift errors, template errors and computational complexity. TWM suffers from the necessity to select the two rectangual windows for each P-wave to average. DTW compresses and extends the time axes of couples of signals to reduce the effects shape differences caused by noise and normal shape variability. Indeed, the quantification of the amplitude differences that remain after DTW can be used as an index of waveform shape similarity [15]. In this study simulated signals were generated to mimic the jitter phenomenon caused by real PR interval fluctuations. Effect of shape changes in terms of extention or compression of theP-wave have not be addressed in this study.

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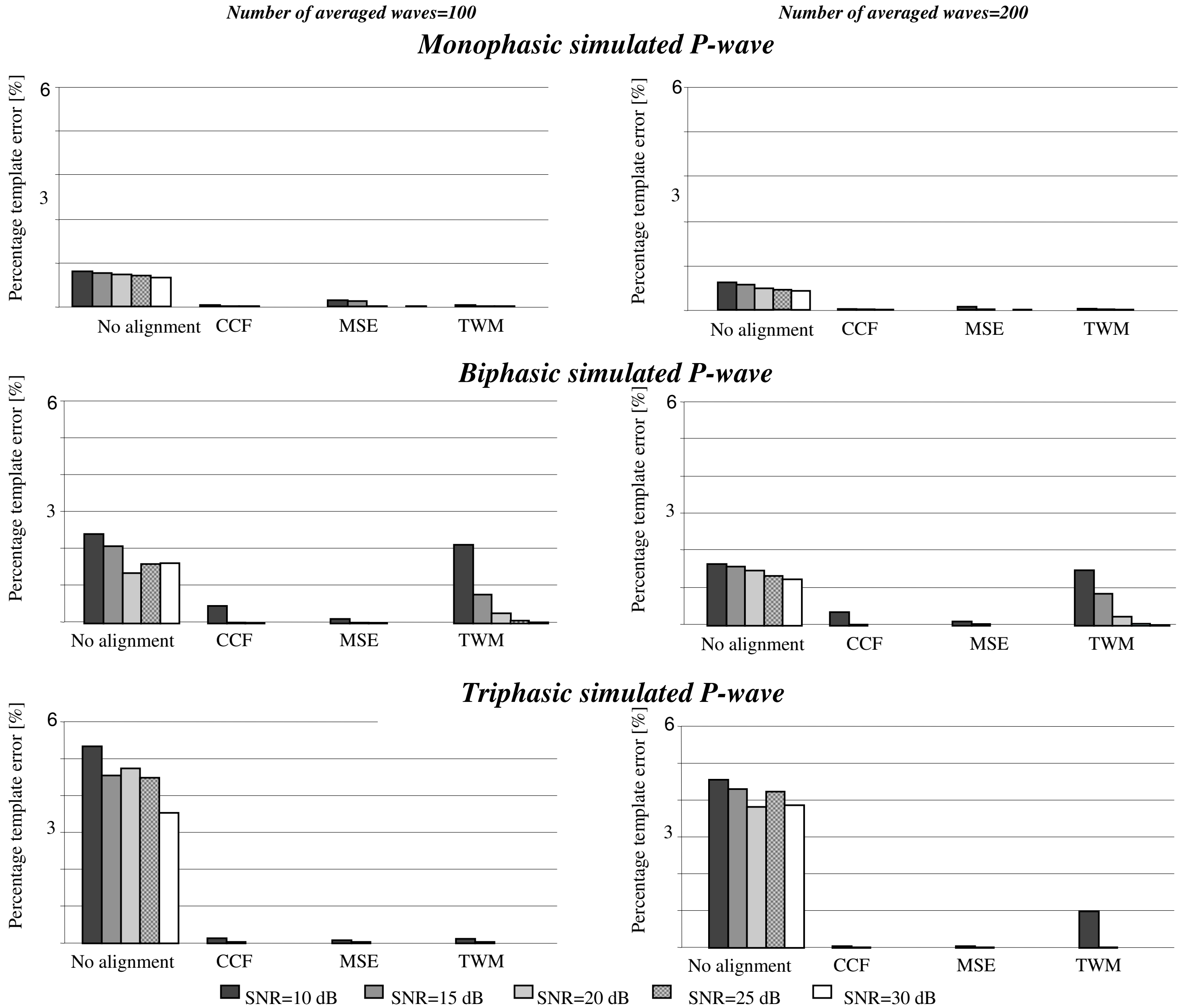

Fig. 3. Percentage template error estimated as the percentage error between the real waveform and the estimated template, for 100 (left) and to 200 (right) monophasic, biphasic and triphasic simulated P-waves. Results obtained for different levels of added random noise are shown.

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