Bi-Dimensional Cross-Correlation of Spectro-Temporal Maps for the Detection of Beat-to-Beat Variable Late Potentials

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Abstract

The aim of this paper is to detect the presence of beat-to-beat variable late potentials (LP) in high resolution ECG (HRECG) records. In order to evaluate the LP activity, we use the bi-dimensional cross-correlation between a template spectro-temporal map (STM) of LP and the STM of each individual beat of the HRECG record.

The method was applied to simulated HRECG records with different types of LP: a) Stable LP, b) Alternating LP, and c) LP of beat-to-beat variable amplitude. The simulated records were constructed using beats extracted from real HRECG records and were contaminated with white noise of different RMS levels.

Our results show that the proposed method is able to detect a high percentage of stable LP and beat-to-beat variable LP, still in presence of high noise levels. We conclude that the method is a promising technique for the detection of beat-to-beat LP activity in HRECG records.

1. Introduction

Ventricular late potentials (LP) are low-level, high frequency, fractionated signals within the terminal region of the QRS complex and the beginning of the ST segment. The detection of these micropotentials in high resolution ECG (HRECG) records is used for the identification of postinfarction patients with high risk of ventricular tachycardia and cardiac sudden death [1].

Due to their low amplitude, LP are usually masked by the background noise in HRECG records. Coherent signal averaging is the classical method to improve the signal-to-noise ratio (SNR) of LP [2]. It is based on the hypothesis that the signal of interest repeats itself in each beat and that the noise is random and uncorrelated with the signal. However, the process of averaging eliminates any dynamic information of LP that could be of diagnostic utility. Previous studies [3,4] have showed that LP can exhibit a dynamic behaviour and the beat-to-beat variability of LP can be associated with risk of malignant arrhythmias. Nevertheless, the detection of LP in individual beats is difficult due to the low amplitude of these micropotentials and the characteristics of the background noise in HRECG records.

In this work, we propose the use of the bi-dimensional (2-D) cross-correlation between a template spectro-temporal map (STM) of LP and the STM of each individual beat, in order to detect the beat-to-beat LP activity. The method was applied to simulated HRECG records with different types of LP in order to study its performance and it was compared with the results obtained from the temporal (1-D) cross-correlation between the template temporal segment of LP and the signal of each individual beat.

2. Methods

2.1. Spectro-temporal mapping

Spectro-temporal mapping is a technique that reveals the time-frequency content of a signal. This technique has been previously used in HRECG records for the detection of LP in the averaged beat [5] and also for the beat-to-beat LP analysis [6].

In this work, the STM technique was applied to the filtered vector magnitude (VM) of each detected beat, which is computed as

$$VM = \sqrt{X_f^{\,2} + Y_f^{\,2} + Z_f^{\,2}}$$

where X_f, Y_f and Z_f are the filtered signals with a 40-250 Hz, bandpass, bidirectional (forward and reverse direction), 4th-pole, Butterworth filter of the X, Y and Z leads. Also, we computed the STM of the VM of the averaged beat, which was used for the extraction of the template STM of LP.

In each case, the STM was obtained by combining a set of power spectra corresponding to a 80 ms segment moving through the signal in 1 ms step. A 256 points FFT was used for the computation of the power spectral density. Each segment was detrending and multiplying by a Blackman-Harris window before the estimation of its spectrum. The resultant spectra are structured in a three-dimensional plot, where the horizontal axes correspond to the time and frequency variables, and the vertical axis represents the power spectral density.

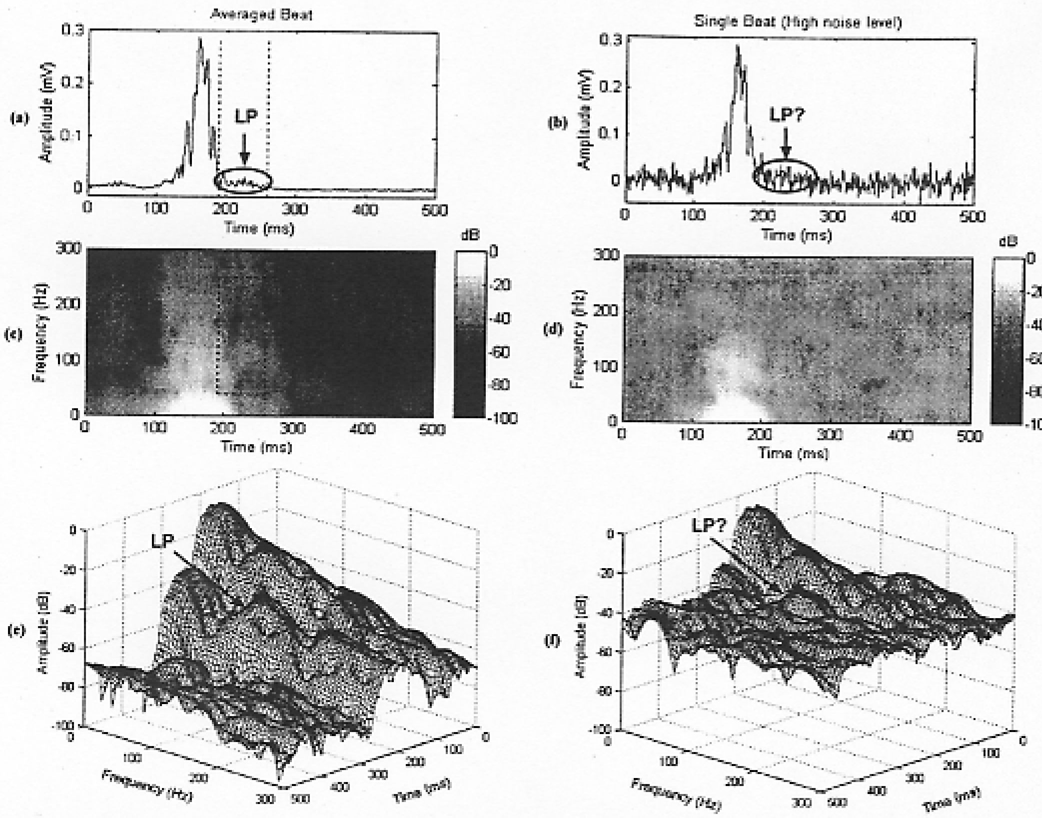

Figure 1. (a) Vector magnitude (VM) of the averaged beat, (b) VM of an individual noisy beat, (c,e) STM of the averaged beat, and (d,f) STM of the noisy beat. LP are easily identified in the VM and STM of the averaged beat, but their identification is difficult for the individual beat due to its higher noise level. In (c), the dot lines mark out the boundaries of template STM of LP used in the cross-correlation stage.

Figure 1 illustrates the STM technique for a patient with LP. The VM of its averaged beat and the VM of an individual noisy beat are represented respectively in Figs. 1a and 1b. Their corresponding STM are shown in bi-dimensional format in Figs. 1c and 1d. and as three-dimensional plot in Figs. 1e and 1f. Note that LP are clearly visible in the VM and STM of the averaged beat, but they are masked by the higher background noise in the VM and STM of individual noisy beat.

2.2. Bi-dimensional cross-correlation

Bi-dimensional (2-D) cross-correlation is a technique frequently used for pattern recognition in image processing [7]. This technique enables to find matches of a subimage $w(x,y)$ of size $K \times L$ within an image $f(x,y)$ of size $M \times N$, with the condition of $K \leq M$ and $L \leq N$.

The 2-D cross-correlation coefficient ρ between $f(x,y)$ and $w(x,y)$ at point (s,t) is defined as

$$\rho(s,t)=\frac{\sum_{x=0}^{K-1}\sum_{y=0}^{L-1}\left(f(x,y)-\bar{f}(x,y)\right)\left(w(x-s,y-t)-\bar{w}\right)}{\left[\sum_{x=0}^{K-1}\sum_{y=0}^{L-1}\left(f(x,y)-\bar{f}(x,y)\right)^2\right]^{1/2}\left[\sum_{x=0}^{K-1}\sum_{y=0}^{L-1}\left(w(x-s,y-t)-\bar{w}\right)^2\right]^{1/2}}$$

where $s=0,1,\ldots,M-1$ and $t=0,1,\ldots,N-1$, $\bar{w}$ is the average value of the pixels in $w(x,y)$ (computed only once), $\bar{f}(x,y)$ is the average value of $f(x,y)$ in the region coincident with the current location of w. Figure 2 illustrates the axes convention for the computation of the 2-D cross-correlation coefficient ρ.

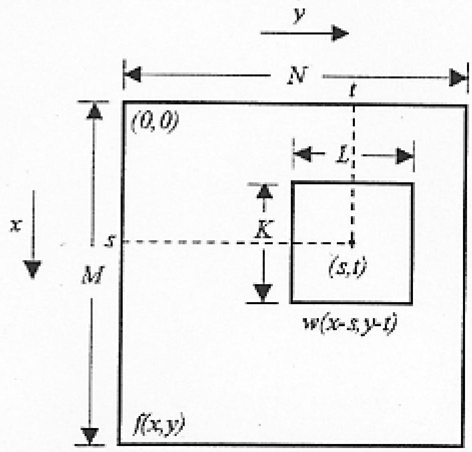

Figure 2: Axes convention for the computation of the 2-D cross-correlation coefficient ρ between the image $f(x,y)$ and the subimage $w(x,y)$ at point (s,t).

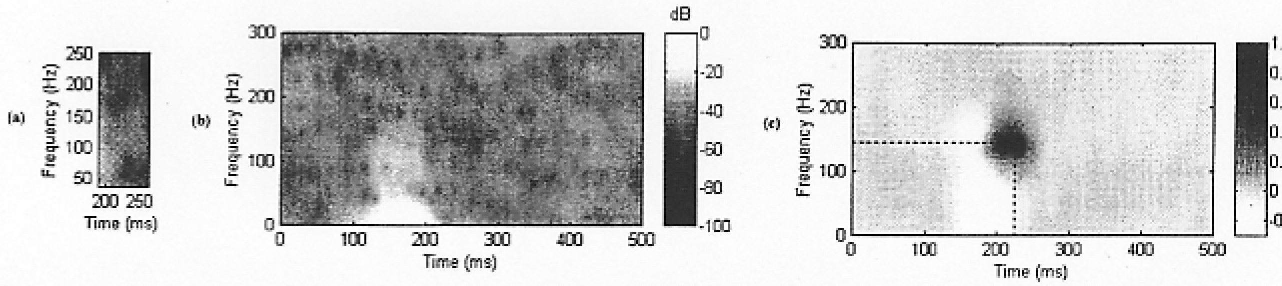

Figure 3. (a) Template STM of LP, (b) STM of an individual noisy beat, and (c) Bi-dimensional cross-correlation coefficient. The latter has a maximum near to 1, indicating the presence of LP in the noisy beat.

The 2-D cross-correlation coefficient $\rho(s,t)$ is scaled in the range −1 to 1. It is equal to 1 if the subimage w is identical to the corresponding region in the image f, it is equal to −1 if w is opposite in phase to f, and it is equal to 0 if w is not related with f.

Due to this coefficient is capable of identify patterns in images with high noise levels, we can compute the 2-D cross-correlation between a template STM of LP and the STM of each individual noisy beat in order to detect the presence of the LP in individual beats. The template STM of LP was visually extracted from the STM of the averaged beat, choosing the time-frequency region where LP are located (see Fig. 1c). Figure 3 shows the proposed method. The template STM of LP and the STM of an individual noisy beat are respectively shown in Figs. 3a and 3b. The 2-D cross-correlation coefficient of both maps is illustrated in Fig. 3c, which have a maximum near to 1 revealing the presence of LP in the individual beat.

3. Results

The proposed technique has been tested in simulated HRECG records of 100 beats each with different types of LP: a) Stable LP, b) Alternating LP, and c) LP of beat-to-beat variable amplitude. Each simulated record was constructed by repeating in time the averaged beat of a normal subject (without LP) and then adding the LP extracted from the averaged beat of a patient with high risk of ventricular tachycardia.

In case a), the LP were added to all beats of the simulated record; in b), the occurrence of the LP in each beat was randomly selected in order to model alternating LP; and in c), the amplitude of LP was randomly adjusted in five discrete levels (20, 40, 60, 80 and 100% of its original amplitude) to simulate LP of variable amplitude. Figure 4 illustrates a temporal segment of the simulated HRECG records. Additionally, all simulated records were corrupted with stationary white noise of different level (5 and 10 µV RMS) in order to emulate the real situation where LP are masked by the background noise in individual beats.

In this work, the maximum value of the 2-D cross-correlation coefficient (ρ_{max}) is used as the single parameter for the detection of LP in individual beats. Due to the cross-correlation coefficient can have several local maxima produced by noise effects and also by the high energy of QRS complex, it was limited the search area of ρ_{max} in the 2-D cross-correlation map to the region delimited by the same temporal and frequency boundaries of the template STM of LP.

The range of ρ_{max} obtained with alternating LP was divided in five equi-spaced bands in order to detect not only the presence of LP but also to estimate its relative amplitude in each beat. A correct LP detection was considered if the value of ρ_{max} obtained for a beat was included in the band corresponding to the relative amplitude of the simulated LP for that beat.

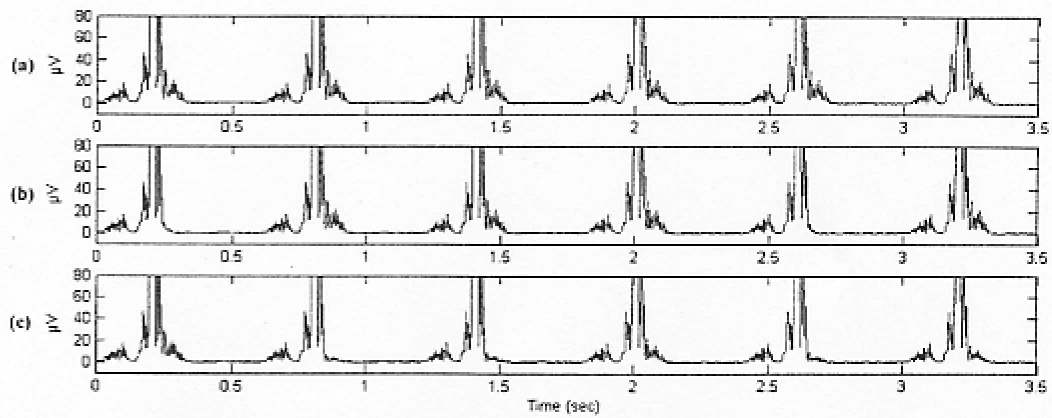

Figure 4. Simulated HRECG records with: (a) Stable LP, (b) Alternating LP, and (c) LP of variable amplitude.

Table 1 shows the percentages of LP correct detection using the 2-D cross-correlation for all beats of the simulated HRECG records.

Table 1. LP detection percentages using 2-D cross-correlation for different types of LP and noise levels.

Type of simulated LP	White noise RMS level		
	0 µV	5 µV	10 µV
Stable LP	100 %	87 %	77 %
Alternating LP	100 %	79 %	72 %
Var. Ampl. LP	100 %	75 %	68 %

In order to compare the performance of the studied technique, we also computed the temporal (1-D) cross-correlation coefficient between the template temporal segment of LP (extracted from the VM of the averaged beat and delimited by dot lines in Fig. 1a) and the VM of each individual beat (represented in Fig. 1b). Using the maximum of this 1-D cross-correlation as the detection parameter, we obtained the percentages of LP detection shown in Table 2.

Table 2. LP detection percentages using temporal (1-D) cross-correlation for different types of simulated LP and noise levels.

Type of simulated LP	White noise RMS level		
	0 µV	5 µV	10 µV
Stable LP	100 %	78 %	50 %
Alternating LP	100 %	65 %	39 %
Var. Ampl. LP	100 %	47 %	27 %

4. Discussion and conclusions

In this work, we have presented a method for the beat-to-beat detection of LP in HRECG records. The method is based in the use of 2-D cross-correlation between a template STM of LP and the STM of each individual beat. The maximum value of the 2-D cross-correlation is used as the LP detection parameter.

The results indicate that the method is capable of detect the 100% of stable and variable LP in the simulated noisy-free records. In these records, the selected parameter is able to detect the presence and amplitude of LP. However, we have observed that the LP detection percentages decrease as the noise level of the record increases. It is due to a higher noise level produces a higher decrease in the value of the maximum of cross-correlation, affecting the detector performance.

For the same noise level, we can also observed that the higher detection percentage is achieved with stable LP whereas the lower detection performance is obtained with LP of variable discrete amplitude. It is due to the higher difficulty to discriminate an amplitude level than to detect the presence or absence of the LP in each beat. Nevertheless, the presented method is able to detect a higher percentage of stable LP, alternating LP and LP of amplitude variable in simulated HRECG records corrupted with significant noise levels.

Finally, the studied 2-D method was compared with the temporal (1-D) cross-correlation between the template temporal segment of LP and the signal of each individual beat. We have observed that the 2-D method exhibits a better performance than the 1-D method in all noisy records. It is due to the 2-D cross-correlation measures the similarity of the time and frequency characteristics between the template LP and each detected beat whereas the 1-D cross-correlation takes only account the temporal similarity of the template LP with each individual beat.

We concluded that the 2-D method is a promising technique for the detection of beat-to-beat LP activity in HRECG records. Further investigations should be carried out to examine the performance of this method in real HRECG records.

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