Cancellation of Ventricular Activity in Endocavitary Recordings during Atrial Fibrillation by Particle Swarm Optimization

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Abstract

The cancellation of ventricular activity (VA) from atrial electrogram (AEG) is commonly performed by template matching and subtraction (TMS): a running template, built by adaptive averaging of AEG segments in correspondence of QRS, is subtracted from AEG to uncover atrial activity (AA). In our approach, before subtraction, templates are modulated by a set of coefficients which are estimated by maximizing, via Multiple Particle Swarm Optimization (MPSO), a fitness function based on: 1) the energy of the estimated and measured AA; 2) the first derivative of the estimated and measured AA; 3) the similarity between the template and its modulated version. To validate the method, three datasets of 500 synthetic AEG were built. Each signal included background AA, localized AA and VA. We observed that TMS+MPSO provided better performances then TMS alone when the ratio of VA/AA amplitude is large (VA/AA $\geq$ 3), while the performances get closer when the ratio decreases.

1. Introduction

Atrial fibrillation (AF), the most common arrhythmia encountered in the clinical practice, is characterized by a highly irregular atrial activity. The level of irregularity depends on the number of circulating wavefronts in the atria and its quantification can be used to classify AF events (from type–I to type–III according to Wells' classes [1]), to predict spontanuoes termination of AF or the response to ablation therapy [2].

To assess the levels of AA organization, several signal processing methods were developed in the last years including nonlinear, spectral and morphological analyses [3]. Regardless of the method used, in most cases the first processing step is the cancellation of ventricular activity superimposed to the atrial one. This cancellation is commonly performed by means of template matching and subtraction (TMS). While the template might be fixed, better results are obtained by adapting it over time, *i.e.* building a running template by adaptive averaging AEG segments, taken in correspondence of QRS complexes on a concurrent surface ECG recording [4]. Apart from how it is built, the template is then simply subtracted from the endocardial recordings. The method is simple and mostly effective but there are situations in which an appropriate cancellation is not achieved and the residuals may corrupt the successive analysis. To overcome this problem, before subtracting it from the AEG, we propose to modulate the template by a set of coefficients, estimated via Multiple Particle Swarm Optimization (MPSO) [5].

2. Methods

In the following, AEGs recorded during AF are modeled as

$$s(n) = a(n) + v(n) + b(n) \qquad (1)$$

where $v(n)$ is the VA, $a(n)$ describes localized AA and $b(n)$ is the background, wide–band AA. During AF, $a(n)$ and $v(n)$ may overlap in time and thus cancellation of $v(n)$ is required to uncover the atrial components. In the traditional template matching and subtraction method, the template $t(n)$ is built by adaptive averaging of electrogram segments taken in correspondence of QRSs on surface ECG. The running template is then subtracted from the electrogram $s(n)$. The resulting quantity

$$r(n) = s(n) - t(n) = a(n) + b(n) + [v(n) - t(n)]$$

is called *residue* and will contain atrial contributions only when $t(n) \approx v(n)$, *i.e.*, when the template is a good estimator of the VA.

In our approach, instead of subtracting $t(n)$, we used a modulated version of it. If we indicate the template shape by $\mathbf{t} = [t(1), t(2), ..., t(N)]^T$, being N the number of samples, our estimator of the VA becomes

$$\hat{\mathbf{v}} = \mathbf{W}\mathbf{t},$$

where the diagonal matrix $\mathbf{W}$ is the weighting (modulating) matrix, whose elements need to be estimated at each beat, as described in the next section.

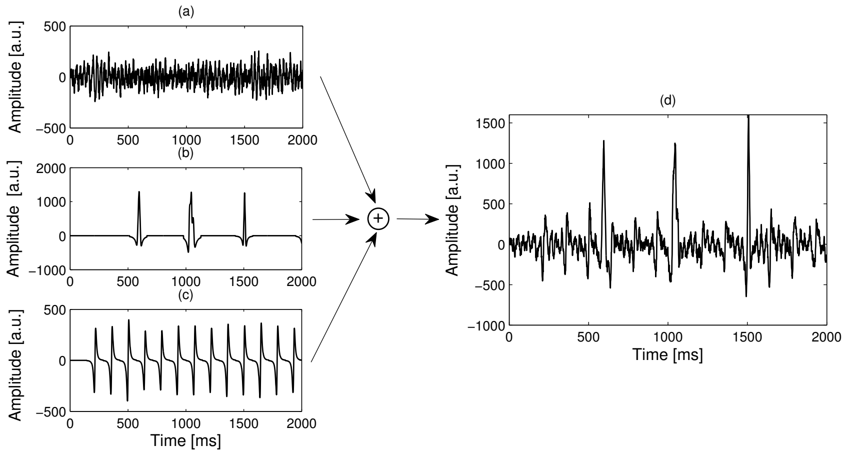

Figure 1. Example of simulated data (d) given as the sum of (a) background AA, (b) VA and (c) localized AA.

2.1. Particle Swarm Algorithm (PSO)

PSO is an iterative computational method able to solve optimization problems. The idea behind the algorithm is simple: a swarm of particles (representing the problem's solutions) is moved within a search area to find the optimal spot (solution to a given problem). At each iteration step, with M particles, M potential solutions are obtained and, among them, the best one is selected (*i.e.*, the one which maximizes a predefined, problem–specific *fitness function*). These solutions identify positions in the search space which will be transformed into basins of attraction that will guide the movement of particles in successive iteration. The process is repeated until a stop criterion is reached.

The law which governs the movement of particles is the most important part of the algorithm. Three factors are usually considered: i) inertia, ii) local movements and iii) global movements. Formally,

$$z_i(k) = \omega z_i(k-1) + \psi_p \rho_p [l_i - y_i(k)] + \psi_g \rho_g [g - y_i(k)]$$

where $z_i(k)$ is the vector of velocity of the i-th particle at the k-th iteration, $y_i(k+1) = y_i(k) + z_i(k)$ is the new position of the i-th particle, l_i is the local optimum of i-th particle, g is the global optimum, ρ_p and ρ_g are random numbers extract from a uniform distribution.

The values of the coefficients ω, ψ_p and ψ_g govern the behavior of the algorithm in term of convergence and stability. Low values provide a secure local or global solution, but a small search space is spammed. Instead, higher values of the coefficients allow to enlarge the search space. There is not a unique strategy for setting these parameters. In our work, ω decreased linearly with each iteration from a value of 0.9 to 0.1, while $\psi_p = \psi_g = 2$ were kept fixed.

The algorithm used in this work is an extension of PSO and is typically termed Multiple Particle Swarm Optimization. In MPSO a multi-initialization with N concurrent swarms is employed. Also, the search space is enlarged by exchanging particles between swarms after a fixed number of iterations (the worst solution is traded for the best one of another swarm). The extra parameters which need to be set are the topology of the set of swarms, the number of particle exchanged across them and the number of iterations before swaps of particles. In here we selected a ring topology with 10 swarms of 12 particles each. Swarms were initialized into a hypersphere of center equal to 1. Every 10 iterations, 5 particles were exchanged from a swarm to another.

2.1.1. The Fitness Function

The core of PSO is the fitness function J which is maximized at each step. In this paper, it has been tailored on the characteristics of the signal. At each beat it was computed as the sum of three terms

$$J = \alpha J_1 + \beta J_2 - (\alpha + \beta) J_3, \tag{2}$$

where J_1 depends on the energy of the residue, J_2 is a function of the mean absolute first derivative of estimated and measured AA and J_3 quantifies the distance between the template and its modulated version. The positive constants in (2) were empirically set to $\alpha = 4$ and $\beta = 1$, after some tests on a train dataset.

In details, J_1 quantify how much the the energy of the residual signal matches that of the AEG when no VA is present. It is defined as

$$J_1 = \frac{1}{1 + \exp\left(\sigma_r - \theta \sigma_a\right)}, \tag{3}$$

where σ_r is the standard deviation of the residue and σ_a is the standard deviation of the AA (in practise computed on

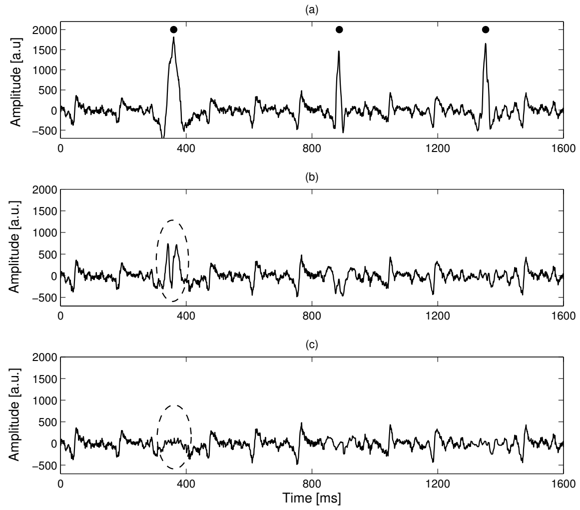

Figure 2. Example of cancellation of VA from an AEG, using (a) TMS or (b) TMS+MPSO. Occurrences of VA are identified by black dots. See text for details.

the portion of AEG recording immediately preceding the VA to be canceled). The quantity in (3) is monotonically decreasing and penalizes solutions in which $\sigma_r > \theta\sigma_a$, which usually happens when some components of VA remained in $r(n)$. The additional parameter θ is added for generalization and it is used to consider only a fraction of the total energy of AA in the computation of the fitness.

J_2 has a similar design, but it quantifies the discrepancy in the derivatives of the the signals. It was defined as:

$$J_2 = \frac{1}{1 + \exp\left(m_r - m_a\right)}, \tag{4}$$

where

$$m_x = \frac{1}{N}\sum_{1}^{N} |\underbrace{x(n) - x(n-1)}_{\approx\, x'(n)}|,$$

being x either $r(n)$ or $a(n)$. The term (4) penalizes solutions in which the mean value of the absolute first derivative of the residue is larger than that of AA. Therefore it tends to discharge solutions in which high–frequency, high–amplitude oscillations remain in the residue.

Finally, J_3 is used to constrain $\hat{\mathbf{v}}$ to remain close to $\mathbf{t}$. We quantified the distance between $\hat{\mathbf{v}}$ and $\mathbf{t}$ as

$$d = \frac{1}{\pi}\arccos\left(\frac{\mathbf{t}^T\hat{\mathbf{v}}}{\|\mathbf{t}\|\|\mathbf{v}\|}\right)$$

and thus $0 \le d \le 1$ and, when $\hat{\mathbf{v}}$ and $\mathbf{t}$ have similar shapes, $d \approx 0$. The term J_3 is then defined as

$$J_3 = \Theta(d - \theta_d),$$

where Θ is the Heaviside step function. Therefore the threshold θ_d defines the maximum acceptable distance from the template. Note that the particular arrangement of coefficients in equation (2) renders the selection of solutions for which $J_3 = 1$ very unlikely.

2.2. Data simulation

To evaluate the performance of the method, simulated signals were built according to the model (1), as described in the following sections.

2.2.1. Atrial activity

Two AA components are considered in the model: background and localized components. The background AA signal was obtained using the autoregressive model

$$b(n) = \sum_{k=1}^{p} a_k b(n-k) + w(n)$$

where the model order p, model coefficients a_k and the properties of the white noise process $w(n) \sim N(0, \sigma^2)$ were derived by fitting a set of real AEG signals and deriving an average model.

To simulate *localized AA*, the activation of atria fibers was approximated by a current dipole, $\mathbf{p}$, moving along a straight line. The potential generated by this dipole in a uniform infinite medium (with conductivity σ) is

$$\phi = \frac{\mathbf{p}\cdot\mathbf{a_r}}{4\pi\sigma r^2} \tag{5}$$

where $\mathbf{a_r}$ is the unit vector directed from the source point to the field point and r is the distance between these two points. We hypothesized that dipole is constant in its physical properties (amplitude, direction and versus) and moves in the medium at constant velocity passing by the recording electrode. The resulting localized AA's are shown in Fig.1 (c): a biphasic shape is obtained as those observed when propagation wavefronts pass by an exploring electrode.

2.2.2. Ventricular activity

To build the VA, both the occurrence and the morphology of the wave had to be simulated.

To determine the occurrence of each QRS, we considered that the timing of ventricular activation is approximately erratic during AF. While the ventricular rate (f_v) is in the range 100-200 bpm, the beat–to–beat variability is very pronounced. Therefore, in our simulations, the position of the i^{th} QRS was given by

$$p_{\text{QRS}}(i) = i f_v^{-1} + w_i + p^0_{\text{QRS}} \tag{6}$$

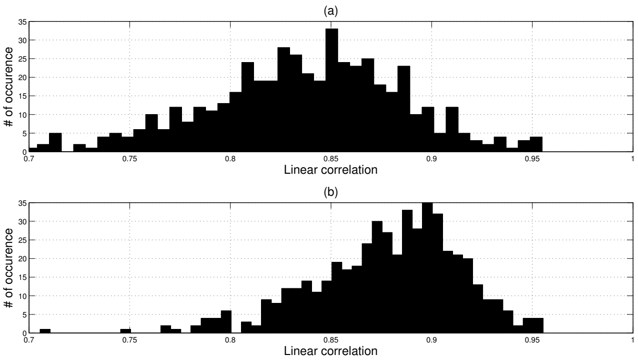

Figure 3. Histograms of the correlation coefficients between simulated AA and $r(t)$, obtained after VA cancellation, using (a) TMS or (b) TMS+MPSO.

where w_i is a white noise process used to model the erratic QRS occurrences and where p^0_{QRS} is a constant term defining the position of the first QRS.

The ventricular morphology is obtained as the sum of potentials generated by a pair of dipoles. Two dipoles were used to create a double peaked VA, as sometimes observed in real recordings. The contribute of each dipole is computed using (5) and then composed to create the VA.

2.2.3. Composition of the synthetic AEG

The amplitude of the background atrial activity $b(n)$ was tuned to obtain a fixed ratio between the amplitude of the localized AA and the standard deviation of the background AA itself. This ratio was set to 4.

In assembling the various terms in equation (1), we took into account the fact that AA and VA may have different amplitudes. We therefore explored three distinct cases in which VA/AA (*i.e.*, the ratio between ventricular and atrial amplitudes) was equal to 3, 4 or 5 respectively. For each case a set of 500 simulated AEG was created. An example of simulated data is shown in Fig.1(d).

3. Results

Fig.2 shows the cancellation of VA from a simulated AEG. A clear residual is still present when TMS is employed (see ellipses in Fig.2(b)). Conversely, using TMS+MPSO (Fig.2(c)), no significant remainder of VA is observed. The same happened for all the 500 synthetic records. To quantitatively compare the performances of the two methods, the correlation between the simulated AA and $r(t)$, obtained after VA cancellation, was estimated. Fig.3 shows the histograms of the correlation coefficients obtained on all the records. The histogram in Fig.3(b) is right-shifted compared to that in Fig.3(a): on average, higher correlations are obtained using TMS+MPSO.

Table 1. Mean±standard deviation (SD) of the correlation coefficients between simulated AA and $r(t)$, obtained after VA cancellation. $(*)$: mean values significantly higher for TMS+MPSO ($p < 0.05$, t-test). (§): SD values significantly smaller for TMS+MPSO ($p < 0.05$, F-test).

VA/AA	TMS	TMS+MPSO
3	0.905 ± 0.029	$0.911^* \pm 0.025^{\S}$
4	0.872 ± 0.039	$0.894^* \pm 0.031^{\S}$
5	0.836 ± 0.049	$0.877^* \pm 0.036^{\S}$

Table 1 shows the same correlation coefficients but for different values of the ratio VA/AA. The mean values are always significantly larger using TMS+MPSO, and the corresponding standard deviations smaller, implying that the signals obtained are closer to the original ones, leading to more reliable results.

4. Conclusions

Cancellation of VA in AEG is the very first step for many different further analyses. To improve this cancellation, we proposed a modulation of the template obtained via TMS by a set of coefficients estimated using MPSO. The results showed an improvement in the estimates of AA: the correlation coefficients between the residue and the simulated AA increased and the standard deviations decreased.

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