Body-Surface Atrial Vector Similarity as a New Way to Investigate Atrial Fibrillation Propagation Dynamics

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Abstract

Atrial propagation patterns during atrial fibrillation (AF) can be characterized by a certain degree of recurrence (associated with different types of reentrant circuits that can drive the arrhythmia). In this study, we investigated this recurrent activity at the level of the body-surface, by measuring the level of similarity between pairs of consecutive atrial vectors. High-density body surface potential maps (120 anterior, 64 posterior electrodes) were recorded in 75 patients in persistent AF. For each patient, atrial vectors were created by taking the samples from all electrodes at each time instant. Similarity between consecutive vectors was measured in terms of the value of the cosine of the angle between two vectors. In all patients, the series of cosine values showed a quasi-periodic behavior, with atrial vectors alternating between phases of slow motion, and phases of fast motion. Moreover, the frequency of this behavior is about twice the AF dominant frequency, which suggests that within one AF cycle there are two phases of slow motion and two of fast motion, alternating. Finally, the amount of slow phases is positively correlated with a higher long-term recurrent behavior of the atrial propagation patterns. This seems to indicate that atrial vectors may provide a new way to noninvasively investigate atrial fibrillation dynamics.

1. Introduction

Atrial propagation patterns during atrial fibrillation (AF) can be characterize by a certain degree of recurrence [1–6], which can be associated with different types of reentrant circuits that can drive the arrhythmia. The investigation of how well this dynamic behavior of atrial activity (AA) propagation patterns during AF can be noninvasively characterized by analyzing ECG signals is relevant in order to improve AF patient stratification and treatment selection, without resorting to invasive analysis. In this respect, previous studies have shown that propagation of AA during AF is a process characterized by different short- (or a single cycle) and long-term (related to several cycles of propagation) recurrent behaviours [8, 11], while another study suggested that the time-varying spatio-temporal properties of this behavior seem mainly due to a spatially uncoordinated propagation of the AF waveforms [9]. In this study, we investigated this recurrent activity at the level of the body-surface, by measuring the level of similarity between pairs of consecutive body-surface atrial vectors. Results show that body-surface atrial vectors contain information about AA dynamics during AF, and they may represent an alternative way to noninvasively analyze AF dynamics.

2. Methods

2.1. BSPM data and pre-processing

Body surface potential maps (BSPMs) were recorded in 75 patients in persistent AF, with 120 anterior and 64 posterior leads (ActiveTwo BSM Panels Carbon Electrodes, Biosemi B.V., The Netherlands; Fig. 1). All patients underwent electrical cardioversion, and 32 patients showed AF recurrence 4 to 6 weeks after procedure. ECGs were sampled at 2048Hz, and downsampled at 256Hz. A one-minute segment was selected for each subject, low-quality leads were excluded (low signal-to-noise ratio, poor electrode contact, motion artefacts), and Wilson's Central Terminal was subtracted in line with conventional ECG analysis. After band-pass filtering the signals between 1 and 100Hz (3rd order Chebyshev), QRST cancellation was performed using an adaptive singular value decomposition method, inspired by [7], with multiple QRST window templates defined using hierarchical clustering. The extracted

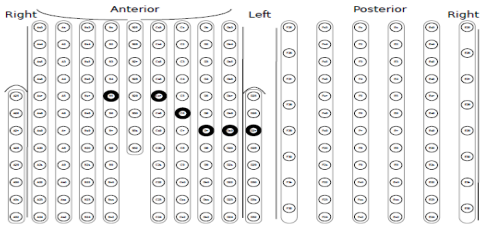

Figure 1. BSPM electrode configuration, comprising 120 anterior leads and 64 posterior leads. Thick circles: default positions of the precordial leads $V_1, \ldots, V_6$.

AA signals were post-filtered with a zerophase notch filter at 50Hz to suppress power line noise, and with a 3Hz zerophase highpass filter (3rd order Chebyshev) to remove low-frequency residuals not related to (persistent) AF.

2.2. Atrial vectors and similarity signal

For each patient, atrial vectors were created as follows: assuming that all extracted AA signals from a patient (ℓ leads, and N samples) are collected in a matrix X of size $\ell \times N$, each column of X provides an $\ell \times 1$ vector $\mathbf{x}(n)$, $n = 1, \ldots, N$, which represents the overall spatial AA from all electrodes at a given time instant. $\mathbf{x}(n)$ can be interpreted as a snapshot of atrial potentials reflected on the body surface at discrete time n (or as a sort of atrial dipole, defined in a space of dimension ℓ, similar to the 3-D cardiac dipole in vectorcardiography). Similarity between pairs of consecutive vectors (1 sample apart) can then be measured in terms of the value of the cosine of the angle between the two vectors:

$$\text{sim}_1(n) = \frac{\mathbf{x}(n)^T \mathbf{x}(n+1)}{||\mathbf{x}(n)||_2 ||\mathbf{x}(n+1)||_2}, \; n = 1, \ldots, N-1. \tag{1}$$

$\text{sim}_1(n)$ is expected to give values close to 1 (small angles, or high similarity) for spatial AA wave fronts with similar morphologies even when their corresponding amplitudes are different, in order to highlight the presence of self-similar patterns in the data. Fig. 2 provides a schematic representation of the generation of a similarity signal $\text{sim}_1(n)$ from body-surface AA signals. As it can be seen in the figure, these signals show a very similar quasi-periodic behavior, with periods of values close to 1 (similar vectors), and very short periods of values closer to 0 (sometimes negative - not in the figure; dissimilar vectors), and quick transitions between the two. This suggests that the vectors alternate between phases of slow motion (values close to 1), and phases of fast motion (values close to 0). Therefore, it is interesting to analyze the time and frequency properties of similarity signals, in order to understand if and to what extent they can provide an alternative way to look at AA propagation dynamics during atrial fibrillation, as reflected on the body-surface. Moreover, it is also relevant to investigate their relation to the recurrent behavior of those dynamics, which we already described in previous studies [8–11]. Indeed, in [8] we suggested that AA propagation as recorded on the body surface is a process characterized by short- and long-term recurrent behaviors. Namely, an early phase characterized by a decrease of the similarity between an atrial vector and the following so many vectors within approximately one AF cycle, and a later phase characterized by an approximately constant similarity. The long-term recurrent behavior in particular can be considered as a measure of long-term recurrent behaviour of AA propagation in a patient, and it is assumed to be related to the overall AF substrate complexity (with a higher value to be related to a lower degree of electro-structural remodelling) [9, 11].

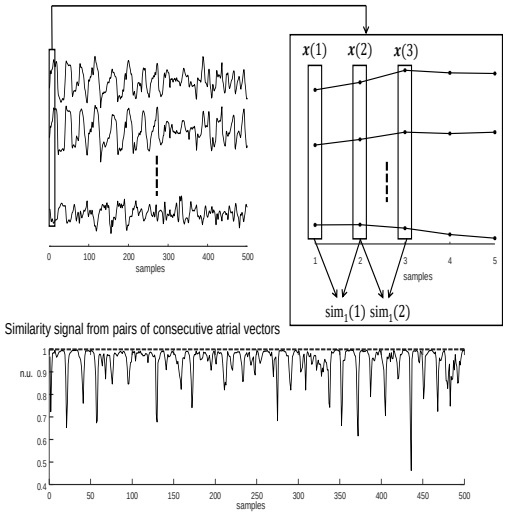

Figure 2. Schematic representation of the construction of a similarity signal $\text{sim}_1(n)$ (bottom), starting from AA signals extracted from ECG recordings (top left), and by measuring the level of similarity between consecutive atrial vectors (defined as the samples from all signals at a specific time point; top right).

3. Analyses and Results

Fig. 3 shows the percent of points close to 1 (phases of slow motion) and close to 0 (phases of fast motion) for all patients. It can be noticed that phases of slow motion are more prevalent in all patients than phases of fast motion (although there is a large variability in the amount of phases of slow motion among patients). We then identified the 3% of largest absolute vector similarities in each patient, selected the corresponding subset of k columns of matrix X, and decomposed the corresponding submatrix

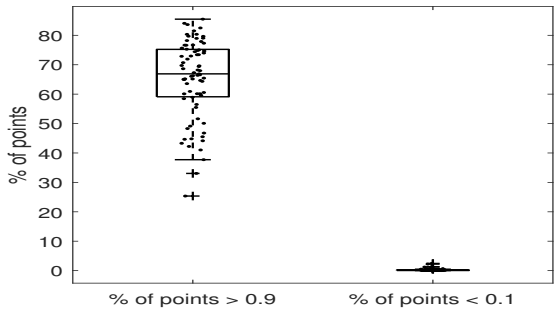

Figure 3. Boxplots of percent of points in a similarity signal close to 1 (threshold 0.9) and close to 0 (threshold 0.1).

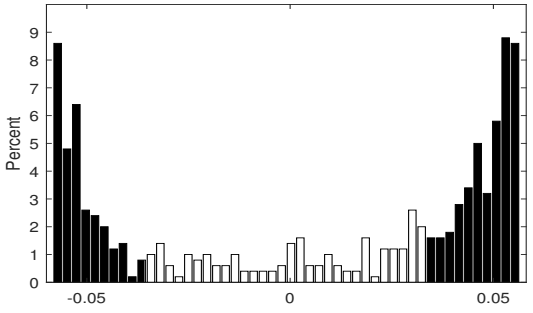

Figure 4. Example of distribution of the values of the first principal component PC1 of submatrix $\ell \times k$ of X collecting the samples associated with the most relevant vector similarities in a patient from the data set. The distribution is bimodal, with the two main modes located at the extremes (black bars).

of size $\ell \times k$ by means of singular value decomposition. In general, we noticed that the values of the first principal component of the submatrix $\ell \times k$ show a bimodal distribution, with values concentrated at the negative and positive extremes (see Fig. 4, which depicts the distribution of the first principal component for the same patient as in Fig. 2). Spatially, that means that vectors from two consecutive slow regions are in opposition of phase. Fig. 5 shows the percent of points in the first principal component of the submatrix $\ell \times k$ which are located at the extremes of the distribution (first and last ten bins), for all patients. It can be noticed that in all patients at least more than 50 % of the points are located at the extremes of the distribution. When looking at the frequency content of a similarity signal, we noticed that in general such signals show a dominant frequency which is about twice the dominant frequency of the AF in a patient. A representative example is given in Fig. 6, which shows the average power spectral densities of the body-surface AA signals and of the

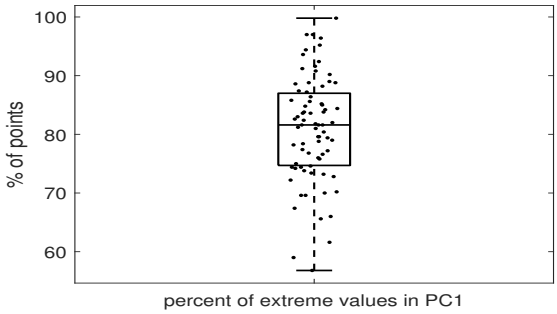

Figure 5. Boxplots of percent of points in the first principal component PC1 of the submatrix $\ell \times k$ which are located at the extremes of the distribution (first and last ten bins), for all patients.

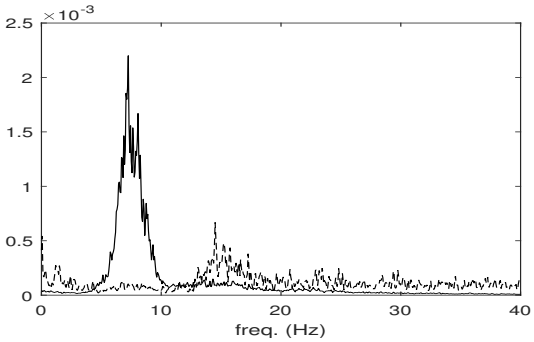

Figure 6. Power spectral densities of the body-surface AA signals (continuous line; average for all signals) and of the similarity signal (dashed line) for the same patient as in Fig. 2.

similarity signal for the same patient as in Fig. 2. Fig. 7 shows the boxplots of dominant frequencies of the AA signals and similarity signals for all patients, which confirms that in general the frequency of the periodic alternation between phases of slow motion and phases of fast motion in a similarity signal is about twice the AF dominant frequency (13.6(1.8) Hz vs. 6.6(1.1) Hz, respectively; median(IQR)). Together with the results presented in Fig. 4 and 5, this suggests that within one AF cycle there are two phases of slow motion and two of fast motion, alternating. Finally, we found a positive correlation between the long-term recurrence of the AA during AF, as defined in [8, 9, 11], and the amount of slow phases in a patient (0.59, $p < 10^4$); Fig. 8; no significant association with electrical cardioversion outcome).

4. Conclusions

This study investigated whether AA dynamics during AF can be characterized by measuring the level of similar-

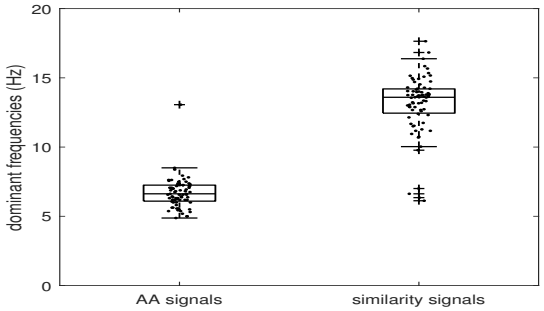

Figure 7. Boxplots of dominant frequencies of the AA signals and similarity signals for all patients.

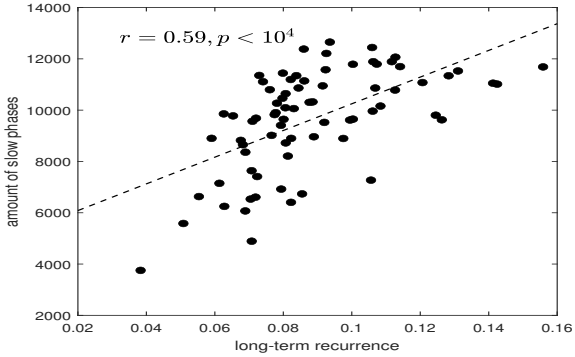

Figure 8. Scatter plot of the amount of slow phases vs. the long-term recurrence. The corresponding line of best fit and the Pearson correlation coefficients r are also shown.

ity between pairs of atrial vectors. The similarity signals obtained by measuring similarity of consecutive atrial vectors showed a quasi-period behavior in all patients, with periods of slow motion (similar vectors) alternating with periods of fast motion (dissimilar vectors), with a frequency of about twice the AF dominant frequency. This suggests that within one AF cycle there are two phases of slow motion and two of fast motion, alternating, with the two phases of slow motion in opposition of phase. In general, we found that there are more phases of slow motion than of fast motion in a patient, and that the amount of time spent in phases of slow motion positively correlates with the long-term recurrent behavior of the atrial propagation patterns. Overall, this seems to suggest that atrial vectors are able to capture to some extent information about AA dynamics during AF, as reflected on the body-surface, and therefore they may represent an alternative way to noninvasively analyze AF dynamics, and the organization of the underlying AA propagation patterns.

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