Analysis of Atrial Fibrillation Dynamics in Body Surface Potential Maps and Electrocardiographic Imaging

Rubén Molero[1], Olivier Meste[2], Joël Karel[3], Ralf Peeters[3], Pietro Bonizzi[3*], María S. Guillem[1*]

[1]ITACA Institute, Universitat Politècnica de València, València, Spain
[2]Laboratoire I3S, UNSA-CNRS, Nice, France
[3]Department of Advanced Computing Sciences, Maastricht University, Maastricht, The Netherlands

Abstract

Previous studies have shown that global short- (ST) and long-term (LT) atrial fibrillation (AF) dynamics can be characterized non-invasively by Body Surface Potentials (BSPM). Also, Electrocardiographic Imaging (ECGI) may add information as it can characterize locally the atrial substrate. The objective of this study is to compare AF dynamics characterized on both BSPM and ECGI signals.

Two consecutive 4-second BSPM signals from 34 AF patients (23 male, 8 paroxysmal, 63.1± 9.5 years) were recorded, followed by ECGI computation. ST and LT dynamics metrics were computed in both BSPM and ECGI, assessed from a multivariate autocorrelation of the signals. BSPM features of ST dynamics positively correlated with LT dynamics (0.52 and 0.78). Analogous values of correlation were obtained in ECGI. When normalized by the LT dynamics, the ST inversely correlated with the speed of propagation of AF at half AF cycle (BSPM, r = -0.28 vs. ECGI, r = -0.45), showing higher stability in the ST propagation for faster AF.

BSPM and ECGI reflected similar relationships in the analysis of AF propagation dynamics. Results were consistent with previous studies and suggest that BSPM are sufficient to characterize global AF dynamics, while ECGI may become relevant when more localized information is required.

1. Introduction

Atrial fibrillation (AF) is characterized by its complex propagation on the atrial surface. The propagation dynamics of AF are characterized by different short- and long-term recurrent (i.e., repetitive) patterns, that have been previously defined and studied in surface ECG signals [1, 2]. This recurrence analysis showed promising results in differentiating between persistent AF patients with opposite prognosis after electrical cardioversion. Assessment of AF dynamics and its propagation can be a valuable tool for improving PVI candidate selection, as a predictor of arrhythmia recurrence after an ablation procedure. In the present study, recurrence dynamics are studied in BSPM and ECGI signals to evaluate the AF propagation dynamics. The objective of this study is to validate the study of AF dynamics on ECGI signals and compare the results with the observed dynamics on BSPM.

2. Material and methods

2.1. Data acquisition and processing

Body Surface Potential Mapping (BSPM) recordings of 34 patients (23 male, 8 paroxysmal, 63.1 ± 9.5 years old) were recorded before pulmonary vein isolation (PVI) with rotor ablation at a sampling frequency of 1kHz. Torso geometry and lead positioning of the patients were reconstructed by photogrammetry [3]. The atrial anatomy of each patient was obtained from a database of MRI segmented atria.

Baseline of surface electrograms was removed and then signals were band-pass filtered between 2 and 45 Hz. Two consecutive signals per patient were selected with a mean duration of (4.58 ± 0.51s) and ventricular activity was cancelled by using a single-lead Principal Component Analysis approach described in [4]. To obtain the ECGI of each patient, the inverse problem was computed using zero-order Tikhonov regularization and L-curve optimization.

2.2. Recurrence signal and temporal metrics of recurrence

Atrial propagation dynamics were studied by computing the multivariable autocorrelation function of the spatial atrial activity in BSPM and ECGI signals as described in [1, 2]. Briefly, a square matrix R of size $M \times M$ is generated by computing:

$$R_{i,j} = \frac{x(i)^T x(i+j-1)}{||x(i)||_2 ||x(i+j-1)||_2}, \; with\; i,j = 1, \ldots, M,$$

Where $x(i)$ represents the overall spatial atrial activity from all electrodes (hence multi-variable) at a given time instant i (being BSPM or ECGI), thus generating a square matrix of size M x M, being M the window size of the analyses as half of the signal samples [2]. Each entry of R is therefore a measure of the cosine of the angle between two vectors. Moreover, column j of M includes correlation values at lag $p = j - 1$. The average over each column (per lag) provides a multi-variable autocorrelation function (MAF) of the spatial AA oscillatory patterns, for lags $p = 0, \ldots, M - 1$. In Fig 1, an example of the multivariable autocorrelation of an ECGI signal is represented. Descriptive features of recurrence were obtained for each recurrence signal as described in [2] and averaged per patient. Short-term recurrence metrics associated with half AF cycle ($|P_1|$) and full AF cycle (P_2) were obtained together with the long term recurrent (LTR) behavior (median of the multivariable autocorrelation function between 150 and 450 lags). Additionally, the time lags of the short-term recurrence peaks of the AF half (tP_1) and full cycle (tP_2) were computed. These lags are associated with the speed of propagation of the atrial activity on the short-term (half or full AF cycle). Finally, P_1 and P_2 were normalized by LTR [2].

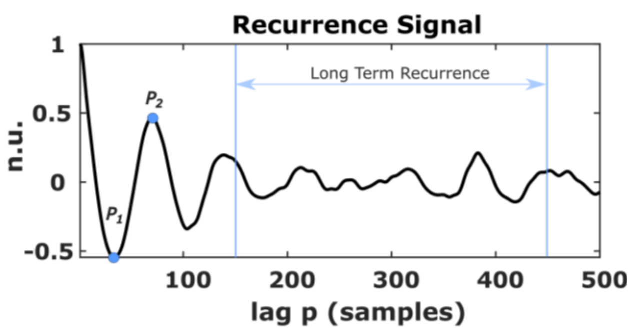

Figure 1. Multivariable autocorrelation function computed from a set of ECGI signals. The peaks associated with half (P_1) and full (P_2) AF cycle length (short-term recurrence) and the interval characterizing the long-term recurrence (LTR) are indicated.

2.3. Statistical analysis

Correlation between short-term recurrence parameters and LTR was computed in BSPM and ECGI signals. Moreover, the correlation between times (tP_1, tP_2) and the respective normalized recurrence values were calculated. Correlation analyses were performed for the totality of the population. Moreover, to see if the studied metrics had the ability to differentiate between different AF propagation patterns, non-parametric Wilcoxon rank-sum test was computed between paroxysmal and persistent AF patients. A p-value < 0.05 was considered statistically significant.

3. Analyses and Results

3.1. BSPM and ECGI short and long-term recurrence

In Fig 2 it is shown the correlation between the short- and long-term parameters for BSPM (A) and ECGI (B) signals. For both type of signals, there is a positive correlation between the recurrent behavior at half and full AF cycle with LTR. BSPM and ECGI signals showed analogous values of correlation, being higher between full AF cycle dynamics and LTR ($r > 0.78$, $p < 0.01$) This shows that more regular AF (high short-term recurrence values) is correlated with high LTR, meaning a less complex atrial substrate is reflected by a higher recurrent and organized behavior of the dynamics of the signal.

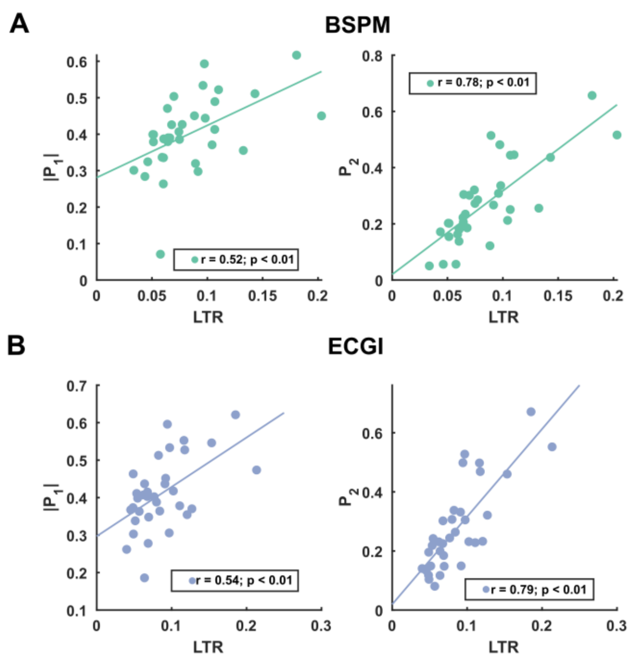

Figure 2. A. Scatter plot of $|P_1|$ and P_2 with the long-term recurrence (LTR) for BSPM signals (A) and ECGI signals (B).

3.2. Recurrent behavior and temporal dynamics of AF in ECGI

In Fig 3A, the correlation of normalized $|P_1|$ and P_2 with tP_1 and tP_2 for ECGI signals is shown for BSPM (A) and ECGI (B) signals. As in Fig. 2, BSPM and ECGI had similar correlation values, being in this case, higher for the metrics obtained with ECGI signals. The values of AF dynamics correlated negatively with the AF propagation speed. Low correlations were observed, with only significant values for normalized $|P_1|$ and tP_1, ($r = -0.45$, $p < 0.01$), showing that the faster the AF is propagating on the short-term (half AF cycle), the more stable the propagation is (higher correlation, as shown in [2] as well). Nevertheless, for the full AF cycle, no correlation between the propagation speed and recurrence was found (Fig 3 right).

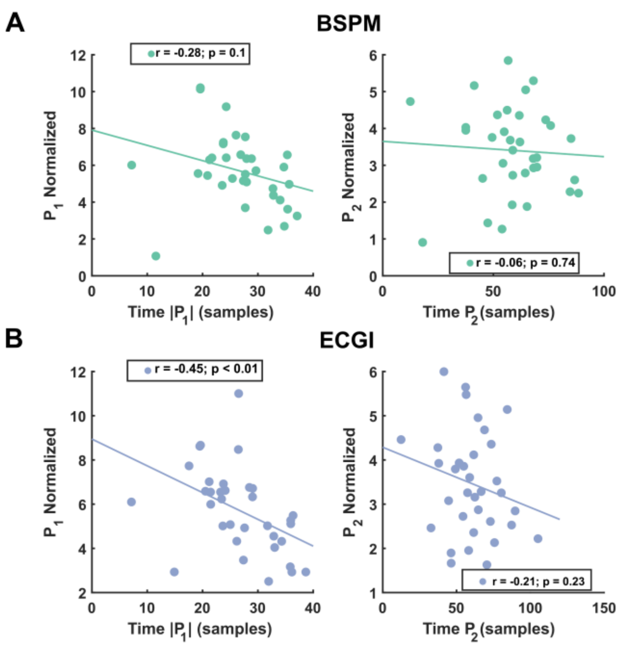

Figure 3. A. Scatter plot of normalized $|P_1|$ and P_2 with speed of propagation for BSPM signals (A) and ECGI signals (B) for half and full AF cycle.

3.3. Recurrent behavior and AF progression

In order to validate the presented metrics and their ability to differentiate between different AF populations, statistical hypothesis tests were carried out between the metrics of paroxysmal and persistent AF patients. Most of the metrics for paroxysmal patients showed less complexity, especially for half AF cycle, compared to the persistent AF patients. Only significant differences were found for AF propagation speed at half AF cycle (tP_1) for both, BSPM and ECGI signals, see Fig. 4. The same trend was observed for tP_2, but with no significance, Fig 4B. This shows the lower degree of structural remodeling present in paroxysmal patients.

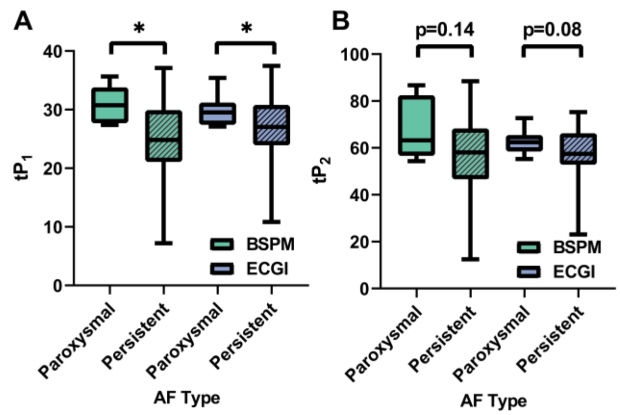

Figure 4. Boxplot diagram of propagation speeds of AF dynamics for half (A) and complete (B) AF cycle for BSPM (green) and ECGI (blue) signals. The asterisks and values between brackets show the p-values from independence test between paroxysmal and persistent AF patients.

4. Discussion

In this study, we evaluated the atrial substrate of AF patients based on an analysis of the propagation dynamics of BSPM and ECGI signals. The results validated previous conclusions about the relationship between short- and long- term AF recurrence, where high recurrence at short-term correlates with long-term AF recurrent behavior [2]. In the present study, this evidence was extended for paroxysmal AF patients and epicardial signals computed with ECGI, illustrating that similar dynamics are reflected in the epicardium and torso's surface for patients at different stages of the arrhythmia. Besides, our analyses showed that although the results are similar, they seem to be stronger on ECGI rather than on BSPM signals, suggesting that incorporation of spatial information on top of the recorded electrical information would improve the interpretability of AF propagation dynamics. On the other hand, results showed that for the half AF cycle metrics, patients negatively correlated with the AF propagation speed, although with low correlation values. This is in line with previous analyses, showing that the faster the atrial activity is propagating, the more stable its propagation is in the short-term [2].

Additionally, we wanted to test the ability of the analyzed metrics to differentiate between different AF types. Paroxysmal AF patients presented higher values of short-term propagation speed, especially for the full AF cycle. This may indicate that when AF progresses in these patients, higher recurrent dynamics are observed. This can be explained because paroxysmal AF patients may have a less complex AF substrate, with a less pronounced electro-structural remodelling that eases the electrical propagation on the atrial surface. On the contrary, persistent AF patients have lower stability as the disease is more advanced [5]. The differences in the behavior between patients based on AF type at different AF cycle times illustrate that at the initiation of the atrial activity, the arrhythmia remains less chaotic and its propagation is more affected with the progression of the disease, probably caused by a higher presence of local microstructural changes that result in critical patterns that affect AF progression [6]. Nevertheless, it should be noted, that the analyzed groups are unbalanced, and further analysis should be carried out to confirm these differences. The ability of these metrics to differentiate between AF types opens the possibility for the use to predict treatment outcome, like following pulmonary vein isolation. Furthermore, the analogous results observed in ECGI, show that BSPM seems to be sufficient for determining AF recurrent behavior on a global scale. However, an ECGI regional analysis of these metrics may discern between AF patients with different local dynamics, that may explain the success of ablation treatments on AF patients.

5. Conclusion

BSPM and ECGI reflected similar relationships in the analysis of AF propagation dynamics. Results were consistent with previous studies and suggest that BSPM are sufficient to characterize global AF dynamics, while ECGI may become relevant when more localized information is required.

In future studies, the analysis of the presented metrics in ECGI per atrial regions may clarify if they can differentiate between AF with different prognosis in the patients.

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*P. Bonizzi and M.S. Guillem share the last authorship

Address for correspondence:

Rubén Molero Alabau
ITACA. Edificio 8G acceso B. Universitat Politècnica de València. Camino de Vera s/n. 46022 Valencia, Spain.
rumoal1@itaca.upv.es