Characterizing Surface Fibrillatory Waves Through the Lagged Poincaré Plot for Preoperative Prediction of Ablation Success in Persistent Atrial Fibrillation

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Abstract

Atrial fibrillation (AF) management poses a significant challenge for healthcare systems due to the high mid–term recurrence rate following catheter ablation (CA) for persistent AF. Analyzing the morphological variability of fibrillatory waves (f–waves) from the electrocardiogram (ECG) has provided insights about the atrial electrical activity organization, which is a crucial indicator for CA outcome prediction. This work introduces an innovative analysis of f–waves morphology evolution over time based on the lagged Poincaré plots (PP) technique. Traditional ellipse–fitting quantifiers and centroid–derived PP features were evaluated in 94 f–waves excerpts (34 from patient that relapsed to AF 9 months after the intervention) reporting a higher predictive capability than common CA outcome predictors, such as the dominant frequency or the amplitude of the f–waves. Specifically, PP-based measures, such as the minor ($SD1$) and major ($SD2$) axes of the optimally fitted imaginary ellipse, their ratio ($SD12$) and the standard deviation of the distance between PP points and the distribution centroid (S_d) showed a predictive accuracy of 70–80%. The combination of PP features with time and frequency domain f–waves characteristics improved accuracy up to 85%. The lagged PP has proven to be a valuable tool in characterizing f–waves, paving the way for a more personalized approach in AF treatment.

1. Introduction

The high mid-term recurrence rate among patients with persistent atrial fibrillation (AF) who undergo catheter ablation (CA), about 35% within the first year after the treatment, represents a significant burden on healthcare systems [1]. Consequently, there is growing clinical interest in accurately predicting the procedure outcome prior to the intervention, since CA remains the primary treatment for AF [2, 3]. Accurate prediction of CA success would allow for better patient selection, minimizing unnecessary risks, considering alternative therapies, and lowering healthcare costs associated with AF management [4].

Prior research has suggested that increased disorganization in cardiac fibrillatory activity may be linked to an unsuccessful mid–term CA outcome. These studies, primarily focused on characterizing fibrillatory waves (f–waves) extracted from the electrocardiogram (ECG) in both time and frequency domains,identified metrics that could serve as potential predictors of CA treatment success [5–7].

Examination of the variability in the morphological pattern of f–waves provides insights into the organization of atrial electrical activity over time, which could be crucial in predicting AF ablation outcomes [8]. The Poincaré plot (PP) was previously demonstrated to be an useful tool in characterizing heart rate variability (HRV) through the analysis of RR intervals [9, 10]. This has motivated the present study, where PP were applied for the first time in analyzing the variability of the f–waves time series. Specifically, the objective of this study is to analyze the lagged PP of f–waves time series, quantify its properties, and evaluate its capability to predict CA treatment outcome in patients with persistent AF.

2. Materials and methods

2.1. Study population

This study involved 52 patients with persistent AF undergoing their first radiofrequency CA at Toledo and Albacete University Hospitals under standard clinical indications [7]. After a 9–month follow–up period, 18 patients relapsed to AF, while 34 maintained sinus rhythm (SR).

2.2. Signal acquisition and preprocessing

Prior to the CA procedure, a 12–lead surface ECG signal was recorded at a sampling frequency of 977 Hz (re-

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sampled to 1 kHz) with 16–bit resolution. The extraction of f–waves was focused on lead V1, given its prominent atrial activity amplitude relative to ventricular activity [11]. Signals were preprocessed by conventional filtering techniques and wavelet transform–based methods to mitigate baseline wander, powerline interference, and high–frequency noise components [12, 13]. Then, the extraction of the f–waves was carried out using an adaptive singular value cancellation method of the QRST complexes [14].

To minimize PP distortions due to the presence of ventricular residual activity, a novel technique was applied to extract high–quality f–waves segments [15]. A maximum of three 6 second–length segments per patient were considered. This led to the construction of a database of signals segments including 60 segments from patients maintaining SR and 34 from those experiencing relapse into AF.

2.3. Characterization of the f–waves

The PP is a tool that highlights nonlinear patterns in time series by plotting its successive pairs of samples $(x(n), x(n+1))$ on a scatter plot. Its lagged version, known as lagged PP, introduces a lag m between the represented pairs of samples $(x(n), x(n+m))$ [16]. The lagged PP could be valuable in analyzing the morphology of the f–waves to assess the evolution of different patterns over time. It was analyzed for a m value ranging from 1 to 400 samples, which allowed to examine short–term variations within the f–waves at small lags and to compare morphological changes between successive f–waves at large lags. Before PP analysis, f–waves time series were normalized between their minimum and maximum values so that they fall within the range from 0 to 1 in the PP representation, thus enabling their comparison.

Classic PP metrics devised for the evaluation of HRV were tested to characterize f–waves morphology variability (see Figure 1), including ellipse-fitting and centroid derived quantifiers. On the one hand, ellipse–fitting metrics of the PP comprised the ellipse major and minor axes, referred to as $SD1$ and $SD2$, respectively. $SD1$ was estimated from the standard deviation of the points in the graph along the direction perpendicular to the line of identity, while $SD2$ was similarly obtained by considering the parallel direction. The ratio $SD1/SD2$, indicated by $SD12$, and the area of the ellipse, S, were also computed [9, 17].

On the other hand, centroid–derived PP features included the centroid coordinates, Cd_x and Cd_y, which represented the mean values of the time series plotted on the two PP axes, and the mean (M_d) and standard deviation (S_d) of the geometrical distances between the centroid and each PP point [17].

Common predictors of persistent AF relapse after CA were also evaluated for comparative purposes. Specifically, these included the normalized amplitude of the f–waves signal ($n\mathcal{A}_{avg}$) and its dominant frequency (f_0), as well as the recently proposed power rate index (φ), which demonstrated superior predictive ability compared to previous metrics. These parameters were computed as described in [7].

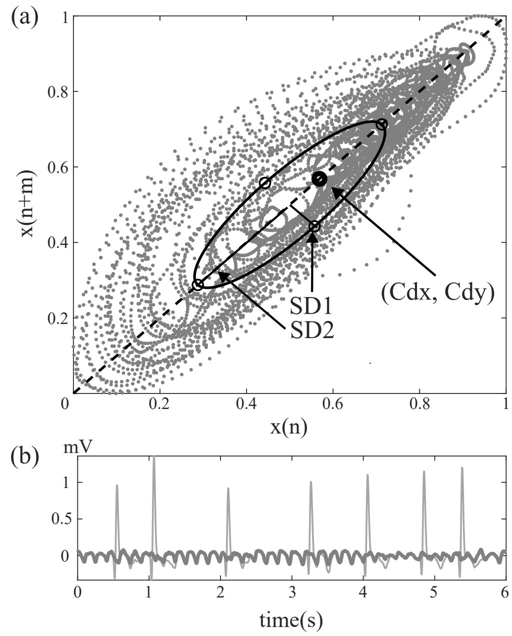

Figure 1. Example of a lagged PP (a, $m = 10$) of a f–waves signal (b) extracted from the ECG in AF rhythm.

2.4. Performance assessment

The results of the metrics were expressed through their mean $\pm$ standard deviation values within each patient groups. Statistical differentiation between groups was evaluated using the Student's t–test, when the normal distribution assumption was met, and the non–parametric Mann–Whitney U test otherwise.

The discriminant ability of the predictors was assessed applying a linear discriminant analysis (LDA) and performing a 10–fold cross validation, which was repeated 50 times to mitigate the bias that could be introduced by single database partition. In the training phase, a receiver operating characteristic (ROC) curve was employed to determine the optimal threshold for discriminating between the two groups of patients. The threshold was selected to achieve the optimal balance between sensitivity (Se) and specificity (Sp), which represent the rates of correctly classified patients experiencing AF relapse and maintaining SR, respectively. It is noteworthy that this approach may not necessarily maximize accuracy (Acc), defined as the percentage of correctly classified patients. The area under the ROC curve (AUC) was also computed as a comprehensive measure of each predictive model performance across all possible classification thresholds.

A LDA–based multivariate approach was also applied to point out complementary information among single predictors. A forward sequential feature selection algorithm, which minimizes the misclassification error, was used to select the optimal set of metrics to be combined.

It is worth noting that the optimal output result of each PP predictor was selected for the PP lag m_{opt} that maximized the Acc, AUC, and statistical differentiation (minimum p–value) of the corresponding classifier. This was achieved by identifying the maximum of the joint variable: $\frac{Acc \cdot AUC}{p-value}$.

3. Results

Table 1 displays the values of the individual indices, obtained for m_{opt}, in the two groups of patients. The dependence of the classifier $SD2$ performance metrics on the lag m is exemplified in Figure 2, where the optimal result was obtained for a m value of 152. All analyzed predictors, except for the centroid coordinates, showed statistically significant differences (p–values < 0.05) between the two groups. These indices presented higher values within the AF relapse group, indicating increased dispersion of the PP points and more variable f–waves patterns. Moreover, the results of the reference metrics were consistent with the expected trends in each group [7].

Table 2 presents the classification performance of each single parameter. The highest discriminant ability in terms of Se, Sp and Acc was achieved by $SD2$, which was slightly superior to φ, while the largest AUC value was obtained for $SD12$. The combination of $SD2$, S_d, φ, and $n\mathcal{A}_{avg}$ improved the performance of the predictive model, which reached Se, Sp, Acc and AUC values of 84.91, 85.08, 85.02 and 91.50%, respectively.

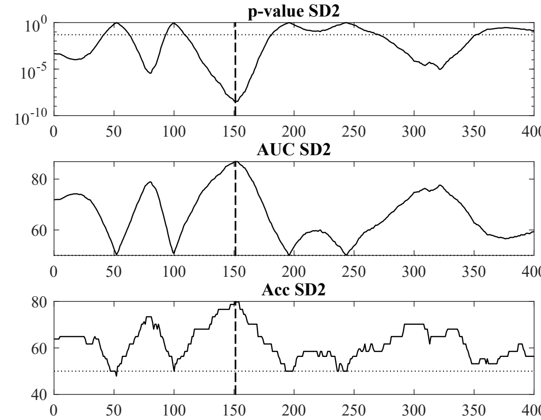

Figure 2. Tracking p–value and classification performance metrics (Acc and AUC) for $SD2$ as a function of the lag considered in the lagged PP of the f–waves time series. The vertical dashed lines indicate the optimal m_{opt} lag.

Table 1. Results per group and statistical differentiation of the analyzed metrics for the optimal m_{opt} lag.

	Group of patients who			
Index	Maintained SR	Relapsed to AF	p–value	m_{opt}
$SD1$	0.172 ± 0.031	0.207 ± 0.023	< 0.001	229
$SD2$	0.183 ± 0.026	0.222 ± 0.022	< 0.001	152
$SD12$	1.59 ± 0.21	2.07 ± 0.31	< 0.001	80
S	0.091 ± 0.014	0.106 ± 0.015	< 0.001	115
Cd_x	0.536 ± 0.056	0.520 ± 0.045	0.1625	218
Cd_y	0.537 ± 0.056	0.520 ± 0.045	0.1412	89
M_d	0.216 ± 0.021	0.238 ± 0.021	< 0.001	194
S_d	0.117 ± 0.009	0.126 ± 0.009	< 0.001	82
f_0 (Hz)	5.87 ± 1.21	6.29 ± 0.765	0.0140	–
φ	0.398 ± 0.243	0.164 ± 0.062	< 0.001	–
$n\mathcal{A}_{avg}$	0.237 ± 0.138	0.167 ± 0.080	0.0025	–

4. Discussion and conclusions

Analyzing the variability of the morphological structure of f–waves signal provides insights into the organization of atrial electrical activity, which is considered to play a significant role for CA outcome prediction in persistent AF [7,8]. This innovative work has introduced the analysis of lagged PP of the f–waves to estimate the variability of its morphological patterns over time.

A novel approach was also devised to capture the optimal lag that maximizes the discriminative capability be-

Table 2. Results of the performance metrics of individual classifiers for the optimal m_{opt} lag.

Index	Se (%)	Sp (%)	Acc (%)	AUC (%)
$SD1$	72.12	72.40	72.30	81.35
$SD2$	79.03	79.13	79.10	86.19
$SD12$	77.03	77.08	77.06	89.18
S	68.68	68.92	68.83	74.21
Cd_x	58.68	58.27	58.41	56.74
Cd_y	58.74	58.33	58.48	57.13
M_d	67.85	68.45	68.23	75.23
S_d	69.29	69.35	69.33	75.18
f_0	60.18	60.60	60.45	62.75
φ	77.29	77.20	77.23	85.04
$n\mathcal{A}_{avg}$	64.62	64.68	64.66	67.79

tween the two groups of patients for each studied index. The identified optimal lags fell within the approximate range of 80–200 ms, often associated with the AF cycle length of the f–waves [5]. This suggests that the features extracted from the PP primarily highlight morphological differences between successive f–waves, thus characterizing the level of signal organization.

This study presents a pioneering method for characterizing the morphology of f–waves through the PP. The indices derived from the PP were demonstrated to contain information useful for predicting the outcome of CA. Indeed, they exhibited superior predictive capabilities compared to common predictors of CA outcome, and yielded comparable results to the recently-introduced promising metric φ. Moreover, integrating features from diverse f–waves signal analyses significantly enhanced predictive accuracy up to 85%, marking a notable step toward the development of optimal predictive models to guide clinical decisions in the treatment of persistent AF. Nevertheless, further studies with larger databases should be developed to validate these findings.

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