Time-Frequency Analysis for Early Classification of Persistent and Long-Standing Persistent Atrial Fibrillation

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Abstract

This study aimed to assess an early classification of persistent and long-standing persistent atrial fibrillation patients by means of the time-frequency analysis of the surface ECG, which would allow electrophysiologists to choose the most suitable therapeutic approach to treat this arrhythmia.

140 consecutive unselected patients suffering from atrial fibrillation conformed the study population (84 persistent and 56 long-standing persistent). After ventricular activity cancellation, time-frequency analysis of the atrial activity was performed. Then, the study of phase variations along time for those frequency bands where the average power of atrial activity is concentrated, together with the mean distance between R peaks determined to be significative to allow early classification.

Classification was performed with a Support Vector Machine trained with 20 ECGs (10 corresponding to persistent and 10 to long-standing persistent AF). Classification results were: Accuracy = 74.16%, Sensitivity = 71.72%, Specificity = 78.26%. These results would provide electrophysiologists a tool to classify persistent AF patients, in order to choose the most suitable treatment in each case.

1. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia [1, 2] in clinical practice. AF is characterized by rapid, disorganized propagation of electrical signals through the atria. Thus, the atria and ventricles do not beat in a coordinate way, creating a fast and irregular heart rhythm.

AF patients can be classified as paroxysmal (who present self-terminating episodes, usually within 7 days), persistent (recurrent episodes which last for more than 7 days or which need cardioversion), long-standing persistent (persistent episodes which last for more than one year), and permanent (patients for whom sinus rhythm can not be restored and the arrhythmia is accepted for both the patient and the physician) [1].

AF treatment includes antiarrhythmic drugs and non-pharmacological therapies, such as electric isolation of the pulmonary veins using catheter ablation. The efficacy of each treatment depends on the clinical classification of the arrhythmia [3]. Paroxysmal AF patients are the ones who present higher percentages of freedom from arrhythmia episodes off antiarrhythmic drugs when catheter ablation is used (about 80%), whereas its efficacy is drastically reduced for long-standing persistent patients, for whom it is not recommended because of atrial remodeling [4].

AF detection and classification by means of the surface ECG has been addressed in many references of the state-of-the-art [5–7]. Most of them have studied the differentiation between paroxysmal and persistent episodes.

Discrimination between persistent and long-standing persistent has not been deeply explored yet. Indeed, to to best of our knowledge, apart from the works presented in [8] and [9] there are no references which have analyzed the ECG in order to predict progression of persistent and long-standing persistent AF patients.

In this paper we propose a method for their early classification by means of the study of phase variation of the time-frequency transform of the ECG. Classification is done using a Support Vector Machine.

2. Materials

140 consecutive unselected patients (84 persistent and 56 long-standing persistent) suffering from atrial fibrillation conformed the study population. ECGs were recorded in a specific arrhythmia clinic of a tertiary center, and they were clinically categorized according to current clinical guidelines [1, 2].

Pharmacological and surgical therapies to manage each AF episode were left at the discretion of the attending cardiologist. Patients with long-standing persistent AF presented more structural heart diseases, larger left atrial di-

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ameters, and were more frequently treated with ACE inhibitors and ARBs.

3. Methods

3.1. Signal preprocessing

The surface ECG signal is first filtered in order to remove baseline wander (by means of cubic splines [10]) and powerline interference (using a Notch filter at 50Hz).

Then, ventricular activity is cancelled in order to only analyze atrial activity. This is done taking into account that atrial and ventricular activities are not coupled during atrial fibrillation episodes [5]. In this way, R-peaks are detected using the Pan & Tompkins algorithm [11] and they are aligned. Then, Principal Component Analysis is performed and the first principal component is subtracted to each QRST complex.

3.2. Time-frequency analysis

The Fourier Transform has been typically used to analyze ECG recordings, in order to provide information about frequency content. Despite its merits, it is not able to provide information about how the frequency content varies along time. This is a substantial drawback when studying non-stationary signals (such as the surface ECG).

As it is also known that atrial fibrillation presents time-dependent properties [12], time-frequency analysis of ECG recordings seemed to be an excellent tool to extract significant features.

There are several time-frequency transforms, with different properties and drawbacks. The simplest form of the Short-Time Fourier Transform consists of dividing the signal into short and usually overlapping segments which are subjected to the Fourier Transform [13]. The length of these segments determines the resolution in time and frequency: the shorter the window, the better the time resolution, but the poorer the frequency resolution. Opposite situation is presented when a longer window is used.

In order to overcome this uncertainty principle, Stockwell et al. presented the Stockwell Transform in 1996 [14]. The Stockwell Transform (ST) offers progressive resolution and globally referenced phase: it can be seen as a Short-Time Fourier Transform whose window length varies according to the frequency (this is, larger windows for low frequencies and shorter windows for high frequencies). The ST is expressed as

$$(Sf)(\tau,\nu) = |\nu| \int_{-\infty}^{\infty} g_0(\nu(t-\tau)) e^{-2\pi i \nu t} f(t)\, dt, \quad (1)$$

where f is the signal to transform and g_0 is a Gaussian window.

Regrettably, the ST presents high computational cost and memory requirements. This is the reason why Brown et al. presented an efficient implementation of it based on a dyadic sampling scheme of the time-frequency spectrum, which is called the general Fourier-family transform (GFT) [15]. In this study we have used this efficient implementation when analyzing the ECG recordings.

3.3. Feature extraction

Once the atrial activity was extracted from the ECG signals (in particular, over bipolar lead II), we proceeded to perform time-frequency analysis and extract their relevant features. The GFT was computed as detailed in [15] using adaptive Gaussian windows, and then it was normalized to the range [0,1].

As recent references have pointed out that phase variations of ECG recordings of patients with persistent atrial fibrillation were larger than for paroxysmal AF patients [16, 17], we studied whether these differences would be even larger for long-standing persistent AF patients.

With this purpose, we only looked for phase variations along those frequencies in which the average power of atrial activity is concentrated [1.71-7.57Hz] [18].

In this manner, we extracted the L^1 norm of the phase of the variations of the GFT for each frequency band relevant for atrial activity. That is, if we denote as $\{a_{b1}, a_{b2}, \ldots, a_{bN}\}$ the coefficients of the samples of the time-frequency spectrum (where b refers to the frequency band and N is the number of samples of the time axis), we have considered the phase variations $\sum_{k=1}^{k=N-1} |\varphi_k|$, where $z_k e^{i\varphi_k} = a_{bk-1} - a_{bk}$, $z_k \geq 0$, and $-\pi \leq \varphi_k \leq \pi$.

In addition, in order to emphasize the largest differences, we have applied weights β to the phase differences for those cases in which they are larger than α-times the mean of the variation for each frequency band. Therefore, apart from the distance between R-peaks extracted during the ventricular activity cancellation, features used in the subsequent classification process were:

$$F_p = \begin{cases} \sum_{k=1}^{N-1} |\varphi_k|, & \text{if } \sum_{k=1}^{N-1} |\varphi_k| < \alpha_p \dfrac{\sum_{k=1}^{N-1} |z_{k+1} - z_k|}{N} \\[2ex] \beta_p \sum_{k=1}^{N-1} |\varphi_k|, & \text{if } \sum_{k=1}^{N-1} |\varphi_k| \geq \alpha_p \dfrac{\sum_{k=1}^{N-1} |z_{k+1} - z_k|}{N} \end{cases}$$

where $p = 4, 5$ are the frequency bands of the GFT transform where the power of the atrial activity is concentrated. The values of the parameters α_p and β_p have been experimentally set and they will be detailed in Section 4.

3.4. Classification

In this study we have trained a Support Vector Machine with 20 patients (10 persistent and 10 long-standing persistent) in order to maximize the global accuracy of the classification process.

We used the package LIBSVM for MatLab [19] with a non-linear kernel (radial basis function), which performed well in our study.

4. Results

As above-said, our dataset consisted of 140 ECGs of patients with AF episodes. The cohort of patients corresponded to an heterogeneous group, who has been treated with several antiarrhythmic therapies. There were 84 patients with persistent AF and 56 patients with long-standing persistent AF.

20 patients were used in the training process, who corresponded to those clinically more significant in terms of progression of the arrhythmia and treatment. Parameters α and β were experimentally found using extensive experimentation and iteratively searched until both were optimized.

The optimum values for parameters β_p were experimentally found to 2.8, whereas optimum α_p parameters were set to $\alpha_4 = 1.4$ and $\alpha_5 = 1.2$, for the two frequency bands significant for atrial activity (up to 8Hz).

We have measured performances in terms of global accuracy, sensitivity and specificity (number of persistent and long-standing persistent patients correctly classified, respectively).

Table 1 shows performances and classification results for the test dataset (74 persistent and 46 long-standing persistent AF patients), whereas Figure 1 shows the Receiver Operating Characteristic curve for the SVM classifier.

Table 1. Classification results for the whole dataset and only for the test dataset.

	Accuracy	Sensitivity	Specificity
Whole dataset	0.7643	0.7381	0.8036
Test dataset	0.7416	0.7162	0.7826

It can be observed that sensitivity and specificity results are balanced, despite the heterogeneous cohort of patients under different pharmacological and invasive treatments, and with different states of progression of the arrhythmia.

One value-add of the study is the cohort of patients, since it includes patients under different antiarrhythmic treatments, structural heart diseases, or several comorbidities. Table 2 details classification results for the subset of the test dataset of those patients who are absent of the different baseline characteristics which can modify the electrical behaviour of the AF wave, and which create confusion when performing the early classification. Thus, classification results improve when analyzing this specific subset.

Table 2. Classification results for the test dataset for several baseline characteristics.

Clinical characteristic absent	Accuracy	Sensitivity	Specificity
Structural heart disease	0.8095	0.7879	0.8889
Previous cardioversion	0.8	0.7742	0.8235
Left atrium dilatation	0.85	0.8125	1
Antiarrhythmic drugs	0.8108	0.7846	0.75

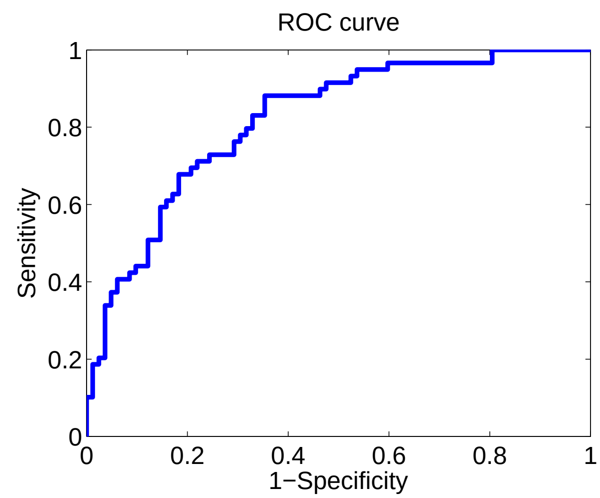

Figure 1. Receiver operating characteristic curve for the proposed method. Area under ROC curve is 0.8189.

5. Conclusions

In this paper we have presented a study whose aim is the early classification of persistent and long-standing persistent atrial fibrillation patients by means of time-frequency analysis. It has been shown that phase variation of atrial activity is a significant feature when classifying these clinical subtypes of atrial fibrillation. In this manner, long-standing persistent AF patients present larger phase variations than persistent AF patients.

Nowadays the clinical classification of AF is done afterwards, once the progression of the arrhythmia has been disclosed. These results may represent an early classification tool to help clinicians to choose the most appropriate therapeutic approach, or reduce the catheter ablation application on long-standing persistent patients, for whom the effectiveness when maintaining sinus rhythm on the longterm is low.

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References

[1] Wann L, Curtis A, January C, Ellenbogen K, Lowe J, Estes N, Ezekowitz M, Slotwiner D, Jackman W, Stevenson W, C.M Tracy; 2011 Writing Group Members VF, Rydén L, Cannom D, Heuzey JL, Crijns H, Lowe J, Curtis A, Olsson S, Ellenbogen K, Prystowsky E, Halperin J, Tamargo J, Kay G, L. Wann; 2006 Writing Committee Members AJ, Anderson J, Albert N, Hochman J, Buller C, Kushner F, Creager M, Ohman E, Ettinger S, Stevenson W, Guyton R, Tarkington L, Halperin J, Yancy C. 2011 ACCF/AHA/HRS focused update on the management of patients with atrial fibrillation (updating the 2006 guideline): a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines. Circulation 2011; 123(1):104–123.

[2] January C, Wann L, Alpert J, Calkins H, Cigarroa J, Cleveland J, Conti J, Ellinor P, Ezekowitz M, Field M, Murray K, Sacco R, Stevenson W, Tchou P, Tracy C, Yancy C. 2014 AHA/ACC/HRS Guideline for the Management of Patients With Atrial Fibrillation. A Report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines and the Heart Rhythm Society. J Am Coll Cardiol December 2014;64(21):e1–e76.

[3] Melichercik J. New frontiers in the evaluation and treatment of patients with atrial fibrillation. Biomed Tech 2012;57(1).

[4] Calkins H, Kuck K, Cappato R, Brugada J, Camm A, Chen SA, et al. 2012 HRS/EHRA/ECAS Expert Consensus Statement on Catheter and Surgical Ablation of Atrial Fibrillation: Recommendations for Patient Selection, Procedural Techniques, Patient Management and Follow-up, Definitions, Endpoints, and Research Trial Design. Heart Rhythm April 2012;9(4):632–696.

[5] Alcaraz R, Sandberg F, Sörnmo L, Rieta J. Classification of Paroxysmal and Persistent Atrial Fibrillation in Ambulatory ECG Recordings. IEEE Trans Biomed Eng May 2011; 58(5):1441–1449.

[6] Sandberg F, Stridh M, Sörnmo L. Frequency Tracking of Atrial Fibrillation Using Hidden Markov Models. IEEE Trans Biomed Eng February 2008;55(2):502–511.

[7] Nilsson F, Stridh M, Bollmann A, Sörnmo L. Predicting spontaneous termination of atrial fibrillation using the surface ECG. Med Eng Phys October 2006;28(8):802–808.

[8] Uldry L, Zaen JV, Prudat Y, Kappenberger L, Vesin J. Measures of spatiotemporal organization differentiate persistent from long-standing atrial fibrillation. Europace August 2012;14(8):1125–1131.

[9] Ortigosa N, Fernández C, Galbis A, Cano O. Classification of persistent and long-standing persistent atrial fibrillation by means of surface electrocardiograms. Biomed Eng Biomed Tech 2016;61(1):19–27.

[10] C. R. Meyer and H. N. Keiser. Electrocardiogram baseline noise estimation and removal using cubic splines and state-space computation techniques. Comput Biomed Res 1977; 10:459–470.

[11] Pan J, Tompkins W. A real-time QRS detection algorithm. IEEE Trans Biomed Eng 1985;32(3):230–236.

[12] Rieta J, Alcaraz R. Atrial Fibrillation - Mechanisms and Treatment (Chapter 7: Applications of Signal Analysis to Atrial Fibrillation). Intech, 2013.

[13] Cohen L. Time-Frequency analysis. Boston, MA: Prentice Hall, 1995.

[14] Stockwell R, Mansinha L, R.P.Lowe. Localization of the complex spectrum: The S transform. IEEE Trans Signal Process April 1996;44(4):998–1001.

[15] Brown R, Lauzon M, Frayne R. A general description of linear time-frequency transforms and formulation of a fast, invertible transform that samples the continuous S-transform spectrum nonredundantly. IEEE Trans Signal Process January 2010;58(1):281–290.

[16] Ortigosa N, Cano O, Ayala G, Galbis A, Fernández C. Atrial fibrillation subtypes classification using the General Fourier-family Transform. Med Eng Phys April 2014; 36(4):554–560.

[17] Ortigosa N, Fernández C, Galbis A, Cano O. Phase information of time-frequency transforms as a key feature for classification of atrial fibrillation episodes. Physiol Meas March 2015;36(3):409–424.

[18] Salinet J, Madeiro J, Cortez P, Stafford P, Andre G, Schlindwein F. Analysis of QRS-T subtraction in unipolar atrial fibrillation electrograms. Med Biol Eng Comput 2013;51(12):1381–1391.

[19] Chang C, Lin C. LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology 2011;2(3):27:1–27:27.

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