Atrial Fibrillation Classification Method for Patients with Different Pharmacological or Surgical Therapies

Nuria Ortigosa[1], Antonio Galbis[2], Carmen Fernández[2], Guillermo Ayala[3], Óscar Cano[4], Ana Andrés[4]

[1] I.U. Matemática Pura y Aplicada, Universidad Politécnica de Valencia, Spain
[2] Univ. Valencia, Dept. Math. Analysis, Burjassot, Spain
[3] Univ. Valencia, Dept. Stat. & Operat. Res., Burjassot, Spain
[4] Hospital Universitari i Politècnic La Fe, Servicio de Cardiología, IIS-La Fe, Valencia, Spain

Abstract

This method aimed to assess electrophysiologists to choose the most suitable therapy for patients suffering from atrial fibrillation (AF), depending on whether a paroxysmal or persistent episode is presented. Since the surface ECG masks the differentiation between subtypes of AF, an early detection of paroxysmal episodes allows a clinically preventive treatment to stop recurrence and the natural progression towards persistent AF.

Features of the General Fourier-family time-frequency transform were used as inputs of a Linear Discriminant Analysis classifier. Accuracy, sensitivity and specificity were measured to evaluate performance.

AF episodes are mostly correctly classified, having into account that, from a clinical point of view, it is more important to detect almost every paroxysmal episode than viceversa, in order to stop the progression of these patients towards persistent AF.

1. Introduction

Atrial fibrillation (AF) is the most common cardiac arrhythmia [1]. It is characterized by rapid, disorganized propagation of electrical signals through the atria. In AF, the heart's electrical signals begin in any part of the atria or nearby pulmonary veins (instead of beginning in the sinoatrial node). Thus, the atria and ventricles do not longer beat in a coordinate way, creating a fast and irregular heart rhythm. AF patients can be classified as paroxysmal (who present self-terminating episodes within 7 days), persistent (recurrent episodes which are unlikely to self-terminate and require cardioversion), and permanent (patients where cardioversion is unsuccessful and sinus rhythm can not be restored) [1]. So as to slow the heart rate to normal ranges, AF can be treated with antiarrhythmic drug therapies. Non-pharmacological treatments include surgical and catheter-based therapies to prevent recurrence of AF in certain individuals. As stated above, it is not possible to differentiate the different subtypes of AF by directly observing the surface electrocardiogram. Thus, there are many references in the state-of-the-art which detect and classify AF episodes by means of the ECG. For example, all participants in Computers in Cardiology Challenge 2004 [2]. Other relevant references are [3], [4] and [5], which employ different features and analysis for classification. However, there is still not a classification method which can be able to perform well across diverse groups of patients treated with different pharmacological or surgical therapies [6]. Thus, in this paper we present a classification method which works with an heterogeneous group of patients, so as to help the electrophysiologist to choose the most suitable therapy for each subject, depending whether he presents a paroxysmal or a persistent AF episode.

2. Materials

76 consecutive unselected ECG AF signals of a tertiary center (15 paroxysmal and 61 persistent) conformed the study population (including first AF episodes, and recurrent AF with pharmacological or electrical cardioversion treatments). AF episodes were defined according to the current guidelines [1, 7]. Duration of signals were 5 seconds, which is a common duration of ECGs with 6×2 printout display. Pharmacological and surgical therapies to manage each AF episode were left at the discretion of the attending cardiologist. In particular, electric cardioversion has been more frequently applied to persistent AF patients than to paroxysmal ones.

3. Methods

3.1. Feature extraction

Once powerline and baseline noise has been removed from the ECG signals, we proceed to analyze those signals and extract their relevant features. Papers presented at 2004 Computers in Cardiology Challenge, showed that analysis of the main components of frequency could be used as a differentiating element to distinguish non-terminating from immediately or soon-terminating AF episodes [2].

For example, [8] predicts the spontaneous termination of AF by analyzing the peak frequency of the remainder signal once QRST has been subtracted to cancel ventricular activity, whereas [9] calculates the major AF frequency of atrial activity. However, it is known that atrial fibrillation presents time-dependent properties, which point to time-frequency analysis as a more suitable tool for their analysis [10].

When choosing a time-frequency transform, it is important to take into account its accuracy both in time and frequency. We decided to use the General Fourier-family Transform [11], since it combines progressive resolution (i.e. good resolution for low frequencies and good temporal resolution at high frequencies) with high computational efficiency (which is of paramount importance when analyzing large segments of signal). We observed that total variations of the modulus of the General Fourier-family transform along time could be used as a relevant feature to distinguish persistent from paroxysmal AF episodes. Electrocardiogram power spectrum is mostly concentrated for frequencies that are below 60Hz [12]. Thus, we extracted features information for each relevant frequency band along time. We noticed that patients under a paroxysmal AF episode presented lower total variation values for all relevant frequency bands than patients under a persistent episode, regardless of whether they were under any pharmacological or surgical therapy.

3.2. Classification

Linear Discriminant Analysis (LDA) classifiers seek to reduce dimensionality of the data and preserve most of the class discriminatory information. This is done by performing the projections of feature vectors and defining a measure of separation between the projections. LDA objective is to maximize the ratio between-class variance to the within-class variance to guarantee maximal separability between classes.

One of the most important LDA advantages is the fact that it does not require multiple iterations over the data for optimization. Therefore, it presents a low computational cost. So, we chose this classifier to perform the presented first approach.

4. Results

As above-said, our dataset consists of 76 electrocardiograms of AF episodes. Patients correspond to an heterogeneous group, who has been treated with different pharmacological and surgical therapies. There were 15 episodes of paroxysmal AF and 61 episodes of persistent AF.

This unbalanced data hampers to train using the leaving-one-out technique (classify each patient when the rest of the patients have been used as training data). So, the dataset was divided into two groups. We first trained the LDA classifier using 15 signals (6 paroxysmal and 9 persistent), and then test was performed with the rest of the 61 patients (9 paroxysmal and 52 persistent).

In our case, as our dataset contains signals from a very heterogeneous group (in which many patients also present other cardiac illnesses), a random choice of signals to train the classifier is not a good option. Thus, for the training process, we have selected AF episodes that behave as "clinical models" for each subtype of AF.

The LDA classifier has been trained to maximize the global accuracy (i.e. proportion of correctly classified patients):

$$ACC = \frac{TP}{TP + FP} \tag{1}$$

where TP (true positives) is the number of paroxysmal and persistent patients correctly classified, whereas FP is the number of paroxysmal and persistent patients erroneously classified.

Classification performance was also measured by specificity (proportion of persistent patients correctly classified) and sensitivity (proportion of paroxysmal patients properly classified, also known as recall). They are defined as:

$$Specificity = \frac{TP_{pe}}{TP_{pe} + FP_{pa}} \tag{2}$$

$$Sensitivity = \frac{TP_{pa}}{TP_{pa} + FP_{pe}} \tag{3}$$

where TP_{pa} and TP_{pe} are the paroxysmal and persistent segments correctly classified, respectively. FP_{pa} are the paroxysmal segments which are classified as persistent, whereas FP_{pe} are the persistent segments which are erroneously classified as paroxysmal.

Table 1 shows performances and classification results for the whole dataset (i.e. including training and testing signals) and results only taking into account the test signals. Of the 61 testing patients (9 paroxysmal and 52 persistent), 43 were correctly classified (7 paroxysmal and 36 persistent). Obtained performances were: accuracy 70%, specificity 69%, and sensitivity 78%.

According to this results, we can see that AF episodes are mostly correctly classified. In addition, we have to remark that, in terms of clinical practice, it is more important to avoid classifying a paroxysmal AF episode as persistent than viceversa, since being able to detect subjects suffering from paroxysmal AF can help electrophysiologists to stop natural progression towards persistent AF by means of surgical ablation.

Thus, although our data set is unbalanced and this could have biased the results, similar performances for accuracy and both Specificity and Sensitivity show that our method could be used by physicians as an aid to choose the most suitable therapy for each patient.

Table 1. Classification results. Whole dataset shows performances for both training and testing signals, whereas Test set shows performances without taking into account signals used to train the classifier.

	Accuracy	Specificity	Sensitivity
Whole dataset	0.7237	0.7213	0.7333
Test set	0.7049	0.6923	0.7778

5. Conclusions

In this paper we have presented a method to classify paroxysmal and persistent atrial fibrillation episodes. It is based on time-frequency analysis of short segments of surface electrocardiograms. Extracted features are classified using a Linear Discriminant Analysis classifier. The dataset is composed by an heterogeneous group of patients, including first AF episodes and patients under different pharmacological and surgical therapies. Although the dataset used for training and testing is unbalanced, test results show good performances both for Sensitivity and Specificity parameters.

Future work will focus on improving results and enlarge signals available in the dataset, but maintaining the heterogeneity of the subjects.

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Address for correspondence:
Nuria Ortigosa
I.U. Matemática Pura y Aplicada,
Universidad Politécnica de Valencia
Camino de Vera s/n, 46022 Valencia (Spain)
nuorar@upvnet.upv.es