Nuria Ortigosa*, Carmen Fernández, Antonio Galbis and Óscar Cano

Classification of persistent and long-standing persistent atrial fibrillation by means of surface electrocardiograms

Abstract: Atrial fibrillation, which is the most common cardiac arrhythmia, is typically classified into four clinical subtypes: paroxysmal, persistent, long-standing persistent and permanent. The ability to distinguish between them is of crucial significance in choosing the most suitable therapy for each patient. Nevertheless, classification is currently established once the natural history of the arrhythmia has been disclosed as it is not possible to make an early differentiation. This paper presents a novel method to discriminate persistent and long-standing atrial fibrillation patients by means of a time-frequency analysis of the surface electrocardiogram. Classification results provide approximately 75% accuracy when evaluating ECGs of consecutive unselected patients from a tertiary center and higher than 80% when patients are not under antiarrhythmic treatment or do not have structural heart disease (76% sensitivity and 88% specificity). Moreover, to our knowledge, this is the first study that discriminates between persistent and long-standing persistent subtypes in a heterogeneous population sample and without discontinuing antiarrhythmic therapy to patients. Thus, it can help clinicians to address the most suitable therapeutic approach for each patient.

Keywords: cardiac arrhythmias; electrocardiography; time-frequency analysis.

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Introduction

Atrial fibrillation (AF) is the most frequent arrhythmia in the general population. Its prevalence increases with age and, given the current increase in life expectancy, its relevance is likely to rise, especially when compared to other heart diseases.

AF can be classified into four subtypes depending on the presentation and duration of the arrhythmia [31]: paroxysmal (episodes that terminate spontaneously, usually within 7 days), persistent (episodes that last more than 7 days or where the patient requires pharmacological, electrical or ablation procedures), long-standing persistent (episodes that last for more than 1 year) and permanent (when the presence of the arrhythmia is accepted by the patient and the physician).

Therapeutic options for the treatment of AF include pharmacological and invasive treatment. Currently, electric isolation of the pulmonary veins using catheter ablation remains the cornerstone of invasive treatment for this condition [7]. Catheter ablation is indicated for patients with either paroxysmal or persistent atrial fibrillation who remain symptomatic in spite of antiarrhythmic pharmacological treatment [14]. However, the efficacy and durability of catheter ablation significantly differs depending on the clinical subtype of the arrhythmia [16]. Thus, paroxysmal AF patients show the best results after catheter ablation with percentages of freedom from arrhythmia episodes off anti-arrhythmic drugs around 75–80%. In contrast, catheter ablation efficacy is significantly reduced for persistent AF and, consequently, it is not systematically recommended for long-standing persistent AF [14]. According to current clinical data, atrial fibrillation ablation for long-lasting AF patients has very poor outcomes when compared with persistent AF patients. Hence, for a great number of patients with long-lasting atrial fibrillation a rate control strategy would be acceptable considering the low probability of long-term maintenance of sinus rhythm.

Research on AF analysis has been extensive, especially studying the surface electrocardiogram (ECG) [23]

as it is a inexpensive, non-invasive and widely available technique (it is present in almost every health center). Nevertheless, the objective of most studies has been the classification of paroxysmal and persistent AF episodes, whereas discrimination between persistent and long-standing persistent patients has not been explored yet.

Additionally, Fourier, time-frequency analysis and non-linear techniques have also been applied to AF detection and analysis but not to the presented problem [2, 9, 25]. Thus, in this paper, we propose a method for early classification of these subtypes of AF patients (persistent and long-standing persistent) by means of the estimation of phase variations obtained from a time-frequency analysis of the surface ECG and a SVM classifier.

Moreover, to our knowledge, apart from the work presented in [29] (which recorded and evaluated ECG signals once antiarrhythmic treatments were restricted to patients and also excluded subjects with multiple pathologies), there are no previous references in the current literature that have analyzed persistent and long-standing persistent AF discrimination.

This paper is organized as follows. The Materials and Methods section describes the ECG signals and the study population and also details the signal preprocessing steps, the feature extraction of the time-frequency transform and the classifier used in this study. Data and performance measures are presented in the Results section, followed by Discussion and Conclusion sections.

Materials and methods

Materials

ECG signals correspond to 5 s of bipolar lead II, which were extracted from PDF files using the software presented in [21] and freely available at its author's website. They were acquired using the Philips PageWriter TC50 at a sampling rate of 500 Hz with an amplitude resolution of 5 μV over an amplitude range of ±5 mV.

Our population sample was conformed by 112 test signals, of which 66 corresponded to persistent AF and 46 were long-standing persistent AF patients. These signals were acquired from consecutive unselected patients who were treated in a specific arrhythmia clinic of a tertiary center.

Table 1 shows the baseline clinical characteristics of the subjects included in the study. Patients exhibited a different profile depending on the clinical subtype of AF. Thus, patients with persistent AF had less structural heart disease, smaller left atrial diameters and were more frequently treated with class III antiarrhythmic drugs or electric cardioversion when compared with patients with long-standing

Table 1: Statistical comparison of clinical characteristics of our test database.

	Persistent AF (n=66)	Long-standing AF (n=46)	Overall (n=112)	p-value
Age (mean, range)	64 (47–86)	70 (39–87)	66 (39–87)	0.049
Male (n,%)	52 (79%)	32 (70%)	84 (75%)	0.375
Hypertension (n,%)	37 (56%)	36 (78%)	86 (65%)	0.026
Diabetes (n,%)	18 (27%)	23 (50%)	41 (37%)	0.024
Hypercholesterolemia (n,%)	27 (41%)	18 (39%)	45 (40%)	1
Obesity (n,%)	7 (11%)	5 (11%)	11 (10%)	1
Smoker/former smoker (n,%)	24 (36%)	13 (28%)	37 (33%)	0.489
Any structural heart disease (n,%)	37 (56%)	37 (80%)	74 (66%)	0.013
Valvular heart disease (n,%)	10 (15%)	16 (28%)	26 (23%)	0.028
Previous electric cardioversion (n,%)	35 (53%)	12 (26%)	47 (42%)	0.008
Previous AF ablation (n,%)	3 (5%)	0 (0%)	3 (3%)	0.384
Left atrium dilatation (n,%)	53 (80%)	42 (91%)	95 (85%)	0.184
ACE inhibitors/ARBs (n,%)	21 (32%)	26 (57%)	47 (42%)	0.016
Lipid-lowering agents (n,%)	26 (39%)	19 (41%)	45 (40%)	0.994
Betablockers (n,%)	32 (48%)	21 (46%)	53 (47%)	0.918
Amiodarone (n,%)	22 (33%)	14 (30%)	36 (32%)	0.907
Flecainide/Propafenone (n,%)	10 (15%)	1 (2%)	11 (10%)	0.051
Calcium channel antagonists (n,%)	6 (9%)	1 (2%)	7 (6%)	0.275

Hypertension was defined as a systolic blood pressure ≥140 mm Hg, a diastolic blood pressure ≥90 mm Hg or the patient having been prescribed antihypertensive medication(s). Diabetes mellitus was defined as a serum fasting glucose ≥7.0 mmol/l or on diabetes medications. Hypercolesterolemia was defined as cholesterol ≥6.4 mmol/l or treatment with lipid-lowering drugs. Structural heart disease was defined as LV hypertrophy >15 mm, LVEF <50%, moderate or greater degrees of valvulopathy, prior myocardial infarction, significant coronary artery disease or the presence of primary myocardial diseases. AF, atrial fibrillation; LV, left ventricle.

Table 2: Statistical comparison of clinical characteristics of patients used for training the classifier.

	Persistent AF (n=10)	Long-standing AF (n=10)	Overall (n=20)	p-value
Age (mean, range)	59 (42–83)	63 (39–81)	61 (39–83)	0.507
Male (n,%)	9	4	13 (65%)	0.061
Hypertension (n,%)	5	7	12 (60%)	0.648
Diabetes (n,%)	2	2	4 (20%)	1
Hypercholesterolemia (n,%)	4	6	10 (50%)	0.655
Obesity (n,%)	1	2	3 (15%)	1
Smoker/former smoker (n,%)	3	4	7 (35%)	1
Any structural heart disease (n,%)	4	7	11 (55%)	0.369
Valvular heart disease (n,%)	1	4	5 (20%)	0.302
Previous electric cardioversion (n,%)	0	3	3 (15%)	0.210
Previous AF ablation (n,%)	1	2	3 (20%)	1
Left atrium dilatation (n,%)	5	7	12 (60%)	0.648
ACE inhibitors /ARBs (n,%)	3	4	7 (35%)	1
Lipid-lowering agents (n,%)	4	6	10 (50%)	0.655
Betablockers (n,%)	5	6	11 (55%)	1
Amiodarone (n,%)	2	3	5 (25%)	1
Flecainide/Propafenone (n,%)	1	0	1 (5%)	1
Calcium channel antagonists (n,%)	1	1	2 (10%)	1

Clinical definitions are the same as in Table 1.

persistent AF. In Table 2, clinical characteristics of the patients chosen to train the classifier are detailed. The training data set includes a heterogeneous group of patients, in terms of antiarrhythmic medications and multiple pathologies, that covers most of the different cases occurring in clinical practice.

Signal preprocessing

The ECG signal was first preprocessed to remove baseline wander noise (by means of high-pass filtering with a 0.5-Hz cut-off frequency), powerline noise (using a 50-Hz linear notch filter) and electromyographic interference (through a low-pass filter with a cut-off frequency of 70 Hz) [26]. We then proceeded to cancel the ventricular activity of the signal by removing the QRST complexes [1], taking advantage of the fact that atrial and ventricular activities are uncoupled during atrial fibrillation and that the QRST complex usually presents a recurrent pattern along the signal [3].

Thus, we upsampled the ECG signals to 1000 Hz to improve the accuracy of R-peaks detection (using the algorithm proposed in [22]) and their later alignment. Afterwards, we performed a principal component analysis (PCA) over each QRST complex detected and subtracted a template that corresponded to the first principal component of each QRST complex under analysis. Furthermore, to remove ventricular activity without sudden transitions, the template amplitude was individually customized to each complex as detailed in [1].

Time-frequency transforms

Fourier analysis has been extensively used for biomedical signal analysis and, in particular, to characterize the atrial fibrillation process: AF onset detection [15], paroxysmal AF episodes termination [13, 18], evaluation of recurrences [17] and classification of paroxysmal and persistent AF episodes [3].

Time-frequency analysis has also become popular for signal processing and feature extraction as it is able to provide information about how the frequency content of signals varies along time. Several time-frequency transforms have been proposed for surface ECG analysis, such as the short-time Fourier transform (STFT) [11], Choi-Williams transform [10] or Wigner-Ville transform [30].

In 1996, Stockwell et al. [28] defined the Stockwell transform (ST), which can be understood as a hybrid between the STFT and wavelet transform that is able to combine their desirable features (providing globally referenced frequency and phase information, and progressive resolution, respectively). The ST of a signal f is defined 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 $g_0(\nu(t-\tau))$ is the adaptive gaussian window with a width that varies depending on frequency. Indeed, this is another advantage of the ST, along with the fact that it does not present cross-terms (unlike the Choi-Williams and Wigner-Ville transforms) [27].

Unfortunately, ST presents high computational cost and memory requirements, which represent an important drawback when computing large signals [4]. It is for this reason that Brown et al. [6] presented a computationally efficient implementation of the ST called the general Fourier-family transform (GFT), which minimizes computational time and resources making possible its application for biomedical signal processing [5].

The implementation of the GFT, which has a computational cost of $O(NlogN)$, presents a dyadic sampling scheme of the time-frequency spectrum, obtaining N points when transforming a signal length of N samples. In our case, for signal segments 5000 samples in length, this octave sampling turns into 12 frequency bands in which frequency width is doubled as frequency grows.

Feature extraction

Once noise and artifacts were removed from the bipolar lead II of the surface ECG signal, as mentioned in the Signal Processing section, we extracted the signal corresponding to atrial activity by canceling the QRST complexes (as detailed in [1]).

We then performed the GFT time-frequency transform using adaptive Gaussian windows and normalized it to the range [0, 1]. We then extracted the L^1 norm of the phase of the variations for each frequency band (which will be named as phase variations henceforth): if $\{a_{b1}, a_{b2}, ..., a_{bN}\}$ denotes the time-frequency samples of frequency band b along the time axis [1, N], we consider $\sum_{h=1}^{N-1}|\phi_h|$, where $z_h e^{i\phi_h}=a_{bh+1}-a_{bh}$, $z_h\geq 0$, and $-\pi\leq\phi_h\leq\pi$.

Recent prior studies have pointed out that phase variations of AF persistent patients were larger than those for paroxysmal patients [19, 20]. These references analyze AF episodes that can terminate spontaneously versus those that require pharmacological or electrical cardioversion to restore sinus rhythm. Thus, our hypothesis was that long-standing persistent patients would present even larger phase differences than the GFT time-frequency transform of persistent patients. Therefore, as the purpose of our study was to differentiate two subtypes of the AF classification (persistent subtype versus those persistent episodes that last for more than 1 year, i.e., long-standing persistent), we decided to first cancel the ventricular activity of the ECG to perform a thorough analysis of atrial activity. Then, we looked for phase variations of the 4th and 5th frequency bands, which correspond to the range 1.71–7.57 Hz in the spectrum and concentrate the average power of atrial activity [24].

Furthermore, we propose applying weights to phase differences when they are larger than μ-times the mean of the total variation for each frequency band to emphasize large differences. In this manner, we will use as features F_k

$$F_k=\begin{cases}\sum_{h=1}^{N-1}|\phi_h|, & if\ \sum_{h=1}^{N-1}|\phi_h|<\mu_k\dfrac{\sum_{h=1}^{N-1}|z_{h+1}-z_h|}{N}\\ \gamma_k\sum_{h=1}^{N-1}|\phi_h|, & if\ \sum_{h=1}^{N-1}|\phi_h|\geq\mu_k\dfrac{\sum_{h=1}^{N-1}|z_{h+1}-z_h|}{N}\end{cases},$$

where k=4,5 refers to the frequency band of the GFT transform and γ_k are the weights applied to the total variations when they are μ_k-times larger than their respective means. The values of the parameters γ_k and μ_k will be discussed in the Experimental Results section.

We considered as a third feature the mean (for each patient) of the distance between R peaks of the ECG signals, which were previously calculated when extracting the atrial activity.

Classification

We trained a support vector machine (SVM) classifier using the features described in the Feature Extraction section and a training dataset of 20 patients (10 persistent and 10 long-standing persistent).

We used the package LIBSVM [8], which is currently one of the most widely used for SVM classification. We performed the five-fold cross-validation procedure to prevent an overfitting problem and used a radial basis function (RBF) non-linear kernel as it presents fewer numerical difficulties and performed well in our study.

Results

Performance measures

The SVM classifier was trained to maximize the global accuracy, which is defined as:

$$Accuracy=\frac{TP}{TP+FP}, \tag{2}$$

where *TP* and *FP* refer to the total number of "true positives" (i.e., number of patients correctly classified) and "false positives" (number of patients, both persistent and long-standing persistent, mistakenly classified), respectively.

We have also measured classification performance by using sensitivity (ratio of persistent patients correctly classified from the total number of persistent AF episodes), specificity (ratio of long-standing persistent AF properly classified from the total number of long-standing patients) and F-score (measure that takes into account both precision and recall performances), which are defined below:

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

$$Specificity=\frac{TP_{ls}}{TP_{ls}+FP_{pe}} \tag{4}$$

$$F\text{-}score=\frac{2TP_{pe}}{2TP_{pe}+FP_{pe}+FP_{ls}}, \tag{5}$$

where the subscripts *pe* and *ls* refer to persistent and long-standing persistent AF patients, respectively.

Experimental results

Our entire dataset consisted of 132 unconsecutive patients: 76 persistent and 56 long-standing persistent signals. To choose the number of signals used to train the SVM classifier, we will give the 95% confidence intervals of bootstrap estimators for sensitivity, specificity and accuracy measures. In Table 3, classification results using randomly chosen signals are shown. According to these results, we

Table 3: 95% bootstrap confidence intervals for sensitivity, specificity and accuracy for 400 simulations, varying the number of signals included in the training dataset.

Number of signals in the training dataset	Sensitivity	Specificity	Accuracy
16 (8 persistent and 8 long-standing)	[0.6026–0.6704]	[0.5339–0.6045]	[0.5956–0.6196]
18 (9 persistent and 9 long-standing)	[0.6120–0.6776]	[0.5326–0.6004]	[0.6009–0.6227]
20 (10 persistent and 10 long-standing)	[0.6491–0.7043]	[0.5371–0.5973]	[0.6215–0.6395]
22 (11 persistent and 11 long-standing)	[0.6268–0.6878]	[0.5342–0.6066]	[0.6087–0.6345]

used 20 signals (10 persistent and 10 long-standing persistent) to train the SVM classifier. These signals were selected to include and maintain the heterogeneity (in terms of antiarrhythmic treatment and other relevant heart diseases) of the group of patients under study to provide robustness to the classifier. Thus, we considered 112 signals (66 persistent and 46 long-standing persistent) for test results.

We avoided using the leaving-one-out technique for test results as our dataset is not balanced (there are more persistent than long-standing persistent patients in our study). Hence, we prevent any bias in results toward the persistent AF subtype.

We experimentally found (using the defined training set) that we should fix the mean weight thresholds (μ_4, μ_5) and the weights applied to the total variations (γ_4, γ_5) as follows:

- Mean of L^1 norm of phase variations of the 4th frequency band: μ_4=1.4
- Mean of L^1 norm of phase variations of the 5th frequency band: μ_5=1.2
- Weight applied to differences of the 4th frequency band when adjacent phase differences are larger than μ_4-times its mean: γ_4=2.8
- Weight applied to differences of the 5th frequency band when adjacent phase differences are larger than μ_5-times its mean: γ_5=2.8

The adjustment of parameters was made in an iterative way. First, each parameter was fixed with an initial value. Next, for each one we carried out extensive experimentation and selected the best result found (the one that maximized accuracy and maintained sensitivity and specificity measures as equally as possible). Afterwards, we evaluated a new parameter setting and repeated the extensive experimentation until all parameters were optimized.

Figures 1–4 show performances when each of the weights were varied and the rest were held fixed at their optimal values. We observed that each one has been found to maximize accuracy (and also maximize the number of both persistent and long-standing persistent patients correctly classified). We also observed that the performances shown in Figures 3 and 4 were very similar, and that is why the weights applied to phase differences were the same for the 4th and 5th frequency bands.

Regarding classification results, Table 4 shows the classifier performances for the test dataset and the entire dataset (both including training and test signals), whereas Figure 5 shows the receiver operating characteristic (ROC) curve for our classifier, including the area under ROC curve (AUC) and its 95% confidence interval, where the standard error (SE) of the AUC was obtained as follows [12]:

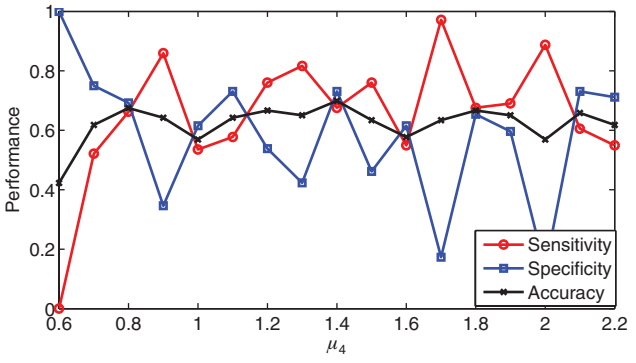

Figure 1: Test performances obtained by varying μ_4 values when the other weights are set as follows: μ_5=1.2, γ_4=2.8, γ_5=2.8.

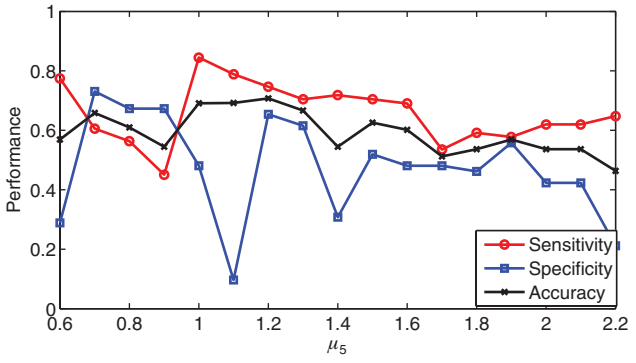

Figure 2: Test performances obtained by varying μ_5 values when the other weights are set as follows: μ_4=1.4, γ_4=2.8, γ_5=2.8.

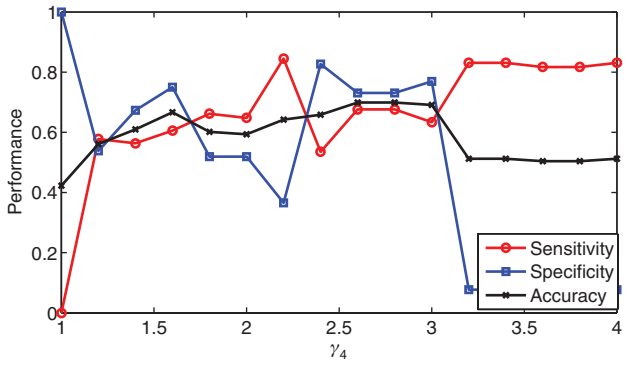

Figure 3: Test performances obtained by varying γ_4 values when the other weights are set as follows: μ_4=1.4, μ_5=1.2, γ_5=2.8.

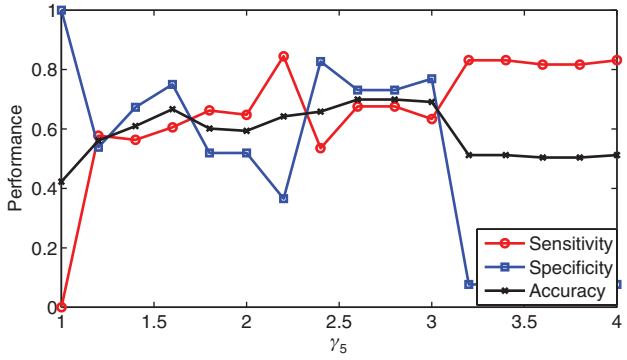

Figure 4: Test performances obtained by varying γ_5 values, when the rest of weights are set as follows: μ_4=1.4, μ_5=1.2, γ_4=2.8.

$$SE(AUC) = \sqrt{\frac{AUC(1\text{-}AUC)+(N_1\text{-}1)(Q_1\text{-}AUC^2)+(N_2\text{-}1)(Q_2\text{-}AUC^2)}{N_1 N_2}} \quad (6)$$

where $Q_1=\frac{AUC}{2\text{-}AUC}$, $Q_2=\frac{2AUC^2}{1+AUC}$, and N_1 and N_2 are the number of persistent and long-standing persistent patients, respectively.

Finally, Table 5 shows classification results for several subsets of patients that were grouped according to the absence of different treatments and their

Table 4: Classification results for the training dataset (20 patients) and the test dataset (112 patients).

	Sensitivity	Specificity	Accuracy	F-score
Training dataset	0.8	0.9	0.85	0.8421
Test set	0.7273	0.74	0.7328	0.7619

SVM classifier has been trained with 10 persistent and 10 long-standing persistent AF patients.

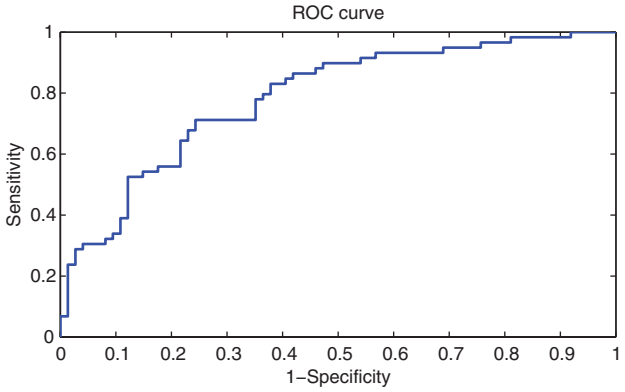

Figure 5: Receiver operating characteristic (ROC) curve for support vector machine (SVM) classifier using the features described above. Area under the ROC curve is 0.7856, with a 95% confidence interval [0.7092–0.8620].

baseline characteristics. Correct classification results were found to be larger than 80% on average for patients without previous electric cardioversion, left atrium dilatation or antiarrhythmic treatment, providing in all cases balanced results between persistent and long-standing persistent patients properly classified. In addition, Figure 5 shows that we also obtained a good value for the area under the ROC curve, which reflects that the classifier performed well, especially when taking into account the heterogeneity of the dataset used in this study.

Discussion

The main result of the presented study is a classification method that offers clinicians an early classification of persistent and long-standing persistent AF patients by analyzing the surface ECG. Performances show promising results in clinical practice, especially when taking into account that the population under study is heterogeneous in terms of related heart diseases, antiarrhythmic therapies and baseline characteristics.

In Table 6, classification results for our heterogeneous dataset are compared with [29] and also the methods of several references that have been proposed for differentiating paroxysmal and persistent AF episodes. These references propose using Fourier analysis and non-linear parameters of atrial activity as features. We observed that the proposed method is the one that provides the best classification results on a population sample in which patients with other cardiomyopathies have not been excluded and without discontinuing their respective antiarrhythmic medications. Moreover, it seems that

Table 5: Detailed test classification results according to those baseline characteristics that present better performances.

Characteristics	$N_{persistent}$	$N_{long\text{-}standing}$	Sensitivity	Specificity	Accuracy
No structural heart disease	29	9	0.7586	0.8889	0.7895
No previous electric cardioversion	31	34	0.7742	0.8235	0.8
No left atrium dilatation	13	4	0.7692	1	0.8235
No antiarrhythmic drugs	28	37	0.75	0.8108	0.7846
Mean			0.7630	0.8840	0.8008

Table 6: Classification results for the test dataset (112 patients) compared to other relevant references that classify paroxysmal from persistent AF episodes and the work of Uldry et al. [29].

	Sensitivity	Specificity	Accuracy	F-score
Dominant frequency of atrial activity (AA) [25]	0.5	0.4375	0.4754	0.5362
Dominant frequency of AA, RR_{mean}, heart rate [9]	0.7837	0.5	0.6721	0.7436
Sample entropy of main atrial wave [2]	0.1351	0.8125	0.4016	0.2151
Modulus, phase and energy variations of ECG [19]	0.3378	0.8542	0.5410	0.4717
Multivariate organization index (MOI) [29]	0.2162	0.7708	0.4344	0.3168
Multivariate spectral entropy (MSE) [29]	0.1081	0.7917	0.3770	0.1739
MOI and MSE [29]	0.2973	0.75	0.4754	0.4074
Proposed method	0.7273	0.74	0.7328	0.7619

Support vector machine (SVM) classifier was trained with 10 persistent and 10 long-standing persistent patients.

the dominant frequencies of atrial activity and non-linear measures may help to differentiate from paroxysmal and persistent AF patients, but are not good enough when attempting to classify between subtypes of persistent AF episodes. Similarly, RR irregularity measures have been extensively used by several references to study the AF paroxysmal onset and termination but, for the presented problem, results were significantly improved when the mean distance between R peaks was used instead.

Table 4 shows that the classifier was trained to maximize both correct persistent and long-standing persistent labels, and that result was obtained despite the unbalanced number of patients of each subtype. These figures confirm that the algorithm works well and suitably classifies persistent and long-standing persistent patients.

In addition, detailed results depicted in Table 5 reveal that performances are better in those patients that are not under any antiarrhythmic treatment, have no structural heart diseases or no dilatation of left atrium. It is consistent that the classifier works best when those variables are absent as they usually modify the electrical characteristics of the AF wave and create confusion. A "perfect example" of an AF patient is one who does not present these baseline characteristics, making easier its classification. Unfortunately, in actual clinical practice most of the patients present numerous coexisting comorbidities, leading to an unclear result. Therefore, the true usefulness of a classifier requires it to be reliable in real cohorts of patients in tertiary centers. It presents little utility if its performances are excellent only in "prototype" patients without comorbidities, who are actually the exception in the daily clinical practice.

As noted above, one value-added of the presented work is the population sample, as it is similar to the one that clinicians work with at tertiary centers. In fact, to our knowledge, this is the first study focused on persistent and long-standing persistent AF differentiation (at least the first one that includes patients with multiple pathologies treated with rate-control strategies [29]). Thus, the current literature presents many articles that classify paroxysmal and persistent atrial fibrillation episodes, but there is a lack of studies that try to distinguish persistent patients from those whose atrial fibrillation episodes are more likely to progress toward a permanent state (as long-standing patients have remained fibrillating for more than 1 year).

Finally, it is important to note that the clinical implications of the ability to differentiate persistent and long-standing persistent atrial fibrillation early are of great significance. The therapeutic approach to these conditions significantly differs. Thus, patients with persistent atrial fibrillation are usually treated with antiarrhythmic drugs and, in case of arrhythmia recurrences, catheter ablation offers a reliable therapeutic tool for maintaining

sinus rhythm. In contrast, catheter ablation is rarely useful in patients with long-standing persistent atrial fibrillation as they present few possibilities for maintaining sinus rhythm over the long term (it is usually assumed that patients will remain in AF, and a heart-rate control strategy is pursued). Taking into account these considerations, if a simple surface ECG can effectively discriminate early between these two AF clinical subtypes, clinicians could potentially apply the most effective treatment to each patient.

Conclusion

In this paper, we have presented a novel method that allows early classification of persistent and long-standing persistent atrial fibrillation patients by means of a surface ECG. It is based on an analysis of phase variations of the atrial activity using an efficient implementation of the Stockwell transform.

To our knowledge, there are no studies that present discrimination results between these subtypes of atrial fibrillation, especially when taking into account our heterogeneous population sample (in terms of antiarrhythmic therapies and multiple pathologies), which is a value-added factor. Future work will focus on enlarging the population sample and performing a combined analysis of multiple leads to improve results.

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