Classification of atrial electrograms in atrial fibrillation using Information Theory-based measures

J.J.C. Nicolet †* , J.F. Restrepo †, G. Schlotthauer †

†*Laboratorio de Señales y Dinámicas no Lineales, FI-UNER*
Corresponding author: *jnicolet@ingenieria.uner.edu.ar

I. Introduction

Atrial fibrillation (AF) is the most common type of tachyarrythmia, highly prevalent and clinically relevant because all current therapeutic approaches have important limitations. Reentrant activity and focal ectopic firing are the primary mechanisms of initiation and maintenance of AF. Even in paroxysmal forms, the changes induced in the tissue leads to the development of persistent forms with complex reentrant mechanisms, which are irreversible and more resistant to therapy [1]. This, in addition to the progression of the associated comorbidities, results in a complex clinical condition.

Since the description of complex fractionated atrial electrograms (CFAEs) in 2004 [2], the scientific community have been focused their efforts to characterize CFAEs and its automatic classification considering degree of fractionation, a clinical scale used in ablation procedures. Endocardial sites associated to CFAEs are usual targets in ablation therapy, as is though that they play a role in maintenance of the arrhythmia [3], [4].

In this work, we aim to classify short atrial electrograms, labeled by expert electrophysiologists in 4 different classes considering degree of organization in electrical activity. Several measures based on information theory were calculated, and obtained results were compared with previous works over the same dataset.

II. Materials and Methods

A. Database

The CFAEs database consists on 113 recordings of 1500 ms of duration. Atrial electrograms (AEGMs) were collected during left atrial endocardial mapping in 12 patients with persistent AF, using 4-mm irrigated-tip ablation catheter (NaviStar, Biosense-Webster), band-pass filtered (30-400 Hz) and sampled at 997 Hz by CardioLab 7000 (Prucka Inc.), and then resampled to 1 kHz [5].

The signals were classified by three independent expert electrophysiologists into four classes of fractionation [6]: Organized activity, non-fractionated (22 signals), Mildly fractionated activity (42 signals), Intermediate fractionated activity (36 signals) and High degree of fractionation (13 signals), referred as (C0,C1,C2,C3).

The three experts never disagreed in their classification by more than one neighboring class, being classes C1 and C2 the most confused [5], [7]. Experts classified identically a 60% of the recordings [6]. We will refer to the complete set of 113 signals as *full dataset*, and to the group of 68 signals labeled in agreement by the three experts as *reduced dataset*.

The database contains not only raw signals, but also two sets of filtered signals. The first set have signals in which CFAEs events were emphasized, and the second set contains denoised signals [6], [8], [9].

Numerous previous works [10]–[12] demonstrate effectiveness in characterization of biomedical signals using Renyi entropy, Shannon entropy and Tsallis entropy. In atrial fibrillation, these measures can be used to characterize AEGMs, helping to identify sites of ablation because of its fractionated activity. Considering that, the following features were calculated: Approximate entropy, Dispersion entropy, Fuzzy entropy, Permutation entropy, Tsallis entropy, Shannon entropy, Renyi entropy and Lempel-Ziv complexity.

Regarding feature selection, in this work we selected the gradient ascent technique to maximize the classification accuracy with a regularization term, as presented in [13]. Specifically, a 10-fold scheme were used to estimate feature weights, searching the best value of the regularization parameter by minimization of mean square error in classification. A relative threshold were applied to select features with the maximum weight. This allow us to choose the best features to each classification task.

Tested classifiers were linear and quadratic discriminants, and linear and quadratic Support Vector Machine (SVM). They were chosen because of their simple structure, aiming to give a major importance to adequate descriptive features of AEGMs. We will see in the next section that even with these simple classifiers, obtained results beat those shown in the state of the art, as far as we know.

III. Results

Results of classification are presented in this section. Signals can be grouped in different ways considering classes or groups of classes, and even new categories developed in function of multiple classification performed by the three experts. Performance measures of classification are shown in Table I. Note that each performance measure is expressed by mean value and standard deviation (μ and σ).

	Classification performance over 4 classes - Reduced dataset			
	Accuracy (μ and σ)	**Sensitivity (μ and σ)**	**Specificity (μ and σ)**	**AUC ROC**
C0	98.15% (0.59%)	99.89% (0.06%)	97.41% (0.79%)	0.99
C1	93.06% (1.27%)	84.08% (2.8%)	96.54% (1.19%)	0.98
C2	91.89% (1.13%)	84.07% (2.19%)	96% (1.05%)	0.96
C3	96.85% (0.04%)	99.95% (0.05%)	96.32% (0.05%)	0.99

Table I: Results on classification over 4 classes of fractionation in Full Dataset.

Another choice is to separate most fractionated signals from the rest, and classify over Refined and Full datasets. Our results in this task are presented in Table II.

Classification performance (C0+C1+C2 vs C3)							
	Full dataset				**Refined dataset**		
Classifiers	**Acc**	**Se**	**Sp**		**Acc**	**Se**	**Sp**
Linear Discriminant	95.29% (0.77%)	97.02% (0.65%)	81.28% (3.79%)		93.56% (0.72%)	79.23% (3.34%)	96.47% (0.3%)
Quadratic Discriminant	96.32% (0.95%)	96.64% (0.55%)	93.83% (7.74%)		94.68% (1.02%)	97.44% (4.89%)	94.36% (0.9%)
Linear SVM	94.40% (0.88%)	97.04% (0.57%)	82.06% (4.83%)		97.06% (0.01%)	99.98% (0.0015%)	96.61% (0.002%)
Quadratic SVM	96.18% (0.94%)	97.03% (0.37%)	88.80% (6.33%)		96.15% (0.83%)	94.36% (5.06%)	96.48% (0.39%)

Table II: Results on classification of C3 signals over the rest of classes of fractionation.

IV. Discussion and Conclusions

Previous results in 4 classes classification reported features values (mean and standard deviation) and mentioned that C0 is successfully separated from C3 [5]. In other work ([14]) classification error, both in each class and average over all classes, is reported. There is not specified if shown errors were obtained in Full or Refined dataset, and no other measures of performance in classification were showed. Results presented in [6] about classification of signals in class C3 from the rest, reported sensitivity of 81.8% and specificity of 90.2%, while results of this work shows sensitivity of 96.64%, specificity of 93.83% and accuracy of 96.32%. Our results over these different classification experiments shows the usefulness of combining several information theory based measures in atrial fibrillation electrograms analysis. In most cases, overall performance of different classifiers tested were similar, but for practical reasons only the best was selected and reported. We consider that the clinical use of an adapted version of this framework can help in the determination of sites associated to the generation and maintenance of atrial fibrillation.

V. References

https://drive.google.com/file/d/1QEt7lsEdaVOYXxipov9V0oO6H9EDg2lv/view?usp=sharing

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