Atrial Fibrillation Driver Localization From Body Surface Potentials Using Deep Learning

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Abstract

Atrial fibrillation (AF) is characterized by complex and irregular propagation patterns. Multipoint intracardiac mapping systems present a limited spatial resolution, which makes it difficult to identify AF drivers and ablation targets. These AF onset locations and drivers responsible for AF perpetuation are main targets for ablation procedures. Although noninvasive electrocardiographic imaging (ECGI) and inverse problem-based methods have been tested during AF conditions, they need an accurate mathematical modeling of atria and torso to get good results. In this work, we propose to model the location of AF drivers from body surface potentials (BPS) as a supervised classification problem. We used deep learning techniques to address the problem. We were able to correctly locate the 92% and 96% of drivers in the test and training sets, respectively (accuracy of 0.92 and 0.96), while the Cohen's Kappa was 0.89 for both sets. Therefore, proposed method can help to identify target regions for ablation using a noninvasive procedure as BSP mapping.

1. Introduction

Atrial fibrillation (AF) is the most common type of arrhythmia in clinical practice. AF affects more than 33 million patients in the world [1]. Patients with this condition have an increased risk of suffering embolism, cardiac failure, stroke and, in the worst of cases, death [2]. One of the clinical goals in AF patients is to restore sinus rhythm, usually by ablation. Main targets of ablation are AF onset locations and drivers responsible for AF perpetuation [3]. Several studies have proposed different strategies to locate these AF drivers by applying the inverse problem of ECG Imaging (ECGI) with promising results [4–7]. However, the inverse problem approach still needs further improvement. We propose to model the location of AF drivers from body surface potentials (BPS) as a supervised classification problem. We used deep learning techniques, as a supervised model, to address the location of AF drivers from conveniently annotated realistic computerized AF models [8].

The use of Deep Learning (DL) techniques have undergone considerable development in bioengineering the last decade. DL has been used in AF detection by using RNNs and CNNs [9], by STFT, stationary wavelet transform and CNNs [10], and in the detection of individuals at risk of suffering from Paroxysmal AF by CNNs [11].

The remaining of the paper is organized as follows. In Section 2 we introduce the computational models used for this study, the experimental set-up, performance metrics and Deep Learning architecture. Final results are summarized in Section 3 and in Section 4 main conclusions are presented.

2. Methods

2.1. Computerized Models

We used realistic computerized models of atria (N=2039 nodes) and torso (M=659 nodes)[6, 8, 12]. This geometrical model considers a simplified unique endocardium-epicardium layer for the atrial tissue. Atria and torso models were used to simulate 13 different AF propagation patterns in both left atria (LA) and right atria (RA), with different complexity and driver positions: Posterior Left Atrial Wall (PLAW), Left Inferior Pulmonary Vein (LIPV), Left Superior Pulmonary Vein (LSPV), Right Inferior Pulmonary Vein (RIPV), Right Superior Pulmonary Vein (RSPV), Right Atrial Appendage (RAA) and Right Atria Free Wall (RAFW).

2.2. Modeling AF driver location as a classification problem

We proposed to address the location of AF drivers as a supervised classification problem. We divided the atria into 7 regions (Figure 1-a) where the AF drive can be localized [13]. Each region represent a class to which the
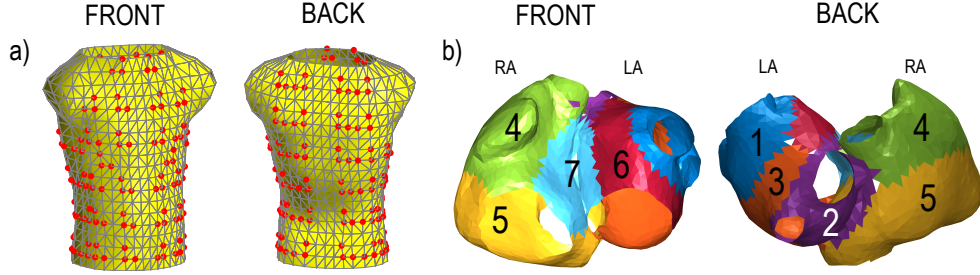
Figure 1. a) Selected BSP in torso and back. b) Regions in atria where AF drivers are found.
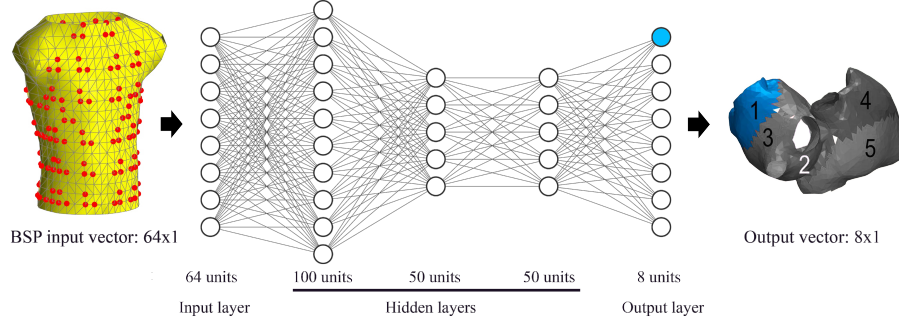

Figure 2. Schematic overview of the Multilayer Perceptron (MLP)-based proposed method.

AF driver belongs. To obtain labeled data, AF driver location from the computerized model were manually classified into one region for each time-instant.

To obtain the input data (simulated BSP), the forward problem of ECGI was solved by computing the $M \times N$ transfer matrix $\mathbf{A}$ using the boundary element method [6, 14, 15]. Simulated BSP were referenced to the Wilson Terminal Center, corrupted with additive Gaussian noise (SNR = 20 dBs) and filtered using a 4th-order bandpass Butterworth filter (fc$_1$=3 Hz and fc$_2$=30Hz) [6, 8].

A set of 64 electrodes from the whole torso geometry were selected to represent realistic multi-electrode vest used in electrophysiological studies, see Figure 1-a).

2.3. Deep-Learning Architecture

One typical Artificial Neural Network (ANN) is the Multilayer Perceptron (MLP). It consists on a series of groups of neurons (layers) that are connected between them. Each neuron applies an activation function for the weighted sum of its inputs, and the result is transmitted to the next neuron. This type of non-linear model is inspired by the neural architecture of the brain [16].

For this study we trained an MLP with 3 hidden layers (100,50,50) units each. The output layer consists on 8 units, one per region, and one for no AF driver. We used ReLu activation function in hidden layers and Softmax in the output. This Softmax layer allows to obtain the probability of the input sample to belong to each region. A schematic overview of this model can be seen in Figure 2.

2.4. Performance metrics

To assess the performance of the implemented DL models, we used two different metrics. The first one is the accuracy (Acc), measured as the fraction of well-classified drivers (true positives, TP) over the total of drivers (Total):

$$Acc = \frac{TP}{Total}$$

The second performance metric is the Cohen's kappa. It is a robust statistic used for rating reliability testing [17]. A score of 0 means the agreement that can be expected from random chance, whereas a score of 1 represents perfect agreement between the raters. Scores less than 0 means that there is less agreement than chance. It is computed as:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

where p_o is the relative agreement among raters (identical to accuracy), and p_e the hypothetical probability of chance agreement.

2.5. Experimental set-up

We first addressed the problem considering each time instant independently. So that, the whole data set is comprised of input data vectors with 64 entries from the BSP

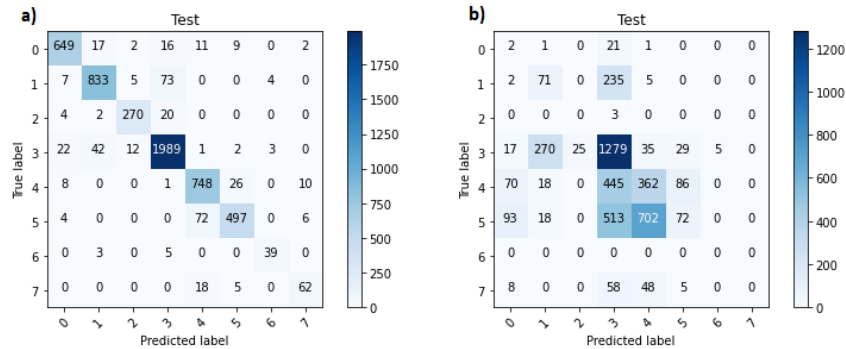|	Train Acc	Test Acc	Train Kappa	Test Kappa
Independent time instants	0.955	0.912	0.893	0.893
Independent time instants (CW)	0.961	0.925	0.895	0.895
Model independence	0.823	0.452	0.724	0.723
Model independence (CW)	0.815	0.439	0.727	0.725

Figure 3. Confusion matrices obtained for independent time instants (a) and model independence methods (b).

electrodes, x_i, and the corresponding label y_i which can have values $0, 1, \ldots, 7$. The whole data set was split into training (80%) and test (20%) sets. This approach allowed samples from the same model to be in the training and in the test set. Secondly, to avoid the bias introduced by the first approach, we consider model independence, thus samples from a model are not allowed to be simultaneously in training and test set.

The problem is imbalanced, since there are several atria regions which are over represented in the data set. In order to address this problem we tried to weigh the classes accordingly to the probability of occurrence.

3. Results

Table 1 shows the results considering each time instant as an independent sample, thus allowing samples from the same model to be in the training and in the test set. Table 1 shows also results considering independence by models, where samples from a given model cannot be simultaneously in training and test sets. With this approach, we were able to correctly locate the 95% and 91% of drivers in the training and test sets, respectively (accuracy of 0.95 and 0.91), while the Cohen's Kappa was 0.893 for both sets.

Using class weight (CW) to fight imbalance we slightly improved the metrics, being able to correctly locate the 96% and 92% of drivers in the training and test sets, respectively, while the Cohen's Kappa was 0.895 for both sets.

In Figure 3-a the confusion matrix for this approach (test set, CW) is shown. In the case of the label 3, the 96% of drivers are well classified, but this percentage drops to the 77% in the case of the label 7, with much less data available.

Table 1 shows results for the approach of splitting the data set by Models (using also class weight). This is a more realistic and fair scenario. The accuracy for the training set are 0.82 and 0.81 using CW (0.72 for Cohen's Kappa), while accuracy for the test set was 0.45 and 0.44 using CW. These results suggest that we are overfitting the model to the training set. However, Cohen's Kappa maintains a value of 0.72, which indicated that the model is able to fight the imbalance problem.

In Figure 3-b the confusion matrix for this approach (test set, CW) is shown.

4. Discussion and conclusions

The deep learning method we proposed can help to identify target regions for ablation using a non-invasive procedure, as BSP mapping. The main advantage of this methodology is to predict those regions without using ECGI, which requires accurate mathematical modeling of torso and atria.

Although the results we got are very promising, there are some drawbacks that should be addressed. The main problem we had to face is the imbalance of input data. Our dataset is composed by only 13 models that represent different propagation patterns, but the distribution of drivers across the 7 defined atrial regions is not balanced. Therefore, the results on those less represented regions are going to be worse. It also can lead to overfitting to the training set (problem that can be shown in the second proposed model). One way to solve this problem is to test

our methodology with a higher number of propagation patterns. Overfitting to the training set can be also fixed using dropout, regularization or data augmentation. For example, data augmentation can be achieved by training the models with signals with different SNRs.

Finally, future work is to apply this methodology with real patient data, where driver tagging can be difficult. For this task, Convolutional Neural Networks could be useful, since they can use the spatial characteristics of BSP that are omitted when using MLP.

Acknowledgements

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