A Novel Deep-Learning Method for Fibrillatory Waves Extraction from Electrocardiograms

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Abstract

Atrial fibrillation (AF) is the most common supraventricular arrhythmia and its most specific feature on the electrocardiogram (ECG) is the presence of fibrillatory waves (F-waves). The aim of this study is to present a new method that innovatively uses deep-learning (DL) as a filter to optimize the extraction of F-waves from ECGs. To do so, the CPSC database, containing 918 12-lead ECGs showing normal sinus rhythm (NSR), and Reference database, containing 30 12-lead ECG created by combining real F-waves and QRST complexes, were used. Zero-padding vectors and the real F-waves were used as ground truth to evaluate the method. ECGs were segmented into 1-second windows, that represent the inputs of the method. The DL method comprises two convolutional neural networks having the same architecture (six sequential multipath modules), but different loss functions. The root mean squared error (RMSE) between amplitudes of the estimated and ground truth F-waves was computed, together with the area under the curve (AUC) of the receiver operating characteristics. Results indicate a low testing RMSE (NSR: 6.02 µV; AF: 11.14 µV) and a high testing AUC (>99%). In conclusion, our DL method can reliably extract reliably extract F-waves from ECGs; their estimated amplitude permits reliable discrimination of AF patients.

1. Introduction

Atrial fibrillation (AF) is the most common supraventricular arrhythmia [1]. It affects millions of people worldwide, can cause blood clots in the heart and increases the risk of stroke, heart failure and other heart-related complications. Thus, AF represents an important economic burden and is associated with significant morbidity and mortality.

AF is caused by a dysfunction of atrial electrical activity, which is no longer able to provide syncronized atrial depolarization and, consequently, ventricular depolarization [1]. The identification of characterization of patients with AF has clinical relevance since leading therapeutic choices and supporting prediction of therapy outcomes (for example, catheter ablation is known to be more effective in case of paroxysmal rather than persistent AF) [2]. Thus, early diagnosis of AF is important to ensure timely and correct management of the condition and avoid the recurrence of the arrhythmia as much as possible.

According to the European guidelines for the diagnosis and management of patients with AF [2], the diagnosis process requires rhythm documentation acquired by a single-lead or 12-lead ECG tracing. Indeed, the ECG of a patient affected by AF is characterized by irregular, often rapid heart rate (non-specific feature); however, FA is also characterized by the presence of fibrillatory waves (F-waves; specific feature) that replace the P waves. In general, F-waves amplitude is low (less than 50 µV) and their frequency content falls in the 4-10 Hz range; still, their shape and duration may vary from patient to patient.

Most algorithms for the automatic identification of FA rely on heart-rate variability analysis. The few that perform F-waves analysis exploit different signal processing techniques, such as average beat subtraction and variants [3, 4], principal component analysis [5], independent component analysis [6], adaptive filtering using an echo state network [7] and diffusion geometry [8]. The main limitations of these techniques consist in the presence confounding residual of the QRS complexes in the processed tracing [3, 4] and/or in their applicability to multiple leads ECG acquisitions only [5]. The latter limitation, in particular, limits use of the above-mentioned techniques to single-lead ECG signals provided by most wearable or portable sensors, which are becoming more and more popular. Recently, deep learning (DL) algorithms have been used to analyze biomedical signals, among which ECG tracings. Their main applications are finalized to solve classification problems, such as discrimination between healthy subjects from patients affected by the various types of AF [9]. Still, the most innovative uses of DL algorithms suggest their use as filtering procedures finalized to improve features extraction in signals. To the best of our knowledge no study has investigate use of DL algorithms to extract F-waves from ECG signals. Thus, the aim of this study is to present and test a new DL algorithm for F-wave extractions from ECG signals of patients affected by AF.

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2. Materials and Methods

2.1. Database

Data belong to the open source “CPSC” and “Reference” databases [10, 11]. The “CPSC” database [10] contains 12-lead ECG recordings (sampled at 500Hz) collected in 11 hospitals. It includes 918 recordings showing normal sinus rhythm (NSR), that were considered in this study. For each of them, the absence of F waves was assumed, and a ground-truth null F-wave (zero vector) was created. The “Reference” database [11] contains 30 5-minute 12-lead ECG recordings (sampled at 1000Hz) created by combining real F-waves and real QRST complexes. The tracings containing only the real F-waves were considered as ground-truth. All ground-truth F waves, including the null one, are referred as FW.

For all ECG recordings, the 8 independent leads only were considered (I, II, V1-V6) and resampled at 512 Hz. Then, ECG signals and the corresponding FW were segmented into 1-second windows, obtaining a database counting 112’928 NSR and 71’520 AF 8-lead ECG windows. The database was divided into three datasets, ensuring subjects division: the training dataset, composed of 88’504 NSR windows and 57’120 AF windows; the validation dataset, composed of 10’664 NSR windows and 7’200 AF windows; and, the testing dataset, composed of 13’760 NSR windows and 7’200 AF windows.

2.2. Deep-Learning Method for Fibrillatory Waves Extraction

The DL method (Figure 1) for F-wave extraction comprises two models. The first model considers as inputs the ECG windows and the corresponding FW, while the second model considers as inputs the output of the first model and the corresponding FW. Both models consist of convolutional neural networks (CNN) composed of six sequential multipath modules, called Multi-Kernel Linear And Non-Linear (MKLANL) [12]. The first and the second modules include a total of 64 convolutional filters, the third and fourth modules include a total of 32 convolutional filters, and, finally, the fifth and sixth modules include 16 convolutional filters. The second, the fourth, and the sixth modules present a dilatation factor equal to 3. Each module is composed of 4 1D kernels (3, 5, 9, and 15) having linear activation functions, and 4 1D kernels (3, 5, 9, and 15) having non-linear activation functions.

Both models present a loss function that combines Cosine Similarity (CosSim) and the Mean Squared Error (MSE). Specifically, considering FW and the outputs of the models (OUT1 and OUT2 for the first and the second models, respectively), the loss functions are:

$$\text{Loss1} = \text{CosSim}(\text{FW}, \text{OUT1}) + \text{MSE}(\text{FW}, \text{OUT1}) \quad (1)$$

$$\text{Loss2} = \text{CosSim}(\text{FW}, \text{OUT2}) + \lambda \cdot \text{MSE}(\text{FW}, \text{OUT2}) \quad (2)$$

Differently from the loss function of the first model, the loss function of the second model weighted the MSE component (λ empirically set equal to 500). OUT2 corresponds to the final estimated F-waves ($\widehat{\text{FW}}$, µV). Amplitudes of FW (A, µV) and of $\widehat{\text{FW}}$ ($\widehat{\text{A}}$, µV) were estimated as four times standard deviation.

2.3. Statistics

Normality of A and $\widehat{\text{A}}$ distributions were evaluated by Lilliefors test. Non-normal distributions were described in terms of second [first; third] quartiles and compared by the pair Wilcoxon ranksum test (statistical significance was set at 0.05). Goodness of $\widehat{\text{A}}$ was evaluated by computing the root mean squared error (RMSE, µV) with respect to A. Assessment of $\widehat{\text{A}}$ in discriminating between NSR and AF was evaluated by computing the receiver operating characteristic, its area under the curve (AUC) and 95% confidence intervals (CI) in all datasets.

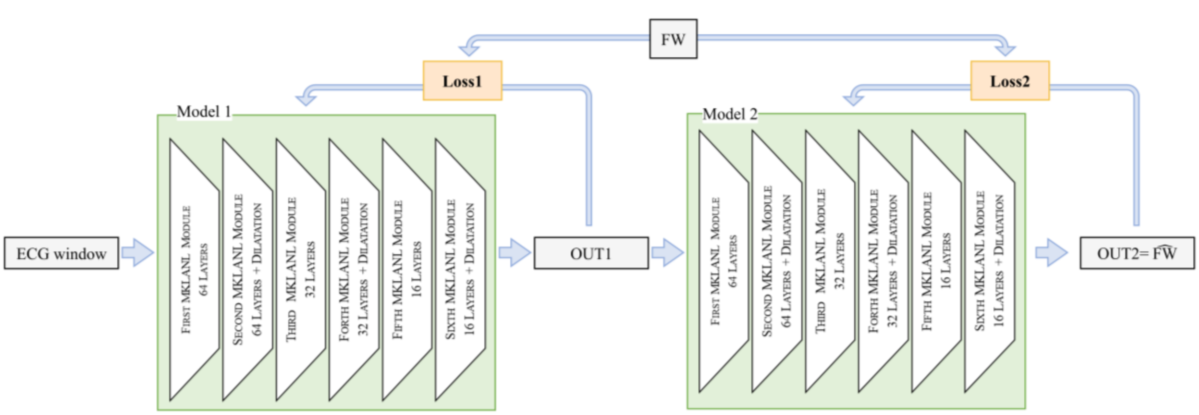

Figure 1. Block diagram of the DL method for F waves extraction from ECG.

3. Results

Distributions of $\widehat{A}$, A and RMSE of 1-second ECG windows presenting NSR and AF patterns in all datasets are reported in Table 1. Moreover, representative examples of the DL method application on ECG windows showing NSR (panel A) and AF (panel B) are depicted in Figure 2.

The median (second quartile) values of $\widehat{A}$, although statistically different, were clinically comparable to those obtained in A; indeed, their difference in the testing dataset was 5.43 µV and 2.05 µV for NSR and AF, respectively. Such good result was also confirmed by the RMSE values, whose median values in the testing dataset was 6.02 µV and 11.14 µV in the NSR and AF, respectively.

Figure 3 reports the receiver operating characteristic of the training (panel A), validation (panel B), and testing (panel C) constructed using the feature $\widehat{A}$. The performance of $\widehat{A}$ in discriminating between the two electrocardiographic patterns was very good, as shown by the high values of AUC (training: 99.41%, validation: 99.39%, testing: 99.43%) and by the low values of CI (training: 0.09%, validation: 0.26%, testing: 0.15%).

Table 1. Distributions of $\widehat{A}$, A and RMSE of 1-second ECG windows presenting NSR and AF patterns in all datasets.

		NSR	**AF**
TRAINING	$\widehat{A}$ (µV)	5.42* [4.14;7.02]	35.66* [24.37;50.78]
	A (µV)	0.00 [0.00;0.00]	33.65 [14.65;78.37]
	RMSE (µV)	5.99 [4.46;8.16]	11.03 [7.99;21.92]
VALIDATION	$\widehat{A}$ (µV)	5.41* [4.12;7.05]	35.46* [24.45;50.81]
	A (µV)	0.00 [0.00;0.00]	33.54 [14.58;78.46]
	RMSE (µV)	5.97 [4.46;8.08]	11.00 [7.92;21.51]
TESTING	$\widehat{A}$ (µV)	5.43* [4.15;7.01]	35.51* [24.58;50.72]
	A (µV)	0.00 [0.00;0.00]	33.46 [14.61;78.65]
	RMSE (µV)	6.02 [4.49;8.09]	11.14 [8.00;21.67]

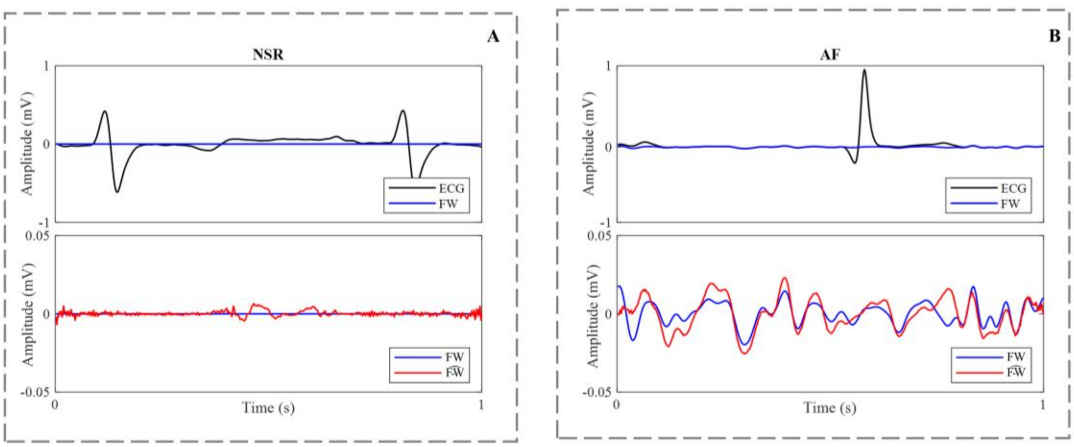

Figure 2. Examples of applications of the DL method on ECG windows showing NSR (panel A) and AF (panel B).

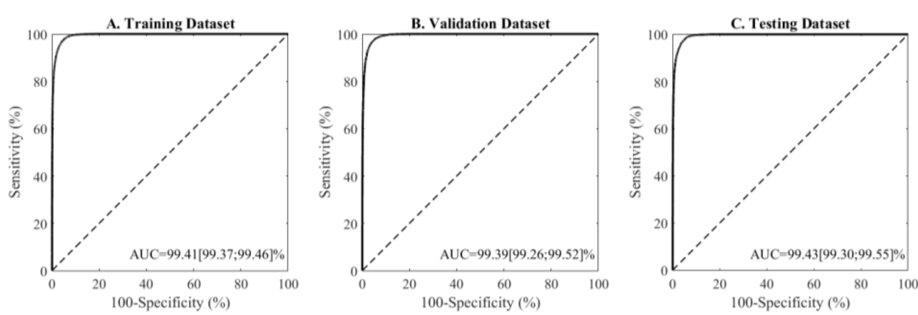

Figure 3. Receiver operating characteristic of the training (panel A), validation (panel B) and testing (panel C) constructed by using the feature $\widehat{A}$.

4. Discussion

In this work, we proposed a new two-stage DL, CNN-based method to extract F-waves from 8-lead ECG signals.

To evaluate the generalization properties of the algorithm, we also included ECG tracings of subjects with normal sinus rhythm (and, thus, no F-waves). In order to perform data augmentation without losing the clinical information, ECGs were split into 1-second windows, and the obtained windows were randomized. Windows were not supposed to include 1 complete heartbeat but could include random segments of ECG tracings.

The proposed method is composed of two DL models, that have 1D CNN architectures based on multipath modules. The hyperparameters of the network and the loss functions were defined empirically by using a grid search algorithm. The idea behind the use of two networks on cascade was based on the attribution of different tasks to each of them: the first network was designed to estimate the morphology of the F-waves, while the second network was designed to optimize F-waves amplitude.

Results indicate a very good performance of the proposed method. Of note, errors in the amplitude estimates of extracted F-waves were very low in all datasets, demonstrating the ability of the method to generalize the problem. The input signals differed in terms of ECG lead, sequence of ECG waves (due to the 1s windowing), F-waves amplitude and F-waves morphology; thus, the proposed DL method proved to be robust to morphological variations of the ECG in input.

The main drawbacks of this work can be related to the data used. Since it is impossible to directly measure-wave only, the F-waves used here as ground truth were extracted using another F-wave extraction algorithm [11]. This evidence does not allow a rigid standard comparison between the two F-wave extraction methods. Additionally, our method proved to be promising when extracting F-waves from a 1-second ECG window; thus, to be used in clinical settings, it needs to be tested in longer ECG windows (30 seconds at least, according to [1]), which however can also be obtained as sequences of 1-second windows. Eventually, if its use on single-lead ECG is desired, the method may be modified to support it; indeed, even in its current form, it provides an F-wave for each input ECG lead separately. The choice of using the 8 independent leads here derives from the requirements for its diagnosis indicated by the European guidelines [2].

5. Conclusion

Deep learning can be efficiently used for ECG filtering. Our innovative deep-learning method can reliably extract F-waves from ECG tracing; their estimated amplitude permits reliable discrimination between healthy and atrial fibrillation subjects.

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