Atrial Fibrillation Detection Using Convolutional Neural Networks

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Abstract

As part of the PhysioNet/Computing in Cardiology Challenge 2017, this work focuses on the classification of a single channel short electrocardiogram (ECG) signal into normal, atrial fibrillation (AF), others and noise classes. To this end, we propose a shallow convolutional neural network architecture which learns suitable features pertaining to each class while eliminating the need to extract the traditionally used ad hoc features. In particular, we first developed a robust R-peak detector and stacked sequence of fixed number of detected beats with R-peaks aligned. These stack of beats corresponding to a segment of ECG record are classified into one of the four aforementioned classes. To improve the robustness, multiple classifiers were trained to classify these segments. Overall record classification was then generated using an voting scheme from the classification results of individual segments. Our best submission result during the official phase has a score of 71% with F1 scores of 86%, 73% and 56% respectively for normal, AF and other classes respectively.

1. Introduction

Cardiovascular diseases (CVDs) are a leading cause of death worldwide [1]. An indispensable tool in diagnosing and monitoring CVDs is electrocardiogram (ECG). In certain scenarios, ECG from the patient is continuously monitored to detect various arrhythmic conditions. In particular, atrial fibrillation (AF) is the most common cardiac arrhythmia with a prevalence of 1-2% in general population, and could result in a catastrophe when unattended. In this work, we propose to detect the incidence of AF as part of the Physionet/CinC 2017 challenge. Specifically our goal is to classify each of the recordings in the challenge database into one of the four classes, namely *normal*, *AF*, *other* and *noise*.

Electrocardiographic presentation of AF is characterized by irregular RR intervals and absence of P-waves. Based on the above characteristics various algorithms have been developed for detecting AF from the ECG waveform. Such detection approaches include Poincaré plot analysis, Lorenz plot analysis and analysis based on the histogram of RR intervals [2–4]. In the context of P-wave fibrillation detection, echo state neural network and wavelet-based methods have been reported [5, 6]. There have also been attempts based on modeling a combination of features such as RR interval irregularity, PR interval variability P wave morphology, P-wave absence, f-wave presence, and noise level [7, 8]. Although such algorithms have reported high classification performance, majority of them remain unreliable to be used in practice. In generally, most of the classification algorithms used a fixed set of hand-crafted features in the classifier design. However, ECG signals with rhythm changing from normal to AF or otherwise has high variation, and such generic features may not be adequate to fully represent the underlying characteristic of the signal. In addition, many non-AF rhythms exhibit irregular RR intervals similar to AF. Indeed, with the broad variety of rhythms makes the detection of AF from a single short lead of ECG signal challenging.

Against this backdrop, we propose a shallow convolutional neural network (CNN) architecture that learns suitable features from training data to achieve the desired classification task. Specifically, from the training data and labels provided in the challenge database, we first detect the location of R-peaks and stack a fixed number of beats with their R-peaks aligned. Such beat stack vectors corresponding to multiple overlapping segments of ECG record and the corresponding record label are used to train the proposed CNN. Intuitively, our training would compare and combine multiple adjacent beats appropriately and learns suitable features to discriminate four classes, providing an advantage. Now, given a test record, we form stacked beat vectors corresponding to multiple overlapping segments of ECG record and assign it to one of the four classes. To improve robustness, we trained multiple classifiers to achieve segment classification. Finally, the sequence label for the beats are mapped to signal classification based on a voting scheme or averaging operation.

The rest of the paper is organized as follows. In Section 2 we present the methodology. In Section 3 we present the proposed solution. Results are presented in Section 4. Finally in Section 5 we conclude the paper with a discussion.

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2. Methodology

In this section, we first present a mathematical formalism for ECG classification, then present the architecture of the proposed CNN based classifier.

2.1. Formalism

The desired ECG signal classification task takes an ECG signal $X = [x_1, x_2 \ldots x_k]$ as an input, and outputs a labels O_i, where $i \in \{N, A, O, \sim\}$, corresponding to normal, AF, others and noise classes respectively. Our goal is to find the labels such that the F1-score[1] for each class and the overall F1 measure, which is an average of the F1 scores of normal, AF and other class are maximized.

2.2. Convolutional neural networks

In this paper, we proposed an ECG classification approach based on convolutional neural networks (CNNs). CNNs add convolution layers below the input layer and above the hidden and output layers of usual neural networks [9]. CNN architecture used in the present work is illustrated in Figure 1 with a single convolution layer followed by the the fully connected network to output layer. Input of the proposed CNN takes n stacked beat vectors of length m. Convolutional layer will have k filters (or kernels) of size $q \times n$, where q is smaller than the length of the input vector. Each filter is convolved with the input, and is followed by nonlinear activation (sigmoid) to produce k feature maps of size $(m - q + 1) \times 1$. The output from multiple filters are then stacked together to form a single feature vector. Following the convolution layer we used a single fully connected layer with softmax activation. The densely connected layers are identical to the layers in a standard multilayer neural network. We optimized the weights of the convolution and fully connected layers using the stochastic gradient descent method with cross entropy cost function [10].

For the present classification task, we denote the output of the final layer to be P_N, P_A, P_O and $P_\sim$. We interpret P_i as the probability of occurrence of each class (i.e., $P_N + P_A + P_O + P_\sim = 1$), and assign the input vector to the class that has maximum probability of occurrence.

3. Proposed solution

The proposed solution for the desired classification task is is depicted in Figure 2. We now elaborate on the major blocks of the proposed solution.

[1]F1-score for class i is twice the ratio of true positives of class i to the sum of total samples in class i and the samples labeled as class i.

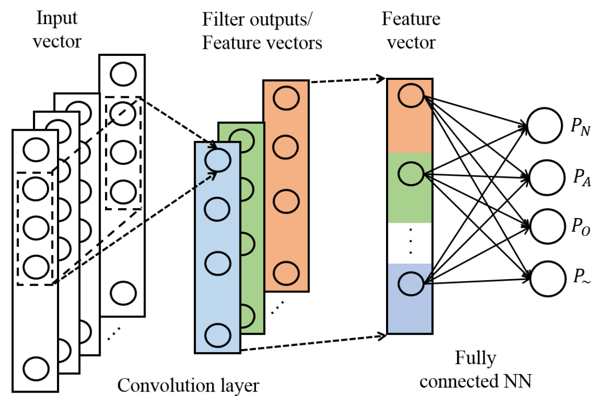

Figure 1. Convolutional neural network architecture.

3.1. Preprocessing

Given a test signal, we first resample the signal to 300Hz, then remove the baseline wander, and normalize the signal to lie between [-1, 1]. Specifically, to remove baseline wander, we pass the signal through a cascade of two median filters of window sizes 200ms and 600ms respectively to obtain the baseline wander signal, which is then subtracted from the original signal to obtain the baseline corrected signal. We normalize the baseline corrected signal with the maximum value in the non overlapping window of 3 sec.

3.2. R-peak detection

In this study, we proposed a robust R-peak detector based on 1D CNNs. The CNN architecture used for R-peak detection differs from the architecture shown in Figure 1 only at the input and output layers. Specifically, the input is a signal vector of 300 samples corresponding to the chunk of ECG signal while output is a binary decision indicating 1 for an R-peak and 0 otherwise. To train the proposed CNN, we used MIT-BIH arrhythmia database, containing 48 recording of half-hour duration with each R-peak location and its type were annotated by two independent cardiologists. Specifically, our training data include multiple overlapping beat vectors from a given record whose label is marked as 1 if an R-peak annotator lies in a narrow (around 150 ms) neighborhood in the middle of the signal vector.

In the proposed CNN architecture for R-peak detector, we used a single convolution layer with 3 filters of length 30 followed by fully connected layer to output layer. As alluded earlier, the proposed CNN learns suitable features to perform the desired classification task (here detecting whether the given segment has an R-peak). The labels generated for each of the segments are further processed to detect the R-peak locations. Figure 3 illustrates the R-

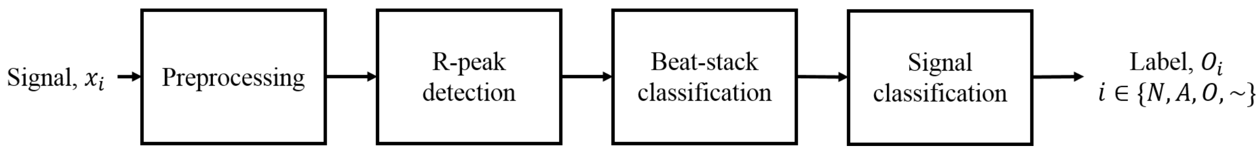

Figure 2. Proposed end-to-end classification system.

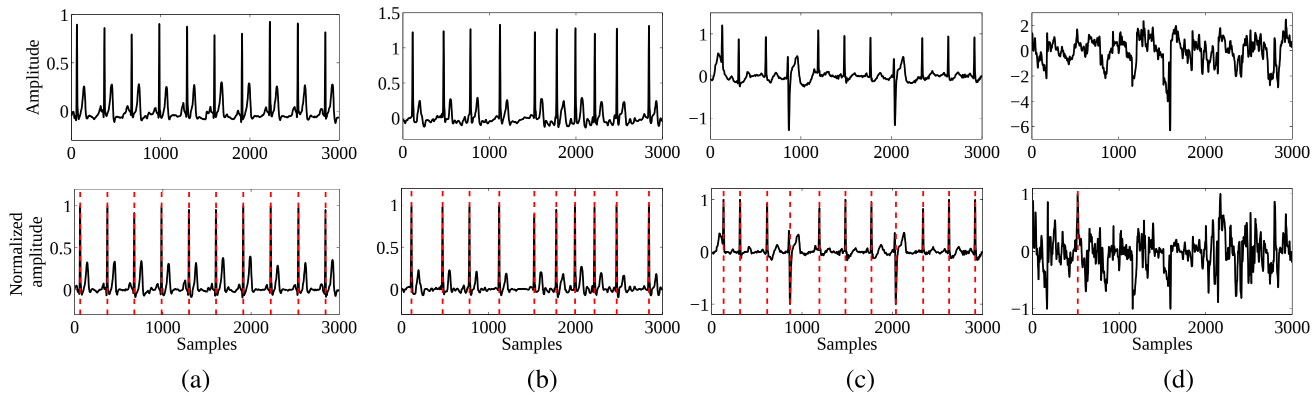

Figure 3. Original signal (top row) and the corresponding baseline wander removed and normalized signal along with R-peak detections for (a) normal; (b) AF; (c) other (d) noise signals (bottom row).

peak detected for various classes of signals considered in the present work.

3.3. Beat-stack classification

Using the proposed CNN based R-peak detector, we estimate the location of R-peaks. Then, for each detected R-peak, we collected 350 samples before R-peak value and 350 samples after R-peak value, to form a beat vector of length 701 samples. Now, 8 consecutive beat vectors are stacked together to form a beat-stack. Note that multiple beat-stacks can be formed for a given signal and are given as input to the classifier. Figure 4 (top row) illustrates the stacked beat vectors corresponding to normal, AF and other class signals. Clearly, the center R-peaks are aligned while the previous R-peak and next R-peaks are not aligned across multiple beats due to irregularity in RR intervals, which is a characteristic of AF signals. Also notice the stacked beat vector are non overlapping due to differing morphology of the beats corresponding to other class signal. Such stacked beat vectors are then passed as input to convolution layer to learn the discriminative features that aid the desired classification goal.

We used a single convolution layer followed by fully connected layer to output with softmax activation. We used 10 filter kernels with length 100. The feature vector generated after convolving one of the filter with normal, AF and other signals is shown in Figure 4 (bottom row). Clearly R-peak misalignment for various signals is captured which is an indicator of regularity of RR interval. To increase the robustness of the classifier, we trained four independent classifiers and all the beat-stacks corresponding to a signal are assigned with four labels corresponding to four classifiers.

3.4. Signal classification

Finally, multiple labels corresponding to multiple beat-stacks of the given signal are mapped to signal label based on unanimous voting and averaging operation. In the former, beat-stacks of the signal which are classified into a single class by all the classifiers are considered and rest of the beat-stacks are discarded. Now, for a given signal, whichever class has a larger number of beat-stacks is output as the signal-level prediction. If none of the beat-stacks are labeled to single class by all the classifiers, we compute the record classification probability for each classifier, defined as the ratio of numbers of beat-stacks corresponding to each class to total number of beat-stacks. Then the signal classification probability is averaged across all the classifiers and class with highest value is assigned as record level prediction.

4. Results

Using the proposed shallow CNN architecture, we achieved an overall F1-score 71%. A detailed listing of F1-scores for each of the normal AF and other class are presented in Table 1. Considering the computational complexity, our submitted entry on an average uses less than

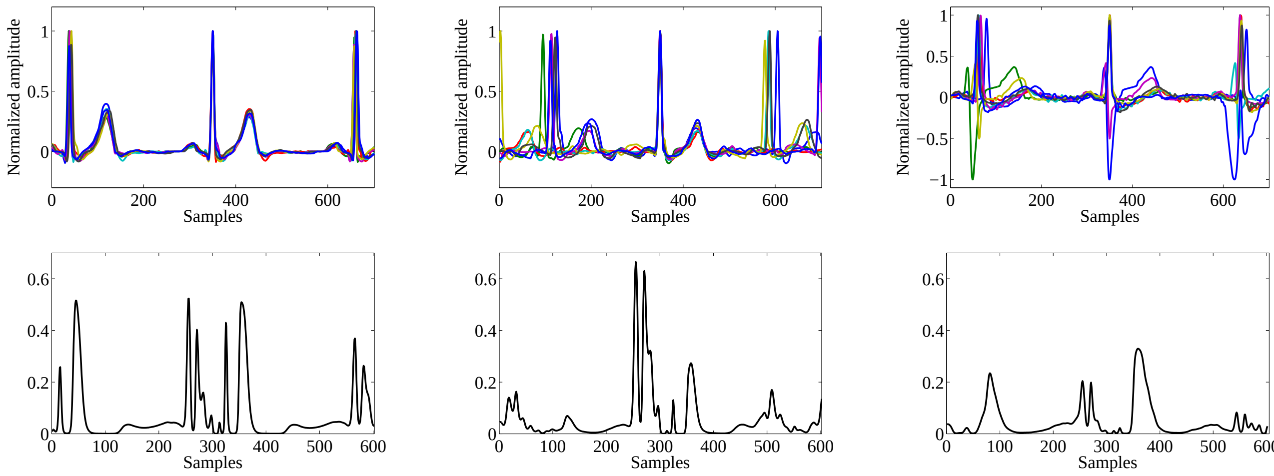

Figure 4. Stacked beat vectors (top row) and output of convolution layer (bottom row) for the corresponding signal of (a) normal (b) AF and (c) other class.

Method	F1 score
Normal	0.86
AF	0.73
Other	0.56
Overall	0.71

Table 1. Classification performance

25% of the allocated quota on the challenge sandbox environment making it suitable for resource constrained scenarios.

5. Discussion

In this study, we proposed a CNN based solution to the 2017 PhysioNet/CinC Challenge. We optimized weights of the convolutional layer to extract the features specific to the class that maximizes the underlying classifier performance. Strength of our solution lies at learning the discriminative features for multiple classes. Further the low-complexity execution makes it to be readily useful for real-time applications. The proposed method yields an F1-score of 86% and 73% respectively for normal and atrial fibrillation signals. However, it achieves only 56% F1-score for others class. Additional work is necessary to improve the predictive power of other class which could penitentially improve the overall F1-score.

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