Deep-Learning Premature Contraction Localization Using Gaussian Based Predicted Data

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Abstract

Detection of cardiac arrhythmias is still an ongoing challenge. Here we focus on premature ventricular contraction (PVC) and premature atrial contraction (PAC) and introduce a deep-learning-based method for PVC/PAC localization in ECG. Our method is based on involving the time series with non-zero values corresponding to the ground truth PVC/PAC positions into the training process. To improve the efficiency of deep model training, the transition between the non-zero and zero areas in the train output time series was smoothed by introducing a Gaussian function. When applied to the new ECGs, the output signal (time series including Gaussians) is processed by a robust peak detector with Bayesian optimization of threshold, minimal distance and peak prominence. Positions of the detected peaks correspond to the desired PVC/PAC positions. The proposed method was evaluated on China Physiological Signal Challenge 2018 (CPSC2018) using own-created ground truth positions of PVC/PAC. The proposed method reached F1 score 0.923 and 0.688 for PAC and PVC, respectively, which is better than our previous results obtained via multiple instance learning-based method.

1. Introduction

Detection of cardiac arrhythmias is still an ongoing challenge. Most of the standard methods for premature ventricular contraction (PVC) and premature atrial contraction (PAC) detection are based on the extraction of the ECG features and/or applying specific decision rules (e.g. [1–4]). Even though the mentioned methods' results are satisfying, the feature extraction and decision-making process is time-consuming and requires cooperation with highly qualified medical experts.

In our previous study, [5] we introduced the premature contraction localization technique based on a deep neural network with max-pooling-based multiple instance learning (MIL). This method has no above limitations, as it requires only raw ECGs and global annotations (i.e. 'normal ECG'/'ECG with PVCs') with no previous information about the positions of PVCs. The MIL-based approach generally reached promising results. It, however, failed in the localization of some premature beats. Moreover, the MIL-based method seems to be unsuitable for the localization of less morphology-specific arrhythmias, such as premature atrial contraction (PAC) included in this study.

Here, we aimed to improve the previous localization method by involving the information about ground-truth PAC/PVC positions in the training process. Thus, besides the global annotations (global labels), our method uses positional labels of PVC/PAC for the creation of a signal with Gaussians on the positions of pathologies, and this predicted signal is then used for final detection. We adjusted the model to be applicable with the above approach as well as with our previous MIL-based approach, so we can compare them to each other. We believe that the model will result in accurate PAC/PVC localization in highly variable ECG datasets.

2. Methods

There are three main steps for PVC localization implementation in the presented approach: 1) creation of a signal with Gaussians on the positions of pathologies, 2) prediction of this signal using a convolutional neural network, 3) localization of PVCs/PACs via detecting the peaks in the predicted output signal.

2.1. Training data

The dataset consists of 4778 12-lead ECG recordings originating from China Physiological Signal Challenge 2018 (CPSC2018) [6]. Of them, 463 recordings was marked as PACs, 543 as PVCs, 650 as normal sinus rhythm and 3122 falls into the category of other pathologies such as atrial fibrillation, atrio-ventricular or bundle branch blockades. Each of the provided labels is for the whole

recording only. On top of that, we created additional positional annotations of each PAC and PVC in the dataset. The dataset was randomly split into training, validation, and test subsets in 7:1:2 ratio. Preprocessing steps before passing data into the model consisted of: (1) resampling to a frequency of 150 Hz using decimation and anti-aliasing FIR filter; (2) 50/60 Hz noise suppression by a second-order IIR notch filter; (3) baseline wander removal by a subtraction of a weighted (6s Blackman window) moving averaged signal [7]. To deal with a variable signal lengths in a batch, signals were padded by zeros to match the longest sequence in the batch.

2.2. Deep model configuration

In our work, the baseline model was based on modified convolutional neural network (CNN) previously reported by our team in [5]. Briefly, the architecture consists of 4-layer residual encoder [8] with five 1D convolutional filters in each layer, and additional global skip connection. Number of layers leads to 2^4-fold undersampled output signal compared to original sequence.

Decoding part of the model comprises of various types of layers given by a task actually solved. In case of MIL with only global label either global max-pooling or attention layer is used. In case of regression of a reference signal with Gaussian functions the output is predicted directly from the encoder output. Each of those two tasks requires different loss function, in our case weighted cross entropy (MCE) in the former approach and mean square root (MSE) in the latter. Basic schematic configuration for both is depicted in Figure1. In addition to previous work [5], we have extended the MIL-based variant of the model by an attention mechanism from [9].

2.3. Learning setup

Model was trained with Adam optimizer [10] with $\beta_1 = 0.9$, $\beta_2 = 0.999$ and experimentally estimated batch size of 64. The learning rate was initially set to 0.001 and then was reduced to 10 % after 60, 30 and 15 epochs. Several data augmentation techniques were applied with the probability of 0.8 each, including random circular shift, signal amplification along the voltage axis (up to ± 20 %) and signal stretch along the temporal axis (up to ± 10 %). The code is available at `https://github.com/PetraNovotna/Gauss_arrhytmia_localization`.

2.4. Postprocessing

During the inference (i.e., when applied to new ECGs), the model output in form of a sequence with Gaussian-like functions indicating the most probable position of the pathology, is further processed by a robust yet simple peak detector in order to get time quantity representing premature beat localisation. The detector parameters (threshold, minimal distance and peak prominence) were optimised on the validation set via Bayesian optimisation technique [11] to target the best performance possible. Positions of the detected peaks correspond to the desired PVC/PAC positions.

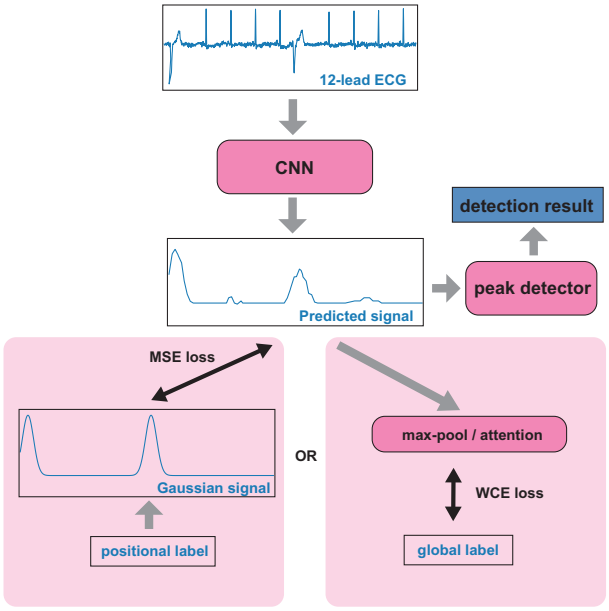

Figure 1: Schematic diagram of the proposed method. The left part is prediction using Gaussian signal regression, and the right part is a prediction with multiple instance learning (MIL)

3. Results and Discussion

The model was trained in three different ways according to used configuration, i.e. prediction of the output signal with Gaussians (with 3 standard deviations σ tested), MIL with max-pooling and MIL with attention. In each training session, the detection accuracy was evaluated by calculating precision, recall, and F1-score, which are summarized in Table 1. Moreover, we trained separate models using two different datasets - the arrhythmia-specific data (where only Normal/PVC/PAC were selected from the database) and the whole database (with all pathological categories included). Each mentioned model was trained (and evaluated) to detect a) only PVC, b) only PAC, c) PVC and PAC simultaneously, where the network output consists of two signals (one for PAC and one for PVC).

From the results obtained on the whole database (with all pathologies included), our method seems to be robust to the occurrence of different pathologies in the same signal. However, as the evaluation datasets are different, di-

Table 1: Detection results for Gaussian-based method (for various Gaussian widths σ) and models with max-pooling (MP) and Attention (Att.) layers. Left: trained on Normal/PVC/PAC data from database. Right: trained on the whole database. sep. – separate training of the individual network for each pathology; sim. – simultaneous training of one network for both PAC and PVC localization (but evaluated only for specified pathology).

	Normal, PVC, PAC data					All patologies data				
	Precision					Precision				
	σ 20	σ 30	σ 40	MP	Att.	σ 20	σ 30	σ 40	MP	Att.
PAC sep.	.743	.806	.719	.751	.282	.681	.780	.759	.577	.099
PAC sim.	.822	.796	.890	.778	.234	.724	.750	.750	.726	.273
PVC sep.	.901	.918	.909	.899	.521	.888	.897	.915	.901	.251
PVC sim.	.963	.971	.932	.970	.702	.918	.871	.933	.932	.266
	Recall					Recall				
	σ 20	σ 30	σ 40	MP	Att.	σ 20	σ 30	σ 40	MP	Att.
PAC sep.	.763	.728	.756	.620	.337	.613	.594	.606	.479	.155
PAC sim.	.729	.726	.682	.592	.362	.648	.621	.636	.613	.322
PVC sep.	.910	.898	.916	.885	.374	.925	.920	.861	.868	.370
PVC sim.	.923	.937	.963	.849	.558	.900	.918	.913	.866	.355
	F1 score					F1 score				
	σ 20	σ 30	σ 40	MP	Att.	σ 20	σ 30	σ 40	MP	Att.
PAC sep.	.753	.765	.737	.679	.307	.646	.674	.674	.523	.121
PAC sim.	.773	.759	.772	.672	.284	.684	.679	.688	.665	.295
PVC sep.	.905	.908	.912	.892	.436	.906	.908	.887	.884	.299
PVC sim.	.943	.954	.947	.906	.622	.909	.894	.923	.898	.304

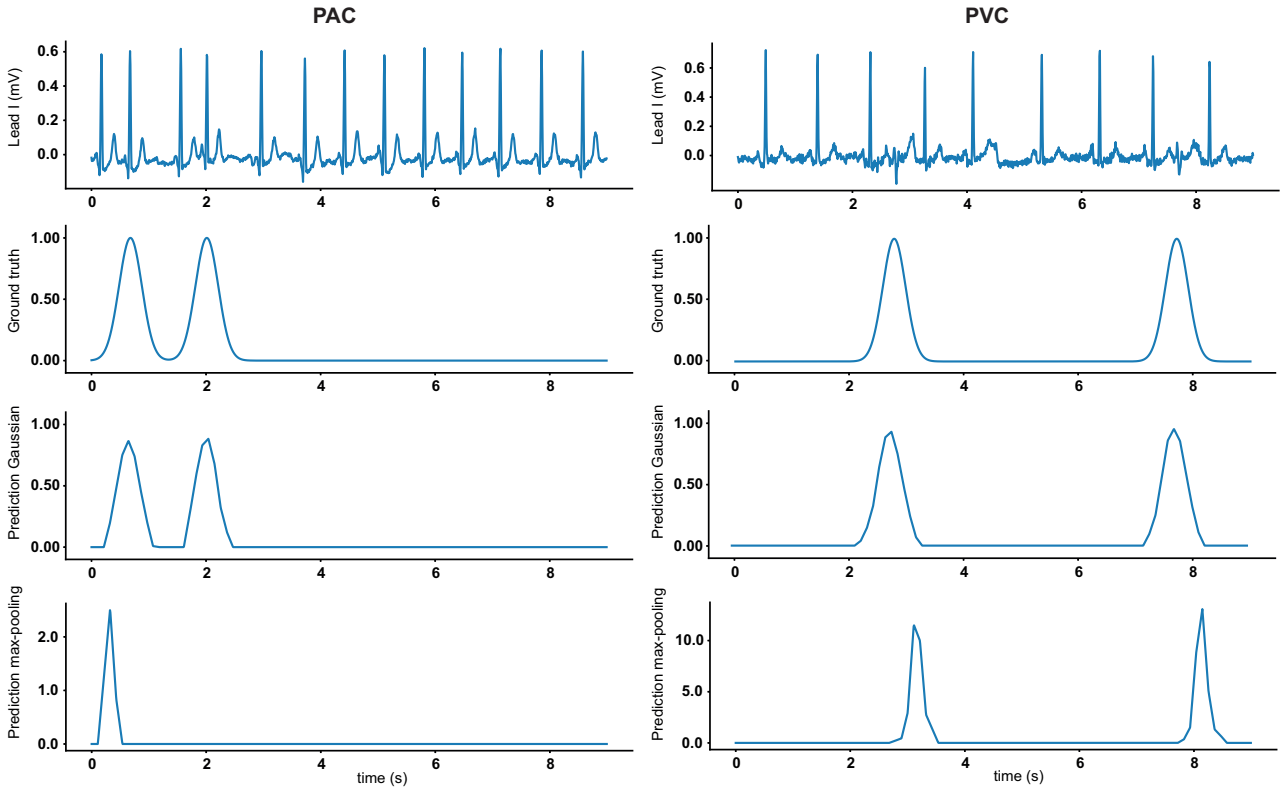

Figure 2: Example of ECG signals with premature beats and corresponding predicted Gaussian-based signals and max-pooling-based MIL signals used for the premature beats localization.

rect comparison of the results for different categories (Normal, PVC, PAC, and all pathologies) is difficult.

Next finding is that the training of a single network for localization of both PVC and PAC yields better results than the training of two networks, for PVC and PAC separately. Compared to the separate training for PVC/PAC, F1 score of the binary-task network was about 0.014 and 0.036 higher for PVC and PAC, respectively (when training on the whole database and using σ 40).

The method using Gaussian position signal is quite robust against the variable Gaussian width σ and is more successful than MIL with global pooling. However, the differences between the methods are not significant, especially considering the fact that the latter uses only global labels with no positional information: F1 score for PAC 0.688 (Gauss. σ 40) vs. 0.665 (max-pooling); F1 score for PVC 0.923 (Gauss. σ 40) vs. 0.898 (max-pooling), when training for PAC/PVC simultaneously on the whole database. The performance of the model with attention layer was significantly worse for any configuration. Examples of the predicted output signals are illustrated in Figure2. Both shown methods are able to localize morphologically-specific arrhythmia – PVC – successfully. The Gaussian-based method accurately detected both PACs, although no prominent morphological changes are present in ECG in this case. On the contrary, MIL max-pooling method localized only one of two PACs. The shapes of the predicted Gaussian signals are very similar to that of the ground truth outputs, since the Gaussian-based model is trained to reproduce the ground-truth. In case of the max-pooling method, the predicted signals are created as the byproduct of the network classification.

4. Conclusions

In this paper, we introduced a new deep-net method for localization of PVC/PAC by involving the premature beats ground-truth positions into the training process. Although the method requires detailed, time-consuming annotation of ECGs, it allows achieving accurate localization of both morphologically-specific (PVC) and non-specific (PAC) premature beats. This approach slightly surpasses our previous results obtained by using MIL-based method.

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