Swarm Decomposition Enhances the Discrimination of Cardiac Arrhythmias in Varied-lead ECG Using ResNet-BiLSTM Network Activations

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Abstract

The standard screening tool for cardiac arrhythmias remains to be the 12-lead electrocardiography (ECG). Despite carrying rich information about different types of arrhythmias, it is considered bulky, high-cost, and often hard to use. In this study, we sought to investigate the efficiency of using 6-lead, 4-lead, 3-lead, and 2-lead ECG in discriminating between 26 arrhythmia types and compare them with the standard 12-lead ECG. as part of PhysioNet/Computing in Cardiology 2021 Challenge. Our team, Care4MyHeart, developed a deep learning approach based on residual convolutional neural networks and Bi-directional long short term memory (ResNet-BiLSTM) to extract deep-activated features from ECG oscillatory components obtained using a novel swarm decomposition (SWD) algorithm. Alongside age and sex, these automated features were combined with hand-crafted features from heart rate variability and SWD components for training and classification. Our approach achieved a challenge score of 0.45, 0.43, 0.44, 0.43, and 0.42 using 10-fold cross-validation using the training set and 0.41, 0.39, 0.40, 0.39, and 0.37 using the hidden testing set for 12-lead, 6-lead, 4-lead, 3-lead, and 2-lead, respectively. Our final entry (12-lead) was ranked the 158th out of 264.

1. Introduction

Cardiovascular disease (CVD) is considered the major cause of death worldwide with an estimated 17.9 million people suffering from its conditions that led to death (31% of all deaths) [1]. Most of CVDs are caused by arrhythmias that are usually miss-diagnosed by clinicians [2]. The standard tool to diagnose cardiac arrhythmias is the 12-lead electrocardiography (ECG). However, the limited accessibility of 12-lead recording devices makes it essential to find smaller, cost-effective, and comparable alternatives.

To address this concern, we present in this study a complete deep learning approach that utilizes residual convolutional and recurrent neural networks alongside hand-crafted features to discriminate between cardiac arrhythmias in 12-lead, 6-lead, 4-lead, 3-lead, and 2-lead ECG from patient data obtained from the PhysioNet/Computing in Cardiology Challenge 2021 [3, 4]. The novelty of the proposed approach, which is an extension to the our 2020 challenge algorithm [5], lies in utilizing a novel swarm decomposition (SWD) algorithm for the first time in cardiology applications to decompose ECG signals, and thus, making it simpler for feature extraction techniques to obtain specific per-arrhythmia characteristics.

2. Material and methods

2.1. Database preparation

A total of 88,253 labeled recordings obtained from 6 different international 12-lead ECG datasets were provided in the challenge. All recordings of multiple labels (arrhythmia types) were duplicated to ensure a signal for each label. In addition, only 30 arrhythmia types were selected for challenge scoring out of 133 arrhythmia types. From these 30 types, 8 arrhythmia types were merged to represent the same label; namely complete right bundle branch block and right bundle branch block, complete left bundle branch block and left bundle branch block, premature atrial contraction and supraventricular premature beats, and premature ventricular contractions and ventricular premature beats. Thus, the resulting dataset included a total of 26 arrhythmia types/labels. To reduce the size of the dataset as well as the unbalance in labels, each arrhythmia type was reduced to be only with 7,500 samples or less. Therefore, the final dataset included a total of 89,165 samples. The 5 leads scenarios followed in the challenge were as follows,

- 12-lead: I, II, III, aVR, aVL, aVF, V1, ..., V6
- 6-lead: I, II, III, aVR, aVL, aVF
- 4-lead: I, II, III, V2
- 3-lead: I, II, V2
- 2-lead: I, II

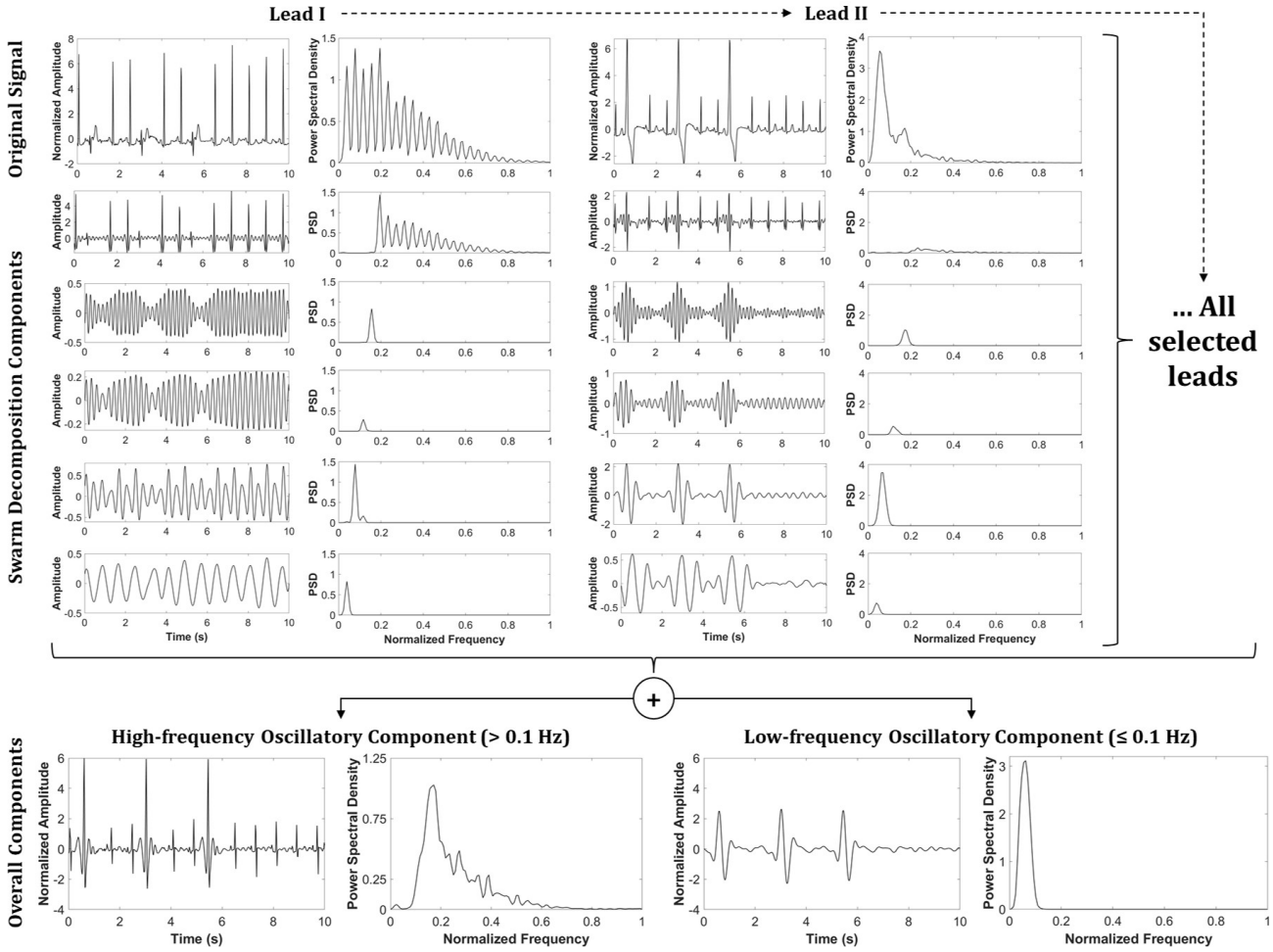

Figure 1. Swarm decomposition (SWD) mechanism to extract low and high oscillatory components from ECG signals.

2.2. Pre-processing

The proposed approach applies minimal pre-processing steps to enhance ECG signals as well as to reduce noise components before any further processing. First, all signals were re-sampled to 64 Hz and trimmed to cover only the first 10 seconds of the recording, i.e, 640 samples. Then, each signal was subjected to baseline wandering removal to discard the low frequency component that results from strong movements or electrodes displacement. To achieve this, the Gaussian-weighted moving average filter was adopted with a window size of 100 samples. All signals were normalized based on z-score normalization to ensure a mean of 0 and standard deviation of 1.

2.3. Swarm decomposition

In this work, we introduce for the first time the use of the novel swarm decomposition (SWD) algorithm in cardiac signals analysis. SWD is based on swarm filtering (SWF); where the decomposition of signals is represented by a virtual swarm-prey hunting with an objective of obtaining corresponding oscillatory components (OCs) [6]. SWD parameters were initially fine-tuned to ensure accurate decomposition. The components' threshold was set to 0.1 with a standard deviation of 0.1 and a Welch window size of 30% of the original signal length. The decomposition of each ECG signal (Fig. 1) results in a varied number of OCs (mostly 5-10 components), and the total number of these OCs varies according to the number of the selected leads scenario. However, the final overall OCs were formed after merging all OCs from all leads with frequencies less than 0.1 Hz to form the low-frequency OC of patient's ECG and frequencies more than 0.1 to form the high-frequency OC accordingly. At the end, two OCs (low and high frequencies) were obtained as an overall transformation of the selected leads scenario, thus, reducing the complexity when analyzing ECG signals.

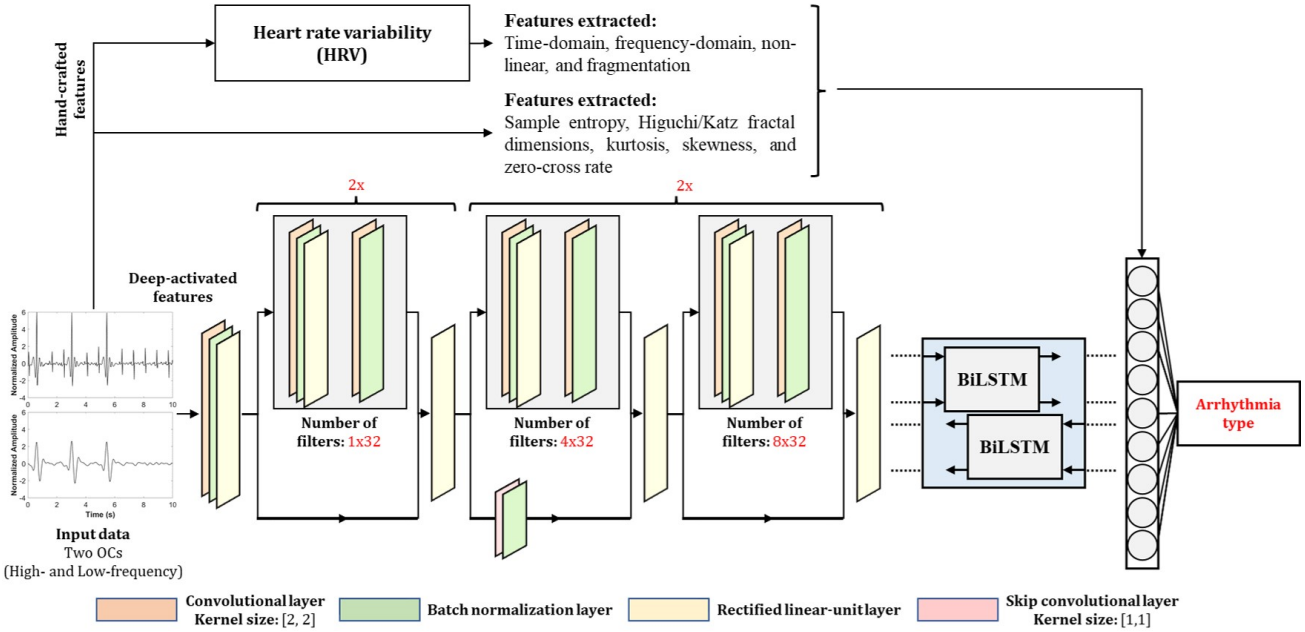

Figure 2. The proposed deep learning model based on ResNet-BiLSTM alongside hand-crafted features used for training.

2.4. Deep learning framework

The proposed deep learning model consisted of two main stages. First, the model was trained to extract deep-activated features from the final overall two SWD OCs (mentioned in previous section) in a form of network activations. Then, these activations were combined with a set of hand-crafted features and used accordingly to train the final model.

2.4.1. Deep-activated features

Deep-activated features refer to the attributes extracted automatically through deep learning network training. The network was built as a combination of residual convolutional neural networks and Bi-directional long short term memory (ResNet-BiLSTM). First, the convolutional neural network was designed as a residual neural network (ResNet) to ensure a better performance as well as to train on deeper details. Then, the network was concatenated with a 512 BiLSTM layer to extract additional features across the time sequence in the forward and backward directions. The complete architecture is represented in Fig. 2 with more information about the layers and parameters used.

2.4.2. Hand-crafted features

Alongside age and sex, hand-crafted features included for this work were from heart rate variability (HRV) as well as from the two extracted SWD OCs. All features were extracted from the overall SWD OCs of the 5th leads scenario (2-lead: I and II), as these two leads were represented in all 5 leads scenarios in the challenge. For HRV, time-domain, frequency-domain, non-linear, and fragmentation metrics mentioned in [7] were extracted. In addition, kurtosis and skewness values of the overall HRV data were calculated. For SWD OCs, features were extracted from each OC including sample entropy, Higuchi and Katz fractal dimensions, kurtosis, skewness, and zero-crossing.

2.4.3. Training and classification

The training was optimized based on the adaptive moment estimation (ADAM) solver. The initial learning rate was set to 0.001, with a dropping factor of 0.1 occurring once at the 12th epoch. The model was trained for a total of 15 epochs using a mini-batch size of 512 samples. In addition, the L2-regularization was set to 10^{-5}. During training, initial weights for every class were calculated empirically and used within the classification layer that included a weighted cross-entropy loss function to optimize the final weights and network parameters. For predictions, we followed a voting mechanism based on the total number of leads scenarios. For example, for 12-lead, because all leads are available, we used 5 trained models representing each leads scenario; namely 12-lead, 6-lead, 4-lead, 3-lead, and 2-lead. Each scenario's model returned a prediction score for each arrhythmia type for every patient. The predictions from every model were summed and normalized between 0 to 1, and all classes with a score ≥ 0.5 were assigned as positive for the selected arrhythmia type.

Leads	Training	Validation	Test	Ranking
12	0.45	0.41	TBU	158
6	0.43	0.39	TBU	153
4	0.44	0.40	TBU	150
3	0.43	0.39	TBU	157
2	0.42	0.37	TBU	168

Table 1. Challenge scores for our final selected entry (team Care4MyHeart) using 10-fold cross validation on the public training set, repeated scoring on the hidden validation set, and one-time scoring on the hidden test set (TBU: to be updated) as well as the ranking on the hidden test set.

Leads	Using original ECG signals	Using SWD components
12	0.32	0.41
6	0.31	0.39
4	0.32	0.40
3	0.31	0.39
2	0.29	0.37

Table 2. Challenge scores comparison between final entries using original ECG signals and swarm decomposition (SWD) components on the hidden validation set of 12-lead

3. Results

The proposed model was evaluated (Fig.1) initially using k-fold cross-validation of 10 folds. The performance on the same dataset used for training reached an overall challenge score of 0.45, 0.43, 0.44, 0.43, and 0.42 using 12-lead, 6-lead, 4-lead, 3-lead, and 2-lead ECG, respectively. In addition, the model was evaluated on a hidden testing set for each leads scenario. The model based achieved an overall challenge score of 0.41, 0.39, 0.40, 0.39, and 0.37 on each scenario. Our team's final entry (using 12-lead) was ranked the 158th out of 264 entries. Table 2 compares the performance between SWD and the original ECG signals when used for training and prediction on the hidden validation set using 12-lead.

4. Discussion and conclusions

The utilization of SWD allowed for training the model on a simpler transformation of the varied-lead ECG signals. Although the model have achieved decent levels of performance, it can be further improved following several steps. Initially, the reduction of the total number of samples prevented the model from training on a wider set of data. However, it was an essential step in this challenge to ensure not to exceed the training time limit (48 hours). In addition, despite of the accurate extraction of OCs by the SWD algorithm, reducing the values of its parameters (to less than 0.1) usually results in an even better decomposition of the signals. Thus, better transformation would have been achieved to enhance the extraction of deep-activated and hand-crafted features even further as well as the model's performance accordingly.

In conclusion, SWD showed strong potential in enhancing the prediction ability of deep learning in cardiac arrhythmias identification. Future works would focus on a better preparation of the algorithm, complete comparison between it and other decomposition algorithms such as the empirical mode decomposition (EMD), and the utilization of more sophisticated deep learning neural networks.

Acknowledgments

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