Diagnosis of Cardiac Abnormalities Applying Scattering Transform and Fourier-Bessel Expansion on ECG Signals

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Abstract

This work intends to devise an efficient feature extraction scheme for identifying common cardiac abnormalities using the Fourier-Bessel (FB) expansion of RR-intervals and time-frequency based features of Electrocardiogram (ECG) signals. The Bessel basis, when used for representing the RR-intervals, meaningfully enhances the pathologically induced low-frequency changes in terms of FB coefficients. To ensure the characterization of diverse pathological variability present in the ECG signals, time-frequency domain features are also extracted using scattering transform. The multi-label classification of the ECG signals, for five different lead combinations as mentioned in the PhysioNet/CinC Challenge 2021, is performed using Gated recurrent unit into specified twenty-six categories. We have participated in this Challenge as team "Medics". Our code failed to run on the validation set during the official phase of the Challenge, hence our entry was not officially ranked in the Challenge. The experimental outcomes, for five-fold cross validation using 2021 PhysioNet/CinC Challenge dataset, demonstrates the mean Challenge scoring metric on the twelve-lead, six-lead, four-lead, three-lead, and two-lead combinations as 0.40, 0.43, 0.43, 0.44, and 0.45 respectively. According to the results, the proposed method justifies the use of the FB and scattering transform together for the detection and identification of common cardiac problems using ECG signals.

1. Introduction

Cardiac abnormalities are the leading cause of the death globally [1]. Prompt diagnosis of these abnormalities can significantly reduce the mortality rate across the world. The 12-lead electrocardiogram (ECG) is commonly used in practice for diagnosis of cardiac abnormalities[2]. However, reading an ECG requires a highly trained professional to perform the task and it is a time consuming process. Therefore, the system that can automatically classify ECG signals to detect cardiac abnormalities can help physicians to diagnose and handle more patients. A number of automatic ECG signal classifiers have evolved over the last decade.

However,the majority of them make use of small or homogeneous datasets with a limited number of cardiac abnormalities and thus they can not be used in general settings [2]. In an attempt to promote the further development of robust automatic ECG classification, the PhysioNet/CinC Challenge 2020 provided data from a wide range of sources with various cardiac abnormalities [2]. Many participants of this challenge employed deep neural networks (DNN) for 12-lead ECG classification into twenty seven categories [3–5]. In one of studies, residual convolutional neural network was developed to classify clinical cardiac abnormalities from 12-lead ECGs [3]. Additionally, two residual neural network modules with squeeze-and-excitation blocks to classify the ECG signals are developed in one of the method [4]. Another study incorporated scattering transform of the ECG with deep residual neural network for the intended classification [5]. One of the participants built a hybrid model for the twenty-seven class classification utilising the scattering transform as input to a depthwise separable convolutional network and a bidirectional long short-term memory network [6].

In this paper, as part of the PhysioNet / CinC Challenge 2021 [7], we developed an multi-label classification model using the amalgamation of Fourier-Bessel (FB) expansion of RR-intervals and scattering transform coefficients as input features to the classifier. The scattering transform generates translation-invariant and deformation-stable representations of ECG signals.

The FB coefficients characterizes the heart rate variability for various cardiac abnormalities. The amalgamated features are fed to the Gated recurrent unit based classifier to classify ECGs into specified twenty-six categories.The developed system is evaluated using five-fold cross validation scheme.

2. Methodology

The major steps involved in the proposed methodology are pre-processing of ECG signals, feature extraction, and multi label classification. The overall system design is

shown in Figure 1 and the details of each involved step is described below.

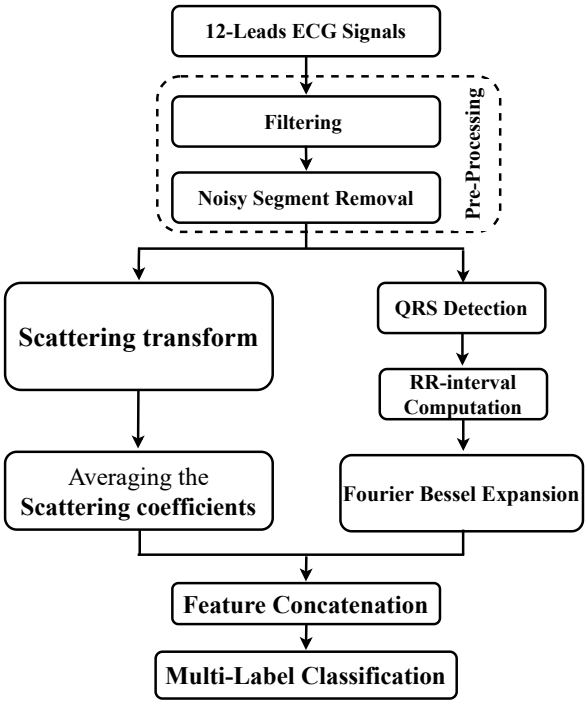

Figure 1. Proposed methodology.

2.1. Data

This study is validated using the PhysioNet/CinC Challenge 2021 dataset. This dataset comprises of eight different databases which are collected from across the world. Each database contained 12-lead ECG recordings and their annotations in terms of SNOMED CT codes [7]. There are 133 labeled abnormalities in total, out of which 30 are included in the final scoring metrics. The complete dataset comprises of 88253 12-lead ECG records which are sampled at either 250 Hz or 500 Hz or 1000 Hz frequency.

2.2. Pre-Processing

The data pre-processing step includes the various data processing operations such as re-sampling, filtering, and noise cancellation applied on whole raw ECG records. Initially, the entire data set was examined in terms of sampling frequency and all the ECG signal were re-sampled to 500 Hz to maintain the uniformity with respect to sampling frequencies. A Butterworth band pass filter with cut-off frequency of 0.5 Hz and 35 Hz is used to remove baseline wander and high-frequency noise from the re-sampled ECG signals. Further, a noisy segment identification and removal method is applied to remove the noisy segments. This method utilizes the idea of energy thresholding over the spectrogram of a ECG record. Based on the threshold, the noisy segment is identified and removed from the ECG record. [8]. Prior to feature extraction, only ten seconds initial segments of the data are considered in order to maintain the uniform length for each ECG records. This choice of length complies with the fact that most of the records in the dataset are of 10 seconds and above in length.

2.3. Feature Extraction

The Proposed methodology focuses on fusion of two different feature extraction strategies to capture the heart rate variability and the morphological information applied separately on the processed ECG. In one of the strategy, FB expansion is applied on the RR interval sequence to yield the related coefficients in order to capture the pathological information associated with the heart rate variability. In the another strategy, time-frequency domain features are obtained from the processed ECG signal by employing scattering transform [9].

2.3.1. Fourier-Bessel Expansion

The analysis and synthesis of arbitrary signals using FB expansion involves the use of the Bessel functions as the basis. The decaying nature of the Bessel basis function has been proven useful to extract the information from the RR interval sequences[10]. Therefore, the FB coefficients for the RR interval sequence are computed and considered as one set of features. The RR sequences are generated by applying QRS detection on lead II. In general, the FB coefficients can be obtained by using the following equation:

$$\chi_m = \frac{2\int_0^a tR(t)J_n\left(\lambda_m t\right)dt}{a^2\left[J_{n+1}\left(\lambda_m a\right)\right]^2} \tag{1}$$

where, $R(t)$ is the RR interval sequence, J_n and J_{n+1} are the Bessel functions of first kind, λ_m are the roots of $J_n(t) = 0$, m is a integer value and a is range of time t.

2.3.2. Scattering Transform

The time-frequency domain features are obtained from the processed ECG signal by employing scattering transform [9]. The scattering transform is capable to produce a stable and translation invariant signal representation. Further this representation has the discriminating potential among the classes making it suitable for the feature extraction task intended for classification.

The scattering transform is obtained by cascading the wavelet transform with a nonlinear modulus and averaging operators [9]. The first layer scattering coefficients are obtained using wavelet transform of signal $s(t)$ given as:

$$\chi_s^1(t, j_1) = |s(t) * \psi_{j_1}(t)| * \phi(t), \quad j_1 = 1, \ldots, \lambda_1 \tag{2}$$

where j_1 and λ_1 denotes different scales and orientations for the first layer. The scaling function $\phi(t)$ is a low pass filer and $\psi(t)$ is band pass filter for higher frequency bands. Further to make the representation translation invariant modulus and averaging operation are carried out. The scaling function is considered as an averaging operation. Further to recover the lost high frequency information the other set of wavelets $\psi(t)$ are used. Thus the second layer coefficients can be expressed as:

$$\chi_s^2(t, j_1, j_2) = \|s(t) * \psi_{j_1}(t)\,|*\psi_{j_2}(t)| * \phi(t). \quad (3)$$

This process of layer creation is continued up to the m^{th} layer in order to make the representation invariant and to recover the deleted information. The m^{th} layer coefficients are given as:

$$\chi_s^m(t, j_1, j_2, .., j_m) = |||s(t) * \psi_{j_1}(t)| * \psi_{j_2}(t)|... \\ *\psi_{j_m}(t)| * \phi(t), j_i \in \{0, \ldots, \lambda_i\}, i \in \{1, 2, \ldots, m\} \quad (4)$$

The scattering transform coefficients in terms of number of orientations by number of scales are obtained by concatenating the outputs of each layer.

Finally, averaging the scattering transform coefficients thus obtained forms the other feature set used in this study. To build the entire feature set, both the FB and scattering transform features are combined.

2.4. Classification

In this study, a multi-label classification schemes is developed for classification of ECGs. One multi-label classifier is designed for each of the five different specified ECG lead combinations. The deployed multi-label classifier architecture includes the GRU layer, max pooling layer, fully connect layer and a sigmoid layer as shown in the Figure 2. The concatenated features are fed as input to the said network with batch size of 1000 and learning rate of 0.01. The network is trained for 70 epochs. The hidden units of 100 is set for the GRU layer. GRU layer is like long short-term memory layer with no output gate but there is a forget gate and less number of parameters. GRU is able to learn time step dependencies within time series data. The input weights and the recurrent weights of the GRU layer are initialised using Glorot initialisation. Whereas the weights of the fully connected layer are initialised using Gaussian distribution with zero mean and standard deviation of 0.01. For the each of the multi-label classifier's training, 80% of the data was chosen at random, with records containing at least one label from the twenty-six scored labels. The generated models were then tested on the 20% of the validation data as per five-fold cross-validation scheme.

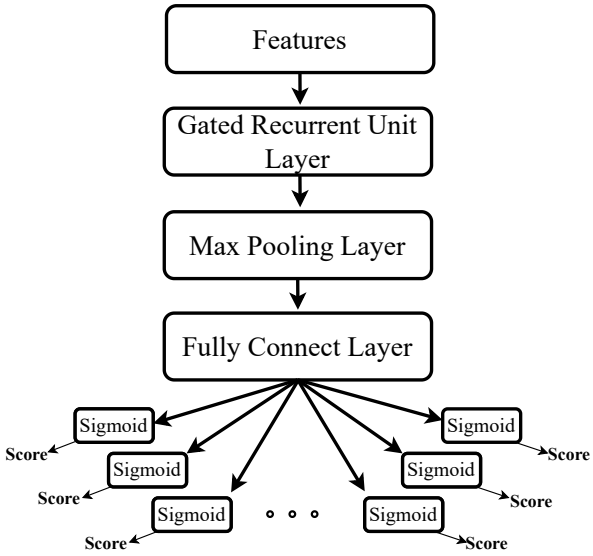

Figure 2. Multi-label Classifier Architecture

3. Results and Discussion

The five-fold cross-validation results using the training data for the different lead combinations are presented in Table 1. The performance measures considered to validate the study are: accuracy, F-measure, area under the receiver operating characteristic (AUROC), area under the precision-recall curve (AUPRC), and the challenge scoring metric [7]. The challenge scoring metric used for scoring is designed in such a way that correct diagnoses will get full credit whereas misdiagnoses with similar risks or outcomes as the true diagnosis will get partial credit [7].

Unfortunately, our official phase entry failed because the training time for the twelve-lead setup exceeded the given time limit. Thus, we were unable to obtain the challenge scoring metric scores on the hidden test set. Therefore, average results of the five-fold cross-validation performed on the publicly available training data of the challenge are shown in Table 1. The feature extraction strategies utilised in this study were successful in distinguishing various abnormalities present in the ECG signal. The proposed algorithm gives satisfactory performance on all lead combinations, as observed from Table 1. It is noteworthy that all the performance measures for the two-lead combinations is the highest among all the lead combinations. Further it is observed that, with the fixed model parameters the performance improves significantly as the number of leads in the lead combinations decreases. The results in terms of the challenge scoring metric of each fold for all lead combinations is shown in Figure 3.

Table 1. Performance measures for five-fold cross validation using training data.

Lead combination	Accuracy	F-measure	AUROC	AUPRC	Challenge Scoring Metric
Twelve-lead	0.35	0.26	0.63	0.18	0.40
Six-lead	0.37	0.29	0.64	0.19	0.43
Four-lead	0.38	0.29	0.64	0.20	0.43
Three-lead	0.34	0.28	0.64	0.19	0.44
Two-lead	0.38	0.30	0.64	0.20	0.45

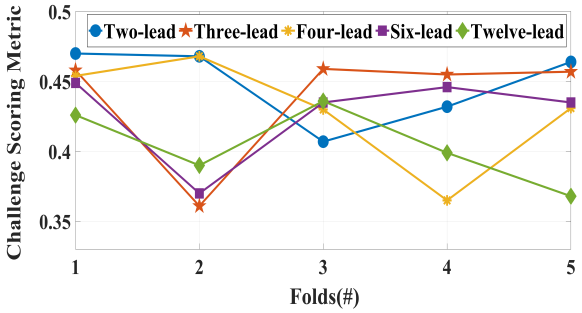

Figure 3. Five-fold results in terms of challenge scoring metric.

4. Conclusion

In this study, we have devised an efficient feature extraction scheme for ECG classification incorporating the FB expansion and scattering transform. The results demonstrates that, the proposed feature extraction strategy and a multi label classification algorithm provides a competitive solution for classification of ECGs. The models developed in this study are not optimal and thus, the optimization of model parameters and exploration of other feature extraction techniques can be done in the future work.

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