Biomedical Signal Processing and Control 45 (2018) 22–32

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Multiple-feature-branch convolutional neural network for myocardial infarction diagnosis using electrocardiogram

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ARTICLE INFO

Article history:
Received 9 January 2018
Received in revised form 1 May 2018
Accepted 19 May 2018

Keywords:
Convolutional Neural Network (CNN)
Electrocardiogram (ECG)
Myocardial Infarction (MI)
Automated diagnosis
Patient-specific

ABSTRACT

Generally, 12-lead electrocardiogram (ECG) is widely used in MI diagnosis. It has two unique attributes namely integrity and diversity. But most of the previous studies on automated MI diagnosis algorithm didn't utilize these two attributes simultaneously. In this paper, a novel Multiple-Feature-Branch Convolutional Neural Network (MFB-CNN) is proposed for automated MI detection and localization using ECG. Each independent feature branch of the MFB-CNN corresponds to a certain lead. Individual features of a lead can be learned by a feature branch, exploiting the diversity among the 12 leads. Global fully-connected softmax layer can exploit the integrity, summarizing all the feature branches. Based on deep learning framework, no hand-designed features are required for analysis. Furthermore, patient-specific paradigm is adopted to manage the inter-patient variability, which is a significant challenge for automated diagnosis. Also, class-based experiment (regardless of the inter-patient variability) is performed. The proposed algorithm is evaluated using the ECG data from PTB diagnostic database. It can achieve a good performance in MI diagnosis. For class-based MI detection and localization, the average accuracies are up to 99.95% and 99.81%, respectively; for patient-specific experiment, the average accuracies of MI detection and localization are 98.79% and 94.82%, respectively. Considering its excellent performance, the MFB-CNN can be applied to computer-aided diagnosis platform to assist the real-world MI detection and localization.

1. Introduction

Myocardial infarction (MI) is one of the most common cardiovascular diseases (CVDs) worldwide. It is mainly caused by the blockage of the coronary arteries and the following reduction of the oxygen-rich blood flow to the myocardium [1]. Due to the lack of oxygen, myocardial necrosis will occur and expand, resulting in severe heart attacks. According to the American Health Association [2], approximated 750,000 Americans have a heart attack every year, 15.5% of them died. Hence, it is of utmost important for the early diagnosis of MI, which can be accomplished with the electrocardiogram (ECG).

The ECG is a typical diagnostic tool to monitor the cardiac electrical activity. It consists of 12 leads (I, II, III, aVR, aVL, aVF, V1–V6), corresponding to special regions of the heart [3]. 12-lead ECG has been widely used in medical institutions nowadays, it plays a vital role in the early diagnosis of MI. Different types of MI, such as anterior, anterolateral and inferior MI, can be detected and distinguished by evaluating the alterations in different leads [4]. For example, ST elevations and pathological Q-waves in V1 to V4 may indicate an anterior MI. If similar changes apear in II, IIIand aVF, the patient may suffer from an inferior MI. Therefore, it is essential to evaluate more leads in the MI diagnosis. However, this process is a strenuous and time-consuming task for the cardiologists, and the diagnostic results may not be objective enough. To address the limitations of manual ECG analysis, various automated MI detection and localization algorithms are proposed to perform effective and reliable examinations.

According to the present studies on MI detection and localization algorithms, most of them focus on the conventional machine learning framework. Generally, it involves feature extraction, feature selection, and classification. These conventional approaches require independent feature extractor to obtain expected features, such as the durations, magnitudes of specific waveforms [5–8]. Coefficients of some transforms are also used as features, for instance, the approximation and detail subband coefficients of the wavelet transform [9–11]. Feature selection is an optimization process to get significant and critical features. Meta-heuristic algorithms like particle swarm optimization (PSO) [12] and dimension reduction techniques like principal component analysis (PCA)

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https://doi.org/10.1016/j.bspc.2018.05.013
1746-8094/

[9,11] are commonly used. Then the feature vectors can be classified by the classifiers, such as neural network (NN) [5], [11–14], support vector machine (SVM) [9,11,12,14] and k-nearest neighbor (KNN) [9,10,12,14]. Although these methods demonstrate favorable performances, they have obvious drawbacks as well. On the one hand, extra feature extraction and selection algorithms lead to an increase of computational complexity; on the other hand, the ECG patterns always vary overtime due to the pathological change of MIs and the influence of some external factors, such as the patient age, gender and so on. These variations can manifest as the dynamic changes of the explicit or implicit "features" of the ECG. Thus, it is difficult to maintain the generalization ability when fixed hand-designed features are used.

Thus, to overcome these disadvantages of conventional methods, deep learning framework is introduced. Unlike the conventional machine learning algorithms, deep learning models can learn the critical features automatically from the huge dataset [15]. Feature extraction and selection are not explicitly defined in the deep learning framework. In other words, they are fused in the whole model. Furthermore, deep learning models can automatically discover the representations needed for prediction from the raw data, they have the potential to manage heterogeneous data types and demonstrate greater generalization [16]. It means that the deep learning models can adapt to the aforementioned dynamic changes of ECGs. Convolutional neural network (CNN) is one of the most widely used deep learning models. It consists of 3 types of basic layers namely convolutional layers, pooling layers and fully-connected layers. The CNN-based algorithms have achieved remarkable performances in image classification [17], object detection [18], and health informatics [19]. Also, several ECG analysis algorithms based on CNN have been developed recently. Kiranyaz et al. [20] employed a 1-D CNN to detect arrhythmia using single-lead ECG. Rajpurkar et al. [21] developed a 34-layer CNN to diagnose irregular heart rhythms based on single-lead ECG. The algorithm exceeded the performance of cardiologists in their experiment. In particular, Acharya et al. [22] proposed an 11-layer 1-D CNN for MI detection using lead II ECG signals. The model can achieve a highest accuracy of 95.22% in the 10-fold cross-validation. Overall, the present CNN-based ECG algorithms didn't exploit all the 12 leads, which is essential for the MI diagnosis [4]. Furthermore, the commonly used 1-D CNNs are not suitable for the 12-lead ECG. They can't utilize the information from all the 12 leads simultaneously.

To address the aforementioned limitations, a novel multiple feature branch CNN (MFB-CNN) is proposed for MI detection and localization using 12-lead ECG. Each feature branch includes independent convolutional and pooling layers, corresponding to a certain lead. Global fully-connected softmax layer is employed to summarize all the feature branches, determining the final diagnostic result. The main contributions of the paper lie in:

1) An MFB-CNN is developed to exploit the diversity and integrity of the 12-lead ECG. The independent feature branches consist of 1-D convolutional and pooling layers. They can learn different features from different leads by training, so the diversity can be utilized. Global fully-connected layer can utilize information from all the 12 leads simultaneously, exploiting the integrity. Based on deep learning framework, extra hand-designed feature extraction and selection are not required. Compared with the conventional 1-D CNNs, it is designed for 12-lead ECG processing specially, which is more suitable for automated MI diagnosis.
2) MI detection and localization are both implemented in the experiments. Compared with other studies, our algorithm can achieve a good and robust performance. Since all the 12 leads are utilized, it can manage more types of MI than the algorithms using fewer leads.
3) To alleviate the inter-patient variability, patient-specific scheme is adopted in the MI detection and localization. Besides, regardless of the inter-patient variability, class-based experiments are also performed. In terms of the patient-specific experiments, the MFB-CNN can be adapted to learn the unique features of a specific patient. It is necessary since the physical condition of a patient can interfere with the ECG patterns.

Table 1
Statistics of the ECG signals used.

Class	No. of subjects	No. of records	No. of 12-lead heartbeats
AMI	23	54	7336
ASMI	29	79	11971
ALMI	17	44	6877
IMI	35	94	13531
ILMI	24	57	8976
HC	52	80	10646
Total	180	408	59336

The rest of the paper is organized as follows. Section 2 introduces the ECG dataset and the preprocessing. Section 3 explains the detailed principles of our MFB-CNN. Experiments and discussions are shown in Section 4. Finally, the conclusion is given in Section 5.

2. Dataset and preprocessing

In this study, the 12-lead ECG signals are derived from the open-source Physikalisch-Technische Bundesanstalt (PTB) diagnostic ECG database [23]. It provides 549 records from 290 subjects, and each record is given a diagnostic result by the cardiologists. The ECG signals are sampled at 1 kHz with 16-bit resolution over a range of 16.384 mV. Most of the ECG records were typically of ∼2 min duration, and all the records were recorded at least 30 s. In particular, 148 MI patients are contained in the database. Also, 52 healthy control (HC) subjects are provided. 5 types of MI, including anterior MI (AMI), anteroseptal MI (ASMI), anterolateral MI (ALMI), inferior MI (IMI), and inferolateral MI (ILMI) are used for evaluation. In addition, HC samples are also involved in the experiments. Subjects that have other types of MI in the database are too few to analyze by the deep learning-based algorithm. In total, 6 classes of the ECG signals are considered in the work. It can be seen that there are different numbers of sample records for MI and HC classes in the PTB database. Although a balanced distribution of the sample records is benefit for the model training, but imbalanced data distributions are more common in the real-world applications [16]. Thus, the imbalanced distributions of sample records are maintained in the paper.

According to the database, there are multiple records for each patient, and each record consists of many heartbeats. The following algorithm is based on the heartbeat, which is the basic unit of ECG signals. All the beats are segmented by the QRS-wave detection, using Pan-Tompkins algorithm [24]. Each heartbeat contains 600 samples, including 199 samples before the QRS-peak point and 400 samples after the QRS-peak point. In addition, to eliminate the offset effect of the ECG signals, each heartbeat in a certain lead is "centralized" by removing the mean value of its amplitudes. Fig. 1 shows examples of the anterior MI, interior MI and the healthy heartbeat (lead II, V3 and V5, for the pathological changes are visually apparent in these 3 leads [4]). In summary, the detailed statistics of the ECG signals used in this study is shown in Table 1.

3. Methods

From a medical viewpoint, the 12 leads of ECG reflect different regions of the same heart [3,25]. They can provide a more comprehensive view of the heart than the single-lead ECGs. By 12-lead