

Arrhythmia Analysis in a Non-contact cECG Chair using Convolutional Neural Network

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Introduction

Arrhythmia is a cardiac-related condition with certain irregular patterns of a heartbeat, caused by abnormal contraction sequence of the heart. The efficiency of blood pumping can significantly be reduced and it may lead to some other life-threatening conditions such as stroke or heart failure in many cases. Arrhythmias can usually be detected by a traditional electrocardiogram (ECG) record so that the electrical activity in the heart can intensively be analyzed. Therefore, the analyses of P wave, QRS complex, T wave, or R-R interval are of great importance. For instance, the increasing amplitude of P wave (> 0.25 mV) indicates right atrial enlargement [1] or the variation in R-R intervals more than 120 ms corresponds to sinus bradycardia (the slow heartbeat of below 60 bpm).

For processing a large volume of ECG signals or big data, various system platforms and algorithms have been implemented for automatic detection and classification of arrhythmias in order to save the cost in healthcare and to optimize medical decisions. Classical classification techniques have been implemented by performing feature extraction and processing further decisions based on the extracted features. Various feature extraction techniques are for example autocorrelation function [2], time-frequency analysis [3], Fourier-transform neural network [4], and wavelet transform [5]. Additionally, a statistical modelling technique has been applied based on Hidden Markov Models (HMM) [6]. The modern technique based on learning algorithms is also applied such as genetic algorithm [7] or least-squares support vector machine (LS-SVM).

In this particular work, the combination of feature extraction and a supervised learning algorithm using a convolutional neural network (CNN) is proposed for the classification of arrhythmia in a non-contact capacitive electrocardiogram (cECG) system, which is set up in a chair for real-time analysis. The system should be able not only to classify every single heartbeat into four different categories i.e. normal (N), left bundle branch block (LBBB), right bundle branch block (RBBB), and premature ventricular contraction (PVC), but also to transfer the data into a cloud storage for further possible batch processing as well as to represent the real-time stream data in a tablet. This work is to demonstrate that cECG signals can be used for predicting cardiac arrhythmias and

they can be applied in many clinical scenarios such as for elderlies at home, in a car seat, in a pilot seat, or even in a passenger seat, where medical attention is required. The proposed system should ultimately support industry 4.0 and medicine 4.0 [8], respectively.

Materials and Methods

Hardware Platform

A set of non-contact cECG electrodes and a driven ground plane have been set up in a chair for data acquisition. Two electrodes were symmetrically positioned at the level of a heart with the distance of 15 cm between each other. The size of each electrode was 7.7 cm x 3.7 cm and this resulted in the area of 28.49 cm² for one electrode. The distance between electrodes was 14.3 cm. The clothing of a subject functions as a dielectric material, which was surrounded by the active electrodes and the skin of the subject acting as conductive plates. These settings formed capacitive sensing surfaces for monitoring electrical activity of the heart.

The acquired ECG signal was then preprocessed and amplified by an analog filter and an amplifier. The filtered signal was subsequently converted into digital signal by an analog-to-digital (A/D) converter. A computer was used for data processing, classification of arrhythmias, monitoring, and data transmission into a cloud storage. In the scope of this work, an Android application was also programmed for monitoring of vital parameters, cECG signals, and labels of arrhythmias. The overall system platform is shown in Figure 1.

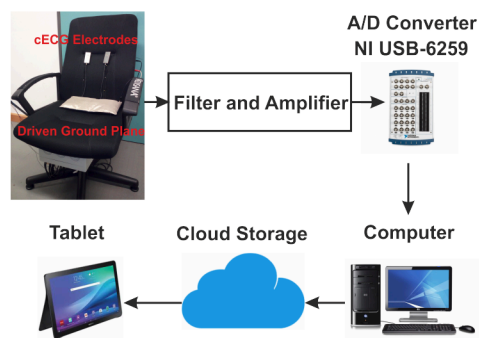


Figure 1: A system platform for arrhythmia analysis.

The personal computer used for this work is based on DELL Intel® Core™ i5-4570 CPU @3.20 GHz, 4 cores with 8 GB random access memory (RAM). The computer is operated under Windows 10. Whilst NEXUS 7 ASUS of quad-core processor is used as a tablet for on-hand data monitoring, where the data are acquired from the cloud storage system.

Software Layers

Python programming language is used for encoding the overall software platform, which consists of three main layers: data layer, processing layer, and diagnostic layer, shown in Figure 2. Since the prediction or classification of arrhythmia is based on a beat-by-beat basis, the cloud storage using InfluxDB database platform is proposed in the data layer for this particular real-time system. InfluxDB developed by InfluxData is an open source database platform for metrics and time series data that is suitable for Internet of Thing (IoT) application and real-time analytics. In this work, a tablet-based application is presented for the data retrieval from the cloud storage and the cECG signals with labels of arrhythmias can be represented on the screen upon request.

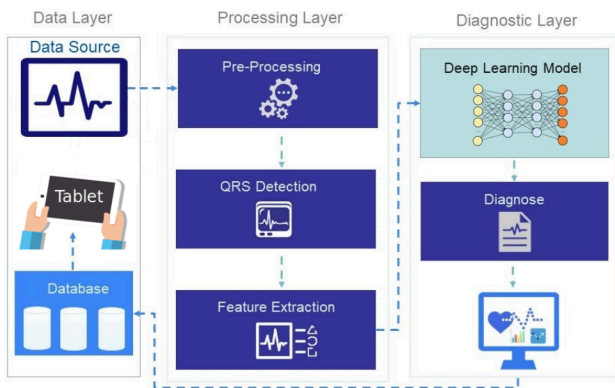


Figure 2: Software layers for real-time processing in arrhythmia analysis.

Once the cECG signal in data layer is acquired from the cECG measurement system, it is transmitted to the next processing layer, where preprocessing and feature extraction are implemented. This layer is a crucial step for the successful prediction of arrhythmia. In processing layer, many processes are implemented, for example, denoising, filtering, normalising, detecting P wave, QRS complex, or T wave, and extracting features (i.e. the amplitude of P wave or R-R interval). Biorthogonal wavelet filter bank has been implemented for specifying the positions of R wave, Q wave, S wave, P wave, and T wave, respectively, so that further feature extraction can be easily implemented. In the last diagnostic layer, a deep learning model based on convolutional neural network (CNN) is designed and trained using Keras (an open source library written with Python and run on top of TensorFlow) from the ECG dataset with

the known labels of arrhythmias. The classification is subsequently performed in the diagnostic layer.

Biorthogonal Wavelet Filter Bank

In this article, the discrete wavelet transform was applied to decompose the cECG signals with the main purpose to identify the position of each particular wave, starting from the detection of R wave or the highest amplitude in a cECG beat. Biorthogonal wavelet filter bank is therefore proposed in order to handle the nonstationary cECG signals and to analyse a local area of signals in multiresolution scales. The basic structure of biorthogonal wavelet filter bank is shown in Figure 3. It consists of the following filters.

- Analysis filters that split the input signal into mutually orthogonal subbands (low-pass filter and high-pass filter) and the filtered signals are then downsampled by two.
- Synthesis filters that upsample the input signals and reconstruct the original input signals $x(n)$ by combining both subbands.

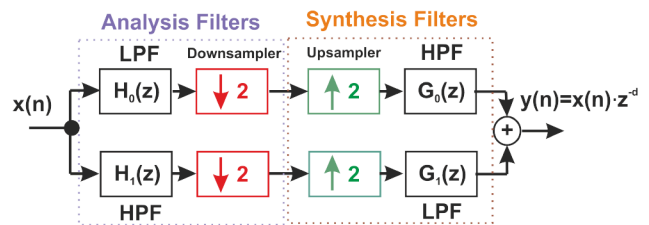


Figure 3: One stage biorthogonal wavelet filter.

There are a number of mother wavelet families that contain energy spectrum concentrated at the low-frequency band similar to the cECG signals. In this study, we use biorthogonal spline wavelet by Mallet pyramid decomposition. These filters are $H_0(z)$ and $H_1(z)$ in the analysis phase and $G_0(z)$ and $G_1(z)$ in the synthesis phase, which are defined by the following equations using Z transforms.

$$H_0(z) = \frac{1}{4} + \frac{3}{4} \cdot z^{-1} + \frac{3}{4} \cdot z^{-2} + \frac{1}{4} \cdot z^{-3} \quad (1)$$

$$H_1(z) = -\frac{1}{4} - \frac{3}{4} \cdot z^{-1} + \frac{3}{4} \cdot z^{-2} + \frac{1}{4} \cdot z^{-3} \quad (2)$$

$$G_0(z) = H_1(-z) = -\frac{1}{4} + \frac{3}{4} \cdot z^{-1} + \frac{3}{4} \cdot z^{-2} - \frac{1}{4} \cdot z^{-3} \quad (3)$$

$$G_1(z) = -H_0(-z) = -\frac{1}{4} + \frac{3}{4} \cdot z^{-1} - \frac{3}{4} \cdot z^{-2} + \frac{1}{4} \cdot z^{-3} \quad (4)$$

These kernels [9] have the structure of symmetric half-band polynomial and an important property of regularity (smooth scaling). For detecting the best position of R peak, further decomposition levels must be chosen by iteration of higher stages of biorthogonal wavelet filter after analysis filter at the low-pass filter (LPF) or the approximation subband, resulting in a tree structure.

Architecture of Deep Learning Model

With the purpose of classification, deep learning model comprises numerous levels of representation by organizing nonlinear modules that transform the representation starting from the raw input into a representation at a higher level with slightly more abstraction [10]. With the sufficient composition of such transformations, the underlying complicated functions can be learned or identified. We typically require supervised learning approach with a huge data set. The MIT-BIH Arrhythmia dataset [11] is therefore used for the model training. It contains 48-h records of 47 subjects. All of the records have two signals, namely modified limb lead II (MLII) and a lead V5, with a 30-min time frame. The sampling rate is 360 samples per second per channel. The deep learning model based on convolutional neural network (CNN) is applied for the classification of arrhythmia, shown in Figure 4.

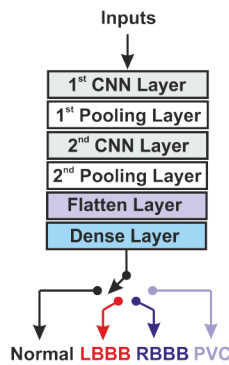


Figure 4: A proposed deep learning model of six layers for the classification of cardiac arrhythmias.

In this particular problem, one-dimensional convolution layer is applied for the beat-by-beat classification. The details of all layers are specified in Table 1.

Table 1: Defined parameters in the deep learning model.

Type	No. of Filters	No. of Parameters
1 st CNN Layer	64	256
1 st Pooling Layer	64	0
2 nd CNN Layer	32	6,176
2 nd Pooling Layer	32	0
Flatten Layer	-	0
Dense Layer	-	9,640

The first and the second CNN layers have kernel size of 3. This deep learning model requires the optimisation of overall 16,036 parameters: 256 in the first CNN layer, 6,176 in the second CNN layer and 9,640 in the dense layer. The activation functions in both CNN layers are set to the rectified linear units (ReLU). CNN layers compute the output of neurons. Each CNN layer is directly followed by a pooling layer, which performs a downsampling operation. In flatten layer, it converts the output of convolutional part into one-dimensional feature vector and the final classification

is carried out in a dense layer. Both flatten and dense layers utilize softmax activation function. With the proposed model, the batch size of 1,000 samples is used for training the model using categorical cross-entropy loss function and Adam algorithm to optimise the CNN model.

Results

Detection of R-peaks

Based on the physiobank, MIT-BIT Arrhythmia Database [11] is used for selection of typical patterns. Biorthogonal wavelet filter bank is applied up to the fourth scale and the first derivative is carried out for each scale. The extreme values in the first derivative of different scales can then be localised. R-peaks are defined at the zero crossing points between maximum and minimum points of the first derivative curve at the third or the fourth scales. Using this approach, it can identify the onset of R-peaks and some of the results are shown in Figure 5.

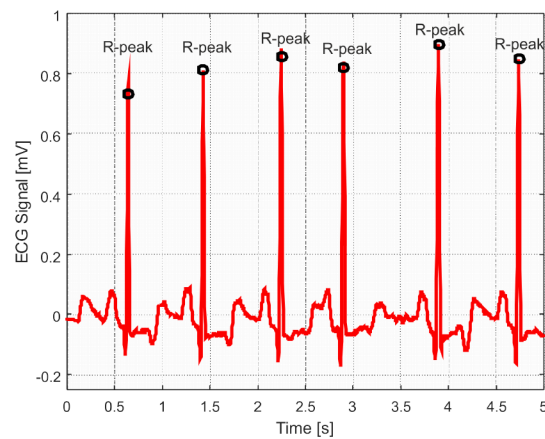


Figure 5: Feature extraction of R-peaks [12].

With similar procedure by defining appropriate window size, the onsets of other waves (i.e. Q waves, S waves, P waves, and T waves, respectively) can be detected and further feature extraction can be implemented such as the amplitude of P waves, R-R intervals, or the heart rate.

Training of the Deep Learning Model

The data of 16,415 ECG records are separated into 67% for the training of this deep learning model and 33% for model validation. The training performance is stable after the 30 iterations or epochs with the best accuracy of 99.2%.

Model Prediction

Based on the validation data of 5,417 records, it consists of the following dataset: 1,648 normal records, 1,308 LBBB records, 1,285 RBBB records, and 1,176 PVC records. The classification performance is summarised in Table 2.

Real-time Detection of Arrhythmias

Grafana is an open platform for analytics and monitoring of time series data. In this work, the dashboards were de-

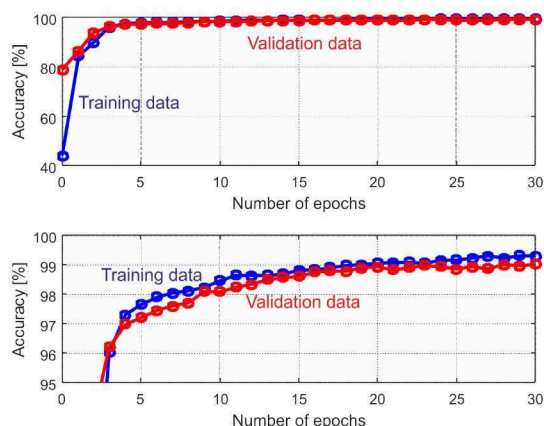


Figure 6: Training performance of the model [12].

Table 2: Classification performance of the CNN model.

	Normal	LBBB	RBBB	PVC	Total
Correct Prediction	1,643	1,302	1,277	1,153	5,375
Accuracy [%]	99.7	99.5	99.4	98.0	99.2

signed to represent the cECG signals with classification based on the trained CNN model. The result of this work is given on the monitor of the personal computer in Figure 7.



Figure 7: Online classification of arrhythmias on a Grafana platform [12].

In addition, an Android application has been implemented to retrieve the dataset from a cloud storage based on a NEXUS 7 ASUS tablet, shown in Figure 8.

Conclusions

Deep learning model of six layers has been applied for the classification of arrhythmias into four main categories, namely normal, left bundle branch block (LBBB), right bundle branch block (RBBB), and premature ventricle contraction (PVC) with the average accuracy of 99.2%. We also demonstrated that the real-time monitoring and classification of arrhythmias can be accomplished using the proposed architecture on a beat-by-beat basis based on a non-contact cECG system with the aid of biorthogonal wavelet filter bank at the fourth level. The classification data was

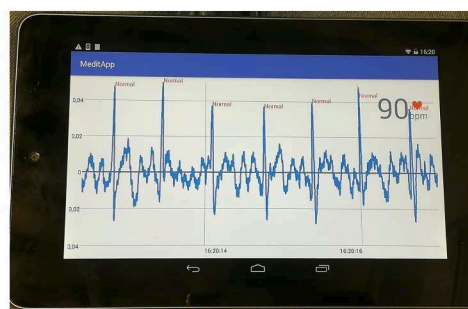


Figure 8: Real-time classification of arrhythmias [12].

directly stored in a cloud storage for evaluating them in real-time as well as in historical records.

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