An Abnormal Heart Rhythm Warning System based on a Low-cost Two-electrode ECG Signal using Threshold and Neural Network Approaches

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Abstract. Early detection methods of abnormal heart rhythms are extremely demanded to support effective diagnosis and treatment of patient heart diseases and avoid heart stroke which is the main cause of human death. This study proposes a low-cost system to continuously record electrocardiogram signals by two electrode plates placed on the chest for the purpose of monitoring cardiac electrical signals, and detecting abnormalities in heart rhythm using the threshold-based and neural network-based approaches. A device for signal acquisition and pre-processing has been designed, fabricated and tested with normal people to create a self-built normal ECG database. The recognition results obtained from our self-built database and a published online ECG database. It shows high performance in normal and abnormal heart rhythm recognition which would be helpful for physicians to diagnose the abnormal signal of the heart in time.

Keywords: ECG, Abnormal Heart Rhythm Warning, 2-electrode ECG, R-R interval.

1 Introduction

According to WHO, cardiovascular diseases (CVDs) are the leading cause of death globally. An estimated 17.9 million people died from CVDs in 2019, accounting for 32% of all deaths globally. Of these deaths, 85% were due to heart attack and stroke [1]. In Vietnam, cardiovascular disease was the cause of 31% of all deaths in 2016 equivalent to more than 170,000 deaths. Cardiovascular manifestations often appear suddenly and often show no signs on examination. Early detection of abnormalities through heart rhythm is therefore really necessary.

Today methods used to measure heart rate include Electrocardiography, Photoplethysmography, Oscillometry and Phonocardiography. According to the manual of exercise testing, Electrocardiography is the best way to measure and calculate instantaneously through the R-R interval [2]. However, measurements taken through such ECG devices are often encrypted and can only be decoded with software provided by the manufacturer. Recently, some manufacturers provide devices that allow users to develop applications associated with the devices with quite an expensive cost [3]. Currently, the 12-lead ECG (10-electrode ECG) and 5-lead ECG (5-electrode ECG), 3-lead ECG (3-electrode ECG) systems are considered as common ECG systems in the world. The 12-lead ECG is considered the gold standard in clinical practice [4], with ten electrodes merged on the patient's chest, arms and legs, and operated by qualified physicians in hospital due to its complexity.

However, this 12-lead ECG device is not suitable for patients with chronic heart disease who want home care and athletes who want to monitor their health while exercising. For the same reason, this measurement method is also not suitable for soldiers, firefighters, policemen, mine rescuers, etc. Furthermore, the cost and discomfort caused by the electrodes in contact with the skin makes it impossible for patients to use 12-lead ECG measurement for daily heart rate monitoring. The same problem occurs with the 5-lead ECG and the 3-electrode ECG device.

It is therefore desirable to have two electrodes to reduce the costs and increase patient comfort. However, removal of the third electrode is challenging due to the significantly higher electromagnetic interference and lower signal-to-noise ratio in two-electrode compared to three-electrode ECG acquisition systems. A number of recent studies [5] [6] [7] [8] are aimed at designing a system to measure ECG from 2 electrode plates with good results like the 3-electrode ECG device. This paper presents our proposal on designing and fabricating an low-cost electrocardiogram signal acquisition system using only two electrode plates. The synthesized ECG signal is then automatically monitored and analyzed for abnormal heart rhythm detection using threshold-based and neural network-based approaches.

2 Methodology and Materials

In order to meet the stated demands above, an abnormal heart rhythm monitoring and warning system has been designed in this study with three blocks shown in Fig. 1.

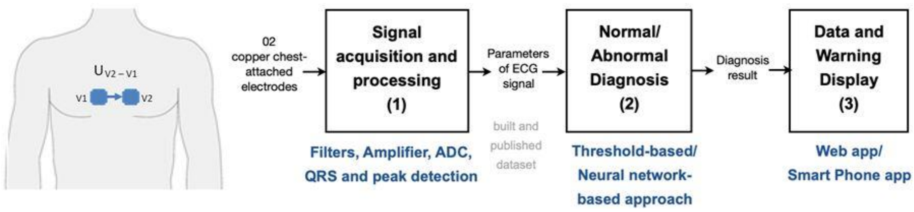

Fig. 1. The electrocardiogram monitoring and warning system block diagram.

The hardware and software design process is demonstrated in Fig. 2. Particularly, the power (source) block employs a power filter composed of a series of capacitors and resistors, which aids in the reduction of source noise created by conventional power sources, which has a significant impact on the ECG signal. The ECG signal is then recorded by utilizing two electrode plates positioned on the patient's chest. In the hardware signal processing block, output of the DRL circuit (for noise cancellation) is connected to the input electrodes via high-value resistors in order to create a two-electrode ECG. The STM32 microcontroller receives the output ECG signal amplitude from the hardware signal processing block and converts it to digital signal. Finally, in the software signal processing block, the 4th order Butterworth low-pass filter with cutoff frequency fc = 25Hz is then applied to reduce noise. The Fig. 3 describes the hardware prototype of signal acquisition and processing device.

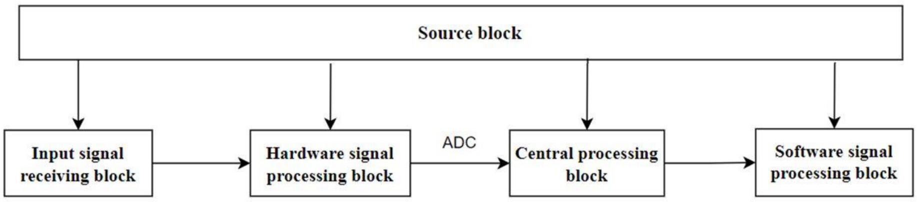

Fig. 2. Block diagram of the acquisition and processing of electrocardiogram signals.

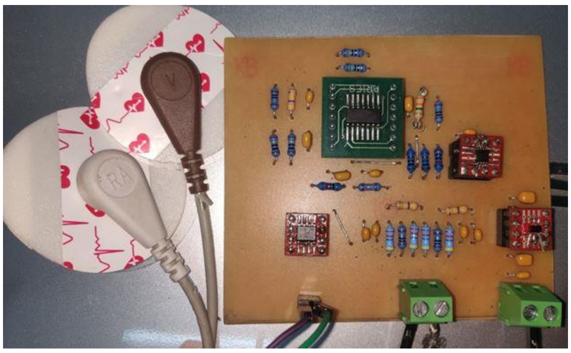

Fig. 3. Hardware prototype of signal acquisition and processing device.

In order to detect the QRS complex container, the following processes are performed in sequence: obtaining the signal derivative, squaring the signal amplitude difference, and applying the threshold extraction technique. The R peaks are the positive peaks of the QRS complex. They are detected by comparing the relative magnitudes in each QRS region. In order to ensure that the output data is valid, the signal acquisition and processing unit's output signal is normalized with the standard ECG signal model. We also analyzed and compared the measured results of the device that the research team performed with the signals published at the ECG-ID Database published at PhysioNet [9]. Extracting a data sample with a duration of 5 seconds from the reference database (upper part of Fig. 4) and data collected from the equipment performed by our research (lower part of Fig. 4). We can recognize all the characteristic ECG waves obtained from the device, the R-R intervals are similar and within the normal heart rate range. R-R interval is a feature that we use in this study. The ECG data obtained from the device will be used for identification by threshold method and neural network method presented in the next section of this paper.

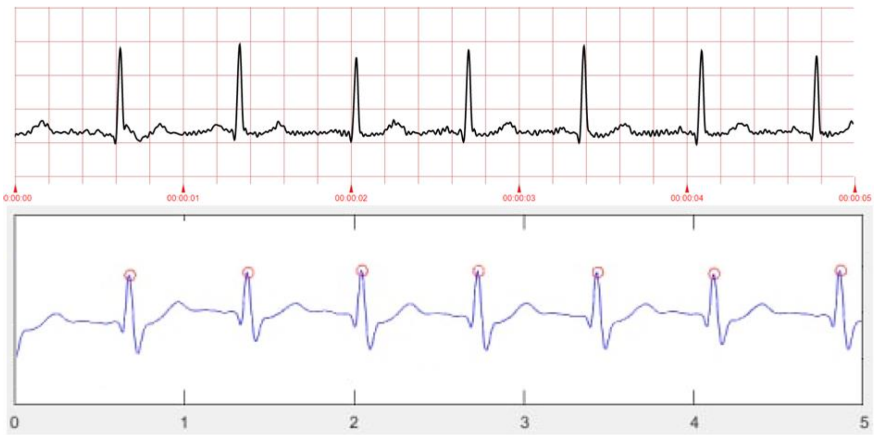

Fig. 4. The ECG waves obtained from the device and from the reference database.

2.1 Normal/Abnormal Diagnosis

Threshold-based approach. The heart rates which are calculated from the R-R intervals are compared with the normal human heart rates in 60-100 beats per minute. A tachycardia signal is one in which the number of beats is greater than 100 bpm, whereas a bradycardia signal is one in which the number of beats is fewer than 60 bpm. There are several factors influencing the average human heart rates are age, exercise level, etc.

Convolutional Neural Network-based approach. A high-accuracy ECG arrhythmia classification method based on convolutional neural network (CNN) has been proposed in [10] with quite good accuracy of heart disease classification. In this study, a CNN model has been built up of basically three types of main layers [11], where a one dimensional signal is classified. The CNN model takes the time series data in one dimensional form wherein the data are arranged in the order of sequential time instants. The input multiplier network is a time series of a 6-second ECG signal sampled at 200Hz. The network has an architecture of 33 convolutional layers, followed by a fully connected layer and softmax.

2.2 Data and Warning Display

For user-friendly heart rate signal monitoring and analysis, a web application has been designed to display raw heart rate waveform after hardware and software filtering (described in section 2.1). In addition, the application displays the number of beats and a list of timing when abnormal heart rhythm is detected, more specifically, the status of the abnormality is tachycardia or bradycardia.

3 Results and Evaluation

3.1 Threshold-based model

MIT-BIH Arrhythmia database. This database of cardiac electrical signals is divided into two abnormal data sets ("Atrial premature beat" (A) and "Premature ventricular contraction" (V)) and one normal data set. The recognition rate of 90% is obtained from the 10 abnormal A signal samples, and 97.67% obtained from the 43 abnormal V signal samples. From 2174 normal cardiac electrical signal samples, a recognition rate of 90.98% is achieved by the thresholding approach.

TAPIT Self-built database. TAPIT self-built data set consisting of 551 samples of normal ECG signals measured from 100 normal people using the designed 2-electrode ECG device described in section 2. The results show that the normal ECG signals are recognized with Recall of 99%.

3.2 Neural Network-based model

MIT - BIH Arrhythmia database. This dataset was divided into the train and test set with the ratio of 7:3 (9936 training and 4333 testing samples). The CNN model with configuration described in section 2.2 has been trained and tested. As shown in Table 1, the obtained accuracy of 97.7% for two abnormal data sets and one normal data set is much higher than the one of 90.98% derived by the threshold-based approach.

Table 1. The training and testing results on the MIT - BIT Arrhythmia dataset.

Metrics	AUC	Accuracy	Recall	Precision	Specificity	Prevalence
Training	0.996	0.981	0.965	0.975	0.989	0.315
Testing	0.993	0.977	0.959	0.968	0.985	0.313

TAPIT Self-built database. The trained CNN model is then tested on the normal self-built data set consisting of only normal 2-electrode ECG signals. The obtained results show accuracy of 98.2% which is quite similar to performance resulting from the threshold-based method. With the usage of the CNN model trained on the ECG signals collected from the conventional 12-electrode ECG device (MIT - BIH Arrhythmia database), this recognition result also reflects the quality of the ECG signals measured from the self-designed 2-electrode ECG device.

Table 2. CNN model's evaluation on TAPIT normal Self-built data set.

Metrics	AUC	Accuracy	Recall	Precision	Specificity	Prevalence
Testing	0.991	0.982	0.963	0.976	0.986	0.314

4 Conclusions and Discussion

In this paper, we first built the 2-electrode ECG device using the hardware and software co-designing process. The ECG signal measured by the device was then compared with the published one from a standardized 12-electrode ECG device for validation. Two different threshold-based (at low complexity) and neural network-based approaches have been trained to detect normal/abnormal heart rhythms. The results tested on a self-built database and standardized database show high recognition rates of normal and abnormal ECG signals. Thus this system can be potentially used in practice to early warn users and assist doctors in electrocardiograms-based heart disease diagnosis. In the future, we may develop abnormal heart rhythms equipment/systems for a variety of people, including active subjects, athletes, and so on. We also integrated some new development directions, such as adding more methods for distinguishing normal and abnormal ECG signals to the project. In addition, a more complete EDGE AI hardware will be designed in the upcoming projects to be able to train and deploy the CNN model for real-time electrical signals. However, this study only puts forward suggestions for improvement of the ECG signal devices and abnormal warning software in terms of early detection of a variety of heart disease while people still can wear the device in daily working life.

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