Original Article

Diagnosis and classification of cardiac arrhythmias by analyzing and extracting of ECG signal features by means of dwt and artificial neural network

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ABSTRACT

Electrocardiogram (ECG) signals provide important information about heart function and structure. ECG signals are used to diagnose heart disease and classify cardiac arrhythmias. These signals are provided using the PQRSTU waveform. In this paper, extraction of the characteristics of P wave, PR interval, QRS complex, ST segment, QT interval, and T wave of ECG signal is performed using discrete wavelet transform method. After extracting the desired features, MLP neural network with 30 hidden layers and 20 epoch for training, were introduced for classification of cardiac arrhythmias. This article used the 70 samples of ECG signals MIT BIH database.

Keywords: Electrocardiogram signal, PQRSTU wave, arrhythmia, MLP neural network, statistical features, DWT.

Introduction

ECG recording is a non-invasive diagnostic tool used to evaluate a patient's heart condition. The electrocardiogram signal is the result of alternative depolarization of heart muscle, which starts from the senatorial node and spreads throughout the whole heart muscle. A complete cycle of this signal, which lasts from 1,000 to 7,000 milliseconds in a perfect human, has a definite waveform, each component of which results from a certain physiological function in the heart. The characteristics of the ECG signal along with heart rate, when recognized by simple observations, can lead to accurate and rapid diagnosis.

Electrocardiography

Electrocardiography is the recording of waves resulted from the electrical activity of the heart muscle, which is carried out by placing the electrode on the chest and around the heart.

Concept of Lead in Electrocardiography

In a complete electrocardiographic bar, there are 12 leads. The first six are limb leads and the other six are precordial leads. Limb leads include bipolar standard leads and reinforced unipolar leads.

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PQRSTU waves

These waves stimulate the sinusoidal node in the heart signal, stimulating the atrium and creating the P wave, which is the wave of atrial depolarization. Subsequently, the ventricular depolarization wave is created as a QRS complex, followed by ventricular depolarization wave created in the form of a T wave. Sometimes another short wave is seen after the T wave, called U wave. The cause of this wave is repolarization of papillary muscles in the heart. At intervals of these waves, which do not have a proper electrical activity, the electrocardiogram draws a horizontal line, which is called as isoelectric line.

P wave

This wave is produced by depolarization of the atria and the wave amplitude is 2-3 mm. The p-wave time is about .04 to .11 s. P wave is positive in AVF, D2, D1, and V3-V6 leads and is negative in AVR and mostly in V1 leads. It is often biphasic in D3 lead. The peak is usually limited and should not be sharp or toothed. If this wave is negative in leads 1 and 2, it is likely that either the patient's heart is on the right side or the leads have been mistakenly placed. If the P wave is wide and toothed, it represents enlargement of left atrium due to stenosis and mitral insufficiency. Various references have referred to these points in various forms.

QRS complex

This complex, which is the most important component of electrocardiogram, relates to the ventricular depolarization, indicating the ventricular myocardial stimulation. The first downward (negative) wave is called Q wave. The first upward (positive) wave is called R wave. The second downward (negative) wave after R wave is known as S wave. If the next positive waves appear, they are called R' or R" and the next negative waves are called S' and S". If there is only one upward R wave, the start and end points are called Q and S, and if there is only a negative wave, it is called QS.

PR interval

This interval is from the beginning of the P wave to the beginning of the QRS complex. It reflects the amount of time the electrical impulse takes to travel from sinusoidal node to the ventricular myocardial fibers. The natural PR interval is .12 to .20 seconds. This interval is slightly lower in children. This interval is prolonged in the ventricular blocks and shorter in cases such as Wolf syndrome, Parkinson, and White syndrome, with an additional conduction relation between the atrium and the ventricle.

ST segment

It is a segment of the isoelectric line between the QRS complex and the T wave. This segment immediately begins at the end of the QRS complex, and this point, the so-called j point, is the beginning of the ST segment. It ends at the beginning of the T wave. ST elevation and depression are important for diagnosis of ischemia and infarction. ST elevation is sometimes seen in healthy people, especially black people, and its depression is called ST depression.

T wave

This wave represents the repolarization of the ventricles and is examined in three respects, namely T wave length, the height, and its overall shape. T wave is positive in V6, D1, D2, and AVF-V3 leads, negative in AVF lead, and variable in other leads. It is such that if R value is longer than 5 mm in AVL and AVF leads, T wave is positive; otherwise, it may be negative.

The T waveform is usually a bit symmetry; it starts slowly and ends up faster. In addition, its peak is circular. A peaked and toothed T wave is usually abnormal. The T wave height does not exceed 5 mm in standard leads and 10 mm in precordial leads. Long T wave may be seen in hypercalmic infarction.

QT interval

This is the distance from the beginning of Q to the end of the T wave and the full duration of the ventricular systole. The duration of QT varies with factors such as heart rate, age, and gender. This interval also varies with rate. Changes in this interval help diagnose some diseases.

U wave

The U wave is a small wave with a small voltage, sometimes seen following the T wave. Its direction is usually the same as the T wave. That is, if the T wave is positive, the U wave is positive and vice versa. The most obvious U wave is seen in the V3 lead and the U wave is more obvious in the hypokalemia. Like the T wave, it is also negative in myocardial ischemia. Pharmacological factors such as digitalis, quinidine, epinephrine, and diseases such as thyrotoxicosis may increase the height of this wave.

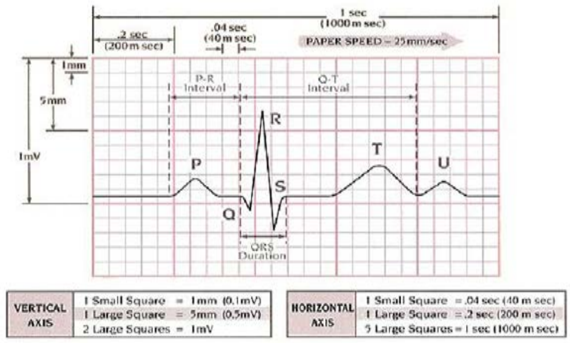

Figure 1: ECG components

Wavelet transform

Continuous Wavelet Transform (CWT)

The continuous wavelet transform is defined as follows:

$$\mathrm{CWT}_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*\left(\frac{t-\tau}{s}\right) dt$$

The scale parameter in the wavelet analysis is similar to the scale used in the maps. Like maps, large scales represent a generalized view lacking details of the signal and small scales represent a more detailed view. Similarly, in the case of frequencies, low frequencies in large scales represent the general information of a signal that normally covers the entire range of a signal, whereas high frequencies in small scales show the partial information of a hidden pattern in the signal, which is usually related to a relatively short period of time. The cosine signals of different scales are shown in Fig. 2:

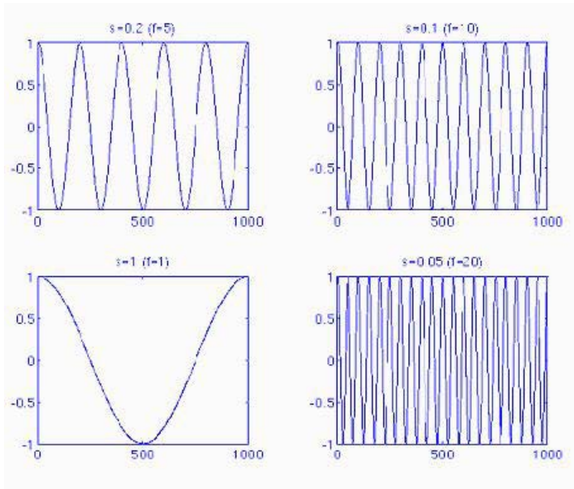

Figure 2: Different scales of a cosine function

In practical applications, the low scales do not cover the whole signal period contrary to what is shown in the figure and appear explosively over time, while the large scales usually persist throughout the entire signaling period. Scaling, as a mathematical operation, may compress or open a signal. Larger scales represent opened signals and smaller scales represent compressed signals. All signals of the above figure are derived from a similar cosine signal. In figure 2-4, $s = 1$ is the smallest scale and $s = .05$ is the largest scale. In the definition of wavelet transformation, the scale is used in the denominator, that is, contrary to the above phrase is established. $S > 1$ opens the signal and $S < 1$ compresses the signal.

Discrete wavelet transform (DWT)

The disconnection of the continuous wavelet transform allows computing it with the computer. The wavelet series is actually a sample of information that is especially provided when rebuilding the signal is intended. This information of DWT need to be duplicated and, on the other hand, requires considerable computing time and resources. Discrete wavelet transform provides well-structured information for both the analysis and the combination of the main signal, with a significant percentage reduction in computing time. Implementing DWT is much easier compared to CWT.

Its main idea is like CWT. A time-scale representation of the digital signal is obtained using the filtering techniques. CWT was calculated by changing the scale of the parsing window, changing the window position in time, multiplying it in the signal, and integrating at all times. In the case of discrete transform, filters of different discrete frequencies are used for signal decomposition at different scales. The signal is transmitted from a series of high-pass filters to decompose high frequencies and from a series of low-pass filters to decompose low frequencies. The degree of signal separation, which is a measure of the amount of detail in the signal, varies with filtering and scale varies with up sampling and down sampling (subsampling) operations. Subsampling of a signal is equal to decreasing the sampling rate or removing some samples from the signal.

Single-step approximation and detail filtering

In this analysis, the main signal passes through two high and low pass filters. Therefore, 2 signals are obtained as output. After the signal passes through the high-pass filter, the details are produced and after passing the signal from the low-pass filter, approximations are produced.

Approximations

Approximations include high-level components and low-frequency signal components. The approximation signal is similar to the original signal, with the difference that it has less variation, since some of these changes have been removed through the passage through low-pass filter. The length of the approximation signal is half the original signal.

Details

Details are the components of small scale and high frequency. The length of the detail signal is half the original signal.

By doing this on a digital signal, double data is generated. To solve this problem, the drop in the sampling rate is used, and from each of the two data, one is discarded.

Multi-level decomposition

In many signals, low frequency content is the most important part. This section is identified as the identity signal.

Sequential approximations

Approximations are the components of low frequency. The content of the low frequency is very important, so the decomposition process continues with sequential approximations that are analyzed in turn. Here, D is the detail signal and A is the approximation signal. In the following figure, the multistage process of signal decomposition into two approximation and details signals is displayed. Initially, the main signal is divided into two approximation and details signals. In the next step, the approximation signal of the previous stage is treated the same as the main signal and the approximation and detail signals of stage 2 are obtained. The approximation signal of stage 2 is more approximate than the approximation signal of step 1. The details signal of step 2 also has a finer detail of the original signal than the details signal of step 1.

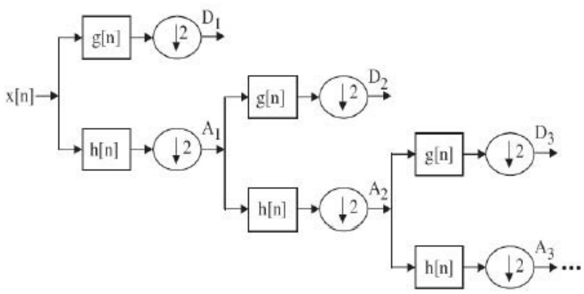

Figure 3: sequential approximations

Implementation

Extraction of ECG signal features

Given that the wavelet coefficients are able to describe the time-frequency signal together, they are the best option for extracting the characteristics from an electrocardiographic signal. First, the number of decomposition level and wavelet types are determined. The number of wavelet decomposition levels is selected based on the frequency component of the signal template in such a way that the information of the parts of the signal that matches the frequency required for the classification of the signal is well-preserved in the wavelet coefficients. Also, the results of previous research indicate that for extraction of the characteristics of Electrocardiography signals, Daubechies and Haar families are more suitable than other wavelets. To calculate the wavelet transform, each wavelet family has a number of filters (wavelets). In Table 1, different families of wavelets are displayed in MATLAB software.

Table 1: Family of Wavelets

Wavelet Family Name	Wavelet Family Short Name
Haar wavelet	'haar'
Daubechies wavelet	'db'
Symlets	'sys
Coiflets	'coif'
Biorthogonal wavelets	'bior'
Reverse biorthogonal wavelets	'rbio'
Meyer wavelet	'meyr'
Discrete approximation of Meyer wavelet	'dmey'
Gaussian wavelets	'gaus'
Mexican hat wavelet	'mexh'
Morlet wavelet	'morl'
Complex Gaussian wavelets	'cgau'
Shannon wavelets	'shan'
Frequency B-Spline wavelets	'fbsp'
Complex Morlet wavelets	'cmor'

MIT BIH database

Data recording is an important component in the processing of medical signals. One of the most important medical databases available is the MIT BIH database. In this base, the heart and brain signals of various diseases such as coronary artery disease, arrhythmias, sleep disorders and epilepsy are available. The

ECG signals in this section are not just for heart patients, but also other diseases that can be diagnosed with the help of ECG.

Extraction of ECG signal features with MATLAB software

70 samples of the ECG signal are selected from the MIT BIH database, then the db7 Daubechies wavelet family. ECG signal's Statistical features involves average, standard deviation, skewness and kurtosis over details of level 5 ,level 6 and level 7.

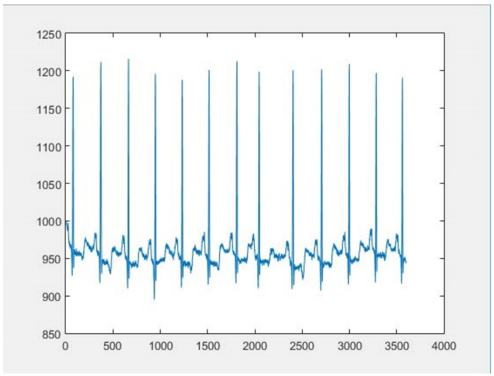

Figure 4: the main signal

The signal is analyzed up to level 2 and the values of the details signal and the approximation signal are stored in the variables. In this paper, the signal is decomposed into seven levels and outputs of the signal are represented in the following figures.

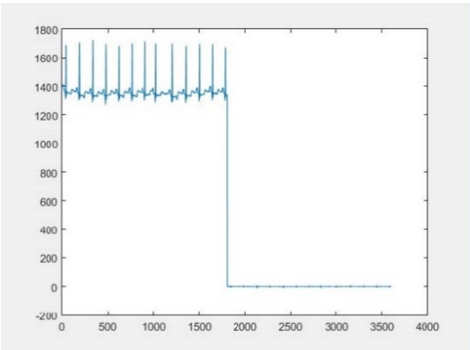

Figure 5: details signal of level 1

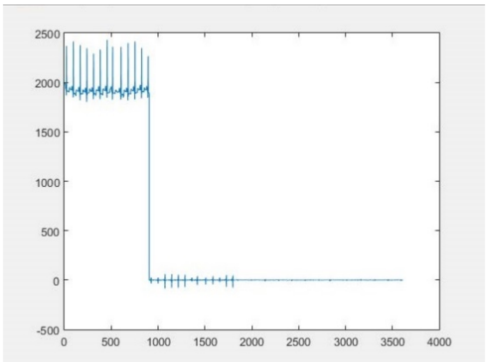

Figure 6: details signal of level 2

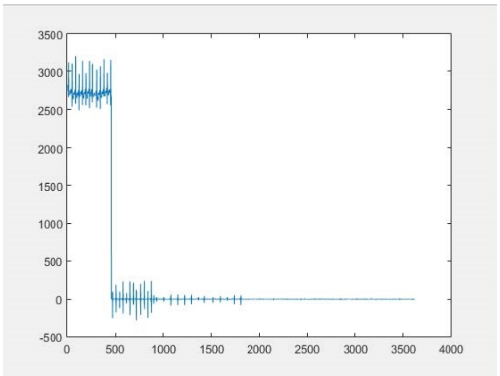

Figure 7: details signal of level 3

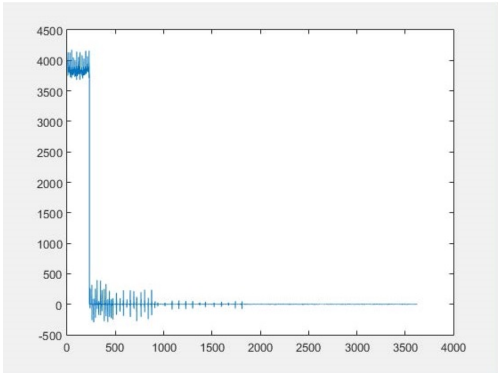

Figure 8: details signal of level 4

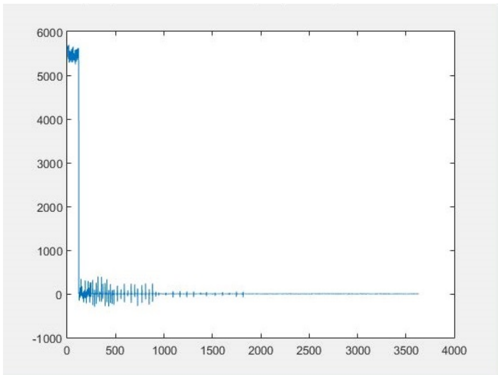

Figure 9: details signal of level 5

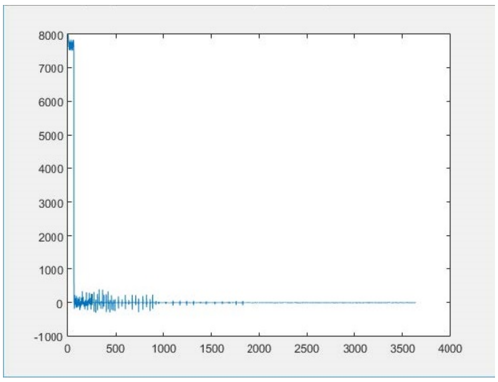

Figure 10: details signal of level 6

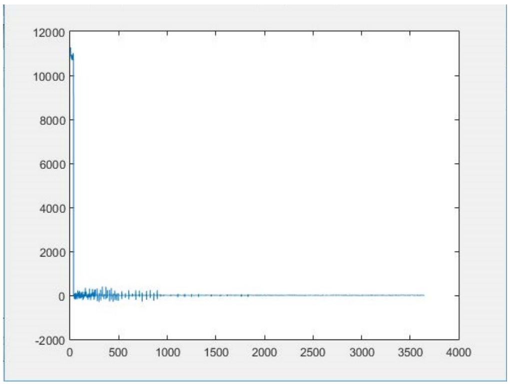

Figure 11: details signal of level 7

The first and second levels of the wavelet decomposition store the low frequency noise information. Ignoring these coefficients will cause a slight loss of signal information. Levels 3 and 4 contain overlapping information that causes the reconstructed signal not to be a smooth signal with considering these initial decomposition levels. Considering the above points, levels 5, 6 and 7 are used to extract features.

Diagnosis with MLP neural network

MLP neural network is used to diagnose and categorize cardiac arrhythmias.

Types of cardiac arrhythmias

1. Sinus bradycardia

In this case, heart rate is less than 60 beats per minute. It occurs in trained athletes and patients with increased cranial pressure.

Figure 12: Sinus bradycardia

2. Atrial tachycardia and atrial flutter

It is due to an inappropriate cornea in the atrium that causes the beats to be irregularly faster. P wave is abnormal, but the QRS complex is normal.

Figure 13: Atrial tachycardia and atrial flutter

3. Atrial fibrillation

There is no atrial activity, including mechanical and electrical, in this case. Fibrillation waves are placed instead of P waves. The QRS complex is normal.

Figure 14: Atrial fibrillation

4. Atrial Blocks or Cardiac Blocks

There are three types of first-degree, second-degree, and third-degree atrial blocks.

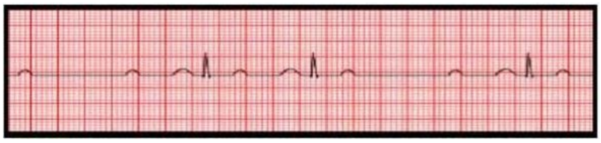

Figure 15: Atrial Block

As seen in the figures, each of the cardiac arrhythmias has its own waveforms. For example, atrial tachycardia has abnormal P waveforms. Based on what was said and according to the wavelet transform operation, the characteristics of each ECG signal can be extracted using a wavelet transform. The result of the wavelet transform is information about P wave, PR interval, QRS complex, ST segment, QT interval, and T wave.

To train neural networks, several signals of each type of arrhythmia can be taken from the physionet MIT BIH database and, after the operation of the wavelet transform, the resulting characteristics can be used as inputs of the neural networks. In this article, 70 signals of each type of arrhythmia are selected and trained. After training and testing the neural network, this network classifies and diagnoses the cardiac arrhythmia. 15-layer perceptron neural network is proposed for this purpose. In this article, use from MLP neural network with 30 hidden layers for 70 sample of ECG signals with 100 frames for every signal. Number of optimal iterations is 20. Information and conclusion of error rate show in figure 16.

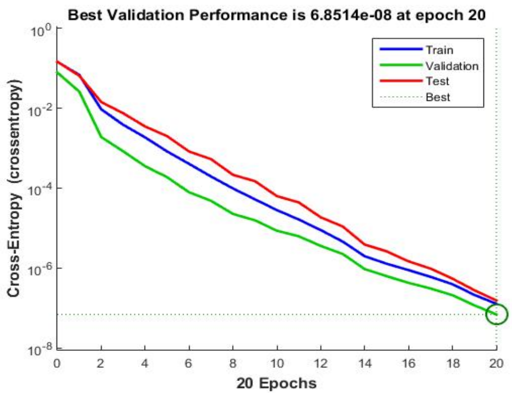

Figure 16: Cross-Entropy of results.

Conclusion

This paper addressed the diagnosis of cardiac disorders through ECG signal analysis. First, the heart and how it functions was explained to understand how to create an electric shock. After describing the heart and describing the ECG, the extraction of P wave, PR interval, QRS complex, ST segment, QT interval, and T wave characteristics of ECG was performed using discrete wavelet transform. In the end, MLP neural networks were introduced for classification of cardiac arrhythmias and the Multi-Layer Perceptron Artificial Neural Network was proposed. This article used the 70 samples of ECG signals MIT BIH database. Results shows MLP neural network with 30 hidden layers and 20 iteration is the best and optimal state.

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