Wavelet Based Method for Localization of Myocardial Infarction using the Electrocardiogram

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Abstract

This paper presents detection and localization of myocardial infarction (MI) using RBF neural networks classifier with wavelet coefficient as features extracted from frank leads.

Detection of MI aim to classify healthy and having MI and Localization aim to specify the infracted region of the heart.

The electrocardiogram (ECG) source used in the PTB database available on physio-bank.

Frank lead vx,vy,vz is get from 12 lead ECG using Dower transformation. Wavelet coefficient of different levels and families of each beat are extracted. We extract wavelet coefficient in three level 3, 4, 5 from threewavelethaar,db4,db10 to evaluate the different kinds of wavelet

1. Introduction

Heart disease is one of the leading cause of death all over the world. Among these cardiac disorders myocardial ischemia and infarction is the most common.

Myocardial ischemia and infarction stem from the insufficient supply of blood to the heart muscles (myocardium) due to blockage in coronary artery.

Electrocardiogram is a classical diagnosis to detect heart malfunctioning and heart muscle damage.

And also it is the most readily available and fastest method for diagnosis.

MI produces certain changes in the ECG signal (Q wave, ST elevation, and T wave inversion) and VCG signals.

Two basic technique used in electrocardiography are:

1. Standard 12 lead ECG
2. VCG(XYZ)

The 12- lead system was suggested around 80 years ago by Wilson[1].

VCG is another system for electrocardiography[2]

Among various ECG lead systems, the orthogonal Frank XYZ lead is known for use of fewer leads compared to the widely used 12 lead ECG systems.

A lot of works have done to evaluate the VCG advantages in electrocardiograph analyze.

In 1959 G Howwitt et al analyzed the vectorcardiogram of patients with myocardial infarction and normal subjects and the problems of analysis,the VCG of patients with MI and normal subjects.[3] in 1962 H Abramson discussed several cases of inferior and anterior MI to find out which one, ECG or VCG was better as a diagnostic aid[4] In 1983 M Sederholm et al used continuous recording of Frank leads to follow ST and QRS vector changes during MI[5].

In cinc challenge 2007 M Ghasemi proposed a method based vectorcardiography for MI localization further. S Sabouri continued this method using an ANN[6].

In 2010 M Arif used a method based KNN for classification.he used T wave Q wave and ST segment as features and the accuracy was about 98/9% for MI localization[7].

In another study in 2010 M Arif used a method based back propogation ANN for classification he used T wave Q wave and ST segment as features and the accuracy was about 93/7% for MI localization[8].

In another study by LU a neuro-fuzzy system was used for MI localization. ST segmentwas used as feature and the accuracy was a bout 95% for localization[9].

The aim of this study is to determine the infracted region in the heart using ECG signal which is discussed briefly in the following sections.

2. Materials and methods

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2.1. Data collection

We use 50 records of 12-lead standard s to train and test the proposed algorithm with 3611 beats extracted from these records.

We get the data from PTB database available in physionet. the collected ECG traces contain different kinds of MI (Inferior –lateral, Inferior-posterior-lateral, Inferior, Antero-septal, Antero-lateral ,Anterior, Posterior-lateral, Lateral, Posterior) and healthy cases;all the ECG records had been diagnosed by cardiologist.

2.2. Signal pre-processing

There are many source of noise in a clinical environment that affect ECG signals A noisy signal extracted from the PTB database is shown in figure 1

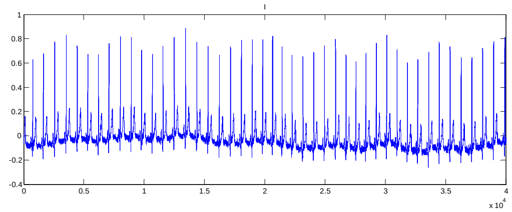

Figure 1. A noisy signal extracted from the PTB database

In this project we remove two noise as follows:

1. Power line interference
2. Baseline wandering noise

In power line interference, we use second order IIR notch filter and in baseline wondering noise, we use a median filter

2.3. Dower transformation

It is often useful to transform standard ECG to VCG data when the dipolar nature of heart need to be observed. Transformation to 3-dimensional space has also other advantages such as reduction of the amount of data. One of the most commonly used VCG measurement system is Frank lead system. it is a corrected lead setting which consist of 3 orthogonal components x ,y , z. the most commonly utilized method to change between VCG and ECG data spaces is to use the constant matrix of Dower.[10]

Let x denote a sample vector from the 3-dimentional VCG space and y the vector from the 12-dimentional standard ECG space then

$$Ax=y \qquad (1)$$

Where A is a 12×3 transformation matrix.we can also determine VCG from ECG. This is done using its pseudoinverse which provides a least square solution approximation to a system of linear equations.

We get vx,vy,vz from ECG using dower

Table 1 Lead vectors for deriving standard 12- lead ECG from 3-dimensional VCG signal transformation.

Lead vectors	X	Y	Z
I	0.632	-0.235	0.059
II	0.235	1.066	-0.132
III	-0.397	1.301	-0.191
AVR	-0.434	-0.415	0.037
AVL	0.515	-0.768	0.125
AVF	-0.081	1.184	-0.162
V1	-0.515	0.157	-0.917
V2	0.044	0.164	-1.387
V3	0.882	0.098	-1.277
V4	1.213	0.127	-0.601
V5	1.125	0.127	-0.086
V6	0.831	0.076	0.230

Also we calculate the magnitude and phase of the heart vector using equations as follows:

$$|V|=\sqrt{(VX^2+VY^2+VZ^2)} \qquad (2)$$

$$\varphi = \text{arctang}\,\frac{vz}{(\sqrt{vx^2+vy^2})} \qquad (3)$$

2.4. Wavelet decomposition

The wavelet transform describes a multi-resolution decomposition process in terms of expansion of a signal onto a set of wavelet basis functions. Discrete wavelet transformation has its own excellent frequency localization property that has many engineering and scientific application.

Multilevel discrete wavelet decomposition of each data window were calculated using Daubchies wavelets of different orders. The coefficient of level 1 and 2 was discarded as these features almost represent noises. Thus for a level m decomposition, coefficients associated with approximation level m and details level 3 to m.

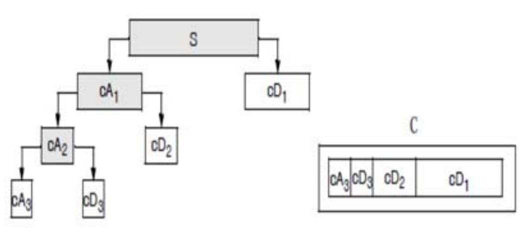

Figure 2. Wavelet decomposition tree

In this study we use haar, db4 and db10 wavelet as the mother wavelets and considered level 3, 4 and 5.

2.5. Principal component analysis (PCA)

PCA algorithm is the most important technique to reduce the dimension of data. (PCA) rotates the original data space such that the axes of the new coordinate system point into the directions of highest variance of the data. The axes or new variables are termed principal components (PCs) and are ordered by variance: The first component, PC 1, represents the direction of the highest variance of the data. The direction of the second component, PC 2, represents the highest of the remaining variance orthogonal to the first component. This can be naturally extended to obtain the required number of components which together span a component space covering the desired amount of variance. Since components describe specific directions in the data space, each component depends by certain amounts on each of the original variables: Each component is a linear combination of all original variables.

In this study we use PCA to reduce the dimension of feature vector. Finally we have 9 feature vectors which are different in wavelet order and level.(table 2)

Feature vector	Wavelet	coefficient
Wavecoef1	Haar	Approx3,det3
Wavecoef2	Haar	Approx4,det4,det3
Wavecoef3	Haar	Approx5,det5,det4 ,det3
Wavecoef4	Db4	Approx3,det3
Wavecoef5	Db4	Approx4,det4,det3
Wavecoef6	Db4	Approx5,det5,det ,det3
Wavecoef7	Db10	Approx3,det3
Wavecoef8	Db10	Approx4,det4,det3
Wavecoef9	Db10	Approx5,det5,det4 ,det3

Table 2. extracted feature vectors.

2.6. RBF artificial neural network

The artificial neural network will be used in this project for classification. We use a RBF neural network in this project.

Construction of a RBF, in its most basic form, involves three layers .the input layer is made up of source nodes connecting the network to its environment. The second layer, the only hidden layer in network, applies a nonlinear transformation from the input layer space to the hidden layer space. In most applications the hidden space is of high dimensionality. The output layer is linear, supplying the network response to the activation signal applied to the input layer.

We use 70% data (about 2504 beat) for training the network and 30% data (about 1099 ECG beat) for test the system.. We used matlab software to run our proposed algorithm. The RMS error was about 0.01 and we ran the system for different value of spread.

3. Results

The performance of the proposed algorithm was tested by computing the percentage of three parameters; sensitivity (SE), specificity (SE) and accuracy(AC) as follows

$$SE = \frac{TP}{(TP+FN)} \times 100 \qquad (4)$$

$$SP=\frac{TN}{(TN+FP)} \times 100 \qquad (5)$$

$$AC=\frac{TP+TN}{TN+FP+FN+TP} \times 100 \qquad (6)$$

FP: classifies normal as abnormal
TP: classifies abnormal as abnormal
FN: classifies abnormal as normal
TN: classifies normal as normal
We evaluate our proposed system in to stages:

1. First, we divided data into two classes(normal-having MI).and for all 9 feature vectors ,SE and SP were calculated.
2. Then we divided data into 10 classes (normal-different kind of MI) and for all 9 feature vectors AC was calculated.

We calculated the all three parameters for different values of spread in RBF and compared them with each others.

The best values for accuracy was about 95/35% that found in level 4 of db10. In this state the sensitivity and specificity were found about and results are shown in table 3 and 4.

kind MI	Total beat	True diagnosis	Fulse diagnosis
Infero-lateral	83	80	3
Inferior-posterior-lateral	73	71	2
Inferior	221	213	8
Antero-septal	182	168	14

Antero-lateral	149	148	1
Anterior	82	76	6
Postero-lateral	99	89	10
lateral	71	69	2
posterior	35	35	0
healthy	104	99	5

Table 3. Tthe result of proposed algorithm.

4. Discussion and conclusion

In this work, wavelet and neural net work methodology was employed to extract features and classify signals for MI localization.We assessed the proposed algorithm on PTB database available in physio-bank.The results evaluated by three parameters (accuracy,sensitivity,specificity).

We use different level(3,4,5) and order of three wavelet(haar,db4,db10) and the results show that the best accuracy was found in level 4 at db10.in other hand the wavelet coefficient of db10(in compare with two others) are the best feature vector to localize MI.

wavelet	Haar	Db4	Db10
accuracy	90/17	94/26	95/35

Table 4. Comparing accuracy for different wavelets.

The high value for accuracy (95/35%) shows the high ability of proposed system to find the infracted region.

Also the high value for sensitivity and specificity (99/09%, 94/23%) shows the system ability to detect MI.

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