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Detection and Classification of QRS and ST segment using WNN

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Abstract

ECG consists of various waveforms of electric signals. In order to decide wavelet generating function that can remove baseline by minimizing the distortion of raw signals, we apply various wavelet generating functions to remove baseline. We have evaluated the algorithm on MIT-BIH Database for validation purpose. ECG signal was de-noised by removing the corresponding wavelet coefficients at higher scales. In this process we use Maxima – Minima algorithm to extract QRS and ST segment of ECG. The detected QRS and ST segment is compared with normal QRS and ST segment value. On this basis we find abnormalities in QRS and ST segment, which helps us to detect the diseases. We authenticate the results with the cardiologists data. This is done using LVQ neural networks. Almost 300 samples of different patients from cardiologists with attributes was normalized to train neural network. Neural Network normally obtain the results around 90 percent efficiency. All results we obtain using MATLAB

Keywords: *ECG, wavelet, LVQ neural network, MATLAB*

1. Introduction

Despite a great deal of research efforts, misdiagnosis is still frequent in relation to myocardial ischemia (ischemia is a restriction in blood supply) and myocardial infarction (AMI or MI). Diagnosis of such diseases is based on the up and down of the level or the gradient of ST segment of ECG signal. ST segment has a frequency band below 1Hz, it shares the same frequency band with the baseline variation noise of low frequency and muscle artifact that exists in every frequency band. Thus inaccurate removal of noises causes signal distortion, which in turn causes misdiagnosis. Currently available pre-processing methods to remove baseline variation noise are spline interpolation technique, FIR filtering, adaptive filtering, neural network, wavelet transform technique, etc. These techniques minimize signal distortion and remove baseline variation noise. Among the methods, wavelet transform processes signals in multiple resolution, and transformed signals have high resolution in the domains of time and frequency [1]. Thus the method is suggested as an advantageous method for analyzing non-stationary signals. Because the entire process of wavelet transform is performed through mother wavelet, even if the same wavelet transform method is used, the wrong selection of the generating function may bring about the severe distortion of signals. Overall efforts is done to develop automatic system that will detect ST-SEGMENT and QRS of ECG signal [2] with utmost accuracy .We have used different wavelets for detection purpose. We compare the results of all the wavelets and best wavelet is selected for particular disease detection.

During recent years artificial neural networks have been proposed as a diagnostic tool in different fields of cardiology. Most of the studies have utilized the multilayer perception with back propagation learning rule for the design of the network [12]. As a new approach, Learning Vector Quantization (LVQ) which belongs to the class of competitive learning networks, was developed particularly for classification problems. Classification is done among the number of patients who are dealing with ST segment abnormalities. This is done using MATLAB.

2. ST and QRS Segment in ECG and Extraction

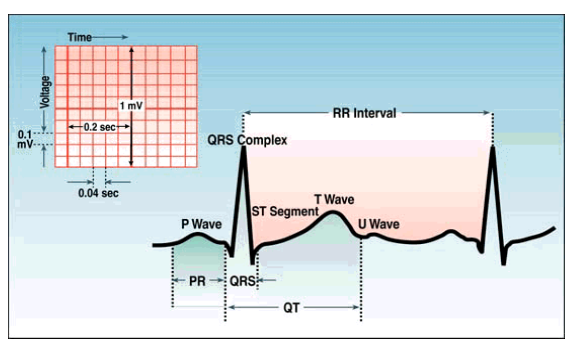

Fig 1 Electrocardiogram.

The ST segment is the portion of the ECG tracing that begins from the J point to the beginning of the T wave. It is a pause after the QRS complex as shown in Fig 1. It is essentially a period of diastole for the heart and represents the period from the end of systole to the beginning of repolarization of the ventricles. It may appear as a flat line between the QRS and the T wave or it may be up sloping from the J point from 1-2 mm in its amplitude and may be 2-3 mm in its duration. The ST segment [2] is a crucial part of the ECG tracing. The appearance of the ST segment changes dramatically in the presence of ischemia or during a myocardial infarction. During ischemia, the ST segment will become depressed and have a long duration and a large amplitude before it joins the T wave. The ST segment is elevated during an acute myocardial infarction. The ST segment is, therefore, a diagnostic segment of the ECG strip that is very important in the diagnoses of heart problems. Normal Amplitude for ST SEGMENT is 1-2mv and duration is 0.04 - 0.12sec.

For extracting ST Interval [4], we first calculate QRS-Offset, which is the location where S wave ends. T-Offset location is calculated by searching 0.2P-peak distance from T-Peak location. In this case ST interval is calculated as (T-Offset –

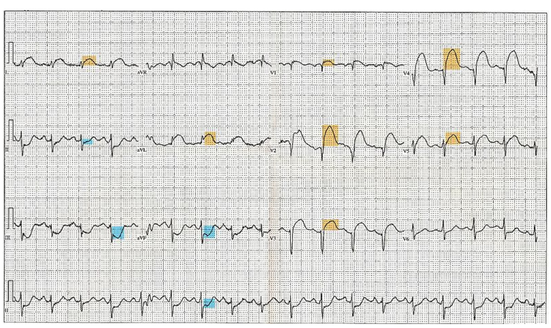

Fig 2-lead electrocardiogram showing ST-segment elevation (orange) in I, aVL and V1-V5 with reciprocal changes (blue) in the inferior leads, indicative of an anterior wall myocardial infarction

Fig 2 shows 12 Lead ECG showing ST Elevation (STEMI), Tachycardia, Anterior Fascicular Block, Anterior Infarct, Heart Attack. Color Key: ST Elevation in anterior leads=Orange, ST Depression in inferior leads=Blue.

2.1 The QRS Complex

QRS complex is the electrical wave that signals the depolarization of the myocardial cells of the ventricles. The duration for a normal QRS is no greater than 3 mm or about .06 - .12 seconds (1.5 - 3.0 mm). If the duration is greater than 3 mm (.12 seconds), then you have to suspect an abnormal intraventricular conduction velocity.

3. Wavelets

Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. The fundamental idea behind wavelets is to analyze according to scale. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large "window," we would notice gross features. Similarly, if we look at a signal with a small "window," we would notice small features. An advantage of wavelet transforms is that the windows vary. In order to isolate signal discontinuities, one would like to have some very short basis functions. At the same time, in order to obtain detailed frequency analysis, one would like to have some very long basis functions. A way to achieve this is to have short high-frequency basis functions and long low-frequency ones. This medium is exactly what you get with wavelet transforms. Figure 3 shows the coverage in the time-frequency plane with one wavelet function, the Daubechies wavelet.

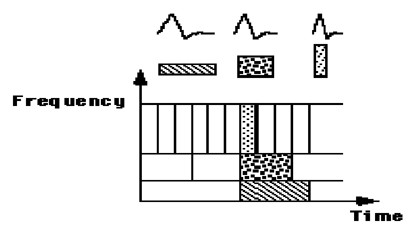

Fig.3 Daubechies wavelet basis functions, time-frequency tiles, and coverage of the time-frequency plane.

We can classify wavelets into two classes: (a) orthogonal and (b) biorthogonal. Based on the application, either of them can be used. The coefficients of orthogonal filters are real numbers. The filters are of the same length and are not symmetric. The low pass filter, G_0 and the high pass filter, H_0 are related to each other by

$$H_0(z) = z^{-N} G_0(-z^{-1})$$

The two filters are alternated flip of each other. The alternating flip automatically gives double-shift orthogonality between the lowpass and highpass filters, i.e., the scalar product of the filters, for a shift by two is zero. i.e., $\Sigma G[k]\ H[k-2l] = 0$, where $k,l \in Z$. Filters that satisfy equation are known as Conjugate Mirror Filters (CMF). In the case of the biorthogonal wavelet filters, the low pass and the high pass filters do not have the same length. The low pass filter is always symmetric, while the high pass filter could be either symmetric or anti-symmetric. The coefficients of the filters are either real numbers or integers.

All these wavelet filters functions are applied to ECG signal for best possible extraction of ST segment. This helps to select best wavelet for detection.

4. LVQ Neural Network

The world is a noisy and messy source of data - virtually nothing is known with certainty. Knowledge, then, is based on analysis that accommodates uncertainty. There are no facts, only interpretations. Interpretation implies, in fact requires, acquiring data, cleaning data (preparing the data for analysis), analyzing data, and finally presenting data in a way that interpretations are actionable, that decisions can be made based on the knowledge gained from the data. We need to build models of the world (or activities in the world) based on data from the world - we need empirical models. In turn, models must rapidly and accurately find the patterns buried in data that reflect knowledge that is useful in the world. Neural networks are mathematical constructs that emulate the processes people use to recognize patterns, learn tasks, and solve problems. Neural networks are usually characterized in terms of the number and types of connections between individual processing elements, called neurons, and the learning rules used when data is presented to the network. Every neuron has a transfer function, typically non-linear, that generates a single output value from all of the input values that are applied to the neuron. Every connection has a weight that is applied to the input value associated with the connection. A particular organization of neurons and connections is often referred to as a neural network architecture. The power of neural networks comes from their ability to learn from experience (that is, from historical data collected in some problem domain). A neural network learns how to identify patterns by adjusting its weights in response to data input. The learning that occurs in a neural network can be supervised or unsupervised. With supervised learning, every training sample has an associated known output value. The difference between the known output value and the neural network output value is used during training to adjust the connection weights in the network. With unsupervised learning, the neural network identifies clusters in the input data that are close to each other based on some mathematical definition of distance. In either case, after a neural network has been trained, it can be deployed within an application and used to make decisions or perform actions when new data is presented.

LVQ can be understood as a special case of an artificial neural network. It applies a winner-take-all Hebbian learning-based approach. The network has three layers, an input layer, a Kohonen classification layer, and a competitive output layer. The network is given by prototypes W=(w(i),...,w(n)). It changes the weights of the network in order to classify the data correctly. Learning Vector Quantization (LVQ) is a supervised version of vector quantization, similar to Selforganising Maps (SOM). As supervised method, LVQ uses known target output classifications for each input pattern of the form. It directly defines class boundaries based on prototypes, a nearest-neighbor rule and a winner-takes-it-all paradigm. The main idea is to cover the input space of samples with 'codebook vectors' (CVs), each representing a region labeled with a class. As shown in Fig. 4 a CV can be seen as a prototype of a class member, localized in the centre of a class or decision region ('Voronoï cell') in the input space. As a result, the space is partitioned by a 'Voronoï net' of hyperplanes perpendicular to the linking line of two CVs. A class can be represented by an arbitrarily number of CVs, but one CV represents one class only.

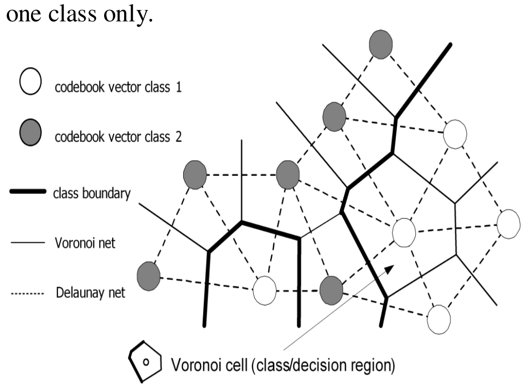

Fig.4 Tessellation of input space into decision/class regions by codebook vectors represented as neurons positioned in a two-dimensional feature space

In terms of neural networks a LVQ is a feedforward net with one hidden layer of neurons, fully connected with the input layer. A CV can be seen as a hidden neuron ('Kohonen neuron') or a weight vector of the weights between all input neurons and the regarded Kohonen neuron respectively (see Fig 5).

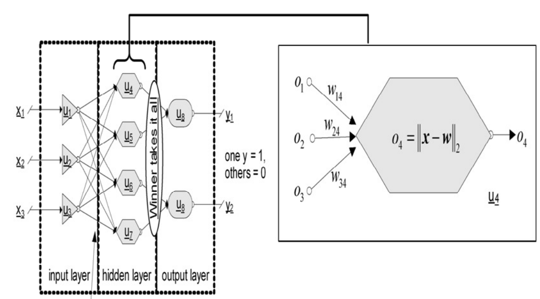

Fig.5 LVQ architecture: one hidden layer with Kohonen neurons, adjustable weights between input and hidden layer and a winner takes it all mechanism

Learning means modifying the weights in accordance with adapting rules and, therefore, changing the position of a CV in the input space. Classification after learning is based on a presented sample's vicinity to the CVs. This is based on a distance function usually the Euclidean distance is used – for comparison between an input vector and the class

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representatives. The distance expresses the degree of similarity between presented input vector and CVs. Small distance corresponds with a high degree of similarity and a higher probability for the presented vector to be a member of the class represented by the nearest CV. The accuracy of classification and, therefore, generalization and the learning speed depend on several factors such as learning schedule, the number of CVs for each class , the rule for stopping the learning process as well as the initialization method. This determines the results.

5. Implementation and Algorithm

5.1 Implementation

ECG data is taken from MIT-BIH database. We have used text form of ECG data. QRS and ST segment feature extraction is done using wavelet. QRS and ST segment interval is identified. Classification is done with the help of neural network. For this database has to be generated, which gives us information about various intervals of QRS and ST segment for large number of patients. Neural network will classify the normal and abnormal patients. Neural network is trained separately for QRS and ST segment interval for which the study has to be done. This classified signal values are compared with the neural network input to find the accuracy of the network.

5.2 Algorithm

1) Read ECG data
2) Select the wavelet for QRS and ST segment feature extraction.
3) Make the classification of detected QRS and ST segment with the help of neural network
4) Compare the classified values of QRS and ST segment with the normal value of ST segment for disease detection.
5) Check out for correct diagnosis of disease .
6) If diagnosed disease matches with the actual disease.
7) Calculate the Efficiency otherwise calculate Error and select another wavelet and repeat from step 2.
8) Calculate deviation
9) Check out for minimum deviation
10) If deviation is less than or equal to0.01, stop the process, otherwise select another wavelet and repeat from step 2.

6. Results and Analysis

6.1 Results

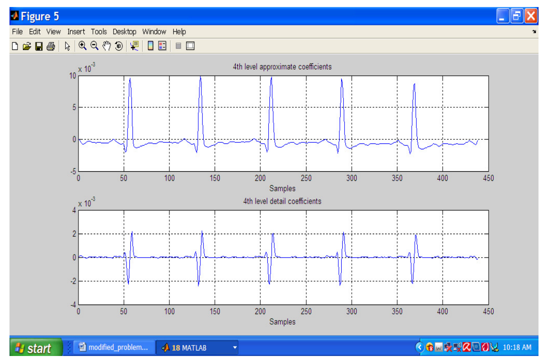

Fig 6. Detected ECG by HAAR, DB1, SYM1, BIOR1.1, RBIO1.1

Table 1
Efficiency for ST width

Sr. No	Wavelet	Detected ST width (sec)	Deviation (sec)	Normal Range (sec)	Actual Disease	Detected Disease	% Err	% Eff
1	Haar,Db1,Sym1, Bior1.1, Rbio1.1	0.140625333	0.015624666	0.04--0.12	**Ischemia**	**Ischemia**	--	100

Table 2
Efficiency for QRS width

Sr. No	Wavelet	Detected QRS width(sec)	Deviation (sec)	Normal Range (sec)	Actual Disease	Detected Disease	% Err	% Eff
1	Haar,Db1,Sym1,Bior1.1, Rbio1.1	0.0664065	0.0195315	0.06 --0.12	Myocardial cells	Normal	10	90

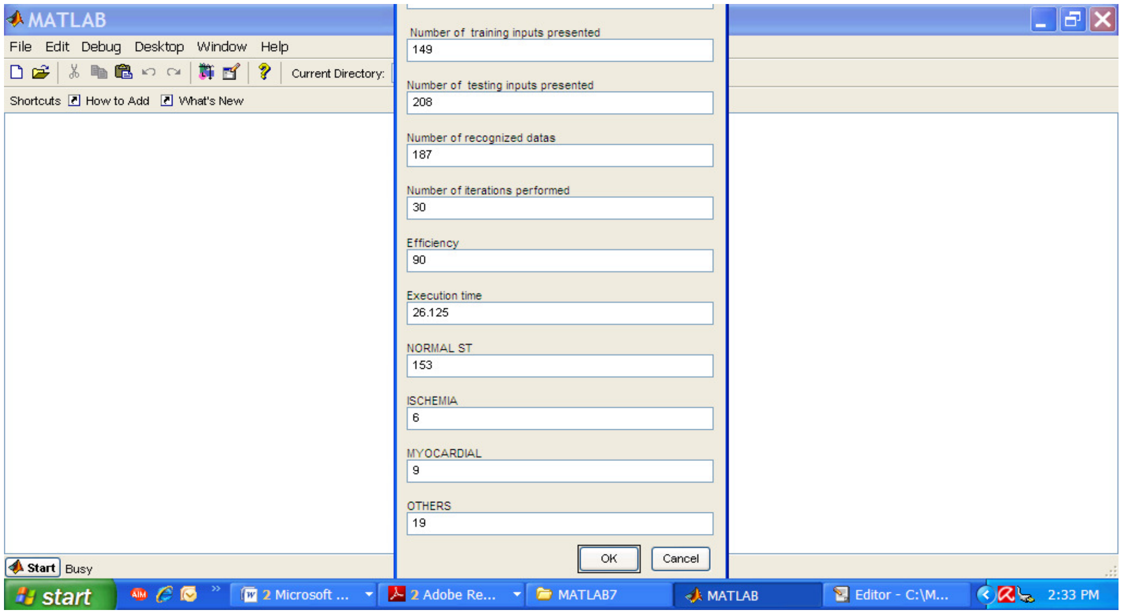

Fig. 7 Classified values from Neural Network

6.2 Analysis

Above results shows that the wavelet with maximum Efficiency can be selected for that particular disease detection. But the best wavelet can be further selected which shows the minimum deviation from the normal value. Actual disease to be detected is taken as a choice. This choice is based on number of ECG signals for which the disease detected is maximum times. If this sometimes does not satisfied, we choose from the no of wavelets that detects the disease maximum times. Average value from all detected values is calculated. Deviation value is calculated which is positive and negative. This covers the complete range of detected values. Average value is compare with normal and abnormal range for disease diagnoses. If this values matches with the actual required range, the efficiency is said to be maximum. otherwise error is calculated to know the percentage error. This gives us percentage efficiency. Best wavelet can be selected which matches maximum times with the actual required results, also which gives us minimum deviation from the reference normal value, when the disease is to be detected. This reference normal value may be either of two end values of normal range. Abnormal range is defined which is below or above the end values of normal range. If the actual disease to be detected is below the normal range, then reference normal value is the first value of normal range. Similarly if actual disease to be detected is above the normal range, then reference normal value is the last value of normal range.

Almost 300 patients data was normalizes and applied to neural network. 50% of the data was used for training and 70% for testing. Classified results were obtained with a efficiency of 90% as shown in fig 7.

7. Conclusion

From the above results we can conclude that basic wavelets filter like Haar, DB1,Bior1.1, SYM1 etc are the best wavelet to detect ST and QRS interval of ECG signal. It is observed based on the classification result done by neural network , we can prove our disease detection capability to be more accurate in large number of patients. More work can be done to improve the accuracy factor if we can build a automated learning network using genetic algorithm.

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