Automatic Detection of Premature Complexes in ECG Using Wavelet Features and Fuzzy Hybrid Neural Network

F. Farrokhi, M. H. Moradi, and R. Miri

Abstract—This paper will propose a beat recognition algorithm using discrete wavelet coefficients and fuzzy hybrid neural network. Cardiac beats have been detected from differential of compressed wavelet coefficients by Linear Approximation Data Transfer (LADT) algorithm and adaptive thresholds. The variance and sum of the squared wavelet coefficients and the R-R ratio of successive beats have been applied to the self organizing subnetwork connected in cascade with a multi layer perceptron as final classifier. The c-means and Gustafson-Kessel algorithms have been applied for the self-organizing layer. Potential of the method was examined using MIT_BIH arrhythmia database. Results show high detection (99.43%) and high sensitivity (99.65%) on 59864 detected beats and 100% sensitivity and specificity on premature beat recognition.

Index Terms—Premature ventricular complex, premature atrial complex, ECG beat detection, ECG beat recognition, neuro fuzzy classifier, discrete wavelet transform.

I. INTRODUCTION

ECG has become the most common diagnostic tool for monitoring the patients believed to suffer from cardiac disease. The long term recorded ECG allows physicians to analyze a patient’s heart function up to 24 hours continuously. These ECG signals provide information that can be used to detect the transient arrhythmias, which may not be presented during the regular or exercise ECG tests in hospitals. Many useful parameters, such as the heart rate variations, atrial/ventricular arrhythmias, and ST-segment deviations are the most general information used to evaluate the symptomatic patients and those who have had myocardial infarction.

Premature ventricular contractions (PVC) are the most common ventricular arrhythmias. PVC may occur as an isolated single extra cardiac beat or in sequence with another to cause serious arrhythmias such as ventricular tachycardia (VT). The detection of PVC’s in the analysis of electrocardiogram (ECG) may prognosticate ventricular fibrillation (VF), which is preceded by runs of PVC’s or ventricular tachycardia [1]. Although one should remember that the major problem in detection of PVC’s is their shape variations.

According to the past experiences, premature beat diagnosis methods have been classified into three groups. The first method of detection is based on comparing beats, in which a template has been compared to other beats [2]. Since PVC’s are very different in shapes, classification of PVC’s was not accurate enough. The second method however is based on time domain features of beats such as duration and area, waveform and R-R interval relations [3]. In this method just PVC’s with an evident peak are considered, therefore if the occurred PVC has R’ peak, it has not been classified correctly. The last method uses parametric models [4], [5]. The most common problem, like the previous two, is the shape variations of premature beats especially premature ventricular complexes, causing frequent errors in classification. Therefore the solution to this problem should contain optimized features and an intelligent classifier which can solve the problem of shape variations.

In most feature extraction methods for ECG classification there are two ways of analyzing ECGs; one is to use information taken from a single beat and the other is to use an algorithm, which selects time intervals containing more beats. There is no evidence that using either method produces better results. Cardiologists also use both beat features and heart rate in diagnosing a patient’s disease. Since the wavelet transformation provides a description of the signal in the time scale domain and permits the representation of temporal characteristics, in this paper discrete wavelet coefficients and their statistical parameters have been used as classification features and continuous wavelet coefficients for general beat detection algorithm. Wavelet based features are used as beat features in this work. To complete features information, heart rate information has also been used along with them to detect premature beats.

The combined features are used as inputs to a fuzzy hybrid neural network, which is composed of a self-organizing layer in cascade with a multi-layer perceptron. The fuzzy self-organizing layer preclassified input vectors by different membership values. These values are applied to the MLP subnetwork for final classification.

Conventional approaches of pattern classification involve clustering training samples and associating clusters to given categories. The complexity and limitation of previous mechanisms are largely due to the lack of an effective way of defining the boundaries among clusters. This problem becomes more intractable when the number of features used for classification increases. On the contrary, fuzzy classification assumes the boundary between two neighboring classes as a continuous,
overlapping area within which an object has partial membership in each class. Self-organizing layer in a fuzzy hybrid neural network helps to minimize overlapping of classes.

The results presented here will help for a better recognition of premature beats from normal ones. Therefore a combination of beat information by rhythm, and using a fuzzy hybrid neural network as a classifier will lead to a better result.

II. THEORY AND METHODS

A. Beat Detection Algorithm

The first step for beat classification is detection of heart beats. The major problem in detection process is the variations of the heart beat shape. In this section we will present an algorithm that gives a presentation of a heart beat which is not affected by beat shapes.

So far the following methods have been used for beat detection:
1. Simple mathematical relations [6]-[10].
2. Parametric models [11], [12].
4. Algorithms based on amplitude and slope are most immune to EMG noise. These algorithms are sensitive to changes in baseline which can be corrected by high pass filtering. Filtering of EMG noise is more difficult due to the frequency spectrum overlap with the QRS complex. Consequently algorithms which are insensitive to baseline changes but sensitive to high frequency noise show less potential than the amplitude –slope algorithms or reliable performance in a clinical setting.
5. Fuzzy methods (Fuzzy rule based & Neuro Fuzzy Methods) [14], [15].

The ability of the algorithms is to recognize different forms of normal or abnormal QRS complexes or to ignore large peaked T-waves. Even by using more than one channel in parametric model based algorithms, the problems of misdetection persist.

B. Wavelet Transform

In this paper the selected prototype wavelet was the Mexican hat, which has required properties. By studying the transformed signal, it is cleared that the transformed signal is proportional to the derivative of the original signal once lowpass filtered at a given scale. Consequently the transformed signal shows zeros at different scales in the positions where original signal shows local maxima or minima. Whenever signal has abrupt changes the transform shows positive maxima or negative minima [24].

Here by considering the time-scale abilities of wavelet Transform, an algorithm is presented which has wonderful results in detecting normal and abnormal ECG beats. The mentioned algorithm is very important for the beat classification algorithms and any classification algorithms which need the beats occurring time intervals.

If we choose the derivative of a lowpass function as a prototype in the continuous wavelet integral, the transformed signal, is proportional to the derivative of the signal once lowpass filtered at a given scale. Consequently the transformed signal shows zeros at different scales in the positions where original signal shows local maxima or minima. Whenever signal has abrupt changes the transform shows positive maxima or negative minima [24].

In this paper the selected prototype wavelet was the Mexican hat, which has required properties. By studying the transformed signal, it is cleared that when the beat takes place in wavelet transform there is an evident wavelet template, but detecting the presence of the prototype needs some consideration. Through trial and error the algorithm was obtained. The algorithm steps are as follows:
1. The selected ECG record, which is one of the MIT_BIH arrhythmia database records, is filtered by a bandpass (1 to 35 HZ) zero phase filter.
2. Filtered signal is averaged in a moving 10-point window (sampling frequency is 360 HZ).
3. The continuous wavelet transform of the preceded step was computed. The wavelet prototype is Mexican hat and the scale is five.
4. The transformed signal is compressed by Linear Approximation Data Transfer (LADT) algorithm [25], which approximates the curve by lines. The distance for discarding points is five, and the points which their distance of them is less than five are kept.
5. In this step two thresholds are determined, if we consider the result of step 4 in a matrix called C (linear approximated data):
Fig. 1. Normalized features (R-R ratio, variance and square of the wavelet coefficient).

\[
CP = C > 0 \quad (1)
\]

\[
CN = \frac{-1 \times C}{C} < 0 \quad (2)
\]

\[
BP = \text{Mean} (CP) \text{ in a 3 second window} \quad (3)
\]

\[
BN = \text{Mean} (CN) \text{ in a 3 second window} \quad (4)
\]

Then the positive and negative thresholds are:

\[
THP = \frac{1}{3}(BP + \text{Max} (CP)) \quad (5)
\]

\[
THN = \frac{1}{3}(BN + \text{Max} (CN)) \quad (6)
\]

6. The derivatives (difference of samples) of \( CP \) and \( CN \) are simply calculated.

7. If for any of points in the result of the preceding step the amplitude is greater than \( BP \) or less than \( BN \) then from 50 points before to 50 points after the detected point is searched. If there is any point, which is greater than the previous, and the next point, this point is written in the temporary detected beat matrix.

8. By consideration of low amplitude fast VF waves as beats; the heart needs at least 200msec to beat again. If the time interval of any of the following points was less than 200 msec, then the detected beat is discarded.

**B. Premature Beat Detection Algorithm**

This algorithm consists of the following steps:

1. The selected ECG record which is one of the MIT_BIH arrhythmia database records is filtered by a bandpass (1 to 35 Hz) zero phase filter and is averaged in a moving 10 point window.

2. In this step ECG beats are detect by the algorithm of the previous subsection.

3. The detected beats are centered in a 200msec window and then the isopotential value (the mean) is subtracted and the window multiplied with a Hanning window to ensure the end points are zero, thus eliminating possible edge effects.

4. A 6-level discrete wavelet transform decomposition of each characteristic beat is achieved using a 10th order Daubechies wavelet. The wavelet type and decomposition level were chosen after some initial trials but they remain an area of the research requiring further investigation.

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By analyzing the result and considering the advantages of combined features, the selected features are as follows:

1. The variance of the wavelet coefficients.
2. The energy of the wavelet coefficients (sum of squared coefficients).
3. The R-R ratio for the consecutive beats.

The characteristics of the features are shown in Fig. 1, and indicate that they are distinct enough to be classified by an intelligent classifier.

**C. Fuzzy Hybrid Neural Network**

In order to classify features, we applied a fuzzy hybrid neural network, which composed of two subnetworks connecting in cascade. The network structure is shown in Fig. 2. The first network is a fuzzy self-organizing layer, which performs a preclassification task and is responsible for managing the data in a way that makes the data of a class more similar by using different membership values.

Assume the vector representing the features under classification is denoted by \( x_k \) for \( k, 1, 2, \ldots \), where \( x_k = [x_{k1}, x_{k2}, \ldots, x_{km}]^T \in \mathbb{R}^m \). Let these vectors be partitioned into the \( C \) cluster, each represented by the center vector \( c_i = [c_{i1}, c_{i2}, \ldots, c_{in}]^T \). The membership degree of each data vector \( x_j (j = 1, 2, \ldots, p) \) into \( i \)-th cluster \( (i = 1, 2, \ldots, c) \) called \( \mu_{ij} \) is in a matrix denoted by \( \mu \in \mathbb{R}^{c \times p} \). The clustering algorithm determines the membership matrix in a way, which minimizes the objective function \( E \):

\[
E = \sum_{i=1}^{c} \sum_{j=1}^{p} \mu_{ij}^m d^2(x_j, c_i) \quad (7)
\]

subject to

\[
\sum_{i=1}^{c} \mu_{ij} = 1 \quad (8)
\]

The parameter \( m \) controls the fuzziness of clustering (typically \( m = 1.2 \)). The function \( d(x_j, c_i) \) measures the distance between the data vector \( x_j \) and the cluster center \( c_i \).

The Gustafson and Kessel (GK) method is an extension of fuzzy C-means Method (FCM) [26]. Different distributions and cluster sizes usually lead to sub optimal results with FCM. In order to adapt to different structures in data, GK used the covariance matrix to capture ellipsoidal properties of clusters. Gustafson and Kessel (1979) have extended the fuzzy C-Means algorithm for an inner-product metric norm:

\[
d^2(x_j, c_i) = (x_j - c_i)^T M(x_j - c_i) \quad (9)
\]
where \( M_i \) is a positive definite matrix adopted according into the actual shapes of the individual clusters described approximately by the cluster covariance matrices \( F_i \). \( M_i \) and \( F_i \) are as follows:

\[
M_i = \frac{1}{\text{det}(F_i)^{1/2}} F_i^{-1}. \tag{11}
\]

The Gustafson-Kessel algorithm can be presented in the following way. At a given dataset \( x_k \in \mathbb{R}^N \), choose the number of clusters \( 1 < c < N \), the weighting exponent \( m > 1 \) and the termination tolerance \( \varepsilon > 0 \). Initialize the fuzzy partition matrix \( \mu \) randomly in a way that

\[
\sum_{i=1}^{c} \mu_{ij} = 1 \tag{12}
\]

is satisfied. Then iterate through the following steps.

1) Compute the cluster prototypes (centers) \( c_i (i = 1, 2, ..., c) \)

\[
c_i = \frac{\sum_{j=1}^{p} \mu_{ij}^m \mathbf{x}_j}{\sum_{j=1}^{p} \mu_{ij}^m} \tag{13}
\]

2) Calculate the cluster covariance matrix \( F_i (i = 1, 2, ..., c) \) according to (10).

3) Compute the distances between the input vector \( \mathbf{x}_j \) and the cluster center \( c_i \), using (9) and (11).

4) Update the fuzzy partition matrix

\[
\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{d_{ij}}{d_{ik}} \right)^{2(m-1)}} \tag{14}
\]

If \( d_{ij} = 0 \) for some \( i = I \), take \( \mu_{ij} = 1 \) and \( \mu_{ij} = 0 \) for \( i \neq I \). Iterations continued until for two succeeding iterations

\[
\|U' - U^{i-1}\| \leq \varepsilon .
\]

After training the fuzzy self-organizing layer, the MLP subnetwork has been trained by use of membership coefficient matrix \( \mu \) as input.

The input vectors into the MLP subnetwork are the membership degrees determined by the fuzzy self-organizing layer. Thus, the number of input nodes equals the self-organizing neurons and the output neurons are equal to the number of classes. Number of neurons in the hidden layer is very important and in this work has been selected through some trial and errors.

The MLP has been trained by back propagation algorithm.

### III. RESULTS

The potential of our beat detection method was examined using MIT_BIH arrhythmia database as shown in Figs. 3 and 4. The results are depicted in Table I (results for each files) and Table II (average performance). Sensitivity and specificity are calculated according to (15) and (16)

\[
Se = \frac{TP}{TP + FN}, \tag{15}
\]

\[
Sp = \frac{TP}{TP + FP}. \tag{16}
\]

where \( TP \) stands for number of true positives, \( FN \) for false negatives and \( FP \) for False positives.

In classification section, the information of the ECG beats through the discrete wavelet transform coefficients are applied to the fuzzy hybrid neural network. The inputs are the R-R ratio of the succeeding beats and the variances and the square of the wavelet coefficients.

To test the best recognition ability, we select 1000 beats randomly by uniform distribution from any of the classes (Premature Ventricular Complexes, Premature Atrial Complexes and Normal, for a total population of 3000 beats) from MIT_BIH arrhythmia database for training and 3000 different beats for testing. The tolerance for self-organizing layer training is selected \( 1e^{-6} \).
After training the self-organizing layer, the vectors of membership degrees are applied to a $W_{3,10,203}$ MLP, which is trained by back propagation algorithm. The training error has been selected $1e-8$.

To test the whole network performance like training sets of data, we select 3000 beats (1000 from each class). The results are depicted in Table III.

### IV. CONCLUSION

We purposed a beat detection algorithm based on the derivative of the compressed continuous wavelet coefficients and adaptive thresholds, which shows good detection (99.43%) and sensitivity (99.65%) on 59864 beats of database. Presented algorithm have better sensitivity in 18 records among 25 selected MIT_BIH beats of database. Presented algorithm have better detection (99.43%) and sensitivity (99.65%) on 59864 coefficients and adaptive thresholds, which shows good derivative of the compressed continuous wavelet in this paper.

The features used for classification are managed by G-K algorithm and classified by a MLP neural network shows good efficiency and the best results.

These investigations show that using the abilities of continuous wavelet for abrupt change detection and abilities of discrete wavelet transform for details detection in combined features along with fuzzy hybrid learning process can reach outstanding accuracy (100%) and sensitivity (100%) even in difficult cases such as Fig. 5 and may have find practical applications in recognition of different types of ECG beats. These are the subjects of further studies.

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