JDL Fusion Model for ECG Arrhythmia Detection

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Abstract

In this paper a novel quick automatic method is proposed for electrocardiogram (ECG). Signal classification to three classes include: the normal heart beats from the left bundle branch block (LBBB), right bundle branch block (RBBB), and paced beats. After noise reduction using wavelet threshold, appropriate features are extracted from the time-voltage waves including P, Q, S, and T waves in ECG signals. Novelty of this work is utilization of fast decision based on non-parametric statistical classifier and Multi Features Data Fusion (MFDF) strategy. Two stages of MFDF include feature classification into normal and abnormal categories. Based on decision template, first stage, and second part are voting and weighting the procedure. Post processing block is added for impulsive noise reduction in order to improve the results. We emphasized on the performance and efficiency of the optimized presented algorithm and minimum cost of system learning. The accuracy of final results is reliable and well performed.

Keywords: *electrocardiogram (ECG), wavelet thresholding, Otsu thresholding, Multi Features Data Fusion*

1. Introduction

The electrocardiogram (ECG) is a low cost, and effective test for arrhythmia analysis that has become the standard diagnostic tool. A crucial step toward identifying an arrhythmia is the classification of heartbeats. The classification of an electrocardiogram (ECG) into diverse disease categories is a complex pattern recognition task. Classification of heartbeats can be very time-consuming. Hence, any automated processing of the ECG that works with this process is the focus of this study. And also would be assisting this research.

Conventionally, a typical heart beat is identified from the ECG. The component waves of the QRS, T, and possibly P waves are characterized in using measurements such as magnitude, duration, and area. Datasets using for heart diseases involve different features. Some of them are based on laboratory experiments, while others include clinical symptoms. However, one of the most popular and useful databases is the MIT-BIH.

Automated classification of heartbeats has been previously reported by other researchers. Several methods have been proposed for the classification of ECG signal. Classifiers employing methods include linear discriminate [1], back propagation neural networks [2-3], self-organizing maps with learning vector quantization [4], and self-organizing networks.

[5] describes a method for clustering ECG heart beats from a recording into 25 clusters determined that on average 98.5% of the heartbeats in any one cluster were from the same heart beat class. This translates to a classification performance of 98.5% if an expert can correctly identify the dominant beat of a cluster. In [6] a SVM based method for PVC arrhythmia detection shown that has a better efficient rather than ANFIS. In [7] a new approach PSO-SVM based has been proposed for feature selection and classification of cardiac arrhythmias. In [8], a neuro -fuzzy approach for the ECG-based classification of heart rhythms is described. Here, the QRS complex signal is characterized by Hermit polynomials, whose coefficients feed the neuro -fuzzy classifier. Detection of arrhythmia by means of Independent Component Analysis (ICA) and wavelet transform to extract important features is proposed in [9]. Finally, in [10], the authors present an approach for classifying beats of a large dataset by training a neural network classifier using wavelet and timing features. The authors found that the fourth scale of dyadic wavelet transform in conjunction with a quadratic spline wavelet together and also alongside the pre/post RR-interval ratio is very effective in distinguishing normal and PVC from other beats.

The paper is structured as follows. In Section 2 preliminaries is explained. This section covers an overview of thresholding method and MSDF strategy. The structure of the proposed classifier is given in Section 3. The sufficiency of the proposed approach is illustrated by experimental results in Section 4. Eventually, Section 5 asserts the concluding remarks and future work.

2. Preliminaries

2.1 Wavelet Transform Thresholding

Unlike Fourier transform, wavelet transform is a multi-resolution analysis which is able to analysis signals in both time domain and frequency domain. It's a common method to use wavelet functions for extracting features from ECG signals.

Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. Wavelets are orthogonal, orthonormal or biorthogonal functions. In continuous case, wavelet transform a signal with scaling parameter S and. shifting parameter τ is defined by:

$$X_{\omega}(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \psi^{*}\left(\frac{t-\tau}{s}\right) dt$$

That $\psi(t)$ is called mother wavelet.

In discrete form, wavelet transform (DWT) converts an input series $x_0, x_1, \dots, x_n$ into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series given by:

$$y_{high}[n] = \sum_{k=-\infty}^{+\infty} x[k]h[2n-k] \; y_{low}[n] = \sum_{k=-\infty}^{+\infty} x[k]g[2n-k]$$

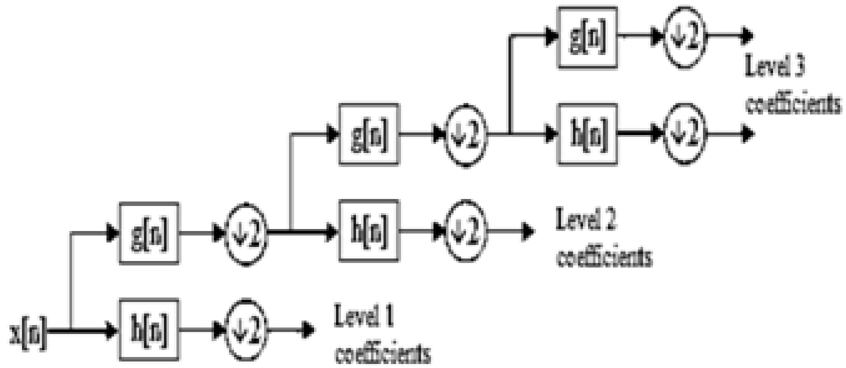

Figure 2. Wavelet Filter Bank

Which $h[n]$ and $g[n]$ are called wavelet filters. In discrete case the wavelet transform is considered as a filter bank which decomposes the input signal into the basis functions.

Wavelet concentrating ability is the main idea that its function is to remove noise form signal. If a signal has its energy concentrating in a small number of wavelet dimensions, its coefficients will be relatively large compared to any other signal or noise that has its energy spread over a large number of coefficient. It means that thresholding or shrinking the wavelet transform will remove the low amplitude noise or undesired signal.

In general, removing noise from signal by wavelet transform thresholding method is divided into following steps:

1- Decomposing signal noise by discrediting wavelet transform to several levels and computing the wavelet coefficients.

2- Computing and applying a threshold value for each level coefficient. The coefficients below of this value will remove. Threshold value commonly is determined by:

$$T = \sqrt{2.\log(n)}$$

That n is number of samples.

3- Reconstructing original signal uses new wavelet coefficients and inverts discrete wavelet transform (IDWT).

Often two types of soft thresholding and hard thresholding are used in the wavelet domain to applying threshold value.

In the soft thresholding, all coefficient values are less than the threshold in each sub-band that replaced by zero then values above the threshold are subtracted to the level of the threshold.

According to equation:

$$\eta(y) = sign(y).\max\big((|y| - T, 0)\big)$$

Where, $\eta(Y)$ is the function of soft threshold which is applied on y coefficient, T indicates in threshold value.Two different thresholding functions (in most cases the soft thresholding) are used, since obtaining the lower mean square errors.

The mother wavelet Daubechies (db4) is used to decompose the ECG signal into 6 levels in proposed method. The noise in the ECG signal is removed by applying the threshold value by soft thresholding method.

2.2 Otsu Thresholding Method

A nonparametric approach to threshold determination assumes no knowledge of statistical parameters that derive from a signal's value. The main idea in Otsu method is to select a threshold to segment the signal into the labeled regions of minimal variance in signal levels. Let P_L and P_H be the probability of background values and true signal values, respectively.

A measure of within group variance is:

$$\sigma_w^2(t) = P_L(t)\sigma_L^2(t) + P_H(t)\sigma_H^2(t) \quad (2\text{-}2\text{-}1)$$

Where σ_L and σ_H are the standard deviations of the noise and the meaningful signal, respectively. The goal of Otsu method is to find a threshold value t so that the above equation is minimized.

To finding a threshold value that satisfies the equation (2-2-1) we need to approximate $P_L$andP_H. For an arbitrary signal f with domain $Dom(f)$and range $Ran(f)$ we suppose that

$$Ran(f) \subseteq [0\,, N-1]$$

And $S_k = \{k\}$ for $0 < k < N$, and suppose that $Dom(f)$ is finite. Then $\{\mathrm{S_k}\}$ is a partition of $Ran(f)$. Define

$$p_k = \frac{\#(f^{-1}(S_k))}{\#Dom(f)}$$

Then p_k is a discrete probability density function for f. Hence

$$P_L(t) = \sum_{k=0}^{t-1} p_k \; P_H(t) = \sum_{k=t}^{N-1} p_k$$

Now we can compute mean and variance for the signal and noise by equations below:

$$\mu_L(t) = \sum_{k=0}^{t-1} k\frac{p_k}{P_L} \mu_H(t) = \sum_{k=t}^{N-1} k\frac{p_k}{P_H}$$

$$\sigma_L^2(t) = \sum_{k=0}^{t-1} (k-\mu_L(t))^2 \frac{p_k}{P_L} \sigma_H^2(t) = \sum_{k=t}^{N-1} (k-\mu_H(t))^2 \frac{p_k}{P_H}$$

Having found the histogram statistics that follow from each possible threshold value, we are in a position to search over all threshold values for T which minimize the within group variance. Specifically, by an exhaustive search we found the optimal threshold T which satisfies

$$\sigma_w^2(T) = \min_{0 \le t < N} \sigma_w^2$$

Otsu thresholding is used as a learning method for separation of two classes of features in this paper, normal and abnormal features which are obtained in feature extraction stage. For each feature, the optimum threshold is applied to distinguish normal and abnormal heart beats.

2.3 Multi Sensor Data Fusion

In our study, each of the extracted features is considered as a single sensor that gives us information about the heart behavior. The goal is combining this information and estimating heart condition.

MSDF is a system-theoretic process (a synergy of sensing, signal and data processing, estimation, control, and decision making) that is very involved, and hence an overall model that interconnects the various aspects and tasks of the DF activities is demanded highly.

There are various architectures for data fusion, but the most widely cited model for data fusion is JDL model which was created by the American Joint Directors of Laboratories Data Fusion Subpanel. The JDL model has five levels of data processing and a database. These levels are interconnected by a common bus and do not need to be processed in a sequential order; nevertheless, they can be executed concurrently. There are three main levels: levels 1, 2, and 3, as shown in Figure 3, these levels and their application are explained in our research.

JDL Level 1 – Object Refinement: This level consists of numerical procedures, such as estimation and pattern recognition. Object refinement aids in object assessments by combining the location, parametric, and identity information to achieve refined representations of individual objects. Object refinement is usually partitioned into data registration and data association.

One of the simplest forms of association algorithm is Nearest Neighbor method that is applied in this paper. In proposed method, this level of JDL includes feature extraction stage and processing them.

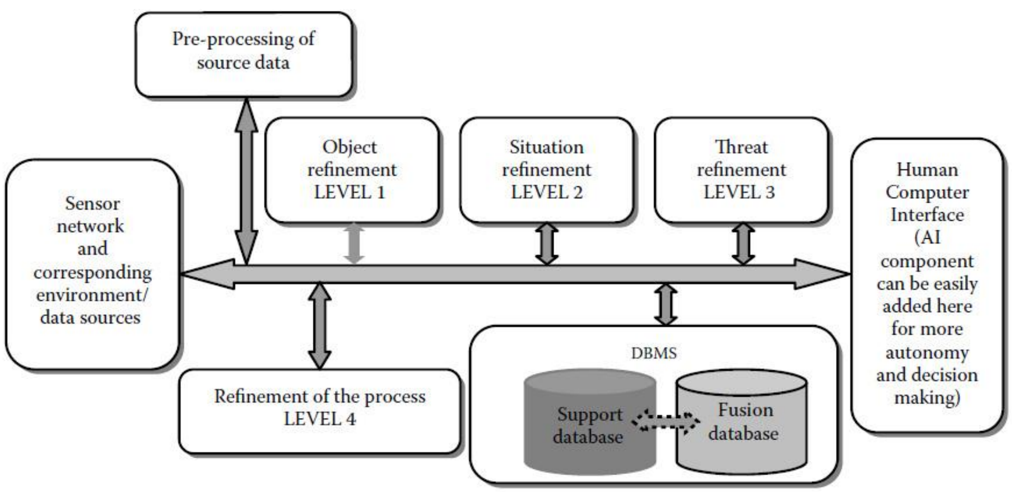

Figure 3. General JDL Fusion Process Model

JDL Level 2 – Situation Refinement: In this level, an attempt is made to find a contextual description of the relationship between the objects and observed events. After processing the data at level 1, the situation is curtained. Further analysis is carried out to refine the situation if needed. The main goal is to obtain a total picture of the future events.

In this level, normal and abnormal heart beats is classified into two classes. To reach this goal, a decision template is formed for each feature. Some post process such as KNN method and impulsive noise reduction using mean and median filtering, is accomplished to improve final decision.

JDL Level 3 – Threat Assessment: On the basis of a priori knowledge and predictions about the future situation, inferences about vulnerabilities and opportunities for operation are constructed. The ultimate aim is to obtain our finding assessment of the threat (and its perception), on which important decisions and actions can be based. In this level according to our method, type of drug which is most prescribed is determined.

JDL Level 4 – Process Assessment: The process management stage is an ongoing assessment of the other fusion stages to ensure that the data acquisition and fusion is being performed in a way that will give optimal results [11].

3. The Proposed

In this section characteristic of the classifier and the procedure designed for the ECG arrhythmia detection is explained. Figure 4, presents the block diagram of the proposed arrhythmia classification.

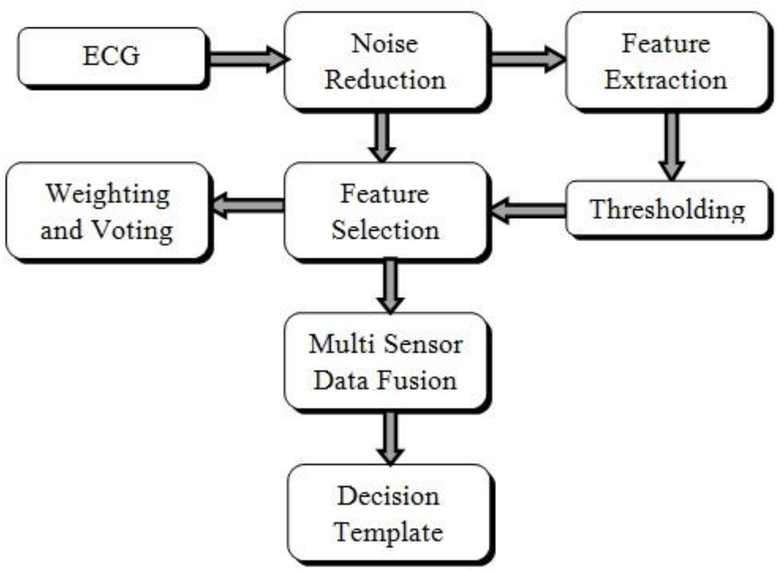

Figure 4. Block Diagram Of The Proposed Classifier

3.1. Data Set Description

In this article, the ECG records, available at the MIT-BIH arrhythmia database are used. The database has 48 records with each record being an ECG signal for the duration of 30 minutes. Each data was recorded in two channels, modified limb lead II and modified lead VI. In particular, considered beat types refer to following classes: normal sinus rhythm (N), right bundle branch block (RB), left bundle branch block (LB), and paced beat (P). The beats were selected from the recording of following patients, 100, 106, 107, 109, 118, 202, 209,212, 214, 215 and 217.

Table 1. Data Set Descriptions and Numbers Used in the Simulation

Class No.	Record Use from MIT-BIH	No. of beats used	Description
1.	**100,105**	**290**	**Normal**
2.	**107,217**	**215**	**Paced**
3.	**111,214**	**190**	**LBBB**
4.	**118,212**	**180**	**RBBB**

3.2. Noise Reduction

As mentioned, a wavelet transform thresholding is performed to reduce noises before feature extraction stage. Db4 mother wavelet is used and ECG signals are decomposed to 6 levels. In each level, threshold value is applied by soft thresholding method.

3.3. Feature Extraction

In this section, optimal features based PQRST waves that have been called heart beat interval features are automatically extracted. Each signal analyzed for 60 beats. The features for each beat saved in a vector called feature vector. At first by applying an edge detector filter, R peaks in the ECG signals have been recognized, then by using local maximum and minimum determination algorithms, the positions of P, Q, S and T waves have been found. A simple algorithm is used for detecting S and Q waves with respect to the R location:

$$\Delta R = R_2 - R_1$$

$$S \; is \; a \; minimum \; ininterval \; [\, R_1 \, , R_1 + \frac{\Delta R}{5} \,]$$

$$Q \; is \; a \; minimum \; ininterval \; [\, R_1 \, , R_1 - \frac{\Delta R}{5} \,]$$

Where R_1 , the location of R wave in current beat, is analyzed then R_2 is for the next one. Location of T and P waves is found similarly.

These features have been extracted after detecting PQRST waves:

- ST interval
- PQ interval
- S voltage
- T voltage
- Q voltage
- Morphological Features

These three morphological features are extracted by computing the maximum and minimum values of a beat in the ECG signal. Signals of each beat are scaled, using the following formula, which the range of every signal is between zero and one.

$$f(t) = \frac{f(t) - \min(t)}{\max(t) - \min(t)}$$

The minimum and maximum voltages between the first and second R feature is computed first and the normalization action is performed [0 1]. As mentioned before, percent that are higher than 0.2, 0.5 and 0.8 is considered as three features called Morphological 2, Morphological 5 and Morphological 8 respectively.

The system which is designed for feature extraction has good accuracy in major cases. However, some diseases of P wave or T wave have a different shape or are not present in the signal; consequently system wrongly detects these points. This error is considered as feature extraction noise.

3.4 Feature Thresholding

We use 5 normal samples and 6 abnormal samples as learning samples. For each sample, optimal features are extracted, and then the features for normal samples are concatenated and form a new vector called Normal features. Similarly features for the abnormal samples are concatenated and form a new vector called abnormal features. Afterward these features come in together in a new vector called Total features. For this vector which includes both normal and abnormal features thresholding method is used as a classifier to separate normal and abnormal beats. Otsu thresholding method is used for each feature and its singular threshold value is saved for future processes. This stage followed an object refinement block of the JDL process model.

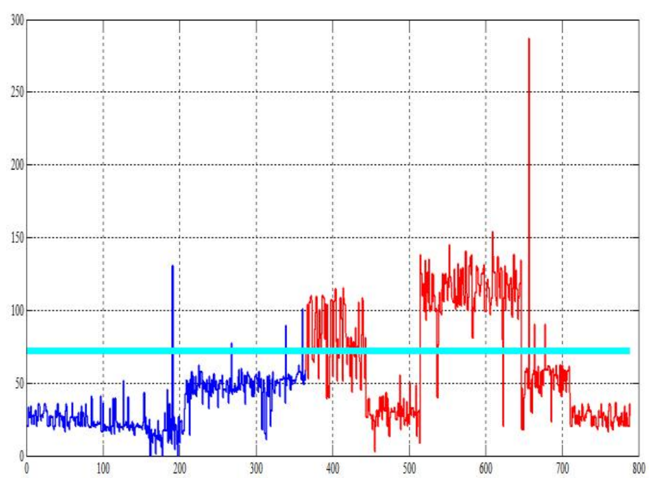

Figure 5. PQ Feature and the Threshold Line which Separate Normal and Abnormal Features

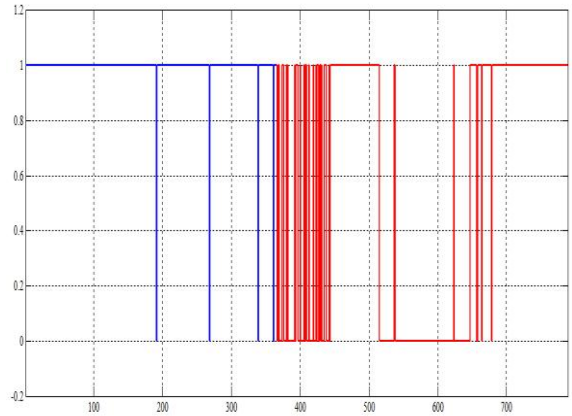

Figure 6. PQ Feature after Thresholding

3.5 Voting

A voting among total features is performed after thresholding. In voting procedure the system does in the following manner: For each sample numbers of 1s and 0s is counted for all features. The priority for normality or abnormality is given to the more one. This procedure works well for all normal samples, but for half of abnormal samples detects wrongly.

3.6 Feature Selection

In this stage, the error of feature extraction is reduced by using KNN method and a feature selection procedure. In KNN method, value for each sample determines based on odd numbers value of its nearest neighbors. The determination manner is selected from median or averaging filter. Furthermore, in this stage the Morphological features are ignored because of their high noises. Using KNN method and ignoring morphological features improve the final result. Object refinement in JDL model is the basic of this stage and voting.

3.7 Making Decision Template

As mentioned, each feature is considered as a sensor that provides information about the heart activities. The goal in this stage - that followed the situation refinement in JDL model - is to make decision based on fusion data observed from sensors. Decision Template (DT) is made for each feature of schema that assists the decision procedure.

In our study the decision template includes 4 average values and variances which are shown in the table below:

Table 2. Decision Template for a Sensor

DT - Sensor 1	Normal Learn Samples	Abnormal Learn Samples
Normal	$\mu_{11}\sigma_{11}^2$	$\mu_{12}\sigma_{12}^2$
Abnormal	$\mu_{21}\sigma_{21}^2$	$\mu_{22}\sigma_{22}^2$

Based on each measured sensor threshold, the variances and averages for each DT is obtained. These variances and averages are found for estimating the membership degree for each sample. Membership function is a Gaussian probability density function which its parameters is computed in DT. In thresholding stage, there is no distinction between points below or above the threshold value. All samples are below or above this value, considered as 0 or 1.

In this stage, the samples below or above the threshold are distinguished. Thus, their values are set fundamental distance from the threshold line. Threshold lines separating line between two classes. A close learn sample to the border line which separating the two classes, is not a good learn sample because it is close to both classes. While it is desirable that learn samples be away from threshold line, consequently the grade of membership for samples are defined based on distance from threshold value and with respect to the maximum distance between threshold and all samples. For each feature, the distance from threshold line is determined for all samples and is divided by maximum distance from threshold line in that feature, as probability for membership. Then the variance and average is computed for that feature. Obviously, the maximum distance from threshold is an important parameter in each feature. Any error in determining this value causes all the variances and averages corrupted. To avoid this, impulsive noise reduction procedure using median filtering method is applied. Moreover, the error in classification based on threshold value will cause the $\mu_{12}\sigma_{12}^2$ and σ_{21}^2 to have non-zero value. After making DT, the membership degree for each sample is computed by using a Gaussian function. As if a feature have a high membership degree for abnormal class, the heart is considered as patient else is normal.

4. Experimental Result

In this section the results of classification of learn samples are evaluated, also the effect of processing method like KNN or median filtering is shown.

Table 3. Result of Feature Selection Procedure

Ignored Feature	Accuracy without KNN	Accuracy using KNN
-	67%	69%
Morphological	80%	81%
Morphological 5 & 8	67%	65%
Morphological 8	71%	70%
PQ	75%	75%
Q	71%	72%
S	69%	65%
ST	72%	72%
T	76%	74%

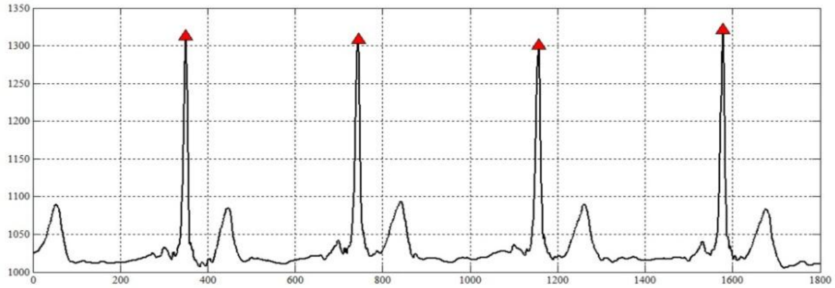

Figure 7. Finding R Peaks in a Normal Sample

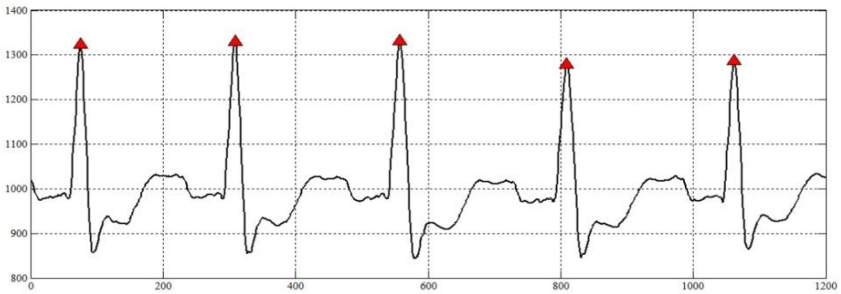

Figure 8. Finding R Peaks in a LBBB Sample

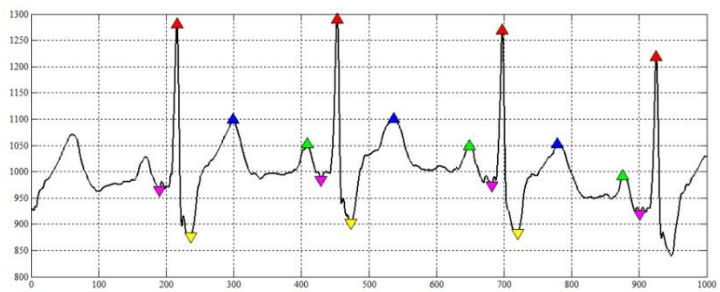

Figure 9. PQRST Detection in a Normal Sample

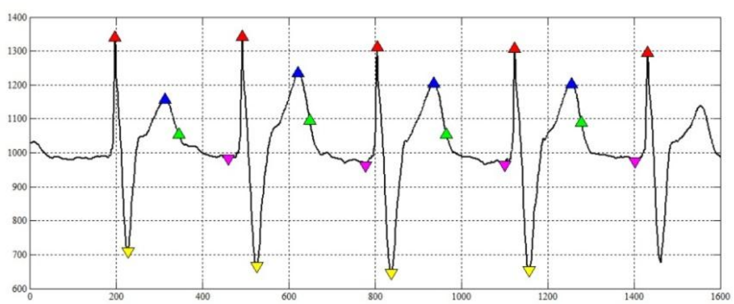

Figure 10. PQRST Detection in a P sample. Error in P Wave Detection is Noticeable

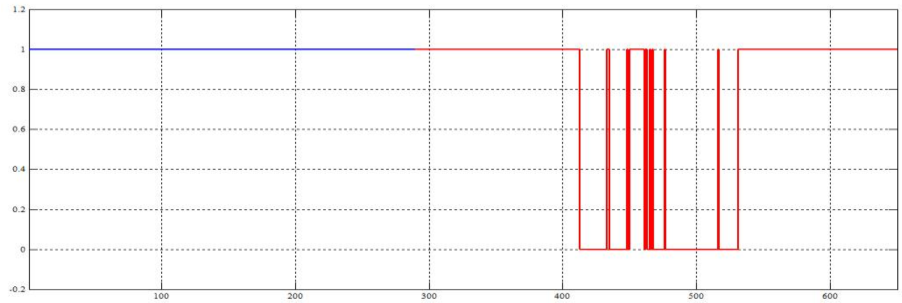

Figure 11. Result of voting before Feature Selection and KNN – Accuracy = 70%

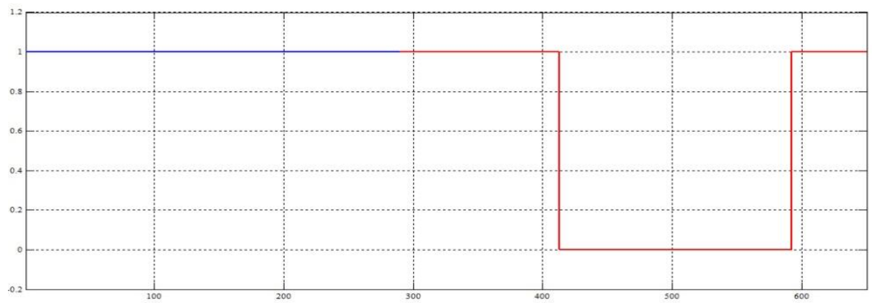

Figure 12. Result of voting after Feature Selection and KNN – Accuracy = 80%

Table 4. DT Template for PQ Sensor After Median Filtering

DT - Sensor PQ	Normal Learn Samples	Abnormal Learn Samples
Normal	$\mu_{11} = 0.590\ \sigma_{11}^2 = 0.046$	$\boldsymbol{\mu_{12} = 0.006\ \sigma_{12}^2 = 0.001}$
Abnormal	$\mu_{21} = 0\ \sigma_{21}^2 = 0$	$\boldsymbol{\mu_{22} = 0.316\ \sigma_{22}^2 = 0.103}$

Table 5. DT Template for PQ Sensor Before Median Filtering

DT - Sensor PQ	Normal Learn Samples	Abnormal Learn Samples
Normal	$\mu_{11} = 0.544\ \sigma_{11}^2 = 0.045$	$\boldsymbol{\mu_{12} = 0.276\ \sigma_{12}^2 = 0.088}$
Abnormal	$\mu_{21} = 0.004\ \sigma_{21}^2 = 0.003$	$\boldsymbol{\mu_{22} = 0.080\ \sigma_{22}^2 = 0.012}$

Table 6. Membership Probability for Learn Samples

Test Sample	Membership Probability
Normal 1	**100%**
Normal 2	**70%**
Normal 3	**100%**
Normal 4	**100%**
Normal 5	**80%**
LBBB 1	**80%**
LBBB 2	**0%**
Paced 1	**65%**
Paced 2	**60%**
RBBB 1	**93%**
RBBB 2	**0%**

5. Conclusion

In this paper, a new method based on utilization of fast decision based on non-parametric statistical classifier and Multi Features Data Fusion (MFDF) strategy for electrocardiogram (ECG) signal classification is proposed. Experimental results show a perfect classification base on extracted features, each of the extracted features is considered as a single sensor that gives us information about the heart behavior. Also for improving final result, some noise reduction methods by using wavelet thresholding are applied.

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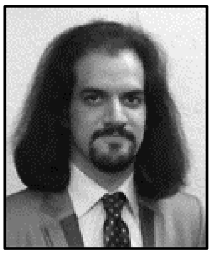

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