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Heart Disease Diagnosis using Electrocardiogram (ECG) Signal Processing

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Abstract: Heart beat classification is considered as the main tool for recognizing and diagnosing different heart diseases. The automation of heart beat classification is very necessary due to the exhaustive process of the 24 h mentoring of Electro Cardio Gram (ECG) signal of the heart. Moreover, ECG is considered as one of the most powerful tools for the diagnosis of heartbeats. In this study, a reliable automatic method is proposed separately on lead 1 and lead 2 to discriminate 15 classes of heart beat mapped into five main categories keeping into consideration the accuracy of each class besides the overall one. A dynamic segmentation strategy is applied to consider the heart rate variation. Discrete Wavelet Transform (DWT) is applied to extract beat features. Thereafter, the extracted features are subjected to Principle Component Analysis (PCA) to reduce the features dimension. Two different classifiers (Support Vector Machine (SVM) and random forests) are then applied on the reduced features to get the best results from the SVM classifier. Finally, the rejection method is applied to fuse the results from both leads 1 and 2. Using MIT-BIH as a validation database, SVM classifier achieved an overall accuracy of 99.5% and an average accuracy of 96.35% while random forests classifier achieved the best overall accuracy of 99.99% but an average accuracy of 84.26%. The study introduced also a comprehensive survey of recently researched work in the same application.

Key words: Electro Cardio Gram (ECG) signal, heart diseases diagnosis, heart beat classification, Discrete Wavelet Transform (DWT), Principle Component Analysis (PCA), Support Vector Machine (SVM), random forest

INTRODUCTION

ECG is the electrical activity of the heart over time which describes the cardio-physiology of the subject. The ECG mainly contains three main traces: P, QRS and T waves to construct the main signal structure. Thus, cardiac arrhythmias can be indicated by the change in shape of one of these traces as cardiac arrhythmias are the result of abnormal heart activity upon some certain conditions (Tantawi *et al*., 2014).

Automation of cardiac arrhythmias using ECG is considered as one of the most important recent fields of research by Yazdanian *et al*. (2013) as ECG is considered a reliable tool for the task in hand. Cardiac arrhythmias can be divided mainly into two types: arrhythmias that can cause sudden death such as; tachycardia and ventricular fibrillation (Minami *et al*., 1999; Afonso *et al*., 1999) while the second type which is our main interest in this study, needs more attention but it is not as critical as the first type.

There are many studies that have been done as shown in the literature, to automate the disease diagnosis (Osowski and Linh 2001; Prasad and Sahamb, 2003; Ayub and Saini, 2011; Kallas *et al*., 2012; Martis *et al*., 2012, 2013; Ye *et al*., 2012; Khazaee, 2013; Yazdanian *et al*., 2013). The segmentation is done in all these studies using fixed beats segmentation strategy which is unrealistic as it may result in truncated beats as in the case of a low heart rate while more than one beat revealed in one segment as in the case of high heart rate (El-Saadawy *et al*., 2016). Moreover, most studies in the literature consider only the overall accuracy as an evaluation measure which is unrealistic as the data size in the classes are not equally distributed. Thus, the overall accuracy is biased towards the accuracy of the class with the largest data size even if the other classes have very low accuracies.

In this study medical background, brief description of ECG and related studies to our study will be presented.

Medical background: The heart is a powerful muscle that lies in the chest. The heart consists of four chambers, two upper (the atria) and two lower (the ventricles) as shown in Fig. 1 and the physical contraction of the heart muscle for pumping blood is the heartbeat (Tantawi *et al*., 2014).

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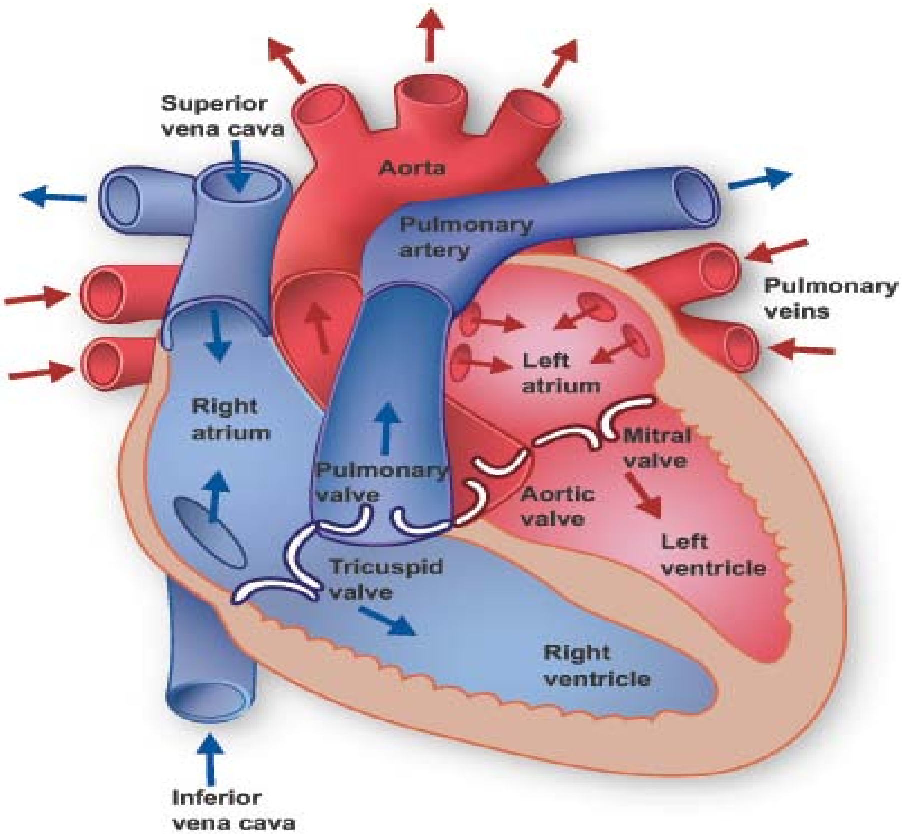

Fig. 1: Heart anatomy

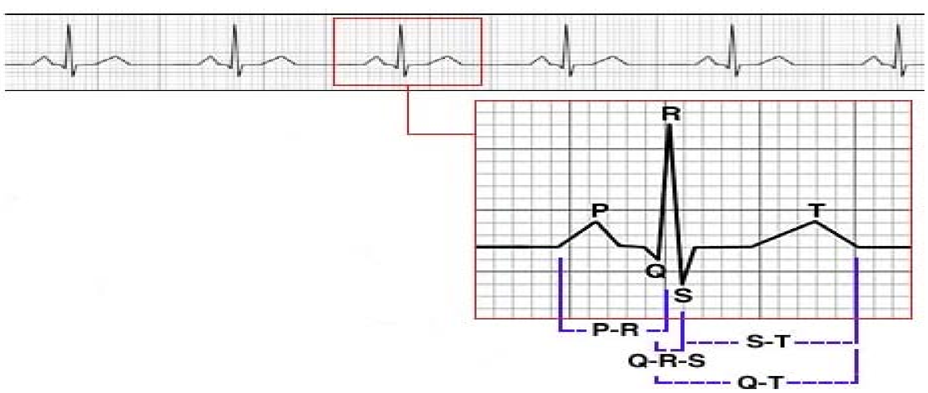

Fig. 2: ECG trace (Sornmo and Laguna, 2005)

A muscle divides the heart into two cavities, the right cavity and the left one. Each side is composed of two chambers, the atrium (upper chamber) and ventricle (lower chamber). The four chambers are called atria and ventricles. The left cavity receives oxygen rich blood from the lungs to distribute it through the entire body. On the other hand, the right cavity receives the deoxygenated blood from the entire body except the lungs (Tantawi *et al*., 2014).

Electrocardiogram (ECG): For the first time in 1893, the term Electro Cardio Gram (ECG) was introduced by Willem Einthoven. Placing electrodes (up to 12 electrodes) at various body points is the way in which the ECG can record the electrical activity of the heart. Figure 2 represents a heartbeat which traces three complex waves: P, QRS and T complexes (Tantawi *et al*., 2014).

Figure 3 shows a description of the ECG complex waves. Both the right and left atria contraction show

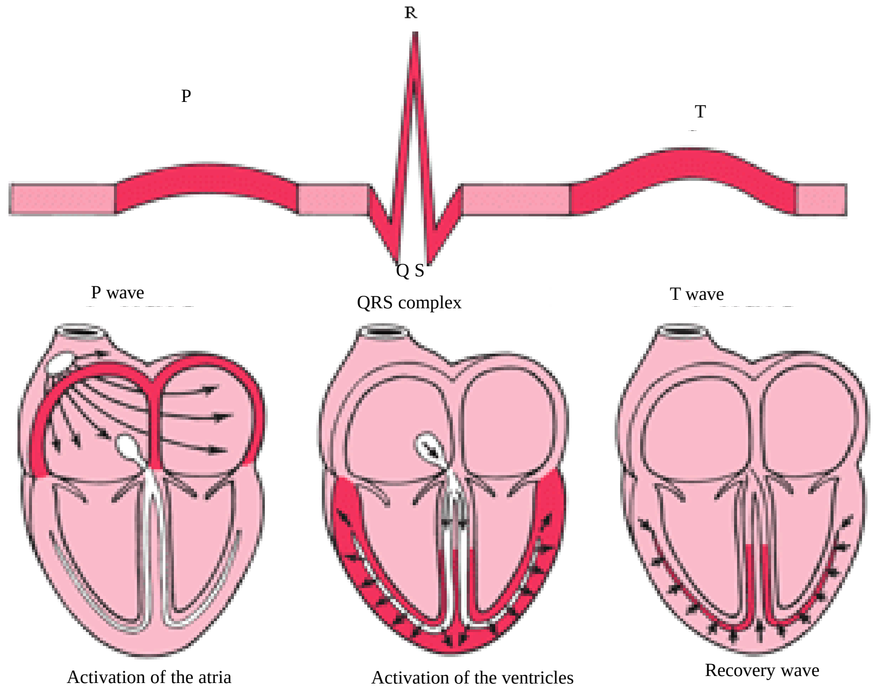

Fig. 3: The interpretation of the three traces of the ECG beat (Sornmo and Laguna, 2005)

up as the p-wave with a duration of <120 msec. While both the right and left ventricular contraction show up as the series QRS wave with a duration of about 70-110 msec in a normal heartbeat.

The electrical activity produced when the ventricles are recharging for the next contraction represents the T wave with a duration of about 300 msec after the QRS complex. Actually, the heart rate influences the position of the T wave as it becomes narrower to the QRS complex at the rapid rates (Tantawi *et al*., 2014).

ECG is a rich source of information as it can be used as a diagnostic tool. Due to the fact that the ECG carries information about the heart and rhythm, it can be used to indicate any defect or damage in the heart muscle. Many studies (Osowski and Linh; 2001; Prasad and Sahamb, 200; Ayub and Saini, 2011; Kallas *et al*., 2012; Martis *et al*., 2012, 2013; Ye *et al*., 2012; Khazaee, 2013; Yazdanian *et al*., 2013) have been done on this point by observing any change that occurs in the three main complex waves (Tantawi *et al*., 2014).

Literature review: As ECG classification is considered as one of the most powerful tools for the classification of the heartbeats, many studies have been done in this area with different methodologies. The heartbeat classification process using ECG consists of four main steps: preprocessing, features extraction, features reduction and classification step.

For the preprocessing step, digital filters are widely used due to their simplicity for noise removal while Pan and Tompkins (1985) proposed to enhance the R peak and adaptive detection threshold. Moreover, neural networks (Llamedo and Martinez, 2011) genetic algorithms (Poli *et al*., 1995) wavelet transform (Kadambe *et al*., 1999; Jung and Tompkins, 2003; Martinez *et al*., 2004) filter banks (Afonso *et al*., 1999) and Quad Level Vectors (Kim *et al*., 2010) are considered in the sophisticated methods in this step (Luz *et al*., 2016).

Regarding the features extraction step which is considered from the main steps that effect directly on the classification results, some studies consider only the RR Features (Exarchos *et al*., 2005, 2007; Bazi *et al*., 2013) while other studies use linear predictive coding (Ham and Han, 1996), high order accumulates (Osowski and Linh, 2001; Osowski *et al*., 2004), clustering (Ozbay *et al*., 2006; Ceylan *et al*. 2009), correlation dimension and the largest Lyapunov exponent (Owis *et al*., 2002; Ubeyli, 2009). Hermite transform (Jiang and Kong, 2007) and local fractal dimensions (Mishra and Raghav, 2010). However, wavelet transforms (Prasad and Sahambi, 2003; Guler and Ubeyli, 2005; Lin *et al*., 2008; Kutlu and Kuntalp, 2012; Martis *et al*., 2012, 213; Ye *et al*., 2012; Yazdanian *et al*., 2013) is the most commonly used method. For the features reduction step, the most commonly used techniques are Independent Component Analysis (ICA) (Yu and Chou, 2008, 2009;

Table 1: Comparison between the last studies for Heart beat classification

ReferenceS	Segmentation strategy	Evaluation method	No.of leads	No.of classes	Features extraction	Classification method	Total accuracy (%)	Average accuracy
Prasad and Sahamb (2003)	Static	Class oriented	One	13	DWT, RR features	Back-propagation neural network	96.77	-
Khazaee (2013)	Static	Class oriented	One	3	Morphological, time interval features	SVM	98.38	-
Ayub and Saini (2011)	Static	Class oriented	One	4	-	Cascade forward back network	99.9	-
Martis *et al*. (2012)	Static	Class oriented	One	5	DWT	Feed forward Neural Network (NN)	98.1	-
Martis *et al*. (2013)	Static	Class oriented	One	15 Mapped into 5	Features from the QRS wave, DWT	Probabilistic neural network	99.28	-
Yazdanian *et al*. (2013)	Static	Class oriented	One	5	Wavelet Transform	SVM	96.67	-
Kallas *et al*. (2012)	Static	Class oriented	One	3	Kernel Principal Component Analysis	SVM Gaussian multiple-classfier	97.39	-
Osowski and Luin (2001)	Static	Subject oriented	Two	15 Mapped to 5	Segmented ECG morphological features, heartbeat interval features, RR-interval features	Linear discriminant	-	-
Ye *et al*. (2012)	Static	Class oriented Subject oriented	Two	15 15 Mapped into 5	RR-Interval, ICA,wavelet transform	SVM	99.3 (99.7 with 2.4rejection) 86.4	-
Proposed method	Dynamic	Class oriented	Two	15 mapped into 5	DWT	SVM	Before fusion Lead1:97.38 Lead2: 96.22 99.50 %	Afterfusion 96.35 %
						Random forests	Before fusion Lead1:98.34 After fusion Lead2: 98.70 After fusion: 99.99	Afterfusion 84.24 %

Martis *et al*., 2013) and PCA (Castells *et al*., 2007; Ceylan and Ozbay, 2007; Kim *et al*., 2009; Martis *et al*., 2012, 2013).

For the classification step, mainly there are four algorithms usually used due to their efficiency: Artificial Neural Network (ANN) (Ubeyli, 2009; Kumar and Kumaraswamy, 2013), SVM (Kallas *et al*., 2012; Bazi *et al*., 2013; Khazaee, 2013; Yazdanian *et al*., 2013), Linear Discriminant (LD) (Llamedo and Martinez 2011, 2012) and Reservoir Computing with Logistic Regression (RC) (Escalona *et al*., 2015).

Finally, the most used dataset in the related studies (Prasad and Sahamb, 2003; Chazal *et al*., 2004; Ayub and Saini, 2011; Kallas *et al*., 2012; Martis *et al*., 2012, 2013; Ye *et al*., 2012; Khazaee, 2013; Yazdanian *et al*., 2013) is MIT-BIH as it's the most representative database. Moreover, it's the first database used in these studies due to its availability and rich information about most of the diseases in it (Moody and Mark 2001).

Later in this study, most important relevant studies to our research work are presented and discussed in terms of the used techniques in each step of the classification process and the achieved accuracy. Table 1 will summarize this comparison.

Prasad and Sahamb (2003) developed an automatic method to classify 13 different classes of heart beats (Normal beat, Left Bundle Branch Block (LBBB) right bundle branch block, atrial premature beat, Abberated Atrial Premature Beat (AAPB) Nodal (junctional) premature beat, ventricular premature beat, fusion of ventricular and normal beat, Ventricular flutter wave, Nodal (junctional) escape beat, Ventricular escape beat, Paced beat and Fusion of Paced and Normal Beat (FPNB). Raw signals are high filtered to remove the DC component. A set of DWT coefficients in addition to information about the RR interval (the difference between the present and previous QRS peaks) are utilized as a description for the statically segmented beats. Thereafter, the extracted features are fed into a back-propagation neural network. An overall accuracy of 96.77% is achieved using MIT-BIH as a validation dataset following class oriented evaluation.

A new method is proposed by Khazaee (2013) to mainly detect the premature ventricular contraction class. Ten morphological features and two timing interval features are utilized as a description for the beats. Thereafter, the extracted features are fed into SVM classifiers with different parameters to classify the beats into three main classes (normal, premature ventricular contraction and other). An overall accuracy of 98.38% is achieved and increases to 99.9% by applying Particle Swarm Optimization (PSO) using MIT-BIH database as a validation dataset following class oriented evaluation.

An automatic method to classify four different classes (normal, fusion beats, premature ventricular contraction, unclassified) is developed by Ayub and Saini (2011). The beats are statically segmented and the extracted features are then fed into different networks and different algorithms. Cascade forward back network achieved the best results to get an overall accuracy of 99.9% by using MIT-BIH as a validation database following class oriented evaluation.

Another automatic method is proposed by Martis *et al.* (2012) to classify five different classes (normal, right bundle branch block, left bundle branch block, atrial premature contraction and ventricular premature contraction). Raw signals are filtered to remove the noise. Thereafter, for feature extraction, three approaches have been applied on the statically segmented beats where PCA has been applied to the segmented beats; the error signals of a linear prediction model; the resulting DWT coefficients after decomposing the segmented beats. The features extracted are then fed into a feed forward Neural Network (NN) and Least Square Support Vector Machine (LS-SVM). The first approach has achieved the best results where the overall accuracy of 98.1% by using MIT-BIH database as a validation dataset following the class oriented evaluation.

A new approach is proposed by Ye *et al.* (2012) to automatically classify the beats into different classes using both the class and subject oriented evaluation, the signals are band filtered to remove the noise. The filtered beats are then segmented using a static method. The combination of both morphological and dynamic features has been utilized as a description for the segmented heartbeats. DWT and Independent Component Analysis (ICA) techniques have been considered to extract the morphological features. On the other hand, RR interval features have been extracted to describe the dynamic features, the extracted features are then classified using a support vector machine into 16 classes, following class oriented evaluation and five main categories are mapped following the subject oriented one. Overall accuracies of 99.3% (99.7% with 2.4% rejection) and 86.4% are achieved respectively following the class and subject oriented evaluations using MIT-BIH database as an evaluation dataset.

Features from the QRS wave along with DWT coefficients have been utilized by Martis *et al.* (2013) to classify 15 classes mapped to five main categories. The extracted features have been reduced using three different algorithms ICA; PCA; Linear Discriminant Analysis (LDA) to feed into three different classifiers PNN; Neural Network (NN); SVM. Combination between both ICA and PNN achieved the best results to get an overall accuracy of 99.28% following class oriented evaluation using MIT-BIH as a validation database.

A new method is proposed by Yazdanian *et al.* (2013) to classify five different classes (normal, left bundle branch block, right bundle branch block, premature ventricular contraction and atrial premature contraction). Time and apparent properties of the wavelet transform are utilized as a description for the beats. The extracted features are then fed into a support vector machine classifier to get an overall accuracy of 96.67% using MIT-BIH as a validation dataset following class oriented evaluation.

A new method is developed by Kallas *et al.* (2012) by the combination between SVM and the Kernel Principal Component Analysis (KPCA) to classify three classes (normal, premature ventricular contraction and left bundle branch block). Beats are fed into KPCA for feature extraction. Thereafter, the extracted features are classified by using SVM Gaussian multiple-classifer (OAA) to get an overall accuracy of 97.39% by using MIT-BIH as a validation dataset following class oriented evaluation.

A new model proposed by Chazal *et al.* (2004) to classify 15 classes mapped into five main categories (standard normal beat, Ventricular Ectopic Beat (VEB) Supraventricular Ectopic Beat (SVEB) fusion of a normal and a VEB or unknown beat type) as recommended by ANSI/AAMI EC57: 1998. Segmented ECG morphological features, heartbeat interval features and RR-interval features are utilized as a description of the heartbeat. The extracted features are then fed into a linear discriminate classifier. The proposed method is done on lead 1 and 2 separately with different parameters to get the final decision by fusing the decisions from the two leads. An independent performance assessment is done by dividing the MIT-BIH database into two separate data sets to get sensitivity (is defned as the percentage between the instance from the given class, correctly classifed as from a certain class and the summation between both the instances correctly classified and those from the same instance but are incorrectly classified to another instance) being incorrectly classifed as from other classes) of 75.9% for the SVEB class and 77.7% for VEB class.

Generally speaking, the already existing studies consider only the overall accuracy as an evaluation measurement which is unrealistic as the size of the data in each class is not equally distributed, thus the overall accuracy may be biased towards the accuracy of the classes with the largest data size. Few classes are considered in the classification process and fixed segmentation strategy has been considered which is unrealistic as it may cause the beat to be truncated due to the heart rate variation.

Table 1 shows a summarized comparison between the recent studies in the area in terms of the main points of comparison which are: the segmentation method, whether the study depends on the static segmentation method or a dynamic one; the evaluation method, subject or class oriented; number of leads used to get the final classification result; number of classes in the discrimination process; features extraction method; classification algorithm; total accuracy; average accuracy.

In this study, a new method is proposed for heart beat classification to keep into consideration both the heart rate variations and the accuracy of each class separately. A dynamic segmentation strategy is utilized. DWT is applied on the segmented beats to extract the features. PCA is then applied to reduce the high dimension of the features extracted from DWT. Thereafter, the reduced features are subjected to two different classifiers (SVM and Random forests). The proposed method is applied on both the data from lead 1 and 2 separately to be fused in the last step using the rejection method. MIT-BIH database is utilized as an evaluation dataset to get an overall accuracy of 99.5% and an average accuracy of 96.35% using SVM classifier and an overall accuracy of 99.99% and an average accuracy of 84.26% using random forests classifier. This result overcomes most of the results from the previous studies in this application for the overall accuracy while preserving also a high value for the average accuracy (using SVM) the measure that wasn't considered before in all previous research and used here to express the efficiency of the proposed method in recognizing each considered class with the same quality.

MATERIALS AND METHODS

The proposed method has mainly five steps as shown in Fig. 4. Each step is applied separately on the data from both lead 1 and 2 to give the final decision by fusing the results from both leads. A detailed description of the utilized dataset and the proposed method is provided in this study.

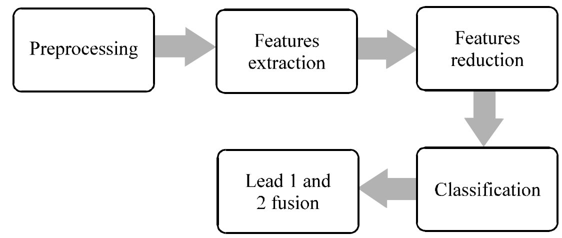

Fig. 4: Steps of the proposed method

Dataset: The MIT-BIH [GB and RG 2001] is utilized in the proposed method as it is the most utilized dataset in the literature (Prasad and Sahamb, 2003; Chazal *et al*., 2004; Ayub and Saini, 2011; Kallas *et al*., 2012; Martis *et al*., 2012, 2013; Ye *et al*., 2012; Khazaee, 2013; Yazdanian *et al*., 2013) as recommended by ANSI/AAMI EC57: 1998 standard. MIT-HIH has 48 records each of 30 min and sampled with a frequency of 360 Hz. As mentioned by ANSI/AAMI EC57:1998. Standard, there are four paced records which are not included in this study. Besides, the signal values, there is a file which contains the annotations of the diseases along with their positions (i.e., the positions of the R-Peak) provided by the dataset to be used as a ground truth for the study.

The data size in the classes are not equally distributed at all, thereafter the division of the data differs upon the size of the data as mentioned in Table 2. In this study, the data division is done following the data division by Ye *et al*. (2012) where the training set is approximately 13% in the classes with huge numbers of samples while the classes with less data size have utilized 40% as a training set and the classes with a very low number of samples have utilized 50% as a training set.

Thereafter, according to ANSI/AAMI EC57:1998 Standard the 15 classes are mapped into five main categories as shown in Table 3.

Preprocessing: The aim of this step is to remove unwanted high and low frequencies by preserving the ECG spectra in the signal as shown in Fig. 5 and divide the signal into segments using dynamic strategy to keep into consideration the heart rate variation.

Thereafter, dynamic segmentation strategy is applied on the filtered signal as presented in our study. According to the results achieved by El-Saadawy *et al*. (2016), Eq. 1 and 2 represent the method that achieved high performance and is used here for the segmentation.

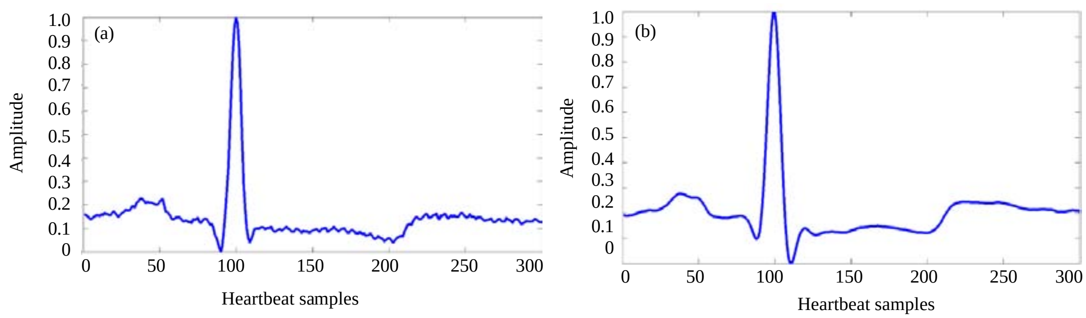

Fig. 5: Normal beat: a) before and b) after preprocessing

Table 2: The percentage of training and testing sets used in the experiments

Heartbeat types	Annotation	Training ratio (%)	Training beats number
Normal "NOR"	N	13.00	9753
Left Bundle Branch Block "LBBB"	L	40.00	3229
Right Bundle Branch Block "RBBB"	R	40.00	2902
Atrial Premature Contraction "APC"	A	40.00	1019
Premature Ventricular Contraction "PVC"	V	40.00	2852
Aberrated Atrial Premature "AP"	a	50.00	75
Ventricular Flutter Wave "VF"	!	50.00	236
Fusion of Ventricular and Normal "VFN"	F	50.00	401
Blocked Atrial Premature "BAP"	x	50.00	97
Nodal (Junctional) Escape "NE"	j	50.00	115
Fusion of Paced and Normal "FPN"	f	50.00	491
Ventricular Escape "VE"	E	50.00	53
Nodal (Junctional) Premature "NP"	J	50.00	42
Atrial Escape "AE"	e	50.00	8
Unclassifiable "UN"	Q	50.00	7
Total	15 Classes	21.89	21280

Table 3: The five main categories according to the ANSI/AAMI EC57: 1998 standard

ANSI/AAMI classes	MIT-BIH classes
N	NOR, LBBB, RBBB, AE, NE
S	APC, AP, BAP, NP
V	PVC, VE, VF
F	VFN
Q	FPN, UN

The proposed method for dynamic segmentation keeps into consideration the duration between the current R-peak and the previous R-peak (RR previous) and the distance between the current and the next one (RR next). Figure 6 shows a normal beat after segmentation using the mentioned equation:

$$\text{Before Rpeak} = \frac{1}{3}\times \text{Max(RRprevious, RRnext)} \quad (1)$$

$$\text{After Rpeak} = \frac{2}{3}\times \text{Max(RRprevious, RRnext)} \quad (2)$$

Features extraction: DWT is utilized in the proposed method due to its efficiency in non-stationary waves (Ye *et al*., 2012). Specifically, daubechies mother wavelet (DB8) is utilized in this proposed method, as it achieved the best results after utilizing many mother wavelets (Biorthogonal, Haar etc.). About 114 coefficients (i.e., 32 from A4, 32 from D4 and 50 from D3) from level 3 and 4 have been chosen to describe each heartbeat. Figure 7 shows a detailed description of the wavelet decomposition of both lead 1 and 2.

Features reduction: After the features extraction step, the features reduction step should be utilized to decrease the high dimension of the features extracted, as the high dimensionality of the features may cause irrelevant information. PCA has been utilized in the proposed method to find a sub-space that preserves the same context as in the original space.

Classification: In this study, two classification algorithms are applied.

Support Vector Machine (SVM): SVM is considered a binary classifier introduced by Vapnik (1995) by building a hyperplane between the classes whatever the size of each class. Recently, new methods have been applied by using the already made SVM to be able to classify more than two classes.

Consider, N is the number of data samples, each features vector and its ground truth is represented as a

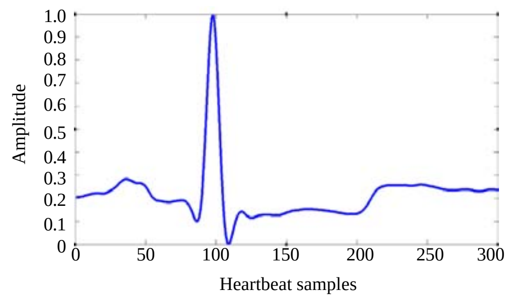

Fig. 6: A segmented heartbeat using dynamic segmentation strategy

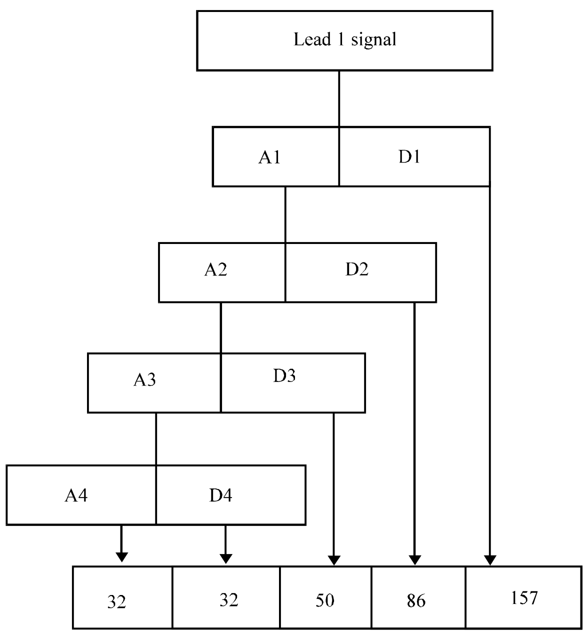

Fig. 7: The discrete wavelet decomposition levels for both lead 1 and 2

data sample {(xi, yi), i = 1, ..., N}. A decision function as mentioned in Eq. 3 can be constructed to be used later in the testing by using the training set:

$$f(x) = \text{sign}\ (\textstyle\sum \alpha i\ yi\ K(xi, x)+b) \qquad (3)$$

Where:

α_i = The Lagrange multiplier for each data sample in the training

$K(x_i, x)$ = The kernel function

In this study Gaussian Kernel function has been utilized specifically as it gave the best results in our previous research by El-Saadawy *et al.* (2016).

Random forests: Random forests, Breiman (2001) are considered a divide and conquer ensemble approach to combine weak leaners to construct a strong one. Each tree with random value samples independently combined with each other to perform the forest with the same distribution for all the trees in the forest such that each random forest is a classifier which consists of numbers of tree structured classifiers {h(x, Θ k), k = 1, ...} where h () is the classifier with an input x and independent distributed random vectors Θk in which each tree votes for the most popular class.

Lead 1 and 2 fusion: Each step in the proposed method is applied on lead 1 and 2 separately until the fusion step. The classification results from both leads are fused to improve the classification accuracy. In the proposed method, the rejection method (Ye *et al*., 2012) has been applied. The rejection method takes the beat into consideration if the classification results from both leads are the same while it neglects it if the classification results are different to a further manual classification. The manual classification step is considered the main drawback of this method.

RESULTS AND DISCUSSION

The proposed method depends mainly on two evaluation measurements: The average accuracy which keeps into consideration the accuracy of each class, the measure that wasn't used before in any one of the relevant studies and the overall accuracy which was utilized in all recent studies. The two evaluation measurements are calculated as shown in Eq. 4 and 5:

$$\text{Overall accuracy} = \frac{\text{Number of correctly classified beats in all categories}}{\text{Total number of all beats}} \qquad (4)$$

$$\text{Average accuracy} = \frac{\sum_{1}^{5} \text{Accuracy of each category}}{5} \qquad (5)$$

The proposed method is applied on the data from lead 1 and 2 separately. Daubechies mother wavelet (dB 8) is utilized to describe the segmented beats where only 114 features are chosen. PCA is then utilized to reduce the features dimension, where 18 components are chosen empirically upon many trials. Thereafter, the reduced features are subjected to two different classifiers as mentioned in study 5.

Table 4 shows the best classification results of both lead 1 and 2 by applying the SVM classifier while Table 5 shows the results after applying random forests. Many trials have been done using different numbers of trees. In the proposed method, the best results were achieved using 90 trees.

Table 4: Classification results after applying SVM on both lead 1 and 2

	Lead 1			Lead 2		
Variables	# Beats classified right	# Beats classified wrong	Accuracy (%)	# Beats classified right	# Beats classified wrong	Accuracy (%)
N	72067	1787	97.58	71646	2208	97.01
S	1632	105	93.10	1421	316	81.81
V	4190	137	96.83	3880	447	89.67
F	345	56	86.03	352	49	87.78
Q	465	34	93.19	468	31	93.79
Average accuracy	-	-	93.52	-	-	90.01
Overall accuracy	-	-	97.38	-	-	96.22

Table 5: Classification results after applying random forests on both lead 1 and 2

	Lead 1			Lead 2		
Variables	# Beats classified right	# Beats classified wrong	Accuracy (%)	# Beats classified right	# Beats classified wrong	Accuracy (%)
N	73293	561	99.24	72894	960	98.70
S	1214	523	69.89	1006	731	57.92
V	4068	259	94.01	3756	571	86.80
F	263	138	65.59	269	132	67.08
Q	393	106	78.76	396	103	79.36
Average accuracy	-	-	81.50	-	-	77.97
Overall accuracy	-	-	98.04	-	-	96.91

Table 6: Classification results after applying the fusion step on SVM and random forests results

	Fusion results	
Variables	SVM (%)	Random forests (%)
N	99.73	99.99
S	92.71	68.91
V	98.54	96.20
F	93.20	73.21
Q	97.57	82.92
Average accuracy	96.35	84.24
Overall accuracy	99.50	99.99

Thereafter, the fusion step is done on the both results from the SVM and random forests classifiers to improve the performance of the classification results. Table 6 shows the classification results after the fusion step with the penalty of rejected beats which will need manual classification.

As shown in Table 6, both the average and the overall accuracies are increased after applying the fusion step, to be 96.35 and 99.50%, respectively using SVM while 84.24 and 99.99% values achieved using random forests, the result that overcomes all the other results from recent studies as shown in Table 1 and it presents also a new measure for the evidence of good classification efficiency for all classes, the average accuracy.

As shown from the results in Table 6, random forests classifier achieved the largest overall accuracy that overcomes all the results and reached near 100%, however, the average accuracy is very low compared with the results using SVM classifier. This is due to that the N class which has the largest data size gets a very high classification accuracy using this classifier and then the overall accuracy is biased towards its accuracy. On the other side, the SVM classifier achieved an overall accuracy slightly less than that achieved using the random forests but it preserves high accuracy for each class separately.

From our study point of view, the SVM classifier is considered better than the Random forests as in this study, the main target is to keep into consideration not only the overall accuracy but also the average one to get high accuracy on each class separately.

CONCLUSION

In this study, a reliable automatic method is proposed to discriminate 15 classes of heart beat mapped into 5 main categories keeping into consideration the accuracy of each class besides the overall one. The proposed method is applied on the 2 leads separately to achieve the best average and overall accuracies. In the proposed method, a dynamic segmentation methodology is applied to keep into consideration the heart rate variation. Daubechies mother wavelet (dB 8) is utilized to describe the segmented beats where only 114 coefficients are chosen from level 3 and 4. Thereafter, PCA is applied to reduce the high dimension features where only 18 components have been chosen. The reduced features are then subjected to two different classifiers, SVM and random forests to get the best results from the SVM classifier. Finally, a rejection methodology is applied on the results from both lead 1 and 2 to get the final decision. Using MIT-BIH as a validation database, Overall accuracies of 99.99% (using random forests) and 99.50% (using SVM) are achieved while the highest average accuracy of 96.35% (with 4.5% rejected beats) is achieved using SVM.

RECOMMENDATIONS

Future work will include considering a fusion methodology other than the rejection methodology to overcome its penalty. Also, trying more different classification algorithms utilizing the subject oriented methodology where the records utilized in the testing are different from that utilized in the training step will be one of the main goals for future work.

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