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Performance Analysis of Arrhythmia Detection using Multiclass Classifier

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Abstract: In this paper, the most authentic and efficacious method for cardiac arrhythmia classification using Multiclass Support Vector Machine (MSVM) is presented. The authors have considered classification of 6 beat types such as normal sinus rhythm (N), Premature Ventricular Contraction (PVC), Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), Tachycardia (TA) and Bradycardia (BR) by implementing MSVM classifier. Radial Basis Function (RBF) kernel with 5 fold cross validation and zero offset value is used for adjusting kernel values. A total of 24 ECG records are used to collect different types of beats. To feed the classifier the features adopted where QRS complex, RR interval, R amplitude, S amplitude and T amplitude. The MSVM classifier performance is measured in terms of accuracy, sensitivity and specificity. The classifier demonstrates its effectiveness and is found to be highly accurate in ECG classification.

Keywords: Accuracy, cardiac irregularity, classifier, ECG, MSVM, sensitivity and specificity

I. INTRODUCTION

Electrocardiogram (ECG) analysis is a standard method used for the detection of arrhythmias and is used regularly for proper diagnosis of cardiovascular diseases in clinical practice. A series of waves and deflections that reflects the electrical activity (in time domain) of the heart is considered as an electrocardiogram (ECG) signal, which is a non-stationary signal [1].
The two primary facts that are to be considered for proper and accurate diagnosis of irregular cardiac rhythm are automatic detection as well as classification of these ECG signals. An ECG is a medical test which measures the electrical activity generated by the heart thereby detecting the heart abnormalities. A change in the characteristics of the ECG signal can be caused due to any kind of damage to the heart muscles or any kind of irregular cardiac rhythm. The cardiac disorders that can be diagnosed using an ECG signal are heart enlargement, cardiac abnormal rhythm or heart stroke. These abnormal activities of the heart is called as arrhythmia and can be classified by analyzing P, Q, R, S and T wave properties of the ECG signal (Fig 1).

The ECG signals were obtained from MIT-BIH arrhythmia database which consist of 48 recordings covering all 16 different heart beats with duration of about 30 minutes [2]. A proper set of feature selection is an important task in classification applications. The important parameters that are to be considered in the treatment of cardiac patient are the spell and the pattern of P wave, QRS complex and the T wave. Any kind of irregularity in the above parameters signifies the ailment of the heart. The pulse phases which are entirely irregular are referred to as arrhythmia and are found to be life threatening for cardiac patients [3].

One of the prominent applications of pattern recognition is ECG signal interpretation, which accordingly labels into one of the group as normal or abnormal. A careful study of these ECG signals is a necessity of the system to gain high accuracy for early diagnosis. To achieve such type of system one of the prominent areas with promising results is Artificial Neural Network (ANN) [4].
The two main strategies of ANN which are not perceptible to human perusal are pattern recognition and pattern differentiation. Innumerable related literature work was carried out for the diagnosis of cardiac irregularities using ANN. In [6], irregular heart beat classification using SVM with logistic regression was done and gained an accuracy of about 76.1%. Ali MirzaMahmoodet. al. [7] used a novel shear approach for ECG classification with an accuracy of 68.47%. In [8], weighted KNN classifier with Kernel differentiator was used and accuracy of about 70% was reported.

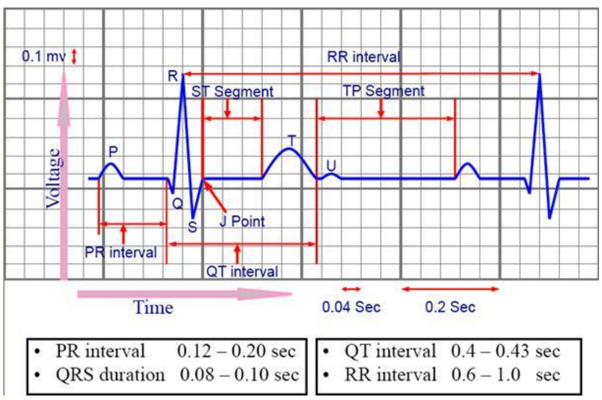

Fig.1. Components and Segments of Normal ECG waveform [5]

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Easy and accurate analysis of cardiac rhythm beats of a particular patient is the main goal of this paper such that the heart specialist will have foremost notice about the abnormality and start the treatment at the earliest. Here six types of beats are considered, normal sinus rhythm (N), Premature Ventricular Contraction (PVC-shorter RR interval), Right Bundle Branch Block (RBBB-widened QRS complex), Left Bundle Branch Block (LBBB-QRS duration > 120msec), Tachycardia (TA- heart rate > 100bpm) and Bradycardia (BR-heart rate < 60bpm).Heart rate is controlled by electrical signals sent across heart tissues. Tachycardia occurs when an abnormal heart produces rapid electrical signals. A heart rate of 60 to 100 beats per minute is consideredas normal for most of the people. If the heart beats less than 60 bpm, it is slower than normal. A slow heart rate can be normal and healthy or could be a sign of irregular electrical system of the heart. Healthy young adults and athletes often have heart rate of less than 60 bpm i. e. a slow heart rate does not cause any problem for few people.

The most important application of Artificial Neural Network(ANN) is complex pattern classification. Pattern classification is employed in numerous areas of signal processingas character recognition, bar code recognition, radar target identification and biomedical signal processing [9]. The neural network classifier used in this paper for ECG beat classification will be conferred in the next section.

II. METHODOLOGY

The intended technique for feature extraction and classification of ECG signalsis delineated in the block diagram (Fig. 2).

The first and the foremost step is loading of raw ECG data from MIT-BIH database used as the data source for the analysis [10]. The database consists of 48 recordings which cover all 16 different heart beat types including normal sinus rhythm with 30 minute duration and 11 bit resolution. Herein, a total of 24 ECG records were used to collect different types of beats.

The second step involves preprocessing of the loaded ECG signal. Preprocessing of ECG signal plays a very significant role in the analysisof the signal to discard noise and interference associated with it [11]. As ECG signal is non-uniform and non-stationary, it is easily corrupted by noise and interference such as power line interference (PLI), motion artifacts and base line drift during its acquisition [12]. For accurate analysis of the signal this noise and interference should be discarded, which is referred to as preprocessing [13]. A cascaded connection of nonlinear LPF (with cut-off frequency 0.5 Hz) and moving average based HPF (with cut-off frequency of 60 Hz) is used for mitigation of base line drift and high frequency noise respectively with resolution of 250 samples per millivolt. Preprocessed ECG signal is given as input to feature extraction, where the temporal features such as P, Q, R, S and T amplitudes are determined. In order to withdraw these features, first QRS beats were detected and then the circumference recognition of ECG waves was done using Hilbert Transform.

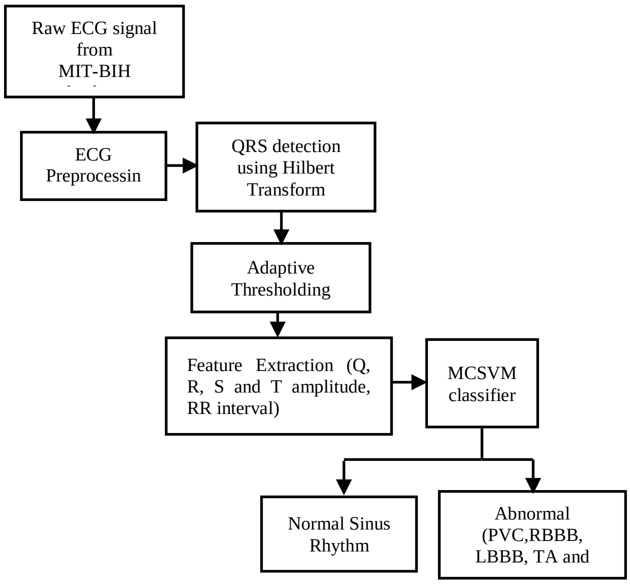

Fig. 2. Block diagram of proposed method for ECG classification

Here Hilbert transform is used for R peak detection which adaptively determines the threshold to point out the peaks in ECG signal. As ECG signals are of finite duration, infinite duration based Fourier series technique is found to be inefficient. Numerical methods that are implemented in QRS complex and R peak detection are Pan Tompkins algorithm [12], Hidden Markov Model [15], and digital filters [16].

The fundamental drawback present in the above methods is low Signal to Noise Ratio (SNR). Here accuracy calculated for Hilbert Transform is high (95%) compared to accuracy of Pan Tompkins algorithm (92%). Hilbert Transform has the ability to differentiate required dominant R peak from other peaks in the ECG signal [17]. The procedure of Hilbert Transform is as follows:

For an ECG signal s(t) the Hilbert transform is defined as [18]

$$H[s(t)] = S(t) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{s(\tau)}{t-\tau}d\tau \quad (1)$$

S(t) is considered as a linear function of s(t), obtained by applying convolution with $(\pi t)^{-1}$

$$\text{i. e.} S(t) = \frac{1}{\pi t} * s(t) \qquad (2)$$

S(t) and s(t) are related to each other in such a way that they together create a strong enhanced analytical signal, which can be written with amplitude and phase, where the derivative of phase is considered as the instantaneous frequency. The Fourier transform of the analytical signal

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gives us one sided spectrum in frequency domain. The enhanced analytical signal which is a complex signal, can be expressed

$$a(t) = s(t) + jS(t)(3)$$

The envelope of the analytical signal

$$E(t) = \sqrt{s(t)^2 + S(t)^2} \quad (4)$$

And the phase angle

$$\varphi(t) = \tan\frac{S(t)}{s(t)} \quad (5)$$

Applying Fourier Transform to Eq. 2 we get

$$F\{S(t)\} = \frac{1}{\pi}F\left\{\frac{1}{t}\right\}F\{s(t)\}$$
$$= -\frac{1}{\pi}j\mathrm{sgn}f\ F\{s(t)\}(6)$$

The envelope determined using Eq. 4 is found to have the same magnitude as that of the original ECG signal s(t). To find the peaks where $\frac{d}{dt}s(t) = 0$, we need to find the envelope of the ECG signal which is considered as the basic principle of Hilbert Transform for R peak detection. Though Hilbert Transform detects the dominant peak points in the ECG signal, one of the pitfalls associated is that it fails to detect low amplitude R waves. Hence we adopt adaptive thresholding technique after Hilbert Transform. In adaptive thresholding technique the peak detection is done by using two threshold limits namely threshold up-limit and threshold down-limit calculated as

$$TH_{u+1} = TH_u\text{-}w_{u\Delta} \quad (7)$$
$$TH_{D+1} = TH_D - w_{D\Delta} \quad (8)$$

w_u and w_D are error weight factors with different values in each stage with respect to number of erroneous detected peaks. Highest local maxima point is marked as R wave and if the signal drops below the threshold value, it is marked as S wave. After the detection of R wave, the Q, S and T wave can be detected (here peaks which are 200 msec before R peak are marked as Q wave and peaks 250 msec after R peak are marked as S wave).

A. Multi-Class SVM Classifier

SVM classifiers are basically binary classifiers used for cardiac arrhythmia classification [19]. As the classification of ECG signal involves simultaneous recognition of various classes, numerous strategies of multi-class classifier can be adopted [20]. To effectively extend binary classification to multiple classifications, MSVM classifier is implemented [21]. SVM performs classification by constructing a C-dimensional (C=6) hyperplane, which desirably classifies the given signal into 6 classes using a kernel function to map testing data into a feature space where a hyperplane is used for classification. SVM model effectively performs complex separation in high dimension using kernel mapping.A kernel is a similarity function which is fed to a machine learning algorithm, which works with the feature vectors. The three kernel functions available in the literature are linear kernel, polynomial kernel and Gaussian kernel (or RBF kernel). Choosing the right kernel is one of the pivotal task to obtain the better abstraction capability in pattern classification [22].

Here, MSVM classifier is trained based on both linear and Radial Basis Function(RBF) Kernel, which are proved to be the most relevant Kernels for cardiac arrhythmia classification[23]. To seek best parameter configuration in SVM model we select the best kernel to perform the classification on both training and testing dataset.

To build a SVM model we need to set kernel parameters gamma (σ) for RBF kernel and determine the penalty parameter [24].Linear kernel is a simplest kernel function used for classification whereas computational properties of RBF kernel can be used to improve classification methods, which substantially increases the overall classification accuracy.RBF kernel with 5 fold cross validation and zero offset value is used effectively, as it is easy to calibrate compared to linear kernel [25].

The most popular MSVM classifier with less training period and reduced number of decompositions is One-Against-All (OAA)[26]. The OAA procedure for classification is as follows:Let

$$K = \{w_1 w_2, w_3 \dots\dots\dots . w_c\}(9)$$

be a set of C (C=6) possible classes related to our desired ECG beat classification. Parallel C (6) SVM classifiers are trained such that each classifier targets to solve the two classification problem at a time. The binary classification is defined by the distinction between one information class i. e. w_i (i=1, 2 …6) against all other classes i. e. $(K - wi$.

For a C class problem, OAA constructs C SVM models. The i^{th} (6^{th}) SVM is trained with all training data sets with some label of reference and other SVM (i. e. 1 to 5) is trained with compliment of above reference label. The resultant of one-against-all method is the class that is compatible to the SVM with highest output value [26]. The decision function of the i^{th}SVM is given as

$$F_i(x) = w_i^T \emptyset(x) + b_i \qquad (10)$$

where w_i^T is a weight vector, x is the training data, $\emptyset(x)$ is mapping function and b_i is a scalar data. The input vector **x** will be assigned to the class that corresponds to the nearest and the highest value of the decision function. The sample **x** is classified into the class based on

$$\mathbf{x} = \arg\max_{i=1,2\dots 6}(F_i(x))(11)$$

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III. RESULTS AND DISCUSSION

The proposed method has been applied to ECG signals loaded from MIT-BIH arrhythmia data base. The loaded raw ECG data was exported using MATLAB into a readable form for further processing and to carry out effective classification process. For sample, here record number 220 is shown in below figures. There are six classes to classify including normal sinus rhythm. The raw ECG signal and its detected peaksare shown in figures below (Fig. 3(a) and (b) respectively). Thesimulation results of Hilbert transform used in ECG beat detection, in feature subspace dimensionalities is depicted in Fig. 3(b).

A total of 13,366 beats were extracted from 24 ECG records, out of which 600 beats used for training, 300 for validation and the remaining 12466 beats are used for testing the classifier. In training and validation phase we have assigned equal number of samples to each class i. e. 100 for training of each class and 50 for validation of each class (Table 1).

Our experiments show that the best applied kernel for ECG signal classification is RBF kernel with kernel parameter σ=0.5 and soft margin cost parameter C=30 with an accuracy of 96.75.

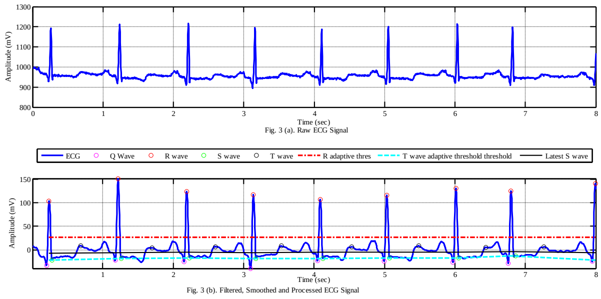

Fig. 3 (a). Raw ECG signal of record number 220 (b). Filtered, Smoothed and ProcessedECG signal

Whereas linear kernel with kernel parameters σ=0.2 and margin cost parameter C=20 we gained accuracy of 95.4% (Table 2). Larger value of σ leads to low conflict and model and high bias. The penalty factor (or regularization coefficient) C is chosen such that, if it is too large we will have high penalty for non-separable features and if it is too low we may have under-fitting (not sufficient to fit the training samples).

Out of 13,336 beats extracted, 12,746 beats are correctly classified under six different classes using linear kernel and gained an accuracy of 95%, whereas 12,950 beats are correctly classified using RBF kernel with an accuracy of about 96.8% (Table 2).

Table 1. Number of Training, Validation and Testing beats used

Class	**N**	**PVC**	**RBBB**	**LBBB**	**TA**	**BR**	**Total**
Training Beats	100	100	100	100	100	100	600
Validation Beats	50	50	50	50	50	50	300
Testing Beats	6200	909	448	1678	1122	2109	12466

Table 2. ECG samples used for training and testing

Class label	Beat type	MIT-BIH record number	Total beats classified per record using Linear kernel	Total beats classified per record using RBF kernel
1	N	100, 103, 115, 123, 220, 234	1100*6=6600	1100*6=6600
2	PVC	208, 233, 119, 221, 200	300*5=1500	300*5=1500
3	RBBB	118	146	150
		124, 212	400*2=800	400*2=800
		107, 231	200*2=400	200*2=400
4	LBBB	109, 111	1000*2=2000	1000*2=2000
		207, 215, 228	300*3=900	200*3=600
5	TA	113, 611	300*2=600	300*2=600
6	BR	101	200	300
Total ECG records=24			Total beats classified=12,746	Total beats classified=12,950

The performance of the classifier is superintended by the operational parameters False Positive rate (FP), False Negative rate (FN), True Positive rate (TP) and True Negative rate (TN).

When a normal ECG signal is categorized as normal TP occurs and when ranked as anomalous FP occurs. Likewise, when abnormal ECG signal is classified as abnormal TN occurs and when labelled as normal FN occurs. The first criterion to show the performance of the classifier is training accuracy (A), which is defined as the percentage of correctly classified training data among the total number of training samples Eq. (12).

$$Ac(\%) = \frac{\text{Correctly classified trained samples}}{\text{Total Training samples}} \qquad (12)$$

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The second criterion to be considered is Sensitivity (Se), which is defined as the percentage of true positive signals among all positively tested signals (Eq. 13).

$$Se(\%) = \frac{\text{True Positive signals}}{\text{TP + FN}} \quad (13)$$

Specificity, a third criterion to measure the effectiveness of the classifier is defined as the percentage of true negative signals among all negatively tested signals (Eq. 14).

$$Sp(\%) = \frac{\text{TrueNegativesig nals}}{\text{TN + FP}} \quad (14)$$

Table 3. Overall performance of MSVM classifier

Classifier	Kernel	Parameters		A (%)	Se (%)	Sp (%)
MSVM	Linear	P=20,	σ =0.2	95.4	82.7	81
	RBF	P=30,	σ =0.5	96.7	82	83.5

The overall accuracy, sensitivity and specificity of MSVM classifier using linear kernel is calculated as 95.4%, 82.7% and 81% respectively. Using RBF kernel we get accuracy as 96.7%, sensitivity as 82% and specificity as 83.5%.
In this paper we have shown that the MSVM classifier using RBF kernel, accurately classifies ECG signal and is remarkably better than linear kernel.

IV. CONCLUSIONS

In this paper we have shown that, One-against-all MSVM classifier is a conventional method which efficiently constructs 6 binary classifiers to differentiate each class from the rest. All the SVM classifiers are equally reliable. Hilbert transform followed by adaptive thresholding has performed efficaciously for ECG feature extraction.

This paper proposes three metrics such as accuracy, sensitivity and specificity to measure the accuracy of the classifier. The experimental results have demonstrated that the proposed methodology is accomplished to improve the overall classification accuracy to 95%. These promising results open the way to a new aspect with respect to assimilate multi SVM's in ECG beat classification.

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BIOGRAPHIES

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