Expert Systems with Applications 39 (2012) 11792–11800

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Application of principal component analysis to ECG signals for automated diagnosis of cardiac health

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ARTICLE INFO

Keywords:
Electrocardiogram
MIT-BIH arrhythmia database
Discrete Wavelet Transform (DWT)
Neural network (NN)
Least Square-Support Vector Machine (LS-SVM)

ABSTRACT

Electrocardiogram (ECG) is the *P*, *QRS*, *T* wave indicating the electrical activity of the heart. The subtle changes in amplitude and duration of ECG cannot be deciphered precisely by the naked eye, hence imposing the need for a computer assisted diagnosis tool. In this paper we have automatically classified five types of ECG beats of MIT-BIH arrhythmia database. The five types of beats are Normal (N), Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB), Atrial Premature Contraction (APC) and Ventricular Premature Contraction (VPC). In this work, we have compared the performances of three approaches. The first approach uses principal components of segmented ECG beats, the second approach uses principal components of error signals of linear prediction model, whereas the third approach uses principal components of Discrete Wavelet Transform (DWT) coefficients as features. These features from three approaches were independently classified using feed forward neural network (NN) and Least Square-Support Vector Machine (LS-SVM). We have obtained the highest accuracy using the first approach using principal components of segmented ECG beats with average sensitivity of 99.90%, specificity of 99.10%, PPV of 99.61% and classification accuracy of 98.11%. The system developed is clinically ready to deploy for mass screening programs.

1. Introduction

Cardiac arrhythmia is a collective term for a heterogeneous group of conditions in which there is abnormal cardiac electrical activity. Arrhythmias are commonly encountered in clinical practice, arising from chaotic electrical activity. Many arrhythmias like ventricular fibrillation and flutter are life threatening medical emergencies that can result in cardiac arrest hemodynamic collapse and sudden death (Huikuri, Castellanos, & Myerburg, 2001; Murphy & Lloyd, 2007; Willerson, Wellens, Cohn, & Holmes, 2007). Cardiac arrhythmias occur most often in individuals with an underlying cardiovascular disease like hypertension, coronary artery disease and cardiomyopathy. They occur due to a defect in impulse formation or impulse conduction or due to both (Fauci et al., 2008).

The electrocardiogram (ECG) is being commonly used as a diagnostic tool to distinguish different types of arrhythmias. Accurate and early detection and differentiation of arrhythmias is important, especially for fatal and life-threatening arrhythmias like ventricular tachy-arrhythmias that can result in sudden cardiac death. Many types of arrhythmias, such as atrial fibrillation, are associated with an increased risk of thromboembolic events and stroke (Wolf, Abbott, & Kannel 1991). The inherent complexity and mechanistic and clinical interrelationships of arrhythmias often brings about diagnostic difficulties for treating physicians and primary health care professionals creating frequent misdiagnoses and cross classifications using visual criteria (Goldberger, 2006; Shiyovich, Wolak, Yacobovich, Grosbard, & Katz, 2010). Computer-aided cardiac arrhythmia detection and classification can play a significant role in the management of cardiovascular diseases. Studies have shown that recent computerized algorithms can identify cardiac arrhythmias with higher diagnostic accuracy with significant reduction in the cost (Krummen et al., 2010).

A minicomputer system was designed to analyze three types of beats (Normal, Supraventricular ectopic beats (SVEB) and ventricular ectopic beats (VEB)) using time domain features in a 24 hour ambulatory ECG tapes (Fancott & Wong, 1980). Linear prediction method was used to detect Ventricular Premature Contraction (VPC) with a sensitivity of 92% (Kang-Ping & Chang, 1989). Time domain features of Normal, SVEB and VEB were modeled using Hidden Markov Model (Coast, Stern, Cano, & Briller, 1990). The ECG morphology along with RR interval features were used for the classification of Normal and five types of arrhythmia beats using particle swarm optimization technique and achieved an average accuracy of 93.27% (Melgani & Bazi, 2008).

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http://dx.doi.org/10.1016/j.eswa.2012.04.072

Normal, Atrial Premature Contraction (APC), Supra Ventricular Tachycardia (SVT), Ventricular Tachycardia (VT), VPC and Ventricular Flutter (VF) ECG beats were classified using autoregressive model and generalized linear model classifier with an accuracy of 93.2% (Dingfei, Srinivasan, & Krishnan, 2002). Principal components of two kinds of abnormal ECG beats were classified using Gaussian Mixture Model (GMM) with an accuracy of more than 94% (Martis, Chakraborty, & Ray, 2009). Normal, congestive heart failure, Ventricular Tachycardia and atrial fibrillation beats of ECG were classified using multilayer perceptron neural network and feature saliency and obtained 97.78% of accuracy (Güler & Übeyli, 2005). The independent components arrangement strategy was proposed with Independent Component Analysis (ICA) and classified eight types of ECG beats (Normal, Left Bundle Branch Block, Right Bundle Branch Block, Ventricular Premature Contraction, Atrial Premature Contraction, paced beats, Ventricular Flutter wave and ventricular ectopic beats) using support vector machine and probabilistic neural network and reported more than 98% of accuracy (Yu & Chou, 2009). Six types of ECG beats (Normal, Ventricular Premature Contraction, fusion of ventricular and Normal beats, Atrial Premature Contraction, Right Bundle Branch Block, fusion of paced and Normal beats) were classified using particle swarm optimization and radial basis function neural network classifier and achieved more than 95% of sensitivity and more than 98% specificity (Korürek & Doğan, 2010). However all these methods were tested on smaller datasets.

Even though many works were reported on arrhythmia beat classification, there is a need to improve the classification accuracy when used for huge database. Also most of the methods reported use complex mathematical features imposing lot of computational burden while evaluating these features. The aim of this paper is to develop a simple methodology for arrhythmia beat classification, with highest diagnostic accuracy even when used for large database.

The paper is organized in the following way. Section 2 presents the material used and the acquired parameters. In Section 3, a detailed description of the features extracted in this study is given. Classifiers used are explained in Section 4. We present the experimental results in Section 5 and the interpretation of the results in Section 6. We conclude the paper in Section 7.

2. Material used

In this work, we have used MIT BIH arrhythmia database (Mark and Moody. 1997) for the ECG analysis and classification. The dataset is sampled at 360 Hz. We have used 10,000 Normal and 24,989 abnormal (7250 Right Bundle Branch Block (RBBB), 8069 Left Bundle Branch Block (LBBB), 2544 Atrial Premature Contraction (APC) and 7126 Ventricular Premature Contraction (VPC)) beats.

A brief description of the various kinds of ECG beats used is explained below:

i. Normal beat: The Normal ECG beat consists of characteristic peaks, *P*, *QRS* complex and *T* wave. The PR interval ranges between 120 ms to 200 ms, heart rate varies between 60 and 100 beats per minute (Goldberger, 2006).
ii. Right Bundle Branch Block (RBBB): Due to rapid depolarization of the left ventricle followed by the slow depolarization of right ventricle, the QRS complex of the ECG signal shows an extra deflection (Goldberger, 2006).
iii. Left Bundle Branch Block (LBBB): In this beat, the activation of the left ventricle is delayed, resulting in the contraction of left ventricle later than the right ventricle. The duration of the QRS complex exceeds 120 ms (Goldberger, 2006).
iv. Atrial Premature Contraction (APC): It is characterized by premature heartbeats originating in the atria. In Normal conditions, sinoatrial node regulates the heartbeat, APCs occur when other region of the atria depolarizes earlier than the sinoatrial node and hence triggers a premature beat (Goldberger, 2006).
v. Ventricular Premature Contraction (VPC): This beat occur when some region in the ventricle depolarizes earlier than the sinoatrial node. QRS complex is widened and abnormal in morphology, not associated with the preceding *P* wave and *T* wave is inverted (Goldberger, 2006).

3. Methodology

Fig. 1 depicts the proposed methodology of classification of Normal and four types abnormal beats in the ECG of arrhythmia. The working of each block is explained in the following sections.

3.1. Preprocessing and segmentation

The ECG signal downloaded from MIT-BIH arrhythmia database may contain artifacts, noise and baseline wander. Therefore it is necessary to denoise the ECG signal to remove all these unwanted parts of the signal. First the raw ECG signal was subjected to wavelet based denoising using db6 wavelet (Singh & Tiwari, 2006). The ECG signal was decomposed upto six levels of decomposition. The sixth level approximation sub band consists of frequency band of 0–2.8125 Hz, which mainly consists of baseline wander. Therefore this sub band is not necessary. Also the ECG will not contain much information after 45 Hz. The necessary sub bands are detail coefficients of 3rd, 4th, 5th and 6th levels. So only these coefficients are retained and all other sub band coefficients are replaced with zeros and inverse wavelet transform is computed to obtain denoised ECG (Addison, 2005). After denoising the ECG, it is subjected to QRS complex detection using Pan Tompkins algorithm (Pan & Tompkins, 1985).

The QRS complex is physiologically an important peak in the ECG signal (Kohler, Hennig, & Orglmeister, 2002), also it is easy to detect by signal processing algorithms due to its sharp and prominent shape. In this study we have used Pan Tompkins algorithm for detection of QRS complex (Pan & Tompkins, 1985). The algorithm consists of computation of derivatives, moving window integrator, squaring and detection of rising edge of pulses. The derivative provides the slope information of ECG waveform, squaring will emphasize higher amplitudes and suppresses smaller amplitudes and moving window integrator performs averaging operation, thereby removes noise.

After detection of QRS complex, 99 samples were chosen from the left side of QRS mid-point and 100 samples after QRS mid-point and the QRS mid-point itself as a segment or beat of 200 samples.

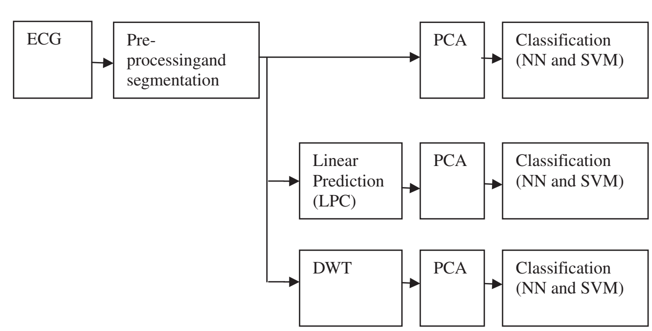

Fig. 1. Block diagram of the proposed system.

3.2. Linear prediction

In linear prediction (LP) analysis (Makhoul, 1975), the ECG signal segment, $x(n)$ is modeled as a linear combination of its past input signals $x(n-k)$, $k = 1, 2, \ldots, p$ where p denote the order of prediction and $a(k)$ is the kth linear prediction coefficient. The error in prediction is given by

$$e(n) = x(n) - y(n) \tag{1}$$

where $y(n)$ is the predicted signal, given by

$$y(n) = \sum_{k=1}^{p} a(k)x(n-k) \tag{2}$$

Substituting Eq. (2) into Eq. (1) and taking Z transform, one obtain

$$\frac{E(z)}{X(z)} = 1 - \sum_{k=1}^{p} a(k)z^{-k} = A(z) \tag{3}$$

When the signal $x(n)$ is fed to the system defined by the transfer function $A(z)$, the Residual Error Signal (RES), $e(n)$ is obtained. Also if signal $e(n)$ is passed through the system $1/A(z)$, we get the reconstructed original signal $y(n)$.Here ECG signal segment $x(n)$ is predicted from the third order linear predictor using the coefficients, $a(k)$. The RES represents the part of the ECG which could not be predicted using LP model. The output of linear predictor is random in nature. In order to compute LP coefficients, Levinson–Durbin recursion (Makhoul, 1975) is used. Again the output of LP filter has same number of samples as that of the input (200 dimensions), But RES signal is not correlated to itself. The 200 samples of RES are used for subsequent analysis.

3.3. Discrete Wavelet Transform (DWT)

The wavelet transform has the capability of providing resolution simultaneously in time and frequency (Strang & Nguyen, 1996). Due to energy compaction property of wavelet transform, it can provide sparser representation than time domain.

To decompose a ECG signal beat into time-frequency components, a basis function at scale a and location b is defined as,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \tag{4}$$

The wavelet transform is sampled on a dyadic grid scale to get discrete wavelet transform, such DWT at scale 2^{-m} and time instant n is given by,

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t - n) \tag{5}$$

Using the dyadic wavelets, the DWT can be written in terms of the inner product between the signal and the wavelet basis function as,

$$T_{m,n} = \int_{-\infty}^{\infty} x(t)\psi_{m,n}(t)dt \tag{6}$$

The inverse discrete wavelet transform is computed as,

$$x(t) = \sum_{m=-\infty}^{\infty}\sum_{n=-\infty}^{\infty} T_{m,n}\psi_{m,n}(t) \tag{7}$$

In order to decompose ECG into DWT, the shape of the wavelet basis function should be similar in morphology to the ECG. Addison (2005) reviewed various applications of wavelet transform to ECG analysis (Addison, 2005).

3.4. Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) is a linear dimensionality reduction technique, that provides projection of the data in the directions of highest variance (Duda, Hart, & Stork, 2001). The PCA algorithm involves computation of covariance matrix from the ensemble of ECG beats, eigenvalue and eigenvector decomposition of covariance matrix, sorting eigenvectors in the descending order of eigenvalues and finally projecting the original ECG data in the directions of sorted eigenvectors. The first few components will represent the most of the variability present in the data. In this work the first 12 components are used after PCA for pattern classification.

4. Classification

In this study a fully connected feed forward neural network (NN) and least square support vector machine are used for pattern identification.

4.1. Neural network

In the current study a fully connected feed forward neural network (Bishop, 1995; Haykin 1999) is used for automated pattern identification. The neural network consists of a layer of input neurons, two layers of hidden neurons and one layer of output neurons. Random weights are initially assumed and the training data is fed to the neural network to obtain network response. Based on the training labels the difference between the obtained output and desired output by the network is computed and it is called as error signal. Based on this error signal, the weights are updated by back propagating the error. The process is repeated until the training error is below a given threshold. After that the testing data is fed to the trained neural network and the classified output is noted and the performance of classification is computed based on testing labels.

4.2. Least Square-Support Vector Machine

Support Vector Machine (SVM) is a highly non linear and single layered network which is having higher generalization ability that it can classify unseen patterns correctly (Christianini & Taylor, 2000; Gunn, 1998). The classifier minimizes structural risk instead of empirical risk as in other classifiers. It maximizes the distance between the patterns and the class separating hyperplane simultaneously in order to discriminate the patterns belonging to different classes. Generally the patterns in the given feature space are not linearly separable, therefore they are projected into a high dimensional space where the features are assumed to be linearly separable and classification is performed. The technique is called kernel trick. Commonly used kernels are linear, quadratic, polynomial of order 3 and radial basis function (RBF) kernels. In the current study a modification of original SVM termed as Least Square SVM (LS-SVM) is used (Suykens & Vandewalle, 1999).

5. Results

The ECG signals from MIT-BIH database were first denoised using wavelet based denoising technique. After the denoising, it was subjected to QRS complex detection using Pan Tompkins algorithm. After detection of QRS complex, the ECG was segmented to obtain 200 samples segment as a beat for subsequent analysis. Three approaches were used in this study.

In the first approach the segmented ECG signal was used for its dimensionality reduction using PCA. The dimensionality reduced principal components were used for the pattern classification of five types of beats in arrhythmia. In total 12 components were used for the pattern classification using feed forward neural

Table 1
Results of feature extraction using PCA on segmented ECG signal.

Principal component	Normal	RBBB	LBBB	APC	VPC	p-value
PC1	−0.3955 ± 0.8384	−0.6756 ± 1.2638	−0.2165 ± 3.3283	1.0221 ± 1.3918	1.1194 ± 4.9156	<0.0001
PC2	−0.5009 ± 0.3656	1.4684 ± 1.2250	−0.2753 ± 1.0774	−0.1531 ± 0.7929	−0.4283 ± 2.8317	<0.0001
PC3	0.9661 ± 0.5001	0.6574 ± 0.5863	−0.7436 ± 0.8784	0.3524 ± 0.6185	−1.2945 ± 1.3887	<0.0001
PC4	0.4619 ± 0.5258	−0.2701 ± 1.0224	−0.2123 ± 0.9045	−0.0280 ± 0.5369	−0.1262 ± 1.4421	<0.0001
PC5	−0.2515 ± 0.3918	−0.0671 ± 0.5683	0.1526 ± 0.7207	−0.2188 ± 0.3671	0.3372 ± 1.3315	<0.0001
PC6	0.0543 ± 0.3045	−0.1071 ± 0.2781	−0.1371 ± 0.6300	0.0389±0.4351	0.1775 ± 0.8704	<0.0001
PC7	−0.1018±0.3388	0.0106 ± 0.5209	−0.0341 ± 0.3921	0.2249 ± 0.3362	0.0936 ± 0.5699	<0.0001
PC8	−0.0506 ± 0.3092	0.0385 ± 0.3898	0.1685 ± 0.3529	−0.2122 ± 0.3755	−0.0805 ± 0.6368	<0.0001
PC9	0.0269 ± 0.2083	−0.0395 ± 0.4296	−0.0036 ± 0.2397	0.1186 ± 0.2568	−0.0319 ± 0.5857	<0.0001
PC10	−0.0200 ± 0.2190	0.0094 ± 0.3426	−0.0184 ± 0.2762	−0.0877 ± 0.2208	0.0705 ± 0.5114	<0.0001
PC11	0.0055 ± 0.2424	0.0198 ± 0.2428	−0.0890 ± 0.1726	0.0422 ± 0.2050	0.0593 ± 0.4727	<0.0001
PC12	−0.0066 ± 0.1663	0.0142 ± 0.1682	0.0381 ± 0.1401	0.0342 ± 0.1832	−0.0608 ± 0.4046	<0.0001

network and LS-SVM. Table 1 provides the results of twelve principal components extracted from segmented ECG beat.

It can be observed from Table 1 that, the p-value is less than 0.0001 for all the features, indicating that all the features are statistically significant. These 12 statistically significant features were used for the classification using NN and LS-SVM with different kernel functions. In this study, we have used ten-fold cross validation scheme for the training and testing of the classifiers.

Fig. 2–4 show the average sensitivity, specificity and classification accuracy using different classifiers for various folds of ten-fold cross validation respectively.

It can be seen from Table 2, that LS-SVM with RBF kernel classifier provided highest average classification accuracy of 97.52%, average sensitivity and average specificity of 99.90% and 99.10% respectively.

The second methodology involves computation of linear predictive coefficients from ECG beats. Based on the linear predictive coefficients, the error signal of the linear prediction model is derived. Since there will be 200 samples per beat of ECG in the error signal, to reduce its dimensionality, PCA was used. In total 12 principal components were used for pattern classification using NN and LS-SVM with different kernel functions. The results of twelve principal components extracted from segmented ECG beat is shown in Table 3. It can be seen from Table 3 that, the p-value for each feature is less than 0.0001, indicating that these features are statistically significant.

Fig. 5–7 show the average sensitivity, specificity and classification accuracy using different classifiers and for each of the ten-fold cross validation respectively.

It can be seen from Table 4, that LS-SVM with RBF kernel provided maximum accuracy of 94.88% for second methodology, average sensitivity and average specificity of 99.32% and 96.96% respectively.

The third methodology involves the computation of DWT coefficients using FIR approximation of Meyer's wavelet ('dmey'). From the power spectral density of five individual beats, it was seen that most of the signal variations occur in the frequency band of 0–22.5 Hz, which is exactly the frequency range of 4th level approximation (0–11.25 Hz) and 4th level detail (11.25–22.5 Hz) sub bands. Therefore these two sub bands were considered for subsequent feature extraction. The PCA applied separately on the coefficients of each of the two sub bands. Six components were chosen from each of the sub bands. The statistics of the principal component features of 4th level approximation and 4th level detail were provided in Tables 5 and 6 respectively. In total these 12 components were used for pattern identification using NN and LS-SVM. Figs. 8–10 show the sensitivity, specificity and accuracy using different classifiers for various folds of ten-fold cross validation respectively.

It can be seen from Table 7, that LS-SVM with RBF kernel provided maximum accuracy of 96.88% for second methodology, average sensitivity and average specificity of 99.95% and 96.68% respectively.

6. Discussion

This paper discusses the ECG beat classification using PCA features in time and DWT domains.

Table 8 provides a summary of studies on automated classification of ECG beats using the data obtained from MIT-BIH arrhythmia database. Four types of ECG beats (Normal, supra-ventricular

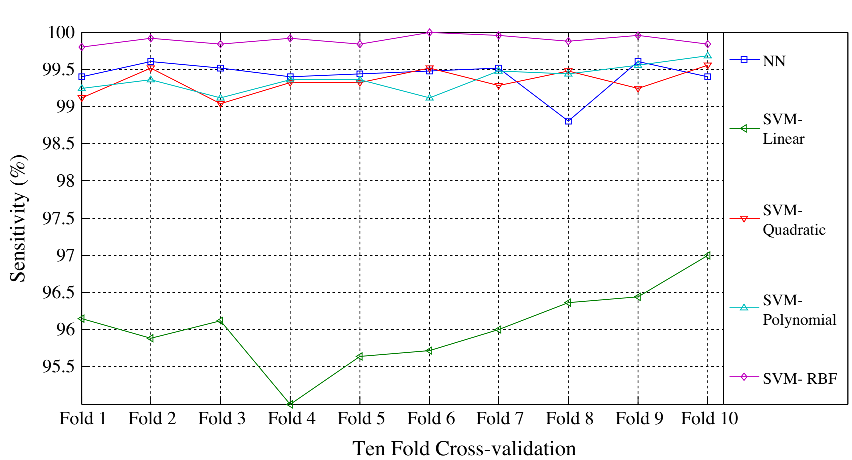

Fig. 2. Plot of average sensitivity (%) versus different folds of ten-fold cross-validation for different classifiers for first methodology.

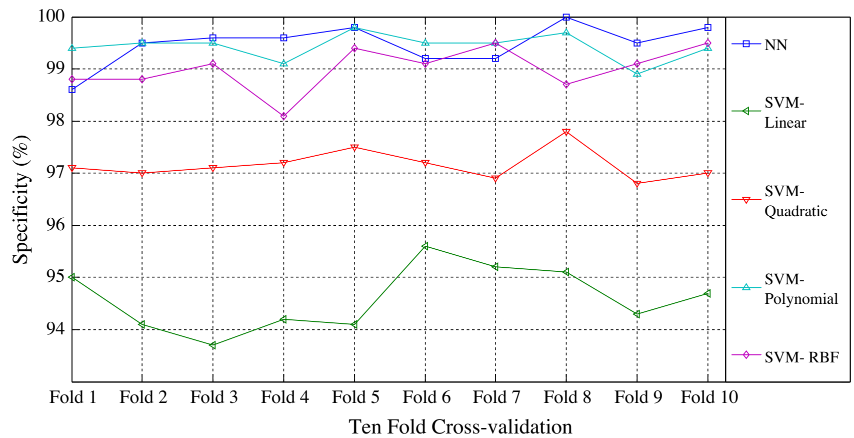

Fig. 3. Plot of average specificity (%) versus different folds of ten-fold cross-validation for different classifiers for first methodology.

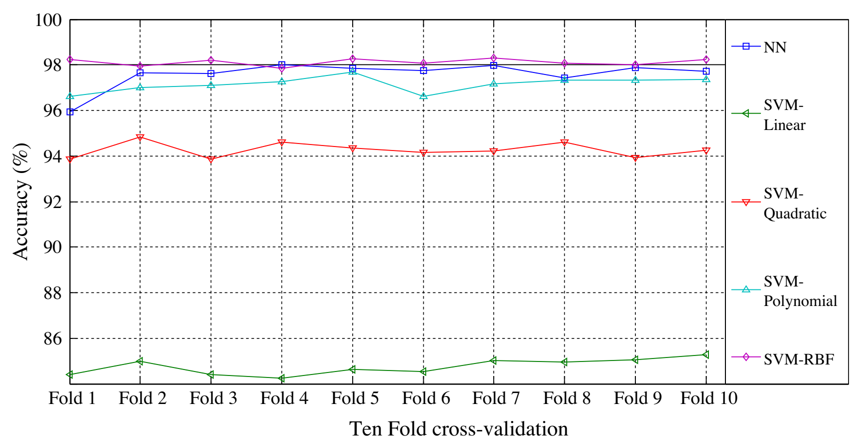

Fig. 4. Plot of average Accuracy (%) versus different folds of ten-fold cross-validation for different classifiers for first methodology.

Table 2
Classification results of different classifiers for the first methodology.

	Average sensitivity (%)	Average specificity (%)	Average PPV (%)	Average accuracy (%)
NN	99.42	99.48	99.79	97.58
LS-SVM with linear kernel	96.03	94.60	97.83	84.75
LS-SVM with quadratic kernel	99.34	97.16	98.90	94.26
LS-SVM with polynomial kernel	99.37	99.43	99.77	97.15
LS-SVM with RBF kernel	99.90	99.10	99.61	98.11

Table 3
Results of feature extraction using PCA on error signals of segmented ECG signal.

Principal component	Normal	RBBB	LBBB	APC	VPC	*p*-value
PC1	-0.0042 ± 0.0779	-0.0529 ± 0.1221	0.0398 ± 0.1312	-0.0251 ± 0.1093	0.0238 ± 0.2653	<0.0001
PC2	0.0005 ± 0.1200	-0.0015 ± 0.1149	0.0011 ± 0.0426	0.0002 ± 0.0992	-0.0004 ± 0.0351	<0.0001
PC3	-0.0042 ± 0.1193	0.0073 ± 0.1139	0.0016 ± 0.0417	0.0027 ± 0.0988	-0.0036 ± 0.0355	<0.0001
PC4	0.0442 ± 0.0648	0.0274 ± 0.0534	-0.0372 ± 0.0659	0.0221 ± 0.0630	-0.0550 ± 0.0823	<0.0001
PC5	-0.0253 ± 0.0616	0.0041 ± 0.0900	0.0035 ± 0.0378	0.0174 ± 0.0606	0.0213 ± 0.0436	<0.0001
PC6	-0.0053 ± 0.0650	0.0091 ± 0.0950	-0.0019 ± 0.0338	0.0028 ± 0.0570	-0.0005 ± 0.0377	<0.0001
PC7	0.0319 ± 0.0489	-0.0125 ± 0.0750	0.0071 ± 0.0370	-0.0211 ± 0.0462	-0.0324 ± 0.0604	<0.0001
PC8	0.0143 ± 0.0457	-0.0253 ± 0.388	0.0039 ± 0.0413	0.0205 ± 0.0345	-0.0055 ± 0.0672	<0.0001
PC9	-0.0029 ± 0.0284	-0.0106 ± 0.0437	0.0199 ± 0.0383	-0.0189 ± 0.0324	-0.0012 ± 0.0803	<0.0001
PC10	0.0071 ± 0.0279	-0.0116 ± 0.0300	-0.0170 ± 0.327	0.0049 ± 0.0213	0.0187 ± 0.0655	<0.0001
PC11	0.0007 ± 0.0329	-0.0334 ± 0.0344	0.0157 ± 0.270	-0.0071 ± 0.0296	0.0178 ± 0.0444	<0.0001
PC12	-0.0105 ± 0.0225	-0.0052 ± 0.0309	0.0168 ± 0.0366	0.0006 ± 0.0208	0.0007 ± 0.0452	<0.0001

ectopic, ventricular ectopic and fusion beats) were classified using mixture of experts approach and reported 94% of accuracy (Hu, Palreddy, & Tompkins, 1997). The Hermite function decomposition coefficients were used for 25 types of arrhythmia beats classification

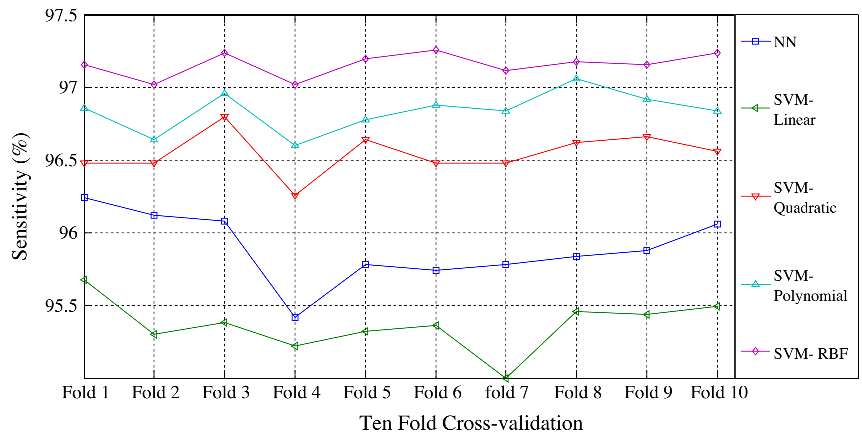

Fig. 5. Plot of average sensitivity (%) versus different folds of ten-fold cross-validation for different classifiers for second methodology.

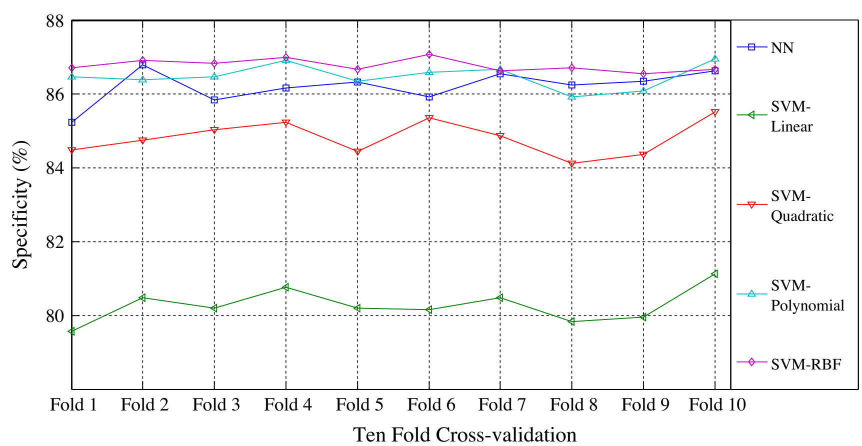

Fig. 6. Plot of average specificity (%) versus different folds of ten-fold cross-validation for different classifiers for second methodology.

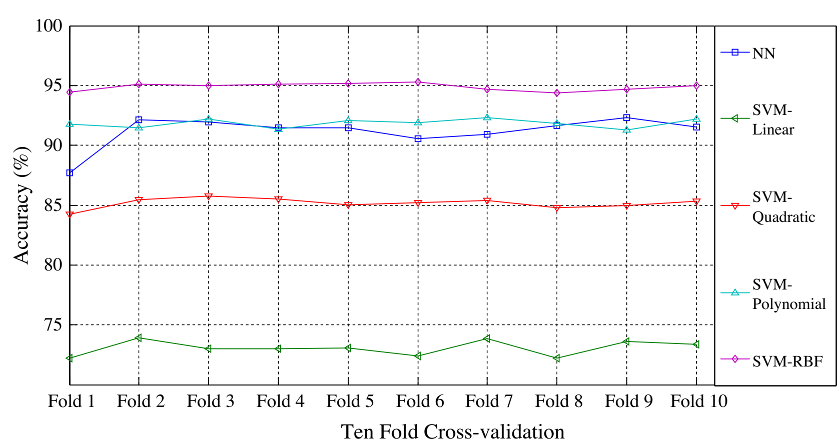

Fig. 7. Plot of average accuracy (%) versus different folds of ten-fold cross-validation for different classifiers for second methodology.

Table 4
Classification results of different classifiers for the second methodology.

Classifier	Average sensitivity (%)	Average specificity (%)	Average PPV (%)	Average accuracy (%)
NN	96.79	95.52	98.18	91.17
LS-SVM with linear kernel	95.73	80.69	92.77	73.07
LS-SVM with quadratic kernel	98.09	92.05	96.90	85.07
LS-SVM with polynomial kernel	98.68	96.22	98.52	91.84
LS-SVM with RBF kernel	99.32	96.96	98.79	94.88

Table 5
Results of feature extraction using PCA on 4th level approximation DWT coefficients of segmented ECG signal.

Principal component	Normal	RBBB	LBBB	APC	VPC	*p*-value
PC1	−0.1084 ± 1.4521	0.9978 ± 2.0138	−1.0774 ± 3.2385	0.6827 ± 1.5583	0.1273 ± 7.1606	<0.0001
PC2	0.4842 ± 1.7987	−0.8436 ± 2.6817	0.0131 ± 2.8544	−0.4392 ± 1.5229	0.2985 ± 4.6616	<0.0001
PC3	−0.0238 ± 1.3439	0.4848 ± 1.6794	−0.1123 ± 2.7581	−0.8111 ± 1.7735	−0.0055 ± 4.1605	<0.0001
PC4	0.9430 ± 0.8274	−1.2522 ± 1.4355	−0.2892 ± 1.8760	0.4528 ± 1.2139	0.1423 ± 3.4903	<0.0001
PC5	−0.6992 ± 1.0582	−1.2956 ± 0.9504	0.6705 ± 1.6225	0.0279 ± 1.2055	1.5272 ± 2.5921	<0.0001
PC6	−0.2774 ± 0.8037	0.2801 ± 1.446	−0.0655 ± 0.8944	0.3299 ± 1.0408	0.0756 ± 2.2820	<0.0001

Table 6
Results of feature extraction using PCA on 4th level Detail DWT coefficients of segmented ECG signal.

Principal component	Normal	RBBB	LBBB	APC	VPC	*p*-value
PC1	0.7688 ± 0.4625	0.7411 ± 0.4647	−0.5311 ± 0.8767	−0.0404 ± 0.7456	−1.2115 ± 1.3111	<0.0001
PC2	0.1941 ± 0.3097	−0.0014 ± 0.5735	−0.1781 ± 0.4432	0.0220 ± 0.2592	−0.0755 ± 0.5460	<0.0001
PC3	−0.2147 ± 0.2341	0.2348 ± 0.2587	0.1405 ± 0.3737	0.2512 ± 0.2347	−0.0061 ± 0.5030	<0.0001
PC4	0.0486 ± 0.1515	0.0291 ± 0.2512	0.0458 ± 0.3065	−0.1210 ± 0.1824	−0.1051 ± 0.5904	<0.0001
PC5	−0.0197 ± 0.2223	−0.1381 ± 0.3165	0.0760 ± 0.2848	−0.0332 ± 0.3167	0.0964 ± 0.4345	<0.0001
PC6	0.0364 ± 0.1608	0.0319 ± 0.2145	−0.0349 ± 0.1960	−0.0265 ± 0.1924	−0.0351 ± 0.4149	<0.0001

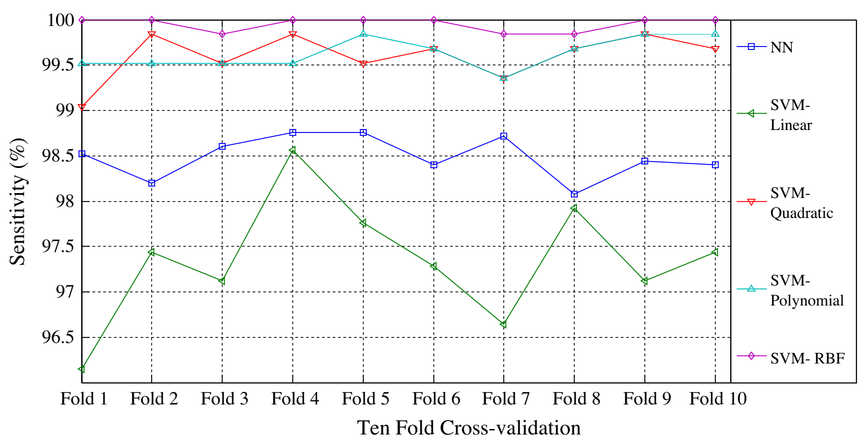

Fig. 8. Plot of sensitivity (%) versus different folds of ten-fold cross-validation for different classifiers for third methodology.

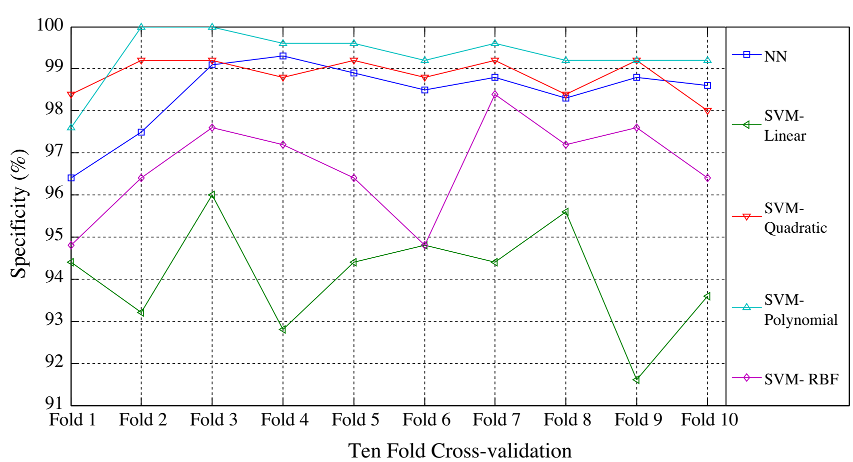

Fig. 9. Plot of specificity (%) versus different folds of ten-fold cross-validation for different classifiers for third methodology.

using Self Organizing Maps (SOM) and achieved 98.51% of accuracy (Lagerholm, Peterson, Braccini, Edenbrandt, & Sornmo, 2000). The Higher Order Spectra Analysis (HOSA) features were used to classify seven types of heart beats using ECG using fuzzy hybrid neural network classifier and achieved 96.06% of accuracy (Osowski & HoaiLinh, 2000). SVEB and VEB beats were classified using a patient adapting heart beat classifier and obtained accuracy of 95.9% and 99.2% respectively. The Hermite transform coefficients and time intervals between two neighboring R-peaks of ECG signals were used as features for block based neural network and classified five

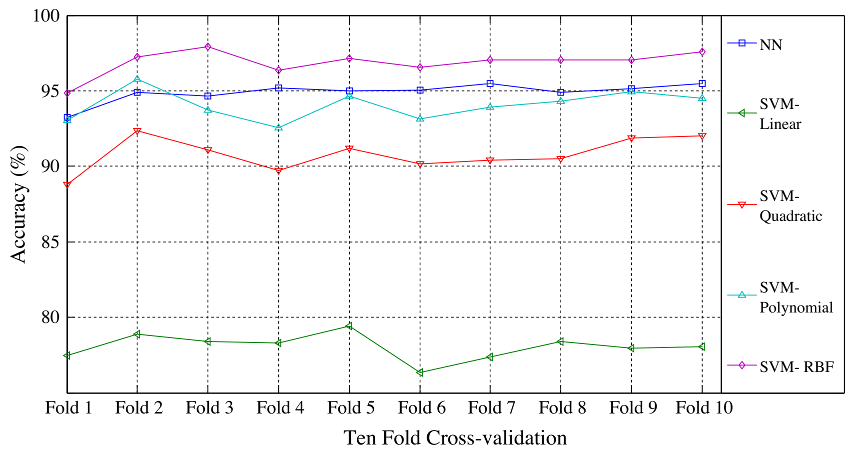

Fig. 10. Plot of accuracy (%) versus different folds of ten-fold cross-validation for different classifiers for third methodology.

Table 7
Classification results of different classifiers for the third methodology.

Classifier	Average sensitivity (%)	Average specificity (%)	Average PPV (%)	Average accuracy (%)
NN	98.49	98.42	99.36	94.90
LS-SVM with linear kernel	97.34	94.08	97.63	78.05
LS-SVM with quadratic kernel	99.60	98.84	99.54	90.81
LS-SVM with polynomial kernel	99.63	99.32	99.73	94.06
LS-SVM with RBF kernel	99.95	96.68	98.69	96.88

Table 8
Summary of the studies on the automated identification of ECG beats obtained using MIT-BIH database.

Literature	Features	Classifier	Classes	Accuracy in (%)
(Hu et al., 1997)	Time domain features	Mixture of experts	2	94.0
(Lagerholm et al., 2000)	Hermite functions	Self organizing map	25	98.51*
(Osowski & Linh, 2000)	HOSA	Hybrid fuzzy NN	7	96.06
(de Chazal et al., 2006)	Morphology and heartbeat interval	Linear discriminant	5	85.9
(Jiang & Seong, 2007)	Hermite function parameters and RR interval	Block based NN	5	96.6
(Inan et al., 2006)	WT and timing interval	Neural network	2	95.2
(Ince et al., 2009)	WT + PCA	Multidimensional particle swarm optimization	5	95.58*
(Sayadi et al., 2010)	Innovation sequence of EKF	Bayesian filtering	2	99.1
Proposed methodology	ECG + PCA	LS-SVM	5	98.11

* Accuracy is computed based on the confusion matrix provided in the paper.

types of ECG beats (Jiang & Seong, 2007). The multiscale wavelet and timing information features were classified into three classes (Normal, VPC and other classes of betas) with accuracy of 95.16% (Inan, Giovangrandi, & Kovacs, 2006). Morphological wavelet transform and temporal features were used to classify five beat types of Association for Advancement of Medical Instrumentation (AAMI) recommended practice and achieved 98.3% and 97.4% accuracy for detection of VEB and SVEB respectively (Ince, Kiranyaz, & Gabbouj, 2009). The ECG signal was modeled as finite characteristic waveforms, and classified into two types of beats in arrhythmia (Normal, VPC and other possible beats) using Bayesian filtering and achieved 99.1% of accuracy (Sayadi, Shamsollahi, & Clifford, 2010).

In this work, we have compared the performance of three approaches: (i) principal components of segmented time domain ECG beats, (ii) the principal components of error signals of linear prediction model of ECG beats and (iii) the principal components of discrete wavelet transform sub bands. The first method performance yielded an highest average classification accuracy of 98.11%, average sensitivity and specificity of 99.90% and 99.10% respectively compared to the other two methods.

Other dimensionality reduction techniques such as Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), Gram-Schmidt orthogonalization procedure etc. can be used instead of PCA during feature extraction. The best subspace providing highest discrimination among the features of different classes can be identified. The performance of classification can be improved and compared using diverse features and other classification strategies.

7. Conclusion

ECG signal can be used as a reliable indicator of heart diseases. In this work, PCA analysis is effectively used as a non-invasive tool for the classification of five types of cardiac classes. In this study, we have compared the performances of three methodologies. The first method uses principal components of segmented ECG beats, the second method uses principal components of error signals of linear prediction model, and the last approach uses principal components of DWT coefficients as features. The first approach principal components of segmented ECG yielded an highest average accuracy of 98.11%, sensitivity and specificity of 99.90% and

99.10% respectively. The proposed methodology has provided improved results and can be used in practical arrhythmia monitoring systems. Our proposed methodology has immense applications in electronic cardiac pacemakers, remote patient monitoring and in intensive care units.

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