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ECG beats classification using multiclass support vector machines with error correcting output codes

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Abstract

A new approach based on the implementation of multiclass support vector machine (SVM) with the error correcting output codes (ECOC) is presented for classification of electrocardiogram (ECG) beats. Four types of ECG beats (normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat) obtained from the Physiobank database were analyzed. The ECG signals were decomposed into time–frequency representations using discrete wavelet transform (DWT) and wavelet coefficients were calculated to represent the signals. The aim of the study is the classification of ECG beats by the combination of wavelet coefficients and multiclass SVM. The purpose is to determine an optimum classification scheme for this problem and also to infer clues about the extracted features. The present research demonstrated that the wavelet coefficients are the features which well represent the ECG signals and the multiclass SVM trained on these features achieved high classification accuracies.

Keywords: Multiclass support vector machine (SVM); Wavelet coefficients; Electrocardiogram (ECG) beats

1. Introduction

Electrocardiography is an important tool in diagnosing the condition of the heart. The electrocardiogram (ECG) is the record of variation of bioelectric potential with respect to time as the human heart beats. It provides valuable information about the functional aspects of the heart and cardiovascular system. Early detection of heart diseases/abnormalities can prolong life and enhance the quality of living through appropriate treatment. Therefore, numerous research and work analyzing the ECG signals have been reported [1–5]. The state of cardiac health is generally reflected in the shape of ECG waveform and heart rate. It may contain important pointers to the nature of diseases afflicting the heart. Since the biosignals are nonstationary signals, this reflection may occur at random in the time scale. In this situation, the disease symptoms may not show up all the time, but would manifest at certain irregular intervals during the day. Therefore, for effective diagnostics, the study of ECG pattern and heart rate variability signal may have to be carried out over several hours. Thus, the volume of the data being enormous, the study is tedious and time consuming. Naturally, the possibility of the analyst missing (or misreading) vital information is high. Therefore, computer-based analysis and classification of diseases can be very helpful in diagnostics [1–5].

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Various methodologies of automated diagnosis have been adopted, however the entire process can generally be subdivided into a number of disjoint processing modules: beat detection, feature extraction/selection, and classification. The initial pre-processing module of beat detection aims to locate each cardiac cycle in each of the recording leads and insert reference markers indicating the beginning and end of each interwave component. The algorithm is designed with two main objectives: firstly, the detector should provide reliable detection of each cardiac cycle in all recording leads and secondly, the temporal location of the reference points should be described accurately. The accuracy of detection of each cardiac cycle is of great importance since it contributes significantly to the overall classification result. The markers are subsequently processed by the feature extraction module, where measurements are produced for wave amplitudes and durations. The collective term for the measurements produced is commonly referred to as the input feature vector, which is considered to describe the morphology of the current recorded signal. The module of feature selection is an optional stage, whereby the feature vector is reduced in size including only, from the classification viewpoint, what may be considered as the most relevant features required for discrimination. The classification module is the final stage in automated diagnosis. It examines the input feature vector and based on its algorithmic nature, produces a suggestive hypothesis [6,7].

The wavelet transform (WT) can be applied to extract the wavelet coefficients of discrete time signals. This procedure makes use of multirate signal processing techniques. The proposed scheme is the subband coding or multiresolution signal analysis [8,9]. The multiresolution feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The WT provides very general techniques which can be applied to many tasks in signal processing. One very important application is the ability to compute and manipulate data in compressed parameters which are often called features [10–13]. Thus, the ECG signal, consisting of many data points, can be compressed into a few parameters. These parameters characterize the behavior of the ECG signal. This feature of using a smaller number of parameters to represent the ECG signal is particularly important for recognition and diagnostic purposes [1,4,5].

There are numerous methods to represent patterns as a grouping of features. The choice of methods appropriate for a given pattern analysis task is rarely obvious. At each level (feature extraction, feature selection, classification) many methods exist [6,7]. In order to discriminate the ECG signals obtained from the Physiobank database [14], multiclass support vector machine (SVM) with the error correcting output codes (ECOC) combined with wavelet preprocessing was implemented (Fig. 1). A significant contribution of the present work was to examine the multiclass SVM with the ECOC on the ECG signals classification. The ability of WT to extract and localize specific transient patterns from the signal makes them a natural complement to the applications of the SVM. Each studied segment of the signals under study was wavelet decomposed into multi-level low- and high-pass subbands, which were then input into the SVM for training and testing purposes. High accuracies were achieved by using the multiclass SVM trained on the wavelet coefficients.

The outline of this study is as follows. In Section 2, the feature extraction by discrete wavelet transform (DWT) is explained. In Section 3, brief review of the multiclass SVM with the ECOC is presented. In Section 4, the results of application of the SVM trained on wavelet coefficients to the studied ECG signals are presented. Discussion of the presented results is performed in the light of existing studies in the literature. Finally, in Section 5, the drawn conclusions are emphasized.

2. Spectral analysis using discrete wavelet transform

The ECG signals are considered as representative signals of cardiac physiology, useful in diagnosing cardiac disorders. The most complete way to display this information is to perform spectral analysis. The ECG signal, consisting of many data points, can be compressed into a few parameters by the WT. These parameters characterize the behavior of the ECG signal and they can be used for recognition and diagnostic purposes. The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study. The concept of being able to decompose a signal totally and then perfectly reconstruct the signal again is practical, but it is not particularly useful by itself. In order to make use of this tool it is necessary to manipulate the wavelet coefficients to identify characteristics of the signal that were not apparent from the original time domain signal [8].

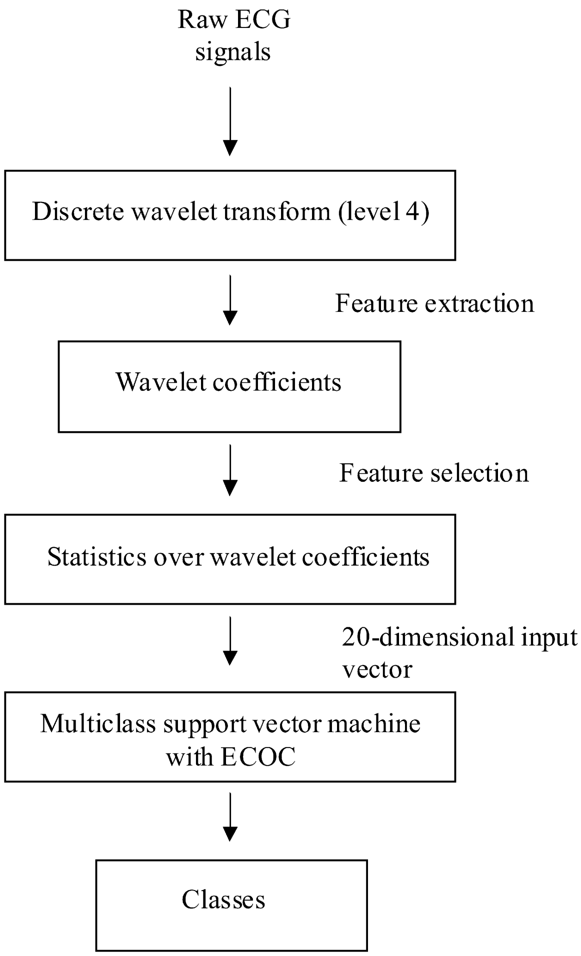

Fig. 1. General structure of the multiclass SVM classifier.

The WT is designed to address the problem of nonstationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis. The WT can be categorized into continuous and discrete. Continuous, in the context of the WT, implies that the scaling and translation parameters change continuously. However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore, DWT is often used [7–13].

3. Support vector machine

The SVM proposed by Vapnik [15] has been studied extensively for classification, regression and density estimation. SVM maps the input patterns into a higher dimensional feature space through some nonlinear mapping chosen a priori. A linear decision surface is then constructed in this high dimensional feature space. Thus, SVM is a linear classifier in the parameter space, but it becomes a nonlinear classifier as a result of the nonlinear mapping of the space of the input patterns into the high dimensional feature space. Training the SVM is a quadratic optimization problem. The construction of a hyperplane $\mathbf{w}^T\mathbf{x} + b = 0$ ($\mathbf{w}$ is the vector of hyperplane coefficients, b is a bias term) so that the margin between the hyperplane and the nearest point is maximized and can be posed as the quadratic optimization problem. SVM has been shown to provide high generalization ability. A proper kernel function for a certain problem is dependent on the specific data and till now there is no good method on how to choose a kernel function [15,16]. In this study, the choice of the kernel functions was studied empirically and optimal results were achieved using radial basis function (RBF) kernel function.

The SVM is a binary classifier which can be extended by fusing several of its kind into a multiclass classifier. In this study, SVM decisions were fused using the ECOC approach, adopted from the digital communication theory [17]. In the ECOC approach, up to $2^{n-1} - 1$ (where n is the number of classes) SVMs are trained, each of them aimed at separating a different combination of classes. For 3 classes (A, B, and C) 3 classifiers are necessary; one SVM classifies A from B and C, a second SVM classifies B from A and C and a third SVM classifies C from A and B. The multiclass classifier output code for a pattern is a combination of targets of all the separate SVMs. That is in the example, vectors from classes A, B, and C have codes $(1, -1, -1)$, $(-1, 1, -1)$, and $(-1, -1, 1)$, respectively. If each of the separate SVMs classifies a pattern correctly, the multiclass classifier target code is met and the ECOC approach reports no error for that pattern. However, if at least one of the SVMs misclassifies the pattern, the class selected for this pattern is the one its target code closest in the Hamming distance sense to the actual output code and this may be an erroneous decision.

4. Results and discussion

4.1. Computing feature vectors using discrete wavelet transform

The WT is better suited to analyzing nonstationary signals, since it is well localized in time and frequency. The property of time and frequency localization is known as compact support and is one of the most attractive features of the WT. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time–frequency resolution in all frequency ranges. Therefore, spectral analysis of the ECG signals was performed using the DWT.

Selection of appropriate wavelet and the number of decomposition levels is very important in analysis of signals using the WT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In order to determine the appropriate number of decomposition levels, different experiments were performed. In the present study, the number of decomposition levels was chosen to be 4 as it was determined in the previous study [5]. Thus, the ECG signals were decomposed into the details $D_1 - D_4$ and one final approximation, A_4. Usually, tests are performed with different types of wavelets and the one which gives maximum efficiency is selected for the particular application. The smoothing feature of the Daubechies wavelet of order 2 (db2) made it more suitable to detect changes of the ECG signals. Therefore, the wavelet coefficients were computed using the db2 in the present study. The wavelet coefficients were computed using the MATLAB software package.

In order to investigate the effect of other wavelets on classifications accuracy, tests were carried out using other wavelets also. Apart from db2, Symmlet of order 10 (sym10), Coiflet of order 4 (coif4), Daubechies of order 1 (db1) and Daubechies of order 6 (db6) were also tried. Total classification accuracy obtained for each wavelet when the ECG signals classified using the SVMs is presented in Table 1. It was seen that the Daubechies wavelet offers better accuracy than the others, and db2 is marginally better than db1 and db6.

The detail wavelet coefficients at the first decomposition level of the four types of ECG beats (normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat) are given in Figs. 2a–2d, respectively. The computed discrete wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency. Therefore, the computed detail and approximation wavelet coefficients of the ECG

Table 1
Total classification accuracy obtained for each wavelet when the ECG signals were classified using the SVMs

Wavelet type	Total classification accuracy (%)
Symmlet of order 10 (sym10)	96.94
Coiflet of order 4 (coif4)	97.22
Daubechies of order 6 (db6)	97.78
Daubechies of order 1 (db1)	98.06
Daubechies of order 2 (db2)	98.61

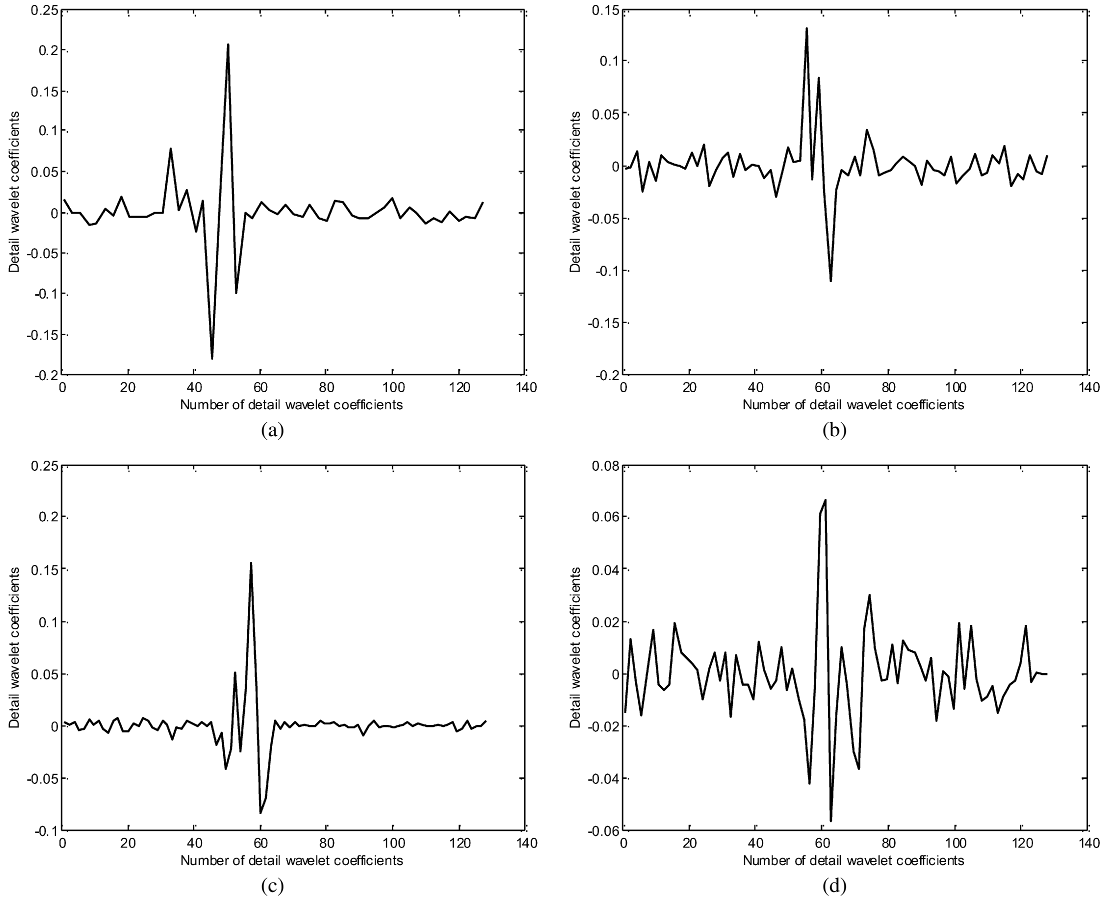

Fig. 2. The detail wavelet coefficients at the first decomposition level of the ECG beats: (a) normal beat, (b) congestive heart failure beat, (c) ventricular tachyarrhythmia beat, (d) atrial fibrillation beat.

signals were used as the feature vectors representing the signals. A rectangular window, which was formed by 256 discrete data, was selected so that it contained a single ECG beat. During ECG beat detection process, the best samples (256 discrete data) representing the class of the ECG records were chosen. For each ECG beat, the detail wavelet coefficients (d^k, $k = 1, 2, 3, 4$) at the first, second, third and fourth levels ($129 + 66 + 34 + 18$ coefficients) and the approximation wavelet coefficients (a^4) at the fourth level (18 coefficients) were computed. Then 265 wavelet coefficients were obtained for each ECG beat. High dimension of feature vectors increased computational complexity and therefore, in order to reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients were used. The following statistical features were used to represent the time–frequency distribution of the ECG signals:

1. Maximum of the wavelet coefficients in each subband.
2. Mean of the wavelet coefficients in each subband.
3. Minimum of the wavelet coefficients in each subband.
4. Standard deviation of the wavelet coefficients in each subband.

These feature vectors were calculated for each subbands and Table 2 presents the extracted features of four exemplary records from four classes.

Two different experiments with different feature vectors were performed. The test sets were created in the same way as the training set as described in the experiments and they were formed from the ECG signals that were not used for training. In the first experiment, 265 wavelet coefficients for each class were used as feature vectors (inputs

Table 2
The extracted features of four exemplary records from four classes

ECG beat types	Extracted features	Wavelet coefficients				
		Subbands				
		D_1	D_2	D_3	D_4	A_4
Normal beat	Maximum	0.2062	1.5757	0.2792	0.9683	0.5843
	Mean	−0.0003	0.0429	−0.0269	0.1097	−0.0941
	Minimum	−0.1814	−0.3593	−0.3977	−0.3625	−0.5159
	Standard deviation	0.0436	0.3174	0.1546	0.3707	0.3116
Congestive heart failure beat	Maximum	0.1316	0.2344	1.3364	1.3463	1.1550
	Mean	−0.0003	−0.0066	−0.0056	−0.0248	−0.3698
	Minimum	−0.1119	−0.1635	−1.0327	−1.9773	−1.2350
	Standard deviation	0.0259	0.0604	0.3995	0.7862	0.4014
Ventricular tachyarrhythmia beat	Maximum	0.1568	0.4554	2.1134	2.5063	4.1980
	Mean	−0.0001	0.0002	0.0344	0.0838	0.9075
	Minimum	−0.0839	−0.3181	−0.8983	−1.4226	−0.5930
	Standard deviation	0.0232	0.0919	0.4845	0.8299	1.1458
Atrial fibrillation beat	Maximum	0.0665	0.4417	0.3574	1.3044	−0.9396
	Mean	−0.0002	0.0037	−0.0058	0.0774	−1.5942
	Minimum	−0.0564	−0.1832	−0.3312	−0.3328	−2.0488
	Standard deviation	0.0173	0.0849	0.1238	0.4051	0.2892

Table 3
The total classification accuracies obtained from various experiments related with the sizes of the training and testing sets of the ECG signals

Number of training vectors	Number of testing vectors	Total classification accuracy (%)
240	480	96.25
250	470	95.96
255	465	95.91
260	460	96.74
290	430	95.35
300	420	95.24
330	390	96.92
340	380	97.11
350	370	97.84
360	360	98.61

of the SVMs). In the second experiment, statistical features (maximum, mean, minimum and standard deviation of the wavelet coefficients in each subband) were used as feature vectors. The results presented in Section 4.3 showed that reducing the dimension of the feature vectors and representing the signals by the selected features significantly increase the classification accuracies.

4.2. Experiments for implementation of SVM

The key design decisions for the neural networks used in classification are the architecture and the training process. The proposed SVM was implemented by using the MATLAB software package (MATLAB version 7.0 with neural networks toolbox). The adequate functioning of neural networks depends on the sizes of the training set and test set. Various experiments were performed for determining the sizes of the training and testing sets of the ECG signals. The total classification accuracies obtained from these experiments are presented in Table 3. In the developed SVM, training and test sets were formed by 720 vectors (180 vectors belonging to 180 subjects records from each class) of 20 dimensions (dimension of the extracted feature vectors). The training and testing have been formed by 360 vectors (90 vectors from each class of 20 dimensions) each. The term vector is used for defining the extracted features of the samples of an ECG beat.

The generalization ability of the SVM is controlled by two different factors: the training error rate and the capacity of the learning machine measured by its Vapnik–Chervonenkis (VC) dimension [15]. The smaller the VC dimension

Table 4
Confusion matrices of the classifiers used for classification of the ECG beats

Classifiers	Desired result	Output result			
		Normal beat	Congestive heart failure beat	Ventricular tachyarrhythmia beat	Atrial fibrillation beat
SVM	Normal beat	89	1	1	0
	Congestive heart failure beat	0	89	1	0
	Ventricular tachyarrhythmia beat	1	0	88	1
	Atrial fibrillation beat	0	0	0	89
MLPNN	Normal beat	82	5	1	0
	Congestive heart failure beat	6	83	6	4
	Ventricular tachyarrhythmia beat	2	2	81	3
	Atrial fibrillation beat	0	0	2	83

of the function set of the learning machine, the larger the value of training error rate. The tradeoff between the complexity of decision rule and training error rate can be controlled by changing a parameter C [16] in the SVM. In order to have the best result, the SVMs were trained for different C values. The best result was obtained for $C = 80$ in the testing procedure. Moreover, when $C = 80$, the number of support vectors in the SVMs training was found. Training algorithm of the SVM, based on quadratic programming, incorporates several optimization techniques such as decomposition and caching. The quadratic programming problem in the SVM was solved by using the MATLAB optimization toolbox. For the implementation of the SVMs with the RBF kernel functions, one has to assume a value for σ. The optimal σ can only be found by systematically varying its value in the different training sessions. To do this, the support vectors were extracted from the training data file with an assumed σ value. After the support vectors have been found and SVM constructed, the model was applied to $1/3$ of the training data set to compute the misclassification rate. The σ value was varied between 0.1 and 0.6, at interval of 0.1. The $\sigma = 0.4$ resulted in the minimum misclassification rate was thus chosen.

In order to compare performance of the different classifiers, for the same classification problem the multilayer perceptron neural network (MLPNN), which is the most commonly used feedforward neural networks, was implemented. The single hidden layered (20 hidden neurons) MLPNN was used to classify the ECG beats based on a feature vector (20 inputs). Different experiments were performed during implementation of these classifiers and the number of hidden neurons was determined by taking into consideration the classification accuracies. In the hidden layers and the output layers, the activation function was the sigmoidal function. The MLPNN was trained by the Levenberg–Marquardt algorithm. The sigmoidal function with the range between zero and one introduces two important properties. First, the sigmoid is nonlinear, allowing the network to perform complex mappings of input to output vector spaces, and secondly it is continuous and differentiable, which allows the gradient of the error to be used in updating the weights.

4.3. Classification errors of classifiers and receiver operating characteristic (ROC) analysis

The total classification accuracy of the SVM obtained in the first experiment (265 wavelet coefficients were used as inputs of the SVM) was 95.56%. This accuracy was extremely low. Since encouraging results were obtained from the second experiment (statistical features were used as inputs of the SVM), the results obtained from the second experiment were presented in details. Classification results of the classifiers were displayed by a confusion matrix. In a confusion matrix, each cell contains the raw number of exemplars classified for the corresponding combination of desired and actual network outputs. The confusion matrices showing the classification results of the classifiers used for classification of the ECG beats are given in Table 4. From these matrices one can tell the frequency with which a ECG beat is misclassified as another.

The test performance of the classifiers can be determined by the computation of sensitivity, specificity and total classification accuracy. The sensitivity, specificity and total classification accuracy are defined as:

Sensitivity: number of true positive decisions/number of actually positive cases.
Specificity: number of true negative decisions/number of actually negative cases.
Total classification accuracy: number of correct decisions/total number of cases.

Table 5
The values of statistical parameters and the CPU times of training of the classifiers

Classifiers	ECG beats	Statistical parameters			CPU time (min s)
		Sensitivity (%)	Specificity (%)	Total classification accuracy (%)	
SVM	Normal beat	98.89	99.25	98.61	7.24
	Congestive heart failure beat	98.89	99.63		
	Ventricular tachyarrhythmia beat	97.78	99.26		
	Atrial fibrillation beat	98.89	100.00		
MLPNN	Normal beat	91.11	97.63	91.39	15.32
	Congestive heart failure beat	92.22	93.89		
	Ventricular tachyarrhythmia beat	90.00	97.25		
	Atrial fibrillation beat	92.22	99.19		

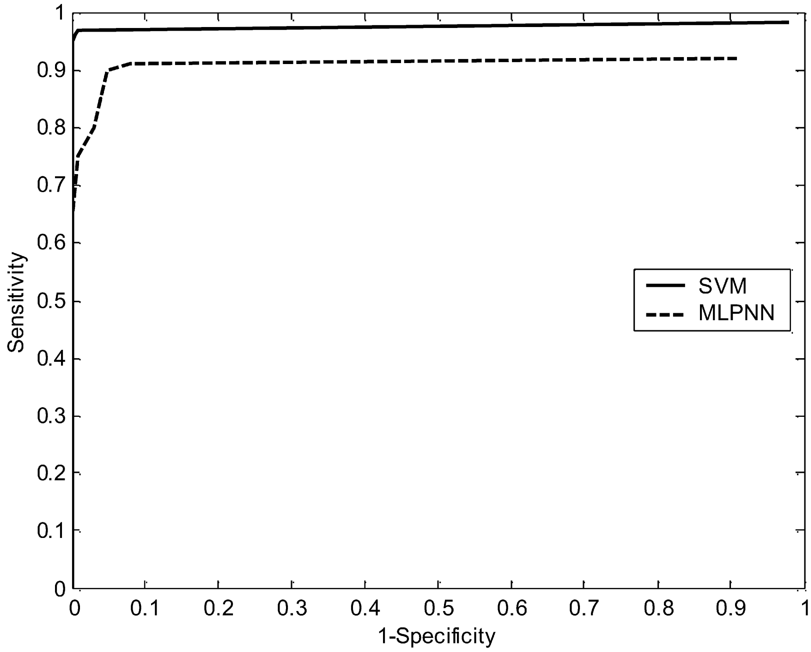

Fig. 3. ROC curves of the classifiers.

In order to determine the performance of the SVM used for classification of the ECG signals, the classification accuracies (specificity, sensitivity, total classification accuracy) and the central processing unit (CPU) times of training (for Pentium 4, 3.00 GHz) of the classifiers on the test sets are presented in Table 5. Receiver operating characteristic (ROC) plots provide a view of the whole spectrum of sensitivities and specificities because all possible sensitivity/specificity pairs for a particular test are graphed. The performance of a test can be evaluated by plotting a ROC curve for the test and therefore, ROC curves were used to describe the performance of the classifiers. A good test is one for which sensitivity rises rapidly and 1-specificity hardly increases at all until sensitivity becomes high. ROC curves which are shown in Fig. 3 demonstrate the performances of the classifiers on the test files. From the classification results presented in Table 5 and Fig. 3 (classification accuracies, ROC curves), one can see that the SVM trained on the extracted feature vectors produce considerably better performance (classification accuracies, CPU times of training, ROC curves) than that of the MLPNN.

4.4. Discussion

Based on the results of the present study and experience in the time-varying biomedical signals classification problems, the followings can be emphasized. Preprocessing and feature extraction methods are important in developing automated diagnostic systems since these stages could change the classification accuracy. In the recent years, the studies related with spectral analysis and automated classification of the ECG signals have demonstrated that the wavelet based analysis give better results than the conventional fast Fourier transform (FFT) based and model based methods [1,4,5]. The high classification accuracy of the multiclass SVM gives insights into the features used for defining the ECG signals. The conclusions drawn in the applications demonstrated that the wavelet coefficients are the features which well represent the ECG signals and by the usage of these features a good distinction between classes can be obtained.

During SVM training, most of the computational effort is spent on solving the quadratic programming problem in order to find the support vectors. The SVM maps the features to higher dimensional space and then uses an optimal hyperplane in the mapped space. This implies that though the original features carry adequate information for good classification, mapping to a higher dimensional feature space could potentially provide better discriminatory clues that are not present in the original feature space. The selection of suitable kernel function appears to be a trial-and-error process. One would not know the suitability of a kernel function and performance of the SVM until one has tried and tested with representative data. For training the SVMs with RBF kernel functions, one has to predetermine the σ values. The optimal or near optimal σ values can only be ascertained after trying out several, or even many values. Beside this, the choice of C parameter in the SVM is very critical in order to have a properly trained SVM. The SVM has to be trained for different C values until to have the best result.

Güler and Übeyli [5] implemented the combined neural network (CNN) trained, cross validated and tested with the extracted features using DWT of the ECG signals. Four types of ECG beats (normal beat, congestive heart failure beat, ventricular tachyarrhythmia beat, atrial fibrillation beat) obtained from the Physiobank database [14] were classified with the accuracy of 96.94% by the CNN. The multiclass SVM used in the present study to classify the ECG signals indicated higher performance than that of the CNN [5].

Osowski et al. [18] presented the application of SVM for reliable heartbeat recognition on the basis of the ECG waveform. The authors used the ECG data from the MIT-BIH arrhythmia database corresponding to the normal sinus rhythm and 12 types of arrhythmias. They applied two different preprocessing methods for generation of features. One method involved the higher order statistics (HOS) while the second the Hermite characterization of QRS complex of the registered ECG waveform. The SVM had the same number of inputs and one output. In learning multiclass recognition problem, they applied the one-against-one strategy leading to many network structures adapted for the recognition between two classes at one time. The classification accuracy of their model was 95.77% for Hermite preprocessing and 94.26% for HOS preprocessing. The multiclass SVM used in the present study to classify the ECG signals indicated higher performance than that of the SVM presented by Osowski et al. [18]. However, the authors [18] classified more than 4 classes (number of classes considered in the present study) and this may decrease the classification accuracy.

Acır [19] used six fast least square support vector machines (LSSVMs) for classification of six types of ECG beats (normal beat, left bundle branch block beat, congestive heart failure beat, premature ventricular contraction beat, non-conducted P-wave, ventricular escape beat) obtained from the MIT-BIH database. The classification accuracy was 95.2% by the proposed fast LSSVMs together with discrete cosine transform. The results of the present study indicated that the usage of multiclass SVM with the ECOC significantly improve the classification accuracy of ECG beats.

5. Conclusion

The purpose of the research was to investigate the accuracy of multiclass SVM with the ECOC trained on the wavelet coefficients for classification of the ECG signals. The multiclass SVM showed a great performance since it maps the features to a higher dimensional space. This may be attributed to several factors including the training algorithms, estimation of the network parameters and the scattered and mixed nature of the features. The results of the present study demonstrated that the multiclass SVM can be used in classification of the ECG signals by taking into consideration the misclassification rates.

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