Support Vector Machine Based Arrhythmia Classification Using Reduced Features

Mi Hye Song, Jeon Lee, Sung Pil Cho, Kyoung Joung Lee, and Sun Kook Yoo

Abstract: In this paper, we proposed an algorithm for arrhythmia classification, which is associated with the reduction of feature dimensions by linear discriminant analysis (LDA) and a support vector machine (SVM) based classifier. Seventeen original input features were extracted from preprocessed signals by wavelet transform, and attempts were then made to reduce these to 4 features, the linear combination of original features, by LDA. The performance of the SVM classifier with reduced features by LDA showed higher than with that by principal component analysis (PCA) and even with original features. For a cross-validation procedure, this SVM classifier was compared with Multilayer Perceptrons (MLP) and Fuzzy Inference System (FIS) classifiers. When all classifiers used the same reduced features, the overall performance of the SVM classifier was comprehensively superior to all others. Especially, the accuracy of discrimination of normal sinus rhythm (NSR), arterial premature contraction (APC), supraventricular tachycardia (SVT), premature ventricular contraction (PVC), ventricular tachycardia (VT) and ventricular fibrillation (VF) were 99.307%, 99.274%, 99.854%, 98.344%, 99.441% and 99.883%, respectively. And, even with smaller learning data, the SVM classifier offered better performance than the MLP classifier.

Keywords: Arrhythmia classification, linear discriminant analysis, reduction of feature dimension, support vector machine, wavelet transform.

1. INTRODUCTION

The electrocardiogram (ECG) remains the simplest non-invasive diagnostic method for determining various heart diseases. Physicians interpret the morphology of the ECG waveform and decide whether the heartbeat belongs to the normal sinus rhythm or to the class of arrhythmia.

Computerized electrocardiography is currently a well-established practice, supporting human diagnosis. Many algorithms have been proposed over previous years for developing the automated systems to accurately classify the electrocardiographic signals in real-time [1-6]. Depending on the type used for the applied method of signal processing techniques and their formal description, we distinguish statistical, syntactic, or artificial intelligent methods [7].

Presently, artificial neural networks have particularly attracted attentions in the area of data processing. Many different neural solutions have been proposed [1-4]. The best known include the multilayer perceptron, the Kohonen self-organizing network, the fuzzy or neuro-fuzzy systems, and the combination of different neural networks within a hybrid system. Even though neural network is recognized as a powerful and promising technique for arrhythmia discrimination, it needs, however, to be learned with much data and has structural complexity. And, even though one of its competing systems, known as the fuzzy inference system, demands just simple computation without learning task, it requires the performance of repetitive experiments with the subjective opinion of specialists for setting membership functions.

In this paper, we proposed an algorithm for arrhythmia classification, which is associated with reduction of feature dimensions by linear discriminant analysis (LDA) and a support vector machine (SVM) based classifier. Since a SVM is known to have the advantage of offering solid performance of

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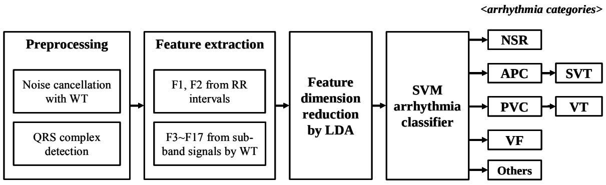


Fig. 1. Block diagram of proposed arrhythmia classifier.

classification with even smaller learning data, we can expect that the proposed algorithm, with relatively small learning data, would demonstrate better performance than other classifiers and be implemented faster on account of the reduction of feature dimensions. For a cross-validation procedure, this algorithm was compared with multilayer perceptrons (MLP) and fuzzy inference system (FIS) classifiers.

2. METHODS AND MATERIALS

2.1. Overview

The proposed algorithm includes preprocessing, feature extraction and feature dimension reduction by LDA and SVM based arrhythmia classification. Fig. 1 shows a block diagram of the proposed algorithm.

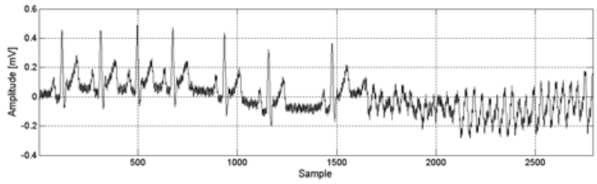
In this paper, the following arrhythmia categories have been considered: normal sinus rhythm (NSR), supraventricular tachycardia (SVT), arterial premature contraction (APC), ventricular tachycardia (VT), premature ventricular contraction (PVC) and ventricular fibrillation (VF).

For collecting arrhythmia data, we have used the ECG data from the MIT/BIH Arrhythmia Database digitized at a sampling rate of 360Hz. In addition, with the lack of VF data, Creighton University Ventricular Tachyarrhythmia Database and MIT-BIH Malignant Ventricular Arrhythmia Database, which had been sampled at 250 Hz, were resampled at 360 Hz and then used for VF.

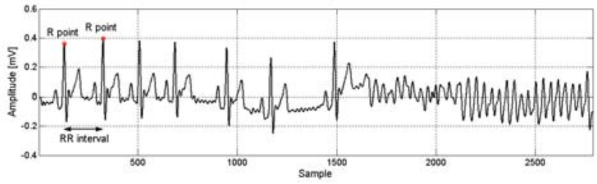
The SVM classifier is the combination of NSR, APC, PVC, VF and other arrhythmia classifiers. The classification results of different classifiers form one output vector and the position of the highest value element of output vector indicates the membership with the appropriate class. Owing to the similar characteristics of the features of APC and SVT, their outputs of SVM are hardly distinguished. Opposed to APC, SVT is, however, inclined to occur in series. PVC and VT have much the same relationship. So, if output vector of said APC beat or PVC beat occurred more than three times consecutively, they were classified into SVT or VT respectively. Consequently, six types of arrhythmia were made to be classified by the proposed algorithm.

2.2. Preprocessing

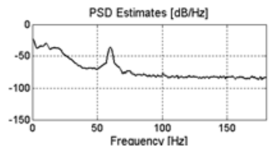
Preprocessing is divided into noise cancellation,

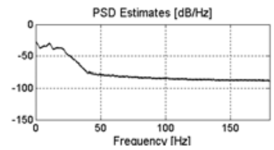


(a) Raw ECG signal.



(b) Filtered ECG signal with WT.





(c) PSD of (a). (d) PSD of (b).

Fig. 2. An example of raw ECG signal and filtered ECG signal.

QRS complex detection and beat segmentation for feature extraction and it cares about ECG signals sampled at 360 Hz. The wavelet transform (WT) has been verified as a good tool for preprocessing and QRS complex detection [8]. For the orthogonal wavelet transform, a discrete signal x(n) can be expanded into the scaling function at j level as follows;

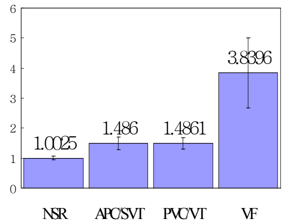
$$x(n) = D_j[x(n)] + A_j[x(n)], \tag{1}$$

where $D_j[x(n)]$ represents the detail signal at j level and $A_j[x(n)]$ represents the approximate signal at j level. Here, j level signifies the decomposition at scale 2j. For noise cancellation such as baseline wander, 60 Hz interference and other high frequency noises, a filtered signal x_f (n) is designed as

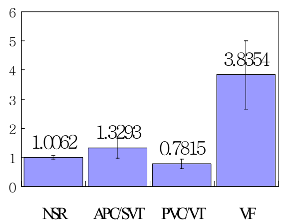
$$x_f(n) = A_2[x(n)] \text{-} A_8[x(n)]. \tag{2}$$

The corresponding bandwidth of the filtered signal is 0.7Hz to 45Hz for 360 Hz sampling rate. In Fig. 2, an example of raw ECG signal and filtered ECG signal are presented and cancellation of unnecessary high and low frequency noises can be found in time domain (Fig. 2(b)) and in frequency domain (Fig. 2(d)).

For the detection of the QRS complex, the wavelet transform based method, proposed by Park et al. [9], was used. For the filtered signal x_f (n), the beat segment was defined to begin at 200 msec (= 72



(a) Feature 1.



(b) Feature 2.

Fig. 3. The mean and variance of feature 1 and feature 2 for arrhythmia beats of 10 records from MIT/BIH arrhythmia database.

sample points) before R peak and to end at 200 msec after R peak so that it could have a total length of 400 msec. All considered features were extracted from this beat segment.

2.3. Feature extraction

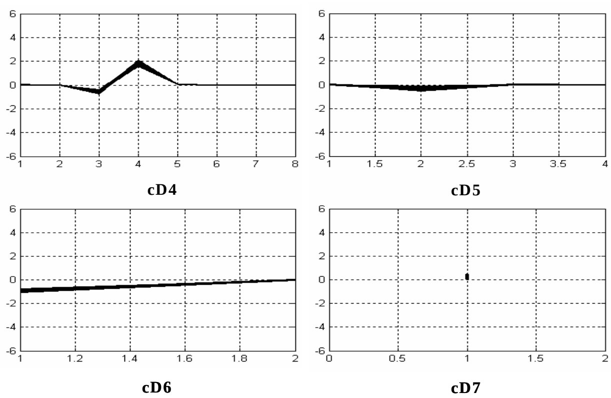
The arrhythmias classification by neural network classifier requires generation of the input vectors. Since a physician classifies arrhythmia with the information of rhythm and morphology, an input vector should include features that represent the rhythm and morphology properly. Therefore, in this paper, the input vector fed to the classifier was determined to be composed of 2 features related to rhythm, and 15 features related to morphology. If we define that R(i) is the RR interval between present and just previous R peaks – an example is shown in Fig. 2(b), and K is a constant that corresponds to an RR interval that all men are generally expected to have, feature 1 and feature 2 can be calculated as

$$Feature \quad 1 = \frac{K}{R(i)} \tag{3}$$

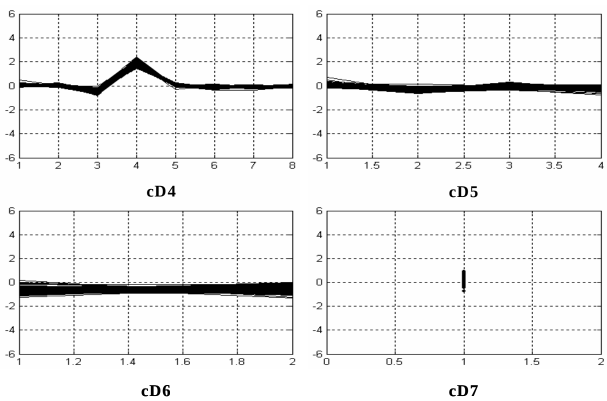
$$Feature \quad 2 = \frac{K}{R(i+1)} \tag{4}$$

considering the sampling rate of 360 Hz, 300 sample points are chosen as K. The mean and variance of feature 1 and feature 2, which were calculated for four different classes (NSR, APC/SVT, PVC/VT and VF), are presented in Fig. 3. For these statistics, arrhythmia beats of 10 records from the MIT/BIH arrhythmia database are used.

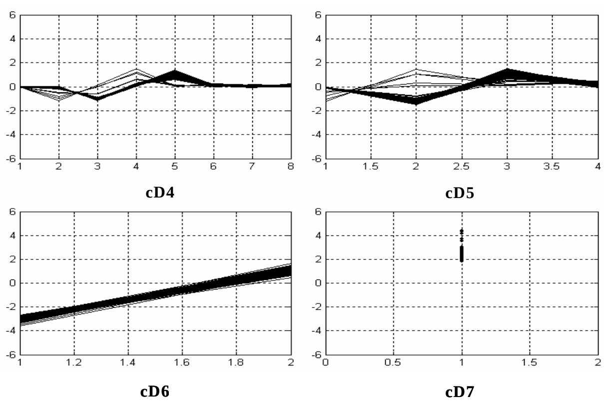
In the mean time, morphology related features should satisfy that the differences among the ECG waveforms are suppressed for the waveforms of the same type but are emphasized for the waveforms



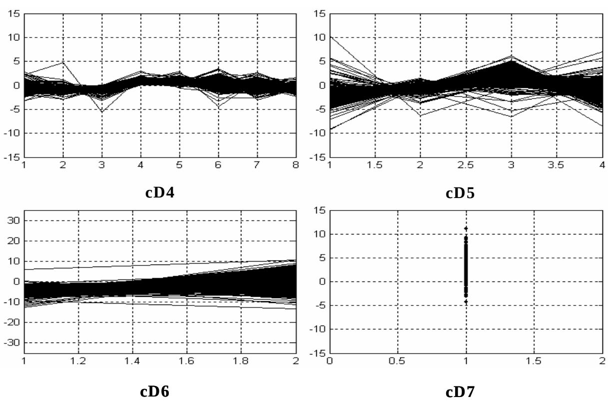
(a) NSR.



(b) APC/SVT.

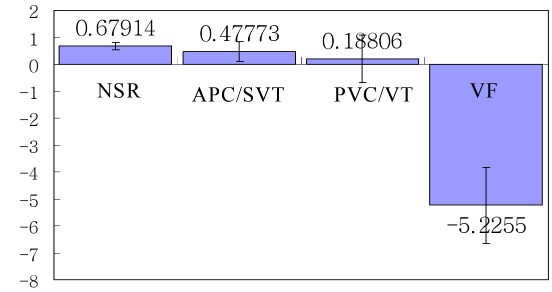


(c) PVC/VT.

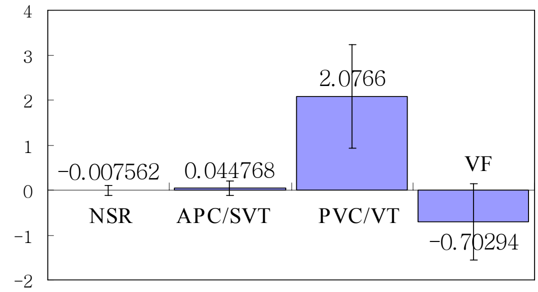


(d) VF.

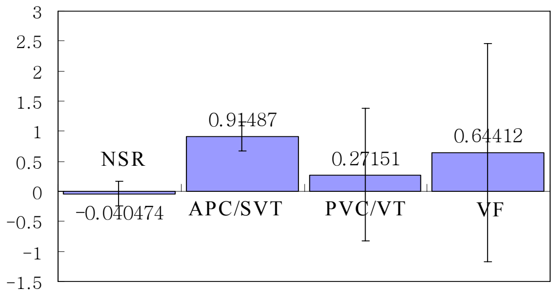
Fig. 4. The differences between detail coefficients' distributions for different types of beats.



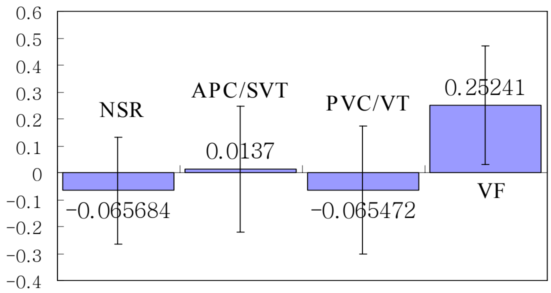
(a)First new feature.



(b) Second new feature.



(c) Third new feature.



(d) Fourth new feature.

Fig. 5. Statistical characteristic of new features for arrhythmia beats of 10 records from MIT/BIH arrhythmia database for different classes.

belonging to different types of beats. Because it is difficult to separate one from the other on the basis of only time or frequency representation, sub-band signals by wavelet transform were utilized for morphology features. For NSR and interested types of arrhythmia, their detail signals at levels 4, 5, 6 and 7 have representative components and obviously different distributions to each other. Level 4 signifies the decomposition at scale 24. Based on these facts, detail coefficients of these detail signals were chosen as features that could discriminate arrhythmia beats from the others. The differences between detail coefficients' distributions for different types of beats can be found in Fig. 4. cD4 means that the detail coefficients at level 4 and the number of coefficients is 8. Similarly, cD5 at level 5, cD6 at level 6, cD7 at level 7 with the number of coefficients being 4, 2 and 1, respectively. These 15 coefficients were defined as feature 3 to feature 17.

2.4. Feature dimension reduction by LDA

Linear Discriminant Analysis (LDA) searches for those vectors in the underlying space that best discriminate among classes rather than those that best describe the data [10]. The goal of LDA is to seek a transformation matrix W that maximizes the ratio of the between-class scatter to the within-class scatter. Initially, we consider a within-class scatter matrix for the within-class scatter. A within-class scatter matrix S_w is defined as

$$S_w = \sum_{i=1}^{c} \sum_{x \in C_i} (x - m_i)(x - m_i)^t, \tag{5}$$

where c is the number of classes, C_i is a set of data belonging to the ith class, and m_i is the mean of the ith class. The within-class scatter matrix represents the degree of scatter within classes as a summation of covariance matrices of all classes. Next, we consider a between-class scatter matrix for between-class scatter. A between-class scatter matrix S_B is defined as

$$S_B = \sum_{i=1}^{c} (m_i - m)(m_i - m)^t, \tag{6}$$

where m is the mean of all classes. The between-class scatter matrix represents the degree of scatter between classes as a covariance matrix of means of all classes. We seek a transformation matrix W that in some sense maximizes the ratio of the between-class scatter and the within-class scatter. The criterion function J(W) can be defined as

$$J(W) = \frac{\left| W^t S_B W \right|}{\left| W^t S_w W \right|}. \tag{7}$$

We can obtain the transformation matrix W as one that maximizes the criterion function J(W). Furthermore, given a number of independent features relative to which data is described, LDA creates a linear combination of these which yields the largest mean differences of the desired classes [11]. As a result, if there are c classes, the dimension of feature can be reduced to c-1 extremely. Using fewer inputs to the arrhythmia classifier, faster computation can be expected.

In this paper, assuming the number of classes is 5, the number of original features was designed to be reduced to 4 by LDA with guarantee of the comparable performance to that prior to reduction. The mean and variance of 4 features, which were newly generated by this process, are presented in Fig. 5. For different arrhythmia beats, their mean and variance are distributed in different ranges so that new features could also provide good tools for discrimination of arrhythmia beats.

2.5. SVM based arrhythmia classifier

The purpose of Support Vector classification is to devise a computationally efficient way of learning good separating hyperplanes in a high dimensional feature space. The SVM works in the high dimensional feature space formed by the nonlinear mapping, φ(x) of the n-dimensional input vector into a K-dimensional feature space. The equation of the hyperplane separating two different classes is given by the relation

$$y(\mathrm{x}) = W^T \varphi(X) = \sum_{j=1}^{K} \omega_j \varphi_j(\mathrm{x}) + \omega_0 = 0 \tag{8}$$

with $w=[\omega_0, \omega_1, ..., \omega_k]^T$ is the weight vector of the network.

By introducing the so-called Lagrange multipliers, α_i the learning task of SVM is reduced to quadratic programming. On account of these facts, there exist many highly effective learning algorithms [12-14], which result in the global minimum of the cost function and the best possible choice of the parameters of the neural network. And all operations in learning and testing are done using so-called kernel functions. The kernel is defined as $K(\mathrm{x}, \mathrm{x_i}) = \varphi^T(\mathrm{x_i})\varphi(\mathrm{x})$.

In this paper, a radial basis function (RBF) was selected as the kernel and the parameters - kernel width σ and margin-losses trade-off C, which provided best classification, were fixed by experiments before learning. Simultaneously, the learning of SVM can be referred to as the separation of learning vectors xi into two classes of the destination values either di=1 or di=-1, with maximal separation margin. And this process is reduced to the dual maximization problem of the function, $Q(\alpha)$ defined as follows [12,15]:

$$Q(\alpha) = \sum_{i=1}^{p} \alpha_i - \frac{1}{2} \sum_{i=1}^{p} \sum_{j=1}^{p} \alpha_i \alpha_j d_i d_j K(\mathrm{x}_i, x_j) \tag{9}$$

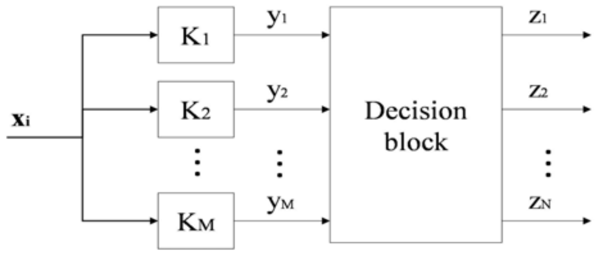


Fig. 6. The scheme of proposed SVM based classifier.

with the constraints

$$\sum_{i=1}^{p} \alpha_i d_i = 0, \quad 0 \le \alpha_i \le C, \tag{10}$$

where C is a user-defined trade-off constant as previously mentioned and p is the number of learning data pair (xi, di). C determines the balance between the complexity of the network, characterized by the weight vector w and the error of classification of data.

The solution with respect to the Lagrange multipliers gives the optimal weight vector W_{opt}, as $w_{opt} = \sum_{i=1}^{N_S} \alpha_{si} d_{si} \varphi(\mathrm{x}_{si})$. The output signal y(x) of the SVM network is determined as the function of

$$y(\mathrm{x}) = \sum_{i=1}^{N_s} \alpha_{si} d_i K(\mathrm{x}_{si}, \mathrm{x}) + \omega_0 \tag{11}$$

kernels and the specific form of the nonlinear function need not be known. The positive value of $\varphi(\mathrm{x})$ s associated with membership of the particular class and the negative one with membership of the opposite class. Although SVM separates the data only into two classes, classification into additional classes is possible by applying either the "one against one" or: "one against all" method [16,17]. We designed a SVM based classifier as shown in Fig. 6.

The feature vectors $\mathbf{x}_i$ fed to the neural classifier K_i and the outputs of each classifier form the vector $\mathbf{y}=[y_1, y_2, ..., y_M]^T$ which signifies the potential of belonging to each class. Subsequently, with user-defined rules, output values y_j for some j may be inhibited and additional output may be generated through a decision block. As a result, final outputs $\mathbf{z}=[z_1, z_2, ..., z_N]^T$ are given. The position of the highest value element of z indicates the membership with the appropriate class.

3. RESULTS AND DISCUSSION

To evaluate the performance of the classifier, three measures are used and defined as:

$$Sensitivity(\%) = \frac{TP}{TP + FN} \times 100, \tag{12}$$

Table 1. Comparisons of the classifier performance for different combination of parameters.

σ	Sensitivity (%)	Specificity (%)	Accuracy (%)
	C=0.1		
1	99.969	92.862	97.851
2	100	91.114	97.351
3	100	88.711	96.635
4	100	85.652	95.723
	C=1		
σ	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	99.907	94.829	98.393
2	99.969	92.935	97.872
3	100	92.061	97.634
4	100	91.697	97.525
	C=10		
σ	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	99.938	95.776	98.697
2	99.907	94.610	98.328
3	99.938	93.518	98.024
4	100	92.935	97.894

$$Specificity(\%) = \frac{TN}{TN + FP} \times 100\,, \tag{13}$$

$$Accuracy(\%) = \frac{(TP + TN)}{(TP + FN + TN + FP)} \times 100\,, \tag{14}$$

where TP stands for true positive, TN for true negative, FP for false positive and FN for false negative. When VF is concerned, TP represents VF being classified as VF and TN represents non-VF beat being classified as non-VF. Moreover, FP represents non-VF being mis-classified as VF and FN represents VF being mis-classified as non-VF [6].

3.1. Parameter selection

SVM classifier parameters, with kernel width σ and margin-losses trade-off C, affect the cost of learning and the classification performance. We have selected optimal parameter values with trial experiments, in which the performance of the classifier was observed for the different combination of parameters. For these experiments, the goal of the classifier was confined to discriminate only NSR with 10 records from the MIT/BIH arrhythmia database. Table 1 presents the performance of the classifier corresponding to each experiment. The performance is likely to get lower as σ increases and the classifier has the better performance with C=10 than with other Cs. So, we chose the parameters - σ and C as 1 and 10 respectively.

3.2. Feature dimension reduction by LDA

Two of the most popular dimensionality reduction techniques are Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). The former one deals with the data in its entirety for the principal component analysis without paying any particular attention to the underlying class structure, whereas the latter one deals with discrimination between classes. To certify the usefulness of LDA, the performance of the classifier was evaluated with original features, features reduced to 4 dimensions by PCA and features reduced to 4 dimensions by LDA. For this, 23 records from the MIT/BIH arrhythmia database, which contain NSR and other types of arrhythmias, were used and the interested classes were confined as NSR and others. For this task, the SVM classifier was used with different input features and Multilayer Perceptrons (MLP) and the Fuzzy Inference System (FIS) were additionally tried with them for cross-validation. The results of classification are summarized in Table 2. ORG indicates the results with the original 17 features, PCA with 4 features by PCA and LDA with 4 features by LDA.

For the SVM classifier, the overall performance of PCA seems to be lower than that of ORG by less than 1%. In the mean time, the overall performance of LDA shows to be higher than both that of PCA and that of ORG. Even though other classifiers were used, the reduced features by LDA indicated usefulness for classification. Consequently, we found that the dimension of features had been reduced effectively by LDA and the better performance could be obtained with a smaller number of features than that of original features. Furthermore, faster learning was possible due to lower dimensions of input features.

3.3. Performance of SVM arrhythmia classifier

To verify the effectiveness of the SVM arrhythmia classifier, its performance was compared with that of well-known classifiers; Multilayer Perceptrons (MLP)

Table 2. Comparisons of the classifier performance for different feature reduction methods (units, %).

	ORG			*PCA*			*LDA*		
	Sensitivity	*Specificity*	*Accuracy*	*Sensitivity*	*Specificity*	*Accuracy*	*Sensitivity*	*Specificity*	*Accuracy*
MLP	99.490	94.680	98.704	99.659	92.652	98.954	99.899	95.643	99.324
FIS	97.896	90.555	96.901	95.415	91.465	94.704	99.395	91.104	98.047
SVM	99.510	96.064	98.742	99.674	93.645	98.865	99.606	98.751	99.521
Average	98.966	93.766	98.116	98.249	92.587	97.508	99.633	95.166	98.964

Table 3. Comparisons of the performances with different classifiers (units, %).

	MLP			*FIS*			*SVM*		
	Sensitivity	*Specificity*	*Accuracy*	*Sensitivity*	*Specificity*	*Accuracy*	*Sensitivity*	*Specificity*	*Accuracy*
NSR	98.984	92.021	98.276	99.623	89.296	98.572	99.657	96.215	99.307
APC	85.185	100	98.374	80.574	100	98.374	88.294	99.951	99.274
SVT	84.706	100	99.148	81.345	100	99.148	82.821	100	99.854
PVC	93.085	97.9	97.505	89.754	99.362	98.377	92.157	98.937	98.344
VT	92.484	98.859	98.701	87.188	99.636	99.444	91.695	99.632	99.441
VF	99.341	99.958	99.903	99.254	100	99.934	99.751	99.993	99.883
Average	92.2975	98.123	98.651	89.623	98.049	98.975	92.396	99.121	99.350

and Fuzzy Inference System (FIS) classifiers.

For a MLP classifier, a three layer structure was used, including an input layer, a hidden layer and an output layer. Each input layer and output layer has 4 nodes and 5 nodes respectively. And, the hidden layer, using sigmoid functions as the membership functions, was made to have 10 nodes with best performance. The learning task was done by an error back propagation algorithm.

For a FIS classifier, input features were translated to linguistic values by the fuzzy inference, in which membership functions and fuzzy logic comprised of IF-THEN statements were used. A Gaussian curve was used for the membership functions, on which the performance of FIS is likely to be dependent, and its characteristic parameters were selected with repetitive experiments. A min-max method, also known as the Mandani inference method, was used for inference and a result was finally obtained by a gravity center defuzzification.

For the evaluation of each classifier, a total of 5630 beats were used and it consisted of 67438 NSR beats, 2318 APC and SVT beats, 8617 PVC and VT beats, 7175 VF beats and 82 other beats. All classifiers equally used 4 dimension features by LDA as input features. Table 3 shows the summarized results of cross-validation. The SVM classifier can discriminate NSR with accuracy of 99.307%, APC with 99.274%, SVT with 99.854%, PVC with 98.344%, VT with 99.441% and VF with 99.883%. The overall performance of the SVM classifier is generally better than that of the MLP classifier and that of the FIS classifier. And, the FIS classifier has the most inferior performance. This may be from the fact that the used features are not suitable for fuzzy inference and we could not find the best membership functions. For NSR and APC, the SVM classifier shows absolute superiority in all performance areas; sensitivity, specificity and accuracy. The sensitivity of the SVM classifier for NSR and VF is higher than that of the SVM classifier for other arrhythmias, for which MLP even demonstrate better sensitivity. And, the SVM classifier has mostly good specificity for all arrhythmias. The majority of errors are caused by some arrhythmias not considered in this paper, such as LBBB (left bundle branch block), RBBB (right bundle branch block) and fusion beat. To obtain the above results, while the SVM classifier used 4135 beats in the learning task, the MLP classifier used 26512 beats, which is about six times more. Undoubtedly, when fewer beats were used for the MLP classifier, lower performances were obtained, but these are not shown here. Moreover, the CPU time taken to build the SVM classifier and MLP classifier were measured as 100.094 and 623.734 secs, respectively.

Finally, we can know that the proposed SVM classifier provides better performance than the MLP classifier with smaller learning data as well as than that of previous studies [1-6].

5. CONCLUSIONS

In this paper, we proposed a SVM based arrhythmia classification algorithm. Seventeen original input features were extracted from preprocessed signals by wavelet transform; 2 rhythm related features and 15 wavelet coefficient features. To improve the learning efficiency of the classifier, we attempted to reduce the original features to 4, the linear combination of original features, by LDA. Comparing the performance of the SVM classifier with different input features, the performance with features by LDA showed higher than with that by PCA and even with original features. So, we could see that LDA could reduce feature dimensions and act as a useful tool to improve the classifier performance at lower learning costs. To evaluate the SVM arrhythmia classifier, a cross-validation method was adopted. That is, the performance of it was compared with that of the MLP classifier and FIS classifier using dimension reduced features. The proposed SVM classifier showed satisfactory performances in discriminating six types of arrhythmia beats. The accuracy of discrimination of NSR, APC, SVT, PVC, VT and VF were 99.307%, 99.274%, 99.854%, 98.344%, 99.441% and 99.883%, respectively. The overall performance of the SVM classifier was comprehensively better than that of the

MLP classifier and the FIS classifier. And, even with smaller learning data, the SVM classifier could provide better performance than the MLP classifier.

Furthermore, the proposed algorithm could be expected to offer faster implementation than other neural networks by the reduction of feature dimensions by LDA and by less-demanding learning data characteristics of the SVM classifier.

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