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The Classification of Electrocardiograph Arrhythmia Patterns using Fuzzy Support Vector Machines

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Abstract

This paper proposes a fuzzy support vector machine ($FSVM_n$) pattern classifier to classify the arrhythmia patterns of an electrocardiograph (ECG). The $FSVM_n$ is a pattern classifier which combines n-dimensional fuzzy membership functions with a slack variable of SVM. To evaluate the performance of the proposed classifier, the MIT/BIH ECG database, which is a standard database for evaluating arrhythmia detection, was used. The pattern classification experiment showed that, when classifying ECG into four patterns - NSR, VT, VF, and NSR, VT, and VF classification rate resulted in 99.42%, 99.00%, and 99.79%, respectively. As a result, the $FSVM_n$ shows better pattern classification performance than the existing SVM and FSVM algorithms.

Keywords: Fuzzy Support Vector Machine, FSVM, ECG pattern classifier, Ventricular Fibrillation, Ventricular Tachycardia

1. Introduction

An electrocardiogram (ECG) signal is a body-surface recording of the systemic heart contraction and release caused by an electrical signal originating from the sinoatrial node. Arrhythmia occurs when ECG signals deviate from the normal range of frequencies or represent an irregular pattern even if they are at a normal frequency. In particular, ventricular tachycardia (VT) and ventricular fibrillation (VF) arrhythmias occur because of disordered electrical activities causing interruptions in simultaneous myocardial contractions. These irregularities can result in decreased or blocked blood supply to the heart, eventually causing sudden cardiac death by cutting off the oxygen supply to the brain and other body organs.[1]. It is very important to recognize the patterns of VT and VF as early as possible because death is imminent without immediate treatment. VT and VF are the most fatal arrhythmias.

Figure 1 shows examples of electrocardiograms of normal sinus rhythm (NSR), VT, and VF. As shown in the figure, the VF waveform has a strange aspect without a systematic pattern and characteristically has an irregular oscillating wave in which the QRS complex and T wave cannot be detected. In contrast, VT is an intermediate stage between regular rhythm and VF and has similar features to VF in terms of cycle and audible frequency. There are existing detection methods that analyze the waveforms of arrhythmias in electrocardiogram signals using linear discriminant analysis[20], nonlinear analysis [15], time frequency analysis [1], neural networks [8,14,19,20], fuzzy reasoning [19,20,22], and support vector machines [8, 19,20].

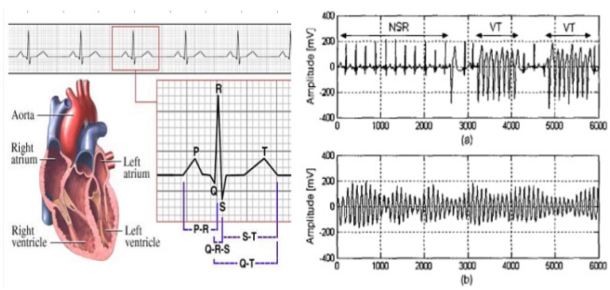

Fig. 1. An example of ECG signals for
(a) NSR and VT (b) VF

For the preprocessing of ECG signals, Fourier transforms [13], wavelet transforms [18], or Hilbert-Huang transforms [6] are used. The present experiment used frequency modulation and detailed variables of wavelet transform to extract specialties.

SVM is a powerful tool for solving classification problems, but there are still some limitations of this theory. Each training datum belongs to either one class or the other. For each class, we can easily determine that all training data are treated uniformly with respect to the theory of SVM. It is often the case that some training data are more important than others in the classification problem. This would require that the meaningful training data must be classified correctly, while paying less attention to unimportant training data like noise. We therefore extend the concept of SVM with fuzzy membership to produce a fuzzy support vector machine (FSVM).

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In this paper, we propose a generalizing fuzzy membership function for FSVM that has better performance than the existing SVMs and FSVMs regarding reduced effects of outliers in nonlinear classification problems and to significantly improve the classification accuracy and generalization.

In the case of a time series where the most recent pattern of data influences future pattern tendencies, a fuzzy membership function containing progressive characteristics is applied to each training datum so that the time variant can be studied to incorporate its effect without including standard influence. The fuzzy membership function suggested in this paper is applied to the pattern classifier model suggested by Lin [9] and Lee [11] as being suitable for pattern perception of ECG signals. That is, a new n-dimension that guarantees the optimum learning rates from various changes in the n-dimension of the fuzzy membership function $s_i = f_n(t_i)$ can be determined.

Therefore, ECG signal is more effective than learning time variant data transformed to emergency situation of VF, after the signal transforms from normal rhythm to VT phase. Research should be performed on FSVM for the distinction and treatment of an urgent situation rather than using the ECG arrhythmia pattern classifier constructed by standard data learning

The FSVM pattern classifier is 0.89% more advanced than the existing SVM pattern classifier and enables a higher recovery success rate by more precisely distinguishing and treating emergency situations of VT and VF.

Meanwhile, applications of FSVM which combine fuzzy theory and SVM have been investigated in various fields. Such applications include image recognition systems in which the fuzzy function is applied to an SVM kernel function [21], iris-recognizing security systems based on the fuzzification of a support vector [13], lung cancer detection systems where FSVM is applied to computer-aided detection [12,17], FSVM processing outliers that classify credit delinquents and superior clients [23], and a decision support system model of data mining for pattern classification of the KOSPI 200 index in the Korean financial market [10, 11].

Song [19, 20] was used as a reference for the existing research about detecting arrhythmias using SVM, and we used ECG signals from MIT-BIH DB, an authorized ECG database.

2. Patterns of ECG signals

Analysis methods, such as the size analysis of the ECG waveform, nonlinear measurements, and frequency transforms are used for pattern classification of VF. Size analysis of a wavelength has low credibility due to its reliance on the measurement environment; nonlinear measurement is sensitive to filtering and noise. In this paper, therefore, rhythm-based information and wavelet transform coefficients were chosen for analysis. For this, ten records of various arrhythmias were selected from the MIT-BIH arrhythmia database.

Figure 2 is a data processing flowchart of the arrhythmia pattern classifiers used to search for arrhythmia patterns among ECG signals.

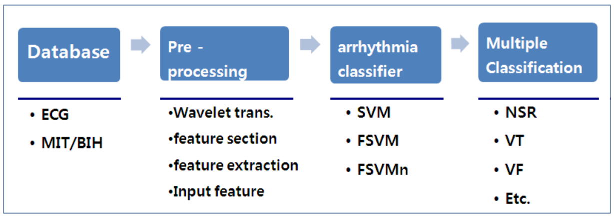

Fig. 2. Flowchart of arrhythmia pattern classifiers

2.1 Database

The ten records used during our experiment contain a total of 89,766 data points including arrhythmia data for 8,810 VT and 7,941 VF data points, and other data that are normal and different. The data set consist of 4,136 (4.61%) training data points and 85,630 (95.39%) test data points.

2.2 Preprocessing

We performed wavelet transform-based band pass filtering, R peak detection, and extraction of input features in order to extract the input features to be entered in the arrhythmia pattern classifier. Rhythm-based information and wavelet transform coefficients were also chosen.

Table 1. Structure of the Arrhythmia Database

DATA BASE (MIT / BIH)	Training Data	Test Data	Sum	Percentage (%)
NSR	2,375	67,438	69,813	77.77%
VT	193	8,617	8,810	9.81%
VF	766	7,175	7,941	8.85%
Etc.	802	2,400	3,202	3.57%
Sum	4,136	85,630	89,766	100%
Percentage(%)	4.61%	95.39%	100%	-

Wavelet transform-based band pass filtering

The Coif 5 wavelet was used to extract input features, and formula (1) represents the wavelet transformed signal at the j -level from $x(n)$. In the equation, $A_j[x(n)]$ is the low frequency signal of the j -level, and $D_j[x(n)]$ indicates the high frequency signal of the j -level.

$$x(n) = A_j[x(n) + D_j[x(n)] \qquad (1)$$

Formula (2) represents a band pass filter to remove 60-Hz noise and transform the baseline. The frequency bandwidth of the filtered signal $x_f(n)$ ranges from 0.7 to 45 Hz.

$$x_f(n) = A_2[x(n)] + D_8[x(n)] \qquad (2)$$

***R* peak detection and extraction of input features**

The coefficients D3 and D4 acquired from the wavelet transform are used to detect the R peak. After trimming the

QRS complex by squaring ECG signals after removing baseline and high frequency noise, formula (3) is $Dadd$, combining the third level high frequency signal (D_3) including the QRS complex and the fourth level high frequency signal (D_4).

$$Dadd = D_3 + D_4 \tag{3}$$

The frequency bandwidth of $Dadd$ ranges between 11.4 and 45 Hz and includes the frequency bandwidth of the QRS complex. Weighting 1 is applied when $Dadd$ is larger than the threshold, and weighting 0 is applied when $Dadd$ is smaller than the threshold. Formula (4) explains the calculation of $Ssub$, the gap between the before and after weighting values of $Dadd$.

$$Ssub(i) = Dadd(i) - Dadd(i+1) \tag{4}$$

After establishing estimated section of possible QRS complex existence, from the section where $Ssub$ suddenly decreases to where 0 continues over $200ms$ consecutively, R peak, maximum and minimum value within the section, is detected. The regularity of the R peak is confirmed to reduce detection errors, and the QRS complex is detected again after decreasing the threshold by 1% in the case where the RR interval is less than 0.5 times or more than 1.5 times greater than the average RR. According to the results with modified errors created by establishing the 90% threshold, when a section is considered to be without a QRS complex when the RR interval is 2~3 times greater than the average RR interval, the peak of the signal will be detected using the fifth level wavelet (A_5). In this paper, the peak signal was detected by interval establishment because VF does not typically contain an R peak.

The standard analysis section 200 ms before and after the R peak was selected as a detection method for input features. For most cases, arrhythmia can be clearly detected within 200 ms (700 samples) before and after sections in which the R peak is standard, and the shapes of the ECG signal and components of frequency are analyzed by establishing the interval.

***R* peak detection and input feature extraction**

The RR interval is used as a rhythm-based input feature for extraction. The RR interval of a normal waveform has similar intervals before and after the R peak standard, or the previous RR interval is longer than the subsequent RR interval. The previous interval is shorter than the subsequent RR interval in cases of unusual waveforms. Specifically, the RR interval of VF is exceedingly shorter than the average RR interval of normal waveforms (5). Therefore, input features were detected using formula (5), where $R(i)$ is the interval between the current R peak and the previous R peak, and K is the average RR interval.

$$Feature\ 1 = \frac{K}{R(i)},\quad Feature\ 2 = \frac{K}{R(i+1)} \tag{5}$$

Figure 3 indicates the $Feature\ 1$ and $Feature\ 2$ rhythm-based input features related to arrhythmia based on formula (5).

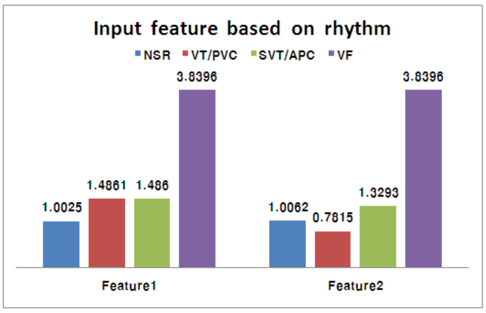

Fig. 3. Features extracted from ten records of the MIT-BIT DB based on rhythm

2.2.4 Input features of the wavelet coefficient base

An input feature is composed utilizing a wavelet transform which is capable of observing both time and frequency features because sorting the shapes of arrhythmia by time domain or frequency domain alone is difficult. Input features include shape information of the QRS complex and minimize the differences among QRS complexes belonging in the same class. Also, differences among the QRS complexes in other classes must be distinguishable.

For this distinction, when entropy is greater than 0.01 during the wavelet transform, wavelet coefficients $cD_4 - cD_7$, of the fourth-, fifth-, sixth- and seventh-level high frequency signals representing the differences between each arrhythmia class, are chosen to be the input features representing the shape information. The total number of wavelet coefficients is 15, including eight for cD_4, four for cD_5, two for cD_6, and one for cD_7. The distributions of these wavelet coefficients have different features based on each arrhythmia. Figure 3 explains the input feature of the wavelet coefficient base for arrhythmia.

3. ECG pattern classifier FSVM$_n$

3.1 SVM

The basic principle of SVM, suggested by Vapnik, is identification of a hyperplane that minimizes the error classification rate while maximizing the margins between two classifications after mapping training patterns to a high-dimensional feature space. However, finding an optimal hyperplane that utilizes kernel function in feature space is challenging without information about the phase. The optimal hyperplane is expressed by a combination of support vectors.

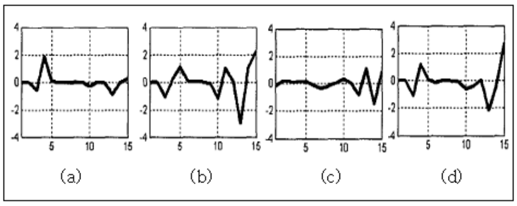

Fig. 4. Features based on wavelet coefficients for (a) NSR (b) VT (c) VF and (d) etc

When the coded training set $S = \{(y_i, x_i) \mid i = 1,...,n\}$ is provided, each training data point $x_i \in R^N$ must belong in one of the two coded parts, and the code is $y_i \in \{-1,+1\}$. Detecting an optimal hyperplane is difficult in the input space, so mapping that input space to a higher-dimensional feature space enables the detection of the expected optimal hyperplane.

When $z = \varphi(X)$ is mapped from R^N to the feature space Z, satisfying $W \circ Z + b = 0$, (W, b) becomes the hyperplane. At this moment, $W \in Z$, $b \in R$, and x_i is divided by the following function:

$$f(x_i) = sign(W \circ Z_i + b) = \begin{cases} +1, y_i = +1 \\ -1, y_i = -1 \end{cases} \tag{6}$$

To process data without linear classification, the slack variable $\xi_i \geq 0$ is defined as a misclassification measure so that (6) is modified to (7),

$$y_i(W \circ Z_i + b) \geq 1 - \xi_i, (i = 1,...l) \tag{7}$$

Thus, ξ_i is the misclassification measure for x_i, and $\sum_{i=1}^{l} \xi_i$ is the misclassification measure for the training set S. Therefore, the optimal hyperplane is expressed using formula (8)

$$\min \frac{1}{2} W \circ W + C \sum_{i=1}^{l} \xi_i \tag{8}$$

subject to $y_i(W \circ Z_i + b) \geq 1 - \xi_i$

The optimal hyperplane can be expressed as in formulas (9) and (10) by Mercer's theorem, when the Lagrange multiplier $\alpha = (\alpha_1, ..., \alpha_l)$ is introduced, and the kernel polynomial K satisfies;

$$K(x_i, x_j) = (1 + x_i \circ x_j)^d = \varphi(x_i) \circ \varphi(x_j) = Z_i \circ Z_j$$

$$\max \; W(\alpha) = \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{9}$$

subject to $\sum_{i=1}^{l} y_i \alpha_i = 0 \; (0 \leq \alpha_i \leq C, \; i = 1,...l)$

$$sign(W \circ Z + b) = sign(\sum_{i=0}^{l} \alpha_i y_i K(x_i, x_j) + b) \tag{10}$$

3.2 FSVM$_n$

The number of applications using the SVM continues to increase. However, some input data may not be precisely assigned to one of the two classes under consideration. For some data, it is critical that they be assigned to a single class so that SVM can correctly separate these points, while other data points corrupted by noise are less meaningful, and it would be better to discard them. SVM lacks this kind of discriminatory ability. Hence, we apply a fuzzy membership scheme to training data of SVM and transform SVM into FSVM such that different input points can make different contributions to the learning of the decision surface.

When the time series data form a tendency influenced largely by the pattern of the most recent data, it is desirable to have a learning machine such that the training data from the recent past is given more weight than the training data from the more distant past. Therefore, we developed a design for an extended pattern classifier model by adding a fuzzy membership function reflecting an orderly character. Even though Lin [9] proposed an FSVM applying a slack variable of an SVM to a fuzzy membership function, the application of a fuzzy membership function to a database with various time series properties needs to be generalized.

Hence, throughout this experiment for the arrhythmia pattern classification of an ECG database that has time series properties and was newly defined by generalizing fuzzy memberships, we used FSVM$_n$ to improve the pattern classification efficiency.

Distinction of FSVM$_n$ is the adjustment to contain flexibility during regulating slope of hyperplane surface from slack variables the misclassification unit influenced by fuzzy membership function, by using discipline data tied up with fuzzy membership function while resolves nonlinear classification problem.

When the coded training set, $S = \{(y_i, x_i, s_i) \mid i = 1,...,l\}$, is provided, each training datum $x_i \in R^N$ must belong to one of the two coded target data groups, $y_i \in \{-1,+1\}$. For a small number α, $(\alpha \leq s_i \leq 1)$, $s_i \in R$ is defined as the fuzzy membership function. The fuzzy membership value s_i is a property indicating the precision of vector x_i belonging to a single class, and $\xi_i \geq 0$ is a scale of the misclassification error, so that $s_i \xi_i$ transforms to a new scale of errors having different weights from one other. Thus, the optimal hyperplane of FSVM is that satisfying formula (11).

$$\min \frac{1}{2} W \circ W + C \sum_{i=1}^{l} s_i \xi_i \tag{11}$$

subject to $y_i(W \circ Z_i + b) \geq \xi_i$

When the training data has time series properties, if the most recent training data is important for improving the learning efficiency of the pattern classifier, the weights will have a gradation from more reliance on learning from the most recent data to less reliance on older data. This will markedly reduce the misclassification rate compared to that of modeling all training data to exercise influence by uniform learning.

Therefore, in the case of data with time series properties, the hyperplane surface of (11) more efficiently increases pattern classification compared to that of formula (8).

Definition 3-1. (Fuzzy Membership Function)

Let $\sigma \in R^+$ be the lower bound of the fuzzy membership function. For a positive number n and time t_i, $(i = 1, \ldots l)$, the fuzzy membership function $s_i = f_n(t_i)$ with time series properties can be generalized to

$$s_i = f_n(t_i) = (1-\sigma)\left(\frac{t_i - t_1}{t_l - t_1}\right)^n + \sigma \qquad (12)$$

where $s_1 = f_n(t_1) = \sigma$ and $s_l = f_n(t_l) = 1$, and let FSVM$_n$ be a fuzzy support vector machine with an n-dimensional fuzzy membership.

4. Experiment and Result Considerations

4.1 Experiment

SVM, FSVM, and our suggested FSVM$_n$ were modeled as arrhythmia pattern classifiers in this experiment. For the experiment, the chosen parameters were d = 1, std = 1, and C = 10, and the kernel was designed using RBF and Polynomial. In this paper, the arrhythmia pattern classifier consisted of four classification models and was originally classified into four types. Figures 4~7 show the hit ratios of NSR, VT, VF, and other arrhythmia patterns, as classified by FSVM$_n$.

Figure 5 shows the classification rate of FSVM$_n$ for the NSR pattern. In the case of a regular rhythm, the highest classification hit ratio reached 99.42% when the degree of fuzzy membership function was $n = 28$.

Figure 6 shows the classification rate of FSVM$_n$ for VT. In the case of VT, the highest classification hit ratio reached 98.99% when the degree of fuzzy membership function was $n = 50$.

Figure 7 shows the classification rate of FSVM$_n$ for VF. In the case of VF, the highest classification hit ratio reached 99.79% when the degree of fuzzy membership function was $n = 5$.

Figure 8 shows the classification rate of FSVM$_n$ for other arrhythmias. The highest classification hit ratio reached 100% when the degree of fuzzy membership function was $n = 4$.

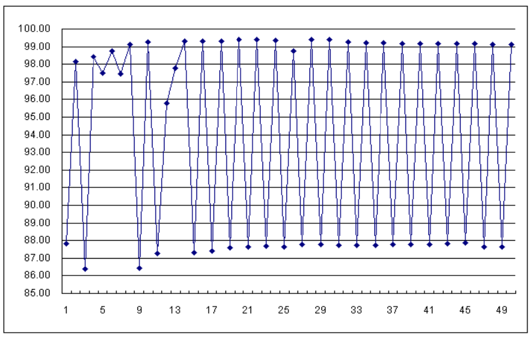

Fig. 5. Pattern classifier of NSR

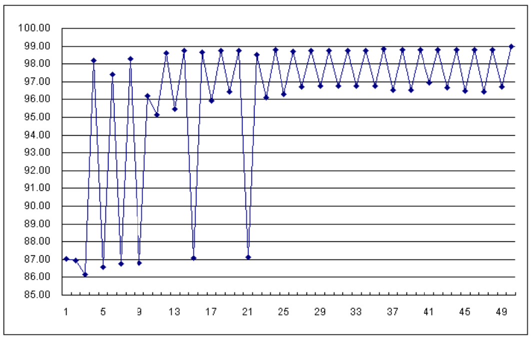

Fig. 6. Pattern classifier of VT

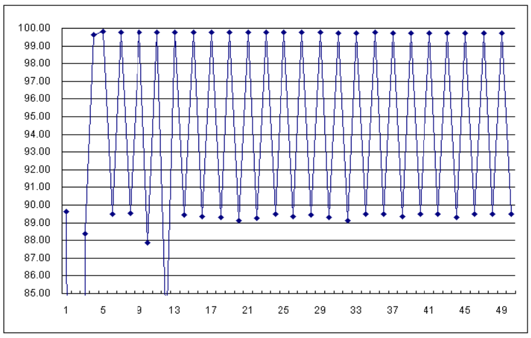

Fig. 7. Pattern classifier of VF

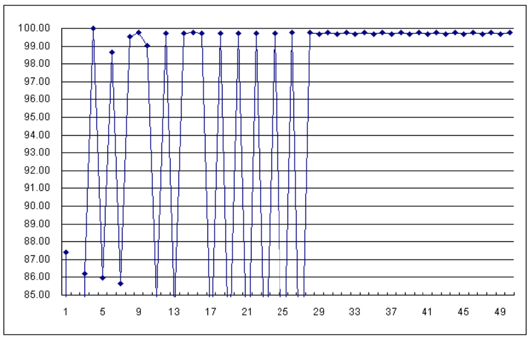

Fig. 8. Pattern classifier of other arrhythmias

Table 2 compares the pattern classifying efficiencies of the arrhythmia pattern classifiers (SVM, FSVM, and FSVM$_n$) studied in this experiment.

Table 2. Comparison of Pattern Classifiers.

Classifier	SVM			FSVM			FSVM$_n$				AVE.
Kernel	Poly	RBF	Ave.	Poly	RBF	Ave.	n	Poly	RBF	Ave.	
NSR	98.68	99.04	98.86	98.46	88.02	93.24	**28**	97.56	**99.42**	98.49	96.86
VT	97.12	98.75	97.94	95.75	97.35	96.55	**50**	89.75	**99.00**	94.38	96.29
VF	89.66	89.65	89.66	89.66	99.74	94.70	**5**	65.29	**99.79**	82.54	88.97
Etc.	98.75	99.77	99.26	89.00	99.69	94.35	**4**	99.88	**100**	99.94	97.85
AVE.	96.05	96.80	96.43	93.22	96.20	94.71	**22**	88.12	**99.55**	93.84	94.99

(n: n-dimensional parameter of fuzzy membership function in FSVM$_n$)

4.2 Considerations

The FSVM$_n$ suggested by this study showed an improved classification accuracy rate that was on average 2.75 to 6.33% better than the existing SVM and FSVM. According to the kernel choice, using RBF increased the accuracy by 0.50% compared to that of Polynomial in SVM, by 3.02% compared to that of Polynomial in FSVM, and showed an outstanding classification accuracy rate 11.43% better than that of Polynomial in the case of $FSVM_n$.

With the suggested fuzzy membership function of $FSVM_n$, $s_i = f_n(t_i)$, the interval of n from $n=1$ to $n=300$ was applied. According to the experimental results within the given interval, the classification of NSR had an accuracy rate of 9.42% when $n=28$, VT had an accuracy rate of 99.00% when $n=50$, VF had an accuracy rate of 99.79% when $n=5$, and other arrhythmias had an accuracy rate of 100% when $n=4$.

Parameter n of the fuzzy membership function is usually selected as the optimal hyperplane within $n=50$ and vibrated within the vicinity under the $\varepsilon - n'bd$ condition of $n=50$ or higher; i.e., for NSR, $\varepsilon = 0.55$; for VT, $\varepsilon = 1.31$; for VF, $\varepsilon = 10.41$; and for other arrhythmias, $\varepsilon = 0.09$. For SVM, FSVM, and $FSVM_n$, the parameters $C=10$, $\alpha = 1$, and $d=1$ were chosen.

5. Conclusions

In the case of a time series where the most recent data pattern influences the future pattern tendency, a fuzzy membership function containing a progressive characteristic is applied to each learning datum so that the time variant can be studied to incorporate its effect without including the standard influence. This will markedly decrease the misclassification rate compared to that of modeling all learning data to exercise uniform influence.

The method suggested in this paper was useful to recognize emergency ECG patterns like VT and VF while learning the patterns of data with time series properties like an ECG signal. Specifically, in recognizing the VT pattern, which is the precursor to VF, our $FSVM_n$ showed an accuracy rate of 99.00%, which is 0.25% higher than that of the existing SVM and 1.65% higher than that of the existing FSVM. Also, the classification accuracy rate of 99.00% is 2.08% higher than the experiment result of 96.92% achieved by Song [18], who used the identical database (MIT-BIH DB) to that used in this study. Consequently, the emergency situations of VT and VF levels can be diagnosed and treated with more precision so that an improvement in the recovery success rate can be expected.

The model design for an $FSVM_n$ classifier generally chooses one-against-all or one-against-one schemes. In this paper, as a one-against-all strategy, the four-category classification problem is transformed to a two-class problem so that $4 \times (4-1)$ pattern classifying models are composed, and the outcomes are integrated by majority decision. Various application methods are needed for the ultimate integration of the classifier results.

This paper applied the model design proposed by Song [16] to expand our existing SVM to $FSVM_n$ in order to detect arrhythmia patterns of an ECG signal. In the case of a kernel RBF, the average hit rate of $FSVM_n$ was 1.75% higher than that of the existing SVM and 3.35% higher than the existing FSVM, indicating a meaningful improvement. The outcome of the pattern classifiers for each kernel indicated that RBF was on average 0.75% better for SVM, 2.98% better for FSVM, and 11.43% better for $FSVM_n$ than is Polynomial. For this, generalizing fuzzy membership function suggested by Lin [8] in order to variously reflect time series properties, proved in this study that capacity of $FSVM_n$ suggested in experiment to detect arrhythmia is improved from existing SVM and FSVM.

Therefore, ECG signal is more effective than learning time variant data transformed to emergency situation of VF, after the signal transforms from normal rhythm to VT phase. Research should be performed on $FSVM_n$ for the distinction and treatment of an urgent situation rather than using the ECG arrhythmia pattern classifier constructed by standard data learning

Hereafter, for the continuing study of fuzzy support vector machines, various applications of fuzzy membership functions suitable to the given database are needed.

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