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Development of an algorithm for detection of fatal cardiac arrhythmia for implantable cardioverter-defibrillator using a self-organizing map

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Abstract— **In this study, we have introduced the pattern classifier using the self-organizing map (SOM) for detecting fatal cardiac arrhythmia in implantable cardioverter-defibrillators (ICDs). The SOM has learned patterns of sinus rhythm, ventricular fibrillation and ventricular tachycardia with the feature vectors extracted from electrocardiogram and right ventricular volume measured during an arrhythmia induction experiment of a dog. After learning, neurons of the SOM were labeled by using the *k*-Nearest Neighbor method. It was shown that the accuracy of the proposed method was higher than other competitive methods applied to the same test data.**

I. Introduction

Nowadays, the number of victims of sudden cardiac death (SCD) are estimated to be about 70,000 per year in Japan. The most common cause of SCD is fatal cardiac arrhythmia, such as ventricular tachycardia (VT) and ventricular fibrillation (VF). Survival rates from these arrhythmias decrease 7% to 10% per minute, so the early treatment is very important [1]. A cardioversion is one of the most effective treatments for these arrhythmias. The implantable cardioverter-defibrillator (ICD) is an effective therapeutic device for rescuing patients with cardiac diseases from death caused by fatal arrhythmia. In order to effectively defibrillate VF or VT, classification algorithms that can distinguish shockable cardiac rhythms from nonshockable cardiac rhythms are required. These algorithms should be as accurate and rapid as possible [2].

However, usual algorithms used in traditional ICD for detecting VF and VT are based almost only on information on cardiac period[3], which makes it difficult to accurately distinguish among normal sinus rhythm, VT, VF, and supraventricular arrhythmia. In addition, existing methods have a lot of parameters to adjust. However, it is difficult to adjust all the parameters automatically and preliminarily because there is a limit in the algorithm in many cases [4], [5].

On the other hand, we are developing a new ICD that can measure information on right ventricular volume (RVV) with an electrode driven by high frequency electric signal. We can estimate the force of ventricular contraction and observe ventricular hypertrophy. Thus, the accuracy of diagnosis is expected to improve because of analyzing ventricular volume information. So, we have proposed a new algorithm for fatal arrhythmia detection that analyzes RVV as well as electrocardiogram (ECG). In this paper, we introduce a method for unsupervised characterization of fatal arrhythmias by using the self-organizing map (SOM), which is planed to be introduced into our developing ICD. We have the advantage that there is no need to adjust the parameter in this method, because the SOM quantizes the feature vector of the training data set, and automatically makes clustering the training data according to the similarity.

II. Methods

To classify fatal arrhythmias, we used the SOM and the *k*-Nearest Neighbor (*k*-NN) method. The SOM is an unsupervised scheme that learns the feature of input data with competitive learning [6], [7]. The *k*-NN method is a supervised learning algorithm that finds *k* examples in training data closest to the test example and assigns the most frequent label among these examples to a new example.

A. Self-organizing map (SOM)

The structure of the SOM consists of two layers: an input layer and an output layer. The input layer is fully connected to the output layer of the map units with weight vectors representing the feature of the units. Given an input vector, the units in the output layer compete among themselves, and the winner updates its weights and its neighbors by moving their weight vectors closer to the input vector. As training progresses, the unit and its neighbors tend to represent similar patterns, while units far from each other in the map represent dissimilar patterns. The desired feature values of patterns are not known beforehand the SOM network will organize themselves according to the natural structure of the input data.

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The final weight vectors usually depend on the sequence of the input data. But we trained the SOM by means of a batch-learning algorithm [6], which is independent of it. The batch-learning algorithm is as follows:

1) Initialization Phase:

The weight vectors are initialized in an orderly form along the linear subspace spanned by the two principal eigenvectors of the input data set.

2) Adaptation Phase:

A weight vector $\boldsymbol{w}_i$ is updated at once only after distance calculation of all the input samples.

$$\boldsymbol{w}_i(t+1) = \frac{\sum_{j=1}^{n} h_{ic(j)}(t)\,\boldsymbol{x}_j}{\sum_{j=1}^{n} h_{ic(j)}(t)}, \quad \forall i \tag{1}$$

$$h_{ic(j)}(t) = \exp\left(-\frac{\left\| \boldsymbol{w}_i(t) - \boldsymbol{x}_{c(j)} \right\|^2}{2\sigma^2(t)} \right) \tag{2}$$

$$c(j) = \arg\min_i \left\| \boldsymbol{x}_j - \boldsymbol{w}_i \right\| \tag{3}$$

where i is an index of the output unit, n is the number of the input vectors, $c(j)$ is the index of winner unit of the data sample $\boldsymbol{x}_j$, $\sigma(t)$ is neighborhood radial, and $h_{ic(j)}(t)$ is a neighborhood kernel which is a non-increasing function of time t.

The updating is done by replacing the weight vector with a weighted average over the samples, where the weighting factors are the neighborhood kernel values.

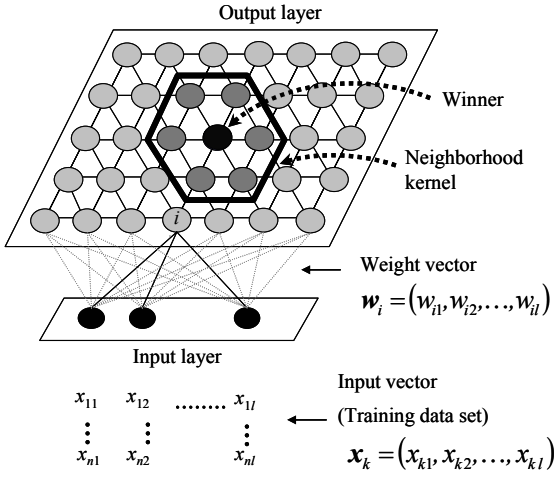

Fig. 1. The structure of the SOM.

B. k-Nearest Neighbor (k-NN) method

1) Labeling algorithm:

The k pieces of adjacent sample $\boldsymbol{x}_i$ (i = 1, 2,…, k) are found to given unknown data $\boldsymbol{x}_q$. And then unknown data label $\hat{f}(\boldsymbol{x}_q, k)$ is measured by the majority decision of sample data label $f(\boldsymbol{x}_i)$.

$$\hat{f}(\boldsymbol{x}_q, k) = \arg\max_{l \in L} \sum_{i=1}^{k} \delta\left(l, f(\boldsymbol{x}_i)\right) \tag{4}$$

where L is a set of k samples, l is a label of k samples, $f(\boldsymbol{x})$ is a label of $\boldsymbol{x}$ and δ is the Kronecker's delta.

2) Selection of proper k:

The k-NN is an estimation method based on a nonparametric probability density function (pdf) [8]. If a vector $\boldsymbol{x}$ is a sample from an unknown pdf $p(\boldsymbol{x})$, probability of existing in region R with $\boldsymbol{x}$ is given by

$$P = \int_R p(\boldsymbol{x}')\,d\boldsymbol{x}' \tag{5}$$

When $p(\boldsymbol{x})$ is continuous and it hardly changes in R, P can be approximated by

$$P \approx p(\boldsymbol{x})V \tag{6}$$

where V is a volume of R. Next, when the n samples are given, the expected value that k samples exist in R is given by

$$E[k] = nP \tag{7}$$

From (5) and (6), $p(\boldsymbol{x})$ can be estimated by

$$p(\boldsymbol{x}) = \frac{k}{nV} \tag{8}$$

The k-NN method estimates the density distribution by deciding V when k is fixed. The radius of a hypersphere that centers on $\boldsymbol{x}$ is enlarged until the k samples are just included in a hypersphere. The k-NN method gradually smoothes the estimated density distribution as it increases the number of sample included in a hypersphere. However, the bias increases as pdf smoothes and the estimation result get worse. Moreover, the density distribution becomes to depend on an individual sample strongly when smoothness is insufficient, and the variance of the estimation result increases. Therefore, it is important to decide k to an appropriate value.

The proper number of nearest neighbors, k, was determined via the method of leave-one-out cross-validation (LOOCV) [9]. An original data set of N samples was partitioned into a test set of one data point and a learning set of N - 1 data points. Given a specific k, the k-NN algorithm predicts the label of test set using a learning set. This procedure was performed using all possible k = {1, 2,..., N-1} and repeated until each of the data points in the original sample was used as a test set. The classification error ε_k, of the learning set was determined by

$$\varepsilon_k = 1 - \sum_{i=1}^{N} \delta\left(\hat{f}(\boldsymbol{x}_i, k), f(\boldsymbol{x}_i)\right) \Big/ N \tag{9}$$

And the number of k took to be producing the smallest classification error, i.e., $\min_k(\varepsilon_k)$.

C. Arrhythmia classification by using SOM and k-NN

The SOM was used to learn patterns of sinus rhythm (SR), VT, and VF with feature extraction from ECG and RVV of each cardiac cycle (R-R interval). The feature vector was composed of

- R-R interval (R-RI)
- Variance of R-RI in the past five beats
- R-SI per R-RI
- The amplitude of S-wave
- The minimum RVV
- The stroke volume

After learning, labels were placed on the units of the SOM by means of *k*-NN algorithm.

In the classification phase, we calculated a feature vector from ECG and RVV, and it was projected into the SOM. Next, the best matching unit (BMU) was chosen to be the weight vector with the greatest similarity with the input vector. We made a diagnosis on the basis of a label of BMU.

D. Competitive Analysis

To validate the SOM classifier and RVV measurement, we compared their performance with other two methods. One is based on only R-RI whose threshold values ware set as 0.16 s for VT-VF and 0.32 s for SR-VT. We decided the threshold so as to minimize the overlap of R-RI of each arrhythmia in the training data set. And the other is based on the SOM and *k*-NN classifier without using RVV information.

III. Data Collection

The learning data set used in our work includes SR, VT, and VF. Each pattern was composed of 80 beats. All data were recorded from a dog during an arrhythmia induction experiment. VF was induced by electrical stimulation to the left ventricle (LV), and LV pacing was used to simulate VT.

ECG was obtained from an intra-right ventricular lead, and RVV was measured by a conductance catheter (20kHz, 30mA-RMS) inserted into the superior vena cava. Each record was sampled at 200 Hz. ECG was bandpass filtered ($1\text{Hz} < f < 40\text{Hz}$) to reduce noise and baseline drift. RVV was lowpass filtered (f_c=40Hz) to remove power line interference.

The test data set was composed of episodes from different arrhythmia episodes induction trials (VT: 6 episodes (368beats), VF: 7 episodes (992 beats), SR: 13 set before VT or VF induction (520 beats).

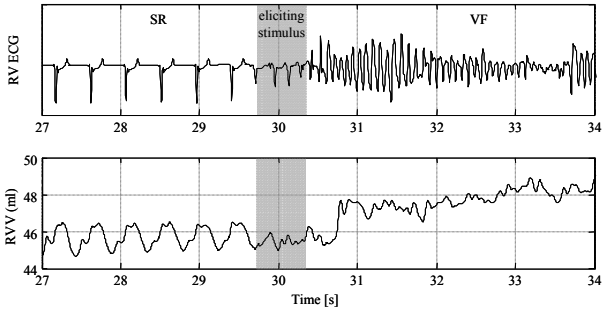

Fig. 2. ECG and RVV signal measured in arrhythmia induction experiment (The shaded area represents the period of eliciting stimulus.) Top: ECG signal in the right ventricle, Bottom: RVV. ECG was bandpass filtered ($1\text{Hz} < f < 40\text{Hz}$). RVV was lowpass filtered (f_c=40Hz). Because absolute amplitude was useful index of cardiac contractile force, we didn't apply highpass filter to RVV signal.

IV. Results

The training was carried out for 10,000 learning epochs. And then, we used the LOOCV error of *k*-NN as the evaluation criterion. We calculated the classification error ε_k only in odd numbers, because even numbers are unsuitable for majority decision. From the result of the LOOCV, the optimal number of *k* was estimated 3 as the minimum value of ε_k.

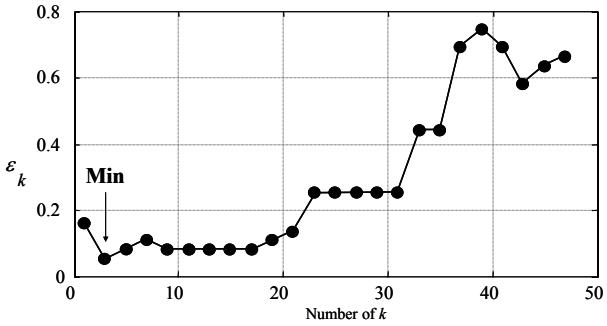

Fig. 3. LOOCV estimated optimal number of *k*. We calculated classification error ε_k only in odd numbers, because even numbers are unsuitable for majority decision.

The resulting SOM is shown in Fig. 4 From this map, we obtain a topological view of the relationships among individual patterns.

Sensitivity and specificity for SR, VT, and VF are calculated in order to measure the performance of arrhythmia classification.

The detection results are shown in Fig. 5. The SOM learning both ECG and RVV patterns classified arrhythmia with the highest accuracy. From the *t*-test, the SOM learning both ECG and RVV patterns showed significant difference from the other methods in sensitivity of VF and specificity of VT, and detection by R-RI in sensitivity of VT ($p < 0.05$).

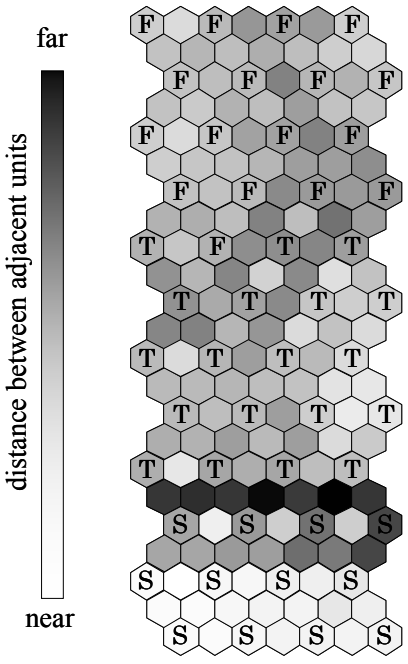

Fig. 4. Visualization of the SOM learning both ECG and RVV information. The SOM were composed of 12×4 units. The lattice of the grid is hexagonal. All SOM units were labeled S: SR, T: VT, F: VF. Additional hexagons exist between all pairs of neighboring map units represent distance between adjacent units.

TABLE I
INDEX OF ACCURACY

		Results of the classifier	
		Fatal arrhythmia	Not fatal arrhythmia
Classification	Fatal arrhythmia	TP (True Positive)	FP (False Positive)
	Not fatal arrhythmia	FN (False Negative)	TN (True Negative)
Index of accuracy		Sensitivity = 100·TP/(TP+FN)	Specificity = 100·TN/(TN+FP)

Fatal arrhythmia is VT or VF. Not fatal arrhythmia is SR. Classification is the true label of each beat.

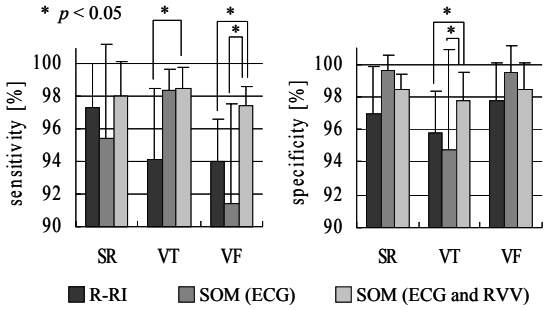

Fig. 5. LOOCV estimated optimal number of k. We calculated classification error ε_k only in odd numbers, because even numbers are unsuitable for majority decision.

TABLE II
PERFORMANCE OF THE SOM CLASSIFIER AFTER LEARNING BOTH ECG AND RVV INFOMATION

Pattern of cardiac rhythms	Sensitivity [%]	Specificity [%]
SR	98.1	98.5
VT	98.5	97.8
VF	97.4	98.5

TABLE III
PERFORMANCE OF THE SOM CLASSIFIER AFTER LEARNING ECG ONLY

Pattern of cardiac rhythms	Sensitivity [%]	Specificity [%]
SR	95.4	99.6
VT	98.4	94.8
VF	91.4	99.5

TABLE IV
PERFORMANCE OF CLASSIFICATION USING THE THRESHOLD WITH RESPECT TO R-RI

Pattern of cardiac rhythms	Sensitivity [%]	Specificity [%]
SR	97.3	97.0
VT	94.1	95.8
VF	94.0	97.8

V. DISCUSSION AND CONCLUSION

In this study, the validity of the proposed method for detecting fatal arrhythmias used for ICD was ascertained in comparison with other ones. Fig. 5 and Tables II to IV indicate that the proposed method for fatal arrhythmia classification with the SOM after learning both ECG and RVV was more accurate than the classification with the threshold of the R-R interval analysis and the SOM after learning ECG only. This result means that information on RVV actually functioned to classify arrhythmias. Therefore, it can be concluded that the proposed method is capable of automatically diagnosing fatal arrhythmias more accurately than existing methods.

Although information on RVV is actually valid, it is necessary to introduce an additional lead with high frequency signal. This consumes electrical energy much more than usual ICDs. To save energy, therefore, we have to begin to measure the RVV signal just after sensing extrasystole.

The limitation of the present study is that the performance of the propose algorithm was tested by just two kinds of arrhythmias (VT and VF). In further studies, we should improve the proposed methods so as to distinguish among SR, VT, VF, and supraventricular arrhythmia such as atrial fibrillation (AF) and atrial tachycardia (AT).

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