Detection Algorithm of Fatal Arrhythmia for a New Implantable Cardioverter Defibrillator using Self-Organizing Map

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Abstract

This article discusses the effectiveness of a new method of detecting fatal arrhythmia used for ICDs. The method utilizes the self-organizing map proposed by Cohonen with an input vector consisting of not only the ECG signal but also the ventricular volume signal to automatically diagnose fatal arrhythmia without setting any thresholds manually. The proposed algorithm was implemented into a single-tip micro computer system and ascertained its effectiveness in an animal experiment using a dog.

1. Introduction

Implantable cardioverter-defibrillators (ICDs) are clinical devices that automatically detect and defibrillate fatal arrhythmia such as ventricular fibrillation (VF) and ventricular tachycardia (VT) [1]. Unfortunately, 100% of ICDs used in Japan are imported and the Japanese share of ICDs was divided by almost only two foreign companies.

To produce ICDs domestically in Japan, a research group led by the National Cardiovasucular Center began a project: "Development of the System for Prevention of Sudden Death" supported by the Grant-in-Aid based on the Ministry of Health and Welfare in 2003. In this project, the research group in Tohoku University is in charge of development of algorithms which can immediately detect fatal arrhythmia for the new ICD.

Traditional ICDs are using information on ECG signal to detect VF and VT [2-6]. It is difficult for usual algorithms based on R-R interval of ECG signal to distinguish between VF and VT certainly. In such algorithms, it is necessary to adjust several parameters included in an ICD according to a patient with the ICD.

On the other hand, the ICD which our project group is developing can provide information on ventricular volume obtained on the basis of the principle of conductance catheters as well as ECG signal. This additional information will enable the ICD to detect fatal arrhythmia more immediately and more accurately.

In this article, a detection algorithm of fatal arrhythmia for the new ICD using self-organizing map (SOM) [7] proposed by the authors will be introduced. Furthermore, a single-chip microcomputer system embedded with the proposed algorithm will be described and the results of an animal experiment with a dog using the proposed detection system will be evaluated.

2. Methods

2.1. Self-organizing map (SOM)

2.1.1. Structure and training algorithm

The self-organizing map (SOM) was originally proposed by Kohonen and has the ability to automatically classify the input vector without supervisors. The training algorithm is described in the following [8].

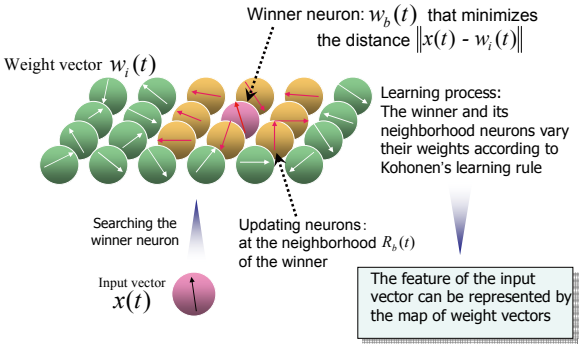


Fig. 1. Training algorithm of SOM.

As shown in Fig.1, the SOM consists of neurons distributed on a plain. The i-th neuron has a weight:

$w_i(t)$. The initial values of the elements of $w_i(t)$ are given randomly. Let $x(t)$ be an input vector to be classified. The index b of the winner neuron is decided by

$$b = \arg\min_i \|x(t) - w_i(t)\|$$

The weight $w_i(t)$ is updated according to

$$w_i(t+1) = \begin{cases} w_i(t) + \alpha(t)[x(t) - w_i(t)] & \text{if } i \in R_b(t) \\ w_i(t) & \text{if } i \notin R_b(t) \end{cases}$$

where $\alpha(t)$ is a scalar gain decreasing with time. The set $R_b(t)$ of the index i is a neighborhood function which assigns neurons to be updated around the winner neuron $w_b(t)$ and decreases its area.

The SOM adopted by the present study had a hexagonally distributed map of neurons and the neighborhood function $R_b(t)$ expressed by a Gaussian function with the initial radius of and the final radius of 1. The number of iteration with respect to training was 600.

As the training process goes by, it is expected that the input vectors with similar feature to each other are projected to the neurons with similar weights to each other whose distance is near while the input vectors with different feature are placed to the neurons with different weights whose distance is far. This process will result in a map where the spatial distribution of neurons corresponds to classification of input vectors.

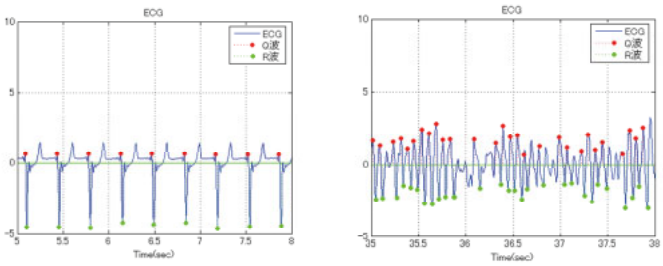
This means that the SOM has a capability of topological self organization, that is to say, the SOM can automatically classify input vectors according to their similarity. In other words, the SOM can map nonlinear multidimensional data into lower-dimensional data with the same spatial topological order.

2.1.2. Selection of input vector

The ECG signal was measured with an electrode inside the right ventricle of a dog and its right ventricular volume signal was measured with a conductance catheter. These two signals were filtered respectively by a band-pass filter (0.5Hz-40Hz) and low-pass filter (-40Hz) implemented with 6-th order Butterworth-type digital filters.

The ECG signal was normalized into zero mean and unit variance, and the volume signal was normalized into zero minimum and unit maximum.

By detecting R-wave of the ECG signal with a threshold, the time positions of R-wave and Q-wave were decided for each cardiac cycle as shown in Fig. 2.



a) An example of peak detection in sinus rhythm for Q-wave and R-wave

b) An example of peak detection in VF for positive and negative peaks

Fig. 2. Detection of R-wave and Q-wave.

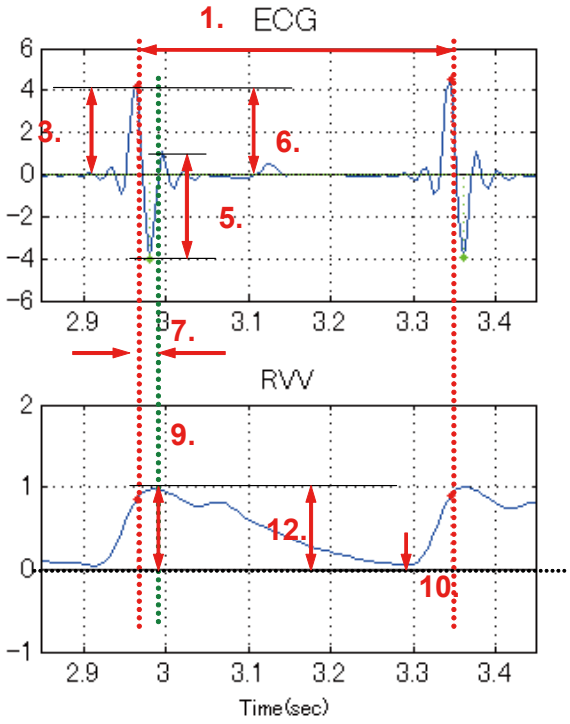


Fig. 3. Elements of input vector.

In each beat, 15 variables shown below are extracted from the data shown in Fig.3 to be the elements of the input vector to the SOM.

1) Heart rate
2) Standard deviation of heart rate over past 5 beats
3) Amplitude of Q-wave
4) Standard deviation of Q-wave over past 5 beats
5) Amplitude of R-wave
6) Standard deviation of R-wave over past 5 beats
7) Q-R interval
8) Standard deviation of maximum ECG over past 5 beats
9) Maximum volume
10) Time maximizes the volume
11) Minimum volume
12) Time minimizes the volume

13) Standard deviation of the maximum volume over past 5 beats
14) Standard deviation of the minimum volume over past 5 beats
15) Difference between the maximum and the minimum volumes

2.1.3. Labeling of neurons and area clustering

To classify the data using the SOM after training, labeling process to the neurons illustrated by Fig.4 is carried out on the basis of the following steps:

1) Label the data to train as kinds of patterns (VF, VT, Shock, Other), where "Shock" means the state in which the electrical shock was charged to induce VF.
2) Input again the data after training to the SOM and find the neuron closest to each data.
3) Label the closest neuron as the same label as the input data.
4) If there are plural closest neurons, remain all labels.
5) Cluster the area of the SOM on the basis of k-means method or k-NN method which will be described later.
6) Label all neurons in each cluster by a majority vote of the closest neurons which have already been labeled in the same cluster.

The *k-means method* is as follows:

1) Put K seeds with random values as the initial representative value of each cluster in the data space and calculate the distance between each data and each seed.
2) Classify each data into the cluster closest to a seed and update the seed so as to be the center of gravity of the data belonging to each cluster.
3) Classify each data into the cluster of the center of gravity closest to the data and update the center of gravity of the data belonging to the new cluster.
4) Repeat from Step 2) to Step 3) until the update of the center of gravity does not execute.

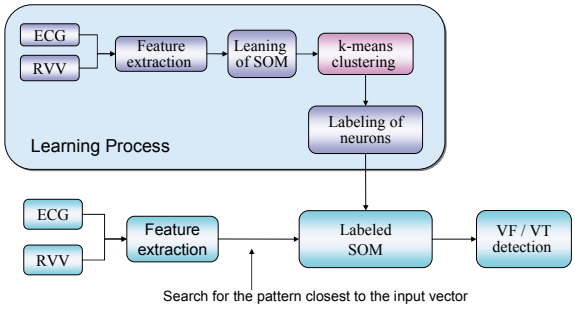


Fig. 4. Process of classification of input vectors.

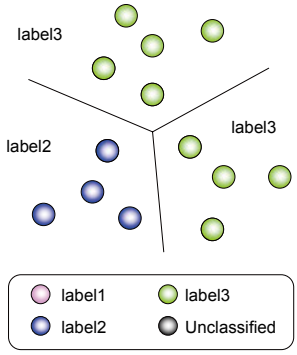


Fig. 5. An example of labeling using the k-means method.

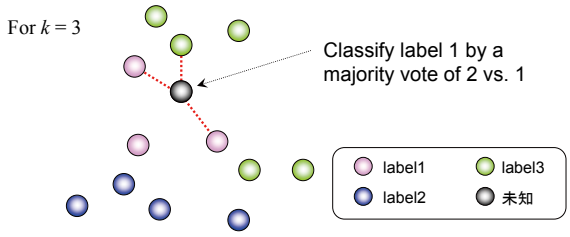


Fig. 6. An example of labeling using the k-NN method.

The k-means method decides the label of a neuron by a majority vote of labels included in each cluster as shown in Fig.5. Such a macroscopic labeling tends to lose a part of topological information on the map.

To cope with this defect, we have adopted the *k-NN method (k-nearest neighbor method)*. This method is as follows:

1) Select K points in order of descending distance to the point of interest.
2) Identify the kind of patterns by a majority vote of the K points.

In this study, the number K was optimized by changing K over 1-20 so that the criterion of Davies-Bouldin index (DBI) [9] can be minimized. This index can judge whether each cluster is compact and placed far from one another.

To detect fatal arrhythmia, the following process was carried out.

1) Configure an input vector based on ECG and RVV signals.
2) Provide the input vector for the SOM.
3) Find the most matching neuron.
4) Classify the input vector as the label corresponding to the most matching neuron.
5) Extract the data classified as VT or VF.

2.1.4. Kinds of events for training and input vectors

In this study, two dogs were used for obtaining the data for training the SOM. By observing the wave form of ECG and RVV signals, the following 4 kinds of events were applied.

- **VF** : 250 beats (5 events)
- **VT** : 280 beats (6 events)
- **Shock** : 125 beats (32 events; electrical stimulation to induce VF)
- **Other** : 335 beats (normal; except "Shock," "VF," and "VT")

2.1.5. Comparison with a method using only ECG signal

To ascertain the effect of introducing the volume signal, we used two kinds of input vectors: the input vector with the full elements 1)-15) mentioned in 2.1.2 and the input vector with 8 elements that consists of the full elements excluding 9)-15) related to RVV signal.

2.2. Improvement of timing of pattern matching

It is easy to carry out the pattern matching process beat by beat. However, the beat contaminated by an isolated artifact will be judged as it is. To improve this trend, as shown in Fig.7, if the result of judgment at t-th beat is different from that at the previous $(t-1)$-th beat, cease the judgment temporarily. If the judgment at the next $(t+1)$-th beat is the same as that at the previous $(t-1)$-th beat, judge the current t-th beat as the same result as that of the previous $(t-1)$-th beat.

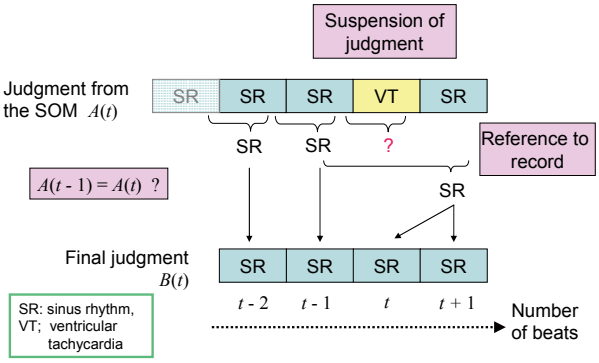


Fig. 7. Timing of pattern matching.

2.3. Reducing computational time and suppression of effects of individual difference, nonstationarity, and positioning of electrodes

To implement the proposed detection system into a single-chip microcomputer system, reduction of the computational time is required. The computational time of matching using the SOM is proportional to the product of the number of elements of the input vector and the number of neurons. It is desirable to optimize these numbers. However, there is no deterministic criterion about this optimization. Thus, we adjusted these numbers in a trial and error manner.

The input vector mentioned in 2.1.2 includes elements consisting of the absolute variables. This means that the features expressed by the vector are too sensitive to changes in wave forms and the situation of the electrodes. The ECG-signal will change its wave form with slightly change in setting positions and the R-wave will change its polarity, for example, from sinus rhythm (SR) to VF. Furthermore, the absolute value of the volume signal will change with the individual and change in pathological conditions. For example, the ventricular volume will increase even in SR if the patient's cardiac function becomes lower.

To reduce the computational time and suppress the effects of individual difference, nonstationarity, and positioning of electrodes, we tried to adopt the different definition of the input vector. In the case of the ECG signal, we should use temporal information such as R-R intervals instead of absolute information such as amplitudes of wave forms. In the case of the volume signal, we should select information on cardiac function although such information needs accurate calibration.

Thus, we change the selection of the input vector as follows:

1) Current R-R interval
2) R-R interval at the previous beat
3) R-R interval at two beat ago
4) Minimum RVV
5) Stroke volume (Difference between maximum and minimum RVV)

To reduce the computational time and suppress the effects of individual difference, nonstationarity, and positioning of electrodes, we tried to adopt the different definition of the input vector. In the case of the ECG signal, we should use temporal information such as R-R intervals instead of absolute information such as amplitudes of wave forms. In the case of the volume signal, we should select information on cardiac function although such information needs accurate calibration.

We set the size of the map (the number of neurons) to be 48. As shown in Fig.8, the neurons which are not adjacent to the border between different patterns on the map never contribute to judgment. Thus, we used only the neurons that are directly adjacent to the border as shown in Fig.9. In this case, the number of neurons used for judgment could be reduced from 48 to 18.

A device based on the principle of a conductance catheter will be used to measure the RVV signal. However, such a device needs a lot of electrical power in comparison with the ICD itself because high frequency current is required for estimation of the ventricular conductance. For implantation of the ICD, we should avoid continuously measuring the RVV signal, and then, in an actual monitoring system, the measurement of the RVV signal will start only if the R-R interval becomes shorter.

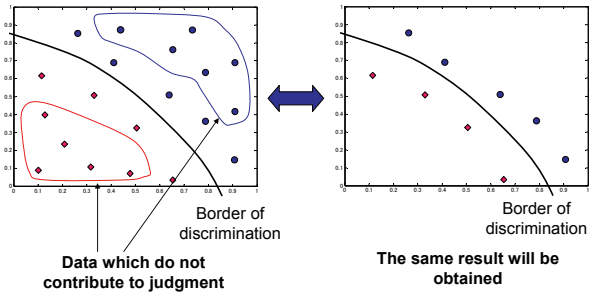


Fig. 8. Neurons contributing to judgment.

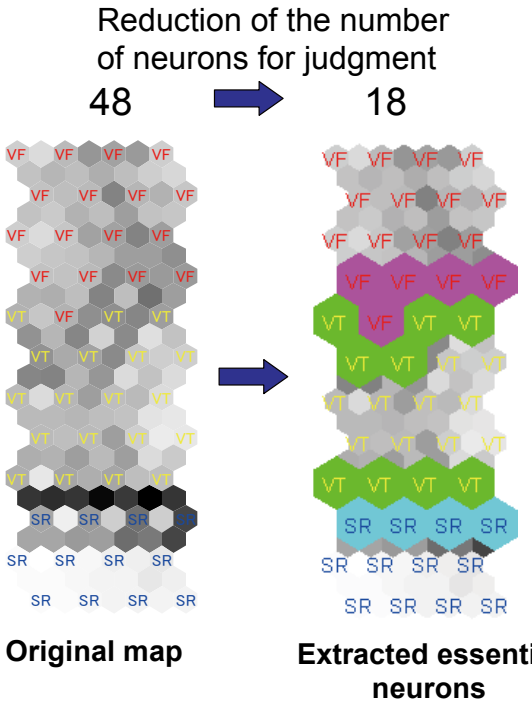


Fig. 9. Reduction of the number of neurons used for judgment.

2.4. Implementation in a single-chip microcomputer system and animal experiment

In this study, the proposed algorithm was implemented in a single-chip microcomputer system using SH-2 (Hitachi; H7045F) made by Alpha Project Co. The flowchart of the software of the system is shown in Fig.10 and the configuration of the animal experiment using a dog is shown in Fig.11.

In the experiment, ECG and RVV signals were measured in three dogs under anesthesia and introduced into the A/D converter of the microcomputer system. The result of classification obtained from the system was output as a 2-bit digital signal to a personal computer which is used to verify the adequacy.

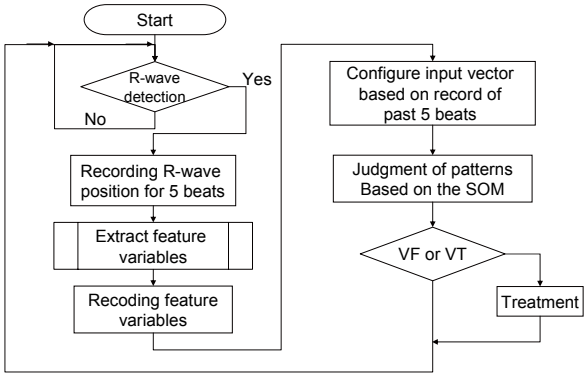


Fig. 10. Flowchart of software.

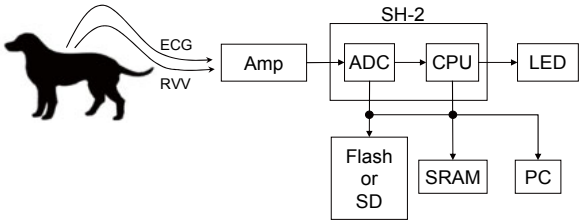


Fig. 11. Animal experiment.

3. Results [10-12]

3.1. Training and clustering of the SOM

3.1.1. State of the SOM after training

The training algorithm described in 2.1 was applied to the SOM in two cases: the case where both ECG and RVV signals were used and the case where only ECG was used.

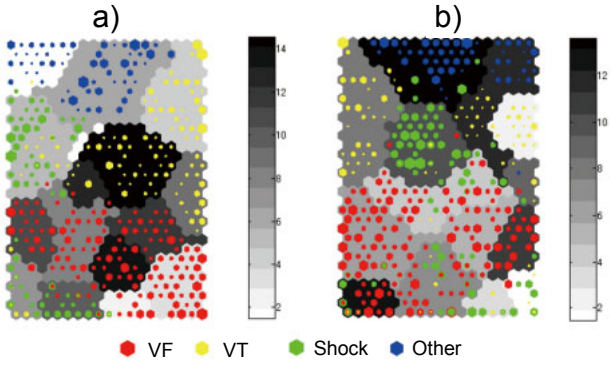


Fig. 12. Distribution of classified result on the SOM after training. a) Both ECG and RVV signals were provided, b) Only ECG signal was provided.

The neurons of the SOM were classified by the k-means method. The number K was optimized so as to minimize the DBI index. The optimum value was K=15 in the case where both ECG and RVV signals were provided while the optimum value was K=14 in the case where only ECG signal was provided.

Figure 12 shows the distribution of classified result on the SOM obtained by using the k-means method. Each hexagon with the colored mark represents the neuron that responded as the most matching neuron to each input vector and the size of the mark is proportional to the number of the input data which were assigned to the neuron as the most matched one. Figure 13 shows the distribution of the clusters on the SOM. Each cluster was labeled as the pattern of the input vector which was most frequently assigned to the cluster.

Figure 12 also indicates that one cluster has almost one label in the case where both ECG and RVV signals were provided while one cluster has a few labels in the case where only ECG signal was provided.

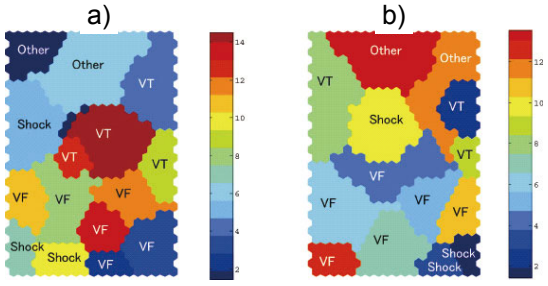


Fig. 13. Clustering resulted from the k-mean method. a) Both ECG and RVV signals were provided, b) Only ECG signal was provided.

3.1.2. Detection of VF/VT resulted from the same data as used in training

The SOM with labeled neurons after training with input vectors was used to detect VF/VT on the basis of the same data as used in training. We applied 645 beats of VF included in 5 episodes consisting of 980 beats, and 288 beats of VT included in 6 episodes consisting of 649 beats. Sensitivity and specificity were used to evaluate detection the accuracy of the system.

The results are shown in Fig.14 while pattern matching was done beat by beat. The sensitivity of VF and the specificity of VT were higher than 95% in the case of only ECG as well as in the case of both ECG and RVV. However, the use of both ECG and RVV was superior to the use of only ECG in the cases of the specificity of VF and the sensitivity of VT.

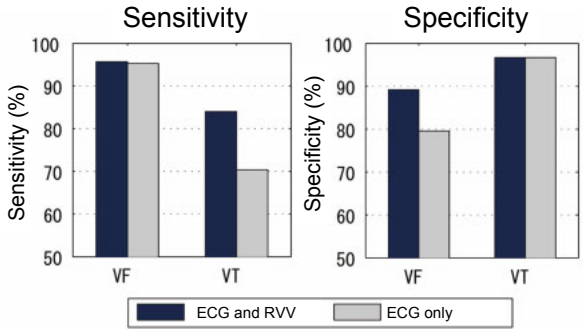


Fig. 14. Detection of VF/VT resulted from the same data as used in training.

3.1.3. Detection of VF/VT resulted from different data not used in training

In the same way as 3.1.2, the SOM was used to detect VF/VT on the basis of different data from those used in training. We applied 1845 beats of VF included in 13 episodes consisting of 298 beats, and 576 beats of VT included in 13 episodes consisting of 1277 beats.

The results are shown in Fig.15. The use of both ECG and RVV was also superior to the use of only ECG in the case of the specificity of VT.

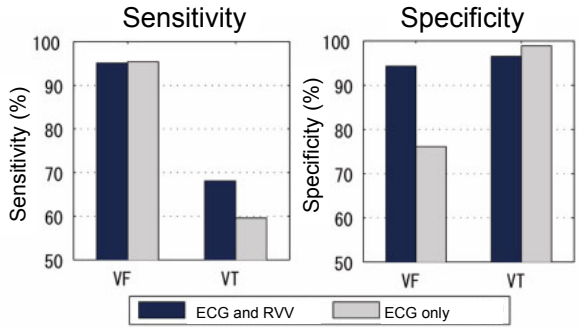


Fig. 15. Detection of VF/VT resulted from different data from those used in training.

3.2. Improvement of detection algorithm by using k-NN method

Figure 16 shows a comparison of the detection result from the same input data between the k-means method and the k-NN method. This figure indicates that the k-NN method yielded superior criteria to the k-means method in all cases.

Thus, we decided to use the k-NN method after this result.

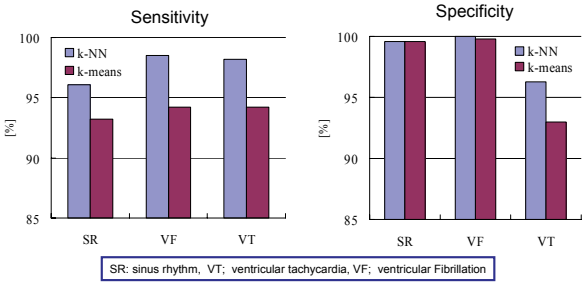


Fig. 16. Comparison of the detection results from the same input data between the k-means method and the k-NN method.

3.3. Comparison among the method using a threshold of R-R intervals, the SOM using only ECG, and the SOM using ECG and RVV

Figure 17 shows a comparison of the detection results among the method using a threshold of R-R intervals, the SOM using only ECG signal, and the SOM using ECG and RVV signals from the data consisting of 13, 6, and 7 episodes of SR, VT, and VF, respectively. In this case, the threshold was set to 0.16 s for discrimination between VT and VF and 0.32 s for discrimination between SR and VT. The k-NN method and the improved pattern matching method described in 2.2 were used for the detection algorithm of the SOM. For use in the microcomputer system, the number of elements of the input vector was reduced as follows:

1) R-R interval
2) standard deviation of R-R interval over past 5 beats
3) R-S interval
4) Value of S-wave
5) Minimum RVV
6) Stroke volume

Figure 17 indicates that the sensitivity of VT and VF and the specificity of VT had significant differences. The SOM input with information of both ECG and RVV signals was most excellent.

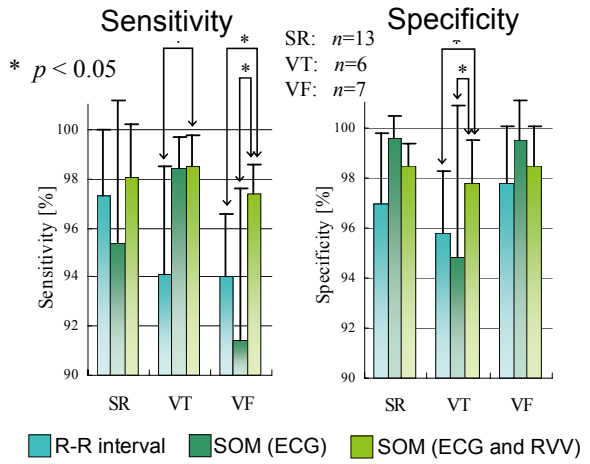


Fig. 17. Comparison among the method using a threshold of R-R intervals, the SOM using only ECG signal, and the SOM using ECG and RVV signals.

3.4. Evaluation of the detection system implemented in a Single-Chip microcomputer system in an animal experiment

The improved algorithm mentioned in 2.3 implemented in a microcomputer system shown in 2.4 was evaluated in the animal experiment using three dogs (A, B, and C).

In Dog A, the neurons of the SOM were configured by the data obtained from the past different dog from Dog A. Figure 18 shows an example of diagnosis of VT changing form SR. In the early stage (11s-13s), VT was misdiagnosed as SR because of mis-triggering R-wave. At some beats, VT was misdiagnosed as VF because the stroke volume was small at these beats.

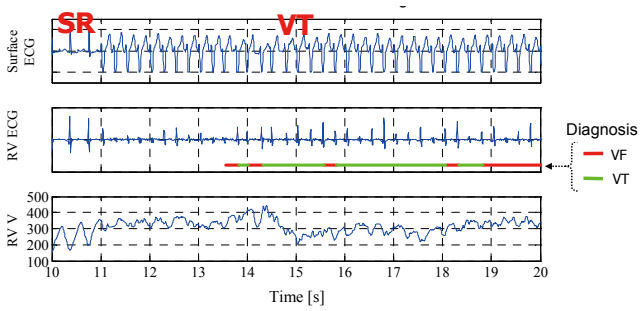


Fig. 18. An example of diagnosis of VT changing form SR (Dog A. The SOM was trained with the data of the different past dog from Dog A).

In Dog B, the neurons of the SOM were configured by the data obtained from Dog B itself. Figure 19 shows an example of diagnosis of VF changing form VT. In this figure, deep respiratory fluctuations can be found. However, the detection was correct at all beats.

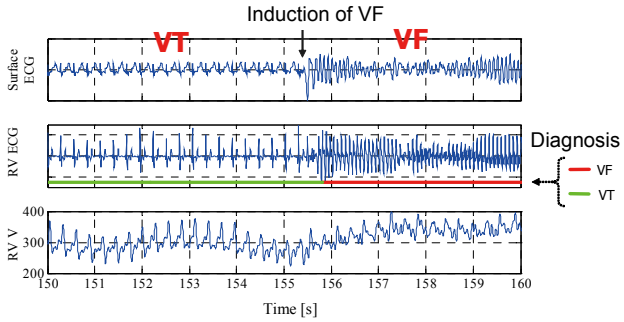


Fig. 19. An example of diagnosis of VF changing form VT (Dog B. The SOM was trained with the data of Dog B itself).

In Dog C, the neurons of the SOM were configured by the data obtained from Dog B. To save electrical power, in this case, the RVV signal was not continuously measured but we used a method in which the measurement will begin only if R-R interval becomes shorter than 0.4s and the measurement will stop if R-R interval which is longer than 0.4s continues more than 5 beats as shown in Fig.20. Examples of the detection using discontinuous measurement of the RVV signal are shown in Figs. 21 (VT changing from SR) and 22 (VF changing from SR). This means that continuous measurement of RVV signal is not always required.

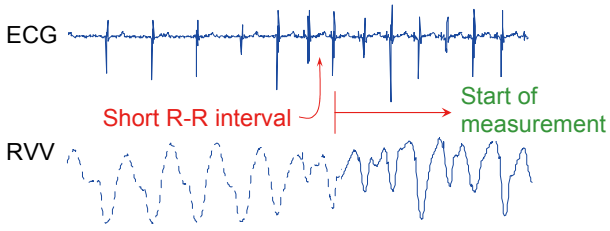


Fig. 20. Discontinuous measurement of RVV signal to save electrical power (Dog C).

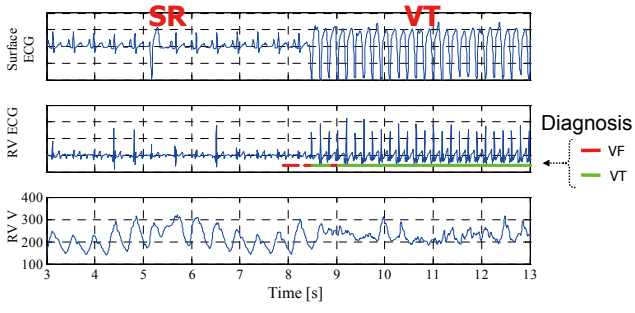


Fig. 21. An example of diagnosis of VT changing from SR (Dog C. The SOM was trained with the data of Dog B).

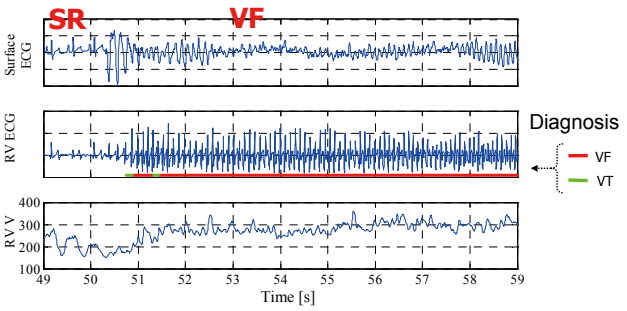


Fig. 22. An example of diagnosis of VF changing form SR (Dog C. The SOM was trained with the data of Dog B).

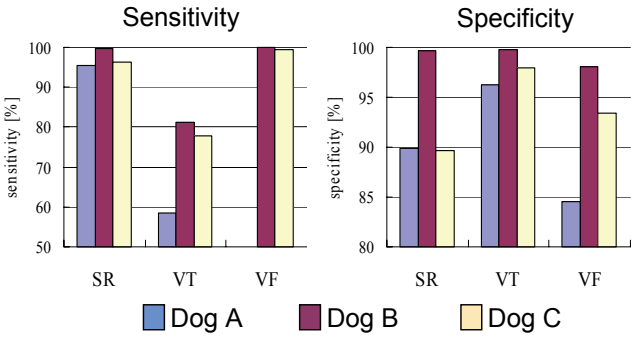


Fig. 23. Detection results from three dogs (A, B, C). In Dogs A and C, the SOM was trained with the data obtained from other dogs. In Dog B, the SOM was trained with the data obtained from Dog B itself. In the case of Dog A, VF was not induced.

The sensitivity and the specificity of the animal experiment of three dogs are shown in Fig.23. In Dog A, however, the sensitivity of VF in Dog A is not shown because the stimulation for inducing VF was not charged. The sensitivity of VT was not high in all dogs. This implies that the SOM configured with the personal data is more effective than the SOM based on other persons' data. However, all results from Dog C were higher than 78% although they were obtained from the SOM based on the different dog. This fact implies that if the RVV signal is calibrated accurately, the SOM based on the different person's data will be still useful.

4. Discussion

4.1. Effectiveness evaluation of SOM

Figs.14 and 15 indicate that VF could be detected in a higher probability than about 95% and that the probability that a beat which is not VT is classified as VT was lower than about 5%. On the other hand, these figures also mean that the specificity of VF was moderate (about 90%-95%) and the sensitivity of VT were not high (about 70%-85%). If a beat which is not VF is regarded as VF, unnecessary electrical shock will be charged on the patient. Thus, it is necessary that the

specificity of VF is improved more than the current rate. Furthermore, these figures show that the method using both ECG and RVV was superior to the method using only ECG. This fact implies effectiveness of measurement of the RVV signal.

Figure 16 suggests that the k-NN method is superior to the k-means method as a clustering method used in the SOM. However, the k-NN method takes a more computational time than the k-means method. In any way, this study has actually demonstrated that the computational time of the k-NN method is not so long as it cannot be implemented in a single-chip microcomputer system.

Figure 17 indicates that the specificity and the sensitivity were still higher than 97% in all cases (SR, VF and VT) even when the number of elements of the input vector was reduced from 15 into 6 in order to install to the single-chip microcomputer system. This result means that the proposed method is suitable enough for practical clinical use.

4.2. Limitation of the proposed method

Figure 18 means that the ventricular volume signal has time-varying characteristics and individual differences. Thus, we need a task of accurate calibration of the volume signal in a surgical operation for implantation of an ICD for overcoming individual differences, and simultaneously, we also need a task of training of the SOM. In our experiment using the microcomputer system, it took only about 5min to carry out the training process of the SOM. This fact suggests that the training process of the SOM can be executed even in the surgical operation.

It has been proved that the cause of the misdiagnosis of VT for VF was the fluctuation of the stroke volume defined as the difference between the minimum and maximum RVV signal. The stroke volume during VT has a roughly periodic fluctuation. If we take this characteristic into account, the detection accuracy will be able to be improved.

To implant an ICD into a patient, the algorithm for the ICD should be compact and work fast, and does not need a lot of electrical power. As verified in Figs. 19, 21, and 22, the proposed algorithm could reduce the order of the input vector from 15 to 6, and adopt the discontinuous measurement of the RVV signal to save electrical power, without decrease in detection accuracy.

Figure 23 suggests that the detection accuracy of the proposed algorithm can become high if the data used for training a SOM is obtained from the same person as the person using the SOM while the difference between the recipient and the person for training may decrease the detection accuracy. Thus, it is necessary to train the SOM and carry out calibration for ventricular volume signal under surgical operation for implantation. This procedure is not too difficult to apply because traditional ICDs also need to adjust several thresholds with respect to R-R intervals on the basis of induced VF or VT by using electrical stimulation under the operation.

5. Conclusion

This article has discussed the effectiveness of a new method of detecting fatal arrhythmia used for ICDs. The method utilizes the self-organizing map with an input vector consisting of not only the ECG signal but also the ventricular volume signal to automatically diagnose fatal arrhythmia without setting any thresholds manually. The proposed algorithm was implemented into a single-tip micro computer system and ascertained its effectiveness in an animal experiment using a dog.

The specificity and the sensitivity were higher than 97% in all cases (SR, VF and VT) when the order of the input vector was 6 in order to install to the single-chip microcomputer system. This result means that the proposed method is suitable enough for practical clinical use.

In further studies, it is necessary to ascertain whether a simpler signal assumed to be used in the actual new ICD instead of the signal obtained from a conductance catheter is still useful for detection.

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