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自己組織化ニューラルネットワークを用いた人工心臓の自動監視システム

An Automatic Monitoring System for Artificial Hearts Based on a Hierarchical Self-Organizing Map

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1. Introduction

For clinical application of artificial hearts, it is necessary to develop an automatic, real-time and on-line monitoring system for detection and classification of abnormalities in measured signals. This is because abnormalities or troubles occurring in an artificial heart immediately threaten the recipient's life.

Many algorithms have been proposed over years for automated diagnosis and classification of various biomedical signals. They include signal processing techniques such as frequency analysis, template matching, and parameter extraction methods. Artificial neural networks were also employed to exploit their natural ability in pattern recognition tasks for successful detection and classification of biomedical signals [1)-5)]. The supervised neural networks such as backpropagation networks or learning vector quantization (LVQ) were usually employed to design a classifier [4)-6)].

However, these supervised learning algorithms have the disadvantage that the class of every pattern used in teaching the classifier must be defined exactly. This is especially troublesome in realistic situations of monitoring artificial hearts where the classes of the signal are fuzzy and often overlap with each other. Furthermore, the number of data which the system has to acquire and process beat by beat is enormous because the heart usually beats over 100 thousand a day. To make matters worse, almost all data are normal and the occurrence rate of abnormal data is usually very low. This means that it is quite difficult to manually get or establish reference patterns or templates necessary for automatic recognition, which can be obtained easily in letter or voice recognition problems. Of course, it is still more difficult to describe objective and mathematical definitions of waveform patterns to distinguish between normal and abnormal states. Consequently, it is necessary to develop a more practical algorithm for automatic recognition and self-organizing detection of abnormalities.

One possible approach to solve this problem is to use the self-organizing map (SOM) which is an artificial neural network based on unsupervised, competitive learning [7)]. The SOM provides a topology preserving smooth mapping from a high-dimensional input space to the feature map units usually arranged as a two-dimensional lattice of neurons. The learning algorithm of the SOM forces adjacent neurons in the feature map to respond to similar input vectors. The SOM can serve as a tool for cluster analysis of complex, high-dimensional data such as biological signals.

The present study has developed a new approach called the *hierarchical SOM* for self-organizing detection of abnormalities to cope with the following problems occurring in actual monitoring situations of artificial hearts. 1) As the occurrence rate of abnormalities is usually very low in measured signals, gathering a training dataset preclassified manually by the clinician is extremely difficult. 2) Even new classes of abnormalities which have never been defined by the clinician in the training procedure must be detected correctly in real-time monitoring. 3) Efficient convergence speed is required. 4) In addition to the ability to detect abnormalities, it is expected that the system can predict the occurrence of abnormalities.

The *hierarchical SOM* has been developed as a combination of two SOMs [8)]. The first SOM is used as a preprocessor for extracting the complex and dynamic feature of the instantaneous waveform of time series signals in an unsupervised way. The second SOM combine the output of the first SOM with the original time-domain features of beat-to-beat data, and it has an extra input vector to represent the class for solving final classification problems.

In the proposed system, the hierarchical SOM has been applied to the aortic pressure (AoP) signal measured from a goat equipped with a total artificial heart (TAH), and its ability of automated recognition and detection abnormalities has been evaluated.

2. Methods

2.1 Monitoring Signal

In general, the AoP signal is considered to mostly represent the state of the circulatory system and almost always measured in experimental studies of artificial hearts[9)10)]. In our study, thus the AoP signal of an adult goat equipped with a pneumatically-driven TAH was measured with a pressure transducer at the outlet-port of the left pump of the TAH and digitized by an A/D converter at 100 Hz to provide for the hierarchical SOM.

An example of the normal AoP signal is shown in Fig.1(a). The dominant oscillatory part of its waveform corresponds to a water hammer caused by closure of an artificial valve. Two kinds of typical abnormal situation were chosen as objects to be detected in the measured signals. One is a break in signal lines resulting in abrupt drop of the signal or a sudden accident of the sensory system as shown in Fig.1(b). The other is a slow change in the state of the circulatory system or a slow drift of the measured signal due to aging of a transducer, an example is shown in Fig.1(c).

The goal of the monitoring system developed in the present study is to detect and distinguish correctly all of the abnormal situations out of the measured signals.

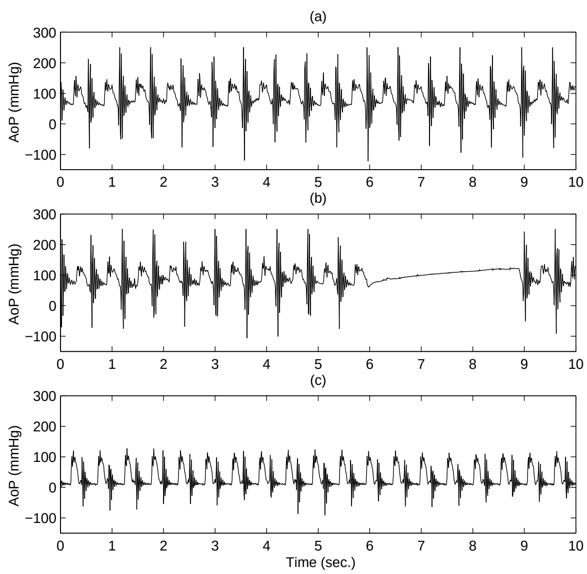

Fig. 1 Examples of AoP signals. (a) Normal signal. (b) Abnormal signal caused by a break of a pressure sensor. (c) Abnormal signal depressed by a drug administration.

2.2 Original SOM

The SOM is an artificial neural network that maps the input vector onto a two-dimensional map through a competitive learning process. The map consists of a two-dimensional regular array of nodes (neurons). The i-th node has an adaptive weight vector $w_i(t)$ whose each element corresponds to each element of the input vector $x(t)$, where $t = 1, 2, ...$ is the step index. Update of $w_i(t)$ is carried out by a sequential regression process as the following.

First, when $x(t)$ is acquired, the index b of the winner neuron (best matching neuron) satisfying

$$||x(t) - w_b(t)|| = \min_i ||x(t) - w_i(t)|| \qquad (1)$$

is searched for. After the determination of b, $w_i(t)$ is updated according to

$$w_i(t+1) = w_i(t) + h_{b(x),i}(t)\{x(t) - w_i(t)\}, \quad (2)$$

where $h_{b(x),i}$ is a real-valued function called "neighborhood function". In our system, a so-called "bubble kernel" [7], which is one of simple neighborhood functions, was used as $h_{b(x),i}$. This function operates in Eq.(2) such that the winner node and only nodes belonging to an adjacent region near around the winner node may be updated and that both the value of $h_{b(x),i}$ and the number of nodes belonging to the adjacent region may decrease monotonically.

As a result of the self-organizing process, the distribution of the weight vectors will approximate the probability distribution of input vectors, and similar inputs will be projected near one another onto the map. On the contrary, different inputs will be projected apart from one another.

On the two dimensional map, an input vector is represented as a point. Consecutive input vectors are thus seen as a trajectory on the map. It is important how to use such a trajectory in the architecture of the monitoring system because the trajectory may represent dynamic changes in time of input AoP signal. Furthermore, for solving the final classification problem, a new classification algorithm has to be introduced into the SOM since the original SOM is an unsupervised learning process. An answer to these problems is found by using a hierarchical SOM as explained below.

2.3 Hierarchical SOM

The digitized AoP signal is interpolated with the cubic spline continuous function and re-sampled to be a vector $p(k) = [p_1, p_2, \cdots, p_{n_p}]^T$ with $n_p = 40$ elements per one heart beat, where k denotes the number of beats. The value of n_p is decided as a compromise between accuracy and computational requirements.

The hierarchical SOM consists of two different SOMs as shown in Fig.2. The first and second SOMs consist of hexagonal lattices with the dimension of $m_{SOM1} = 20 \times 20 = 400$ and $m_{SOM2} = 8 \times 8 = 64$, respectively. Each node of the first SOM has a $n_{SOM1} = n_p = 40$-dimensional weight vector whose elements correspond to the input vector $p(k)$. Each node of the second SOM has a $n_{SOM2} = 11$-dimensional weight vector whose elements correspond to an input vector $q(k)$ defined in the following.

The input vector of the second SOM consists of three subsets of vector as $q(k) = [a(k)^T, b(k)^T, c(k)^T]^T$. The vector $a(k) = [a_1, a_2, a_3, a_4]^T$ consists of the x- and y-coordinates of the previous and the current winner units on the first map. Because the positions of the neurons on the map are considered to be dimension-reduction of the input information, $a(k)$ is supposed to carry the information of dynamic changes in time of AoP signal. The second vector $b(k) = [b_1, b_2, b_3, b_4]^T$ consists of the mean value of AoP signal over the current beat, the length of the beat and their difference values between the previous and the current beat. Furthermore, the third vector $c(k) = [c_1, c_2, c_3]^T$ is introduced to solve classification problem as described below.

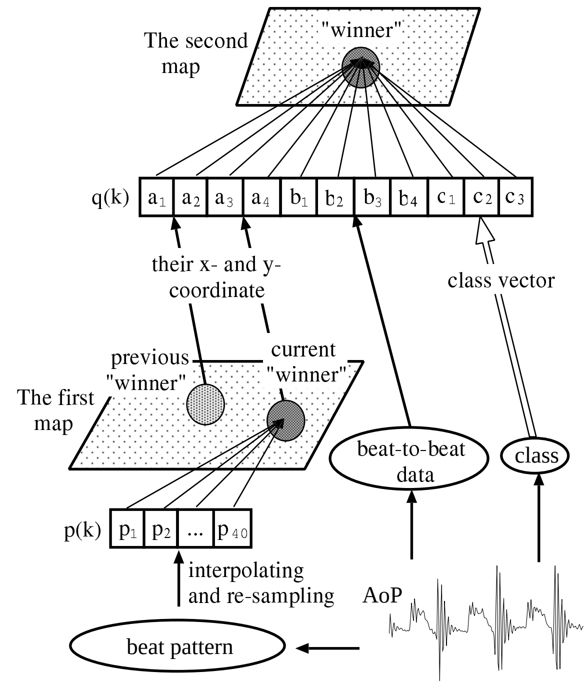

Fig. 2 Training of the hierarchical SOM.

In the proposed system, Class I is defined as a class contains all the normal states, Class II as the first kind of abnormalities, and Class III as the second kind of abnormalities. In the learning process, the clinician judges which class the signal belongs to. When operating, Classes I, II and III are represented as class vectors with binary elements $c(k) = [c_1, c_2, c_3]^T = [1, 0, 0]^T, [0, 1, 0]^T$ and $[0, 0, 1]^T$, respectively. If necessary, the number of classes can be increased more than presented here.

As mentioned in Introduction, in an actual situation of the operation of the TAH, an acquired dataset usually includes the signals which the clinician can not easily classify. It is quite difficult to use these signals as training data in traditional methods. Our method deal with this problem as the following. If some patterns in the training data are not preclassified, each element of their class vectors is filled with the mark 'x' instead of the numerical value 1 or 0. For these input patterns, the distance calculation in Eq.(1) and the weight vector modification in Eq.(2) are computed using the other elements of input vector except the elements of class vector.

2.4 Classification Algorithm

The learning algorithm of the first and second SOMs is the same as Eqs.(1) and (2). Replace x in Eqs.(1) and (2) with p and q in the case of the first and second SOMs, respectively. The class vector c in the second SOM are learned with Kohonen's learning rule in the same way as vector a and b are learned.

After the network has been trained, a testing set is presented to the hierarchical SOM. The output is the class vector $c(k)$. This procedure is depicted in Fig.3.

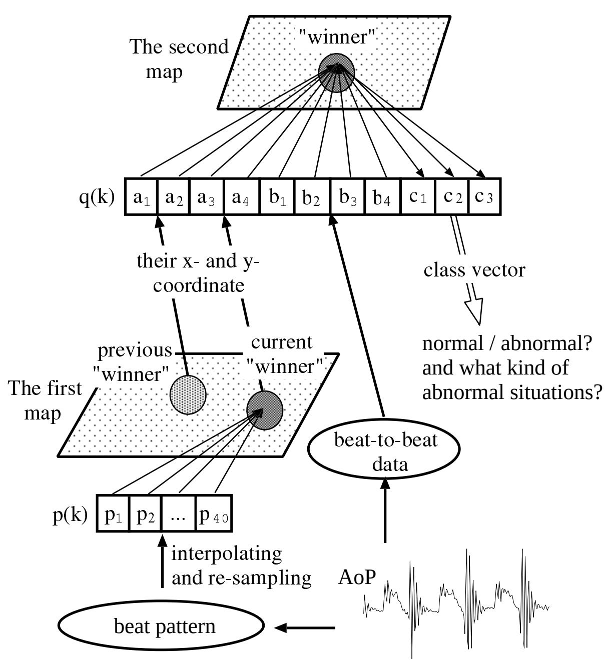

Fig. 3 Monitoring procedure of the hierarchical SOM.

In the case of the second SOM, the input vector in the training stage differs from that in the testing stage. Define two vectors as $q_1(k) = [a(k)^T, b(k)^T]^T$ and $q_2(k) = c(k)$. In the testing stage, only the vector $q_1(k)$ is given as input to the second SOM. The weight vector w_i^q (for $i = 1, 2, ..., m_{SOM2}$) is separated into two parts as $w_i^q = [(w_{1i}^q)^T, (w_{2i}^q)^T]^T$ such that the two segments can correspond to $q_1(k)$ and $q_2(k)$, respectively. Afterwards, the Euclidean distance is calculated to find the winner w_{1b}^q as follows:

$$||q_1(k) - w_{1b}^q|| = \min_i ||q_1(k) - w_{1i}^q||. \quad (3)$$

As a result, the winner's class vector w_{2b}^q is treated as the output of this network as

$$c(k) = w_{2b}^q. \quad (4)$$

Each element of this vector is not binary but real number between 0 and 1. It is clear that the closer to 1 or 0 each element of $c(k)$ is, the better the classification problem is solved by the network.

3. Results

The map was initialized, trained and evaluated by using the routines in the SOM_PAK program package [11]. The Euclidean distance between the best-matching weight vector and input vector gives the quantization error. When inputs differ substantially from weight vectors provided for the self-organization, the quantization errors are large. Fig.4 shows an example of the AoP signal patterns and their quantization errors calculated from the first SOM which was trained by using only normal AoP signal patterns as training data. The length of the signal was about 20 minutes, and the goat's mean heart rate was 107/min. It is clear that the abnormal AoP beat patterns seen at the neighborhood

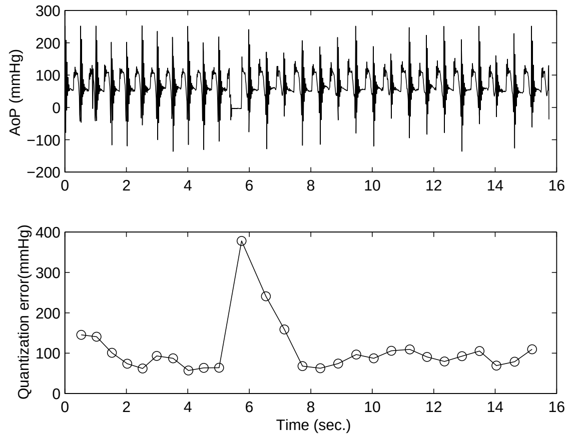

Fig. 4 AoP signal samples and their quantization errors given by the first SOM which was taught with normal AoP signals.

of 5s corresponds to the peak of the quantization errors. This implies that the abnormalities will be able to be detected if the quantization errors exceed an appropriately predetermined threshold. However, a problem exists with this approach owing to the heavy dependence on the set threshold. Also this method can not easily deal with the classification problem of abnormalities.

The hierarchical SOM was taught with about 80 minutes data which was selected from the records during 13 days period. In all training data, 3,902 AoP beat patterns including 3,667 "n", 91 "s" and 144 "d" patterns were preclassified, and their class vectors were defined as Classes I, II and III, respectively in the training procedure of the second SOM. Fig.5 shows an example of the distribution of labeled nodes of the first SOM trained by using the AoP signal patterns acquired in three different states. They were labeled as "n": the normal state; "s": the abnormal state caused by a trouble of the pressure sensor; and "d": the abnormal state after the drug administration of 10mg methoxamine. The locations on the map with identical labels

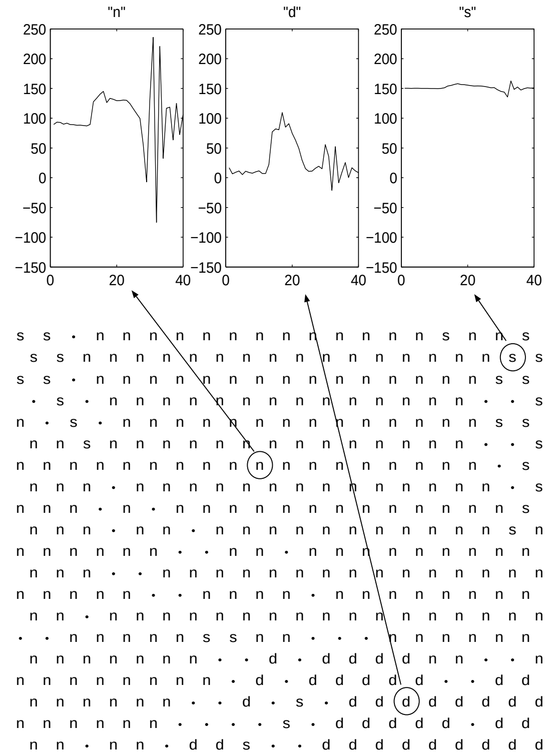

Fig. 5 A trained and labeled map for the first SOM. Three weight vectors, for the labels "n", "s", and "d", are depicted at the top of the map.

formed rather continuous areas. The number of locations with the label "s" or "d" was smaller than "n" because they were infrequent during the self-organization process.

Fig.6 and Fig.7 show two examples of the results identified by the trained hierarchical SOM. In each figure, both the input signal and the output of the network are represented. For simplicity, the output of the system was regarded as the subscript i that maximizes c_i; $i = 1, 2, 3$, i.e., the element of the output vector $c(k)$ defined by Eq.(4). Fig.6 illustrates the result from the abnormalities caused by the trouble of the sensor. It is clear that the abnormalities could be detected and classified correctly in the almost all parts except the neighborhood of 325s. At this neighborhood, the presumably normal state may have incorrectly been classified into the abnormal state. Fig.7 illustrates the result from the abnormal state change in the circulatory system after the drug administration. In the training procedure of the network, the AoP patterns between 140s and 210s were taught as abnormalities of Class III. Three typical AoP signal patterns are shown at the top. Samples (A) and (C) were extracted respectively at the time when the drug had not been effective yet and at the time when the drug had already been effective. Sample (B) is a set of samples which may be classified into a transient state. The output results indicates that the AoP signal could be classified into the correct classes except the transient states such as sample (B).

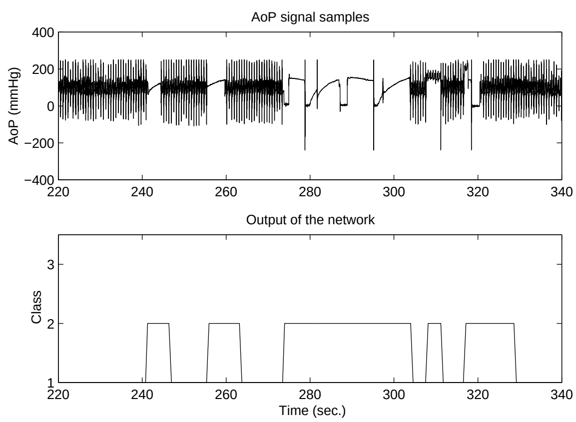

Fig. 6 An example of detection of abnormal patterns caused by the break of the pressure sensor.

From Figs.6 and 7, it was ascertained that two typical abnormal situations were detected and distinguish correctly by the proposed hierarchical SOM. Moreover, as shown in Fig.7, the slow change phenomenon in the state of the circulatory system was identified well and this result implies that the proposed system is useful for prediction of slow change from a normal situation to an abnormal one.

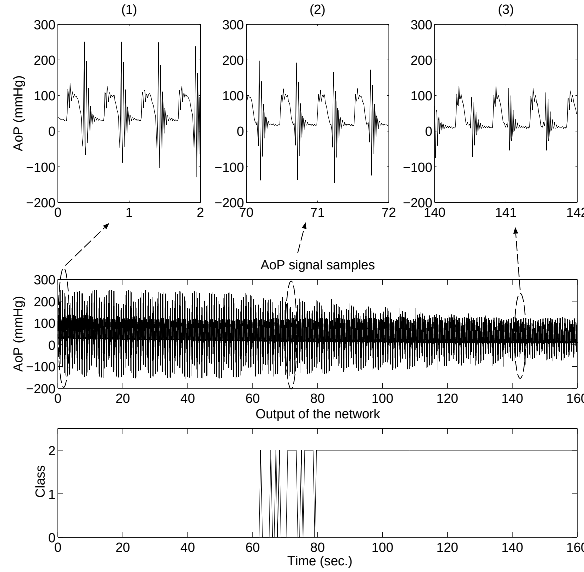

Fig. 7 An example of detection of abnormal patterns depressed by the drug administration.

4. Discussion

4.1 Comparison with a Single SOM

The experimental results shown here have revealed that the proposed monitoring system has a good classification ability for distinguish normal and abnormal states occurring in aortic pressure signals. The key point of the proposed monitoring system is the hierarchical structure of the SOMs. It may be true that, if a single SOM has input vectors including the same information as that of the hierarchical SOM, the single SOM will also have a similar ability to the hierarchical SOM. However, the hierarchical SOM is superior to the single SOM as the following reasons.

In the hierarchical SOM, the first SOM was actually used as a preprocessor which reduced a 40-dimensional input vector to a two-dimensional coordinate vector. The original $2 \times 40 + 7 = 87$-dimensional input vector which should be used in the single SOM was thus reduced to 11-dimensional vector. Therefore, it is obvious that the feature processed by the first SOM can be more easily classified. Although the first SOM itself takes some additional time to converge, the overall convergence is faster.

The learning speed problem was not very critical in this work though, since the network size used here was not very large and the number of training data was limited. If this work is extended to a larger network for monitoring multi-channel signals, the learning speed will become more critical. In the future, we hope to apply the hierarchical SOM to diagnose and classify multi-channel signals.

4.2 Relations to Other Studies

In other studies, many methods for automatic recognition and classification in biomedical signals have been developed, such as a model of combining the SOM and the multilayer feedforward artificial neural network for classification of late potential morphology features [4], and a method based on the SOM and the LVQ for the interpretation and classification of body surface potential map sequences [6]. Our study differs in two aspects from these models.

First, our method has enabled the automatic classifier to effectively utilize even the data for training which the clinician can not easily define but which may be included a lot in actual clinical data. On the other hand, those traditional supervised neural networks cannot utilize such undefined data for training. In our proposed new method, the class vector was used as a part of input vector in the second SOM and learned by Kohonen's learning rule as well as other parts of input vector in the training procedure. As Kohonen's learning algorithm is a useful tool which can handle partial training data [11][12], even those undefined patterns could be assembled near around the similar defined patterns in the self-organizing training procedure of the second SOM. The results as shown in Figs.5-7 showed the usefulness of the proposed classification algorithm for automatic recognition and classification of the normal and abnormal states from the measured signal.

Second, the traditional supervised learning algorithm may fail to detect and diagnose new abnormalities which have never been defined by the clinician in the training procedure. However, the proposed system can easily distinguish them from the normal states, although these new abnormalities may be diagnosed to some similar defined classes of abnormalities. This is because similar inputs were projected near one another onto the maps of both SOMs and different inputs were projected apart from one another during the self-organizing process.

5. Conclusion

In this paper, the hierarchical SOM has been applied to recognition and classification of the AoP signal measured in an adult goat equipped with a TAH. The advantage of the hierarchical structure of two SOMs in the proposed system is that the complex and dynamic feature of the instantaneous waveform of the AoP signal can automatically be simplified to the topological map in the first SOM, and then, the second SOM can easily classify two typical abnormal states as well as normal ones. Although this paper has focused on the analysis of only the AoP signal, the concepts we introduced can be applied to analyses for other biomedical signals. For further studies, it is expected that the hierarchical SOM will be able to be extended to diagnosis and classification of multi-channel signals including left and right arterial blood pressure, left and right outflow of the TAH for establishing a more reliable and sensitive automatic monitoring system.

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