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Self-Organizing Map Considering Winning Frequency

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1. Introduction

The Self-Organizing Map (SOM) [1][2] is an unsupervised neural network introduced by Teuvo Kohonen. SOM has attracted attention in studies of clustering in recent years. In this study, we propose a new type of SOM algorithm, which is called SOM considering Winning Frequency (WF-SOM) algorithm. The most important feature of WF-SOM is that each neuron has individuality by considering winning frequency. Namely, if the winning frequency of a neuron is smaller and the neuron is nearer to the winner neuron, the neuron is updated more greatly. We investigate the behavior of WF-SOM and apply WF-SOM to clustering problems. The efficiencies of WF-SOM are confirmed by several simulation results.

2. WF-SOM

In the WF-SOM algorithm, if the winning frequency of a neuron is smaller and the neuron is nearer to the winner neuron, the neuron is updated more greatly. Namely, even if it is seldom a winner, though it is near the winner neuron, it is updated greatly. Slick neurons always exist. This is similar to an unreasonable situation at human society.

(WF-SOM1) The initial values of all the weight vectors $\boldsymbol{w}_i = (w_{i1}, w_{i2}, \cdots, w_{id})$ $(i = 1, 2, \cdots, M)$ are given between 0 and 1 at random.

(WF-SOM2) An input data $\boldsymbol{x}_j = (x_{j1}, x_{j2}, \cdots, x_{jd})$ $(j = 1, 2, \cdots, N)$ is inputted to all the neurons at the same time in parallel.

(WF-SOM3) We find the winner neuron c by calculating the distance between $\boldsymbol{x}_j$ and $\boldsymbol{w}_i$.

(WF-SOM4) We accumulate the number becoming the winner for each neuron for every learning.

(WF-SOM5) The weight vectors of all the neuron are updated by considering winning frequency. If the winning frequency of a neuron is smaller and the neuron is nearer to the winner neuron, a neuron is more updated.

(WF-SOM6) The steps from (WF-SOM2) to (WF-SOM5) are repeated for all the input data.

4. Simulation results

Input data is 2-dimensional random data of 1000 points whose distribution is non-uniform as Fig. 1(a). The number of learning of SOM and WF-SOM is 3 times. We consider the conventional SOM and the proposed WF-SOM with 100 neurons (10 $\times$ 10). From the results, we can say that in the case of the small number of learning the conventional SOM does not tend to self-organize up to all the corners of the input. On the other hand, in the case of the small number of learning WF-SOM can tend to self-organize up to all the corners of the input. Although WF-SOM can self-organize more exactly and quickly than SOM, it tends to produce twists between the neurons.

In order to evaluate the mapping precision of WF-SOM, we define the average quantization error e_q. For example, if the weight vector of the winner neuron is exactly the same as input data, the value of e_q is 0.

The calculated results are summarized in Table 1. We can evaluate the effectiveness of the method using WF-SOM. Furthermore, the improvement rate is 17.8 [%].

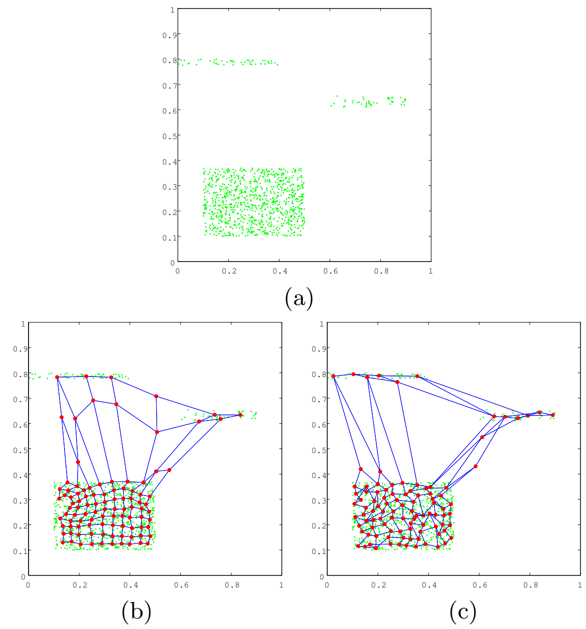

Figure 1: Learning results. (a) Input data. (b) The conventional SOM. (c) WF-SOM.

Table 1: Average quantization error [%] for 2-dimensional input data.

	Conventional SOM	WF-SOM
e_q	1.57	1.33

5. Conclusions

In this study, we have proposed WF-SOM. We have explained the differences between SOM and WF-SOM with learning algorithm and have investigated its behavior. Furthermore, we have applied the proposed WF-SOM to clustering problems in the case of the small number of learning and have confirmed its exact and quick self-organization.

In the future, we try to reduce the twists between neurons.

Reference

[1] T. Kohonen, "The Self-Organizing Maps," *Neurocomputing*, vol. 21, pp. 1-6, 1998.

[2] T. Kohonen, *Self-Organizing Maps*, Berlin, Springer, vol. 30, 1995.