SOM Considering False Neighboring Neuron for Effective Feature Extraction

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Abstract— **In this study, we propose a new Self-Organizing Map (SOM) algorithm which considers the False Neighboring Neuron (called FNN-SOM). The FNN-SOM self-organizes with considering the real neighboring relation. We confirm that we can obtain the more effective map reflecting the distribution state of input data than the conventional SOM.**

I. INTRODUCTION

In real world, it is not always true that the next-door house is close to my house, in other words, "neighbors" are not always "true neighbors". In addition, the synaptic strength is not constant in the brain. There is scarcely any research changing the synaptic strength.

In this study, we propose a new Self-Organizing Map (SOM) algorithm which considers the False Neighboring Neuron (called FNN-SOM). The FNN-SOM self-organizes with considering the real neighboring relation. The neuron, which is the most distant from the input data in a set of direct topological neighbors of winner, is defined as "False Neighboring Neuron (FNN)". Furthermore, all of the connection between each neuron of FNN-SOM has the connection reference vector. The connection reference vectors of FNN are increased, and the connection reference vectors act as burden of the distance between each map node when the weight vectors of neurons are updated.

We confirm that we can obtain the more effective map reflecting the distribution state of input data than the conventional SOM [1].

II. SOM WITH FALSE NEIGHBORING NEURON (FNN-SOM)

We explain a proposed new SOM algorithm, FNN-SOM. All of the connection between each neuron of FNN-SOM has the connection reference vector.

An input vector is inputted to all the neurons at the same time in parallel. Distances between the input vector and all the weight vectors are calculated, and the winner c is defined as the neuron which is closest to the input vector. A False Neighboring Neuron l (called FNN) is found. FNN is the most distant from the input vector in Nc_1, where Nc_1 is the set of direct topological neighbors of c. The connection reference vector between c and l is increased. Conversely, the connection reference vectors between c and its neighbors Nc_1 without l are set to zero. The weight vectors of the neurons are updated by considering the connection reference vector between the

winner c and the each neuron. In other words, the neuron, which is closer to the winner and whose reference vector is smaller, is more significantly updated.

III. LEARNING SIMULATION

We carry out learning simulation for the "C"-shaped 2-dimensional data, shown in Fig. 1(a). The total number if data is 700. All the input data are sorted by random.

The leaning conditions are as follows. Both the conventional SOM and FNN-SOM has 289 neurons (17×17). We repeat the learning 15 times for all input data.
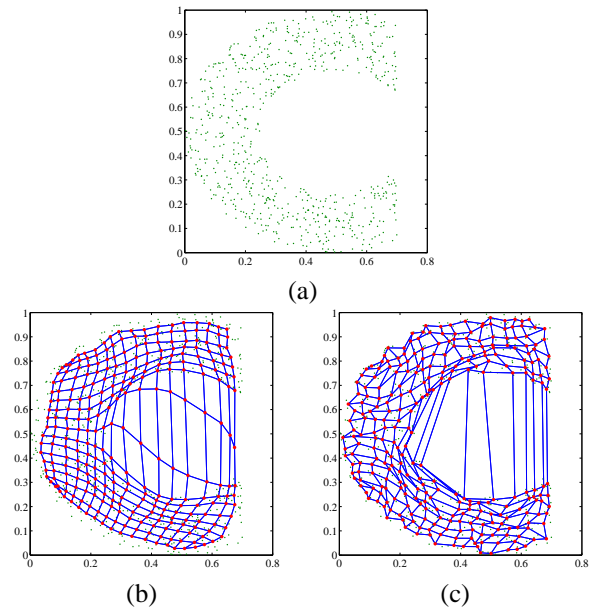

Fig. 1. Learning Simulation. (a) Input data. (b) Simulation result of conventional SOM. (c) Simulation result of FNN-SOM.

The results of SOM and FNN-SOM are shown in Figs. 1(b) and (c). We can see that there are some inactive neurons in the result of SOM, however, there are no inactive neurons in the result of FNN-SOM. This is because the neurons of FNN-SOM are not affected by FNN, so, the neurons can learn more distant for the distant input data. Therefore, FNN-SOM can obtain the more effective map reflecting the distribution state of input data, than the conventional SOM.

REFERENCES

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