

# SOM with False Neighbor Degree between Neurons

Haruna MATSUSHITA  
(Tokushima University)

Yoshifumi NISHIO  
(Tokushima University)

## 1. Introduction

In the real world, it is not always true that the nextdoor house is close to my house, in other words, “neighbors” are not always “true neighbors”. In this study, we propose a new Self-Organizing Map (SOM) algorithm, SOM with False Neighbor degree between neurons (called FN-SOM). The behavior of FN-SOM is investigated with learning for the input data which includes some clusters located at distant locations. We confirm that FN-SOM can obtain more effective map reflecting the distribution state of input data than the conventional SOM [1].

## 2. SOM with False Neighbor Degree

We explain FN-SOM algorithm. Input data  $\mathbf{x}_j = (x_{j1}, x_{j2}, \dots, x_{jd})$  ( $j = 1, 2, \dots, N$ ) is  $d$ -dimensional. Each neuron  $i$  has a weight vector  $\mathbf{w}_i = (w_{i1}, w_{i2}, \dots, w_{id})$  ( $i = 1, 2, \dots, n \times m$ ). False-neighbor degrees of rows  $R_r$  ( $1 \leq r \leq n-1$ ) are allocated between adjacent rows of FN-SOM with the size of  $n \times m$  grid. Likewise, false-neighbor degrees of columns  $C_k$  ( $1 \leq k \leq m-1$ ) are allocated between adjacent columns of FN-SOM. The initial values of all of the false-neighbor degrees are set to zero, and the initial values of all the weight vectors are given over the input space at random. Moreover, a winning frequency  $\gamma_i$  is associated with each neuron and is set to zero initially.

**(FN1)** An input vector  $\mathbf{x}_j$  is inputted to all the neurons.

**(FN2)** A winner  $c$  is found.

**(FN3)** Increment the winning frequency of the winner  $c$  by  $\gamma_c^{\text{new}} = \gamma_c^{\text{old}} + 1$ .

**(FN4)** The neighboring distances between the winner  $c$  and the other neurons are calculated. For instance, for two neurons  $s_1$  and  $s_2$ , the neighboring distance is defined as the following measure;

$$d_f(s_1, s_2) = (|r_{s_1} - r_{s_2}| + \sum_{r=r_{s_1}}^{r_{s_2}-1} R_r)^2 + (|k_{s_1} - k_{s_2}| + \sum_{k=k_{s_1}}^{k_{s_2}-1} C_k)^2, \quad (1)$$

where  $r_{s_1} < r_{s_2}$ ,  $k_{s_1} < k_{s_2}$ .

**(FN5)** The weight vectors of the neurons are updated as

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + h_{F_{c,i}}(t)(\mathbf{x}_j - \mathbf{w}_i(t)), \quad (2)$$

where  $h_{F_{c,i}}(t)$  is the neighborhood function of FN-SOM:

$$h_{F_{c,i}}(t) = \alpha(t) \exp\left(-\frac{d_f(c, i)}{2\sigma^2(t)}\right). \quad (3)$$

**(FN6)** If  $\sum_{i=1}^{nm} \gamma_i \geq \lambda$  is satisfied, we find the false-neighbors and increase the false-neighboring degree, according to the steps from (FN7) to (FN10). If not, we perform step (FN11).

**(FN7)** We find the neuron  $q$  which has become the winner least frequently.

**(FN8)** A false-neighbor  $f$  of  $q$  is chosen from the set of direct topological neighbors of  $q$  denoted as  $N_{q1}$ .  $f$  is the neuron whose weight vector is most distant from  $q$ .

**(FN9)** A false-neighbor degree between  $q$  and its false

neighbor  $f$ ,  $R_r$  or  $C_k$ , is increased. If  $q$  and  $f$  are in the  $r$ -th row and in the  $k$ -th or  $(k+1)$ -th column, the false-neighbor degree  $C_k$  between the columns  $k$  and  $k+1$  is increased according to

$$C_k^{\text{new}} = C_k^{\text{old}} + \left\{ 1 - \exp\left(-\frac{\|\mathbf{w}_f - \mathbf{w}_q\|^4}{2\sigma_F^2}\right) \right\}, \quad (4)$$

where  $\sigma_F$  is a constant parameter.

**(FN10)**  $\gamma_i$  of all the neurons are reset to zero.

**(FN11)** The steps from (FN1) to (FN10) are repeated for all the input data.

## 3. Application to Clustering

We consider 2-dimensional input data as shown in Fig. 1(a). The simulation result of the conventional SOM is shown in Fig. 1(b). We can see that there are some inactive neurons between input data. On the other side, the result of FN-SOM are shown in Fig. 1(c). We confirm that there are no inactive neurons between input data. As we can see from these figures, the clustering ability of using FN-SOM method is effective.

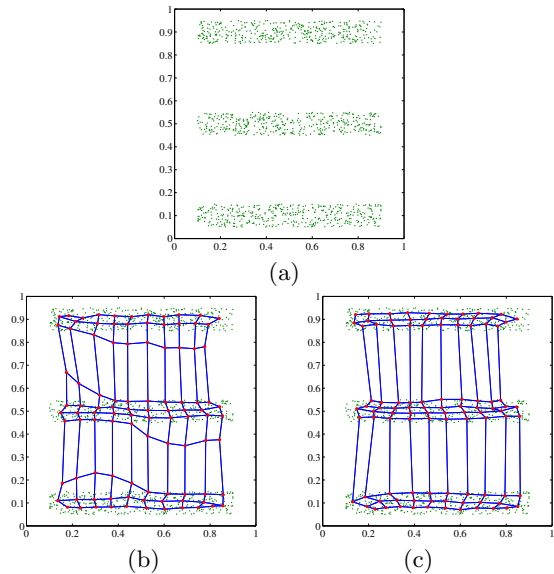


Figure 1: Clustering of 2-dimensional input data. (a) Input data. (b) Result of the conventional SOM. (c) Result of FN-SOM.

## 4. Conclusions

In this study, we have proposed the new SOM algorithm, SOM with False Neighbor degree between neurons. We have investigated its behaviors with an application to clustering, and have confirmed the efficiency.

### Reference

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