17-28

One-dimensional Looking Back SOM for Real-Time Processing

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1. Introduction

The Self-Organizing Map (SOM) is popular algorithm for unsupervised learning and visualization introduced by Teuvo Kohonen. One of the most attractive applications of SOM is real-time processing and several algorithms for various kinds of real-time prediction problems have been reported and investigated. In this study, we propose a new type of one-dimensional SOM algorithm, which is called Looking Back SOM (LBSOM) algorithm. The important feature of LBSOM is that the neurons of LBSOM depend on the distance between each neuron. We run a simulation by using the input data depended on the order of inputting and investigate the behavior of LBSOM. The efficiencies of LBSOM are confirmed by several simulation results.

2. Looking Back SOM (LBSOM)

In the LBSOM algorithm, the neurons of LBSOM depend on the distance between each neuron. In the case of the conventional SOM, we just consider the distance between the winner neuron and each neuron. However, we also consider the distance between the previous neuron and each neuron in the LBSOM algorithm. Namely, the nearer the winner neuron and the previous neuron, a neuron is more updated. Therefore, each neurons of the proposed SOM do not converge the same position.

(LBSOM1) The initial values of all the weight vectors are given between 0 and 1 at random.

(LBSOM2) An input data is inputted to all the neurons at the same time in parallel.

(LBSOM3) We find the winner neuron by calculating the distance between the input data and the weight vector of the neuron.

(LBSOM4) We determine the update rate of all the neurons by calculating the distance between each neurons.

(LBSOM5) The weight vectors of all the neurons are updated.

(LBSOM6) The steps from (LBSOM2) to (LBSOM5) are repeated for all the input data.

3. Simulation results

Input data is 2-dimensional input data depended on the order of inputting of 1000 points whose distribution is non-uniform as Fig. 1(a). We consider the conventional SOM and the proposed LBSOM with 100 neurons. And we repeat the learning for all input data once. Furthermore, we respectively set the best value of parameters to self-organize the input data very well. From the results, we can say that the conventional SOM tends to self-organize out of the order of inputting. On the other hand, LBSOM self-organizes along the order of inputting.

In order to evaluate the mapping precision of LBSOM, we define the average quantization error e_q. For example, if the weight vector of the winner neuron is exactly the same 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 LBSOM. Furthermore, the improvement rate is 43 [%].

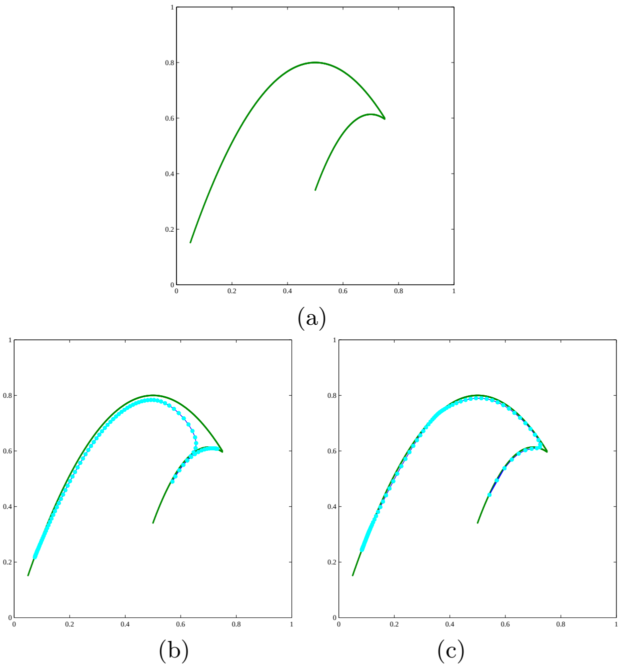

Figure 1: Learning results. (a) Input data. (b) The conventional SOM. (c) LBSOM.

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

	Conventional SOM	LBSOM
e_q	2.14	1.22

4. Conclusions

In this study, we have proposed the Looking Back SOM (LBSOM). We have explained the differences between SOM and LBSOM with learning algorithm and have investigated its behavior. Furthermore, we have applied the proposed LBSOM to the input data depended on the order of inputting and have confirmed its efficiency.

In the future, we try to discover new applications of LBSOM in the real-time processing.

References

[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.