Self-Organized Potential Competitive Learning to Improve Interpretation and Generalization in Neural Networks

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***Abstract*—The present paper proposes a new learning method called "self-organized potential competitive learning" to improve generalization and interpretation performance. In this method, the self-organizing map (SOM) is used to produce knowledge (SOM knowledge) on input patterns. By considering the potentiality of neurons rather than stored information, it can be used to train supervised learning. Highly potential neurons are supposed to respond to as many input patterns and neurons as possible. This property is, for the first approximation, described by the variance of connection weights. The method was applied to real second language learning data (Japanese learners of English) and showed improved generalization performance. In addition, two important input neurons with high potentiality were detected, both of which represented inanimate subjects. This implies that Japanese students have difficulty dealing with inanimate subjects when learning English as a second language. This finding corresponds with the established knowledge on second language learning. The present results affirm the possibility of SOM knowledge to be applied to many different situations.**

***Keywords*–Self-organizing maps; Potentiality; Interpretation; Generalization.**

I. Introduction

The present section shows that it is necessary to focus on the main part of knowledge obtained by the self-organizing maps for applying it to supervise learning.

A. Utility of SOM Knowledge

The self-organizing map (SOM) [1][2] is one of the most important unsupervised techniques in neural networks. In particular, the SOM has good reputation for producing knowledge (SOM knowledge) which can be used to clarify class structure and visualize input patterns [3]-[13]. Because it has been proved that the SOM can produce rich knowledge from input patterns, SOM knowledge has been used for many different purposes in addition to class clarification and visualization.

The present paper tries to show that SOM knowledge can be used to train supervised neural networks. If it is possible to use SOM knowledge in supervised learning, it has one major merit compared with other supervised techniques. The SOM has long been used to visualize complex data over two-dimensional maps. Thus, supervised networks with SOM knowledge can produce easily interpretable representations. It is well-known that the black-box property of neural networks is a major difficulty in extending them to practical problems. To overcome this issue, a number of methods have been developed. For example, some methods have tried to extract rules from obtained connection weights [14]-[18]. However, it is not easy to extract explicit rules when the connection weights are complex. Methods with SOM knowledge can be used to produce neural networks whose inference mechanisms are more easily interpreted.

B. Potentiality of SOM Knowledge

The direct insertion of SOM knowledge into supervised neural networks is particularly effective in decreasing errors between targets and outputs. However, since the SOM is a form of unsupervised learning, knowledge generated by the SOM is not necessarily suitable for training supervised learning. In this context, it is supposed that some form of enhancement of SOM knowledge is necessary to adapt it for supervise learning. More concretely, SOM knowledge needs to be modified before entering the supervised leaning phase in order to make it effective.

In the present paper, we suppose that the fundamental parts of SOM knowledge can be used for general purposes, including supervised learning. The main parts are supposed to be related to as many different situations and patterns as possible. On the other hand, the peripheral parts are exclusively related to specific situations and input patterns. The main part is related to the ability of neurons to respond appropriately to as many new situations as possible. Linsker [19] stated the concept of information in the same way and considered the variance of neurons as one of the candidates for the concept of information. Thus, the present paper adopts the variance of neurons as the potentiality of neurons for the first approximation. Naturally, the variance itself is not always useful in the improvement of performance. Thus, potentiality refers to all processes of transforming variance into a useful form for the sake of improved performance.

C. Paper Organization

In Section 2, we present how to compute the potentiality and how it can be used for learning. In Section 3, the experimental results on the second language learning is presented. First, we show that the selective potentiality is increased when the parameter is increased. Then, we compare

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generalization performance by the present method with that by the conventional learning methods. The present method show better generalization performance compared with the other conventional methods. In addition, connection weights into the highly potential neuron represent the inanimate subjects, corresponding to the established knowledge of the second language learning.

II. THEORY AND COMPUTATIONAL METHODS

In this section, we present how to compute the potentiality and briefly explain how to train supervised learning by this potentiality.

A. Introducing Potentiality

Potentiality refers to how neurons respond differently to as many situations as possible. For the first approximation, potentiality is measured by the variance of neurons. When the variance of neurons becomes larger, the corresponding potentiality becomes higher.

Figure 1 shows the three phases of potential learning. In the first potential determination phase in Figure 1(a), the SOM is used to obtain connection weights from input to hidden neurons. Then, the corresponding potentialities of input and hidden neurons are computed. In the second potentiality actualization phase in Figure 1(b), connection weights and input and hidden potentialities transferred from the potentiality determination phase are given as initial weights. Then, those weights and potentialities are assimilated as much as possible in learning. Finally, in the potentiality adjustment phase, the connection weights obtained in the potentiality actualization phase are slightly adjusted, specifically to eliminate the effects of over-training.

B. Input and Hidden Potentiality

In the potentiality determination phase, first the potentiality is determined by using the variance of connection weights, and then this potentiality is incorporated into the learning processes to assimilate the potentiality. For this, we need to define the potentiality of individual input neurons.

Let w_{jk} denote connection weights from the kth input neuron to the jth output neuron. Then, the variance is defined by

$$v_k = \sum_{j=1}^{M} (w_{jk} - w_k)^2, \tag{1}$$

where M is the number of hidden neurons and

$$w_k = \frac{1}{M} \sum_{j=1}^{M} w_{jk}. \tag{2}$$

Then, the input potentiality is defined by

$$\phi_k = \left(\frac{v_k}{\max_l v_l} \right)^r, \tag{3}$$

where r denotes the potentiality parameter and $r \geq 0$.

The hidden potentiality is defined by

$$v_j = \sum_{k=1}^{L} (w_{jk} - w_j)^2, \tag{4}$$

where L is the number of input neurons and

$$w_j = \frac{1}{L} \sum_{k=1}^{L} w_{jk}, \tag{5}$$

Then, the hidden potentiality is defined by

$$\phi_j = \left(\frac{v_j}{\max_m v_m} \right)^r, \tag{6}$$

C. Selective Potentiality

The number of highly potential neurons should be as small as possible. For this, the selectivity of potentiality is introduced. First, the input potentiality is normalized by

$$\phi_k^{nrm} = \frac{\phi_k}{\sum_{l=1}^{L} \phi_k}. \tag{7}$$

and

$$H_1 = - \sum_{k=1}^{L} \phi_k^{nrm} \log \phi_k^{nrm}. \tag{8}$$

Then, the selective potentiality is defined by

$$SP_1 = \frac{H_1^{max} - H_1}{H_1^{max}}. \tag{9}$$

Finally, the hidden potentiality SP_2 is obtained in the same way.

D. Potentiality Actualization

The potentiality is used to modify connection weights according its magnitude. The modification is implemented for connection weights from the input to hidden, and from hidden to output neurons. For the input-hidden connection weights,

$$^{new}w_{jk} = \phi_j \, ^{old}w_{jk} \phi_k \tag{10}$$

and for the hidden-output connection weights,

$$^{new}w_{ij} = \, ^{old}w_{ij} \phi_j. \tag{11}$$

In the potential actualization phase, connection weights weighted by the corresponding potentialities are given as initial weights. Those initial and weighted connection weights guide the learning processes in the actualization phase.

III. RESULTS AND DISCUSSION

This section deals with an experimental result on the second language learning, stressing that the main findings by the present method correspond to those of the second language learning.

A. Experimental Outline

Real second language learning data was used to test the method. The numbers of input variables and patterns were 42 and 70, respectively. The number of hidden neurons was set to 12. The size was empirically determined for the SOM. The data set was divided into the training (70%), validation (15%) and testing (15%) data. All supervised learning used the default parameter values of the Matlab neural networks package in order to make it easy to trace the results.

The purpose of the experiment was to examine what differentiates Japanese high school and university EFL students in

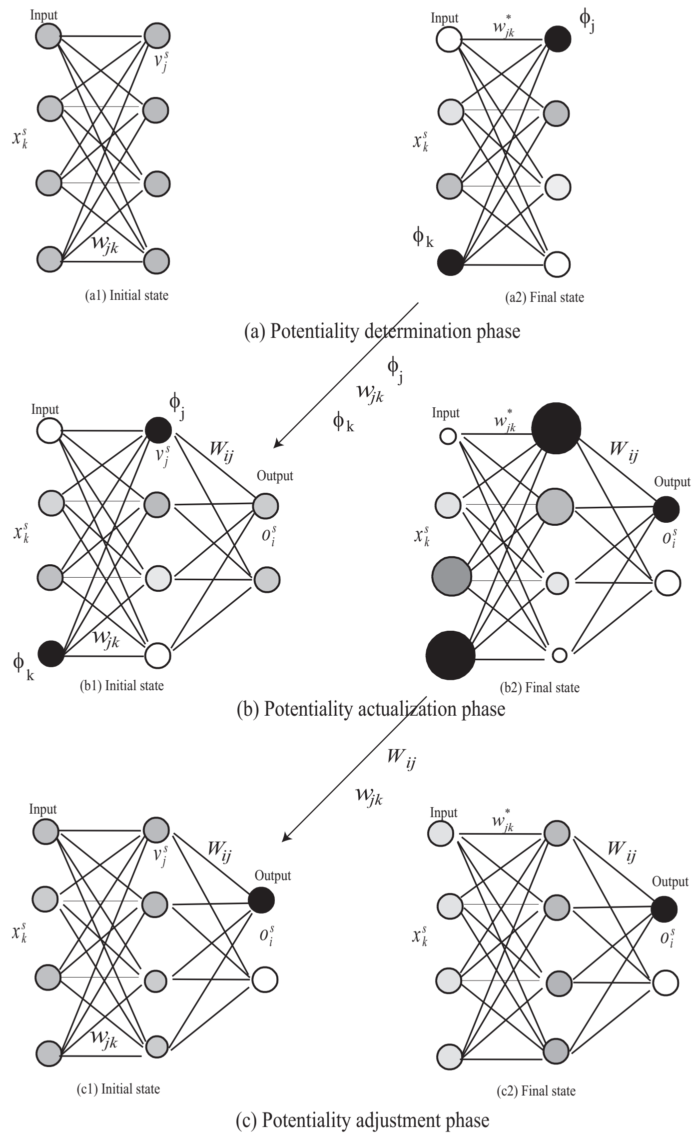


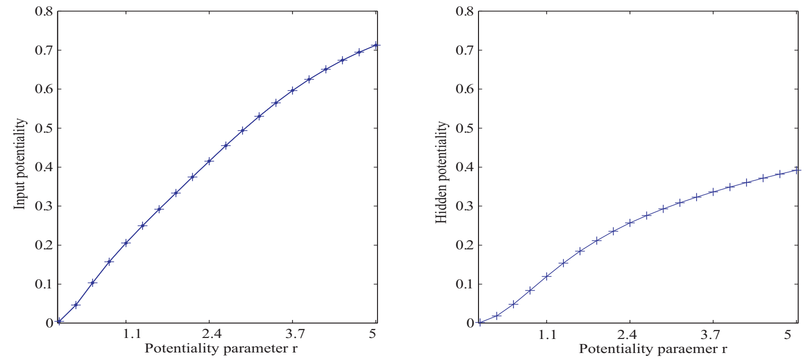
Figure 1. Concept of self-organized potential learning where the potentiality is determined in the potentiality determination phase, and the knowledge obtained in this phase is transferred to the potentiality actualization phase. Finally, minor adjustments are made in the potentiality adjustment phase.

terms of their grammatical competence in writing. Thirty first-year high school and 40 first-year university EFL students participated in the experiment. Both the high school and university students had started studying English in junior high school; therefore, the former group had studied English for three years, while the latter had studied for six years. None of them had experience living or studying in English environments. Both groups of students took a written grammar test consisting of 42 questions, each of which targeted different grammatical structures. The questions were basically taken from model sentences in different lessons in an English high school writing textbook authorized by the Japanese Ministry of Education, Culture, Sports, Science, and Technology. The 42 questions comprised seven different grammatical categories, each of which was further broken down into several questions: tense (8 questions), sentence patterns (11), inanimate subjects as agents (2), auxiliary verbs (3), clauses (4), voice (2), non-finite verbs (9) and comparative/superlative (3). For example, the category ”tense” included questions that asked about different tenses such as past, present progressive, and present perfect. The two groups of students took the test for 35 minutes in a classroom without using a dictionary. For each question, the students were given a Japanese sentence followed by scrambled English words and phrases. Their task was to unscramble those words and phrases to make a sentence that corresponded to the given Japanese sentence.

B. Input and Hidden Selective Potentiality

Figures 2(a) and (b) show input and hidden selective potentiality for the L2 data set. As can be seen in the figure, the input selective potentiality increased to 0.7, while the hidden selective potentiality only reached 0.4. In other words, the input potentiality was easily increased compared with the hidden potentiality.

Figure 3 shows the individual potentialities of input neurons. When the parameter r was 0.1 in Figure 3(a1), the



(a) Input potentiality

(b) Hidden potentiality

Figure 2. Input potentiality (a) and hidden potentiality (b) for the L2 data set.

individual potentialities fluctuated almost evenly. When the parameter r increased from 1.1 in Figure 3(a2) to 5.0 in Figure 3(a4), the potentialities became gradually differentiated. In the end, only two input neurons had higher potentialities, namely, the 19th and 26th input neurons.

Figure 3 shows individual hidden potentialities. Because of the SOM, periodic patterns could be observed. When the parameter r increased from 0.1 in Figure 3(b1) to 5.0 in Figure 3(b4), only two hidden neurons tended to have higher potentiality, namely, the first and seventh hidden neurons.

C. Generalization Performance

Figure 4 shows generalization errors when the parameter r was increased from 0.1 to 5.0. In all cases, the errors by the potentiality method were well lower than those by the BP and the method without the potentiality. By the input potentiality in Figure 4(a), when the parameter r was less than 2.4, the generalization errors were lower than those by the BP and the method without the potentiality. Then, the generalization errors were larger than those by the conventional BP beyond this point.

By using the hidden potentiality in Figure 4(b), the generalization errors were almost always below those by the conventional BP. By using the input and hidden potentiality in Figure 4(c), the generalization errors gradually decreased when the parameter r increased to 2.4, and then began to fluctuate. Those results show that generalization errors by the potential method were lower than those by the other methods. In particular, by using the input and hidden potentiality, better generalization performance could be obtained.

It should be stressed that the generalization error by the method without the potentiality produced the worst errors out of all the methods. The method without the potentiality was one in which the SOM was directly connected with the successive back-propagation networks. As mentioned in the introduction section, direct insertion of SOM knowledge is not useful for training supervised learning. The results show clearly that modification and enhancement by the potentiality have the effect of transforming SOM knowledge to more useful knowledge.

D. Connection Weights

Figure 5(a) shows connection weights in the potentiality determination phase, namely, by the SOM. As can be seen in the figure, many positive connection weights could be seen, and it was difficult to immediately detect any regularity from those connection weights. Figure 5(b) shows connection weights by the potentiality actualization phase with only input potentiality. It could be seen that only two groups of connection weights from the 19th and 26th input neurons were strong. These two input neurons represented inanimate subjects. Figure 5(c) shows connection weights with the hidden neurons' potentialities. As can be seen in the figure, two groups of connection weights into the first and seventh hidden neurons had stronger positive weights. The connection weights into both hidden neurons showed larger variance, as shown in Figure 5(a). By using the input and hidden potentiality in Figure 5(d), strong connection weights similar to those by the input potentiality in Figure 5(b), and by the hidden potentiality in Figure 5(c), were observed. However, the majority of them became weaker and negative in red.

E. Summary of Results

Table I shows a summary of the experimental results in terms of generalization performance. The bold face numbers represent the best values. The method "without" means the one in which the SOM is directly connected with the supervised component. As can be seen in the table, all potential methods showed lower errors compared with those by the methods without potentiality: BP and the support vector machines. By the input potentiality, the generalization error was 0.2. Then, by the hidden potentiality, the generalization error decreased to 0.1909 and the minimum error became zero. By using the input and hidden potentiality, the lowest error of 0.1818 was obtained. By the conventional BP, the error increased to 0.2455, and by the fine-tuned support vector machine, the error further increased to 0.2818. Finally, without the potentiality, the worst error of 0.4364 was obtained, meaning that SOM knowledge did not contribute to the improvement of generalization performance. The potentiality method was essential in order to effectively utilize SOM knowledge.

The better generalization performance was due to the fact that a smaller number of highly potential neurons was detected in Figure 3. In addition, the better performance was due to the connection weights by the SOM in Figure 5(a). The potentiality method tried to those extract connection weights with the largest variance created by the SOM.

Then, it was observed that connection weights were modified only according to the potentialities in Figure 5(b). Only

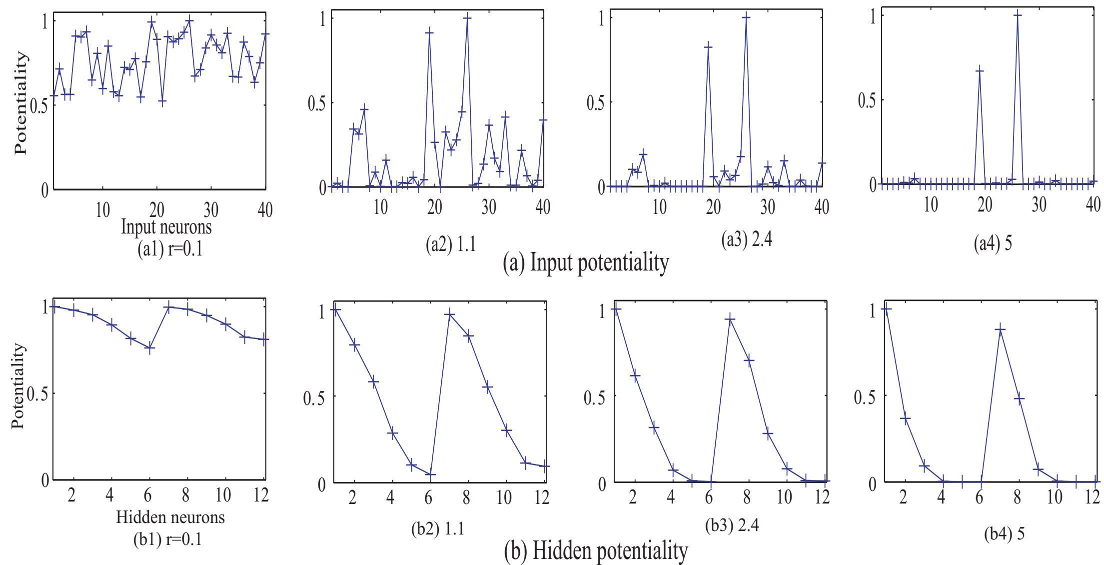


Figure 3. Individual input (a) and hidden (b) potentialities for the L2 data set.

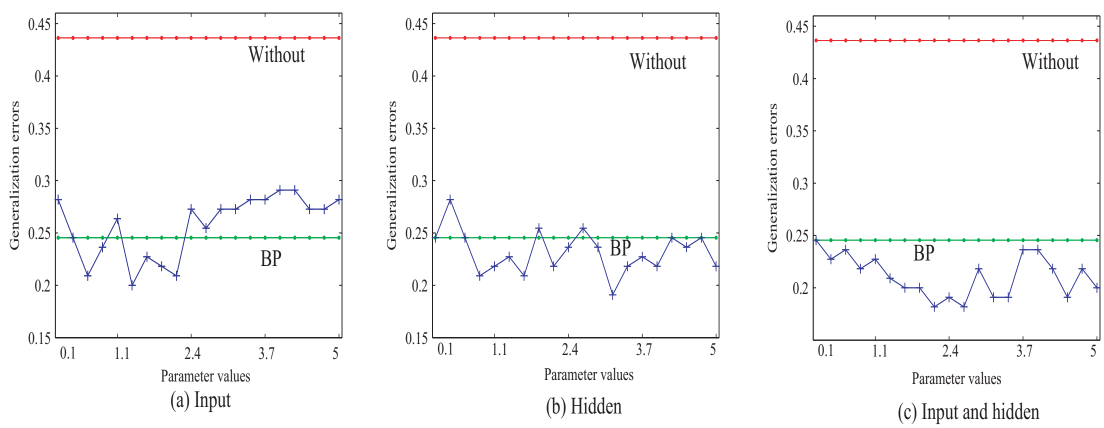


Figure 4. Generalization errors by input (a), hidden (b) and combined (c) potentiality for the L2 data set.

TABLE I. Summary of experimental results for the L2 data set.

Method	Avg	Std dev	Min	Max
Input Potentiality	0.2000	0.1118	0.0909	**0.3636**
Hidden Potentiality	0.1909	**0.1000**	**0.0000**	**0.3636**
Input+hidden	**0.1818**	0.1134	**0.0000**	**0.3636**
Without	0.4364	0.1808	0.2727	0.8182
BP	0.2455	0.1054	**0.0000**	**0.3636**
SVM	0.2818	0.1088	0.0909	0.4545

two important and highly potential input neurons were detected, both of which represented inanimate subjects. The Japanese students had difficulty in using inanimate subjects, which are not common in the Japanese language. This corresponds perfectly to already established knowledge in L2 literature [20][21].

IV. Conclusion

The present paper proposed a new type of learning called "self-organized potential learning". This method aims to utilize SOM knowledge to train supervised learning. The direct use of SOM knowledge is not necessarily useful for supervised training. Thus, SOM knowledge should be seen for its potentiality in many different situations. If the knowledge can be effective for many different situation or patterns, it can have much potentiality. For the first approximation to the potentiality, the variance of neurons is adopted. If neurons have larger variance and respond to input patterns differently, the neurons' potentiality becomes higher.

The method was applied to the actual data from the second language learning. The method could extract a clear result: that Japanese students had the most difficulty dealing with inanimate subjects. This corresponds perfectly to second language learning literature.

One of the main problems is that the quantities of the selective potentiality of input and hidden neurons were different from each other. In the experiments, the input neurons could increase the selectivity more so than the hidden neurons,

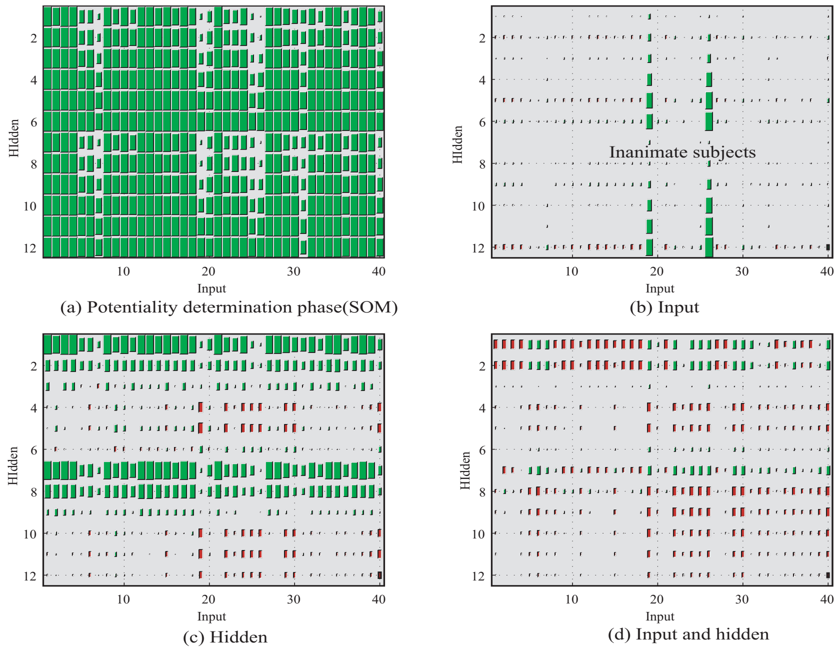


Figure 5. Weights in the potentiality determination phase (a) and actualization phase (b)-(d) by the four methods for the L2 data set. Green and red colors represent positive and negative weights.

as shown in Figure 2. This imbalance between input and hidden potentiality may influence final performance. Thus, it is necessary to examine in more detail the relationship between input and hidden potentiality. Finally, it is important to note that though the present experiment was performed with a small-sized but actual dataset, the method is simple enough to be applied to large-scale data sets.

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