

**AC 2009-143: A METHOD FOR IMPROVING PAIRED COLLABORATIVE
LEARNING THROUGH APPROACHES OF SYSTEM ENGINEERING**

Kazuhiro Shin-ike, Maizuru National College of Technology

A Method for Improving Paired Collaborative Learning Through Approaches of System Engineering

Kazuhiro Shin-ike* and Hitoshi Iima**

* Maizuru National College of Technology, Department of Electrical and Computer Engineering, shinike@maizuru-ct.ac.jp

** Kyoto Institute of Technology, Faculty of Engineering and Design, iima@si.dj.kit.ac.jp

Key Words: Collaborative Learning, Combination of Students, Neural Network, Genetic Algorithm

Abstract

In school education there are many kinds of learning styles, and it is known that group learning (collaborative learning) is more effective than individual learning. In collaborative learning it is very important how to determine the optimal combination of students in order to improve the learning effect. In this paper we propose a method to improve the learning effect of collaborative learning. A neural network model is first applied for predicting learning results of pairs of students in collaborative learning. Then, in order to determine the optimal pairs of students, a genetic algorithm is applied with the prediction results obtained from the neural network. Based on this combination of students, we carried out an experiment of collaborative learning at a college in Japan. It was confirmed from the experimental results that the proposed method was effective.

1 Introduction

In recent years, it is said that academic ability of students belonging to institutions of higher education has been decreasing [1]. Especially math and science skills of the students have been declining, which is a serious problem. One reason for the deterioration

of these skills is a relaxed education that was enforced in compulsory education and upper secondary education. The total number of class hours at these schools decreased in every revision of the Ministry's curriculum guideline by the Ministry of Education, Culture, Sports, Science and Technology (MEXT) [2] [3]. In order to solve this problem, teachers adopt many kinds of learning styles in school education: individual learning, group learning and so on. Some kinds of collaborative learning also began to be adopted into classes.

Collaborative learning is a learning style in which students are grouped and students in each group learn toward a common academic goal, whereas individual learning is a learning style in which students learn individually at their own level and rate toward an academic goal. In individual learning, since the students learn individually, differences of understanding between the students may be great and some students may misunderstand.

In collaborative learning, students can discuss "why" they think as they regard solutions to the problems. They can also listen carefully to comments of other students of the same group and reconsider their own judgments and opinions. It is thought that collaborative learning fosters student's ability to develop critical thinking through discussion, to clarify ideas, and to evaluate others' ideas. In collaborative learning, since interaction among students is very important, group members must be assigned adequately.

In our earlier papers we analyze the factors in improving the learning effect in collaborative learning of pairs of students [4-6]. It is said that collaborative learning makes learning effect higher than individual learning [7] [8]. It is also well known that collaborative learning in groups tends to improve the learning effect through interaction among students [9] [10]. However, the results of learning in the groups do not always improve and it is considered that it depends on the combination of students whether they improve or not. In some cases, a result of collaborative learning may not be more effective than that of individual learning [11]. Therefore, it is very important to determine the optimal combination of students in order to improve the learning effect [12].

In this paper, we propose a method to determine the optimal combination in improving the effect of collaborative learning through approaches of computational intelligence [13]. In this collaborative learning, there are some students, and every two students are grouped in order to solve given problems. For this purpose, a neural network model (NN_p) is first constructed to predict the correctness rates for these problems in collaborative learning. The input variables of the NN_p are fourteen kinds of abilities of paired students and the output variable of the NN_p is the correctness rate of the students. The fourteen abilities consist of academic backgrounds, personalities and the correctness rate for problems in individual learning.

Synthetic Personality Inventory (SPI) test is used in order to measure the academic backgrounds and the personalities of students [14]. The correctness rate is obtained by carrying out an experiment that the students solve the problems individually. Furthermore, the training data of the NN_p are obtained by carrying out a similar experiment

by collaborative learning. As an example, problems given to the students are selected from phenomena in everyday life. The results of SPI test and the data obtained by the experiment are applied to predict unknown correctness rates of pairs. Secondly, a genetic algorithm [15] in which the prediction results are used is proposed in order to find the best pairs. The genetic algorithm searches for the optimal solution in such a way that the worst and mean correctness rate in all students is as large as possible.

This proposed method can determine the combination of students by a simple process in a short time and this neural network model can predict the learning results of many students in a short time, too. When teachers make teaching guidelines to improve the effect of learning under the present curricula, this research can be used effectively for an evaluation and an improvement of teaching.

2 Prediction model

In this section a neural network model [16] is proposed to predict correctness rates of pairs in collaborative learning for given problems. Figure 1 shows the 3-layer neural network model $NN_p(i, j)$ which predicts the correctness rate C_{ij} for the paired collaborative learning of students i and j . $NN_p(i, j)$ has fourteen inputs and one output C_{ij} . The input variables of $NN_p(i, j)$ are as follows:

- L_i : Academic background about linguistic ability for student i .
- M_i : Academic background about nonlinguistic ability for student i .
- P_{1i} : Personality about an interest in matters for student i .
- P_{2i} : View of matters for student i .
- P_{3i} : Judgment of matters for student i .
- P_{4i} : Adaptability to learning environmental change for student i .
- C_i : Correctness rate of student i in individual learning.

$L_j, M_j, P_{1j}, P_{2j}, P_{3j}, P_{4j}$ and C_j for student j are the same as the input variables of student i , respectively.

2.1 Input variables of the neural network

It is thought that the academic backgrounds and personalities used as the input variables of $NN_p(i, j)$ directly influence the result of collaborative learning. These academic backgrounds and personalities are obtained by Synthetic Personality Inventory (SPI) test. SPI test is a general aptitude test that consists of an ability aptitude test and a

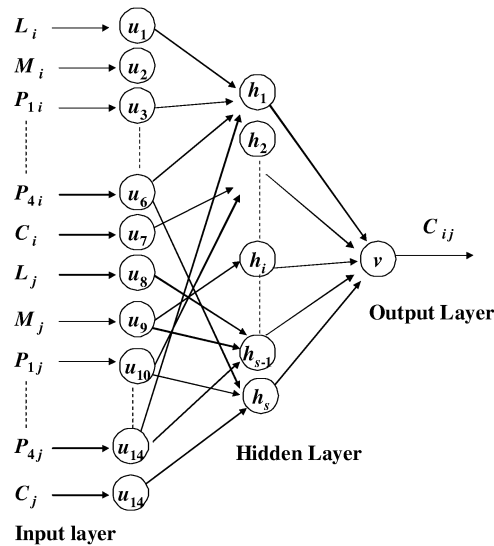


Figure 1: Model $NN_p(i, j)$ for predicting the correctness rate of students i and j

Table 1: The classification of inspection in SPI test

Inspection classification	Inspection name	Kind of inspection	The number of problems	Time limit (minutes)
Capability	Inspection 1	Linguistic ability	40	30
	Inspection 2	Nonlinguistic ability	30	40
Personality	Inspections 3 and 4	Character and volition	500	60

character aptitude test. Division of Nippon Recruit Center developed this test in 1974 based on the psychology test of Minnesota multiphasic personality inventory of University of Minnesota. SPI test is used for inspecting aptitude abilities and is most utilized as employment examinations of private enterprises in Japan. Since linguistic abilities and nonlinguistic abilities and personalities of persons can be measured and evaluated by using SPI test, we adopt it to measure aptitude abilities of students.

Table 1 shows the contents of SPI test. From the results of SPI test, levels of the linguistic ability and the nonlinguistic ability can be measured. Personal characters are classified into four categories based on the personality result of SPI test: an emotional aspect, an active aspect, a volitional aspect and a characteristic aspect. This result is important basic data for an interview of the second examination.

All questions of the test have some alternatives of answers and the thinking time for one question is quite short. The degree of difficulty of the questions in SPI test is for students from the seventh grade to the tenth grade. Inspection items are as follows.

1. Inspection 1 (linguistic ability)
This inspection consists of linguistic questions, and language abilities are measured. They are the ability to understand the meaning of words and phrases, the ability to read, the ability to write, etc.
2. Inspection 2 (nonlinguistic ability)
Questions of mathematics and science are applied. These are questions of graphs, functions, equations and physics selected from various fields.
3. Inspections 3 and 4 (Personality test)
 - (a) Emotional aspect
The objective of this inspection is to measure the emotive stability and the adaptability in an organization.
 - (b) Active aspect
The objective of this inspection is to measure the level of sociability, introspectiveness, vitality and carefulness.
 - (c) Volitional aspect
The objective of this inspection is to measure the level of motivation and volition.
 - (d) Characteristic aspect
The objective of this inspection is to measure the level of interest, concern and judgment ability.

2.2 A design of the neural network

The neurons of the hidden and output layers in NN_p apply a sigmoid function as the activate function. The sigmoid function is given by

$$f(x) = \frac{1}{1 + \exp(x)} \quad (1)$$

As this function value is between 0 and 1, the input variables of NN_p are normalized between 0 and 1 in consideration of the learning time and learning parameters. For example, the normalized linguistic ability L_i of a student i is given by

$$L_i = \frac{l_i - l_{\min}}{l_{\max} - l_{\min}} \quad (2)$$

where l_i is the measurement value of the linguistic ability for student i . l_{\max} and l_{\min} are the maximum and the minimum among the measurement values of all students, respectively. The other input variables are also normalized in a similar way.

The input variables of $\text{NN}_p(i, j)$ are denoted by

$$x = (x_1, x_2, \dots, x_{14})^T \triangleq (L_i, M_i, \dots, P_{4j}, C_j)^T \quad (3)$$

The output g_k of the k -th neuron h_k in the hidden layer is given by

$$g_k = f\left(\sum_{r=1}^{14} w_{kr}x_r + \theta_k\right) \quad (k = 1, 2, \dots, s) \quad (4)$$

where s shows the number of neurons in the hidden layer, w_{kr} shows the weight between input x_r and neuron h_k , and θ_k shows the threshold value of neuron h_k . The output C_{ij} of $\text{NN}_p(i, j)$ in the output layer is given by

$$C_{ij} = f\left(\sum_{k=1}^s z_k g_k + \phi\right) \quad (5)$$

where z_k shows the weight between neuron h_k and the output neuron, and ϕ shows the threshold value of the output neuron.

2.3 The number of neurons for the hidden layer

$\text{NN}_p(i, j)$ is trained by the back propagation method, and a few data of pairs of students are used for training. The number of neurons for the hidden layer should be determined adequately for training $\text{NN}_p(i, j)$. In this paper, the number of neurons is determined by using a two-phase method. In the first phase, candidates for the number of neurons are determined by comparing the sum squared error of training data for each number. In the second phase, to avoid over-fitting the neural network, the number of neurons for the hidden layer is determined from the candidates by considering the generalization capacity.

The first phase is described as follows.

- Step 1 The number of neurons for the hidden layer is given randomly.
- Step 2 $\text{NN}_p(i, j)$ is trained until the number of training reaches twenty thousand or the sum squared error is not greater than a specified value.
- Step 3 After training $\text{NN}_p(i, j)$, the correctness rates for the same input data which were used to train it are predicted.
- Step 4 If the absolute error between the experimental value and the prediction value for any correctness rate predicted any student is not greater than a specified value, the training of $\text{NN}_p(i, j)$ is finished. If not, return to Step 2.
- Step 5 $\text{NN}_p(i, j)$ is re-trained by applying Steps 2-4 with other numbers of neurons for the hidden layer.
- Step 6 Some candidates for the number of neurons are determined from any candidates that the sum squared errors and the absolute errors calculated in Step 4 are smaller.

The second phase is described as follows.

- Step 1 New data which were not used to train the $NN_p(i, j)$ are selected.
- Step 2 Steps 3 and 4 are performed for each of the candidates determined through the first phase.
- Step 3 Let m be the candidate for the neurons. $NN_p(i, j)$ with m neurons is trained three times for different initial weights and thresholds by using the same data as the first phase.
- Step 4 Correctness rates for the data selected in Step 1 are predicted by each of the three trained neural networks. Let n_m be the number of correctness rates each of which is predicted correctly by more than one of the three trained neural networks.
- Step 5 We adopt the number of neurons for hidden layer from the candidates in such a way that n_m is maximized.

3 Method for determining the optimal combination of students

In this section, we propose a method for determining the optimal combination of students in collaborative learning. The problem of determining the optimal combination is a kind of combinatorial optimization problem, and it is well known that it is difficult to solve the problem. Recently stochastic local search methods have been used for solving combinatorial optimization problems, and some studies show that a suboptimal solution is obtained by these methods [17]. Thus, we use a genetic algorithm which is one of the stochastic local search methods.

Our optimization problem is stated as follows. The students are divided into some groups, and two students in every group solve common learning problems collaboratively. The correctness rate of each student for these learning problems depends on the other student in the same group, and can be predicted by $NN_p(i, j)$, as mentioned in Section 2. Our optimization problem is to determine the combination of students in each group in such a way that the minimum and mean of correctness rates of all students is as large as possible.

We have $2p$ students $\{M_i; i = 1, 2, \dots, 2p\}$ two of which form a pair, where p is the number of pairs. The objective of the problem is to maximize the minimum and mean value among the correctness rates predicted for all pairs. The solution x for the problem is described by

$$x = \{y^h = (M_i, M_j) | h = 1, 2, \dots, p; \\ i, j \in \{1, 2, \dots, 2p\}; i \neq j\} \quad (6)$$

where y^h is the combination of students in the h -th pair. The objective function is defined by

$$\max_x f(x) = \min_h C^h + W \frac{1}{p} \sum_{h=1}^p C^h \quad (7)$$

Table 2: The ology of the learning problem and subjects which students study at school

Problem number	Ology	Subject
1	Center of gravity	Science and math
2	Air pressure	Science and math
3	Solid and liquid	Science
4	Magnetism	Science
5	Air and water pressure	Science and math
6	Low of motion	Science and math
7	Refractive index	Science
8	Heat phenomenon	Science
9	Equilibrium of force	Science and math
10	Heat phenomenon	Science

where C^h is the prediction value of the correctness rate of a pair y^h and W is a weight. C^h is the same as C_{ij} shown in Section 2.

The flow of genetic algorithm for solving our optimization problem is as follows.

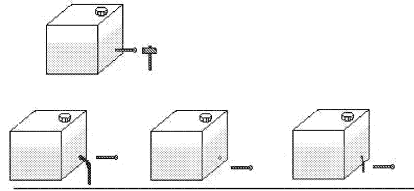
- Step 1 Generate randomly the initial population which consists of plural candidate solutions. Set $g \leftarrow 1$.
- Step 2 Pick up two candidate solutions x_1 and x_2 randomly from the current population, and remove them from the current population.
- Step 3 Generate two new candidate solutions x_3 and x_4 from x_1 and x_2 according to a procedure called the crossover. In the proposed genetic algorithm, these new candidate solutions are generated in such a way that the combination of students is inherited.
- Step 4 Generate a new candidate solution x_5 by changing a part of x_1 . Similarly, generate another new candidate solution x_6 by changing a part of x_2 . These new candidate solutions are generated by a procedure called the mutation.
- Step 5 Select the two best candidate solutions from the six candidate solutions $\{x_1, x_2, \dots, x_6\}$ and add them to the population.
- Step 6 If $g = G$, terminate this algorithm and output the best candidate solution as the answer. If not, set $g \leftarrow g + 1$ and return to Step 2. The value of parameter G is given in advance.

4 Application of the proposed method

In this section, an experiment is carried out to inspect our proposed method.

Problem 2

There is a reservoir which water is poured into and the lid is screwed. Then a nail is driven into a lower part of the reservoir. When the nail is pulled out, does the water in the reservoir spurt out?



1. Water spurts out.
2. Water does not spurt out at all.
3. A little water spurts out.

Figure 2: Another example of science problem

4.1 Learning problems

The learning problems for the individual learning and the collaborative learning are selected from phenomena in everyday life. Figure 2 shows an example of science problem. There are three kinds of choices to answer the problem, and the correct answer is 2. This problem is related to the air pressure.

The number of the learning problems is ten and students select the answer of each problem from among alternatives. Three or four kinds of alternatives are prepared in each learning problem. Table 2 shows the ology of each learning problem and relative subjects which students study at school education.

4.2 Experimental methodology

Thirty students participated in an experiment carried out at a college of technology in Japan. The purpose of colleges of technology is to conduct in-depth learning in specialized disciplines. The term of study is five years and graduates are awarded the title of associate. The participants are four female and twenty six male classmates and have been learning through the same curriculum for four years. It is said that they have similar educational backgrounds.

First of all, they take a simplified SPI test. Usually it takes one hundred thirty minutes to take the original SPI test, but it takes ninety minutes to take this simplified SPI test because one school hour is ninety minutes long at this college of technology. Secondly the

Table 3: The results of individual learning and collaborative learning of pairs determined by student's intention

I.D. of pairs $p_k(s_i, s_j)$	Correctness rate of individuals (c_i, c_j)	Correctness rates of pairs E_{ij}^1
$p_1(s_1, s_2)$	(0.3, 0.4)	0.5
$p_2(s_3, s_4)$	(0.7, 0.6)	0.6
$p_3(s_5, s_6)$	(0.5, 0.5)	0.6
$p_4(s_7, s_8)$	(0.6, 0.5)	0.8
$p_5(s_9, s_{10})$	(0.2, 0.2)	0.2
$p_6(s_{11}, s_{12})$	(0.4, 0.4)	0.5
$p_7(s_{13}, s_{14})$	(0.7, 0.3)	0.5
$p_8(s_{15}, s_{16})$	(0.3, 0.3)	0.3
$p_9(s_{17}, s_{18})$	(0.5, 0.6)	0.6
$p_{10}(s_{19}, s_{20})$	(0.6, 0.3)	0.5
$p_{11}(s_{21}, s_{22})$	(0.6, 0.5)	0.5
$p_{12}(s_{23}, s_{24})$	(0.2, 0.5)	0.2
$p_{13}(s_{25}, s_{26})$	(0.5, 0.4)	0.8
$p_{14}(s_{27}, s_{28})$	(0.3, 0.5)	0.7
$p_{15}(s_{29}, s_{30})$	(0.5, 0.4)	0.5
Average value		0.52
Standard deviation		0.18

students individually solve the ten kinds of problems which are stated in Subsection 4.1. Thirdly, they are assigned to fifteen pairs by their own intention and these pairs solve the same learning problems collaboratively. The obtained data are used for training $NN_p(i, j)$.

Table 3 shows the correctness rates in individual learning and in collaborative learning in pairs. These values are translated on a zero to 1 scale. In this table, $p_k(s_i, s_j)$ means that students s_i and s_j are the members of the k -th pair. c_i and c_j show the correctness rates of students s_i and s_j in individual learning, respectively, and E_{ij}^1 shows the correctness rate of the students s_i and s_j in collaborative learning. It is found from the table that correctness rates of ten pairs are equal to or more than their individual correctness rates. The correctness rates of the other five pairs are between the correctness rate of one member and that of the other member.

4.3 Training results of neural network

In the first phase of Subsection 2.3, the numbers of neurons for the hidden layer are determined in the range from 1 to 50. Initial weights and initial thresholds are given randomly. After $NN_p(i, j)$ was trained in the first phase, the sum squared error for any number of neurons is less than a specified value. In the second phase, neural networks

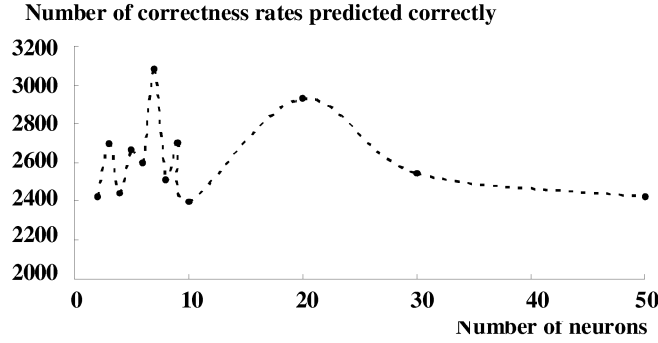


Figure 3: Number of correctness rates predicted correctly

with the various numbers determined through the first phase are compared by predicting the correctness rates of data which are not used in the first phase. k-fold cross validation has been used to train neural networks. In this paper, we adopt two phase method mentioned Section 2.3 in consideration of generalization capability of the neural network.

Figure 3 shows the training results of $NN_p(i, j)$ for the number of neurons in the hidden layer. These results of data are obtained from all the combinations to select two students from the thirty students. In this figure, twelve marks are candidates for the neurons in the hidden layer, as mentioned in Subsection 2.3, and the curved line with broken line is an imaginary line. This figure shows the number n_m of correctness rates each of which is predicted correctly by more than one neural network with m neurons for the hidden layer in Step 4 of the second phase. It is found from this figure that the seven and twenty neurons are better. Although the seven-neuron neural network is better than the twenty-neuron one, the results for the six and eight neurons are much worse than that of the seven neurons and the seven-neuron neural network may not be good stably. Therefore we adopt the twenty neurons, rather than the seven neurons, for the hidden layer.

4.4 Suboptimal combination of students obtained by the genetic algorithm

The number of combinations to select two students from thirty students who participate in the experiment is denoted by the symbol ${}_{30}C_2$. Consequently the number of combinations in which the students are divided into fifteen pairs is given by

$$\prod_{i=0}^{14} ({}_{30-2i}C_2) = {}_{30}C_2 \cdot {}_{28}C_2 \cdots {}_2C_2 \quad (8)$$

The correctness rate of each pair is predicted by $NN_p(i, j)$. The proposed genetic algorithm in which the objective function values are predicted by the $NN_p(i, j)$ is applied to determine a suboptimal combination of students.

Table 4: The results of individual learning and pair learning for a suboptimal combination of pairs

$q_k(s_i, s_j)$	(c_i, c_j)	E_{ij}^2	C_{ij}
$q_1(s_8, s_{28})$	(0.5, 0.5)	0.9	0.8
$q_2(s_{17}, s_{16})$	(0.5, 0.3)	0.6	0.6
$q_3(s_9, s_{13})$	(0.2, 0.7)	0.5	0.7
$q_4(s_3, s_{12})$	(0.7, 0.4)	0.5	0.6
$q_5(s_{24}, s_{26})$	(0.5, 0.4)	0.7	0.6
$q_6(s_{27}, s_{21})$	(0.3, 0.6)	0.5	0.5
$q_7(s_{29}, s_{25})$	(0.5, 0.5)	0.5	0.8
A.V.	4.7	0.60	0.66
S. D.	0.14	0.15	0.11

A. V. : average value.

S. D. : standard deviation.

$q_k(s_i, s_j)$: I.D. of pairs of students s_i and s_j , which is obtained by the genetic algorithm.

(c_i, c_j) : correctness rates of students s_i and s_j in individual learning.

E_{ij}^2 : correctness rate of a pair $q_k(s_i, s_j)$ in the second experiment.

C_{ij} : correctness rate for a pair $q_k(s_i, s_j)$ predicted by using $NN_p(i, j)$.

After the first experiment mentioned in Subsection 4.2, an experiment in collaborative learning was carried out by using the seven suboptimal pairs obtained by our proposed method. The participants are three female and eleven male classmates. The seven suboptimal pairs collaboratively solve the same learning problems as Subsection 4.1. It is thought that using the same learning problems does not affect correctness rates in this experiment, because the experiment is carried out after about one year from the first experiment. Table 4 shows the comparison of correctness rates c_i and c_j in individual learning and those E_{ij}^2 in collaborative learning based on the suboptimal combination of pairs obtained by the proposed genetic algorithm. This table also shows the correctness rates of the same pairs predicted by using $NN_p(i, j)$. From this table, correctness rates of four pairs are equal to or more than their individual correctness rates. The correctness rates of the other three pairs are between the correctness rate of one member and that of the other member.

In collaborative learning in which the pairs of students are determined by their intention, the average value and the standard deviation of the correctness rates are 0.52 and 0.18 from Table 3, respectively. On the other hand, in the case where the pairs are assigned by using the proposed genetic algorithm, those are 0.60 and 0.15 from Table 4, respectively. It is found from these results that the average value of the correctness rates in the pairs by the proposed genetic algorithm is better than that in the pairs determined by the

intention of students. It is also found that the standard deviation of the correctness rates in the pairs by the genetic algorithm is smaller. It is concluded that collaborative learning based on the proposed method is effective. Table 4 also shows that the difference between E_{ij}^2 and C_{ij} for five pairs is equal to or less than 0.1. Therefore it is thought that the proposed neural network model is reliable about predicting the correctness rates in collaborative learning in pairs of students.

5 Conclusion

A method to improve the learning effect in collaborative learning has been proposed. First of all, Synthetic Personality Inventory test is done to investigate the linguistic ability, nonlinguistic ability and four kinds of personalities of students. Secondly, an experiment is carried out to obtain the correctness rates of learning problems in individual learning and collaborative learning of a few pairs. Thirdly, a neural network model has been constructed for predicting the unknown correctness rates. Finally, a genetic algorithm is applied for obtaining a suboptimal combination of pairs. The correctness rates predicted by using the neural network are used as the objective function values of candidate solutions in the genetic algorithm. We have compared the collaborative learning results for the suboptimal pairs and those for pairs based on intention of students. The comparison results show that the proposed method improves the learning effect. Furthermore, the neural network can predict the correctness rates almost accurately.

In general collaborative learning students are assigned into pairs based on their matriculation number or their intention. However this method does not necessarily result in high learning effect. On the other hand, the proposed method does not require manpower, and the suboptimal combination of pairs obtained by the proposed method can bring high correctness rates. Therefore the proposed method is a practical grouping method in school education.

Teachers can perform educational activities effectively by using the proposed method. In many cases, the teachers instruct students by using the same learning problems over several years. Before the students start to learn the problems, the teachers can determine a suboptimal combination by using the neural network model and the genetic algorithm. Consequently the students are expected to attain a certain level required for the problems. A future aim is to find out the background of the learning ability by analyzing the prediction results and propose the best solution for improving the learning effect.

References

- [1] K. Nishimura, "Researches on Education", http://www.kier.kyoto-u.ac.jp/nishimura/n_prof_e/R_Education/r_education.html

- [2] Ministry of Education, Culture, Sports, Science and Technology, "Elementary and Secondary Education", <http://www.mext.go.jp/english/shotou/index.htm>
- [3] Ministry of Education, Culture, Sports, Science and Technology, "Higher Education", <http://www.mext.go.jp/english/koutou/index.htm> (in Japanese)
- [4] K. Shin-ike, "Individual and Pair Behavior in Learning Problem in School Education", *Proc. of the 10th IASTED International Conference, Computers and Advanced Technology in Education*, pp. 441-446, 2007.
- [5] K. Shin-ike, H. Nakamine, & N. Sannomiya, "A Method for Development of Paired Collaborative Learning in a Technical High School", *Proc. of the 2002 American Society for Engineering Education Annual Conference*, Session No. 2793, 2002.
- [6] H. Nakamine, K. Shin-ike & N. Sannomiya, "Analysis of Combination Types in Paired Collaborative Learning by Using a Self-Organizing Neural Network", *Proc. of the 6th World Multiconference on Systemics, Cybernetics and Informatics*, pp. 202-207, 2002.
- [7] K. Dumber, "Concept Discovery in a Scientific Domain", *Cognitive Science*, 17, pp. 397-434, 1993.
- [8] P. R. Laughlin & A. L. Futoran, "Collective Introduction: Social Combination and Sequential Transition" *Journal of Personality and Psychology*, 48, pp. 608-613, 1985.
- [9] K. Dumber, "How Scientists Really Reason: Scientific Reasoning in Real- World Laboratories. In R. J. Sternberg & J. E. Davidson (Eds.)", *The Nature of Insight*, pp. 365-395, MIT Press, 1994.
- [10] T. Okada and H. A. Simon, "Collaborative Discovery in a Scientific Domain", *Cognitive Science*, Vol. 21, No. 2, pp. 109-146, 1997.
- [11] T. Kameda, "Comparison of Individuals and Small Groups in the Rational Solution of Complex Problems", *American Journal of Psychology*, Vol. 44, pp. 491-504, 1997.
- [12] K. Shin-ike, H. Nakamine and J. Kirita, "A Neural Network for Learning Effect Prediction in Collaborative Circuit Board Design Learning", *Journal of the Japanese Society of Technology Education*, Vol. 43, No. 2, pp. 85-92, 2001. (in Japanese)
- [13] A. P. Engelbrecht, "Computational Intelligence: An Introduction", 2nd ed., *John Wiley and Sons*, 2007.
- [14] H. Kaga, "Practice Exercise of SPI Test", *Nagaoka Syoten*, 2000. (in Japanese)
- [15] D. E. Goldberg, "Genetic Algorithm in Search, Optimization and Machine Learning", *Addison - Wesley*, 1989.
- [16] Peter Dayan and L. F. Abbott, "Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems", *Mit Pr*, 2001.
- [17] H. H. Hous and T. Stützle, "Stochastic Local Search: Foundations and Applications", *Morgan Kaufmann*, 2005.

Authors list

KAZUHIRO SHIN-IKE

He received the B.E. degree in Electrical Engineering from Kansai University in 1976 and M.E. degree in Industrial Arts Education from Kyoto University of Education in 2000. Since 2000, he has been a doctor-course student at Division of Information and Production Science, Graduate School of Kyoto Institute of Technology. His research interests include modeling and optimization techniques in collaborative learning at school education. Since 1986 he has been a Teacher at Rakuyo Technical High School in Kyoto.

HITOSHI IIMA

He received the B.E., M.E. and D.E. degrees in Electrical Engineering all from Kyoto Institute of

Technology in 1987, 1989 and 1994, respectively. Since 1986 he has been a Professor at Department of Electronics and Information Science, Kyoto Institute of Technology. His present research interests include modeling and optimization techniques, and their applications. Especially his research works are directed toward genetic algorithm approach to the optimal scheduling of manufacturing systems.