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A Multi-stage Learning Method with the Selection of Training Data for the Layered Neural Networks

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Abstract- This paper proposes an efficient learning method for the layered neural networks based on the selection of training data. The multilayer neural network is widely used due to its simple structure. When learning objects are complicated, the problems, such as unsuccessful learning or a significant time required in learning, remain unsolved. The aims of this paper are to suggest solutions of these problems and to reduce the total learning time.

Focusing on the input data during the learning stage, we undertook an experiment to identify the data that makes large errors and interferes with the learning process. Our method devides the learning process into several stages.

Computational experiments suggest that the proposed method has the capability of higher learning performance and needs less learning time compared with the conventional method. And, compares the QPROP and RPROP methods by computation experiments using function approximation problems as an example and demonstrates the efficacy of integrating the proposed method with either method.

Index Terms- Multi-layer Neural Network, Data Selection, Multi-stage Learning, Integrating the Proposed Method with Either Method

I. Introduction

Majority of neural network research focuses on complicated networks such as pulsed neural networks [1]. However, in reality, multilayer neural networks (NNs) that are composed of sigmoid units using back propagation (BP) are widely used because of their simple structures.

In our previous paper [2], we proposed a comprehensive learning method that features the categorization of training data based on the ease of learning prior to initiating a learning session. Multi-stage learning based on the dynamic adjustment of the learning rate in response to error size and input characteristics to the output layer unit (effectively utilizing amplitude diminishing conditions and desired value acquisition conditions) was applied in complex learning cases that require the use of large quantities of learning data.

Proactive use of the oscillation characteristic of BP through the proposed method [2] is expected be effective when integrated with the Quick-Prop method (QPROP method) [4], an extension of BP, or when integrated with the elastic/resilient BP method (RPROP method) [5]. The QPROP method makes adjustments that are as large as possible to the learning rate while also adding an inertia term to the weight coefficient variation to suppress oscillation. To avoid oscillation due to sudden changes in the weight coefficient, it also applies a maximum variation limit. Generally, three coefficients—the learning coefficient, the maximum variation, and the weight renewal suppression coefficient—are required. Furthermore, the elastic BP method [5] confirms the weight renewal code and suppresses oscillation to accelerate learning. Normally, it is a method that learns by adjusting five parameters such as the learning coefficient in response to current conditions. In both methods, learning occurs with acceleration parameters while oscillation is suppressed.

In this study, we report the effects of the integration of the proposed method with QPROP and RPROP on error and learning time.

The remainder of this paper is composed as follows. Section 2 discusses the QPROP and RPROP methods. Section 3 compares the QPROP and RPROP methods by computation experiments using function approximation problems as an example and demonstrates the efficacy of integrating the proposed method with either method. Section 4 summarizes our findings.

II. Efficient Learning Methods

Paper [2] discusses the dynamic adjustment of the learning coefficient in response to error, input characteristics to the output layer unit, the selection of learning data, and effective learning methods based on these properties. Here we will briefly discuss the QPROP and RPROP methods.

2.1. QPROP method and RPROP method

The QPROP method [5] is one of the BP methods where learning speed is enhanced while learning coefficients are made as large as possible and inertial terms are added to the amount of change of weight coefficients. The inertial terms are where the weights are updated by considering the previous amount of updated weight as well as the present amount of updated weight. That is, when the amount of corrected weight at the time k is obtained, the formula will be as follows by considering the amount of corrected weight of (k-1):

$$\Delta W_{ji}(k)=\rho^k S_{ji}(k)+\alpha_{ji}^k \Delta W_{ji}(k\text{-}1) \quad (1)$$

But,

$$S_{ji}(k)=\frac{\partial E(k)}{\partial W_{ji}(k)}+\lambda\, \Delta W_{ji}(k) \quad (2)$$

and the weight is updated with the Formula (k=1,2,⋯) where the subscript i is a middle layer unit i, and the subscript j means the output layer unit j. The mark λ is a suppressing coefficient of

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updating weights. Let the learning coefficient be $\rho^k=\rho$ when either of the conditions of ρ^k be $\Delta W_{ji}(k-1)=0$ or $S_{ji}(k)\,\Delta W_{ji}(k-1)>0$ is met and let the learning coefficient be $\rho^k=0$ when none of the conditions is met. For the inertial term α_{ji}^k, calculate $\tilde{\alpha}_{ji}^{(k)}=\frac{S_{ji}(k)}{S_{ji}(k)-S_{ji}(k-1)}$ and let $\alpha_{ji}^k=\mu$ when either of the conditions of $\tilde{\alpha}_{ji}^{(k)}>\mu$ or $S_{ji}(k)\tilde{\alpha}_{ji}^{(k)}\Delta W_{ji}(k-1)<0$ is met and let $\alpha_{ji}^k=\tilde{\alpha}_{ji}^{(k)}$ when the answer does not meet any of the conditions.

The RPROP method [6] is where suppressed-vibration learning is carried out by adjusting five parameters in accordance with conditions, while the previous amount of updated weight should be memorized to suppress vibrations and a sign of the previous amount of updated weight and that of the current amount of updated weight are taken into consideration. Let $m=\frac{\partial E(k-1)}{\partial W_{ji}(k-1)}*\frac{\partial E(k)}{\partial W_{ji}(k)}$ and the amount of updated weight varies depending on signs of m. Basically, weights are updated based on the three formulas indicated below. The formulas feature that $\Delta_{\max}$ is set so that the updated amount will not be so large and $\Delta_{\min}$ is set so that the updated amount will not be so small.

m>0

$$\begin{cases} \Delta_{ji}(k)=\min(\Delta_{ji}(k-1)*\mu^{+},\Delta_{\max} \\ \Delta W_{ji}(k)=-\operatorname{sign}(\frac{\partial E(k)}{\partial W_{ji}(k)})*\Delta_{ji}(k) \\ W_{ji}(k+1)=W_{ji}(k)+\Delta W_{ji}(k) \end{cases} \qquad (3)$$

m<0

$$\begin{cases} \Delta_{ji}(k)=\max(\Delta_{ji}(k-1)*\mu^{-},\Delta_{\min} \\ W_{ji}(k+1)=W_{ji}(k)-\Delta W_{ji}(k-1) \\ \frac{\partial E(k)}{\partial W_{ji}(k)}=0 \end{cases} \qquad (4)$$

m=0

$$\begin{cases} \Delta W_{ji}(k)=-\operatorname{sign}(\frac{\partial E(k)}{\partial W_{ji}(k)})*\Delta_{ji}(k) \\ W_{ji}(k+1)=W_{ji}(k)+\Delta W_{ji}(k) \end{cases} \qquad (5)$$

(a) **Rastrigin Function**
f(x,y)=x^2-10cos(2π x) +y^2-10cos (2π y)
-0.8 ≤ x≤ 0.8, -0.8≤ y ≤ 0.8)
-20.0 ≤ f(x,y) ≤ 20.5
(b)**Ridge Function**
f(x,y)= $2x^2$+2xy+y^2
-6.0≤ x≤ 6.0, -6.0≤ y ≤ 6.0
0.0≤ f(x,y) ≤ 180.0

Table 1 Learning Functions

III. Computational Experiments Using Function Approximation Problems as Examples

To demonstrate the efficacy of the multistage learning method proposed in this study, we perform computational experiments using function approximation problems as an example. These problems have been chosen, because the difficulty of learning can be configured with the selection of different functions, and experiments of unlearned data can be verified easily. A number of useful functions are the well-known Rastrigin and Ridge functions for optimization problems. These are given in Table (1).

3.1. Training Data

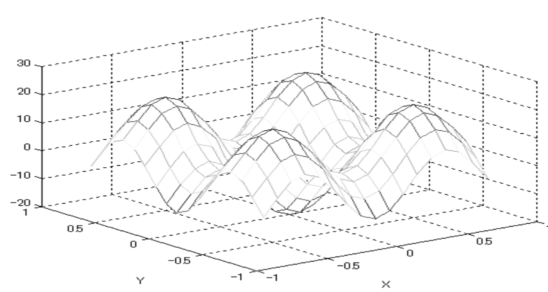
Table (1)(a) is shown in Figure 1. In Figure 1, adjacent training data are shown joined by a solid line. The region to learn in Table (1)(a) is given as $-0.8\le x,\ y\le 0.8$ for the Rastrigin function. The training data sets the *x*, *y* direction stride as 0.1 and partitions the region into a 17 × 17 (289 point) grid given as training data set ***D***.

Table (1)(b) gives the region to learn as $-6.0\le x,\ y\le 6.0$ for the Ridge function. The training data sets the *x*, *y* direction stride as 1.2 and partitions the region into an 11 × 11 (121 point) grid given as the training data set ***D***.

3.2. Training Data Selection

Here we discuss the method used to select the training data in Table (1)(a) for many experiments due to the difficulty of learning. The selection of the training data in table(1)(a)can be substituted with values obtained by the partial differentiation of functions $f_x(x, y)$ or $f_y(x, y)$ in both *x* and *y* directions.

Figure 1. An example of characteristics of the target function



Next, we divide the training data into three steps (s = 3) and perform multistage learning. $\boldsymbol{D}_l^1\cup\boldsymbol{D}_d^1$ uses approximately 30%

of all training data. $\boldsymbol{D}_l^1$ and $\boldsymbol{D}_d^1$ (selected using the values of $f_x(x, y)$ or $f_y(x, y)$ are important, because they grasp the outline of the function. The final number of data included in $\boldsymbol{D}_l^1 \cup \boldsymbol{D}_d^1$ was 31.1% (90 pieces). Within this data, 24 pieces fulfilled $|f(x, y)| \geq 0.90$, 34 fulfilled $|f_x(x, y)| \geq 0.3$, and 34 fulfilled $|f_y(x, y)| \geq 60.3$. Two pieces were repeated; thus, the total was 90 pieces.

Table 2 : The method of Learning(Ridge Function)

Structure	Initial weight vector is modified 5 times. 2 input layer units. 9 middle layer units. 1 output layer unit. Updating a weight vector should be done every 1 epoch.
Learning data	Learning domains are -6.0≤ x≤ 6.0, -6.0≤ y≤ 6.0 Learning data is conditioned equally as the reference table(1)(c). All the domain is divided into 11×11 grid. All the learning data($\boldsymbol{D}$) is divided into 3 parts before learning. $0<D^i<1$, $D^i \subset \boldsymbol{D}$ ($D^i = f(x_i, y_i); i=1, \cdots, 121$)
1st step	$\boldsymbol{D}_d^1 = \{f(x_i, y_i) \| \|f_x(x_i, y_i)\| \geq 20 or \|f_y(x_i, y_i)\| \geq 20$ (38 learning data), $\|\boldsymbol{D}_l^1 \cup \boldsymbol{D}_d^1\|$=6(6 overlapped) 32 learning data are selected. (26.4%)
2nd step	$D_d^2 = \{f(x_i, y_i) \| \|f_x(x_i, y_i)\| \geq 16 \; or \|f_y(x_i, y_i)\| \geq 16 \}$ (70learning data) $\|D_l^2 \cup D_d^2\|$=20(20 overlapped) 50 learning data are selected. (about 41%).
3rd step	121 learning data are selected. (100%)
Each step	Every step are learned for 2,334 times.
Conventional method	Learn 7,000 times with all the learning data and learning coefficient 0.8. Initial weight vector is modified 5 times.

In step 2, the final number of data included in $\boldsymbol{D}_l^2 \cup \boldsymbol{D}_d^2$ was 58.1% (168 pieces). Within this data, 52 pieces fulfilled $|f(x, y)| \geq 0.80$, 68 pieces fulfilled $|f_x(x, y)| \geq 60.1$, and 68 pieces fulfilled $|f_y(x, y)| \geq 60.1$. Twenty pieces were repeated; thus, the total was 168 pieces.

In $\boldsymbol{D}_d^3$ in step 3, all data was used. Thus, 31.1% of all data was used in step 1, 58.1% of all data was used in step 2, and 100% of all data was used in the final step. Table (2) shows this information for Table (1)(b). As a feature of the Ridge function shown in Table (1)(b), because $|f(x_i, y_i)|$ becomes larger when the values of $|f_x(x_i, y_i)|$ or $|f_y(x_i, y_i)|$ increase, the training data was selected on the basis of the values of $|f_x(x_i, y_i)|$ and $|f_y(x_i, y_i)|$.

3.3.Experiment Settings for Methods Used in Comparison

To verify the efficacy of the proposed method, the results of computational experiments were compared with those of existing methods. The NN used for the proposed method, existing method, QPROP method, RPROP method, and learning method, with the integrated proposed method, is a three-layer feed-forward network using sigmoid elements. This is composed of two input-layer elements, nine middle-layer elements, and one output-layer element. The number of middle-layer elements was determined by preliminary experiments. All weight coefficients were renewed once per epoch in each method. The learning count for the proposed method was 2333 epochs for step one, 2333 epochs for step two, and 2334 epochs for step three for a total of 7000 epochs. The two existing methods used all training data for 7000 epochs of learning. Computations were performed on a 3.0GHz Pentium 4 PC with 2GB RAM operating on Windows XP. The basic learning coefficient for the proposed method and existing methods was η = 0.8 (standard). To evaluate the learning results, the RMSE values for the training data and average weight sets for four initial weight coefficient values were used. Weight coefficient initial values were set randomly in a range from −0.01 to 0.01.

By a number of preliminary experiments, the QPROP parameters were set as follows. The weight variation suppression coefficient λ = 0.005, maximum change amount μ = 0.95, learning coefficient $\eta 1$ = 0.80, and by adjusting the direction of weights, the learning coefficient $\eta 2$ = 0.12. For RPROP experiments conducted, the following parameters were used: Δ_{max} = 5.0, Δ_{min} = 0.0025, η^+ = 0.97, η^- = 0.89, η^0 = 0.61.

Figure 2. Input characteristics for the +QPROP methods in the output unit(Ridge function, $\eta = 0.8$)

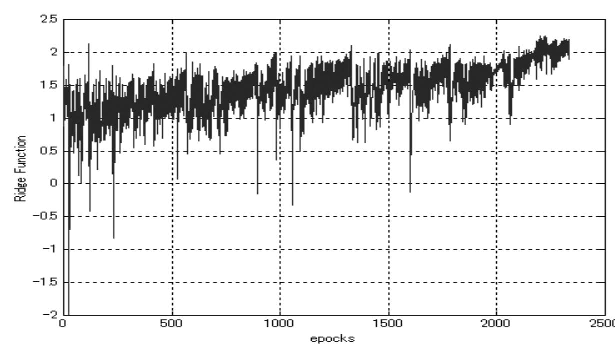
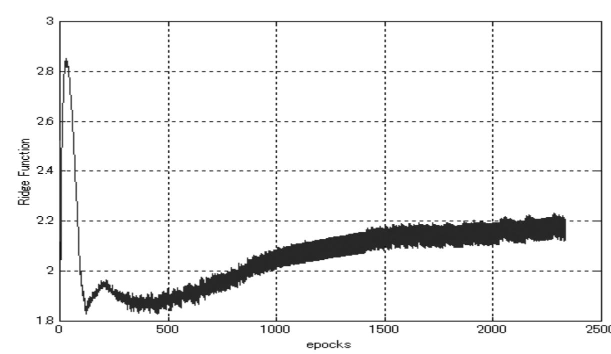


Figure 3. Input characteristics for the +RPROP methods in the output unit(Ridge function, $\eta = 0.8$)



3.4. Computational Experiment Results

Table 3 displays the learning results using the proposed method and the QPROP and RPROP methods independently, as well as the results of using the QPROP and RPROP methods with the proposed method integrated. The values shown in Table 3 is the averages for five experiments conducted with five different initial weight values selected randomly.

As shown in Table 3, integrating the proposed method with the RPROP or QPROP method improved the RMSE (mean) value and decreased the learning time when learning with the Ridge function (Figures 2 and 3).

As shown in Table 4, when the proposed method is applied to the Rastrigin function shown in Table (1)(a), all RMSE values are below 0.1 when the learning coefficient (the standard when using the proposed method) is between 0.9 and 0.2. When the learning coefficient decreases to 0.1 or 0.05, the RMSE values increase above 0.1, but the useful range of the learning coefficient value is extremely wide.

Conversely, as shown in Table 5, learning was carried out while changing the learning coefficient in the range from 0.9 to 0.02 for the two existing methods as well. From 0.9 to 0.3, no learning occurred with the RMSE values above 0.1. From 0.2 to 0.04, the RMSE value decreased below 0.1(Mean learning time = 28 minutes 17 seconds). Conversely, when reduced to 0.02, the RMSE value increased above 0.1.

When learning using existing methods with a constant learning coefficient of 0.04, oscillation occurs in the final 2334 repetitions, and the RMSE value is 0.053. These results are shown in Table 5. The input characteristics to the output layer unit are shown in Figure 4.

3.5. Considering the Experimental Results

Here we consider the performance and calculation time of learning by integrating the proposed method with the QPROP and RPROP methods on an NN and discuss the necessity of oscillation based on the computational experiment results.

<u>Integrating the Proposed Method into QPROP and RPROP Methods</u>

Figure 4. Input characteristics for the traditional methods in the output layer.

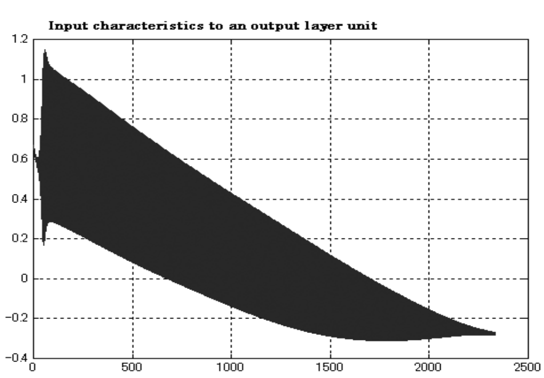


Table 3: RMSE for Proposed Methods and Traditional Methods in Learning of the Ridge Function

	RMSE		
	Mean	**Maximum value**	**Minimum value**
Proposed method	0.107	0.235	0.038
Learning time	Mean 6 minutes 59 seconds		
Proposed method+QPROP	0.058	0.113	0.024
Learning time	Mean 7 minutes 10 seconds		
QPROP method	0.172	0.241	0.108
Learning time	Mean 10 minutes 24 seconds		
RPROP method	0.050	0.080	0.023
Learning time	Mean 13 minutes 52 seconds		
Proposed method+ RPROP method	0.038	0.051	0.030
Learning time	Mean 7 minutes 31 seconds		

As shown in Table 3, by integrating the proposed method with the QPROP and RPROP methods, the RMSE average when learning with the Ridge function reduced in comparison with that before integration. In independent learning before integration, average error values for the RPROP method, proposed method, and QPROP method were 0.050, 0.107, and 0.172, respectively. However, by integrating the proposed method into the RPROP method, error reduced to 0.036. Integration with the QPROP method reduced the error from 0.172 to 0.058. When the QPROP and RPROP methods were used independently, the input characteristics to the output element unit showed almost no oscillation, but integrating the proposed method added a small amount of oscillation.

Table 4: RMSE for Proposed Methods in Learning of the Rastrigin Function

Proposed method	**RMSE**
Learning time	**Mean 15 minutes 56 seconds**
Learning coefficient	RMSE value
0.9	0.050
0.8	0.126
0.7	0.037
0.6	0.027
0.5	0.026
0.4	0.039
0.3	0.081
0.2	0.096
0.1	0.138
0.05	0.135

Table 5: RMSE for Traditional Methods in Learning of the Rastrigin Function

Proposed method	**RMSE**
Learning time	**Mean 28 minutes 17 seconds**
Learning coefficient	**RMSE value**
0.9	0.618
0.8	0.233
0.6	0.185
0.5	0.199
0.4	0.183
0.3	0.162
0.2	0.045
0.1	0.025
0.05	0.035
0.04	0.053
0.02	0.112

IV. CONCLUSION

This study discussed a comprehensive learning method for neural networks that categorized training data based on the ease of learning before learning, performed multistage learning based on those categories, and dynamically adjusted the learning coefficient in response to error size. Experiments were conducted by integrating the method with QPROP and RPROP methods. As a result, the RMSE value decreased, and the learning time improved.

In future studies, we will actively use oscillation characteristics, extend the proposed method to evaluate effects on pattern recognition problems, and investigate further decreases in error.

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