AN IMPLEMENTATION AND EVALUATION OF RANDOMIZED-ANN SIMULATOR USING A PC CLUSTER

Yoshiharu Morita, Tohru Nakagawa, and Hajime Kitagawa

Dept. of Engineering
Toyota Technological Institute
2-12-1 Hisakata, Tempaku-ku,
Nagoya, 468-8511, JAPAN

ABSTRACT

We propose a PC cluster using general-purpose microprocessors and a high-speed network for simulating ANN (Artificial Neural Network) processes on Linux OS. We apply this cluster to intelligent information processing such as ANN simulation. The elapsed time for simulating ANNs can be reduced from 7,295 seconds by a PE (Processing Element) to 1,226 seconds by six PEs. The reliability of a pattern-classification using ANNs can be improved by the proposed ANN, Randomized-ANN. In order to generate a Randomized-ANN, we choose three ANNs and combine the output results from three ANNs by means of logical AND. Results are as follows: The mean *correct* answer rate is 94.4 %, the mean *wrong* answer rate is only 0.1 %, and the mean *unknown* answer rate is 5.5 %. We make sure that Randomized-ANN approach reduces the mean *wrong* answer rate within a tenth part and improves the reliability of Japanese coin classification.

1 INTRODUCTION

The ability to learn is a fundamental trait of intelligence. Hence, a learning process is indispensable for the intelligent information processing. A learning process in ANN, one of the intelligent information processing, needs high computing power and much time. Therefore, few researchers prepare more than one ANN for solving the same problem at the same boundary conditions, and combine the output results from ANNs to improve the reliability of a pattern-classification. On the other hand, computers are developed very rapidly and are becoming much faster, smaller, and cheaper. In addition, high-speed computer networks like a 100 Mbps Ethernet are becoming popular. Hence, it becomes easier and cheaper that some PCs can be connected each other to improve the performance.

In this paper, we propose a PC cluster using general-purpose microprocessors and a high-speed network for simulating ANN processes on Linux OS. We apply this cluster to a simulation of ANN processing which is one of the intelligent information processing. The reliability of a pattern-classification using ANNs can be improved by the proposed ANN, Randomized-ANN[5][6]. We show that Randomized-ANN approach improves the reliability of the Japanese coin classification.

2 ARTIFICIAL NEURAL NETWORK

2.1 The Original ANN

ANN is used to solve a variety of problems in general[1]. In this paper, we use a two layer feed-forward network, and the BP (Back-propagation) algorithm[2][4] is used as a learning algorithm for the original ANN (see Figure 1).

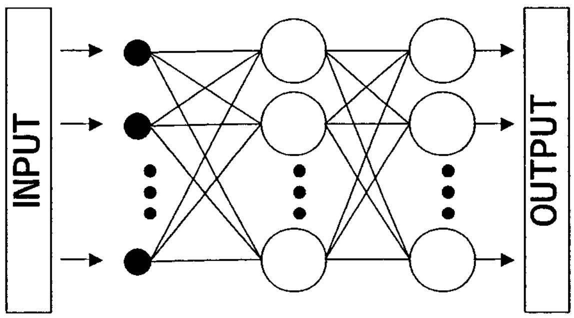

Figure 1. The Original ANN.

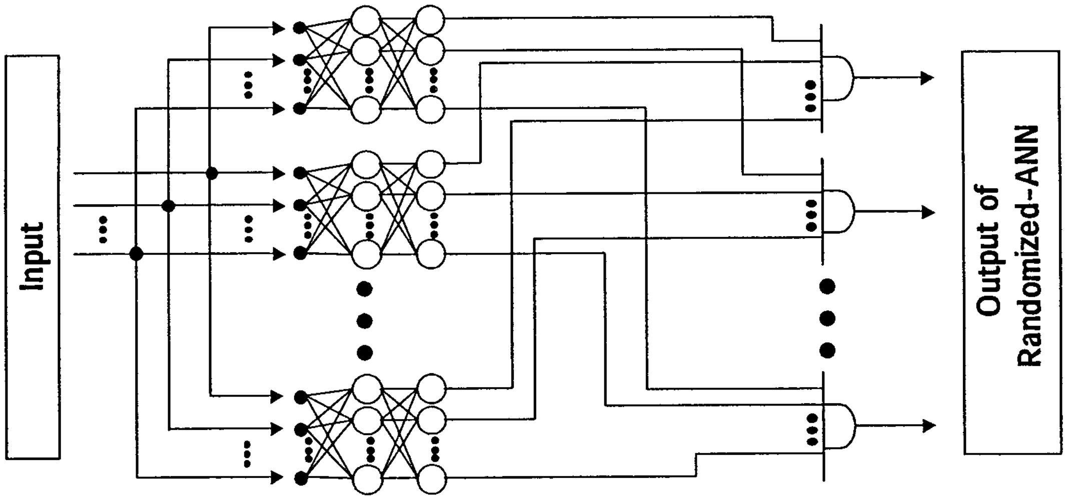

Figure 2. A Randomized-ANN.

2.2 Randomized-ANN

A Randomized-ANN consists of multiple ANNs each of which has a different initial state for BP learning (see figure 2). The original ANNs are arranged in a parallel manner and the classification output results from each ANN are combined by means of logical AND. When the all output results of the depicted logical AND are false, the Randomized-ANN classifies the input pattern as *unknown*. In this manner, the number of error outputs for unexpected input patterns is reduced, although the classification performance for ordinary input patterns is slightly decreased.

3 THE PC CLUSTER FOR RANDOMIZED-ANN

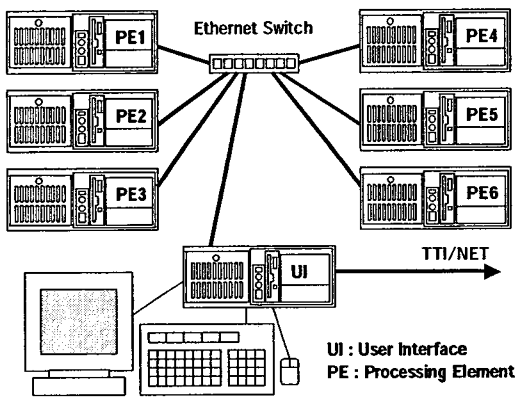

Figure 3. A PC Cluster for simulating Randomized-ANNs.

Each PE (Processing Element) has an Athlon CPU, and is connected to a 100 Mbps Ethernet switch (see Figure 3). We can use this simulator via an operating UI (User Interface). In the UI, we use the remote shell commands on Linux OS to distribute some tasks to PEs.

4 JAPANESE COIN CLASSIFICATION

We make experiments of Japanese coin classification. Japanese coin has six kinds of coins, 1, 5, 10, 50, 100, 500 yen. We take pictures of the head and tail sides in each coin by a CCD camera in the four kinds of different lighting effect (a1, b1, c1, d1). We take pictures in the same condition another day (a2, b2, c2, d2). The pictures are pixelized, changed to grayscale, and normalized in the same size (see figure 4). Then they are used as input data in this study. The selected data in two kinds of different lightning effect are used as training patterns for BP learning and the others are used as patterns to be classified.

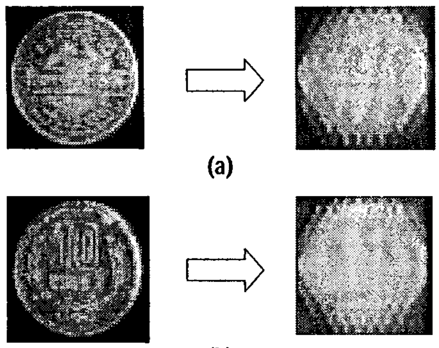

Figure 4. The pictures taken by a CCD camera are pixelized, changed to grayscale, and normalized in same size: (a) head side of a 10 yen coin, (b) tail side of a 10 yen coin.

5 PARALLEL PROCESSING IN LEARNING

A Randomized-ANN consists of multiple ANNs. Each ANN can learn independently, because each one is in a different state as an initial condition for BP learning[3]. So, the task of the learning processes for ANNs can be distributed into each PE. In this study, we measured the elapsed time for 3,000 cases of ANN learning simulation. The elapsed time for simulating ANNs can be reduced from 7,295 seconds by a PE to 1,226 seconds by six PEs (see figure 5). Although the current network speed among PEs is poor (100 Mbps Ethernet), the elapsed time is linearly decreased as the number of PEs is increased. It is the reason why the elapsed time is decreased in this condition that the majority of the time is CPU time.

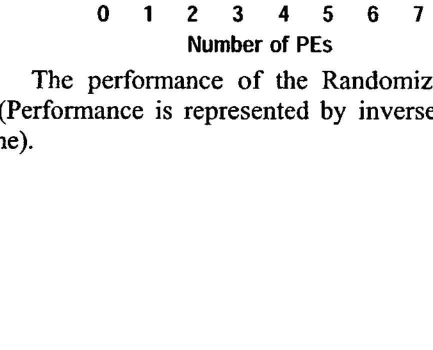

Figure 5. The performance of the Randomized-ANN simulator (Performance is represented by inverses of the elapsed time).

6 RESULTS OF COIN CLASSIFICATION

6.1 Effect of Different Initial Conditions

Moreover, we define a *correct* answer rate C, a *wrong* answer rate W, and an *unknown* answer rate U. For example, the *correct* answer rate C:

$$C = \frac{n_c}{d} \times 100 \quad [\%]$$

where n_c is the total number of *correct* answers, and d is the total number of input patterns to be classified.

Then we show 10,000 cases of Japanese coin classification using 10,000 ANNs each of which is in a different state as its initial condition for BP learning. The results show a wide distribution of the *correct* answer rates C from 86.1 % to 100 % because of the different initial conditions.

6.2 Finding out the Best Learning Data Set

The averages of the *correct* answer rates $\overline{C}$ and the standard deviation change like figure 6. The standard deviation converges when the number of ANNs are over at near 1000 In this study, the combinatorial number of learning data sets are 28, so we show 1,000 cases of the coin classification for each learning data set, and calculate each average of the *correct* answer rates $\overline{C}$, the average of the *wrong* answer rates $\overline{W}$, and the average of the *unknown* answer rates $\overline{U}$ (see table 1). Therefore, we find out the best learning data set from 28 combinations of learning data sets. In the case of the best learning data set (d1&a2), results are as follows: The average of the *correct* answer rates $\overline{C}$ is 96.8 %, the average of the *wrong* answer rates $\overline{W}$ is 1.1 %, and the average of the *unknown* answer rates $\overline{U}$ is 2.2 %.

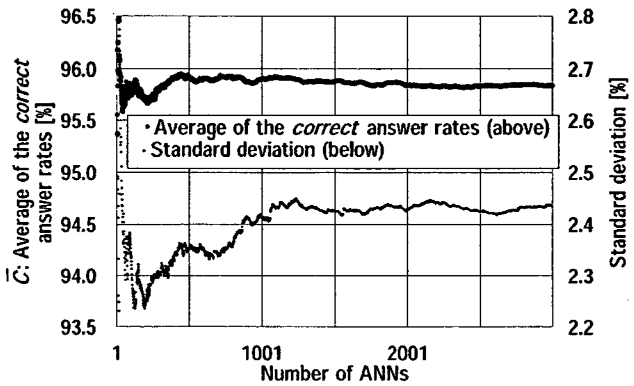

Figure 6. The total number of ANNs vs. the average of the *correct* answer rates $\overline{C}$ and the standard deviation.

Table 1. Result of Japanese coin classification for each learning data set (average of 1,000 cases).

Learning data set	$\overline{C}$: *Correct* [%]	$\overline{W}$: *Wrong* [%]	$\overline{U}$: *Unknown* [%]
d1&a2	96.8	1.1	2.2
b1&d2	96.3	1.4	2.3
a2&d2	95.9	1.4	2.7
...	...	...	...
a1&a2	64.0	16.6	19.4
c1&c2	62.8	13.1	24.1
d1&d2	51.5	24.1	24.4

6.3 Reliability of Classification using Randomized-ANN

We choose three ANNs and combine the output results from three ANNs by means of logical AND. The combinatorial number of three-out-of-1,000 Randomized-ANNs are about 166 millions. We recalculate each average of the defined rate in all combination. Results are as follows: The average of the *correct* answer rates $\overline{C}$ is 94.4 %, the average of the *wrong* answer rates $\overline{W}$ is only 0.1 %, and the average of the average of the *unknown* answer rates $\overline{U}$ is 5.5 %.

7 CONCLUSIONS

This paper presents Randomized-ANN approach. Since a Randomized-ANN needs a few ANNs to consist, it takes a long time to make the combinatorial experiments in Randomized-ANN simulation. However, the elapsed time for simulating ANNs can be reduced about a sixth part using the elementary PC cluster which consists of six PEs. In addition, we make sure that Randomized-ANN approach reduces the average of the *wrong* answer rates $\overline{W}$ from 1.1 % to 0.1 % in Japanese coin classification. In other words, the proposed approach improves the reliability of the classification.

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AUTHOR BIOGRAPHIES

Yoshiharu MORITA is a graduate student in master's program of Engineering at Toyota Technological Institute in Nagoya Japan. His research interest is in the intelligent information processing. His email address is <sd97160@toyota-ti.ac.jp>.

Tohru NAKAGAWA is an associate professor in the Department of Engineering at TTI, Toyota Technological Institute which was endowed by Toyota Motor Corp., and is also a president of the Information Processing Center at TTI. He received the B.E., M.E., and Ph.D. degrees in electrical engineering from Keio University, Japan, in 1976 1978, and 1982, respectively. He is a member of the ACM, the IEEE, the IEICE, the IPSJ, and the JSST. His research interests include parallel/ distributed processing systems, neural networks, campus networks, and dependable computing. His email address is <nakagawa@toyota-ti.ac.jp>.

Hajime KITAGAWA is a Professor of Electronic and Information Engineering Department at Toyota Technological Institute. He received his B.E., M.E., and Ph.D. in Computer Engineering from Kyoto University in 1963, 1965, and 1970, respectively. His interests include computer architecture and system performance evaluation. His email address is <s5tkita@toyota-ti.ac.jp>.