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Hybrid Neural Networks for Pattern Recognition

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***Abstract*— The hybrid neural networks have characteristics such as fast learning times, generality, and simplicity, and are mainly used to classify learning data and to model non-linear systems. The middle layer of a hybrid neural network clusters the learning vectors by grouping homogenous vectors in the same cluster. In the clustering procedure, the homogeneity between learning vectors is represented as the distance between the vectors. Therefore, if the distances between a learning vector and all vectors in a cluster are smaller than a given constant radius, the learning vector is added to the cluster. However, the usage of a constant radius in clustering is the primary source of errors and therefore decreases the recognition success rate.**

To improve the recognition success rate, we proposed the enhanced hybrid network that organizes the middle layer effectively by using the enhanced ART1 network adjusting the vigilance parameter dynamically according to the similarity between patterns. The results of experiments on a large number of calling card images showed that the proposed algorithm greatly improves the character extraction and recognition compared with conventional recognition algorithms.

***Index Terms*— Hybrid Neural Networks, Pattern Recognition, ART1 Network.**

I. INTRODUCTION

THE hybrid neural networks have characteristics such as fast learning times, generality, and simplicity, and are mainly used to the classify learning data and to model non-linear systems[1]-[3]. The middle layer of an hybrid neural network clusters the learning vectors by grouping homogenous vectors in the same cluster. In the clustering procedure, the homogeneity between learning vectors is represented as the distance between the vectors. Therefore, if the distances between a learning vector and all vectors in a cluster are smaller than a given constant radius, the learning vector is added to the cluster. However, the usage of a constant radius in clustering is the primary source of errors and therefore decreases the recognition success rate[4]. To improve the recognition success rate, this paper proposes enhanced hybrid neural networks that adapts the ART1 network to the learning structure between the input layer and the middle layer and applies the output layer of the ART1 network to the middle layer.

In the ART1 network, a vigilance parameter inversely determines the degree of mismatch between any input pattern and saved patterns that is allowed[5]. A high vigilance threshold classifies an input pattern as a new category in spite of a few mismatches between the pattern and the expected patterns, and conversely a low threshold value may allow an input pattern to be classified with an existing cluster in spite of a large number of mismatches. However, because the ART1 network bases its vigilance parameter on empirical derived values the recognition success rate declines. To correct this defect, we propose an enhanced hybrid neural network and apply it to the middle layer in the enhanced hybrid neural network.

II. HYBRID NEURAL NETWORKS FOR PATTERN RECOGNITION

The enhanced ART1 network adjusts the vigilance parameter dynamically according to the homogeneity between the patterns using Yager's union operator [6], which is a fuzzy connection operator. The vigilance parameter is dynamically adjusted only in the case that the homogeneity between the stored pattern and the learning pattern is greater than or equal to the vigilance parameter. Let T^p and $T^{p'}$ be the target value of the learning pattern and the stored pattern respectively. If T^p is equal to $T^{p'}$, the network decreases the vigilance parameter and adjusts the weight of connection between the input layer and the middle layer. Otherwise, the network increases the vigilance parameter and selects the next winner node. The algorithm dynamically adjusts the vigilance parameter as follows:

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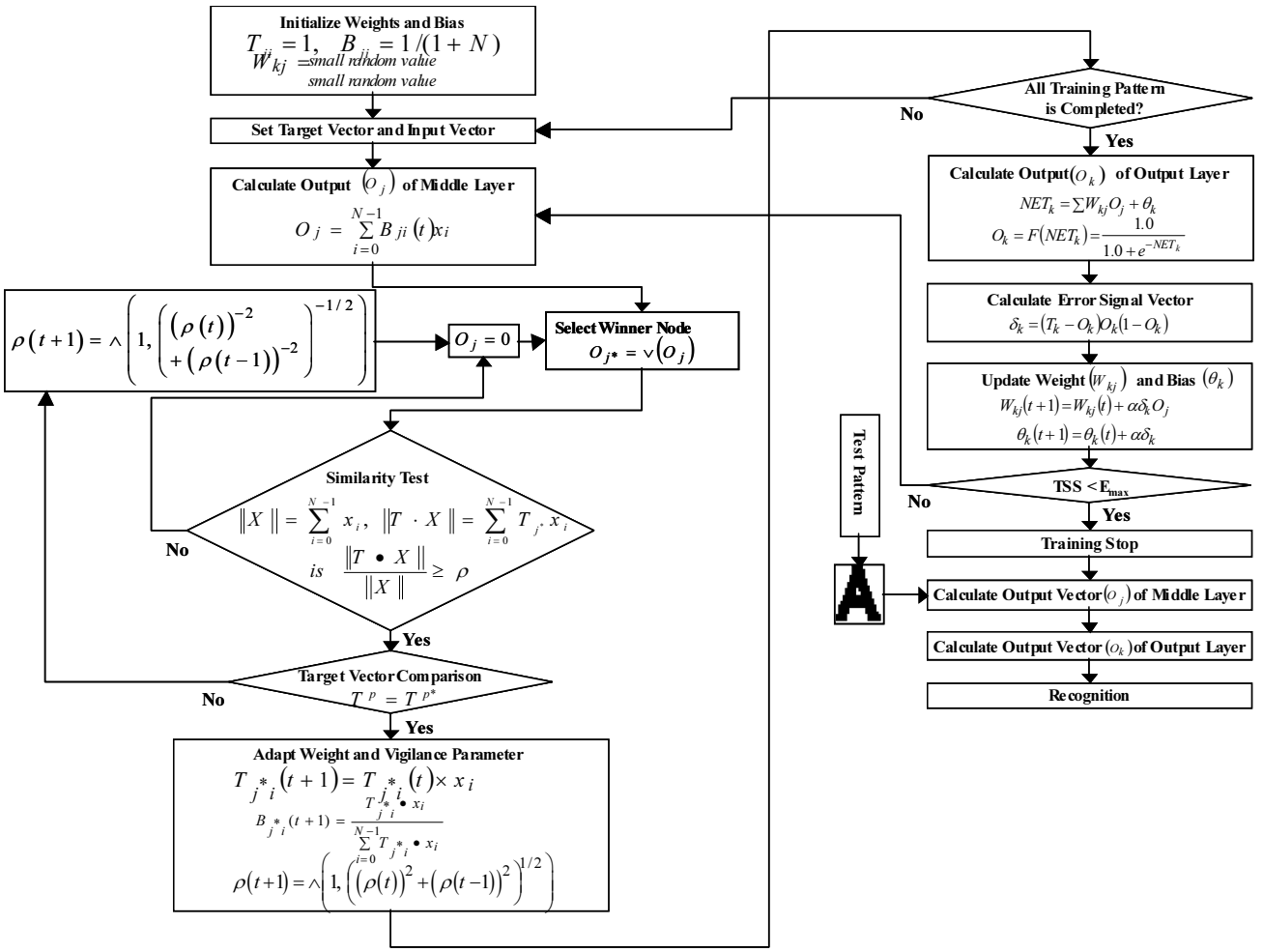

Fig. 1. The learning algorithm of the enhanced hybrid neural network.

$$
\begin{aligned}
&if \quad \left(T_{j^*}^{p} \neq T_{j^*}^{p*}\right) \\
&then \quad \rho(t+1) = \wedge\left(1, \left(\left(\rho(t)\right)^{-2} + \left(\rho(t-1)\right)^{-2}\right)^{-1/2}\right) \\
&else \quad \rho(t+1) = \wedge\left(1, \left(\left(\rho(t)\right)^{2} + \left(\rho(t-1)\right)^{2}\right)^{1/2}\right)
\end{aligned} \tag{1}
$$

where ρ is the vigilance parameter.

The enhanced hybrid neural network proposed in this paper adjusts dynamically to the vigilance parameter according to learning patterns by applying the enhanced ART1 to the middle layer. The learning process in the middle layer of the enhanced hybrid neural network is as follows: In a similarity test, if the similarity between learning patterns and stored patterns is lower than the vigilance parameter, the network searches a new candidate winner node and executes the similarity test with the selected node. If no candidate winner node is selected, the network classifies learning pattern to a new cluster by creating a new node in the middle layer and adjusting the weight of connection between the input layer and the middle layer.

Oppositely, if the similarity is equal to or greater than the vigilance parameter, the network compares the target value of the learning pattern with the one of the stored pattern, since one more stored pattern could have the similarity being equal to or greater than the vigilance parameter. In the case that two target values are equal, the network classifies the learning pattern to the same cluster including the stored pattern, decreasing the vigilance parameter and adjusting the weight of connection to reflect some features of input pattern to the classified cluster. On the other hand, in the case that two target values are not equal, the network increases the vigilance parameter and makes the search for a candidate winner node and the similarity test using the adjusted vigilance parameter. The next process is the same as stated above. But, if no more candidate winner nodes can be searched, the network classifies learning pattern to a new cluster. This paper enhances the hybrid neural network by applying the enhanced ART1 algorithm to the middle layer, as shown in Fig. 1.

III. PERFORMANCE EVALUATIONS

This paper implemented the proposed algorithm using Visual C++ on an IBM compatible Intel(R) Core(TM) Quad Core Processor i5-2500 PC and performed experiments on 50 calling card images with a pixel size of 1500x800. To evaluate the performance of the enhanced hybrid neural network, the proposed enhanced ART1 and the normal ART1 were used on the middle layer of the neural network. Table 1, compares learning and recognition results obtained from recognition experiments using the two algorithms on previously extracted individual characters method [7]. Fig. 2 presents an example of successfully extracted individual characters.

For experiments presented in Table I, all individual characters are separated into three character sets; alphabetic, numeric and special characters, and recognition experiments were performed on each character set.

TABLE I
THE RESULTS OF LEARNING AND RECOGNITION USING THE ENHANCED HYBRID NEURAL NETWORK

	# of hidden layer's nodes (# of nodes / # of input patterns)	Recognition performance (# of successes / # of input patterns)
The proposed hybrid neural network		
Alphabetic characters	218 / 520	3716 / 3723
Numeric characters	91 / 200	2801 / 2821
Special characters	10 / 30	911 / 951
The hybrid neural network based on normal ART1		
Alphabetic characters	496 / 520	3682 / 3723
Numeric characters	175 / 200	2773 / 2821
Special characters	21 / 30	889 / 951

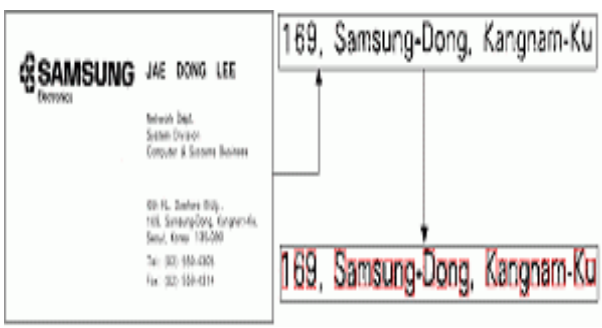

Fig. 2. Examples of individual character extraction.

The initial vigilance parameter in the hybrid neural network based on normal ART1 was fixed to 0.93, and in the enhanced hybrid neural network, the vigilance parameter was initially set at 0.93 and adapted dynamically. For the 520 alphabetic character input patterns, the enhanced hybrid neural network and the hybrid neural network based on the normal ART1 created 218 and 496 middle nodes, respectively, demonstrating that the enhanced hybrid neural network is more efficient at learning individual characters in calling card images. By comparing the number of recognition successes between the two algorithms in Table 1, the enhanced hybrid neural network performed better than the hybrid neural network based on normal ART1. The conventional hybrid neural network classified the same special characters to different clusters in the similarity test so that the number of nodes in the middle layer was increased and the learning performance fell off. But, it was able to classify the same special characters with different fonts to the same cluster, decreasing the number of nodes of the middle layer and improving the learning performance.

Fig. 3 shows a trace of the dynamical change of the vigilance parameter appearing in the procedure that creates or modifies nodes at the middle layer of the enhanced hybrid neural network. In the enhanced hybrid neural network, the vigilance parameter is decreased if the target vector of the input pattern is equal to the one of winner node in the similarity test, or else the vigilance parameter is increased. Therefore, the enhanced hybrid neural network classifies similar patterns to the same cluster, improving the performance of learning and recognition.

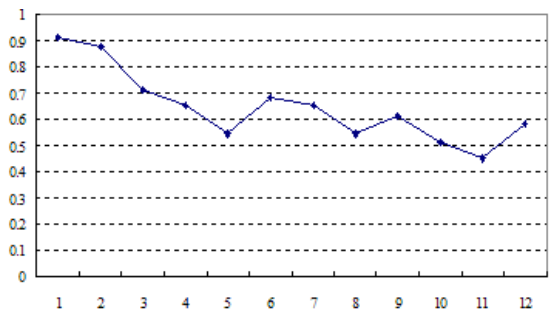

Fig. 3. Dynamical change of the vigilance parameter in the learning process for numeric characters.

IV. CONCLUSIONS

This paper proposed the enhanced hybrid neural network which constructs the middle layer by using the enhanced ART1 network, supporting the dynamical change of the vigilance parameter and applied it to the character recognition phase.

The results of the experiments showed that the enhanced hybrid neural network performed better than previous algorithms used in calling card recognition. Moreover, the enhanced hybrid neural network recognized effectively the individual character thus it showed a high success rate of recognition. And the number of clusters created at the learning process of the enhanced ART1 network was much lower than the conventional ART1 network, which means that it is efficient to use the enhanced ART1 network in the construction of the middle layer in the hybrid neural network.

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