A SCHEME OF ON-LINE CHINESE CHARACTER RECOGNITION USING NEURAL NETWORKS

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ABSTRACT

This paper proposes a scheme of on-line Chinese character recognition, based on neural networks. The supervised backpropagation algorithm is used to train the network. The input character is converted as a sequence of virtual stroke segments as well as real stroke segments, which is a good feature exactly describing the complete structure of a character, and is to be extracted by our system.

In order to simplify recognition process and reduce the recognition time, the neural network is divided into several subnetworks, each of them is responsible for recognizing a group of about 75 character patterns. In other words, the huge set of Chinese characters is divided into several groups according to the numbers of stroke segments in the characters, and for each group of characters, a specific subnetwork is trained in order to recognize every character in the group.

Whenever the system accepts an input Chinese character, it will calculate the number of stroke segments, including virtual stroke segments as well as real stroke segments in that character, and then determine which subnets to enter for recognition process.

The system is allowed to accept and recognize some interconnected characters. The algorithm was experimentally implemented in a personal computer system, accepts interconnected Chinese characters written on an electronic tablet, and performs recognition in real time. Our experiment showed that recognition accuracy exceeded 96% on the test example.

Key words: on-line recognition, neural network, backpropagation, character pattern, feature extraction

1. INTRODUCTION

Since 1966, numerous methods for on-line handwritten English character recognition have been proposed [2,3,4,8,10,17,18,19]. Since then various methods of on-line handwritten Chinese character recognition have been also proposed [1,5,6,7,11,12,13,15], but they do not always have a recognition rate sufficient for a large set of characters. Error in recognition by these methods seems to be caused by the unstability of geometric features of characters.

Neural network models have a great degree of fault tolerance, this motivates us to use them as the base for our system. Most of character recognition systems based on neural networks take digit patterns as features of characters [9,14,16] (or apply the digit patterns to the neural nets' input), for example, an image of 64 $\times$64 pixels for a Chinese character, which need large storage. To solve this problem of storage occupancy, we choose stroke segments (including both real and virtual stroke segments) as features of characters

0-7803-4053-1/97/$10.00 © 1997 IEEE

for our system, which save much more storage.

According to the Minister Of Education in Taiwan, there are 5401 frequently used Chinese characters. The average number of stroke segments of these frequently used characters is about 14. For considering both real and virtual stroke segments, the length of the sequence (or the dimension of feature vector) is about 32 in average. Obviously, our system dramastically reduces the storage of pattern features. In addition, stroke segments describe the complete structures of characters. This is one of the reasons why we choose them as features for our system.

Although neural networks take long time on learning process, it has capability of nonlinear segmentation and high tolerance of variance of written characters. Besides, it speeds up the recognition process. Therefore, the long learning process is paid up by the fast recognition process.

2. FEATURE EXTRACTION AND NORMALIZATION

2.1. Feature Extraction

To extract features, we consider the pen-tip movement loci for a written character and convert it as a sequence of stroke segments. A stroke consists of the writing from pen-down to pen-up. A stroke segment is defined as a segment in the loci such that each of its endpoints is a pen-down, a pen-up, or a turning point. A stroke segment starting at a pen-up and ending at the successive pen-down is called a virtual stroke segment; otherwise, called a real stroke segment. Thus, a real stroke segment is a stroke or portion of a stroke. For example, as in Figure 1(a), the written character "歹" is considered as a sequence of 6 stroke segments $(s_1, s_2, s_3, s_4, s_5, s_6)$, where s_1, s_3, s_4, and s_6 are real stroke segments and s_2 and s_5 are virtual stroke segments. Stroke segment s_1 starts at a pen-down and ends at a pen-up, s_2 starts at a pen-up and ends at a pen-down, s_3 starts at a pen-down and ends at a turning point, ...and so on.

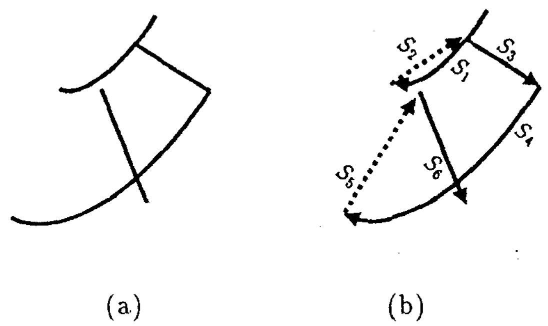


Figure 1. (a) A written Chinese character "歹". (b) Stroke segments obtained from the pen-tip movement loci of a writing for the character in (a).

2.2. Normalization

If the sequence of stroke segments of a written character is $(s_1, s_2, \ldots, s_n)$, let L_i denote the length of s_i and A_i the direction angle of s_i in radians, where A_i is measured counterclockwise from the positive x-axis to the directed stroke segment s_i (see Figure 2); thus, $0 \leq A_i < 2\pi$. We now normalize thses quantities as follows: For each i, let $l_i = L_i / \max_j L_j$ and let $a_i = A_i / 2\pi$ so that $0 < l_i \leq 1$ and $0 \leq a_i < 1$. The feature vector for this written character is then $(l_1, a_1, l_2, a_2, \ldots, l_n, a_n)$. All components are bounded between 0 and 1.

The original and normalized lengths and angles of stroke segments extracted from the written character in Figure 1(a) are shown in Figures 3(a) and 3(b), respectively.

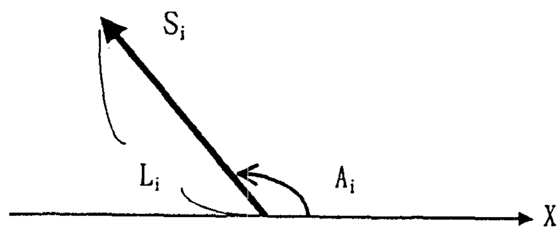


Figure 2. A stroke segment s_i with length L_i and direction angle A_i.

L_1	L_2	L_3	L_4	L_5	L_6
5.5	3.8	3.9	10.4	6.3	5.4
A_1	A_2	A_3	A_4	A_5	A_6
1.27π	0.22π	1.87π	1.21π	0.36π	1.65π

(a)

l_1	l_2	l_3	l_4	l_5	l_6
0.53	0.37	0.38	1.00	0.61	0.52
a_1	a_2	a_3	a_4	a_5	a_6
0.64	0.11	0.94	0.61	0.18	0.83

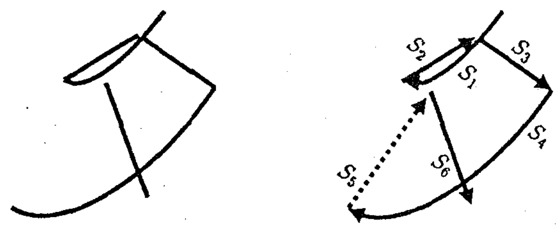
(b)

Figure 3. (a) the lengths and angles of stroke segments of the written character shown in Figure 1(b). (b) the normalized version of (a).

Such kind of feature may overcome most of interconnected problems. For instance, the sequence of stroke segments for the written character in Figure 4, $(s_1', s_2', s_3', s_4', s_5', s_6')$, is like that in Figure 1 except that s_2 is virtual but s_2' is real. However, our system does not need to distinguish between real stroke segments and virtual stroke segments. Hence, these two written characters are identical (or have the same feature vectors) in our system. Adopting both real stroke segments and virtual stroke segments will capture relative positions of every two consecutive real stroke segments; consequently, the feature preserves the whole structure of the character, which is one of the most important informations from the characters.

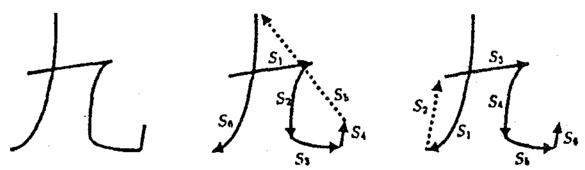
A character might be written in different ways, such as different orders of stroke segments. If a different writing order for a character frequently occurs, we may allow the system to accept it by adding a new pattern feature taken from that writing to the system; that is, we need to add a new pattern for that character into the system since this new writing way forms a different pattern feature. Thus, a character may correspond to more than one pattern in our system. For example, the character "九" in Figure 5(a) might be written in two different ways as shown in Figures 5(b) and 5(c), respectively. In order to accept both writings, it must learn these two writings separately in advance and consider them as different patterns.

For example, if a character has three different patterns in average, a system recognizing 5000 characters should be able to recognize 15000 different patterns; consequently, the total number of nodes in the output layer of the network should be also 15000.



(a) (b)

Figure 4. (a) An interconnected written character. (b) Real and virtual stroke segments obtained from the pen-tip movement loci for the character in (a).



(a) (b) (c)

Figure 5. (a) A written Chinese character "九". (b) Stroke segments obtained from the pen-tip movement loci of a writing of the character in (a). (c) Stroke segments obtained from the pen-tip movement loci of another writing for the character in (a).

3. NEURAL NETWORK ARCHITECTURE

3.1. Learning Part

Our system is based on feed-forward neural networks with the back-propagation learning algorithm. The training of a network via back-propagation is a simple method, although computation intensive. However, to train on such a huge amount of Chinese characters, a back-propagation neural network requires thousands of nodes in its hidden layer, and consequently, millions of connections to the hidden layer are required. It is hardly to train such a huge network efficiently.

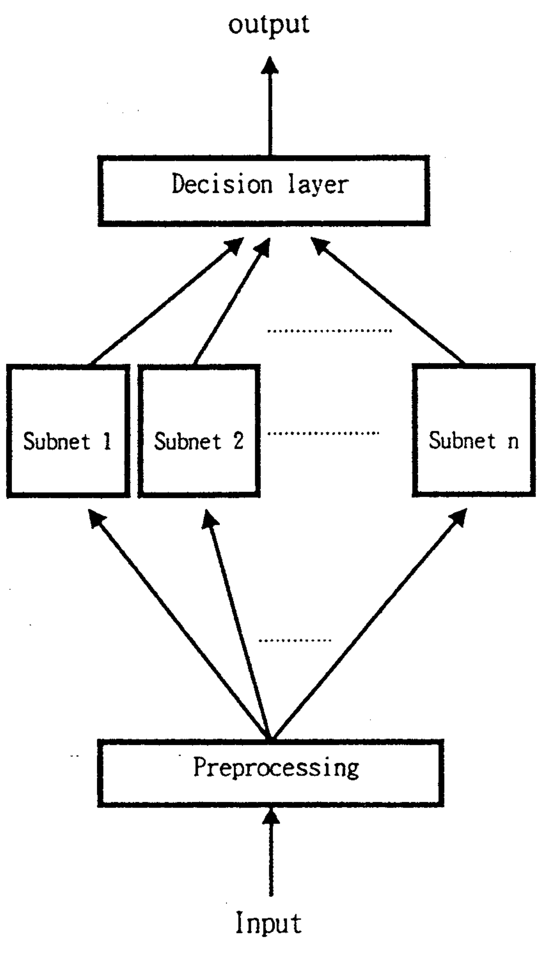


Figure 6. Neural network architecture for the system

As we know, the learning process for a small subnetwork is much easier to converge than that for a huge network. For this reason, the network was split into subnetworks, each of them is trained on a smaller subset of character patterns. Patterns in the same group (or subset) have the same dimension of feature vectors. Therefore, we may efficiently train these subnetworks and then combine them into a more powerful huge network. The proposed network architecture is shown in Figure 6.

Each subnetwork is modeled as follows: The number of hidden layers is settled to one, the number of neurons on the input layer is equal to the dimension of the feature vectors of character patterns in the corresponding group, and the number of neurons on the hidden layer is settled as $\sqrt{m \times n}$, where m is the number of neurons on the input layer and n is the number of neurons on the output layer. The number of neurons on the output layer is just the number of charater patterns in the corresponding group, and the output of each neuron in this layer is between 0 and 1.

3.2. Recognition Part

The system recognizes 5401 frequently used Chinese characters, containing a huge set of more than 15000 patterns. In order to increase the recognition efficiency for the system, such a huge set is divided into small groups, so that patterns in the same group have the same dimension of feature vectors. Our system is composed of several subnetworks, each of which is responsible for recognition for a particular group of patterns as described above.

In the recognition process, the dimension of the feature vector for an input character determines which subnetworks to enter. For example, if the dimension of the feature vector for an input character is n and assume that there are s subnetworks responsible for patterns with dimension n, then the feature vector serves as inputs to each of these s subnetworks. These subnetworks process sequentially (in PC), after then, The decision layer determines the final answer, according to the results of the output layer, for the recognition part. If the maximal value of the outputs for the neurons on the output layer is greater than a given threshold (= .5), the decision layer determines the character corresponding to the neuron with such a maximal output value as the answer for the recognition; otherwise, the resulting answer is "rejection ".

4. EXPERIMENTAL RESULTS

The proposed scheme is composed of several neural subnetworks, each of them is responsible for recognizing about 75 character patterns.

Our experiment tested on a trained subnetwork, which is able to recognize 76 Chinese character patterns. The experimental results showed that the recognition rate is 100% on the training patterns and 96% on the test patterns.

The recognition was performed on a PC-486, DX22-66 with algorithms implemented in Visual Basic. The average recognition speed is 3 characters/sec.

5. CONCLUSIONS AND EXTENSIONS

We describe an on-line recognition system for handwritten Chinese characters. As soon as a character is entered through an electronic tablet, the preprocessor extracts stroke segments in the written character from the pen-tip movement loci on the tablet and normalizes the length and angle of each stroke segment in the character. Thus, the output of the preprocessor is a sequence of these normalized values, which forms a feature vector of the input character.

The system is composed of many multi-layered feed-forward neural networks, each of them is trained separately to recognize a group of character patterns with the same number of stroke segments.

Each pattern concerned by the system corresponds to a stroke order of a Chinese character. We only consider the frequently encountered stroke orders for a character, and regard them as different patterns for our system. However, the system is unable to recognize characters written with an unusual sequence (or order) of strokes, and an increment on number of patterns will enlarge our system. One alternative is to utilize a method of stroke segment ordering, which is in our further research upon this proposed scheme. Such a method provides stable order independent of the writing order of a character. On the basis of this method we may overcome the different writing order problem.

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