

Development of Paper Automation Recognition System Using Brain Modeling of Hippocampal Neural Network Algorithm

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Abstract: In this paper, we present the paper automation recognition system using brain modeling of hippocampal neural network algorithm. The system reads image through scanner, analyzes the content of data, and transforms the letter region into the text form. To recognize the letter effectively, the features of letter image are extracted in the text region and then the text is learned at high speed using brain modeling of hippocampal neural network algorithm. In engineering, this algorithm is based of modeling hippocampus which combines new memories and then makes memory. Experimental results are reported to implement system with a high recognition rate.

1. Introduction

Recently in the field of computer science, the technological innovations are remarkable. Also, the government has supported IT839 policy from 2004. The intelligent information industry is based on U-IT services (ubiquitous information technology). It has an effect on the various fields of industry. Combined with this, computer and internet technology have made greater progress. Accordingly hand works in the daily routine change automation. Therefore, it is benefit to human life.

But so far, the paper is made use of in the general business environment. We must recognize a person's handwriting in the paper manually to confirm information. So, we develop the system to use automatically these many hand works. If the system is used by people, it is reduced to waste of time, work force and money. So, we will pursue many profits. This system is that the paper recognition machine accepts paper's images and sends them to computer and then after pre-processing. The computer recognizes and processes the letter region using hippocampal neural network algorithm.

In the engineering part, the neural network of many applications is applicative in the diversity of field on the basis of learning and memory activity of brain [1]. The modeling of this hippocampus is used to learning and recognition.

The rest of the paper is organized as follows. In Section 2, the pre-processing and thinning algorithm theory for letter recognition is introduced. In Section 3, The implementation of system using brain modeling of

hippocampal neural network algorithm is shown. We present the results of the proposed algorithm in Section 4. In Section 5, Finally, the conclusions are given.

2. Pre-processing and feature extraction

2.1 Pre-processing

2.1.1 Image to text form

Received images for letter recognition pass through pre-processing. It is classified into two steps. First step converts image into text form. There is method processing and recognizing directly acquired image of paper, but in this paper we use method converting image into text form. Figure 1 changes only letter into '*' and the results are used to learning by hippocampal neural network algorithm.



Figure 1. Transform image to text file

2.1.2 Thinning algorithm

Second step is that the result of first step extracts letter's structure through thinning. Figure 2 shows the result of thinning.



Figure 2. The result from the thinning algorithm

The thinning algorithm takes off thick line from the most outer one layer by one layer and extracts the last remained line element. In comparison with edge extraction, it extracts the outer line, while thinning extracts the middle line. We extract structure using Zhang suen thinning algorithm (1984) which is representative thinning algorithm. This is parallel processing method and the basic algorithm is process like figure 3 [2].

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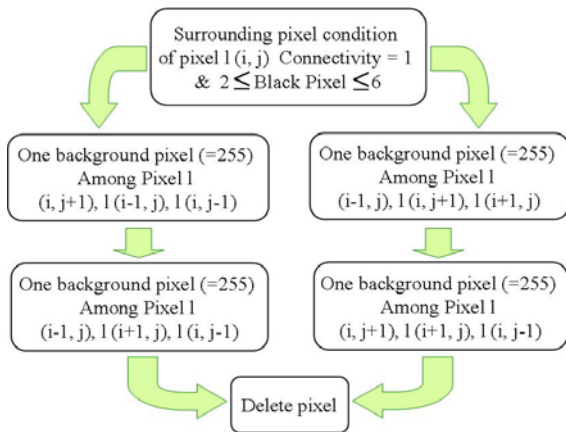


Figure 3. Zhang Suen thinning algorithm

2. 2 Feature extraction

In extracting the feature of each character, the construction of feature is made up vertical stroke, horizontal stroke, curve, location element, as a result of preprocessing at the base of the number and shape of ‘*’ which represents character.

2. 2. 1 The stroke element

Stroke elements are vertical and horizontal strokes to the letter. Example, the letters ‘n’, ‘u’ have two vertical strokes. The letters ‘t’, ‘z’ have each one and two horizontal strokes and the letters ‘a’, ‘c’, ‘e’, ‘o’, ‘s’, ‘v’, ‘w’ have no stroke elements.

2. 2. 2 The curve element

In the recognition of letter, curve element must explain very well the feature. In this paper, the feature of curve is extracted to the number of curve rather the shape of curve. The result of pre-processing has curve under proper critical value when it counts the letter to verticalness and horizontalness. Over critical value continually, it is recognized to curve and has curve. Figure 4 shows the counting method of stroke and curve in a letter. Here, the letter ‘n’ has two vertical strokes and five curve points.

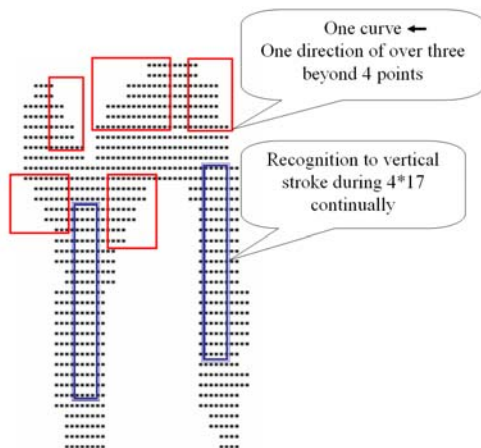


Figure 4. The recognition method of stroke and curve

2. 2. 3 Location element

It finds out location information to the structural access of letter. After the quadrisection to x-axis and y-axis at the center of letter, it finds out important feature of letter. Figure 5 shows the extraction of location feature in comparison to the letter ‘p’ and ‘q’. But the letter has the same number of stroke and curve element, it has the number of opposite stroke and curve to the center of y-axis.

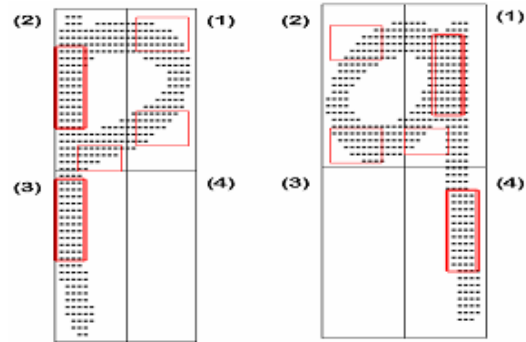


Figure 5. The recognition method of location

3. Hippocampal neural network algorithm

3. 1 Hippocampus

The hippocampus is a part of the middle are of the limbic system. It is located in the medial temporal lobe inferior to the choroidal fissure and temporal horn. In the sagittal plane the hippocampus is a club-shaped structure divided into three parts: head, body, and tail. The gray matter of the hippocampus is extension of the subiculum of the parahippocampal gyrus. In coronal plane the hippocampus and parahippocampal gyrus form an S-shaped configuration. The hippocampus itself consists of two interlocking C-shaped structures: the cornu ammonis and the dentate gyrus. Histologically, the hippocampus is further divided into four sections: CA1 to CA4 [3]. Figure 6 shows analyzing hippocampus.

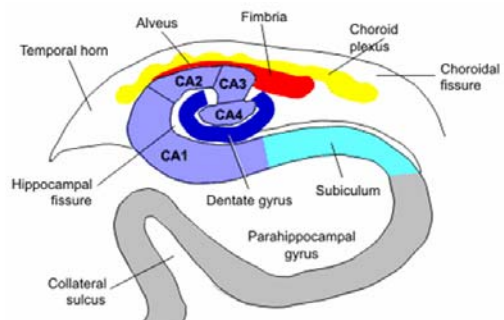


Figure 6. Hippocampal anatomy

3. 2 The neural network model of hippocampus

In the hippocampus importantly related four steps organizations are entorhinal cortex, Dentate Gyrus, CA3, CA1. Their ranges connect comparatively simple excitability path and the most important function of

hippocampus is the expansion from short-term memory to long-term memory [4]. We recognize basic four regions about basic structure modeling neural network.

Entorhinal cortex: It presents input and output of hippocampal neural network model which organizes interface between hippocampus and neocortex.

Dentate gyrus: Dentate gyrus structure which is directly connected the entorhinal cortex simplifies features by comparing variable feature components of the same object in the model with identity in the past input pattern. If it exceeds critical value of variation rate's range to the mean of pattern, it presents 1. Otherwise, it presents -1. It can do binary-coded with identity of feature.

CA3: When we remember some events, we can obtain further good results by repeating associative action. Circular associative memory adopts this circular concept. As we see in Figure 7, circular associative memory is associative memory of the same quality perform feedback from output to input. CA3 area connects the Dentate gyrus, and receive simplified information from the latter structure. In the CA3 area, auto-associate is occurred and it arranges feature information including noise more decisively. When feature of large differences is inputted comparing with learned feature in the past, it can classify as new pattern. In this paper, in order to implement circular associative memory, we follow the Hopfield's model.

CA1: CA1 area connects CA3 area, and it presents last step of information processing. It enables to learn information of auto-associate CA3 to single layer neural network, and decides long-term or short-term memory. If output value doesn't correspond to reacting learned weight, it classifies to short-term memory and stores [5-7].

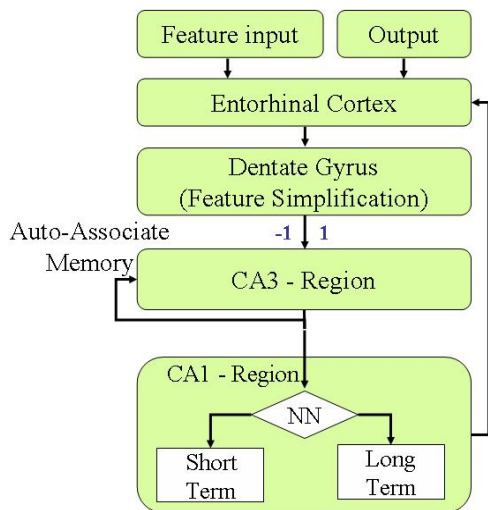


Figure 7. The neural network model of hippocampus

3.3 The implementation of hippocampal algorithm

Previously, we give a full detail of the hippocampal algorithm and now, implement this algorithm. It operates simplification of features (deviation calculation: Dentate Gyrus), proximity of features (Hopfield model learning: CA3), and elevation of recognition. (Perceptron learning added modulator: CA1) Figure 8 is hippocampal algorithm

with Pseudo code order. It is written using STL and MFC of VC++.

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Step 1 : Compute weights to store P patterns

$$W = \sum_{i=1}^p S^T(i)S(i) - PI$$

Step 2 : Determine update  $y_i \leftarrow x_i$  order
Step 3 : Set initial output.
Step 4 : For each unit  $y_i$ 
    do Step 4-1 ~ 4-3
Step 4-1 : Compute  $NET_i = x_i + YW_i^T$ 
Step 4-2 : Update intermediate output

$$y_i = \begin{cases} 1 & ; NET_i > 0 \\ y_i & ; NET_i = 0 \\ 0 & ; NET_i < 0 \end{cases}$$

Step 4-3 : Test condition for goto Step 5
    If y is converged, goto Step 5
    else, change i according to predetermined order
    and goto Step 4
Step 5 : Initialize weights and counter
    w  $\leftarrow$  0 or small random, k  $\leftarrow$  1
    p  $\leftarrow$  number of training pattern pairs
Step 6 : Set learning rate  $\alpha(0 < \alpha \leq 1)$  and  $\beta$ 
Step 7 : For each training pattern pair (X, d),
    do Step 7-1 ~ 7-4 until k=p
Step 7-1 : Compare output  $NET = XW^T$ 

$$y = f(NET) = \begin{cases} +1 & ; NET > T \\ 0 & ; NET = T \\ -1 & ; NET < T \end{cases}$$

Step 7-2 : Compare output and desired output
    If y=d, k  $\leftarrow$  k + 1 and goto Step 7
Step 7-3 : Update weights
    Compare  $\Delta W^{k-1}$  and  $\Delta W^k$ 
    If  $\Delta W^{k-1} \leq 2\Delta W^k$ 

$$\Delta W^k \leftarrow \alpha(d_k - y_k)X_k + \beta\Delta W^{k-1}$$

    Then,  $W \leftarrow W + \Delta W$ 

$$\Delta W^k \leftarrow \alpha(d_k - y_k)X_k$$

    else  $W \leftarrow W + \Delta W$ 
Step 7-4 : Increase counter and goto step 7 and
    k  $\leftarrow$  k + 1
Step 8 : Test stop condition
    If no weights changed in Step 7-1 ~ 7-4, stop
    else, k  $\leftarrow$  1 and goto Step 7

```

Figure 8. The pseudo code of hippocampal algorithm

4. Experiment data and results

4.1 Experiment method

Before experiment, we prepare big and small letter, number from zero to nine written optional one hundred people for database which is necessary to learning. As we see in Figure 9, Experiment method is that first paper recognition machine receives image and after passing by preprocessing it starts learning. Learning is finished and recognition work is conducted.

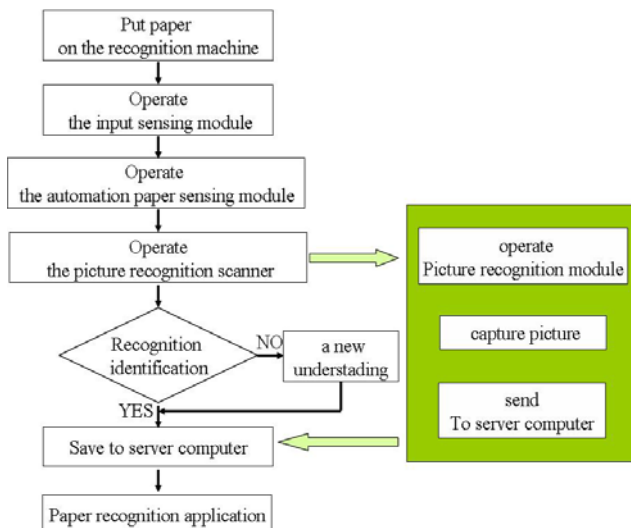


Figure 9. The flow chart of experiment

4.2 Experiment results

We make an experiment on recognizing the handwritten number and letter. But, letter is only English letter. In Figure 10, (a) is the sample of handwritten number, (c) is the results of (a). And (b) is the sample of handwritten letter, (d) is the results of (b).

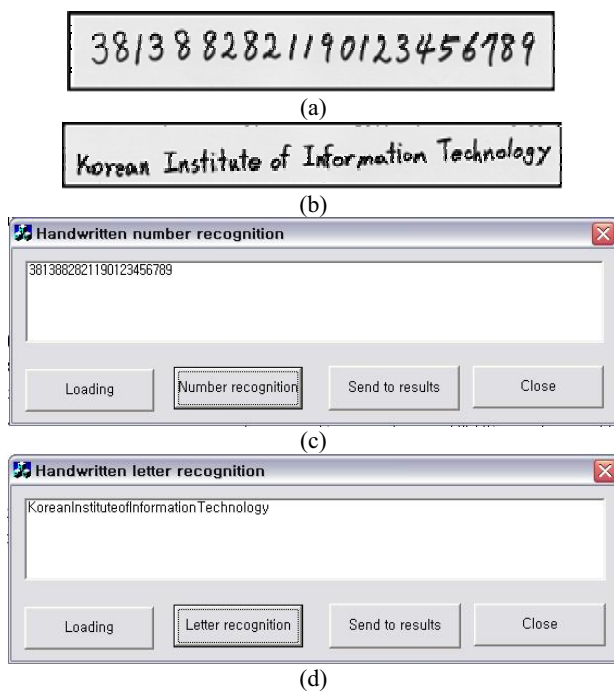


Figure 10. (a) The sample of handwritten number, (b) The sample of handwritten letter, (c) The results of handwritten number, (d) The results of handwritten letter

We get handwritten number and letter sample from ten persons and experiment it. Table 1 shows the results of recognition.

In Table. 1, a/b is used to recognition rate mark and a is the letter and number of correct recognition, b is the total of letter and number using recognition. Comparatively high

recognition rate over 96% is got. But in the analysis, the handwritten number is miss-recognition case of five and two, the handwritten letter is miss-recognition case of j to i and I to l. If we analyze miss-recognition parts more and complement feature extraction method, it will see nearly 100% recognition rate.

Table 1. The result of recognition rate

Case	Handwritten number	Handwritten letter
1	10/10	52/52
2	10/10	50/52
3	9/10	52/52
4	10/10	52/52
5	10/10	51/52
6	10/10	52/52
7	9/10	52/52
8	10/10	51/52
9	10/10	51/52
10	9/10	52/52
Miss recognition type	5, 2	i, j, I, l

5. Conclusions

In this paper, we read automatically data using letter recognition program and can apply to practical application. We show high recognition rate in the letter and recognition part. We expect that system which we suggest will prepare efficient work environment and be the foundation to applicable system development in all recognition environment from now on by powerful algorithm development. But, because personal handwritten is different, the more experiments we use, the more miss-recognition it appears, and miss-recognition of similar letter relation represents problem. If these problems complement feature extraction part, we think that they can be solved. In the future study access will complement these problems and implement system which has recognition rate near to 100%.

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