Neural Network Based Recognition of Machine Printed Hangul Characters of Low Quality

Kil-Taek Lim, Ho-Yon Kim, Yun-Seok Nam, and Hye-Kyu Kim
Postal Technology Research Center,
Electronics and Telecommunications Research Institute,
161 Gajeong-dong, Yuseong-gu, Daejon, 305-350, Korea
Tel. +82-42-860-5808, Fax.: +82-42-860-6508
e-mail : ktlim@etri.re.kr

Abstract: In this paper, we propose a Hangul character recognition method in which new letter components as recognition units are introduced and the MLP (multilayer perceptrons) neural networks are employed for two-step recognition of Hangul. To recognize Hangul character, we divide it into two or three recognition units and extract the direction angle features of them to be fed to the corresponding neural network recognizers. The recognition results of neural network recognizers are combined by another neural network. The experiments were conducted on the Hangul characters from real letter envelopes which are collected in the mail centers in Korea and the results showed that our method performs better than the conventional one.

1. Introduction

Many studies on Hangul character recognition have been conducted in the past 20 years[1-6]. Most of early studies were related to machine-printed character recognition with limited sizes and fonts, and some commercial character recognition systems have been introduced in the middle of 1990s. The mainstream of recent studies is the recognition of hand-written Hangul having a much higher difficulty compared to machine-printed character recognition, whereas studies on machine-printed character recognition have not drawn interest. However, the conventional recognition methods of machine-printed Hangul character remain to be problematic in that they are sensitive to the conditions for acquisition of character images and the types of characters and have unstable recognition rates.

The most representative area among many areas of utilization of character recognition technologies is automatic postal sorting. Since about 80~90% of recent postal matters are machine printed, the machine-printed Hangul character recognition technology is particularly important. In order to sort postal matters at a high speed, a series of processes such as draw-in, feeding, image acquisition, address recognition, barcode processing, loading, etc. of postal matters should be at a fast speed. The most important process for raising the sorting rate among these processes is the recognition process of address images. An address image is acquired by a line scan camera with a low resolution of 200 dpi, since it is difficult to use a high resolution of greater than 300 dpi due to the restrictions of processing speed and the cost. Accordingly, it is very difficult to develop Hangul character recognizers having a high recognition rate.

In this paper, we propose a neural network based recognition method of Hangul characters of low quality. To recognize Hangul character, we divide it into two or three recognition units and extract the direction angle features of them to be fed to the corresponding neural network recognizers. The recognition results of neural network recognizers are combined by another neural network. The experiments are conducted on the Hangul characters from real letter envelopes which are collected in the mail centers in Korea. The experimental results show that our method performs better than the conventional one.

2. Hangul Character Recognition

In this section, we propose a Hangul character recognition method in which new letter components as recognition units are introduced and the MLP (multilayer perceptrons) neural networks [7] are employed for two-step recognition of Hangul.

2.1 Grapheme based Hangul Recognition

For Hangul recognition, we employ the grapheme based recognition method. The basic concept of the grapheme based recognition method lies in the regulations of combination of letter components of Hangul. The regulations of combination of Hangul may be divided into six types as shown in Figure 1 according to the position of a vowel and whether there is any last consonant [3][4].

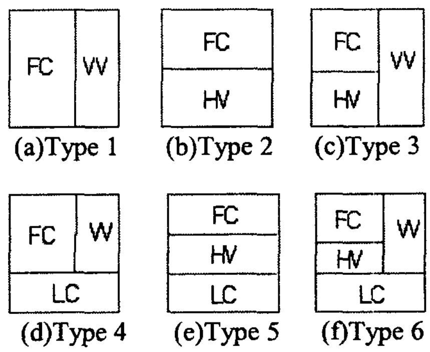

Figure 1. Classification of 6 types of Hangul (FC: First Consonant, LC: Last Consonant, HV: Horizontal Vowel, VV: Vertical Vowel).

In view of whether there is the last consonant, types 1, 2, and 3 have no last consonant, and types 4, 5, and 6 have the last consonant. In view of the vowel in each type, types 1 and 4 have only the vertical vowel, and types 2 and 5 have only the horizontal vowel. On the other hand, types 3 and 6 show the combination of a horizontal vowel and a vertical vowel. The information on the type of Hangul may be utilized for important information in character recognition, since it is performed by estimating the position of a grapheme according to the type of a character, recognizing the letter component, and combining the result. Many studies of machine printed Hangul recognition utilized the type information to construct recognizers [1-4].

In the proposed method, the input character image is recognized after it is divided into several recognition units similar to the graphemes. As shown in Figure 2, Hangul recognition units (HRU) are defined differently according to their types. Here, HRU(T,n) means the nth recognition unit of Hangul type T. In cases of types 1, 2, 4, and 5, the recognition unit is a grapheme, and in cases of types 3 and 6, the first recognition unit is the combination of FC and HV, and the second recognition unit is VV (refer to Figure 1). Presented in Table 1 are HRU(T,n), Hangul letter components corresponding to it, and the corresponding examples.

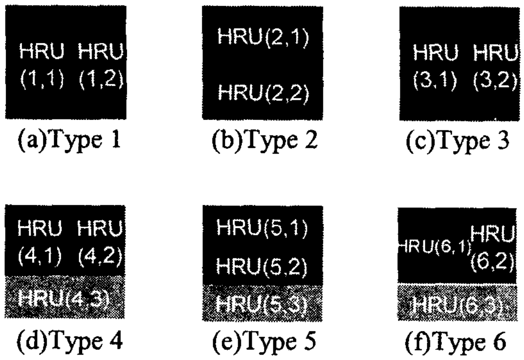

Figure 2. Basic recognition units according to the types of Hangul.

Table 1. Composition of HRU(T,n).

HRU(T,n)	Jaso	Example
HRU(1,1)	FC	ㄱ of 기
HRU(1,2)	VV	ㅣ of 기
HRU(2,1)	FC	ㄴ of 노
HRU(2,2)	HV	ㅗ of 노
HRU(3,1)	FC+HV	구 of 귀
HRU(3,2)	VV	ㅣ of 귀
HRU(4,1)	FC	ㅎ of 한
HRU(4,2)	VV	ㅏ of 한
HRU(4,3)	LC	ㄴ of 한
HRU(5,1)	FC	ㅇ of 을
HRU(5,2)	HV	ㅡ of 을
HRU(5,3)	LC	ㄹ of 을
HRU(6,1)	FC+HV	고 of 관
HRU(6,2)	VV	ㅏ of 관
HRU(6,3)	LC	ㄴ of 관

2.2 Flow of Hangul Character Recognition

Figure 3 shows the proposed process of recognition of Hangul character image. Firstly, HRUs for input character image are separated. The result of type classification is used since it is easy to estimate approximate positions of HRUs if the types of the character are known in advance. In order to recognize separated HRUs, the size of each HRU image is normalized firstly. Next, features are extracted for each HRU image of which size is normalized, and each HRU is recognized primarily by using these features. The result of character recognition may be wrong if any one of HRUs is recognized erroneously and recognized HRUs are combined simply. Also, if it is not possible to separate HRUs accurately due to the contact among HRUs, the results of recognition of characters may be wrong. Therefore, it may be possible to obtain a higher recognition rate by performing further recognition by referring to relative features with other HRUs forming the characters rather than recognition of the features of each HRU. Performing the secondary recognition process after HRUs are recognized can reduce the possibility of mis-recognition occurring according to simple combination of the results of recognition of HRUs. For re-recognition of each HRU, the *recognition aspect features* (RAF) during the process of recognition of each HRU by the primary HRU recognizer are extracted as new features, and they are input into the secondary HRU recognizer thus finishing recognition of HRUs. RAF will be described in the later section. Finally, recognized HRUs are combined and the recognized character is obtained.

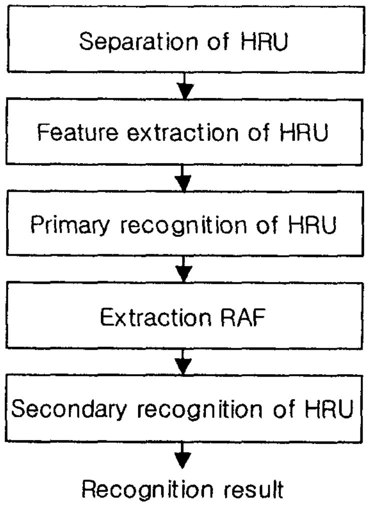

Figure 3. Flowchart of recognition of Hangul character.

2.3 Construction of neural network recognizers

It is necessary to have as many recognizers as the number of HRUs forming each type since Hangul character images are divided into HRUs when they are recognized. For example, in case of type 1, it is necessary to have two HRU recognizers since HRU has the first consonant (FC) and the last consonant (VV). Let's express the primary recognizer for HRU(T,n) which is the nth recognition unit in type T in terms of $\mathbf{FHR}^{Tn}$. Such primary HRU recognizers are implemented with MLP neural network. As an example, $\mathbf{FHR}^{11}$ is shown in Figure 4. The inputs of the neural network recognizer are the features extracted from the separated HRU(1,1) image, and the outputs are the probabilities of HRU(1,1) codes. The number of nodes in the output layer is 19 which is the total number of FCs, and each FC is assigned to one output node.

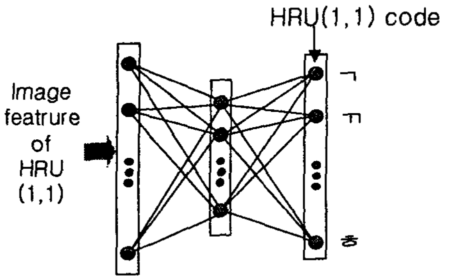

Figure 4. $\mathbf{FHR}^{11}$ for HRU(1,1).

HRUs that are recognized by the primary HRU recognizers are re-recognized through the secondary HRU recognizer. Whereas the primary HRU recognition is performed independently for each HRU, the secondary HRU recognition is done by integrating individual HRUs. The secondary HRU recognizer is also implemented with the MLP neural network. Let's denote the secondary HRU recognizer for type T to $\mathbf{SHR}^{T}$. Figure 5 shows $\mathbf{SHR}^{1}$, the HRU recognizer for type 1 Hangul character. The inputs of the neural network are the *recognition aspect features* (RAF) from $\mathbf{FHR}^{11}$ and $\mathbf{FHR}^{12}$, and the outputs are the probabilities of all codes of HRU(1,1) and HRU(1,2). The number of the nodes in the output layer of the MLP is 28 which is the total number of FCs and VVs, and one FC or VV is assigned to one output node.

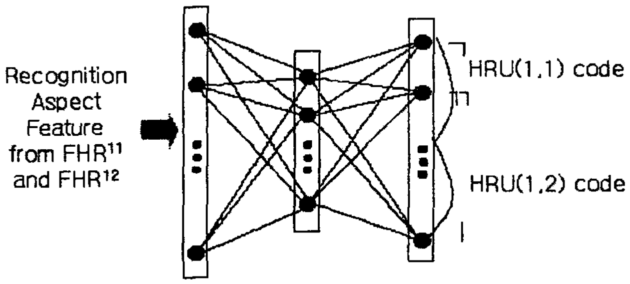

Figure 5. $\mathbf{SHR}^{1}$ for HRU(1,1) and HRU(1,2).

2.4 Features for FHR

The feature used in HRU recognition is the direction angle of a pixel. Based on the position of each pixel forming an image, black adjacent pixels are expressed in terms of vectors, and the directional angle obtained by adding these vectors is the directional angle of a pixel at the corresponding position. If the pixel value at the (x,y) position is expressed in terms of $f(x,y)$, the direction angle of the pixel, $\alpha(x,y)$, is defined as in the following equation,

$$\alpha(x,y) = \tan^{-1}\left(\sum_{a,b} a\cdot f(x+a,y+b), \sum_{a,b} b\cdot f(x+a,y+b)\right)$$

$$-\frac{w-1}{2} \le a,b \le \frac{w-1}{2}$$

where $f(x,y)$is a binary function having the value of 0 or 1, and $f(x+a, y+b)$ shows the value of a pixel positioned at the distance of a from $f(x,y)$ in the x-axis direction, and of b in the y-axis direction. Also, w is the size of a window restricting adjacent pixels included in the computation of a pixel direction angle, and a and b are integers. In our work, w is set to 3. In Figure 6 for an example, there is one black pixel in the window, and the pixel vector is $[1,1]^T$ and the direction angle is 45 degrees.

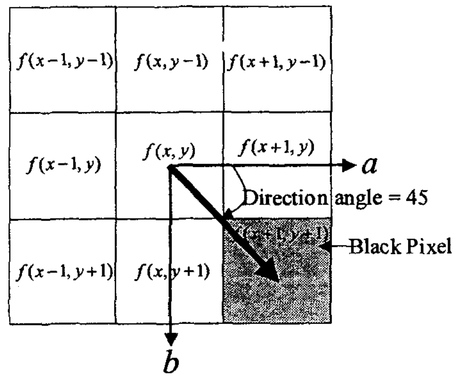

Figure 6. Direction angle example.

2.5 Rcognition Aspect Features (RAF) for SHR

The output values of output layer nodes of the HRU neural network recognizer, **FHR**, reflect the probabilities of the HRU codes (graphemes or combined graphemes). Thus, the HRU (grapheme or combined grapheme) code assigned to a node showing the maximum output value is the result of recognition of the input HRU image. Such output values of output layer nodes of the neural network recognizer are computed by using the output values of hidden layer nodes. So, the results of recognition of the neural network recognizer are determined according to the reaction of hidden layer and output layer nodes with respect to a given input.

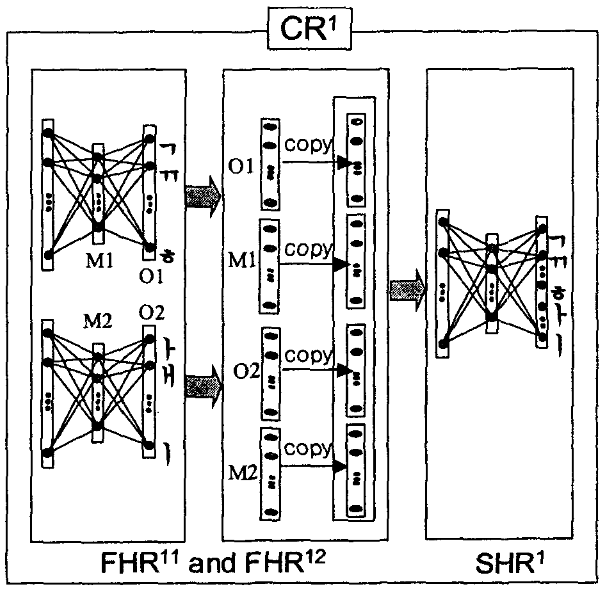

Figure 7. Type 1 character recognizer, $\mathbf{CR}^{1}$.

The vector having the output values of hidden layer nodes and output values of output layer nodes of the HRU recognizer are utilized as the input vector of secondary HRU recognizer, **SHR**. For example, if the recognizer recognizing 19 first consonants (FC) and the recognizer recognizing 9 vertical vowels (VV) are implemented in terms of 30 hidden layer nodes, respectively, for type 1 Hangul characters, 19 RAFs and 30 RAFs are obtained from the output layer and hidden layer of the first consonant recognizer, and further, 9 RAFs and 30 RAFs are obtained from the output layer and hidden layer of the vertical vowel recognizer. Therefore, RAF vector having 88 RAFs in total as the components are extracted. Figure 7 shows an example of such $\mathbf{CR}^T$ in terms of $\mathbf{CR}^1$.

3. Experiments and Results

The experiments were conducted on the Hangul character images from real letter envelopes which are collected in the mail centers in Korea. We extracted the total of 602,149 images of 200 dpi resolution. Among the character images collected, the first 301,078 images were used for training neural network recognizers and the remaining 301,071 ones for testing recognizers.

We trained 15 MLPs for 15 FHRs and 6 MLPs for 6 SHRs. The configurations of MLPs were all the same; one hidden layer with 30 nodes. For all MLPs, the maximum iteration of learning was 100 with the learning rate of 0.1 and the momentum of 0.1.

Table 2. Recognition Results.

<table>
<tr><th rowspan="2">HRU (T,n)</th><th rowspan="2">HRU Recognition Rate</th><th colspan="2">Character Recognition Rate</th></tr>
<tr><th>Conventional Method (Simple Combination of HRUs)</th><th>Proposed Method $\mathbf{CR}^T$</th></tr>
<tr><td>(1,1)</td><td>99.37</td><td rowspan="2">94.86</td><td rowspan="2">96.03</td></tr>
<tr><td>(1,2)</td><td>95.42</td></tr>
<tr><td>(2,1)</td><td>99.68</td><td rowspan="2">98.45</td><td rowspan="2">99.10</td></tr>
<tr><td>(2,2)</td><td>98.75</td></tr>
<tr><td>(3,1)</td><td>98.39</td><td rowspan="2">95.86</td><td rowspan="2">97.49</td></tr>
<tr><td>(3,2)</td><td>97.30</td></tr>
<tr><td>(4,1)</td><td>98.71</td><td rowspan="3">93.89</td><td rowspan="3">95.48</td></tr>
<tr><td>(4,2)</td><td>96.19</td></tr>
<tr><td>(4,3)</td><td>98.79</td></tr>
<tr><td>(5,1)</td><td>99.09</td><td rowspan="3">93.96</td><td rowspan="3">95.57</td></tr>
<tr><td>(5,2)</td><td>95.51</td></tr>
<tr><td>(5,3)</td><td>99.14</td></tr>
<tr><td>(6,1)</td><td>96.72</td><td rowspan="3">85.97</td><td rowspan="3">94.93</td></tr>
<tr><td>(6,2)</td><td>89.39</td></tr>
<tr><td>(6,3)</td><td>99.18</td></tr>
</table>

The results of experiments are shown in Table 2. In the table, (T, n) means n-th recognition unit of the Type T. For examples, (1, 1) means the first recognition object (first consonant) of the Type 1 character and (4, 2) does the second recognition object (vertical vowel) of the Type 4 character. As shown in the table, the performance of the proposed method is much better than that of the previous one. It should be noted that the recognition rates of vowels ((T, 2)) are less than those of consonants ((T, 1) and (T, 3)). From the investigation, we found out that the recognition of vowels are more sensitive than that of consonants because the result of recognition might be erromeous when only one or two pixels of vowel are missing.

4. Conclusion

In this paper, we propose a Hangul character recognition method based on neural networks. The recognition are composed of two steps. At the first step, the input Hangul character is divided into two or three recognition units (HRU) and those HRUs are recognized by primary HRU recognizers (**FHRs**). At the second step, the recognized HRUs are combined by **SHR** utilizing the recognition aspect features of **FHRs**.

The experiments have been conducted on the Hangul characters from real letter envelopes which are collected in the mail centers in Korea and the results have shown that our method performs better than the conventional one.

References

[1] M. K. Kim, O. S. Kwon, and Y. B. Kwon, "Hangul character type clustering based on the structural shapes and the combination rules of vowels," (in Korean), *Journal of Korea Information Science Society (B)*, Vol. 25, no. 4, pp.685-695, 1998.

[2] P. H. Lee, H. D. Jang, and J. C. Nam-Gung, "A study on printed Hangul recognition with dynamic Jaso segmentation and neural network," (in Korean), *Journal of Korean Institute of Communication*, Vol. 19, no. 11, pp.2133-2145, 1994.

[3] S. B. Cho and J. H. Kim, "Hierarchically structured neural networks for printed Hangul character recognition," *International Joint Conference on Neural Networks*, Vol. 1, pp.265-270, 1990.

[4] S. I. Chien, "Hangul(Korean) and English OCR system using multiple hypothesis driven neural nets," *Korean-French Character Recognition Workshop,* pp.37-52, 1994.

[5] S. Lee and J. Park, "Nonlinear shape normalization methods for the recognition of large-set handwritten characters," *Pattern Recognition,* Vol. 27, no. 7, pp.895-902, 1994.

[6] B. K. Sin and J. H. Kim, "A statistical approach with HMMs for on-line cursive Hangul (Korean script) recognition," *Proceedings of the Second International Conference on Document Analysis and Recognition,* pp.147-150, 1993.

[7] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," *Parrallel Distributed Processing,* Vol. 1, pp.319-362, 1986.