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On-line recognition of cursive Korean characters using neural networks

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Abstract

This paper proposes an efficient method for on-line recognition of cursive Korean characters. Since Korean characters are composed of two or three graphemes in two dimensions, strokes, primitive components of the characters, are usually warped into a cursive form. To classify automatically such cursive strokes, an Adaptive Resonance Theory (ART) neural network is used. Fuzzy membership functions are used to adjust the system according to the writing habits of individual users. The positional relation between two consecutive strokes is also computed with fuzzy functions. With a sequence of strokes classified by the ART neural network and their positional relations computed by fuzzy functions, a character is recognized on a multilayer perceptron for character construction. The proposed method works well with the variation of different writing styles. A test with 17,500 hand-written characters shows a recognition rate of 96.5 per cent and a speed of 0.3 second per character.

Keywords: On-line character recognition; ART-1 neural network; Multilayer perception; Fuzzy function

1. Introduction

With the advance of hardware technology, much research has been done on on-line character recognition to realize a more natural and accurate human-machine interface. We need to understand the characteristics of the target character set to develop a recognition method for it. Unlike the characters of Western alphabets such as English, Russian, French, German, etc., some Oriental charac-

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ters, such as Korean and Chinese, have structural characteristics. That is, they are composed of smaller units in a two-dimensional space. As a result, their character set is very large and they have many problems not found in Western alphabets.

Among these structural characteristics, Korean has the following inherent characteristics: (1) Korean is a large-alphabet language, which means that a large number of characters to be recognized exist; (2) since a grapheme is used to construct many different characters, there are many similar characters, so that a recognizer needs a more accurate recognition algorithm to discriminate correctly between similar characters; (3) on-line Korean characters have wide variations in the number of strokes, stroke order and shape.

We can classify character recognition methods according to the recognition unit, such as either character [2], grapheme [3], stroke or stroke segments [4]. Recognizing a character as a unit requires excessive amounts of memory space and processing time. To deal with these problems, a large-classification technique was used, usually resulting in an incomplete algorithm with many errors [2]. Because Korean characters are composed of two or three graphemes, some researchers have used the grapheme as a recognition unit [5]. For hand-printed Korean characters, this approach is efficient since the character recognition problem is reduced to a grapheme recognition problem, which is simpler. However, separating graphemes from a hand-written character itself is very difficult.

Stroke segment is a good recognition unit if a character is mainly composed of straight strokes as in Chinese characters. However, for recognizing cursive characters, this approach is not so efficient. Since there can be many variations of stroke segments for a given stroke, a cursive stroke tends to have many different representations. Hand-printed characters, having no stroke connections, consist of seven or eight basic straight strokes. Several researchers have reported with a good recognition rate [3,6], however, this method has the severe limitation that strokes should be disconnected in writing Korean characters. Statistical reports show that more than 80 per cent of Korean test characters have one or more connected strokes [7]. Furthermore, on-line Korean characters have many similar characters and classifying them depends heavily on correct recognition of cursive and connected strokes. If every cursive stroke is segmented into one or more straight segments, it becomes very difficult to classify similar characters. Thus we decide to consider a whole cursive stroke as a recognition unit [7–9].

In this paper, we propose a novel recognition method that uses ART-based stroke classification and multilayer perceptron-based character recognition. To accommodate various writing styles and correctly classify similar strokes, we use an ART-1 neural network and fuzzy membership functions. For numerous cursive strokes, the available classes into which strokes should be grouped are not easy to know in advance. To overcome this, we use an ART-1 neural network that automatically assembles similar patterns together to form classes in a self-organized manner. Although the self-organizing stroke classifier can handle noisy and deformed input strokes, it cannot discriminate between similar strokes (classified into the same class but different). To classify such similar strokes, we use fuzzy membership functions. With a sequence of the classified strokes including their

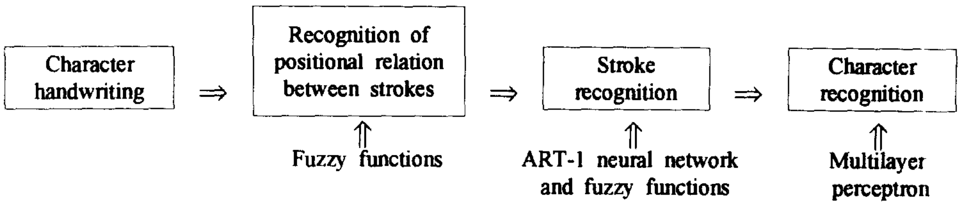


Fig. 1. The overall structure of the recognition system.

positional relations, character recognition is achieved by a multilayer perceptron learned with previous experience. Fig. 1 shows the overall structure of the recognition system.

2. Preprocessing

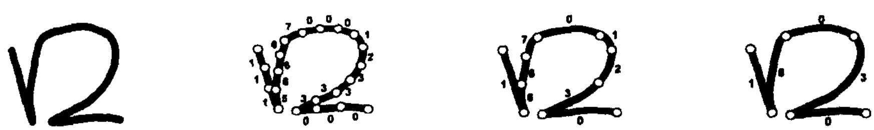
Generally, the data acquired from a tablet with an electronic pen is sampled at regular interval and represented as a sequence of coordinates on an X-Y plane. The sequence may contain variations depending on the writing style and the digitizer's condition. Preprocessings minimize the variations through eliminating noises and hooks, and make the sequence appropriate input for the ART-1 neural network.

2.1. Extraction of feature vectors

Fig. 2 shows the extraction process of a feature vector after eliminating noises and hooks [7]. This process uses the eight direction codes shown in Fig. 3.

2.2. Conversion of strokes into binary input

Since ART-1 deals with binary patterns, the eight direction codes are converted into binary inputs by the rules shown in Table 1. The aim of this transformation is between each direction code to make a reasonable Hamming distance. Additionally, our ART-1 neural network has 120 input neurons, so that the rest of the input vector which is not in eight directions is filled with zeros. For example, an input



(a)after normalization (b)eight direction codes (c)first vector quantization (d)second vector quantization

Fig. 2. Feature vector extraction process.

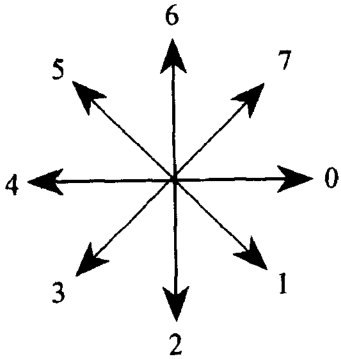


Fig. 3. Eight directions.

vector for Fig. 2 is 10101001 01011010 10101010 10010101 10101010 00000000 ··· 00000000.

2.3. Positional relation

To recognize a character correctly with identified strokes, we need to compute their positional relations. We use four fuzzy words *Up*, *Down*, *Left* and *Right*, which are represented by the fuzzy membership functions, F_U, F_D, F_L and F_R respectively. Let (Lx_i, Ty_i) and (Rx_i, By_i) be, respectively, the top-left point and bottom-right point of the smallest rectangle which contains a stroke i; and let (Cx_i, Cy_i) be its center (see Fig. 4). Let Θ represent an angle between the centers of two consecutive strokes (see Fig. 5); and $Ty_1 - By_2$, $Ty_2 - By_1$, $Lx_1 - Rx_2$ and $Lx_2 - Rx_1$, respectively, represent the four distances between boundaries of two strokes. In Fig. 6, (a) through (e) show the eight fuzzy membership functions to compute positional relations and (f) through (h) show an example calculation of fuzzy relationships for the input character '자' (ja) shown in Fig. 5.

Table 1
Binary input pattern

Code	Binary input							
0	1	0	1	0	1	0	1	0
1	1	0	1	0	1	0	0	1
2	1	0	1	0	0	1	0	1
3	1	0	0	1	0	1	0	1
4	0	1	0	1	0	1	0	1
5	0	1	0	1	0	1	1	0
6	0	1	0	1	1	0	1	0
7	0	1	1	0	1	0	1	0

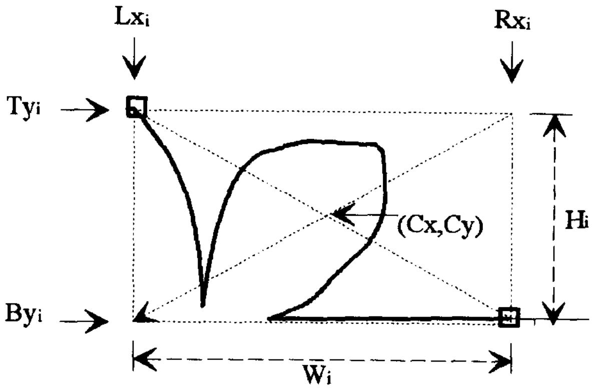


Fig. 4. Symbols of a stroke.

3. Stroke classification

Stroke recognition is undertaken in two steps. In the first step, a class of a given stroke is selected using the ART-1 neural network. In the next step, a stroke recognition is undertaken among a group of similar strokes with fuzzy membership functions.

3.1. Identification of the stroke group

Hand-printed strokes of Korean are usually identified with seven primitive strokes such as '—', '\', '|', '/', 'ㄱ', 'ㄴ', 'ㅇ'. [6]. In hand-printing, no stroke connection is allowed between consecutive primitive strokes. However, most hand-

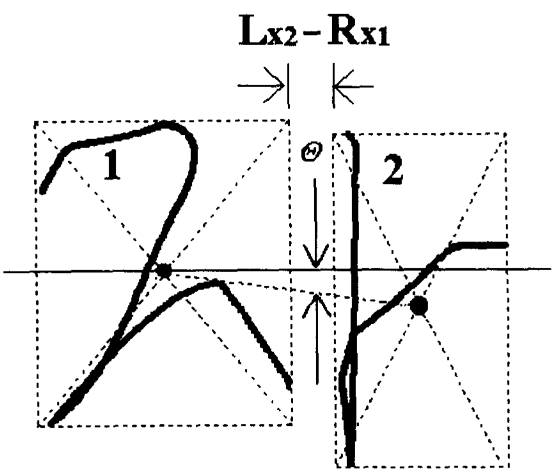


Fig. 5. Symbols between consecutive strokes.

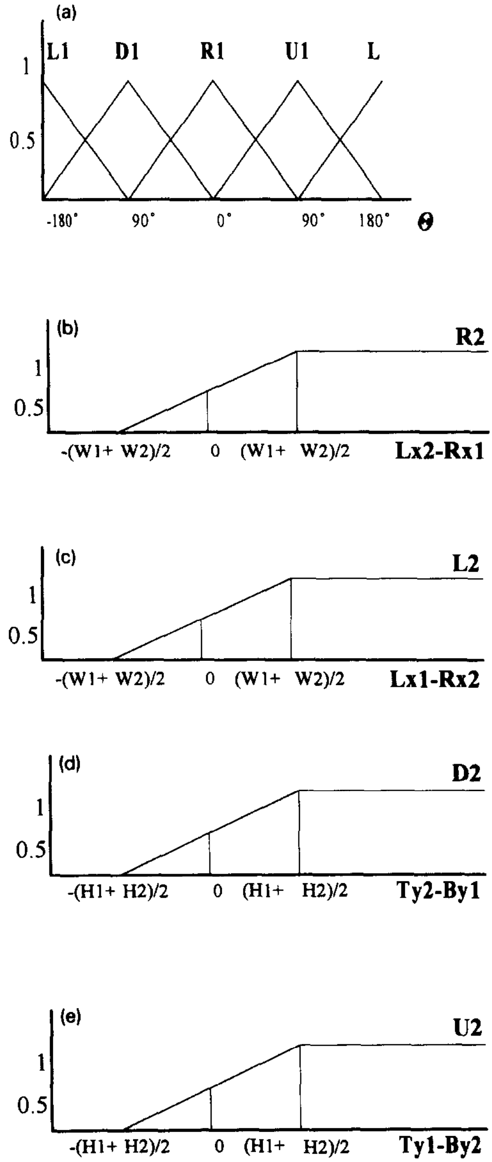


Fig. 6. Fuzzy functions and a defuzzification process.

written Korean characters appear cursive with their primitive strokes connected, making it hard to extract primitive strokes for recognition [7]. Naturally, the classification of such cursive strokes has an important role to guide the correct recognition. To deal with the cursive strokes, neural networks using a supervised

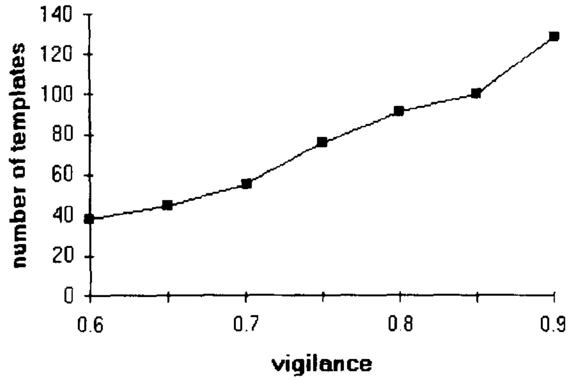


Fig. 7. The number of templates.

learning algorithm are introduced [9,10,11], where the sequence of segmented straight lines or direction code is used as an input, and defining the actual strokes showed in daily writing is tried. However, in these systems, manual effort is needed to group the entire set of Korean strokes into classes, because the pairing of each input pattern with the target output is essential. This process is not only difficult but also prone to error. It would also be complex to build a neural network classifier that directly recognizes each stroke.

We use an ART-1 neural network to classify the cursive strokes. The significant feature of the ART-1 neural network is its ability to self-organize and self-stabilize its recognition codes in response to many binary inputs of variable complexity. In other words, it learns or adapts to new inputs while at the same time attempts to retain its previously learned information in some stable state. It also has the advantage that it is designed to learn quickly and stably in real-time in response to

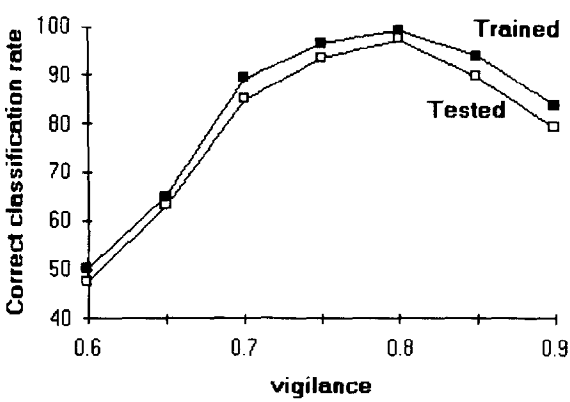


Fig. 8. Correct classification rate.

stroke number	stroke shape	frequency rate	stroke number	stroke shape	frequency rate	stroke number	stroke shape	frequency rate	stroke number	stroke shape	frequency rate
1		12.88	2		23.9	3		0.04	4		17.4
5		6.42	6		0.54	7		1.14	8		1.0
9		0.92	10		0.64	11		3.66	12		0.28
13		0.90	14		3.94	15		0.36	16		0.44
17		0.10	18		0.74	19		0.20	20		0.46
21		0.12	22		0.30	23		0.08	24		3.48
25		1.60	26		0.36	27		0.10	28		0.28
29		0.30	30		0.14	31		0.22	32		0.04
33		0.06	34		0.70	35		0.72	36		1.72
37		0.16	38		0.10	39		0.04	40		0.10
41		0.38	42		0.26	43		0.14	44		0.46
45		1.04	46		0.04	47		0.06	48		1.10
49		0.06	50		1.00	51		0.60	52		0.04
53		1.86	54		2.74	55		0.04	56		0.02
57		0.10	58		0.02	59		0.06	60		0.32
61		0.16	62		0.10	63		0.20	64		0.10
65		0.20	66		0.10	67		0.24	68		0.14
69		0.02	70		0.02	71		0.14	72		0.08
73		0.36	74		0.08	75		0.02	76		0.04
77		0.34	78		0.06	79		0.04	80		0.08
81		0.02	82		0.12	83		0.02	84		0.20
85		0.06	86		0.02	87		0.02	88		0.08
89		0.06	90		0.14	91		0.02			

Fig. 9. Templates when the $\rho = 0.8$.

a changing world with an unlimited number of inputs until it runs out of memory [12,13,14]. These properties reveal the good characteristics of the ART-1 neural network when it is used as a tool for learning of recognition categories and recognizing patterns in real-time.

In the ART neural network, the vigilance parameter(ρ) determines the coarseness of the classification [12,13], that is, the measure of similarity between the input and the categorized templates. Hence, it is important to choose a level appropriate for providing proper discernability in the classification. In the grouping of strokes, we initialize the level of vigilance to 0.6 and increase it by 0.05 each time while categorizing the input strokes. The number of templates varies for each level (see Fig. 7). As the level of vigilance increases, the success rate of the classification improves (see Fig. 8). However, the performance deteriorates steeply around 0.8. Fig. 9 depicts templates and their frequency when vigilance level ρ is 0.8.

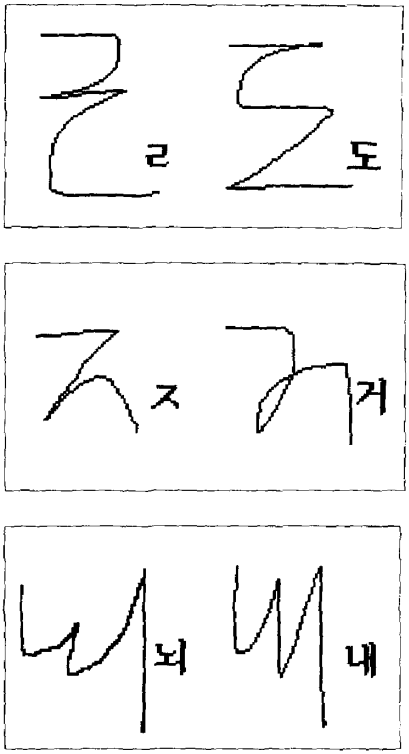


Fig. 10. Examples of similar strokes.

3.2. Stroke recognition using fuzzy functions

Fuzzy membership functions are used to discriminate a stroke from a group of similar strokes. Fig. 10 shows examples of similar strokes with a Korean character or a grapheme corresponding to them. Fig. 11 shows a fuzzy function for discerning 'ㄷ' and 'ㄹ'. The shape of the stroke segment identified with 'L' in the figure plays an important role in classifying 'ㄷ' and 'ㄹ'. If the 'L' of a stroke is a convex, the stroke is classified as 'ㄷ'; otherwise it is classified as 'ㄹ'.

4. Character recognition

If every character is represented as a sequence of stroke codes and positional relationships, many memory and long access time will be needed to find a corresponding sequence for an input character. Thus, a multilayer perceptron with a backpropagation learning algorithm is used to construct a character from a sequence. This network utilizes the construction rules of Korean characters. Fig. 12 shows the structure of the network with an example. The input layer receives an

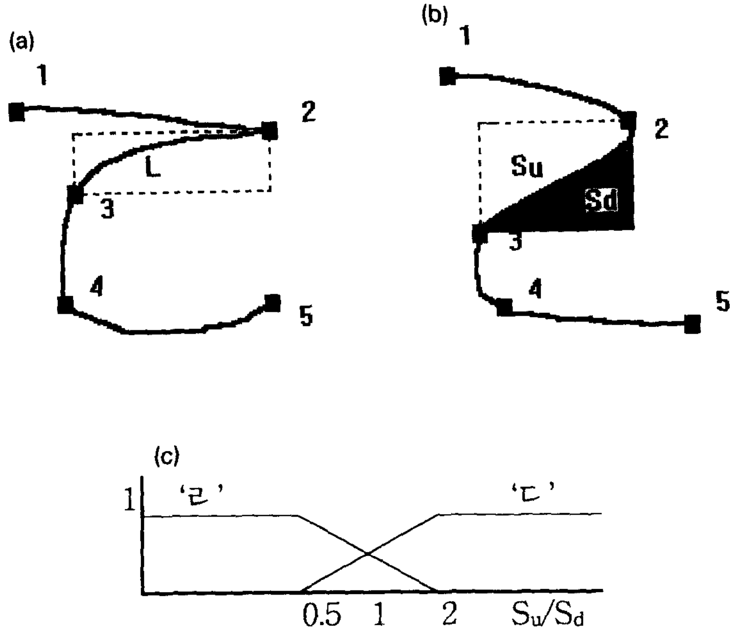


Fig. 11. An example of fuzzy membership function for 'ㄷ' and 'ㄹ'

alternate sequence of stroke codes and positional relationships of a character. A code is represented 7 bits(nodes) and a positional relationship of 2 bits. The output layer has 16 nodes which denote a flag (1), the first consonant (5 bits), a vowel (5 bits) and an optional last consonant (5 bits), respectively. The one-bit flag is used to mean that the result code means a Korean character.

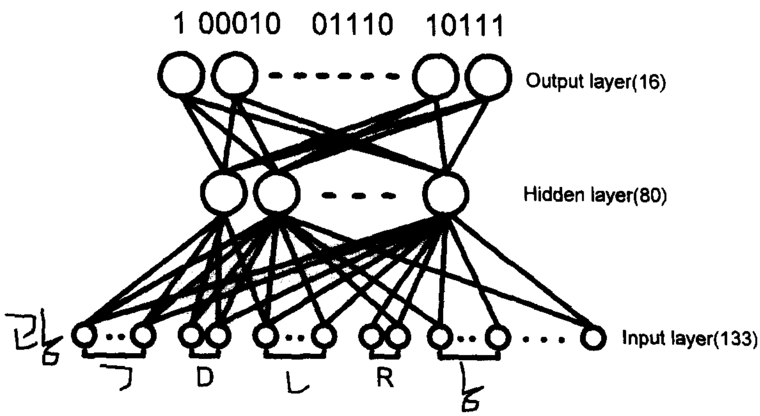


Fig. 12. Multilayer perceptron for character construction.

Table 2
Recognition rate

Char.	# of char.	Correct recog.	Mis-recog.	Reject	Recog. rate (%)
Train	19579	19361	218	0	98.9
Test	17500	16878	170	452	96.5

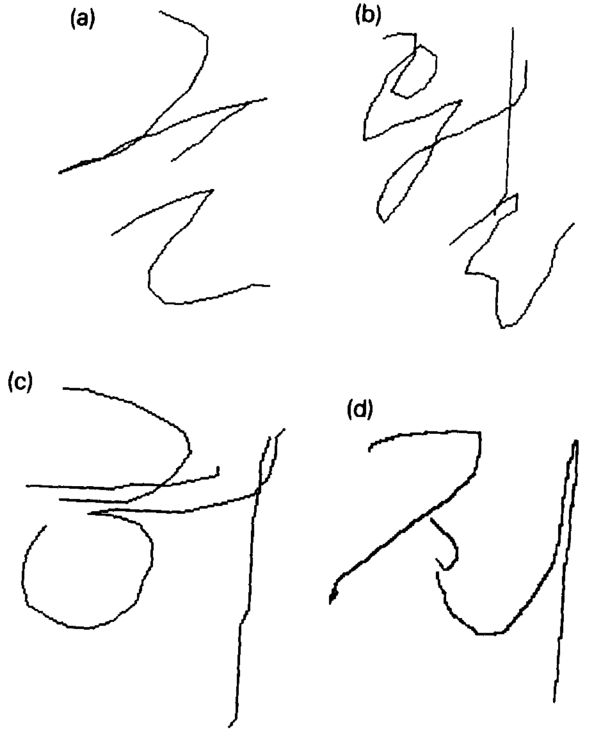


Fig. 13. Examples of recognition error. (a): 글(gul) → 굴(gool), (b): 훨(whirl) → ?, (c): 허(huh) → ?, (d): 죄 (joi) → 재(jae).

Table 3
Relative ratio of error types

Error type	# of error characters	Rate (%)
Abnormal writing	42	24.7
Unlearned strokes	17	10.0
Unlearned char.	101	59.4
Ambiguous positional relation	10	5.9
Total	170	100.0

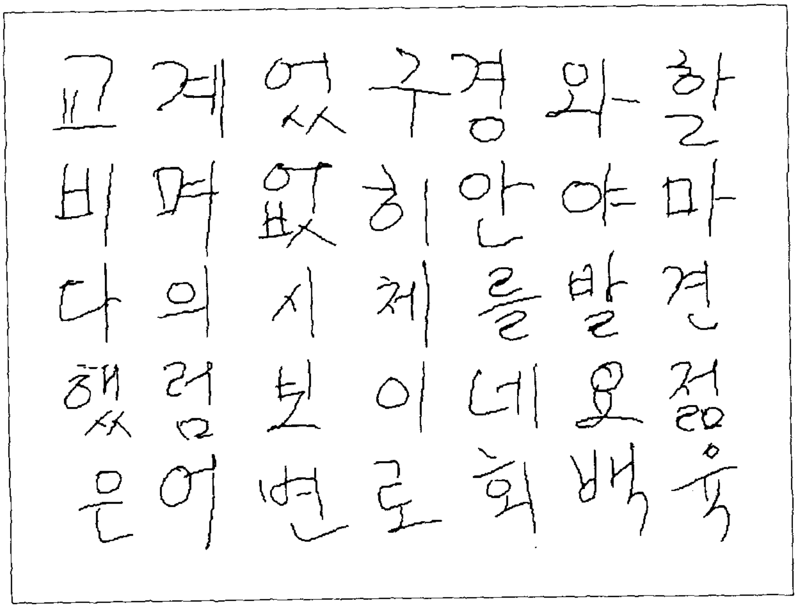


Fig. 14. Sample test characters.

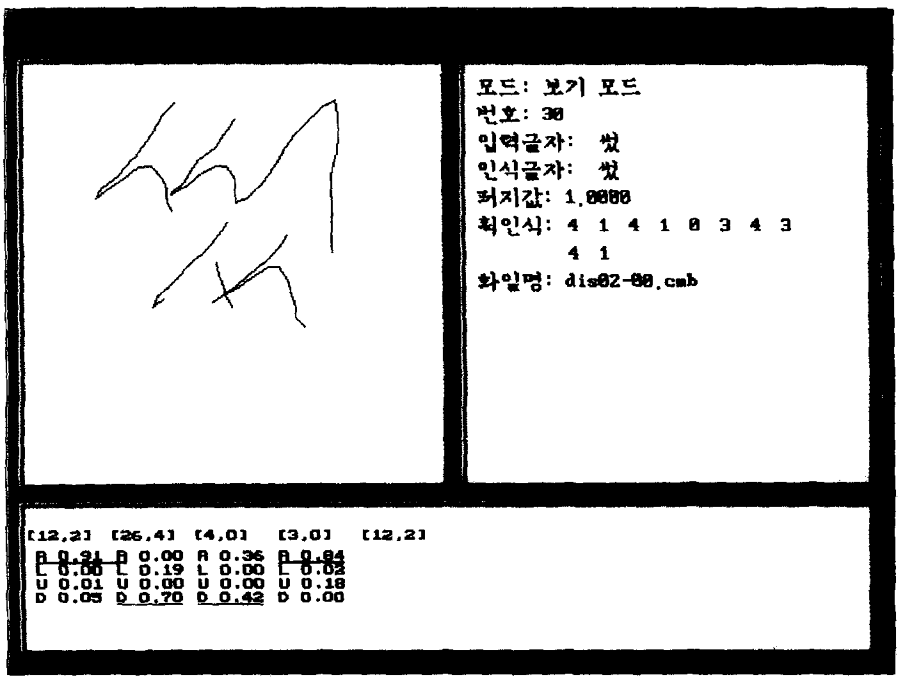


Fig. 15. An implementation of the method.

5. Experimental results

To evaluate the performance of the proposed method, we experimented with a set of 19,579 characters for training and another set of 17,500 characters for testing. The test data were written by 10 different writers without any constraints. We used WACOM HD-648A as an input device and implemented the proposed method in C language on an IBM PC-486. Table 2 shows the result of the experiments. The recognition rate for the test characters was 96.5 per cent with speed of 0.3 second per character.

Recognition errors were mainly caused by abnormal writing, excessive hook, the use of unlearned strokes, unlearned characters and ambiguous positional relations. Only a small percentage of strokes were rejected and this proves the usefulness of ART-based stroke classification. Most rejections in the test data were from unlearned characters. This can be overcome by simply training the unlearned characters. Fig. 13 shows four examples that were mis-recognized and rejected. The character in (a) was mis-recognized as '굴'(gool) because the horizontal vowel 'ㅡ' had an excessive hook at the end of the stroke. The character in (b) was written with only one cursive stroke, which was among the unlearned strokes and was unusual. In (c), the character '허'(huh) was written in an abnormal order and was an unlearned character. Lastly, the character in (d) was mis-recognized because this character required a more accurate positional description. Table 3 shows the relative error ratio according to error types. Sample test characters are shown in Fig. 14. Fig. 15 shows an implementation of the proposed method.

6. Conclusions

In this paper, we have proposed a new method for on-line recognition of cursive Korean characters. This method uses an ART-1 neural network, fuzzy functions and multilayer perceptron. Since the ART-1 stroke classifier automatically assembles similar patterns together, it does not suffer from stroke segmentation, stroke extraction and manual definition of the actual strokes for real-world characters that are critical processes for on-line character recognition. Furthermore, the classifier provides a large degree of flexibility in dealing with distortion of strokes. With the fuzzy membership functions for stroke classification together with the four fuzzy positional relations, we were able to achieve a very high recognition rate.

Learning a character is achieved simply by adding a new character sequence to the training data for the multilayer perceptron for character construction. The network was able to learn to classify correctly all sequences from the training data set, so that it represented Korean characters efficiently.

Though the performance of the proposed method was very good, it could be improved further at least in three respects: (1) through the study of writing behavior, it will be able to accommodate characters written in an abnormal order;

(2) a robust dehooking algorithm preprocessing will improve the recognition rate; (3) above all, more training data will lead to a more practical recognition system. Future work will also include application of the basic principle of the proposed method to other Oriental characters such as Chinese and Japanese.

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