Stroke-number and stroke-order free on-line kanji character recognition as one-to-one stroke correspondence problem

Toru Wakahara
Hosei University

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Stroke-Number and Stroke-Order Free On-Line Kanji Character Recognition as One-to-One Stroke Correspondence Problem

Toru WAKAHARA†, Akira SUZUKI††, Naoki NAKAJIMA†, Sueharu MIYAHARA†, *and* Kazumi ODAKA†, *Members*

SUMMARY This paper describes an on-line Kanji character recognition method that solves the one-to-one stroke correspondence problem with both the stroke-number and stroke-order variations common in cursive Japanese handwriting. We propose two kinds of complementary algorithms: one dissolves excessive mapping and the other dissolves deficient mapping. Their joint use realizes stable optimal stroke correspondence without combinatorial explosion. Also, three kinds of inter-stroke distances are devised to deal with stroke concatenation or splitting and heavy shape distortion. These new ideas greatly improve the stroke matching ability of the selective stroke linkage method reported earlier by the authors. In experiments, only a single reference pattern for each of 2,980 Kanji character categories is generated by using training data composed of 120 patterns written carefully with the correct stroke-number and stroke-order. Recognition tests are made using the training data and two kinds of test data in the square style and in the cursive style written by 36 different people; recognition rates of 99.5%, 97.6%, and 94.1% are obtained, respectively. Moreover, comparative results obtained by the current OCR technique as applied to bitmap patterns of on-line character data are presented. Finally, future work for enhancing the stroke matching approach to cursive Kanji character recognition is discussed.

key words: *on-line Kanji character recognition, cursive handwriting, stroke correspondence, combinatorial optimization, distortion-tolerant matching*

1. Introduction

For large-alphabet languages, like Japanese or Chinese, handwriting input using an on-line recognition technique is essential for input accuracy and speed [1]. However, the thousands of ideographic Japanese characters of Chinese origin (called Kanji) can be written with wide variations in the number and order of strokes and shape distortion.

Yoshida et al. [2] realized stroke-number free recognition by dynamic programming as applied to an entire time series of characteristic points written with the correct stroke-order. Ishii [3] proposed a stroke-order free recognition method by using a set of stroke representative points written with the correct stroke-number. Yurugi *et al.* [4] developed a recognition method permitting stroke-order variations within and between radicals written with the correct stroke-number. On the other hand, the authors proposed a series of robust stroke matching algorithms as stroke correspondence problem permitting both stroke-number and stroke-order variations [5]-[8]. However, it was then made clear that the stroke correspondence ability was insufficient for cursive handwriting [6].

This paper greatly reinforces the selective stroke linkage method reported earlier by the authors [6] so as to deal with natural, cursive handwriting by providing two new, complementary algorithms of one-to-one stroke correspondence determination; their joint use achieves stable stroke correspondence without combinatorial explosion. Moreover, three kinds of inter-stroke distances are devised to realize whole-part or whole-whole and distortion-tolerant matching against stroke concatenation or splitting and shape distortion. Recognition tests are made within 2,980 Kanji character categories using training data written carefully with the correct stroke-number and stroke-order and two kinds of test data written freely in the square style and written fast in the cursive style. Furthermore, future work for enhancing the stroke matching approach is discussed in a comparative study of the current OCR technique as applied to bitmap patterns of on-line cursive character data.

2. Stroke Representation and Inter-Stroke Distances

Optimal selection of feature points is very important so as to deal with arbitrary stroke concatenation or splitting and shape distortion occurring in cursive handwriting. Also, effective inter-stroke distances for whole-part or whole-whole and distortion-tolerant stroke matching should be devised. This section describes our solutions to these problems.

2.1 Feature Point Selection

As preprocessing, position and size normalization is applied to a character pattern: translation of the center of gravity of points to the origin (0, 0) and, then, scaling of the pattern so that the second moment of the pattern around the origin is set at the predetermined value of ρ^2.

Next, we select feature points from each stroke according to two basic principles: one is that the feature points are selected at regular intervals on a stroke with the predetermined stroke-segment length Δ and the other is that the number of feature points is set at $n = 2^p + 1$ ($p = 0, 1, 2, 3, \ldots$), where the value of p is determined as a function of the total stroke length and the value of Δ.

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† The authors are with NTT Human Interface Laboratories, Yokosuka-shi, 238-03 Japan.
†† The author is with NTT Visual Communications Sector, Yokosuka-shi, 238-03 Japan.

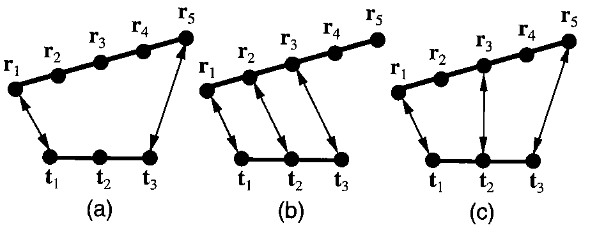

Fig. 1 Inter-stroke distances. (a) Endpoint matching. (b) Initial part matching. (c) Whole-whole matching. Solid lines and black circles denote strokes and feature points, respectively. Each inter-stroke distance is given by the sum of the norms of arrows.

2.2 Inter-Stroke Distance Definition

We denote two strokes by R and T, and represent R and T by m feature points and n feature points ($m \geq n$), respectively, as follows:

$$\mathrm{R} = (\mathbf{r}_1, \dots, \mathbf{r}_i, \dots, \mathbf{r}_m),\ \mathrm{T} = (\mathbf{t}_1, \dots, \mathbf{t}_j, \dots, \mathbf{t}_n), \qquad (1)$$

where $\mathbf{r}_i$ and $\mathbf{t}_j$ are loci vectors of the i-th feature point of R and the j-th feature point of T.

Figure 1 shows three kinds of inter-stroke distances introduced as:

A. Stroke endpoint matching:

$$d_e = \{ |\mathbf{r}_1 - \mathbf{t}_1| + |\mathbf{r}_m - \mathbf{t}_n| \} / 2, \qquad (2)$$

where $|\cdot|$ specifies the city block distance.

B. Initial part stroke matching:

$$d_t = m/n \cdot \Sigma' |\mathbf{r}_i - \mathbf{t}_i|, \qquad (3)$$

where Σ' : the summation for $i = 1, 2, \dots, n$.

C. Whole-whole stroke matching:

$$d_f = \Sigma' |\mathbf{r}_{j(i)} - \mathbf{t}_i| / n, \qquad (4)$$

where $j(i) = [(m-1)/(n-1)](i-1) + 1$.

3. Stroke Correspondence Determination and the Advanced Selective Stroke Linkage Method

The number and order free stroke matching must determine the optimal one-to-one stroke correspondence between reference and input patterns represented by two sets of M strokes and N strokes ($M \geq N$). We propose a basic strategy composed of two steps. The first step is N stroke pair determination to absorb stroke-order variation. The second step is optimal linking of non-corresponding ($M - N$) strokes to absorb stroke-number variation.

3.1 Stroke Correspondence Determination Algorithms

Denote two sets of strokes by $\boldsymbol{R} = \{ \mathrm{R}_1, \dots, \mathrm{R}_M \}$ and $\boldsymbol{T} = \{ \mathrm{T}_1, \dots, \mathrm{T}_N \}$ ($M \geq N$) and, then, calculate a set of M times N inter-stroke distances between $\boldsymbol{R}$ and $\boldsymbol{T}$:

$$d_{ij} = d(\mathrm{R}_i, \mathrm{T}_j). \qquad (1 \leq i \leq M,\ 1 \leq j \leq N) \qquad (5)$$

The optimal N-pairs stroke correspondence problem is then formulated as:

$$\Sigma_j\, d_{u(j)j} = \Sigma_j\, d(\mathrm{R}_{u(j)}, \mathrm{T}_j) \rightarrow \min \text{ for mapping } u, \qquad (6)$$

where $u(j) \in \{1, 2, \dots, M\}$, $u(j) \neq u(k)$ for $j \neq k$, and

Σ_j : the summation for $j = 1, 2, \dots, N$.

We must overcome the combinatorial explosion problem because the total number of N-pairs generation is ${}_MC_N$ times $N!$. In particular, the too simple shortcut search algorithm fails to deal with pattern balance disruption and heavy shape distortion in cursive handwriting [6].

Here, we propose two new stroke correspondence determination algorithms:

Algorithm : Excessive Mapping Dissolution

1. Choose initial values for mapping $\{u(j)\}$ $(1 \leq j \leq N)$ such that $u(j) = p$, where $p = \arg\min_i d(\mathrm{R}_i, \mathrm{T}_j)$.
   Initialize a set of non-corresponding stroke members in $\boldsymbol{T}$: $\Omega = \{ 1, 2, \dots, N \}$.
   Also, initialize a set of non-corresponding stroke members in $\boldsymbol{R}$: $\Pi = \{ 1, 2, \dots, M \}$.

Loop: 2. If $\exists j, k$ such that $u(j) = u(k)$ and $j \neq k$, go to Next; otherwise, stop.

Next: 3. From among $j_1, \dots, j_s$ $(2 \leq s)$ such that $u(\forall j_t) = u(\exists j_u)$ $(t \neq u)$, find $j^* = \arg\min_j d(\mathrm{R}_{u(j)}, \mathrm{T}_j)$ for $j \in \{j_1, \dots, j_s\}$.
   Then, fix the mapping of $\mathrm{R}_{u(j^*)}$ to T_{j^*}.
   Also, change Ω to $\Omega - \{ j^* \}$ and Π to $\Pi - \{u(j^*)\}$, and update other mapping as:
   $u(j)$ for $\forall j \in \{j_1, \dots, j_s\} - \{ j^* \}$ such that $u(j) = p$, where $p = \arg\min_i^* d(\mathrm{R}_i, \mathrm{T}_j)$, and
   $\min_i^*$: the minimization for $i \in \Pi$.
   Go to Loop. □

Algorithm : Deficient Mapping Dissolution

1. Choose initial values for mapping $\{u^{-1}(i)\}$ $(1 \leq i \leq M)$ such that $u^{-1}(i) = p$, where $p = \arg\min_j d(\mathrm{R}_i, \mathrm{T}_j)$.
   Initialize a set of non-corresponding stroke members in $\boldsymbol{R}$: $\Pi = \{ 1, 2, \dots, M \}$.

Loop: 2. Check a set of non-corresponding stroke members in $\boldsymbol{T}$: $\Omega = \{ 1, 2, \dots, N \} - \{u^{-1}(i)\,;\, 1 \leq i \leq M \}$, and, if Ω is not empty, go to Next; otherwise, go to Pause.

Pause: 3. If $\exists i_1, \dots, i_s$ $(2 \leq s)$ such that $u^{-1}(i_1) = \dots = u^{-1}(i_s) = q$, find $i^* = \arg\min_i d(\mathrm{R}_i, \mathrm{T}_q)$ for $i \in \{i_1, \dots, i_s\}$, and fix the one-to-one mapping of R_{i^*} to T_q, i.e., $u(q) = i^*$; then, stop.

Next: 4. For $\forall j \in \Omega = \{j_1, \dots, j_r\}$ $(1 \leq r)$ choose mapping $v(j)$ such that $v(j) = p$, where $p = \arg\min_i^* d(\mathrm{R}_i, \mathrm{T}_j)$, and $\min_i^*$: the minimization for $i \in \Pi$.
   Find the maximal inter-stroke distance as:
   $d(\mathrm{R}_{v(j^*)}, \mathrm{T}_{j^*}) = \max_j^* d(\mathrm{R}_{v(j)}, \mathrm{T}_j)$, where $\max_j^*$: the maximization for $j \in \Omega$.
   Then, fix the mapping of T_{j^*} to $\mathrm{R}_{v(j^*)}$, that is, $u^{-1}(v(j^*)) = j^*$, and update Π to $\Pi - \{u(j^*)\}$.
   Go to Loop. □

Our key idea is the joint use of two complementary algorithms where the isolated use of each algorithm can not

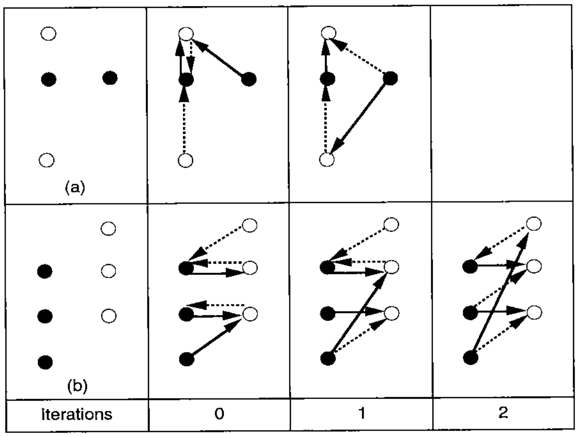

Fig. 2 Complementary behavior of excessive and deficient mapping dissolution algorithms in 2-D point pattern matching. Solid and dotted arrows denote point correspondence by the former and the latter algorithms, respectively, at each iteration.

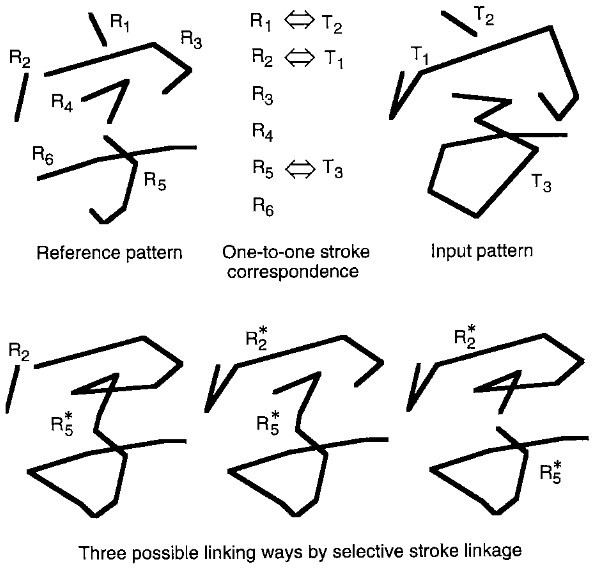

Fig. 3 Selective stroke linkage.

necessarily satisfy the *true* optimization problem. Moreover, both algorithms guarantee convergence within a finite number of iterations whose order equals N.

Figure 2 shows the complementary behavior of the excessive and deficient mapping dissolution algorithms in 2-D point pattern matching; (a) the former is successful in matching and the latter is not, and (b) the latter is successful in matching and the former is not.

3.2 Advanced Selective Stroke Linkage Method

We still have remaining or non-corresponding $(M - N)$ strokes in the M-stroke pattern each of which should be linked to either of the corresponding N strokes.

The problem is to suppress the combinatorial explosion because the total number of stroke linking ways under no constraint is proportional to ${}_{M+N-1}C_{2N-1}$ times $(M-N)!$.

To resolve the above problem, we assume that stroke concatenations in the M-stroke pattern should always occur according to the registered stroke order, i.e., $R_1 \to R_2 \to \dots \to R_M$. This assumption seems too rigid, but, is reasonable for ordinary, cursive handwriting.

Now, let us denote the already determined N-pairs in the M-stroke and N-stroke patterns by $\{ R_{i'}, T_{i''} \}$ where $1 \le 1' < 2' < \dots < N' \le M$ and $\#\{ i'' \} = N$.

Then, each non-corresponding stroke is linked according to the following rule:

1. If $\exists \{ R_i \}$ where $i < 1'$; link all of $\{ R_i \}$ to $R_{1'}$ according to the registered stroke order.
2. If $\exists \{ R_i \}$ where $N' < i$; link all of $\{ R_i \}$ to $R_{N'}$ according to the registered stroke order.
3. If $\exists \{ R_i \}$ where $k' < i < (k+1)'$; let denote a cutting stroke by $R_c \in R_{k'} \cup \{ R_i \}$ and generate two strokes corresponding to $T_{k''}$ and $T_{(k+1)''}$, respectively:

$$R_f = R_{min} \approx \dots \approx R_{k'} \approx \dots \approx R_c \text{, and}$$
$$R_b = R_{c+1} \approx \dots \approx R_{(k+1)'},$$

where R_{min} : the youngest stroke that corresponds to $T_{k''}$, and
$\approx$: a stroke concatenation operation.

Find the optimal cutting stroke R_c such that

$$d(R_f, T_{k''}) + d(R_b, T_{(k+1)''}) \to \min \text{ for } R_c.$$

Then, link $\{ R_i \}$ $(k' < i \le c)$ to $R_{k'}$, and

Link $\{ R_i \}$ $(c+1 \le i < (k+1)')$ to $R_{(k+1)'}$.

Finally, we obtain the transformed N-stroke pattern $\boldsymbol{R}^*$ as:

$$\boldsymbol{R}^* = \{ R^*_1, \dots, R^*_i, \dots, R^*_N \}, \tag{7}$$

where R^*_i corresponds to $T_{i''}$ $(1 \le i \le N)$.

Figure 3 shows the operation of selective stroke linkage between the six-stroke reference pattern and the three-stroke input pattern of Kanji category 字 (means "character"). First, R_6 is linked to R_5 with no choice. Next, regarding R_3 and R_4 we examine only three linking possibilities. The optimal linkage is the middle one that minimizes the sum of inter-stroke distances. It is to be noted that the total number of linking possibilities is suppressed to be just proportional to the number of non-corresponding strokes.

Next, we explain the two-stage recognition strategy.

The first stage is preliminary classification using simple matching of stroke endpoints between an input pattern and each reference pattern as described below:

Let us denote the stroke-number of an input pattern by K and select all reference patterns whose stroke-numbers L satisfy $K - \alpha \le L \le K + \beta$, where α and β specify the permissible maximal numbers of stroke splittings and concatenations, respectively. Then, calculate the temporary inter-pattern distance between the input pattern and each of the selected reference patterns defined as:

$$D_1 = M / N \cdot \Sigma_i \, d_e(R^*_i, T_{i''}) / N. \tag{8}$$

As a result, the first stage outputs candidate categories in increasing order of D_1.

The second stage is discrimination between the first stage candidate categories using fine stroke matching as described below:

First, we determine N-pairs stroke correspondence using the initial part stroke matching distance d_t to deal with the case that the longer stroke is a concatenated stroke or the shorter stroke is a split one. Then, we determine selective stroke linkage based on the whole-whole stroke matching between the original stroke and the artificially concatenated stroke. Hence, we obtain the final inter-pattern distance defined as:

$$D_2 = \Sigma_i \gamma_i \cdot d_f(\mathrm{R}^*_i, \mathrm{T}_{i''}) / N, \tag{9}$$

where $\gamma_i = \max(m, n) / \min(m, n)$ (≥ 1.0) ; if R^*_i is a concatenated stroke, and
$\gamma_i = 1.0$; otherwise; m and n specify the total numbers of feature points of R^*_i and $\mathrm{T}_{i''}$.

The factor of $\{\gamma_i\}$ gives priority to the case that the input pattern is written with the correct stroke number. Namely, a user is sure to input correctly by writing with the correct stroke-number.

Finally, the second stage outputs a predetermined number of candidate categories in increasing order of D_2 as the recognition result.

4. Experimental Results

All character data were gathered at a spatial resolution of 10 points / mm and a sampling rate of 200 samples / s within a square writing box of size 100 mm^2. Size normalization was applied to each character pattern using the value of $\rho = 20$. Then, feature point selection was performed using the stroke-segment length value of $\Delta = 10$.

Training data were composed of 120 patterns for each of 2,980 Kanji character categories carefully written with the correct stroke-number and stroke-order by 120 people. Using this training data, we generated a single reference pattern for each of the 2,980 Kanji character categories by storing the average values of feature points' loci.

Figure 4 shows examples of reference patterns.

On the other hand, two kinds of test data were written by different 36 people: test data A in the square style without any constraint on the stroke-number or stroke-order, and test data B in the cursive style for fast, natural handwriting.

Figure 5 shows examples of character data.

Figure 6 shows the appearance rates of stroke-number change values from the correct stroke-number for test data A and test data B. As shown in Fig. 6, for test data A in the square style 73.5% of character patterns were written with the correct stroke-number. On the other hand, for test data B, the cursive style, over half the character patterns were written with more or fewer strokes.

From this figure, the permissible maximal numbers of stroke splittings and concatenations per character were set at $\alpha = 2$ and $\beta = 10$, respectively. Also, the appearance rates of stroke-order change were almost the same for test data A and test data B; 26.5% and 27.8%, respectively. This means that in fast handwriting a person writes with fewer strokes but rather sticks to his own writing order of strokes.

First, in order to confirm the complementary behavior of two kinds of stroke correspondence determination algorithms, we investigated which algorithm achieved the minimal sum of inter-stroke distances between each input

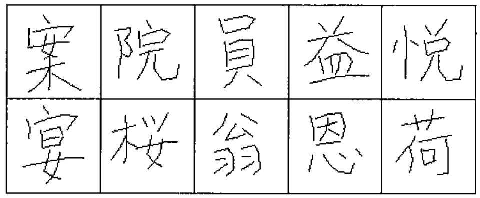

Fig. 4 Examples of reference patterns.

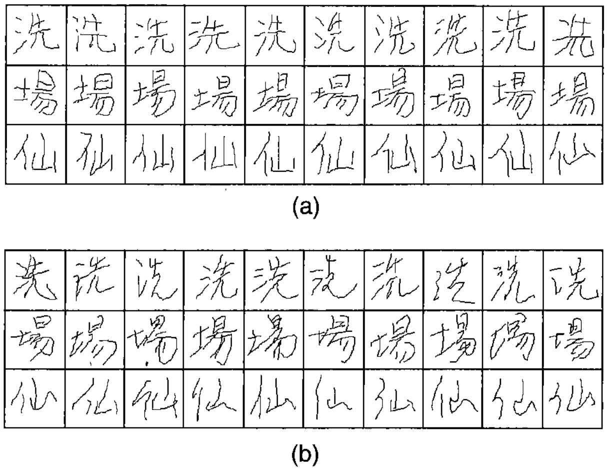

Fig. 5 Examples of character data. (a) Test data A in the square style. (b) Test data B in the cursive style.

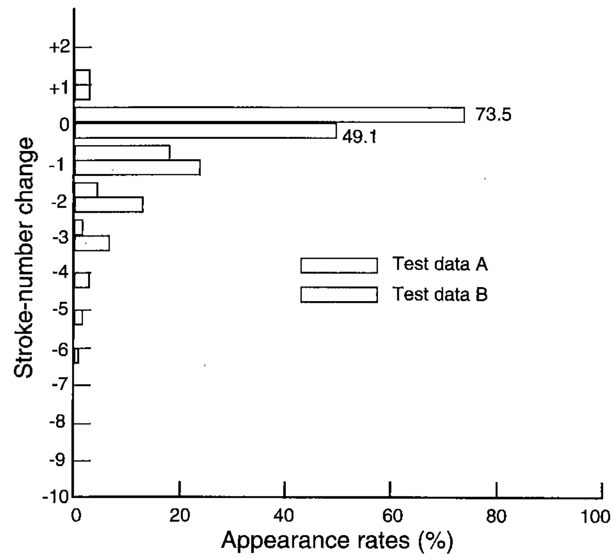

Fig. 6 Appearance rates of stroke-number change.

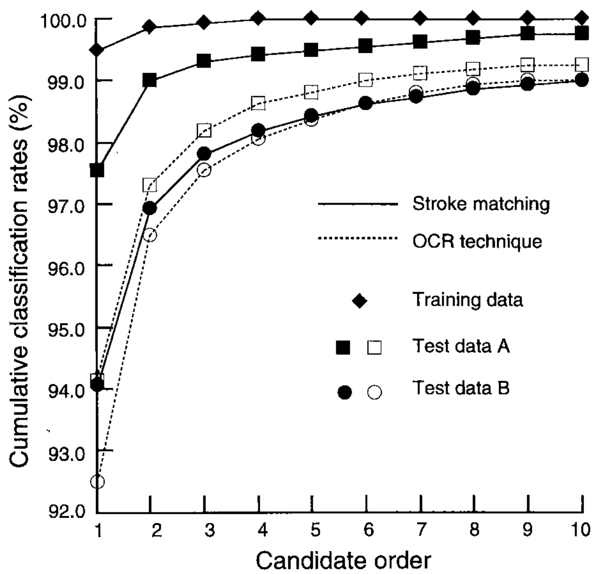

Fig. 7 Cumulative classification rates.

pattern in test data B and the correct reference pattern. The results were as follows: 42.4% for excessive mapping dissolution algorithm; 39.8% for deficient mapping dissolution algorithm; and 17.8% for a tie.

Next, we show recognition results together with a comparative study of the current OCR technique as applied to bitmap patterns of on-line character data. Clearly, the OCR technique is independent of stroke-number and stroke-order variations [9]. Here, we adopted the PDC feature method [10] as one of the best Kanji OCR techniques in Japan. The PDC feature captures a 2-D distribution of contour-segments in horizontal, vertical, left-diagonal, and right-diagonal directions. Reference patterns were generated using a different off-line training character data composed of over one thousand patterns per category. Also, a very sophisticated discriminant function was used.

Figure 7 shows the obtained cumulative classification rates by our stroke matching approach and the OCR technique application, where the cumulative classification rate at the n-th order is the rate that the correct category is included within the top n candidates. From Fig. 7, it is clearly found that the recognition accuracy of the stroke matching approach was fairly higher than that of the current OCR technique not only for the square style, but also for the cursive style.

Regarding the processing time, recognizing one character by our method takes less than a half second on a SUN Sparc 10 machine.

Figure 8 shows the two main causes of misrecognition in the cursive style by our method. The first, shown in Fig. 8(a), is the existence of similarly shaped but different Kanji characters. For this problem we think it is possible to devise a kind of nonlinear shape normalization technique that will enhance the discriminative shape differences. The other problem is excessive shape distortion as shown in Fig. 8(b). This problem is more difficult because the cursive style

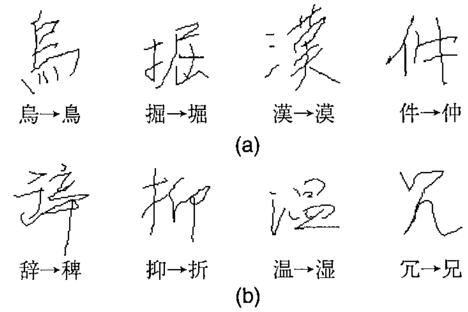

Fig. 8 Misrecognition causes. (a) Existence of similarly shaped Kanji characters. (b) Excessive shape distortion.

strongly depends on the individual's writing style. Hence, it is promising to develop a learnable or custom-built on-line handwriting recognizer for each individual.

Also, improving the classification accuracy is indispensable to facilitate manual candidate selection. One choice is to reinforce the ability of clustering methods and statistical discriminant functions to the fullest extent in OCR techniques. Another choice is, of course, to pursue the robust stroke matching approach with emphasis on the discrimination ability between similarly shaped but different Kanji characters. Here, we insist that the stroke is the most basic unit of shape representation and discrimination and, in this sense, on-line recognition techniques have the great advantage of being able to extract the stroke information.

5. Conclusion

We formulated on-line cursive Kanji character recognition as the one-to-one stroke correspondence problem, and pointed out the need for robust stroke correspondence determination algorithms permitting both the stroke-number and stroke-order variations.

The advanced selective stroke linkage method adopted the joint use of two new, complementary algorithms: one dissolves excessive mapping and the other dissolves deficient mapping without the combinatorial explosion. Also, in order to achieve high stroke matching ability and suppress the processing time, optimal feature point selection, effective inter-stroke and inter-pattern distances definition, and the hierarchical two-stage recognition strategy were devised.

Recognition tests were made on 2,980 Kanji character categories in daily use in Japan. Recognition rates of 97.6% and 94.1% were obtained for test data handwritten freely in the square style and test data written in the fast, cursive handwriting style, respectively. Future work is to improve the discrimination ability by developing an effective tool for extracting pointwise shape distortion and evaluate only discriminative distortion.

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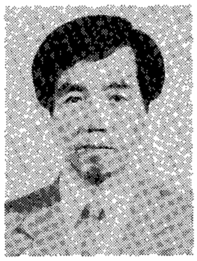
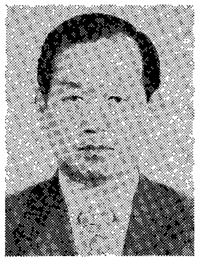
Toru Wakahara received the B.E. and M.E. degrees in applied physics and the Ph.D. degree in mathematical engineering and information physics from the University of Tokyo, Tokyo, Japan, in 1975, 1977, and 1986, respectively. In 1977, he joined the NTT Electrical Communication Laboratories where he has been engaged in research on character recognition and shape understanding. His research interests include learning and generalization in pattern recognition. Dr. Wakahara is a member of AVIRG of Japan and IEEE.

Akira Suzuki received the B.E. and M.E. degrees in electrical engineering from Shizuoka University, Shizuoka, Japan, in 1983 and 1985, respectively. In 1985, he joined the NTT Electrical Communication Laboratories where he was engaged in R & D of Kanji pattern recognition systems. He is presently engaged in development of public facsimile communications systems.



Naoki Nakajima received the B.E. degree in electronics engineering from Tokyo Electric Engineering College, Tokyo, Japan, in 1977. He joined the NTT Electrical Communication Laboratories in 1970. Since then he has been engaged in research on private communication systems and OCR. His current research interests include on-line character recognition and pen interface.



Sueharu Miyahara received the B.E., M.E., and Ph.D. degrees in electronics and information engineering from Kumamoto University, Kumamoto, Japan, in 1969, 1971, and 1995, respectively. In 1971, he joined the NTT Electrical Communication Laboratories. Since then he has been engaged in research and development on OCR and document recognition and retrieval systems. He is a member of IPSJ.

Kazumi Odaka received the B.E. degree in electronics engineering from Kogakuin University, Japan, in 1972, the M.E. degree from Chiba University, Japan, in 1975, and the Ph.D. degree from Keio University, Japan, in 1985. He joined the NTT Electrical Communication Laboratories in 1975. His current interests include pattern recognition and visual perception mechanisms of the brain. Dr. Odaka is a senior member of IEEE.