A Handwritten Character Recognition System Using Directional Element Feature and Asymmetric Mahalanobis Distance

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Abstract—This paper presents a precise system for handwritten Chinese and Japanese character recognition. Before extracting *directional element feature* (DEF) from each character image, *transformation based on partial inclination detection* (TPID) is used to reduce undesired effects of degraded images. In the recognition process, *city block distance with deviation* (CBDD) and *asymmetric Mahalanobis distance* (AMD) are proposed for rough classification and fine classification. With this recognition system, the experimental result of the database ETL9B reaches to 99.42%.

Index Terms—Handwritten Chinese and Japanese character recognition, directional element feature, city block distance with deviation, asymmetric Mahalanobis distance, ETL9B.

1 Introduction

RESEARCH in Chinese character recognition has matured significantly since Casey opened up the field in 1966 [1]. Various approaches of handwritten character recognition have been developed [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13]. The approaches can be classified into two categories: structural analysis and pattern matching. Recently, pattern matching has become the main topic of Chinese character and Japanese character recognition study.

The largest public database of handwritten characters in Japan is the ETL9B [14]. In the ETL9B, 2,965 kinds of Chinese characters (Kanji) and 71 kinds of Japanese characters (Kana), called the first class of Japanese Industrial Standard (JIS), are included. The characters have been written by about 4,000 people and scanned as bitmaps. There are 200 samples of each character, so that 607,200 total character samples are included in the ETL9B.

During the last few years, research in handwritten Kanji and Kana recognition using the ETL9B has made tremendous progress [5], [6], [7], [8], [9], [10], [11], [12], [13]. Tsukumo has developed a nonlinear pattern matching method called Direction Pattern Matching [5]. This is a method that uses shading and shifting of a character pattern based on the direction of the pattern. More recently, using the compression of higher dimensional features, Wakabayashi et al. report the recognition rate of 99.05% [10]. They use the Modified Quadratic Discriminant Function to avoid errors caused by a finite number of samples. The authors of this paper have proposed the directional element feature (DEF) [12] and the image transformation method based on partial inclination detection (TPID) [13]. A recognition rate of 99.08% has been obtained.

The handwritten character recognition system proposed in this paper consists of four major procedures: preprocessing, feature vector extraction, rough classification, and fine classification. In order to construct a more precise recognition system, the following four suggestions are combined.

1) directional element feature (DEF);
2) transformation based on partial inclination detection (TPID);
3) city block distance with deviation for rough classification (CBDD); and
4) asymmetric Mahalanobis distance for fine classification (AMD).

With the proposed recognition system, the experimental result of the ETL9B reaches to 99.42%, which is the highest percentage of recognition obtained so far.

2 Preprocessing

In the case of pattern matching for handwritten character, it is important to remove image distortion as much as possible. Preprocessing is a treatment for decreasing possible negative influence from image distortion. Here, before normalization and smoothing, the transformation based on partial inclination detection is done.

2.1 Image Transformation Based on Partial Inclination Detection

Image distortion because of writers' habits can usually be classified into two types: the whole character image is inclined at the same degree (see Fig. 1a) or only a certain part of a character is inclined (see Fig. 1b and Fig. 1c). The methods of correcting the former distortions are suggested by [5], [15], [16], [17], [18]. But unfortunately, no effective solution to partial inclination has been found. Empirical evidence indicates that inclination usually appears only in horizontal or vertical strokes, but not in diagonal strokes. The valid improvement of correcting partial inclination is expected. In this paper, before normalization, an image conversion method that is the transformation based on partial inclination detection (TPID) is adopted. The TPID constructs transformation functions from inclination angles detected in some subareas of an image, and then converts the image using the transformation functions. Because the TPID corrects the inclinations of horizontal and vertical strokes individually, it can resolve the problem typified by Fig. 1b and Fig. 1c.

First, a character image is separated into two parts (see Fig. 2), and the angle of inclination of each part is computed. Then the images are transformed by the functions constructed from the angles of inclinations. Besides the original image, the TPID produces two images for each character. One is the image in which inclination of vertical strokes are dissolved, the other is that of horizontal strokes are dissolved.

For example, to dissolve vertical strokes, an original character image is split into two parts vertically as shown in Fig. 2b. Then the angle of inclination of each part is calculated. Let the angles for the left half be α and the other angle of the right half be β. Here, α has a clockwise direction and β has a counter-clockwise direction (see Fig. 3). There are two typical cases, and any other cases can be translated into one of them by rotating and mirroring.

$$\alpha \geq 0 \text{ and } \beta \geq 0, \tag{1}$$

$$\alpha < 0 \text{ and } \beta \geq |\alpha|. \tag{2}$$

These two conditions are called *angle conditions*.

Fig. 3a and Fig. 3b are examples in which the angle condition (1) and (2) are satisfied. In the case of Fig. 3a, the trapezoid *LMSR*

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Manuscript received 17 Dec. 1997; revised 2 Dec. 1998. Recommended for acceptance by R. Plamondon.
For information on obtaining reprints of this article, please send e-mail to: tpami@computer.org, and reference IEEECS Log Number 107607.

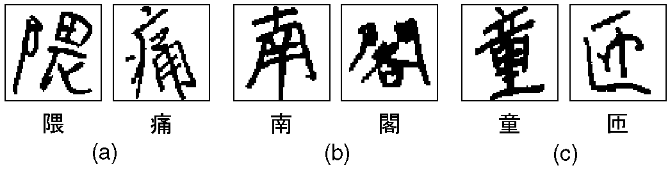

Fig. 1. Distortion samples. The machine-printed same character is shown below each image. (a) Horizontal and vertical strokes are inclined uniformly. (b) Vertical strokes fan out. (c) Horizontal strokes are inclined.

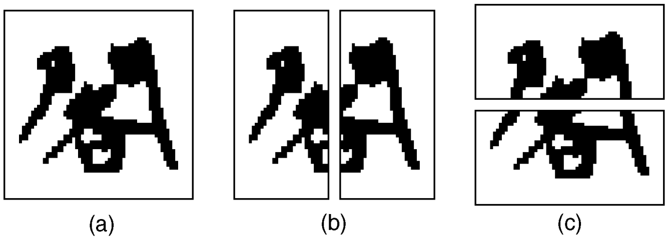

Fig. 2. Image separation for detecting inclination angles. (a) The original image. (b) Separated vertically. (c) Separated horizontally.

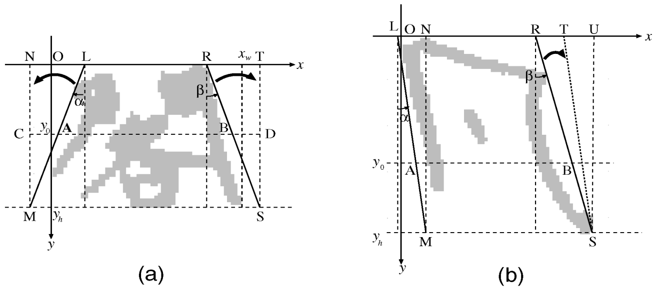

Fig. 3. Transformation of character images. (a) The angle condition (1) is satisfied. (b) The angle condition (2) is satisfied.

is converted to a rectangle *NMST*. In the case of Fig. 3b, the quadrilateral *LMSR* is converted to parallelogram *LMST*,and the whole image is rotated.

2.2 Normalization and Smoothing

An image is normalized and smoothed after dissolving distortions by the TPID. In normalization, a nonlinear normalization method [5] is employed and an input image is adjusted to 64×64 dots. As a result of smoothing, bumps and holes of strokes are patched up by using a 3×3 mask. Fig. 4b shows an example of an image for which preprocessing is applied.

3 FEATURE VECTOR EXTRACTION

In this section, the directional element feature (DEF), which is considered suitable for handwritten Kanji and Kana character recognition, is described. The operation for extracting the DEF includes the following three steps.

3.1 Step 1—Contour Extraction

After preprocessing, contour extraction is done. If a white pixel adjoins a black pixel to the upward, downward, left, or right direction, the black pixel is regarded as on contour. The feature vector is extracted from the pixels of contour.

The feature vector also can be extracted from a skeleton of character image [19]. However, by examining the properties of handwritten characters, it is shown there are a lot of characters that have certain degree of blur. So, using a skeleton method in handwritten character recognition will often lead to a loss of important information of blurred parts. Even in the case that a big part of character is mangled, the strokes on the outside can be measured by using feature vector extracted from the contour. An example of contour is shown in Fig. 4c.

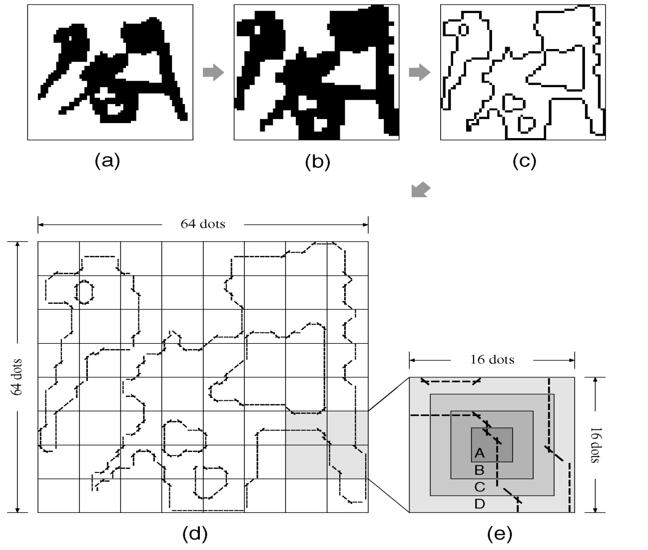

Fig. 4. An example of preprocessing and feature vector extraction. (a) The original image 閣. (b) After preprocessing. (c) Contour image. (d) Oriented-dot image. (e) One subarea.

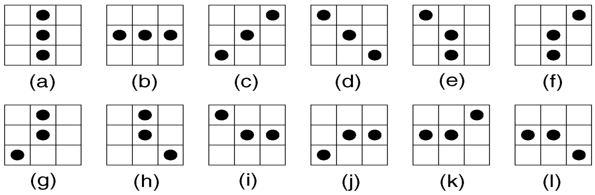

Fig. 5. Types of connections of black pixels. One type of line element is assigned for center pixels in the cases of (a)–(d). Two types of line elements are assigned for center pixels in the cases of (e)–(l).

3.2 Step 2—Dot Orientation

In dot-orientation, four types of line elements, vertical, horizontal and two oblique lines slanted at $\pm 45^\circ$, are assigned to each black pixel. For a center black pixel in a 3×3 mask, two cases are considerable: One type of line element is assigned (see Fig. 5a to Fig. 5d); or if three black pixels are connected as in Fig. 5e to Fig. 5l, two types of line elements are assigned. For example, in the case of Fig. 5f, a 45° line element and a vertical line element are assigned simultaneously. Here, eight-neighbors are used to determine the direction of a black pixel. An example of oriented-dot image is shown in Fig. 4d.

3.3 Step 3—Vector Construction

Consider an input pattern placed in a 64×64 mesh for which dot-orientation has been completed. First, the 64×64 mesh is divided into 49, or 7×7 subareas of 16×16 pixels where each subarea overlaps eight pixels of the adjacent subareas (see Fig. 4e). Furthermore, each subarea is divided into four areas *A*, *B*, *C*, and *D*. *A* is a 4×4 area in the center. *B* is a 8×8 area exclusive of area *A*. *C* is a 12×12 area exclusive of areas *A* and *B*. *D* is a 16×16 area exclusive of areas *A*, *B*, and *C*. In order to reduce the negative effect caused by position variation of image, weighting factors are defined greater at the center of each subarea and decrease towards the edge. The weight of each area is 4, 3, 2, 1 for the areas *A*, *B*, *C*, *D*, respectively. For each subarea, a four-dimensional vector (x_1, x_2, x_3, x_4) is defined where x_1, x_2, x_3, x_4 represent the element quantities

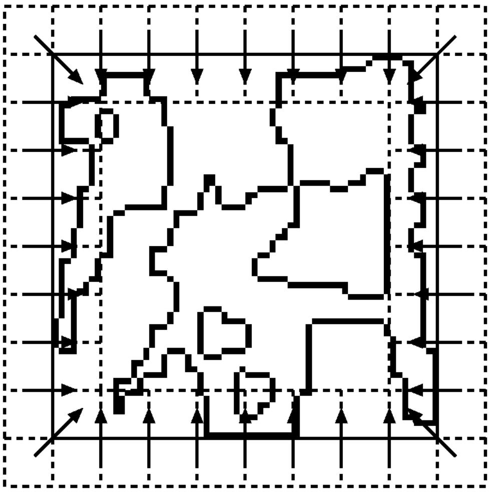

Fig. 6. Virtual subareas. Thick lines denote the 64 × 64 frame, and broken lines denote the virtual subareas.

of the four orientations. Each element quantity is calculated as

$$x_j = 4x_j^{(A)} + 3x_j^{(B)} + 2x_j^{(C)} + x_j^{(D)}, \; j = 1, \ldots, 4 \tag{3}$$

where $x_j^{(A)}, x_j^{(B)}, x_j^{(C)}$, and $x_j^{(D)}$ denote the quantity of each element in A, B, C, and D, respectively. Since each subarea has four dimensions, the vector for one character is 196, or 49×4 dimensions. This vector is called *directional element feature*.

Most Kanji have much more complex structures than numerals and alphabets. By experience, in the case of handwritten characters, the central part of a character is especially easy to deform. So, the surrounding subarea are considered to have higher reliability. Considering this property of handwritten Kanji, virtual subareas are arranged as in Fig. 6. Thick lines denote the 64×64 frame, and broken lines denote the virtual subareas. The virtual subareas also overlap eight mesh of the adjacent ones. The element quantities counted up in each virtual subarea are accumulated to the corresponding elements of the indicated subareas (see arrows in Fig. 6). Therefore, the more reliable information from the surrounding subareas of an image is emphasized and employed effectively.

4 Rough Classification

Compared with numerals and alphabets, the number of Kanji and Kana is extremely large. Therefore, the discrimination processing is separated into two stages: rough classification and fine classification.

Since the purpose of rough classification is to select a few candidates from the large number of categories as rapidly as possible, the first requirement of discriminant function of rough classification is speed. Of course, it does not mean the ability for recognition is unimportant. Although there are a few well-known discriminant functions, such as the Euclidean distance and city block distance function, a new discriminant function, called city block distance with deviation (CBDD), is proposed for rough classification.

4.1 City Block Distance With Deviation

Let $\boldsymbol{v} = (v_1, v_2, \ldots, v_n)$ be an n-dimensional input vector, and $\mu = (\mu_1, \mu_2, \ldots, \mu_n)$ be the standard vector of a category. The CBDD is defined as:

$$d_{CBDD}(\boldsymbol{v}) = \sum_{j=1}^{n} \max\left\{0, \left|v_j - \mu_j\right| - \theta \cdot s_j\right\}, \tag{4}$$

where s_j denotes the standard deviation of jth element, and θ is a constant. The most important property of (4) is that variations of handwritten characters are being taken account in the city block distance measure. Because the distance smaller than $\theta \cdot s_j$ is ignored in each dimension, a small change in shape is completely detected.

4.2 Ability of CBDD

In order to examine the benefits of the CBDD, pre-experiments have been carried out. Twelve sets of the ETL9B with different qualities are used as test data, and the rest of 188 data sets are employed as training data.

The error rates of the Euclidean distance, the city block distance and the CBDD are 8.21%, 7.41%, and 4.34%. The experimental results have shown the CBDD is the most effective discriminant function.

With another experimental result, it is shown the recognition rate saturates if thirty candidates are chosen for one unknown pattern. The average accumulated recognition rate of 30 candidates is 99.86%, which is almost the recognizable maximum. Other experimental results show that in order to gain the same accumulated recognition rate, 51 candidates selected by the Euclidean distance or 47 candidates selected by the city block distance are needed.

Based on the above results, the CBDD is used to select 30 candidates for an unknown pattern from the total 3,036 categories. In fine classification, one candidate will be determined from these 30 candidates. Since the number of candidates is decreased greatly, the next difficult problem is how to choose the correct candidate from structurally similar characters.

5 Fine Classification

The candidates selected by rough classification are usually characters with similar structure. Although the problem of discriminating similar characters is not limited to Kanji and Kana recognition, since there are a great number of similar characters, for example, 鳥 versus 烏 and ぼ versus ぽ, this problem is much more serious for Kanji and Kana. In order to distinguish similar characters, it is necessary to express the original distributions of similar characters as distinctly as possible. By considering the property of distributions of Kanji and Kana, the asymmetric Mahalanobis distance (AMD) is proposed for fine classification. The AMD is a function that can express distributions of images with a small number of parameters.

5.1 Asymmetric Mahalanobis Distance

For fine classification, a function that designates the distribution of samples is necessary. The Mahalanobis distance is derived by a probability density function of multivariate normal distribution, so it is considered as an appropriate function if the distribution of samples is multivariate normal. However, one important result of our research is the distribution of samples in practice is quite different from normal distribution. According to our research, a lot of distributions of samples are asymmetric rather than normal. Therefore, a new probability density function that can describe an asymmetric distribution is proposed.

Let feature vectors of samples of a category denote as follows:

$$\boldsymbol{v}^1, \boldsymbol{v}^2, \ldots, \boldsymbol{v}^N \quad \boldsymbol{v}^i = \left(v_1^i, v_2^i, \ldots, v_n^i\right), \tag{5}$$

where n is the number of dimensions of feature vector and N is the number of samples.

Let μ be the mean vector of these samples, and λ_j and ϕ_j be the jth eigenvalue and jth eigenvector of the covariance matrix of this category. In order to describe the asymmetric distribution, quasi-mean $\hat{m}_j$, quasi-variance $\left(\hat{\sigma}_j^+\right)^2$ and $\left(\hat{\sigma}_j^-\right)^2$ are introduced here (see Fig. 7). The criterion is defined as follows:

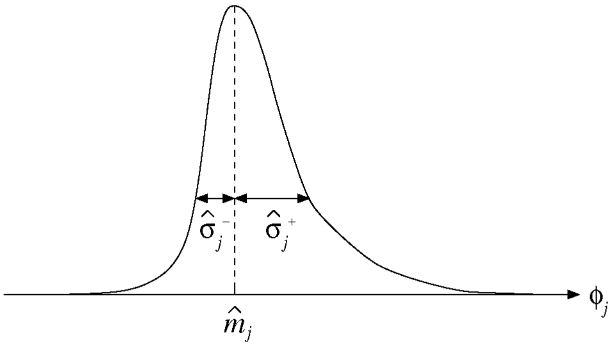

Fig. 7. The asymmetric distribution on an axis described with quasi-mean and quasi-variance.

$$d(\boldsymbol{v}) = \sum_{j=1}^{n} \frac{1}{\left(\hat{\sigma}_j\right)^2}\left(\boldsymbol{v} - \hat{\mu}, \phi_j\right)^2, \tag{6}$$

where

$$\hat{\mu} = \sum_{j=1}^{n} \hat{m}_j \phi_j, \tag{7}$$

$$\hat{\sigma}_j = \begin{cases} \hat{\sigma}_j^+ & \text{if} \left(\boldsymbol{v} - \hat{\mu}, \phi_j\right) \geq 0 \\ \hat{\sigma}_j^- & \text{otherwise} \end{cases} \tag{8}$$

However, it is known that eigenvalues estimated from a finite number of samples usually contain errors [20], [21], and this is a major cause of the drop of recognition rate. As described in [11], compared with Mahalanobis distance, the modified Mahalanobis distance that adds a bias to eigenvalues is effective for handwritten Kanji and Kana recognition. Based on this conclusion, a new function as follows is defined instead of (6).

$$d_{AMD}(\boldsymbol{v}) = \sum_{j=1}^{n} \frac{1}{\left(\hat{\sigma}_j\right)^2 + b}\left(\boldsymbol{v} - \hat{\mu}, \phi_j\right)^2, \tag{9}$$

where b is a bias. This criterion is called *asymmetric Mahalanobis distance* (AMD).

5.2 The Quasi-Mean

According to our investigation, in the feature space, the positions of samples with noise are usually extremely far away from the same character's samples without noise. Because the shape of distribution is changed improperly by noisy samples, it is considered to be more feasible to remove those noisy samples. For this reason, quasi-mean $\hat{m}_j$ and quasi-variance $\left(\hat{\sigma}_j^+\right)^2$ and $\left(\hat{\sigma}_j^-\right)^2$ are calculated without samples far from the majority.

In order to estimate the quasi-mean value of the distribution for each axis $\phi_j (j = 1, 2, \ldots, n)$, a valid data set S_j is selected for the axis. Here, u_j^i represents the component projection of $\boldsymbol{v}^i - \mu (i = 1, 2, \ldots, N)$ onto the vector $\phi_j (j = 1, 2, \ldots, n)$, i.e., $u_j^i = \left(\boldsymbol{v}^i - \boldsymbol{m}, \phi_j\right)$. The value of u_j^i is calculated for each sample $\boldsymbol{v}^i$, and then S_j is defined as

$$S_j = \left\{ u_j^i \middle| \left|u_j^i\right| < \rho\sqrt{\lambda_j} \right\}. \tag{10}$$

Here, ρ is a parameter determined by experiments, which depends on recognition object. Quasi-mean $\hat{m}_j$ is defined as

$$\hat{m}_j = \frac{1}{\left|S_j\right|} \sum_{u \in S_j} u + \left(\mu, \phi_j\right). \tag{11}$$

5.3 The Quasi-Variance

First, $\hat{u}_j^i = \left(\boldsymbol{v}^i - \hat{\mu}, \phi_j\right)$ is computed for each sample $\boldsymbol{v}^i$. Then, the sets of $\hat{S}_j^+$ and $\hat{S}_j^-$ are defined as

$$\hat{S}_j^+ = \left\{ \hat{u}_j^i \middle| 0 \leq \hat{u}_j^i \leq \rho\sqrt{\lambda_j} \right\}, \tag{12}$$

$$\hat{S}_j^- = \left\{ \hat{u}_j^i \middle| -\rho\sqrt{\lambda_j} \leq \hat{u}_j^i < 0 \right\}. \tag{13}$$

The number of elements of $\hat{S}_j^+$ and $\hat{S}_j^-$ are denoted as $\left|\hat{S}_j^+\right|$ and $\left|\hat{S}_j^-\right|$, respectively. Quasi-variance $\left(\hat{\sigma}_j^+\right)^2$ and $\left(\hat{\sigma}_j^-\right)^2$ are defined as

$$\left(\hat{\sigma}_j^+\right)^2 = \frac{1}{\left|\hat{S}_j^+\right|} \sum_{u \in \hat{S}_j^+} u^2, \tag{14}$$

$$\left(\hat{\sigma}_j^-\right)^2 = \frac{1}{\left|\hat{S}_j^-\right|} \sum_{u \in \hat{S}_j^-} u^2. \tag{15}$$

6 EXPERIMENT

6.1 Method

In order to verify the performance of the proposed system, experiments are carried out with the ETL9B. Every 20 sets out of the 200 sets of the ETL9B is considered as a group, thus 10 groups are made in total, named Group A through J. In rotation, nine groups are used as the training data, and the excepted one group is employed as test data.

First, feature vectors are extracted from the training sets, and these are used to generate mean vectors, eigenvalues, and eigenvectors. Then the quasi-mean value and the quasi-variance values of each axis are computed using the method described in Section 5. Finally, test data is recognized.

Some parameters used in the proposed system need to be defined in advance. To determine an optimum value for each parameter, pre-experiments with the same training data and test data described in Section 4.2 are done. Various values are examined, and the optimum values are as follows:

$$\begin{aligned} \theta &= 1.2 \quad (\text{see}\,(4)) \\ b &= 3.5 \quad (\text{see}\,(9)) \\ \rho &= 3.0 \quad (\text{see}\,(10), (12), \text{ and } (13)) \end{aligned} \tag{16}$$

6.2 Experimental Results

The error rate of each group is shown in Table 1. The best results of other existing methods [13] are also shown in Table 1. The average error rate of this proposed system is 0.58%, about half of the rate of

TABLE 1
ERROR RATES (%)

	A	B	C	D	E	F	G	H	I	J	Average
Existing	0.65	0.95	0.68	0.91	0.89	1.04	1.16	0.88	1.04	1.04	0.92
New	0.37	0.57	0.40	0.56	0.52	0.69	0.90	0.52	0.64	0.61	0.58

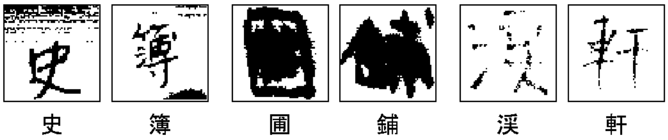

Fig. 8. Examples of mistaken characters. The machine-printed same character is shown below each image. (a) There is extreme noise. (b) The images are blurred. (c) The images are not clear.

the existing method, which means that 99.42% of data can be correctly recognized. The experimental results have shown that the proposed new system is extremely effective for handwritten Chinese and Japanese character recognition. Our system is implemented in C language on Sun Ultra 2. The computation time per character is about 0.6 second.

Although a very high recognition rate is obtained, there are still some characters recognized incorrectly by our system. The examples shown in Fig. 8 are some characters mistaken by the proposed system. It seems that the failure is caused by two major reasons: One is extreme noises, and the other is blur. Since a big mass of black pixels is always considered as a part of character, characters with extreme noise are mistaken easily. It is difficult to distinguish noise from image pattern.

7 CONCLUSIONS

In this paper, a new precise system for recognizing handwritten Chinese and Japanese characters is presented. This recognition system consists of four major procedures, and some suggestions are proposed for each.

The directional element feature makes a solid foundation of this system. By considering the characteristic of handwritten Kanji and Kana, the feature vectors are extracted from the line elements of contours instead of skeletons. Moreover, the surrounding subareas with more reliable information are weighted, so directional element features become more robust to those crushed images.

To obtain better features, in preprocessing, the transformation based on partial inclination detection is used to eliminate some distortions caused by writers' habits. This image conversion processing can clear up several kinds of common distortions that cannot be handled by conventional methods.

Furthermore, the city block distance with deviation and the asymmetric Mahalanobis distance are proposed for rough classification and fine classification. By using the CBDD, 30 candidates are selected with accuracy and speed. To continue, the AMD is adopted to express the original distribution of finite samples faithfully. The experimental results have confirmed the optimal performance of the AMD. Based on the suggestions in this paper, an effective handwritten Kanji and Kana recognition system has been constructed. With this system, the recognition rate of the largest handwritten Chinese and Japanese character database ETL9B reaches to 99.42%, the highest recorded rate until now.

Although the recognition performance of our system is satisfying, it is still important to test the proposed system with a greater variety of handwritten documents. To solve other problems that do not appear in the database ETL9B, such as the recognition of cursive handwriting, are also future work.

ACKNOWLEDGMENTS

The authors wish to thank Dr. Fang Sun at Tohoku University for fruitful advice. They would like to thank Mr. Elias Ross for helpful comments. This work was supported in part by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Scientific Research (B), 08680421, 1996.

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