Rotated Character Recognition and its Properties

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Abstract We present about a characteristic and the performance of the rotated character recognition using eigen-subspace for Japanese characters of 3,133 categories. At first, a few advantages of recognition experiments by noise-free character images are described. Next, it is shown that the multiple-projection method is more effective than the simple projection in low dimension, also the angle is precisely estimated within ±2 degrees. And the tendency of misclassification is considered for both projection methods. Next, although we use 36 character images as learning data, their sufficiency is shown experimentally. Furthermore, it is shown that very high recognition performance is obtained even when 3,133 Japanese categories of popular Mincho and Gothic fonts are used. Finally, when camera images are used, the deterioration of the recognition performance is improved. Also, it is shown that the inclination angle of a document can be estimated by this method without using layout analysis.

Key words: rotated character recognition, a lot of categories, eigen-space, camera image, document

1. Introduction

Some researches on rotated character recognition have been reported so far\(^{1,2}\). Recently, a new scheme based on the eigen-space method was proposed\(^{3,4}\). And also, the other research covering 3D rotation of a character image has been proposed\(^{5}\). Both of them targeted 62 categories of alphanumeric letters, however these are the same method in the meaning of using eigen-subspace.

On the other hand, there was no paper that the rotated character recognition was applied to Japanese characters with a lot of categories until now. So, we have applied this method to Japanese characters of popular Mincho and Gothic fonts. Totally 3,133 categories including First Class of JIS Kanji Set, Hiragana and Katakana categories were used for recognition. Generally, although the font information is not necessary in recognition results, the font information is also output by this method. Therefore, this classifier outputs category, font and character angle. We added a new idea in the basic scheme to cope with a lot of categories, and constituted the system.

This paper presents about characteristics and the performance of the rotated character recognition for Japanese characters as reference data.

First of all, we handle noise-free character images by automatic character image generation, because it makes character image collection easy and the recognition performance of real images is affected by several factors of the field environment. So, we try to acquire a higher quality of image. By using noise-free character images, the recognition rate depends on only three factors, that is, a lack of information by reducing image size and limited dimensions, and a lot of competing categories. Therefore, you could refer to this result as a nearly best value. In the previous work for 62 categories\(^{6}\), a real-time system with a camera showed a good recognition performance close to the result for noise-free characters by controlling the resolution.

Next, the recognition performance for Kanji images acquired with the camera are shown. Especially, accuracy vs. character size, accuracy vs. dimensions and the angle estimation of an inclined document with complicated layout are evaluated.

In section 2, the learning process and the test process of the rotated character recognition are described\(^{7,8}\). In section 3, the recognition performances of the simple projection and the multiple-projection are presented using artificially generated character images. And a precise angle estimation is shown and the tendency of misclassification is considered. Also, since 36 characters rotated every 10 degrees per category were used as learning data, the angle dependency of misclassification is considered. In section 4, how to construct the eigen-space is described when plural fonts are used. Then, some experimental results are shown. In section 5, the recognition performance for Kanji images acquired by a camera are shown. Especially, the accuracy vs. char-
acter size or dimension are presented. In section 6, as an application, it is shown that the angle of an inclined document can be estimated with high precision by using this method without applying layout analysis.

1.1 Kanji image generation

Kanji images are automatically generated by using Free Type library which is a software font engine\(^7\). By this program, we can get any fonts and any size of bitmap Kanji images.

We generated 128×128 binary images of First class of JIS Kanji (2,965 categories), Hiragana and Katakana with Mincho and Gothic fonts. 36 character images rotated by 10 degrees are made for the learning process in each category, and these image sizes are changed into 50×50 pixels after extracting the square surrounding a character area. We also prepared 51 images for recognition test that are from 7 degrees to 357 degrees rotated by 7 degrees. Therefore, five images used in the learning process are included in the test image set in each category. In the previous report\(^6\), it was no difference in accuracy between the recognition results using 32×32 binary images for alphanumeric letters and the experimental results using 8×8 images with 17 levels, which value is the number of black pixels in 4×4 pixels. So, in this paper, we converted from 50×50 binary image into 8×8 image with 65 levels, which value is the number of black pixels in 8×8 pixels. You may think that a 8×8 image is very coarse for Kanji pattern, but 8×8 images keep their information by the pixel value. This feature representation is one of easy ways. Also, the computation becomes very fast by this resizing.

2. Recognition scheme based on eigen-subspace

2.1 Learning process

For example, a 50×50 binary image can be described as a 2,500 dimensional vector. The value of a pixel is 0 or 1. A 8×8 image with 65 levels can be described as a 64 dimensional vector. Now, let an image pattern be \(f^{(k)}_{\theta(i)}\), where \(k\) is the category number, \(\theta(i)\) is the character angle, that is \(\theta(i) = 10 \times i \mid i = 0, 1, 2, \cdots, 35\). Next, we create the eigen-space using 36 image data with respect to each category. The covariance matrix \(\Sigma^{(k)}\) is calculated as follows;

\[
\Sigma^{(k)} = E \left[ \left( f^{(k)}_{\theta(i)} - m^{(k)} \right) \left( f^{(k)}_{\theta(i)} - m^{(k)} \right)^{\top} \right],
\]

where \(m^{(k)}\) is the mean vector of 36 learning samples of the \(k\)-th category. The eigen solution can be obtained by the next equation;

\[
\Sigma^{(k)} \phi = \lambda \phi
\]

where, the category index \(k\) was omitted for \(\lambda \) and \(\phi\). We obtain at most 35 non-zero eigenvalues because the rank of the covariance matrix is at most 35. Let the eigenvectors corresponding to eigenvalues \(\lambda_1, \lambda_2, \cdots, \lambda_{35}\) be \(\phi_1, \phi_2, \cdots, \phi_{35}\). Using the first \(n(\leq 35)\) eigenvectors, the eigen-subspace \(U^{(k)}_n = \{\phi_1, \phi_2, \cdots, \phi_n\}\) can be constructed. Then, as projected \(f^{(k)}_{\theta(i)}(i = 1, 2, \cdots, 35)\) onto the \(U^{(k)}_n\), that is, the projected point \(F^{(k)}_{\theta(i)}\) is calculated by \(U^{(k)}_n(f^{(k)}_{\theta(i)} - m^{(k)})\), a set of the projected points \(\{F^{(k)}_{\theta(i)}\}\) draws a locus sequentially because the angle changes consecutively. We denote the locus as \(L^{(k)}_n\). The locus consists of 36 points is interpolated with 360 points by the periodic spline interpolation. The angle of the interpolated point is an integer which is given by dividing two angles of \(F^{(k)}_{\theta(i-1)}\) and \(F^{(k)}_{\theta(i)}\) into ten. The examples of loci are depicted on 2D eigen-subspace in Figure 1. Their character shapes are similar, however their loci are quite different in this case.

![Fig. 1 Examples of loci(category "ambi" and "andr")](image)

2.2 Recognition process

(1) Recognition by simple projection

An unknown image \(x\) is first projected onto all \(U^{(k)}_n(k = 1, 2, \cdots, C)\). We denote the projected point of \(x\) as \(X\), that is \(X = U^{(k)}_n(x - m^{(k)})\). The verification is carried out by finding the shortest distance between \(X\) and \(L^{(k)}_n\). The shortest distance to the category \(k\) is represented as \(d^{(k)}(X)\). Therefore, we can obtain the recognition result \(k^*\) as follows;

\[
k^* = \arg \min_k \{d^{(k)}(X)\}
\]

The angle of the input character is given as the angle of closest point on the locus. In this way, we can obtain the recognition result and the angle of the input character at the same time. The recognition scheme of the simple projection is illustrated in Figure 2.
Fig. 2 Recognition scheme by simple projection

(2) Recognition by multiple projections

In the previous scheme, there may be many mistakes that the projected point is accidentally closest to the locus of a wrong category. To prevent this accidental misclassification, the multiple-projection scheme was proposed, that multiple images by rotation of the input character image are created, and these rotated images are projected onto every eigen-subspaces. We denote the number of created images including the input image as \( R \). For example, in the case of \( R = 3 \), two images are created by rotating with 120 degrees and 240 degrees. In our previous work, we changed \( R \) from 1 to 5 and tested. As the result, \( R = 3 \) or 5 showed higher performance than \( R = 2 \) or 4. By the way, the simple projection is the case of \( R = 1 \).

Figure 3 illustrates the recognition scheme of the multiple-projection in case of \( R = 3 \). The final distance \( d^k(X) \) to the category \( k \) is defined as the average among three distances.

\[
k^* = \arg\min_k \left\{ \frac{1}{R} \sum_{r=1}^{R} \{d_r^{(k)}(X)\} \right\}
\]

\( E\{\cdot\} \) means the average operation.

Fig. 3 Recognition scheme by multiple projections

The angle of the input character is given as the angle of closest point on the locus. In addition, we adopt a reasonable restriction that the angles of corresponding adjacent points on the locus should have the same angle difference because the rotation angles of multiple created images are known. So, adjacent corresponding points on the locus must have the same angle difference. In the case of Figure 3, using that the angle between neighbouring points is 120 degrees, the shortest distance is obtained by means of the following procedure.

(1) Three rotated images are projected. These are denoted as \( X_0, X_{120}, \) and \( X_{240} \).

(2) A near point on the locus for \( X_0 \) is set to A. The distance is denoted as \( d(X_0,A) \).

(3) A point which is 120 degrees away from A is set to B. The distance is denoted as \( d(X_{120},B) \).

(4) A point which is 240 degrees away from A is set to C. The distance is denoted as \( d(X_{240},C) \).

(5) The shortest distance of \( d(X_0,A)+d(X_{120},B)+d(X_{240},C) \) is searched by shifting A, B, and C by one degree along the locus.

This angle restriction is one of ingenuities for handling a lot of categories. In a prior experiment, when no restriction was applied, 17.39% for three dimensional subspace and 82.27% for five dimensional subspace were observed. However, when the angle restriction was applied, 54.20% and 91.30% for three and five dimensional subspace were obtained respectively. You can see that this restriction is obviously effective.

3. Experimental results

3.1 Dependence of character size

Figure 4 shows the recognition performance by the simple projection (\( R = 1 \)), for 50×50 binary images and 8×8 images with 65 levels. The recognition rate using all 35 dimensions is 99.80% for 50×50 character images, and 99.74% (389 errors in 151,215 samples) for 8×8 character images. The accuracy of 8×8 character images is a little lower than the one of 50×50 character images around 10 dimensions due to a lack of character information. On the other hand, there is little difference between them in the range of high dimension.

Fig. 4 Recognition rates for 50×50 binary images and 8×8 images with 65 levels

It is conceivable that loss of the information is suppressed by 65 levels of 8×8 character image. Therefore,
we will show experimental results using 8×8 character images hereafter.

3.2 Recognition by simple projection

To cope with the deterioration of recognition rate around low dimensions, two-step recognition process will be effective, that is, categories within the p-th place are nominated, then the detailed recognition for the candidate categories is applied. On the other hand, the multiple-projection will be also effective.

First, we show the cumulative recognition rate by 8×8 character images in Figure 5. The parameter p in Figure 5 is the number of best candidates.

The cumulative recognition rate at 10 dimensions for p = 10 is 98.66%. In addition, all true categories are included in best 23 candidates when all 35 dimensions are used. As a further classification for the selected candidates, "image correlation" which is adopted in section 5 will be effective.

3.3 Recognition by multiple projections

Another tactic is the multiple-projection. We show the recognition rate by multiple projections of R = 3, 5 in Figure 6. You can see that the recognition performance of R = 3, 5 in low dimensions is quite higher than that of R = 1.

The recognition rate of R = 3 at the first 10 dimensions was 99.66%, and 99.99%(20 errors in 151,215 test samples) at all 35 dimensions. The recognition rate of R = 5 at the first 10 dimensions is 99.92%, and 99.99%(8 errors in 151,215 test samples) at all 35 dimensions.

The deterioration of the recognition rate in low dimensions will be covered by the two-step classification and/or by the multiple-projection. In recognition by the multiple projections, we can get high recognition rate in low dimensions because the contingency in simple projection is suppressed.

3.4 Angle estimation

We show the histogram of angle difference between the true angle and the estimated one in Figure 7. This graph is depicted using truly recognized samples, and estimated angles were restricted within ±7 degrees because angles of correct data were almost within ±2 degrees. In this case misclassified samples were excluded. Furthermore, 26 samples of category “…” were excluded because the half of their estimated angles were upside down. All samples correctly recognized except “…” are within ±2 degrees. Most of them are high precision within ±1 degrees.

From these results, you can see that interpolated angles of 360 points are almost correct. In recognition by the simple projection and the multiple-projection(R = 3), some examples of misclassification at 35 dimensions are listed in Table 1. Misclassified categories are very similar to the input categories. But, their estimated angles are within ±1 degrees even if they are misclassified. In addition, in misclassified samples by the multiple projections(R = 3), their true categories were included in the best two candidates.
### Table 1 Examples of misclassification

<table>
<thead>
<tr>
<th>Input</th>
<th>Result</th>
<th>$R = 1$</th>
<th>$R = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>合 ⇒ 量</td>
<td>24</td>
<td>14</td>
<td></td>
</tr>
<tr>
<td>埔 ⇒ 境</td>
<td>11</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>蛇 ⇒ 境</td>
<td>11</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>民 ⇒ 量</td>
<td>9</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>木 ⇒ 量</td>
<td>9</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>岛 ⇒ 隼</td>
<td>8</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>蘭 ⇒ 量</td>
<td>7</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>宸 ⇒ 量</td>
<td>6</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>邊 ⇒ 量</td>
<td>6</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>願 ⇒ 隼</td>
<td>6</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>others</td>
<td>292</td>
<td>2</td>
<td></td>
</tr>
</tbody>
</table>

#### 3.5 Angle dependency of misclassification

In this part, the angle dependency of misclassification is considered. Since we use test samples that are rotated by 7 degrees, the number of samples for each category is evenly five for the last digit from 0 to 9 except 357 degrees. The number of total test samples for each last digit is 14,825 data. We examined the tendency of misclassification for the usage of 36 learning data that were rotated by 10 degrees. We show the histogram of misclassification for each last digit by the simple projection and the multiple-projection ($R = 3$) in Figure 8. Both of them used all 35 dimensions. We consider whether 36 learning samples are sufficient or not.

In Figure 8, there are many misclassifications at 5 degrees in the simple projection. The misclassification tends to occur away from the angle of the learning data. That will be due to the error by the spline interpolation. The misclassification for each angle is less than 70 in 14,825 test samples (accuracy is over 99.53%), that is rather very few. Therefore, it can be said that 36 learning data are almost sufficient. The distance between two neighboring points on the locus is different by category and angle. Therefore, it seems to be able to reduce misclassification by adding intermediate data in the learning process.

In recognition by multiple projections, misclassified characters are very few. The angle dependency is not seen. That is why the misclassification will hardly happen because the distance error is reduced by the average operation. In this meaning, the multiple projection has an advantage of robustness.

#### 3.6 Computation time

The specification of the system used for the simulation is as follows;
- CPU : Intel Xeon (6core/12thread), Main memory : 48GB.

The recognition process is executed with parallel computation by dividing all categories into 15 threads.

(a) The case of 50×50 binary images using 35 dimensions;
- Computation time per a character : 2.26[s]
- Memory for the dictionary : 2.43[GB]

(b) The case of 8×8 images with 65 levels using 35 dimensions;
- Computation time per a character : 0.20[s]
- Memory for the dictionary : 353.5[MB]

(c) The case of 8×8 images with 65 levels using the first 10 dimensions by multiple projections ($R = 3$);
- Computation time per a character : 0.15[s]

#### 4. Multi-font kanji recognition

##### 4.1 Learning process

By rotating a character image by 10 degree, we prepare 36 character images per font for each category. We use them as learning samples. Let an image pattern be $f_{\theta(i)}^{(j,k)}$, where $k$ is the index of category number from 1 to C, $j$ is the font, two popular Mincho and Gothic fonts are used in this experiment. And $\theta(i)$ indicates character angle, that is, $\theta(i) = 10 \times i \mid i = 0, 1, 2, \ldots, 35$.

The original image has the size of 50×50 pixels. The value of the pixel is 0 or 1. Then we reduce the image size to 8×8 pixels, which value is from 0 to 64.

Next, we create an eigen-space using 36×(fonts) images with respect to each category. The covariance matrix $\Sigma^{(k)}(= 64 \times 64)$ is calculated as follows:

$$\Sigma^{(k)} = E_{(j,i)} \left[ (f_{\theta(i)}^{(j,k)} - m^{(k)})(f_{\theta(i)}^{(j,k)} - m^{(k)})^T \right]$$

where, $m^{(k)}$ is the mean vector of 72(= 36 × 2 fonts)
learning samples of the $k$-th category. The eigenvectors can be calculated in Eq.(2). We obtain 64 non-zero eigenvalues because the rank of the covariance matrix is at most 64. Using the first $n(\leq 64)$ eigenvectors, the eigen-subspace $U_n^{(k)} = \{\phi_1, \phi_2, \cdots, \phi_n\}$ can be constructed. Then, as projected $f_{\theta(i)}^{(j,k)} (i = 0, 1, \cdots, 35)$ onto the $U_n^{(k)}$, that is, the projected point $F_{\theta(i)}^{(j,k)}$ is calculated by $U_n^{(k)} (f_{\theta(i)}^{(j,k)} - m^{(k)})$, a set of the projected points $\{ F_{\theta(i)}^{(j,k)} \}$ draws a locus sequentially for each font. The locus which consists of 36 points per font is interpolated by 360 points. We denote the locus of font $j$ and $k$-th category as $L_n^{(j,k)}$. We show two loci of the same category on $U_3^{(k)}$ in Figure 9.

4.2 Recognition Process

Given an unknown image $x$, which is first projected onto all $U_n^{(k)} (k = 1, 2, \cdots, C)$. We denote the projected point of $x$ as $X$, i.e. $X = U_n^{(k)} (x - m^{(k)})$. The verification is carried out by finding the shortest distance between $X$ and $L_n^{(j,k)}$. We denote the shortest distance to $L_n^{(j,k)}$ as $d^{(j,k)}(X)$. Therefore we can obtain the recognition result $(j^*, k^*)$ by the simple projection as follows:

$$ (j^*, k^*) = \arg \min_{j,k} \{d^{(j,k)}(X)\} $$

(6)

In multiple projections of $R = 3$, the average of three distances from three projected points to the same locus is denoted as $d^{(j,k)}(X)$. The angle of the input image is given by finding the closest point on the locus close to $X$.

4.3 Experiments

We show the recognition accuracy for 3,133 categories and two fonts in Figure 10. The highest recognition rate was 99.84% at all 64 dimensions. The recognition rate goes up slowly in low dimension as compared with a single font, because the addition of one font equals the doubling of the number of categories.

Fig. 9 Loci of two fonts in category "雪"

Fig. 10 Recognition rate by multi-font

We show the histogram of angle difference between the true angle and the estimated one in Figure 11. The graph shows very high precision within $\pm 1$ degrees like the case of a single font.

Fig. 11 Precision of estimated angle by multfont

We show some examples of misclassification in Table 2 when 64 dimensions are used. (G) and (M) mean font. There are some misclassifications from Mincho to Gothic font in the same category when they are complicated characters.

Table 2 Examples of misclassification by multifont

<table>
<thead>
<tr>
<th>Input Result</th>
<th>$R = 1$</th>
<th>$R = 3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>莠 [M] ⇒ 莠 [G]</td>
<td>35</td>
<td>22</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [M]</td>
<td>22</td>
<td>5</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [G]</td>
<td>17</td>
<td>5</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [M]</td>
<td>14</td>
<td>3</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [G]</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [M]</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [G]</td>
<td>10</td>
<td>4</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [G]</td>
<td>9</td>
<td>0</td>
</tr>
<tr>
<td>莠 [M] ⇒ 莠 [M]</td>
<td>9</td>
<td>2</td>
</tr>
<tr>
<td>others</td>
<td>256</td>
<td>5</td>
</tr>
</tbody>
</table>

5. Recognition using camera images

In section 4, noise-free character images by automatic character image generation were used, because it makes character image collection easy and the performance is affected by only a few factors.

In this section, some experimental results for 3,133
categories and two fonts using camera images are presented. The difference between a camera image and an ideal image is whether the noise by digitization and illumination is contained or not. Furthermore, when an image is acquired, the character size is often different from the size of the learning image. Therefore, the difference of the size will affect the performance.

First, the character size dependency of the recognition rate is considered. The character size(pixels) is determined depending on the size(mm) of character in the viewing field of the camera. Figure 12 represents the recognition rate vs. the character size. The number of test samples for each point in Figure 12 are about 170-200 characters(categories). The learning data is originally 50×50 binary image, it was resized to 8×8 image with 65 levels. In Figure 12, the recognition rate of 45 pixels or more seems to be stable however the recognition rate decreases in a small size of 40×40 pixels or less. The parameters are \( R = 1, R = 3 \) and \( corr \) (explain later). However, those differences were not appeared. That is because the projected point of a small character is far from the locus.

\[ f^k = \sum_{i=1}^{64} c_i \phi_i^k + m^{(k)} \]  

Figure 13 shows the recognition rate vs. dimensions, where the character sizes varying from 45 to 55 pixels are used. From the graph, the effect appears in order of \( corr, R = 3 \) and \( R = 1 \) in low dimension.

6. Angle estimation of a document

In the recognition process, the category, the font and the angle of the input character can be obtained in the same time. Generally, the document with a complicated layout contains various font and size. So, we try to get the angle of an inclined document statistically from the angles of connected components although they do not always constitute one character. The process is as follows; (1) binarization of the document, (2) extraction of connected components, (3) recognition of connected components by our method, (4) vote the output angles, (5) make the mode the angle of inclination.

In this experiment, the components smaller than 40×40 pixels were excluded because they have the high possibility of misclassification. An example of test documents is shown in Figure 14. This document contains horizontal and vertical lines, and even pictures and line frames.

Figure 15 is the histogram of voted angles. The mode of the angle for the test image was 267 degrees, it was correctly estimated. Other 10 documents were tested, all the results were shown correctly. This angle estimation method will be possible even when the layout analysis is difficult for the document.
7. Summary

In this paper, many experimental data of the rotated character recognition were shown for Japanese characters of 3,133 categories including the first class of Japanese Industrial Standard (JIS) Kanji set, Hiragana and Katakana. The system had some devices in order to improve the performance. The following things were obtained as the results of the experiment.

A very high accuracy has been obtained for artificially generated character images. For two projection schema, the results by the multiple-projection gave very higher recognition rate in low dimensions than that of the simple projection. However, although there were some misclassifications from Mincho to Gothic, there was no opposite case. Also there were misclassifications between similar categories.

In the experiments for camera images, characters smaller than the learning data tends to misclassify. A character images with $45 \times 45$ pixels or more showed high accuracy, especially, $R = 3$ was always effective. Furthermore, in order to improve the performance, the correlation between the input image and the reconstructed images of top 10 categories are effective, the recognition rate was improved in low dimensions.

Finally, this method was applied to some inclined documents with complex structure, then their angles were correctly estimated without using layout analysis.

This paper clarified that a high performance can be obtained even for Kanji characters with two fonts under the conditions of the experimental data. In near future, we are planning more effective improvement in the processing of the rotated character recognition.

References


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