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Rotated Kanji Character Recognition

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Abstract

We proposed a rotated character recognition method using eigen-subspace characterized multiple projection and simple projection. Then the multiple projections showed a higher accuracy at low dimensions than a simple projection for alphanumeric 62 categories. This time, we applied it for the first class of Japanese Industrial Standard (JIS) Kanji set which includes 2,965 categories. As the result, very high recognition accuracy over 99.8% was achieved especially by the multiple projections of the input rotated images.

1. Introduction

Some researches on rotated character recognition have been reported so far[1,2]. Recently, A new scheme was proposed for rotated characters[4] which was based on the parametric eigen-space method[3]. 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.

In this paper, we apply this method based on eigen subspace for Japanese characters of First Class of JIS Kanji Set which includes 2,965 categories. We experimented using this method for 2D rotated Kanji characters of Gothic font. In this work, we handle noise-free character image data by automatic character image generation, because it makes character image collection easy and the system performance is affected by various factors of field data. We try to keep a higher image quality as good as possible when we acquire images though it is difficult. Therefore, you will be able to refer to the results of this study as the nearly best result when you could get higher quality image. In this study, 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. In the previous work, some simulations[4] using ideal character images were first carried out, then, good results close to the simulation result was obtained by developing a real-time system with a camera[8].

1.1. Kanji image generation

Kanji images are automatically generated by using Free Type library that 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 pixels binary images of First class of JIS Kanji with gothic font. 36 character images rotated by 10 degrees are used for learning process in each category, and these image sizes are changed into 50×50 pixels after extracting the bounding square of a character area. We also prepared 51 images for recognition test that are from 7 degrees to 357 degrees rotated by 7 degrees. Therefore 5 images for learning are included in the test image set in each category. In the previous paper[8], between the recognition results using 32×32 binary image for alphanumeric letters and the experimental results using 8×8 pixels with 17 levels, it was no difference in recognition rate. So, in this work, we converted from 50×50 pixels binary image to 8×8 pixels 65 levels image. You may think that a 8×8 pixels image is very coarse for Kanji pattern, but 8×8 pixels images keep their information by the pixel value of 65 levels. This feature representation is one of the easy ways. Computing speed becomes very fast by this resizing. In section 3, we compare the recognition performance by image size.

2. Recognition scheme based on eigen subspace

2.1. Learning process

For example, a 50×50 binary image can be described by a 2,500 dimensional vector. The value of a pixel is 0 or 1. A 8×8 image with 65 levels can be described by a 64 dimensional vector. In general, let an image pattern be $f^k_{\theta(i)}$, where k is the category number, $\theta(i)$ is a 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;

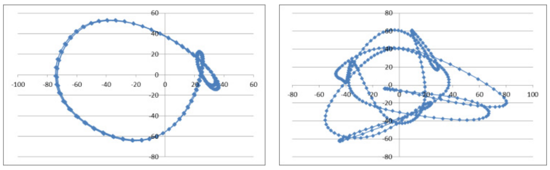
$$\Sigma^{(k)} = \underset{i}{E}\left[(f^k_{\theta(i)} - m^k)(f^k_{\theta(i)} - m^k)^t\right] \qquad (1)$$

where m^k is the mean vector of the k-th category. The covariance matrix can be obtained through eigen expansion;

$$\Sigma^{(k)}\phi = \lambda\phi \qquad (2)$$

where, category index k was omitted for λ and ϕ. 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 (<35) eigenvectors, an eigen-subspace $U^{(k)}_n = \{\phi_1, \phi_2, \cdots, \phi_n\}$ can be created.

Then, as projected $f^k_{\theta(i)} (i = 0,1,\cdots,35)$ onto the $U^{(k)}_n$, that is, the projected point $F^k_{\theta(i)}$ is $U^{(k)^t}_n (f^k_{\theta(i)} - m^k)$, 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 by 36 points can be interpolated. In this research, 360 points were interpolated by the periodic spline interpolation. The angle of an interpolation point is given integer value by dividing two angles of $F^k_{\theta(i-1)}$ and $F^k_{\theta(i)}$ by ten. Therefore, the precision of angle estimation is at least one degree. We show loci of "末" and "末" on 2D eigen-subspace that their character shapes are similar in Figure 1, but their loci are quite different in this case.



(a) category"末"   (b) category"末"

Fig.1 Examples of loci(category "末 and 末")

2.2. Recognition process

(a) Recognition by simple projection

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

$$k^* = \arg\min_k \{d^k(X)\} \qquad (3)$$

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

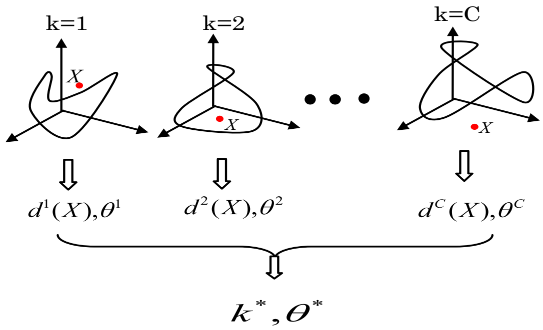


Fig.2 Recognition scheme by simple projection

(b) Recognition by multiple projections

In the previous method, there may be many cases that the projected point is accidentally close to the locus of other category. To prevent this accidental misclassification, we proposed a method that creates multiple images by rotation of an unknown image[4]. These images are projected onto every eigen-subspaces. We obtained higher accuracy for alphanumeric letters. We denote the number of created multiple images including the original image as R. For example, in the case of $R = 3$, two images are created by rotating by 120 degrees and 240 degrees. In our previous work, we changed R from 1 to 5, as the result, R=3 or 5 showed higher performance rather than R=2 or 4. In addition, recognition by simple projection is the case of $R = 1$.

Figure 3 shows a recognition scheme of multiple projections in case of $R = 3$, the distance of category is defined as the average among three distances.

$$k^* = \arg\min_k [E\{d_j^k(X)\}] \qquad (4)$$

$E\{\}$ means the average operation.

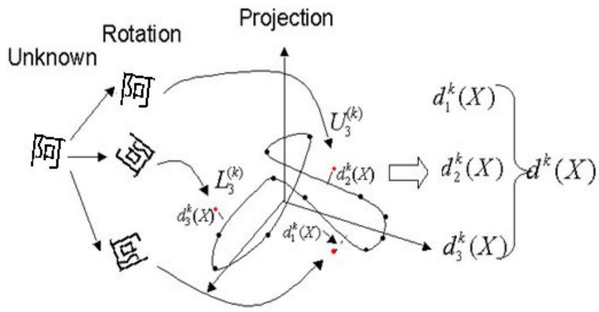


Fig.3 Recognition scheme by multiple projections

The angle is estimated as the angle of corresponding point on the locus to the original unknown image.

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 images are known. So, adjacent corresponding points on the locus must have the same angle difference of 120 degrees in case of Figure 3. In the previous paper[4], we did not use this restriction. This restriction is one of ingenuities for handling a lot of categories.

3. Experimental results

A. Recognition performance for character size

In recognition experiment by simple projection, Figure 4 shows recognition rates by the simple projection using the first n dimensions for 50×50 binary images and 8×8 65 levels images. The recognition rate using the first 35 dimensions is 99.80% for 50×50 character images, and 99.74%(150,826 correct per 151,215 samples) for 8×8 character images. Both results are very high.

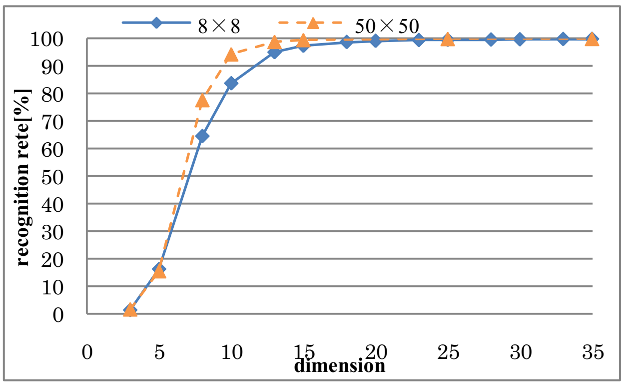


Fig.4 Recognition rates for 50×50 binary images and 8×8 65 level images

The accuracy for 8×8 character images is lower than the one of 50×50 character images at low dimensions. But, the deterioration of recognition rate is not seen at high dimensions. This is conceivable that loss of the information is suppressed by 65 levels of 8×8 character image. Since, we will show some experimental results using 8×8 character images hereafter.

B. Recognition by simple projection

To cope with the deterioration of recognition rate at low dimensions, two-step recognition process will be effective, that is, categories included in the p place are nominated, then apply detailed recognition for the candidate categories. On the other hand, multiple projections by rotated unknown characters will be also effective.

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

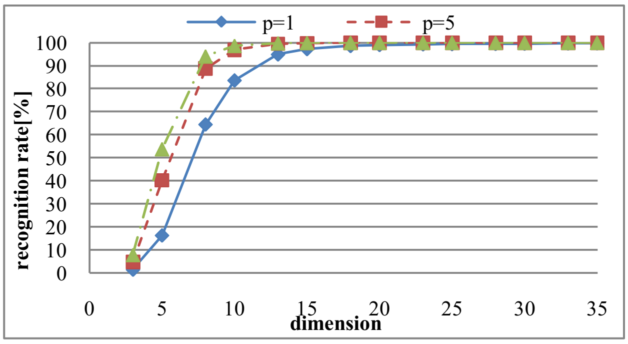


Fig.5 Cumulative recognition rate

The cumulative recognition rate at 10 dimensions for p=10 is 98.66%. In addition, all true categories are included in 23 best candidates with the first 35 dimensions. Further classification for the best candidates will be effective by using high resolution image, as 50×50 images already showed high recognition rate in low dimensions in Figure 4.

C. Recognition by multiple projections

Next, we show the recognition rate by multiple projections of $R=3$ in Figure 6. You can see that the recognition performance at low dimensions is quite higher than that of $R=1$.

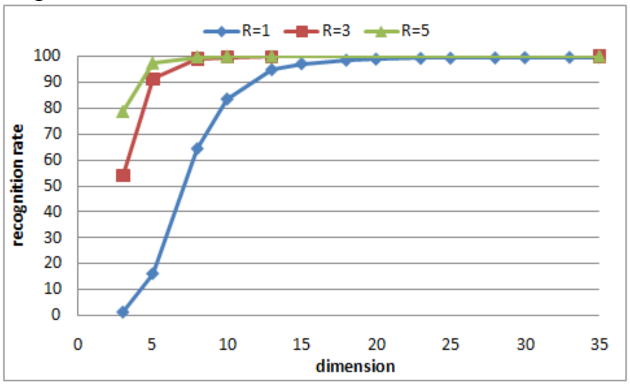


Fig.6 Recognition rate by multiple projections(R=3,5)

The recognition rate of R=3 at the first 10 dimensions is 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.

We can cover the deterioration of recognition rate at low dimensions by the two-stage classification and by the multiple projections. In recognition by the multiple projections, we got high recognition rate at low dimensions because contingency in simple projection can be suppressed.

D. Estimated angle difference

We show a 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 are restricted within ±7 degrees, and misclassified sample are excluded. Furthermore, 26 samples of category "一" are excluded because their estimated angles were upside down. All samples correctly recognized except "一" are within ±3 degrees. The most are high precision within ±1 degrees.

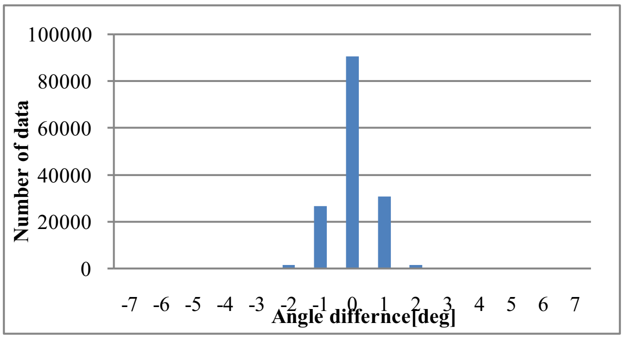


Fig.7 Precision of estimated angle errors

From these results, you can see that interpolated angles of 360 points are nearly correct. In recognition by simple projection and recognition by multiple projections($R=3$), examples of misclassification using the first 35 dimensions are shown in Table 1. Misclassified categories are very similar to the input categories. But, their estimated angles are within ±1 degrees though they are misclassified. In addition, in misclassified samples by the multiple projections(R=3), their true categories are included in the best two candidates.

Table 1 Examples of misclassification

Input ⇒ Result	R=1	R=3
晋 ⇒ 普	24	14
震 ⇒ 霊	11	0
鳳 ⇒ 風	11	0
漬 ⇒ 潰	9	3
漠 ⇒ 漢	9	1
島 ⇒ 鳥	8	0
廷 ⇒ 延	7	0
奥 ⇒ 臭	6	0
筒 ⇒ 簡	6	0
諭 ⇒ 論	6	0
others	292	2

E. Angle dependency of misclassification

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

Because we used 36 learning samples that were rotated by 10 degrees, there are many misclassifications by simple projection at 5 degrees as shown in Figure 8. Misclassification tends to occur in the data away from the learning data angle. That will be due to the error by the spline interpolation. Misclassification for each angle is less than 70 in 14,825 characters(accuracy over 99.53%), that is very few, so 36 learning data are almost enough. The distance between two neighboring projected points on the subspace 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. In recognition by multiple projections, if one distance from projected point on the locus is big, and other two distances are small, misclassification will not happen because the average becomes small. In this meaning, the multiple projection has an advantage of robustness.

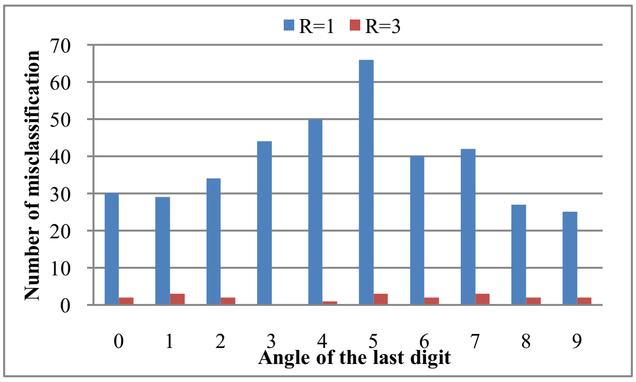


Fig.8 Angle tendency of misclasification

F. Computation time

The specification of the system used for the simuration is as followes;

CPU : Intel Xeon(6core/12thread),Main memory : 48GB.

In the recognition process, all categories are divided into 15 threads for parallel computation.

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

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

(c) case of 8×8 65 levels image using the first 10 dimensions by multiple projections($R=3$)
Computation time per a character is 0.15[s]

4. Summary

We proposed a rotated character recognition method using eigen-subspace for alpha-numeric characters before, In this paper, we applied it for the first class of Japanese Industrial Standard (JIS) Kanji set which includes 2,965 categories. As the result, we have obtained very high recognition rate. At first, we showed that the recognition rates at 35 dimensions for different sizes of image are almost same but at low dimensions, it decreases a little for small image size. Next, we experimented by two recognition methods that were the simple projections using only input image and the multiple projections using rotated images created by rotation of the input image. As the results, we have got very higher recognition rate than simple projection. The recognition rate is 99.74% for simple projection using 35 dimensions, and 99.99% for multiple projections($R=3$)using 35 dimensions. Then, the multiple projections showed high performance at low dimensions. In addition, we considered whether 36 learning data is enough or not by analyzing the angle tendency of misclassification data, then we suggested an improvement of recognition rate. In the future, we will consider the influence of the noise on a real image that exerts to the recognition rate. Furthermore, we try to absorb variations of real image by effective feature extractions. In addition, we want to develop a real time system.

References

[1] Q.Xie, A.Kobayashi, “A Construction of Pattern Recognition System Invariant of Translation, Scale-Change and Rotation Transformation of Patterns(in Japanese), ” Trans. of The Society of Instrument and Control Engineers, Vol.27,No.10, pp.1167-1174 (1991).

[2] S.Sato, S.Miyake and H.Aso, “Evaluation of Two Neocognitron-type Models for Recognition of Rotated Patterns,” ICONIP 2000, WBP-04,pp295-299 (2000).

[3] H.Murase, S. K. Nayar, “3D Object Recognition from Appearance-Parametric Eigenspace Method-(in Japanese),” Trans. of IEICE, Vol.J77-D-II,No.11, pp.2179-2187 (1994).

[4] Toshiyuki Sinokawa, Hiroyuki Hase, Hiroshi Kakutani, Masaaki Yoneda, “Recognition of Rotated Characters by the Parametric Eigen-space Method”, IIEEJ, vol.33,no.6,pp.1123-1131(2004.11)(in Japanese).

[5] Ryo Narita, Wataru Ohyama, Tetsushi, Wakabayashi, Fumitaka Kimura, “3D rotation invariant character recognition”, MIRU2011, OSI-4: 26-32, (2011)(in Japanese).

[6] http://projects.itri.aist.go.jp/etlcdb/etln/etl2/etl2.htm

[7] Shukun NING, Hiroyuki HASE, Shogo TOKAI, “Kanji Character Image Generation for Character Recognition”, 2012 Joint Conference of Hokuriku Chapters of Electrical Societies, F-56, 2012.

[8] Masafumi Yamamoto, Shiori Ssato, Hiroyuki Hase, Shogo Tokai, "Real-time Rotated Character Recognition using Eigen-subspace", IEICE, Pattern Recognition and Media Understanding, PRMU2010-246,55-60,2011-03.