Writer Identification for Offline Handwritten Kanji Characters Using Multiple Features

Ayumu Soma, Kozo Mizutani, and Masayuki Arai

***Abstract*—This paper presents a study on character features and recognizers used for writer identification of offline handwritten Kanji characters. It is shown that a combination of two global features, two local features, and majority voting as a recognizer is efficient for writer identification. We performed experiments using an offline Kanji character database containing one-hundred Kanji characters, each written by one-hundred writers, and fifty samples of each Kanji character for a given writer. The experimental results show that the identification rate is 7 points higher than the conventional method using a single feature and obtained an identification rate higher than 99% by using three character classes.**

***Index Terms*—Multiple features, offline handwritten Kanji character, recognizer, writer identification.**

I. Introduction

Writer identification based on scanned images of handwritten characters is a useful biometric modality with applications in forensic and historical document analysis. Research on writer identification that uses online characters is widespread, but offline characters lack form for conveying dynamic information. Nevertheless, research on writer identification using offline characters has proposed many features to acquire useful information.

We studied efficient character features and recognizers for writer identification of handwritten offline Kanji characters. Kanji consists of logographic Chinese characters adopted in Japanese writing. The text-dependent writer identification in our research uses a character recognition process before writer identification because, in text-dependent writer identification, a character class is assumed to be already recognized. Therefore, most of the research on text-dependent writer identification of handwritten characters has the following characteristics: employs features developed for character recognition, does not use multiple character features, and uses the local features of a character. In this paper, we propose efficient character features and a recognizer for text-dependent writer identification of a handwritten Kanji character [1].

II. Features

We studied efficient character features for writer identification of handwritten offline Kanji characters. As mentioned above, the conventional methods for text-dependent writer identification do not use multiple kinds of character features and employ local features developed for character recognition. We assume that global features are indispensable for writer identification. Therefore, we propose two following local features: (A)the weighted direction index histogram feature and (B) features extracted from each stroke, and two following global features: (C) the size and position of the Kanji character and (D) the two-dimensional space spectrum. This section presents the details of these features.

A. Weighted Direction Index Histogram

The weighted direction index histogram (WDIH) [2], [3] extracts local features by focusing on the character's contour in the following procedure.

1) A character image is separated into some blocks.
2) Chain coding is applied to the contour pixels of each block. The vector sum of adjacent two-chain elements is taken to produce 16 directional codes, as shown in Fig. 1. In the case of Fig. 2, the directional resolution is 13 because of the contour tracing from 12 to 14.
3) The directional resolution is reduced from 16 to 8 by down sampling with a weight vector $[1\ 2\ 1]^T$.
4) Each opposite two-directional resolution is merged to reduce from 8 to 4.
5) Finally, a Gaussian filter is used to distribute the directional codes.

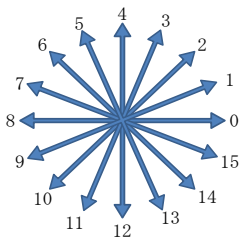

Fig. 1. The sixteen directions in WDIH.

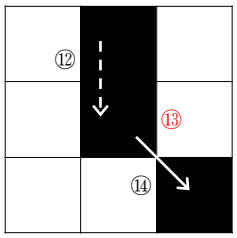

Fig. 2. Example of the directional resolution in WDIH.

B. Features Extracted from Each Stroke

Tokiwa *et al*. reported that the start point and the end point of each stroke of a Kanji character are efficient for writer identification [4]. However, in that work, the strokes were

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extracted manually. We extract them automatically and add the angles of the stroke [5], [6], as shown in Fig. 3.

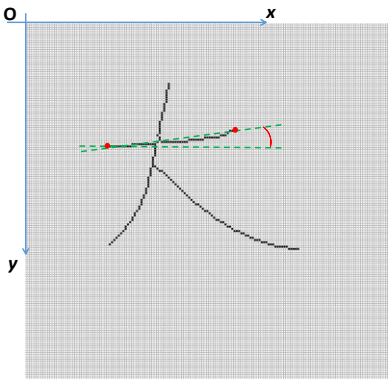

Fig. 3. Example of features extracted from a stroke.

C. Size and Position

This sub-section describes a method to extract the size and position of the Kanji character. The features, shown in Fig. 4, are as follows:

1) the x- and y-coordinates of the upper left point of the inscribed rectangle for the character (Fig. 4, p1)
2) the x- and y-coordinates of the lower right point of the inscribed rectangle for the character (Fig. 4, p2)
3) the x- and y-coordinates of the center point of gravity where all the black pixels are concentrated (Fig. 4, g1)
4) the character width plus the character height (Fig. 4, (w2+h2)×2)
5) the character width divided by the character height (Fig. 4, w2/h2)
6) the character width divided by the frame width (Fig. 4, w1/w2)
7) the character height divided by the frame height (Fig. 4, h1/h2)

Therefore, the features consist of ten elements.

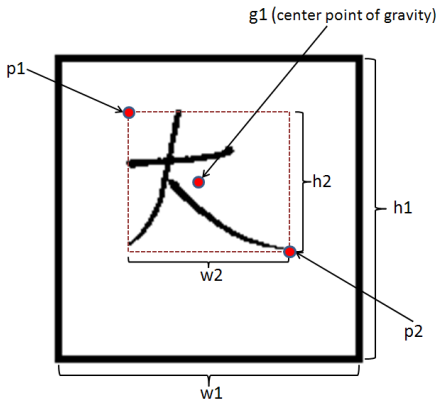

Fig. 4. Example of the size and position of a Kanji character.

D. Two-Dimensional Space Spectrum

The two-dimensional space spectrum is often used for edge detecting in image processing. Hasegawa *et al*. reported that it is useful for writer identification of a handwritten character [7]. The features extracted by this method are shape-independent and robust enough for position aberrations. The feature extraction procedure is as follows:

1) A character image is separated into multiple mesh areas.
2) A spectrum as features is extracted by applying the two-dimensional discrete Fourier transform shown in equation (1) to the image. Here x, y are the x-axis and the y-axis, respectively, $f(x,y)$ is a density function, and M, N are the numbers of mesh squares in the two directions, i.e., it is an $M \times N$ mesh.

$$F(u,v) = \frac{1}{MN}\sum_{M=0}^{M-1}\sum_{N=0}^{N-1} f(x,y)\cdot \exp\left\{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)\right\} \quad (1)$$

III. Study on Recognizers

When employing multiple character features, a recognizer is required to aggregate them. We study the following recognizers often used for character recognition.

A. Majority Voting Method

Majority voting [8] identifies the writer getting the most votes as elected by each feature. Fig. 5 shows an example to identify three writers (A, B, and C) using three kinds of features (α, β, and γ). In case 1 in Fig. 5, writer A gets two votes from features α and β, then the recognizer identifies the writer as A. In case 2, each of the three writers gets one vote, and the recognizer rejects the result.

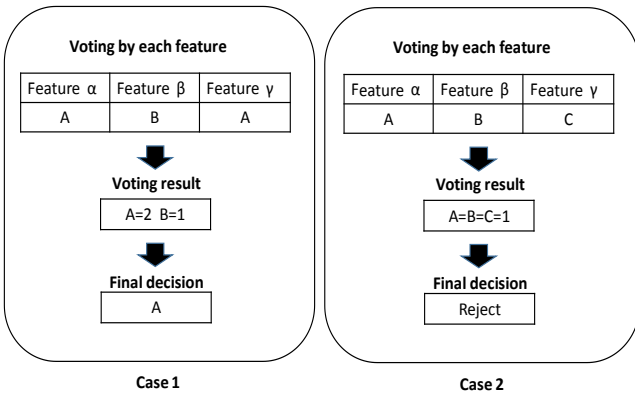

Fig. 5. Example of majority voting.

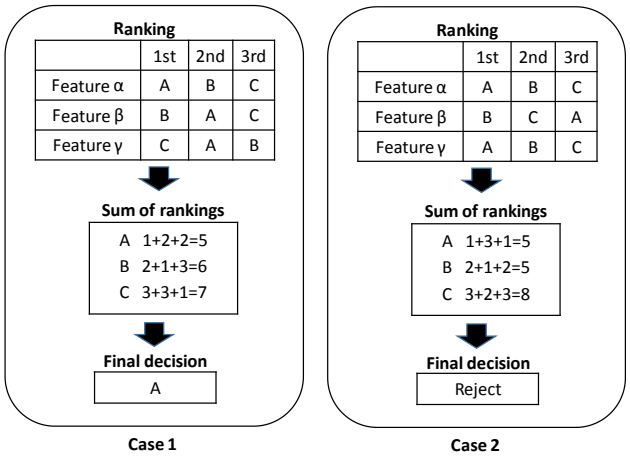

Fig. 6. Example of the sum of rankings.

B. Sum of Rankings

This recognizer identifies the writer who gets the smallest sum of rankings. An example is shown in Fig. 6. In case 1, the sums of rankings of writers A, B and C are 5, 6 and 7, respectively. Therefore, the recognizer identifies A, who has the smallest sum, as the writer. In case 2, A and B have the smallest sum. Then, the recognizer rejects the result.

IV. Experiments and Discussion

A. Experimental Condition

To evaluate the abovementioned character features and recognizers, we performed experiments under the following condition. For WDIH, one block consists of 8 × 8 pixels and one mesh comprises 10 × 10 pixels for the two-dimensional space spectrum. Table I depicts the experimental condition for each feature.

TABLE I: Experimental Conditions for Each Character Feature

	Feature name	Dimension
Local feature	Weighted direction index histogram (WDIH)	400
	Features extracted from each stroke	5*n (n is the number of strokes)
Global feature	Size and position	10
	Two-dimensional space spectrum	256

Table II shows the details of the handwritten Kanji characters database [9] used in the experiments.

TABLE II: Details of the Handwritten Kanji Character Database Used in the Experiments

Number of Kanji classes	100 classes frequently used for Japanese place names
Number of writers	100 writers
Number of samples per class	50 samples/class
Number of samples	100*100*50=50000
Data size	1.5cm*1.5cm
Writing instrument	Black water-based ballpoint pen
Resolution	240dpi binary data

This research is on the text-dependent writer identification; that is, character classes are already recognized before the writer-identification process. Therefore, we used samples of the same character class in every experiment.

For each experiment (each character class), 5,000 samples (100 writers × 50 samples) were used in the tests by the leave-one-out cross validation method. In this method, one sample was used for validation, while the other 4,999 samples were used for training.

B. Experiments on the Recognizers

The first and second lines in Table III depict the identification and the rejection rates for two recognizers using the abovementioned four features. The majority voting identification rate is 13 points higher than that of the sum of rankings. The rejection rate of the majority voting is also higher than the sum of rankings.

TABLE III: Identification and Rejection Rates for Each Recognizer Using Four Features or WDIH

	Identification rate(%)	Rejection rate(%)
Majority voting	89.97	22.46
Sum of rankings	76.43	1.88
WDIH (without rejection)	78.08	
WDIH (with rejection)	82.47	22.46

The third line is the identification rate using feature WDIH, which is frequently used alone for Kanji writer identification [2], [3]. WDIH obtains a 78.08% identification rate. To compare our method (using four kinds of features and majority voting) with WDIH, we employed the rejection in WDIH. To equalize the rejection rate 22.46%, the low-matching samples were rejected in the experiment of WDIH. As a result, the identification rate of WDIH is approximately 82.47%, which is 7 points lower than our method, as shown in the fourth line of Table III.

C. Character Classes

Fig. 7 depicts the relation between the number of character classes, the identification rate and the rejection rate. By using more than three character classes, we obtain an identification rate over 99% with a rejection rate than less 2%.

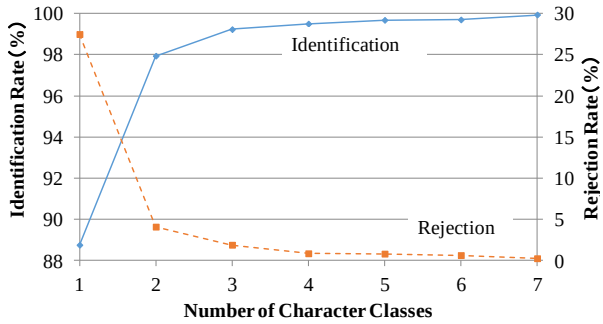

Fig. 7. Number of classes vs. identification and rejection rates.

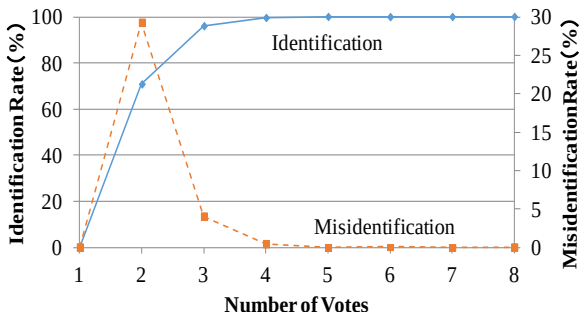

Fig. 8. Number of votes vs. identification and misidentification rates by using two character classes.

D. Number of Votes

Fig. 8 indicates the number of votes vs. the identification and the misidentification rates by using two character classes. In this case the biggest number of votes is 8 because of the four features and two character classes (4 × 2).

Writers receiving the fewest number of votes tend to be misidentified. The result denotes that a rejection method based on the number of votes is efficient for reducing the misidentification rate.

E. Number of Training Samples

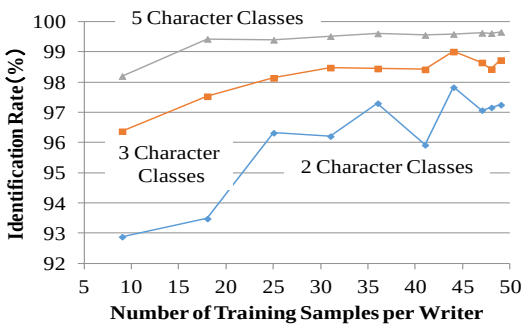

Fig. 9. Number of training samples per writer vs. identification rate.

Fig. 9 depicts the relationship between the number of training samples and the identification rate. The identification rates rise in proportion to the number of samples. For instance, 5 character classes obtain an identification rate more than 99% by using only 20 training samples.

F. Number of Writers

Fig. 10 shows the number of writers vs. the identification rate. The identification decreases in accordance with the number of writers. For instance, for 100 writers, the difference of the identification rates between 2 character classes and 5 classes is approximately 5 points. We must use several character classes to identify more than 100 writers.

Fig. 10. Number of writers vs. identification rate.

V. Related Research

Writer identification using online Kanji characters can realize a higher identification rate than that of offline Kanji, because the online character has much information, such as the strength of the brushstrokes and the stroke order [10], [11].

Writer identification research is classified into two categories: text-dependent and text-independent. For text-dependent writer identification, character classes are known before the writer identification. On the other hand, the text-independent writer identification cannot use the character's class. This section explains the two categories.

A. Text-Independent

Text-independent writer identification is highly desirable because it can be used without character recognition. Most the writer identification research, however, is text-dependent, although some text-independent research exists [12].

The method for extracting features representing individuals is the most significant issue for text-independent writer identification of Kanji characters. Syakunaga *et al.* proposed a method to extract features of the frequency of straight strokes and parallel strokes by resolving the stroke spectrum of second-order statistics to focus on stroke straightness [13], [14]. Yoshimura *et al.* developed a new method for extracting features using a localized arc pattern to concentrate on arcs and curves of strokes [15]. Ando *et al.* found a novel method using stroke variance to examine stroke inclination [16].

B. Text-Dependent

Satoh *et al.* extracted individual features from character strokes by focusing on the straightness and curvature of strokes [17]. Their method utilizes the Hough transform to extract straightness and employs curvature-fitted strokes to extract information on curves. Yoshimura *et al.* also focused on character strokes to extract features [18]. This research acquired the features by applying character images to the localized arc pattern and calculating the arcs statistically.

The method proposed by Yoshimura *et al.* used multiple kinds of character features [18]. In other research, the kinds of features are used for text-dependent writer identification [19]-[21]. Ito *et al.* consolidated some kinds of features to improve the identification rate [19] and proposed the following two recognizers for merging features: the hierarchical recognizer, which has a rough and fine classification part, and the parallel recognizer, such as the majority voting method. As a result, they stated that the parallel recognizer is superior to the hierarchical one and proposed a new recognizer named EID3 to recover the defects of hierarchical recognizers.

VI. Conclusion

We studied character features and recognizers used for writer identification of offline handwritten Kanji characters. As a result, the combination of two global features, two local features, and majority voting as a recognizer is efficient for writer identification. As the local features, the weighted direction index histogram and features extracted from each stroke are proposed; on the other hand, the size and position of a character and the two-dimensional space spectrum are proposed for global features. The experimental result shows that the identification rate is 7 points higher than the conventional method using a single feature and can obtain an identification rate over 99% by using three character classes. In addition, we evaluated our proposed method from the following standpoints: the number of character classes, votes, training samples, and writers.

We plan to study a useful application of our method.

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