Visual Matching of Stroke Order in Robotic Calligraphy

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***Abstract*—Robotic calligraphy is an interesting problem and recently draws much attention. Two major problems in robotic calligraphy are stroke shape and stroke order. Most of previous work focused on controlling brush trajectory, pressure, velocity, and acceleration to draw a desired stroke shape. As for stroke order, it was manually given from a database. Even for a software of optical character recognition (OCR), it cannot recognize the stroke order from a character image. This paper describes the automatic extraction of the stroke order of a Chinese character by visual matching. Specifically speaking, the stroke order of a Chinese character on an image can be automatically generated by the association of the standard image of the same character given with its stroke order. The proposed visual-matching method extracts the features of the Hough Lines of an input image and uses support vector machine (SVM) to associate the features with the ones of the standard image. The features used in the proposed method were evaluated on several Chinese characters. Two famous Chinese characters "Country" and "Dragon" were used to demonstrate the feasibility of the proposed method. The matched rate of the stroke order of "Country" and "Dragon" were 95.8% and 90.3%, respectively.**

***Index Terms*—Robotic calligraphy, stroke shape, stroke order, visual learning, skeletonizing, Hough Line Transform, support vector machine.**

I. Introduction

Many studies aimed at creating robots to perform high-level activities. Robot drawing is one of the high level tasks. In recent years much attention has been paid to enable robots to draw artwork [1]–[3]. Particularly, Chinese calligraphy is an interesting problem because a Chinese character usually consists of multiple strokes which have different writing styles. Thus, the progress of learning robotic calligraphy demonstrates the improvement in robot dexterity and intelligence. Additionally, robotic calligraphy provides a good platform of human-robot interaction [4]. On one hand novices can learn how to write Chinese characters from robotic calligraphy, and on the other experts can teach a robotic calligraphy system to have better Chinese character writing.

Chinese calligraphy is a culture art of drawing Chinese characters using a brush. Typically, a Chinese character is composed of several strokes and each stroke has its writing shape and order. Yao and Shao [5] pointed that the representative skills of Chinese calligraphy were (a) writing brush pressure, (b) writing brush speed, and (c) writing brush rotation angle. They summarized that there were two major problems of Chinese character calligraphy robot: the shape of the stroke and the writing (stroke) order. Most previous work on robotic calligraphy attempted to control brush trajectory using brush footprint parameters [3], [5]–[8]. [5], [7], [8] proposed the methods to acquire parameters from images. Motion parameters of drawing Chinese characters can be also extracted from haptic devices [3]. Parameters were used to describe character skeleton, skeleton coordinate, brush pressure, velocity, and acceleration, and etc. Recently, drawing improvement was another research interest. The issue focused on the improvement of Chinese writing from previous experiences [2] or vision rectification [7].

To perform robotic calligraphy from observing an image, the shape of a Chinese character can be extracted from the image by the technique of image processing such as thinning or skeletonizing [9]. However, the stroke order of the Chinese character must be given because the robot could not recognize this information from the image [5]. To solve this problem, this paper presents a visual-matching method to acquire the stroke order from the image of a target Chinese character. The success of the visual-matching method relies on the database of Chinese characters given with stroke order and the image association method. Figure 1 shows that the proposed method associates the image of the target Chinese character with the standard image of the same character from the database to find the stroke order. In this paper, the association method is implemented by feature extraction and the support vector machine (SVM). Since each stroke of the character on the target image is modeled by several Hough lines, we adopt the Ramer-DouglasPeucker algorithm to reconstruct a simple stroke from these Hough lines, this simple stroke can be assign the stroke order from the Hough lines, and the calligraphy can be implemented by the reconstructed strokes. By doing this, the proposed method can automatically and correctly find the stroke order of the Chinese character shown on an image. With the correct stroke order, it is certain that robotic calligraphy draws Chinese characters naturally.

This paper is organized as follows. Section II introduces

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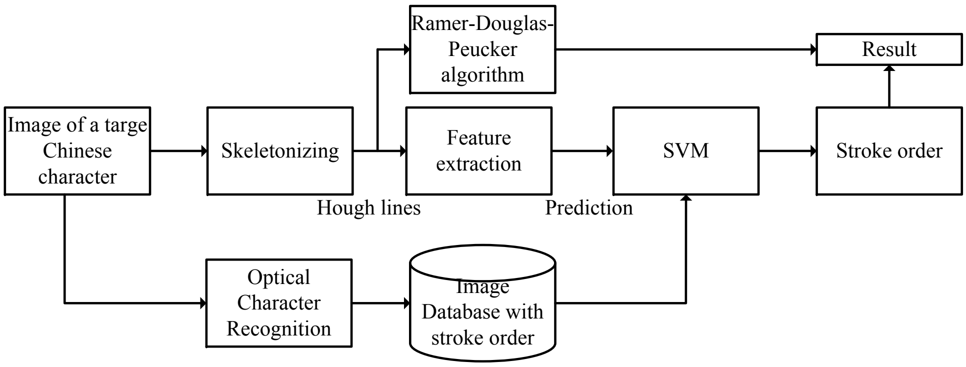

Fig. 1. Proposed method.

the skeletonizing for extracting stokes of a Chinese character and presents the proposed visual-matching method to acquire the stroke order of an Chinese character. In Section III, results are presented. Discussions and conclusions are summarized in Section IV.

II. Proposed method for learning stroke order

A. Skeletonizing

To learn the stroke order from the image of a Chinese character, we need to process the source image to extract some useful features. In this paper, the technique of image processing is skeletonizing. In image processing, skeletonizing is one of the most important techniques because it provides a method to simplify an image. In this paper, we use the skeleton of a Chinese character to extract its stroke order since the image width of a stroke is not helpful to find the stroke order. The technique of skeletonizing is to discard surrounding pixels of an image pattern by an iterative algorithm until the pattern is represented by a line of pixels. During skeletonizing, the end-points cannot be discarded and the connectivity cannot be destroyed. The steps of erosion and dilation are used to obtain skeletonized images. Figure 2 shows the target image of the Chinese character "Country" and the images after binarization and skeletonizing. Before skeletonizing, we apply binarization to the source image to obtain the binary image for skeletonizing.

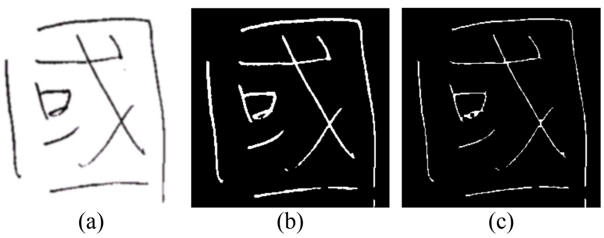

Fig. 2. (a)Target image; (b)image after binarization; (c)image after skeletonizing.

B. Feature extraction of the skeletonized image

Once the skeletonized version of the target image is obtained, the problem to be solved in this paper can be formulated as the classification problem in which the pixels of different strokes should be clustered into different labeled clusters according to a database of Chinese characters with stroke order. Thus, we proposed a visual-matching method to extract features of a skeletonized image and associate these features with the ones of the same character provided by the database to find the stroke order. In other words, the cluster label of the pixels belonging to a stroke is its stroke order.

Before acquiring the features, we model the skeletonized image by straight lines and extract the features from these lines. Barllad [10] proposed generalized Hough Line Transform to derive the curve of any arbitrary shape. Hough Line Transform converts the pixels of an image to the parameter space to find the possible straight lines of the image. Figure 3 shows the skeletonized image and the image after Hough Line Transform.

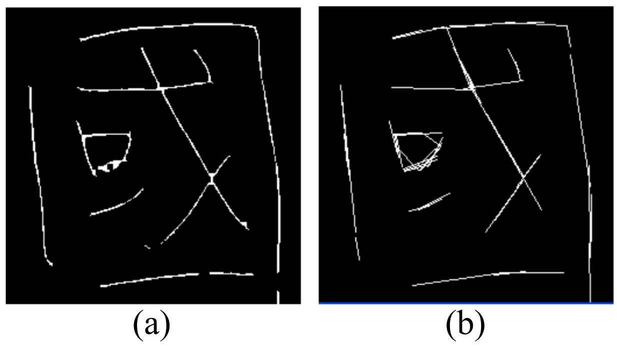

Fig. 3. (a)Skeletonized image; (b)image after Hough Line Transform.

Each Hough line is represented by a function $ax + by + c = 0$ where x and y are variables and a, b, and c are line parameters. In this paper, three candidate features are initially chosen from Hough lines. These three features are (1) the average distance between two lines, (2) the angle between two lines, and (3) the length difference between two lines. To choose effective features out of these three, we define an equation to evaluate the separation degree among data represented by the chosen features. The separation degree helps us find out the effective features for SVM classifiers. The equation is expressed as

$$SEP_{deg} = \frac{||GroupA_{center} - GroupB_{center}||}{\hat{\sigma}_a + \hat{\sigma}_b} \quad (1)$$

$$\hat{\sigma} = \sqrt{trace\{(X - \bar{X})(X - \bar{X})'\}} \quad (2)$$

where X is the data vector and $GroupA_{center}$ is the cluster mean of group A containing the Hough lines of the stroke to be recognized and vice versa. Each Hough line is represented by the chosen features. The numerator is greater; groups A and B are farther. $\hat{\sigma}_a$ and $\hat{\sigma}_b$ denote the dispersion around the centroid of groups A and B, respectively. The denominator is less; the data in group A or B are more aggregate. Thus, the separation degree can be shown by Eq. (2) because the greater value of Eq. (2) means groups A and B are more separate.

The features (1) the average distance and (2) the angle between two lines are calculated in the following steps. To compute the average line distance, there are two cases: the two lines are intersected or not intersected. Figure 5 shows two intersected lines, L_p and L. The average distance L_{ave} between L_p and L is computed as

$$L_{ave} = \frac{|L_1 + L_2|}{2} \tag{3}$$

where $L_1 = \frac{ax_1+by_1+c}{\sqrt{a^2+b^2}}$ and $L_2 = \frac{ax_2+by_2+c}{\sqrt{a^2+b^2}}$.

However, if L_p and L are not intersected, Fig. 4 shows the two non-intersected lines. L_{ave} is calculated as

$$L_{ave} = \frac{L_1^2 + L_2^2}{2(|L_1| + |L_2|)} \tag{4}$$

where $L_1 = \frac{ax_1+by_1+c}{\sqrt{a^2+b^2}}$ and $L_2 = \frac{ax_2+by_2+c}{\sqrt{a^2+b^2}}$. The distance of Eq. (4) is shorter than the one of Eq. (3) because the average distance should be shorter when the two lines are intersected.

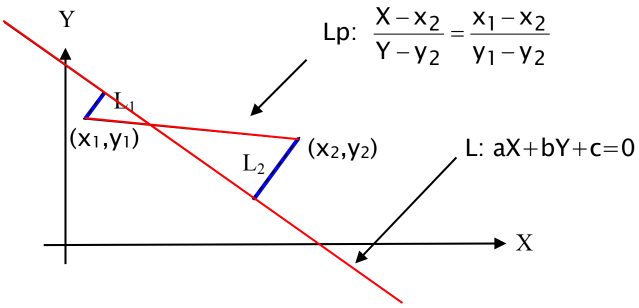

Fig. 4. Average line distance between two intersected lines.

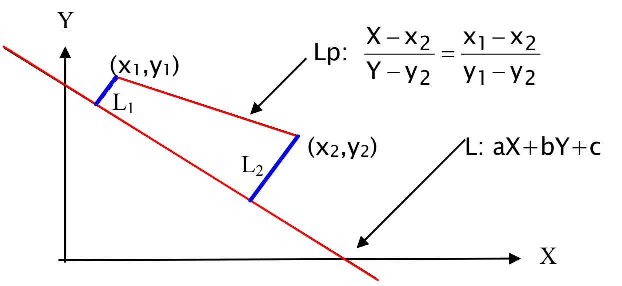

Fig. 5. Average line distance between two non-intersected lines.

As for the angle θ between two lines ($\vec{a} = (a_1, a_2)$ and $\vec{b} = (b_1, b_2)$), it is computed as

$$\theta = cos^{-1} \frac{a_1 b_1 + a_2 b_2}{\sqrt{a_1^2 + a_2^2}\sqrt{b_1^2 + b_2^2}}. \tag{5}$$

In this paper, we choose two features out of three for SVM classifiers. Thus, there are three possible cases: (1)&(2), (1)&(3), and (2)&(3). For each stroke, we evaluate the separation degrees of these three cases. Figure 6 shows the characters for evaluating the separation degree. The average is calculated among the separation degrees of all the strokes. Table I shows the separation degree among these Chinese characters. From Table. 7, using the features (1) and (2) has the greatest separation degree. Figure 7 shows the comparison of the separation degree among these three cases for each stroke of "Country".

C. Learning stroke order by SVM

After the line features are extracted, we use support vector machine (SVM) to train a classifier for recognizing a stroke of a Chinese character. In other words, we need to train a SVM classifier for every stroke. The training data is acquired from the standard Chinese character in the database. The method to train the classifier is described in the following steps. (1) Hough Line Transform is applied to each stroke of the standard Chinese character, (2) the features are extracted from any two lines out of these Hough lines, and (3) the features are used to train the SVM classifier.

Once the SVM classifiers for all strokes are trained, they are used to predict all of the Hough lines found from the target image. For example, to recognize the first stroke of a Chinese character on the target image, the stroke-1 classifier is used to predict the Hough lines obtained from the target image, and the lines that are classified into the same cluster of the first stroke of the standard character are labeled as the first stroke. The procedure is repeated until the stroke order of the character on the target image is found.

In each classifier, there are groups A and B where group A contains the features of the stroke to be classified and group B does not. Since $(0, 0)$ is the only one training

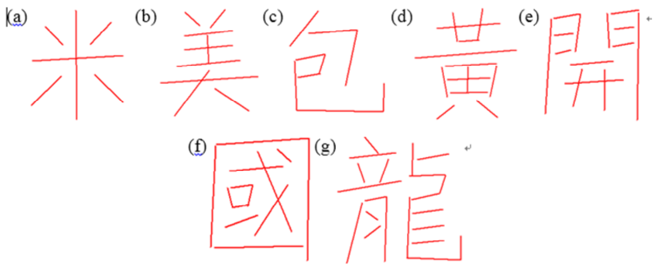

Fig. 6. Characters (a) Mi (b) Mei (c) Bao (d) Huang (e) Kai (f) Country (g) Dragon for evaluating the separation degree.

TABLE I
AVE SEPARATION DEGREE OF THE ALL STROKES.

	(1)+(2)	(2)+(3)	(1)+(3)
Mi	5.07	4.68	3.47
Mei	3.66	3.62	3.30
Bao	3.65	3.61	3.25
Huang	3.70	3.51	3.20
Kai	3.08	3.33	2.59
Country	3.91	3.74	3.37
Dragon	3.32	3.15	3.08
Average	3.77	3.66	3.18

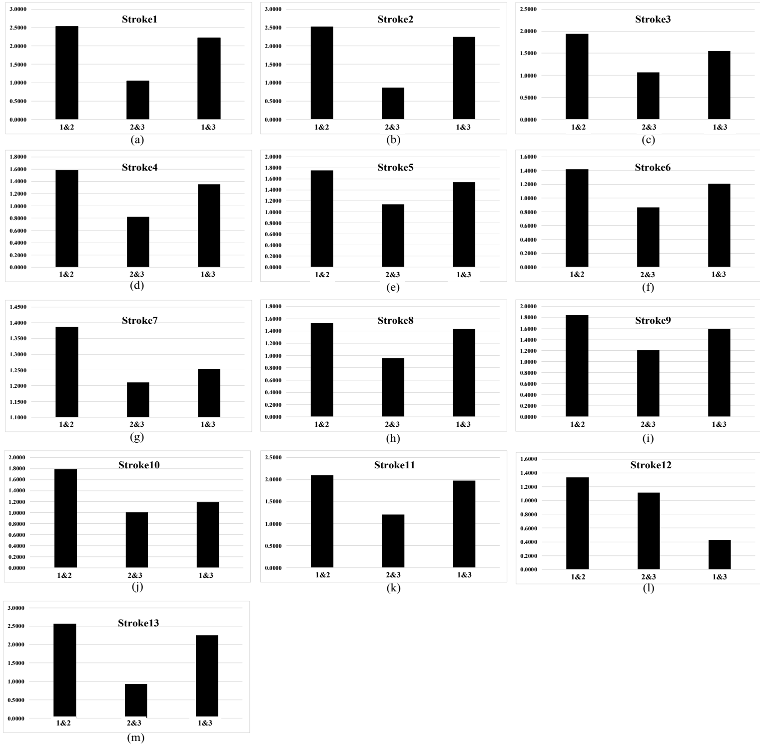

Fig. 7. Comparison of the separation degree among cases (1)&(2), (1)&(3), and (2)&(3) for stroke1$\sim$13 of Chinese character "Country".

datum in group A, we need to add additional data in group A to create the SVM noise margin. The target image we used is 256×256 pixels and the resolution of the standard character is 16×16 pixels. We add $(16, 0)$, $(\frac{16}{\sqrt{2}}, \frac{16}{\sqrt{2}})$, and $(0, 16)$ as three additional data in group A because $256/16 = 16$.

D. Reconstructing a stroke from Hough lines

After the stroker order for each Hough lines is found, the trajectory of each stroke on the target image should be approximated by its Hough lines. Thus, we apply the Ramer-Douglas-Peucker algorithm [11], [12] on the Hough lines of a stroke to approximate them by a smooth curve. The algorithm was proposed by Ramer, Douglas, and Peucker in 1972 and 1973 to reduce the number of points in a curve. In this paper, it is suitable to find a smooth curve from the Hough lines of a stroke. Obviously, the Ramer-Douglas-Peucker algorithm simplifies the curve using few points. Figure 8(a) shows the strokes represented by the Hough lines and Fig. 8(b) shows the stroke in red which is approximated by a smooth curve using the Ramer-Douglas-Peucker algorithm.

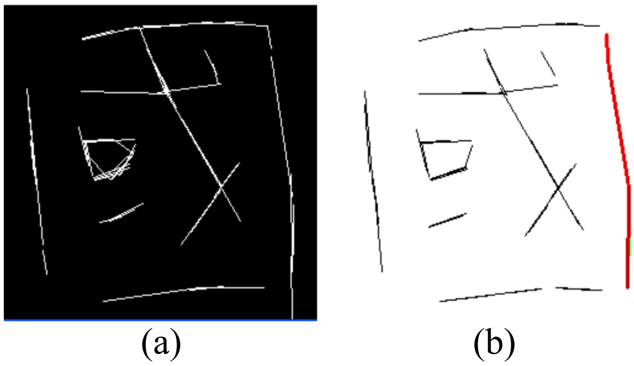

Fig. 8. Result of the Ramer-Douglas-Peucker algorithm.

III. Results

In this paper, we presented two complicated Chinese characters "Country" and "Dragon" to demonstrate the proposed method. The resolution of the target image was 256×256 pixels. The database of Chinese characters was acquired from the website of Ministry of the Interior [13].

A. Parameter setting

In feature extraction, we adopted Probabilistic Hough Line Transform to obtain lines. The pixel resolution was set to 1. The angle resolution was set to $\pi/180$. The resolutions of the target and database images were 256×256 and 16×16, respectively. Because $256/16 = 16$ and there is no very short stroke such as a dot in a Chinese character, the number of pixels less than 16 was regarded as noises. Thus, the minimum length of a line was set to 16 pixels. The gap between two lines was set to 8 pixels, which meant that any two lines closer than 8 pixels were combined as a line.

In SVM setting, a linear discrimination (or regression) was implemented in the feature space. The ϵ, which determined the level of accuracy of the approximated function in SVM, was set to 1e-6. The iteration number was 1000. In each SVM classifier, we defined groups A and B where group A contained the features of the stroke to be classified. For example, the character "Country" had 13 strokes. There were 13 data for training, one of which was in group A and the rest were in group B. The datum in group A was $(0, 0)$. To add some margin for discrimination, three additional data, $(16, 0)$, $(\frac{16}{\sqrt{2}}, \frac{16}{\sqrt{2}})$, and $(0, 16)$, were added in group A.

B. SVMs for "Country" and "Dragon"

Figure 2(a) shows the target image of Chinese character "Country". There were 13 strokes in this character. Using a SVM classifier for every stroke, Fig. 9 shows the recognition results of the 13 strokes of Chinese character "Country". In each figure, the left sub-figure shows the stroke of the target image to be predicted in red, the middle sub-figure shows the same stroke of the standard image in the database in blue, and the the right sub-figure shows the hyperplane of the SVM classifier. The stroke in red or blue was modeled by several Hough lines and a feature was extracted for a Hough line. In the right sub-figure, the red and blue dots were the features extracted from the Hough lines of the stroke of the target image and standard image, respectively, and the green and pink dots were the features of the rest strokes. Obviously, all of the red and blue dots were clustered in group A and the green and pink dots were in group B. The red and blue dots were separated from the green and pink dots by the SVM hyperplane. Thus, the stroke of the target image was recognized as the same stroke of the standard image. Since the stroke order of the standard image was known, the stroke order of the target image was identified. Figures 10 and 11 show all the strokes of Chinese character "Dragon".

C. Matching rate of Characters "Country" and "Dragon"

In this paper, ten different input images for "Country" and "Dragon", respectively, were provided to test the proposed method. We defined P_a as the classification rate for the Hough lines of an input image to their correct stroke and P_b as the matching rate for the strokes of the input image associated with the ones of the standard image in the database. Thus, we defined the total matching rate $P_z = P_a * P_b$ to evaluate the proposed method. The matching rates for "Country" and "Dragon" were 95.8% and 90.3%, respectively.

IV. CONCLUSIONS

In this work we propose a visual-matching method to learn the stroke order of a Chinese character on an image. Compared to the previous work, the idea of the proposed method is novel. With the correct stroke order, robotic calligraphy becomes natural because stroke order is essential in writing a Chinese character. The proposed method learns the stroke order of a Chinese character on a target image using the standard image of the same character with stroke order. We model the strokes of a character by Hough lines and extract the features of these lines to learn the SVM stroke classifiers. We present Chinese characters "Country" and "Dragon" in ten different input images, respectively, to validate the proposed method. The results show that the proposed method is feasible to recognize the stroke order of Chinese characters.

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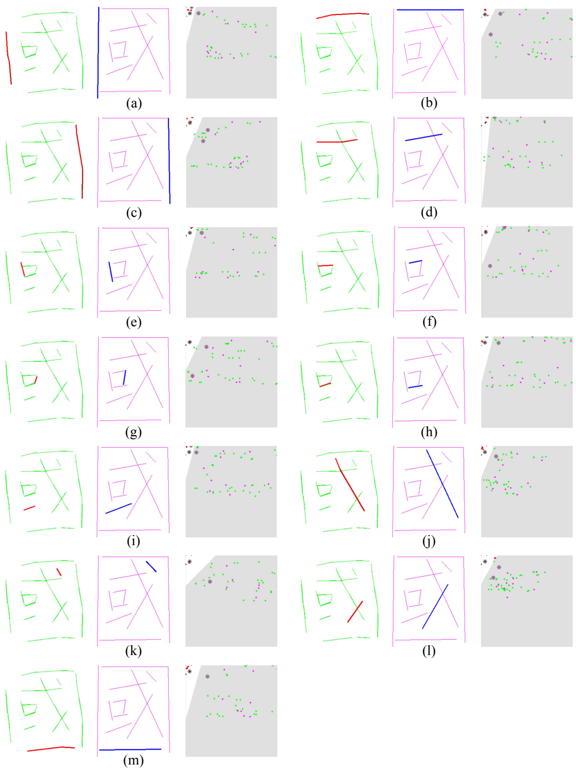

Fig. 9. (a)∼(m) are the strokes 1∼13 of “Country”.

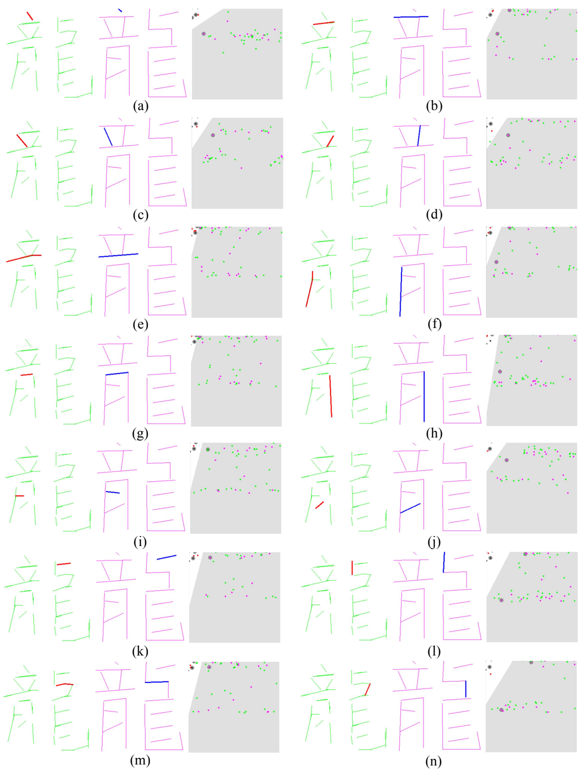

Fig. 10. (a)∼(u) are the strokes 1∼14 of “Dragon”.

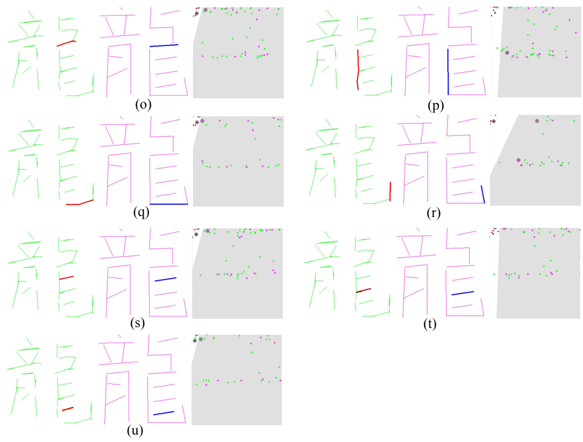

Fig. 11. (a)∼(u) are the strokes 15∼21 of “Dragon”.

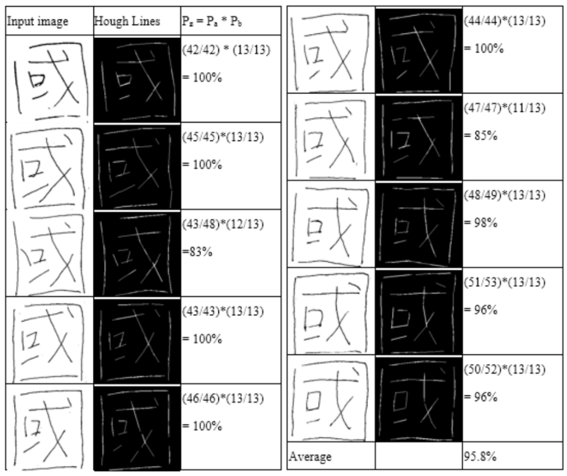

Fig. 12. Matching-rate for ten different “Country” characters.

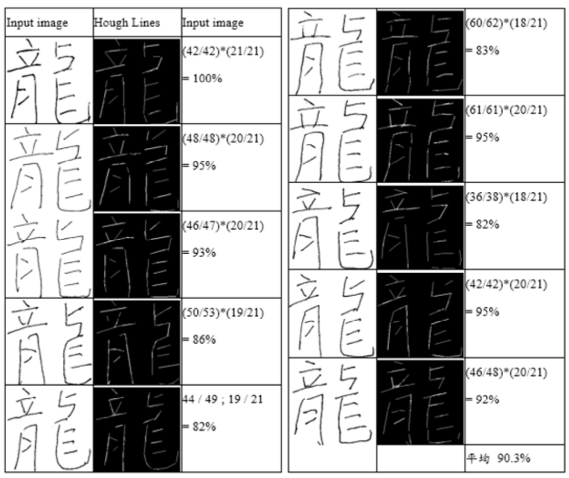

Fig. 13. Matching-rate for ten different “Dragon” characters.