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# A Robot for Classifying Chinese Calligraphic Types and Styles

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***Abstract*— As one of the most unique types of art in Chinese culture, nowadays Chinese calligraphy is attracting increasing interests from researchers. It will be a big step if we have a robot to write Chinese calligraphy, especially in various styles, and it will form a bridge to combine science with art directly. However, there are so many different types and styles in Chinese calligraphy, and to distinguish them is the most basic quality to a green hand, but it is a big challenge for a robot to do so. For the lack of exploration about this, we conduct a lot of experiments to help the robot to accomplish it automatically. We first propose a parametric representation of calligraphic characters, and then adopt the Mahalanobis distance for similarity measurement and classification. The average accuracies of classifying types and styles of the Chinese calligraphy are 96.36% and 95.61% respectively. During the experiments, some interesting phenomena are discovered through similarity measure. Meanwhile, the parametric representation also has some potential applications, such as defining aesthetic grading standards of calligraphy and synthesizing calligraphy. Based on our research, the calligraphy robot can tell which style of calligraphy it sees for mimicking.**

## I. INTRODUCTION

Chinese calligraphy, or *shufa*, defined as to write Chinese characters with brushes, is closely related to Chinese characters and culture. It has been evolved with Chinese history through centuries of development. With the distinctive feature of combining function with aesthetics, it receives a warm welcome from both the literati and the public. With the evolution of Chinese characters, there mainly exist five basic types [1, 2], i.e. seal script (*zhuanshu*), clerical script (*lishu*), regular script (*kaishu*), semi-cursive script (*xingshu*) and cursive script (*caoshu*), as shown in Fig. 1. For each type, a great number of calligraphists have created various styles according to their writing habits and aesthetic standards [1, 2]. Here we chose five styles of them to introduce (Fig. 2). Three of them are from famous calligraphists Yan Zhenqing (709 - 785), Liu Gongquan (778 - 865) and Qi Gong (1912 - 2005), and the other two are selected from printed styles Kai and Weibei (Fig. 2(c) is the same as Fig. 1(c)). As is known to all, the basic quality of a person interested in calligraphy is to recognize different styles and discover the similarity between them. In this research, we aim at training a robot to gain the intelligence for calligraphy style recognition.

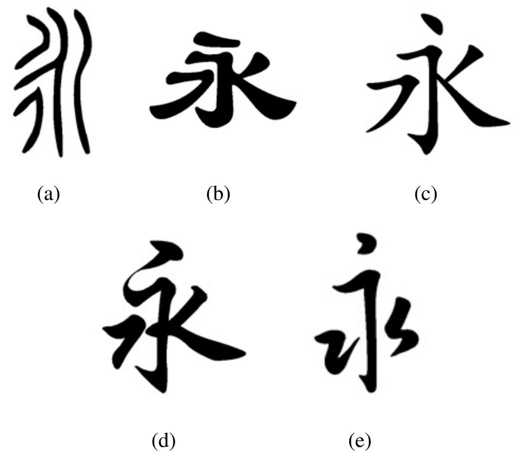

Fig. 1. Five basic types of Chinese characters: (a) seal script (*zhuanshu*), (b) clerical script (*lishu*), (c) regular script (*kaishu*), (d) semi-cursive script (*xingshu*) and (e) cursive script (*caoshu*).

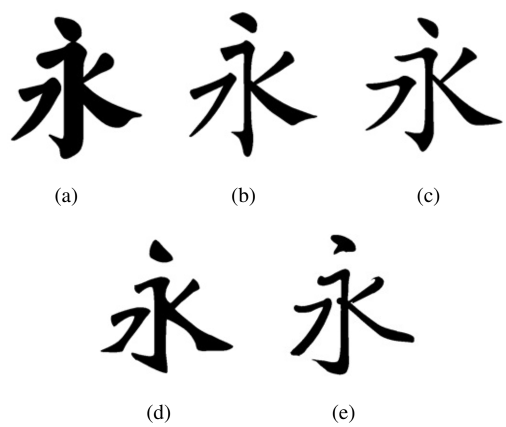

Fig. 2. Five styles of regular script: (a) Yan Zhenqing, (b) Liu Gongquan, (c) Kai, (d) Weibei and (e) Qi Gong.

Chinese calligraphy has been studied in engineering approach since late 1990s. The most pioneering work was the *Virtual Brush* model [3], including geometric parameters of the brush and ink deposition. With which, a computer can synthesize brush written characters. Since then Chinese calligraphy synthesis using brush model had become a major research field [4 - 6]. Besides, two robot platforms were provided to manipulate the brush and write calligraphy [7, 8]. To write or synthesize aesthetic Chinese calligraphy, we could refer to some grading methods which were able to rate the aesthetic quality of Chinese calligraphy [9, 10]. Since

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lots of calligraphy works are digitized and can be obtained through the Internet in image format, we need a way to retrieve required calligraphy automatically and efficiently. Therefore, some approaches were proposed to segment a whole calligraphy work into individual characters for further analysis [11, 12].

There was a rich literature related to Chinese calligraphy, some of which focused on similarity measure and classification. Some approaches were developed to discover style relationships [13, 14]. When users browse or retrieve some calligraphy works, the system will recommend some other similar style works to the users. However, based on this similarity measure, the average accuracy of classification was only 69% for five types. To address classification, a database containing templates of 40 most frequently used characters was established [15]. Every character image was then matched with the templates to determine the font. However, this database of 40 characters can only work well for texts in a particular historical period, since the language usage varies a lot through Chinese history. Other approaches toward font recognition were developed based on texture-analysis [16, 17]. These two approaches had a same problem that all the characters were considered as pen-written characters which only consist of skeleton, without the width information of the strokes. These approaches may feasible for the pen-written Chinese characters classification but not calligraphy. For instance, the texture-analysis-based approach achieved 99.1% accuracy in classification of pen-written characters, whereas it only achieved 84.51% accuracy in classification of calligraphy [18]. Therefore, a parametric representation of a character was proposed [18]. The characters were covered with ellipses whose semi-major axes were chosen as the additional features to combine with the texture analysis. The average accuracy was improved to 94%. However, the experiments were only carried on four types (seal script, clerical script, cursive script and regular script). One basic type, semi-cursive, was missed and no test on different writing styles was provided. The experiments were not comprehensive.

In this paper, we propose a parametric representation of calligraphic characters, chosing stroke and structure features for parametrization. Mahalanobis distance is applied to measure the similarity and classify calligraphic types and styles. The accuracies of classifying types and styles reach to 96.36% and 95.61% respectively.

The rest of the paper is organized as follows. Section II describes the parametric representation of the calligraphic characters and the definition of distance metric. Section III verifies the representation by experiments. Some issues are discussed in Section IV. Section V concludes the paper.

## II. FEATURES AND DISTANCE METRIC

### A. Stroke Features

Assume we have extracted the contours of the characters. Each contour is constructed with ordered discrete points (Fig. 3). All these points constitute a totally ordered set [19]

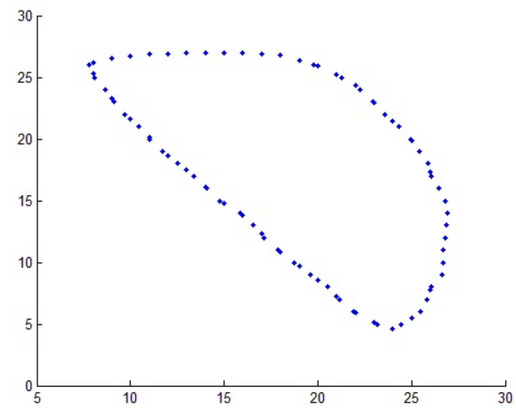



Fig. 3. Contour extracted from a dot stroke.

$$Q = \{(x_1, y_1), (x_1, y_1), \ldots, (x_N, y_N)\}, \tag{1}$$

where $N$ is a finite integer which indicates the number of points on the contours. The order of set $Q$ can be expressed as

$$(x_i, y_i) < (x_{i+1}, y_{i+1}), i = 1, 2, \ldots, N-1. \tag{2}$$

Assume the points are very dense. The direction of the normal line at point $(x_i, y_i)$ can be expressed as

$$\theta_i = atan2(-(x_i - x_{i-1}), y_i - y_{i-1}), i = 2, 3, \ldots, N, \tag{3}$$

where $atan2(y, x)$ returns the angle between the positive-x axis and the line connecting the origin and $(x, y)$. The angle is in the range $(-\pi, \pi]$.

After we have obtained the set $\Theta = \{\theta_i, i = 2, 3, \ldots, N\}$, we calculate the probabilities of $\theta$ that falls into the following 20 ranges:

$$\left(\frac{j-11}{10}\pi, \frac{j-10}{10}\pi\right], j = 1, 2, \ldots, 20, \tag{4}$$

Therefore 20 attributes $(p_1, p_2, \ldots, p_{20})^T$ are obtained.

Since the points are very dense, the length of the curve approximates the Euclidean distance between two adjacent points. Therefore, the curvature at point $(x_i, y_i)$ can be expressed as

$$\rho_i = \frac{\theta_i - \theta_{i-1}}{\sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}}, i = 3, 4, \ldots, N. \tag{5}$$

Normally the curvature is a scalar quantity in a plane. Here we define a curvature vector. If $\theta_i$ is greater than $\theta_{i-1}$, the curvature is positive. Otherwise, it is negative. Fig. 4 illustrates the positive and negative direction visually.

After we have obtained the set $P = \{\rho_i, i = 3, 4, \ldots, N\}$, we calculate the probabilities of $\rho$ that falls into the following 20 ranges:

$$(-\infty, -0.54], k = 1, \tag{6}$$

$$\left(\frac{3(k-11)}{50}, \frac{3(k-10)}{50}\right], k = 2, 3, \ldots, 19, \tag{7}$$

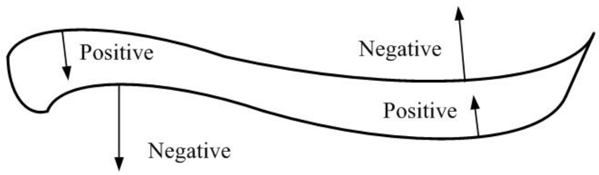



Fig. 4. Direction of curvature vector.

$$(0.54, +\infty), k = 20. \quad (8)$$

Another 20 attributes $(q_1, q_2, \ldots, q_{20})^T$ are obtained.

Then the stroke features can be represented as an 40-dimensional vector

$$C = (p_1, p_2, \ldots, p_{20}, q_1, q_2, \ldots, q_{20})^T. \quad (9)$$

### B. Structure Features

If we regard the character as a mechanical structure, the features of this structure such as mass, center of mass and distribution of mass are of great significance. Here we let the flipped binary level (white=0 and black=1) of the pixel be the density at that point. Therefore, the mass of the character with image size $n \times m$ is

$$M = \sum_{x=1}^{n}\sum_{y=1}^{m} b(x, y), \quad (10)$$

where $b(x, y)$ is the flipped binary value at pixel position $(x, y)$.

The center of mass of a character is calculated as follows:

$$\begin{aligned} u = EX &= \sum_{x=1}^{n} xP(x) = \sum_{x=1}^{n}\left(x\sum_{y=1}^{m} p(x, y)\right) \\ &= \sum_{x=1}^{n}\left(x\sum_{y=1}^{m} \frac{b(x, y)}{M}\right), \end{aligned} \quad (11)$$

$$\begin{aligned} v = EY &= \sum_{y=1}^{m} yP(y) = \sum_{y=1}^{m}\left(y\sum_{x=1}^{n} p(x, y)\right) \\ &= \sum_{y=1}^{m}\left(y\sum_{x=1}^{n} \frac{b(x, y)}{M}\right). \end{aligned} \quad (12)$$

The mass distribution along x axis and y axis are defined as the derivation in both axis:

$$\begin{aligned} DX &= E[X - EX]^2 = EX^2 - (EX)^2 \\ &= \sum_{x=1}^{n}\left(x^2\sum_{y=1}^{m} \frac{b(x, y)}{M}\right) - (EX)^2, \end{aligned} \quad (13)$$

$$\begin{aligned} DY &= E[Y - EY]^2 = EY^2 - (EY)^2 \\ &= \sum_{y=1}^{m}\left(y^2\sum_{x=1}^{n} \frac{b(x, y)}{M}\right) - (EY)^2. \end{aligned} \quad (14)$$

We also calculate the covariance between $X$ and $Y$,

$$\begin{aligned} cov(X, Y) &= E[(X - EX)(Y - EY)] \\ &= EXY - EXEY \\ &= \sum_{x=1}^{n}\sum_{y=1}^{m} xy\frac{b(x, y)}{M} - EXEY. \end{aligned} \quad (15)$$

Then the structure features can be expressed as another vector

$$S = (M, EX, EY, DX, DY, cov(X, Y))^T. \quad (16)$$

### C. Distance Metric for Classification

Each character can be represented as an 46-dimensional vector if we combine above features together. This vector can be also regarded as a point in 46-dimensional space. Therefore, the distance between an unknown-style character and a set of characters sharing the same style come to be the distance between a point and a set of points. If the character has the shortest distance to one set of characters, it is classified into this class. In this research, we choose the Mahalanobis distance among all the distance metrics. The comparison of some typical distance metrics is provided in the next section.

The Mahalanobis distance between a point $p$ and a set of points with mean $\mu$ and covariance matrix $\Sigma$ is

$$d = \sqrt{(p - \mu)^T \Sigma^{-1} (p - \mu)}, \quad (17)$$

where $p$ and $\mu$ are 46-dimensional column vectors and $\Sigma$ is a $46 \times 46$ matrix.

## III. EXPERIMENTS

### A. Data Collection

We select the characters in GB2312 [20] which is an official character set of People's Republic of China containing 6,763 different characters (covers 99.75% of simplified Chinese characters). Each character image is normalized to $450 \times 450$ pixels. The center of the character is closely located in the center of the image and the character covers more than half of the image area. We choose 4,000 characters as training samples and remaining 2,763 characters as testing samples.

9 computer fonts are separated into two groups for two experiments. One group consists of five basic types of Chinese character (Fig. 1). The other group consists of five different styles of regular script chosen from thousands of styles (Fig. 2).

### B. Feature Extraction

As described in Section II, the character can be represented as an 46-dimensional vector. The distributions of normal lines' direction of the training samples are illustrated in Fig. 5 and Fig. 6. Since they are in the range of $(-\pi, \pi]$, the directions of normal lines can be well represented in polar coordinate. There are 20 points in total on the polar plane which represent 20 of 46 attributes of the training samples. The range is evenly divided into 20 intervals. For each point,

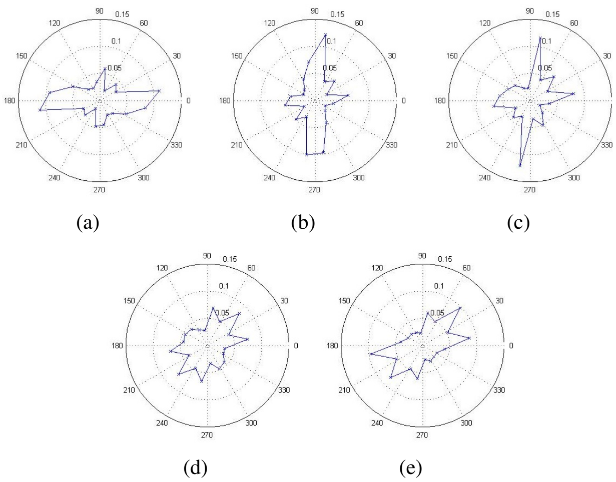


Fig. 5. Normal lines' directions of five types: (a) Seal script, (b) Clerical script, (c) Regular script, (d) Semi-cursive script and (e) Cursive script.

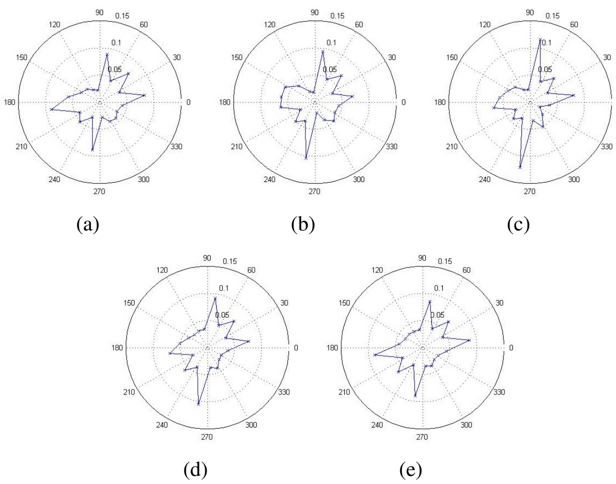


Fig. 6. Normal lines' directions of five styles: (a) Yan Zhenqing, (b) Liu Gongquan, (c) Kai, (d) Weibei and (e) Qi Gong.

the polar angle is set to be the center of one interval. And the radius is the mean value of corresponding attribute. Adjacent points are connected with a straight line.

Through these feature diagrams, two conclusions are proved.

1) The difference between different types is much larger than that between different styles. This is proved comparing Fig. 5 with Fig. 6.

2) Seal script has longer vertical strokes so the directions of normal lines have higher probability appearing in the horizontal direction. On the contrary, clerical script has longer horizontal strokes so the directions of normal lines have higher probability appearing in the vertical direction. Semi-cursive script has lots of inclined strokes and cursive script even has more.

### C. Classification Results

As stated in Section II, the shortest distance is used for classification. The confusion matrix of these two experiments are shown in Table I and Table II. The average distances are

TABLE I

CONFUSION MATRIX - FIVE TYPES

| | Seal | Clerical | Regular | Semi-cursive | Cursive |
|---|---|---|---|---|---|
| Seal | 92.87% | 0.00% | 0.00% | 0.18% | 6.95% |
| Clerical | 0.00% | 96.96% | 0.00% | 1.88% | 1.16% |
| Regular | 0.00% | 0.00% | 95.95% | 0.36% | 3.69% |
| Semi-cursive | 0.00% | 0.00% | 0.07% | 96.31% | 3.62% |
| Cursive | 0.00% | 0.00% | 0.00% | 0.29% | 99.71% |

TABLE II

CONFUSION MATRIX - FIVE STYLES OF REGULAR SCRIPT

| | Yan | Liu | Kai | Weibei | Qi |
|---|---|---|---|---|---|
| Yan | 98.80% | 0.22% | 0.00% | 0.69% | 0.29% |
| Liu | 0.44% | 93.81% | 0.29% | 3.00% | 2.46% |
| Kai | 0.04% | 5.17% | 89.87% | 1.81% | 3.11% |
| Weibei | 0.25% | 0.07% | 0.04% | 99.10% | 0.54% |
| Qi | 0.43% | 0.76% | 0.07% | 2.28% | 96.46% |

shown in Table III and Table IV. The shortest and the second shortest average distance are emphasized in grey colour.

The average accuracy is 96.36% for classifying five types and 95.61% for classifying five styles. Meanwhile, we have tested other classification approaches on the same training and testing samples. The results are shown in Table V. Three popular classifiers, Naive Bayes, Back Propagation Network and Adaptive Boosting achieve similar results. Adaptive Boosting performs a little better. As for shortest distance method, four distance metrics are tested. Mahalanobis distance performs much better than $L_1$ norm, $L_2$ norm and $L_\infty$ norm. Overall, shortest Mahalanobis distance is the best choice for classifying Chinese calligraphic types and styles.

Since the shorter the distance is, the higher the similarity is, there are some discoveries found through Table III and Table IV.

1) Regular script is most similar to semi-cursive script

TABLE III

DISTANCE - FIVE TYPES

| | Seal | Clerical | Regular | Semi-cursive | Cursive |
|---|---|---|---|---|---|
| Seal | 6.76 | 16.86 | 13.02 | 10.23 | 9.69 |
| Clerical | 14.77 | 6.82 | 16.83 | 13.03 | 14.96 |
| Regular | 16.80 | 14.69 | 6.72 | 10.12 | 10.13 |
| Semi-cursive | 13.72 | 12.74 | 11.93 | 6.80 | 8.97 |
| Cursive | 14.36 | 16.11 | 11.86 | 9.74 | 6.84 |

TABLE IV

DISTANCE - FIVE STYLES OF REGULAR SCRIPT

| | Yan | Liu | Kai | Weibei | Qi |
|---|---|---|---|---|---|
| Yan | 6.77 | 11.00 | 13.56 | 9.73 | 9.95 |
| Liu | 9.26 | 6.81 | 9.21 | 8.43 | 8.63 |
| Kai | 9.70 | 8.12 | 6.72 | 8.62 | 8.49 |
| Weibei | 9.53 | 10.03 | 11.00 | 6.83 | 8.96 |
| Qi | 9.24 | 9.03 | 9.75 | 8.48 | 6.72 |

TABLE V
COMPARISON OF DIFFERENT CLASSIFICATION APPROACHES

| | Naive Bayes | BP Network | AdaBoost | Distance metric | | | |
|---|---|---|---|---|---|---|---|
| | | | | $L_1$ norm | $L_2$ norm | $L_\infty$ norm | M-dist |
| Five types | 90.87% | 90.19% | 93.88% | 73.68% | 71.32% | 61.49% | 96.36% |
| Five styles | 80.25% | 79.89% | 83.08% | 52.59% | 51.32% | 52.32% | 95.61% |

since semi-cursive script is derived from regular script.

2) Semi-cursive script and cursive script are similar to each other. Implied in their names, this is apparent.

3) It is difficult to explain why seal script is similar to cursive script. The earliest form of cursive script [1], draft cursive *(zhangcao)*, is derived when seal script was gradually changing to clerical script. However, the cursive script used in this research is called modern cursive *(jincao)* which is derived from regular script and semi-cursive script. There is no direct relation between modern cursive and draft cursive. Except they are both difficult to recognize even for the Chinese, seal script and cursive script should not share any similarity. We will study this more in the future.

4) The styles of Yan Zhenqing, Liu Gongquan and Qi Gong are all similar to Weibei. Although claimed in history that they both learnt from Wang Xizhi (303 - 361), Yan Zhenqing and Liu Gongquan were certainly affected by Weibei since Tang Dynasty is right after Southern and Northern Dynasties when Weibei was popular. Being the famous calligraphist in new China, Qi Gong digests the styles of ancient calligraphists. Therefore, his style is similar to Yan, Liu and Weibei. As a consequence, to become a calligraphist, one should learn from many ancient calligraphists and styles. And Weibei could be a good choice for beginners.

## IV. DISCUSSIONS

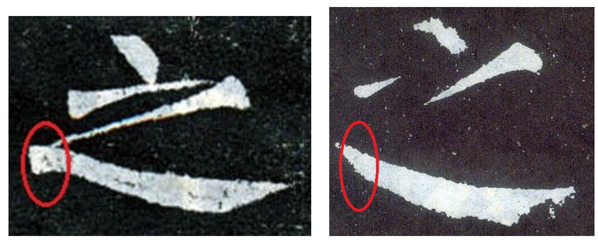
### A. Significance of Three Properties

In this paper, three properties of the contours are examined.

The directions of the normal lines on the contours describe the global trend of the characters. For instance, semi-cursive script and cursive script are much more dynamic than seal script, clerical script and regular script. Therefore, the distributions of the directions in semi-cursive script and cursive script spread in every direction uniformly, whereas the distributions of seal script, clerical script and regular script mainly focus in one direction (Fig. 5).

The curvature expresses the local detailed features of the characters, especially the attacks of the strokes. Mi Fu (1051 - 1107), one of the greatest calligraphists in Song Dynasty once wrote in the letter *My Friend (Wuyou Tie)*, "Also, there are no genuine works by Suo Jing. [You know by] looking at how the brush begins each stroke."[1] Therefore, the local features such as the attacks of the strokes are the key points to distinguish different calligraphists and judge the quality of the calligraphy work (Fig. 7). We define a new curvature vector which describes the direction of the curve besides the

Fig. 7. The attacks of the strokes.



(a) (b)

Fig. 8. Different writing habits of (a) Liu Gongquan and (b) Yan Zhenqing on the same stroke.

curvature scalar. Since different calligraphists have different writing habits, some strokes could be curved to the opposite direction (Fig. 8).

Besides the above two stroke features, the structure features also vary from different types and styles. Sun Guoting (648 - 703) once wrote in his masterpiece *Treatise on Calligraphy (Shupu)*, "A single dot determines the outline of a whole character; a single character sets the standard for a whole piece."[21] Here the character sets the standard for a whole piece by its structure. The structure may vary from different calligraphists due to various aesthetic standards.

In a word, the above three features should be combined together when we are classifying Chinese calligraphic types and styles. This consequence is also verified by experiments. The results are shown in Table VI. Combining three properties together achieves the best performance. The structure features affect both experiments while the stroke features mainly affect the classification of styles. We also test the performance using conventional curvature scalar instead of the newly defined curvature vector. Although the performance is only slightly better, the direction of curvature still conveys some significance.

### B. Potential Applications

There are several potential applications of this research.

1) We have developed an 8-DOF calligraphy robot (6-DOF robot arm, 1-DOF linear rail and 1-DOF paper conveying mechanism, as shown in Fig. 9). The style classification will be the first step for automatic mimicking by the robot.

2) The similarity measure can be used to discover the relationships between famous calligraphists and the evolution

TABLE VI

COMPARISON OF USING DIFFERENT FEATURES

| | Five types | Five styles |
|---|---|---|
| Without normal lines | 93.77% | 89.47% |
| Without curvature | 96.21% | 89.90% |
| Without structure | 89.87% | 88.06% |
| Curvature Scalars | 95.50% | 94.07% |
| Combined together | 96.36% | 95.61% |

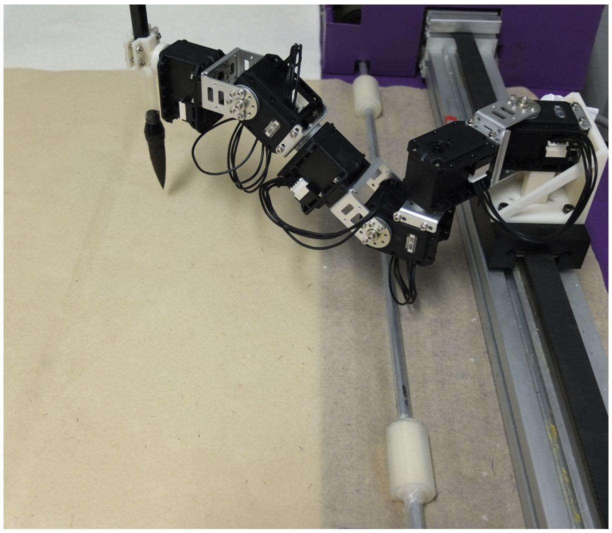


Fig. 9. Calligraphy robot with 6-DOF robot arm, 1-DOF linear rail and 1-DOF paper conveying mechanism.

of calligraphy through the history.

3) The classification of styles can be used to verify the masterpieces of great calligraphists and detect fakes.

4) The parametric representation of characters can be used for defining aesthetic standards of Chinese calligraphy. This is very helpful for self-study.

5) The parametric representation can also be used to synthesize Chinese calligraphy. Then we can generate different styles of Chinese calligraphy automatically.

## V. CONCLUSIONS

In this paper, we first propose a parametric representation of calligraphic characters. Three significant types of properties of the characters are observed. The first one is the direction of normal lines on the contours. This describes the global trend of the characters. The second one is the curvature vector of the contours which reflects the local features the characters. The third are the structure features of the characters which varies from different calligraphists due to various aesthetic standards. Then Mahalanobis distance is chosen for similarity measure and classification. Some interesting phenomena are discovered through similarity measure. The performance is excellent for classification comparing with other methods. The average accuracies of classifying types and styles are 96.36% and 95.61% respectively. Moreover, combining three properties achieves better results than using the properties individually.

As a consequence, this parametric representation describes calligraphic characters successfully. This representation also has some potential applications, such as enabling the calligraphy robot to automatically mimicking the style, defining aesthetic grading standards for calligraphy and synthesizing calligraphy.

## VI. ACKNOWLEDGMENTS

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