Chinese Calligraphy Brushstroke Analysis: Mi Fu's Style Compared

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EE 292F: Image Processing of Fine Art
June 2, 2021

Fig. 1. (a) The five main styles of Chinese calligraphy, reproduced from Xintong Chen [1]. (b) An excerpt of *Poem Written in a Boat on the Wu River* by Mi Fu, reproduced from The Metropolitan Museum of Art. [2]

***Abstract*—A feature extraction algorithm is applied to *Poem Written in a Boat on the Wu River* by Mi Fu and other works of Chinese calligraphy. Features such as contour angle statistics, curvature statistics, and mass distribution are considered. A Principal Component Analysis (PCA) reveals interpretable trends in the features that differ between each art work. A Linear Discriminant Analysis classifier is trained and tested on the dataset with a moderate accuracy of 68.5%. Potential improvements to the dataset and analysis are discussed.**

***Index Terms*—Chinese calligraphy, brushstroke analysis, contour analysis, feature extraction.**

I. Introduction

A. Calligraphy Basics

There are 5 main styles of Chinese calligraphy (illustrated in Fig. 1a):

- Seal script
- Clerical script
- Regular script
- Running or semi-cursive script
- Cursive script

The latter 3 styles (regular, running, and cursive scripts) are most relevant to the works considered in this project, since seal and clerical scripts were primarily used in works which predate those considered here. Regular, running and cursive scripts differ essentially in how "free flowing" they are compared to print characters. Regular character is most similar to print, and can be identified by its mostly straight lines joined by sharp corners. Cursive script is least similar to print, and is characterized by smooth curves. Often times, artistic liberties are taken in repositioning strokes away from their typical locations, or joining multiple strokes together into a single, flowing curved stroke. Running script, also known as semi-cursive, lies somewhere between regular and cursive scripts, incorportaing both straight lines and smooth curves. Each artist may combine characteristics of one or more of these 3 styles, as well as incorporate elements of their own style. Furthermore, an artist's style may vary from work to work, especially in the context of an artist's growth and development over the course of their career.

B. Mi Fu and his peers

Mi Fu was a renowned Chinese calligrapher who lived during the Song Dynasty from 1051–1107. But before he became a master calligrapher himself, he was primarly a connoisseur who collected and studies the works of the old masters. One such master who Mi Fu drew inspiration from was Wang XiZhi. Born during the Qin dynasty in the year 303, Wang XiZhi is widely regarded as the greatest and most influential Chinese calligrapher of all time.

It was only after mastering the skills required to emulate the likes of Wang XiZhi that Mi Fu began to explore and develop his own unique style. Perhaps Mi Fu's best known work is the incredible masterpiece *Poem Written in a Boat on the Wu River*, an excerpt of which is shown in Fig. 1b. This work was executed on a long scroll in large, beautifully-flowing cursive characters. The later artist Sun K'uang praised this work for its marvelous lightness, much like "a sail against the wind or a horse in battle; maked by both a sense of composure and exhiliration." Despite the fact that instruction in Wang XiZhi's style was common during his time, Mi Fu was "proud that his own calligraphy lacked the qualities associated with [Wang XiZhi]'s works, which were essentially popular in their appeal." Indeed, he was able to "avoid its common features while valuing the true elegance and style of the [Qin] masters" [3]. It is thus clear that Mi Fu's earlier and later works may be distinguished by their stylistic similarity to works in the style of Wang XiZhi.

In addition to learning from the old masters and developing his own style, Mi Fu was also influenced by his contemporaries. Su Shi (1037–1101) was a contemporary and good

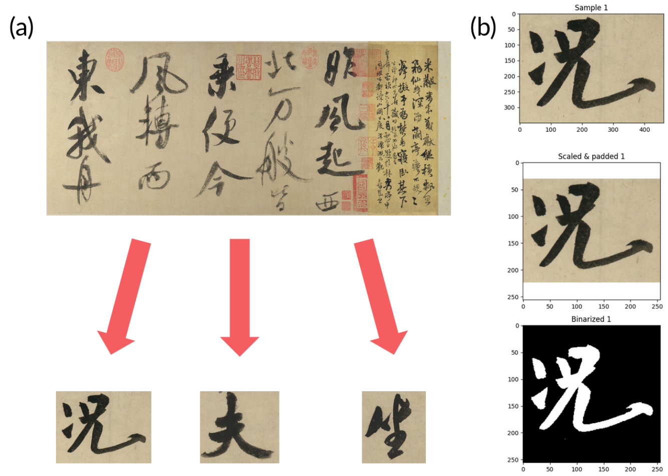

Fig. 2. (a) Data collection by screenshotting individual characters. (b) Preprocessing steps applied to a single character.

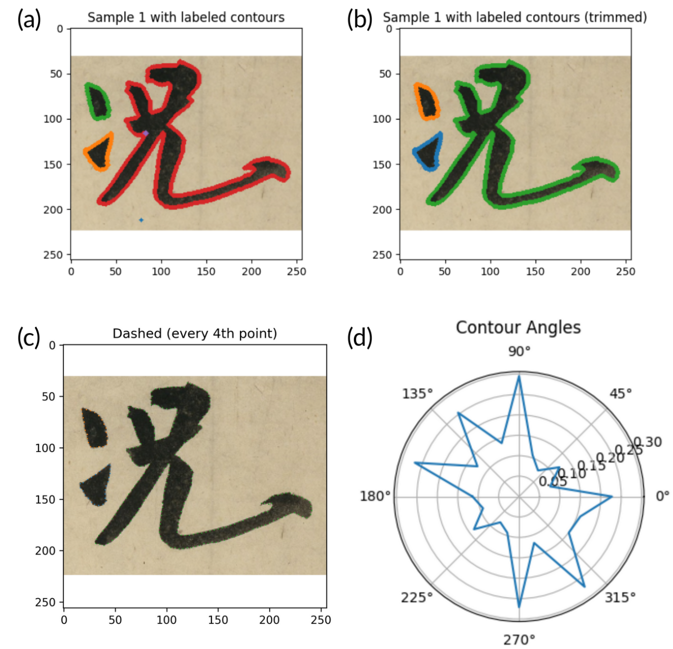

Fig. 3. (a) Unfiltered contours returned by OpenCV. (b) Small contours (< 10 points) removed. (c) Dashed contour by taking every 4th point. (d) PMF of contour angles for a single character.

friend of Mi Fu's. Like Mi Fu, Su Shi is also considered as one of the most important calligraphers in Chinese history [4]. Emperor Huizong (1082–1135), despite his failings as a ruler, was a talented painter and calligrapher. Mi Fu served in Huizong's court as a curator of calligraphy [5]. These contemporaries serve as additional references for comparing and contrasting Mi Fu's style.

Given the multitude of stylistic influences and significant changes in style over Mi Fu's career, an important question pertaining to the technical analysis of Chinese calligraphy is whether any quantifiable features can be used to distinguish between the different styles of each artist or work, and if said features can be interpreted in a humanly-understandable manner.

II. Methods

I performed the following data processing and analysis with the aid of the following Python packages:

- numpy [6]
- matplotlib [7]
- scikit-image [8]
- OpenCV [9]
- Plotly [10]
- scikit-learn [11]

A. Data Collection

I downloaded high resolution images of each calligraphy work from their respective sources. I then performed manual character segmentation using the Flameshot screenshot tool. I ignored any characters which were too small, too porous, or occluded by red ink from a stone seal.

B. Preprocessing

I applied the following preprocessing steps to each image of a character: (1) scale and pad the image to 256×256 pixels and (2) apply a threshold of 50% to produce a binarized image.

C. Feature Extraction

The algorithm for extracting features from each calligraphic characters is summarized below, and is based on a method by Sun et al. [12] with some modifications.

1) Contour Angle Statistics: The contours of each binarized image was extracted using OpenCV's `findContours()` function. This produced one or more ordered lists of co-ordinates representing the pixels in each contour. Before computing the angles of the vectors connecting each point to the next, every 4th point was taken from the list of points while the rest were discarded, thus producing a dashed contour. This step mitigates the quantization error in the angle statistics due to the discrete pixel coordinates (in the extreme case where every point in a contour is kept, the angle between each point and the next can only be a multiple of 45°).

For each dashed contour with N points, the contour angles were calculated as

$$\theta_i = \begin{cases} \text{atan2}\left(\frac{y_i - y_{i-1}}{x_i - x_{i-1}}\right) & i \in \{1, \dots, N-1\} \\ 0 & i = 0 \end{cases}$$

for $i \in \{0, \dots, N-1\}$. Note that in this work, the angle of the vector joining each point to the next is used, rather than the vector normal to the contour as in Sun et al.

The angles for all the contours in a character were aggregated into a single list. The numpy `histogram()` function was used to bin the angles into 20 uniformly-sized angle ranges from $[-\pi, \pi)$, thus producing a Probability Mass Function (PMF) for the contour angle statistics for a single character. The PMFs for all of the characters belonging to a class were then aggregated into a single 20-bin histogram (which itself is not necessearily a PMF, since its weights may not sum to 1).

2) Curvature Statistics: Unlike Sun et al., I simply used the finite differences between subsequent contour angles as an approximation for the curvature. The curvatures were then used to populate a 20 bin histogram, in a manner similar to the contour angle statistics.

3) Mass Distribution: Since the standard form of all Chinese characters is approximately square in proportion, the X and Y mass distributions can be used to quantify the tendency of an artist to write characters taller or wider than normal. These metrics were found by taking the normalized count of non-zero pixels in the binarized image, and then computing the first and second moments of the mass distribution.

4) 46-dim Feature Vector: As in Sun et al., the 20-dim contour angle histogram, 20-dim curvature histogram, and 6 mass distribution features were combined into a 46-dim feature vector for each class.

D. Principal Component Analysis

After computing the 46-dim feature vectors for the entire dataset, the dataset was visualized by means of a Principal Component Analysis (`sklearn.decomposition.PCA`) to reduce the dimensionality of the data to 2 dimensions: Principal Component 1 (PC 1) and Principal Component 2 (PC 2).

E. Classifier

As a simple test of how distinguishable each class was, the dataset was divided into a training set and test set. A variety of simple classifiers, included in `sklearn`, were trained on the training set and then evaluated on the test set.

III. Results

The following art works were analyzed:

- Mi Fu's *Poem Written in a Boat on the Wu River* [2]
- Emperor Huizong's *Finches and bamboo* [13]
- Su Shi's *Inscription of Hanshi* [14]
- Wang XiZhi's *On the Seventeenth Day* [15]
- Mi Fu's *On Cursive Calligraphy* [16]

Each art work was treated as a unique class for the purpose of visualization, training, and classification, with each character within an art work representing one sample of the class.

A. Contour Angle and Curvature Statistics

The contour angle and curvature histograms for each of the 5 classes is shown in Fig. 4.

It can be seen that all of the classes have a contour angle histogram in the shape of an 8 pointed star, which is to be expected because Chinese characters are composed primarily of strokes in directions which are multiples of 45°. However, the relative strengths of each star point varies from class to class. For example, although all of the classes have their strongest components at 90° (straight up) and 270° (straight down), in Mi Fu's *Poem Written in a Boat on the Wu River* the other angles are much weaker, whereas in the other classes the other angles are only slightly weaker. This indicates that

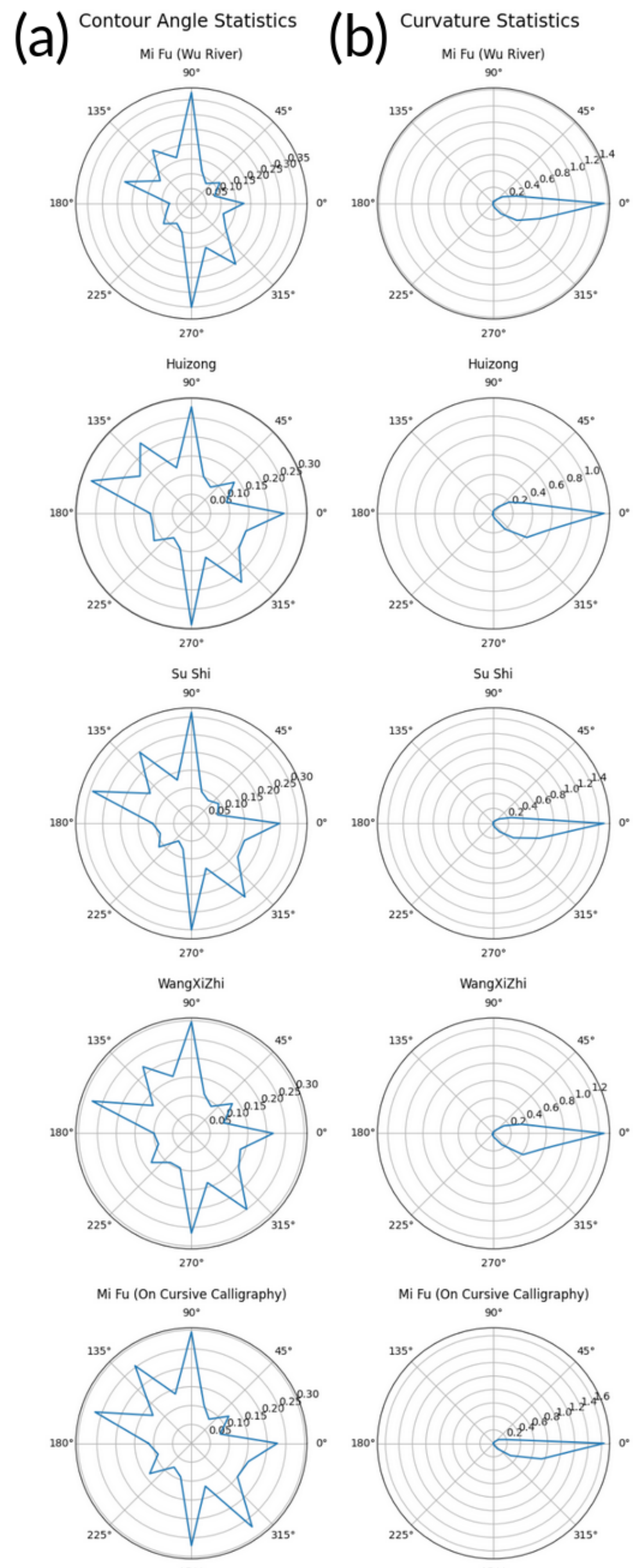

Fig. 4. (a) Contour angle statistics for each class. (b) Curvature statistics for each class.

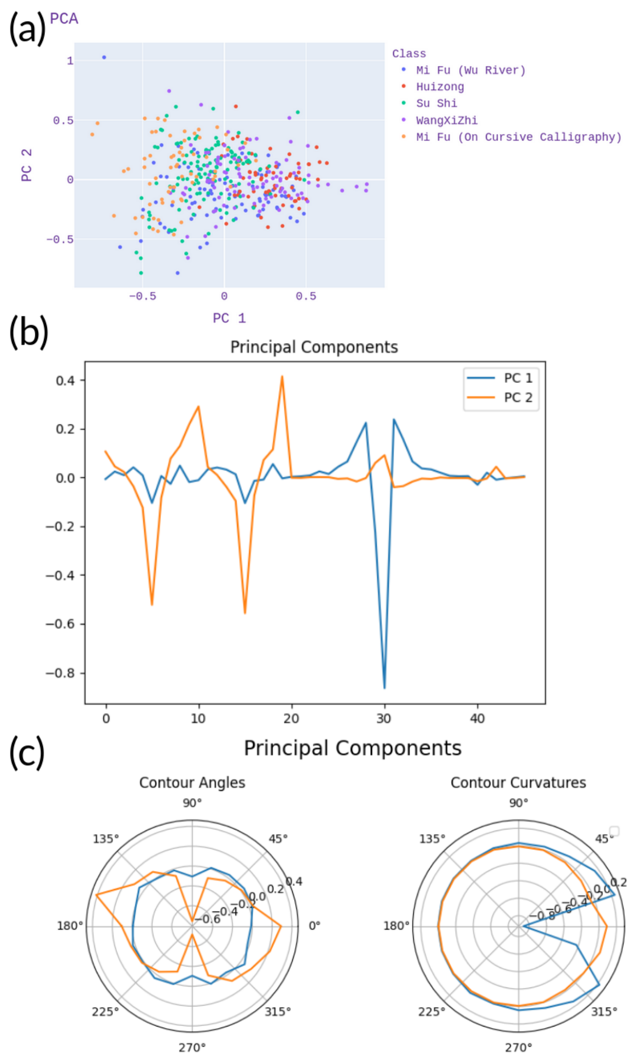

Fig. 5. (a) Principal Component Analysis (PCA) of the 46-dim feature vectors computed over the entire dataset. (b) Plot of the relative contributions of each of the 46 dimensions to each principal component. (c) Polar plot of the relative contributions of each contour angle and curvature to each principal component.

in *Wu River*, Mi Fu had a stronger preference for vertical lines compared to the other works examined here.

The curvature histograms also look fairly similar across all 5 classes with a pointed lobe centered at 0°, but the width of the lobe varies across each class. A sharp and narrow lobe indicates a stronger preference for straight lines, whereas a broader lobe indicates a more significant preference for curved lines.

B. *Principal Component Analysis*

The results of the Principal Component Analysis are shown in Fig. 5.

The scatter plot of the data points with respect to the principal components shows that the 5 classes are not cleanly separable in the space of the 2 principal components.

Fig. 5b shows the relative contributions of each of the 46 dimensions to each principal component. It can be seen that PC 2 has strong peaks in the first 20 dimensions, corresponding to the contour angle histogram, and PC 1 has strong peaks in the next 20 dimensions, corresponding to the curvature histogram. This is more clearly shown in Fig. 5, which visualizes the first 20 dimensions and the next 20 dimensions on a polar plot, respectively indicating the relative contributions of each contour angle and curvature to the principal components.

The significance of the principal components may be interpreted as follows:

- PC 1 measures how straight or curved the contours are within a character. A character with more straight lines will have a smaller PC 1, whereas a character with more curves will have a larger PC 1.
- PC 2 measures the preference for contours pointing in approximately the 160° and 340° directions, relative to the preference for contours pointing in the vertical directions. Recall that the star points in these directions showed large variation across the classes in Fig. 4. A character with more lines pointing along 160° and 340° will have a larger PC 2, whereas a character with more vertical lines will have a smaller PC 2.

The PCA graphs can also be visualized with only 2 classes at a time. A comparative visualization of Mi Fu's *Wu River* versus the other classes is shown in Fig. 6. A qualitative interpretation is given as follows:

- *Wu River* has, on average, a smaller PC 1 than Huizong's work. This suggests that *Wu River* has more straight lines than Huizong's work.
- Again, *Wu River* has a smaller PC 1 than Wang XiZhi's work on average, but the difference is less pronounced than it was for Huizong.
- *Wu River* has, on average, a smaller PC 2 than Su Shi's work. This suggests that *Wu River* has more vertical lines, while Su Shi's work has more lines along 160° and 340°.
- *Wu River* has, on average, a larger PC 1 than *On Cursive Calligraphy*. This suggests that *On Cursive Calligraphy* has even more straight lines than *Wu River*.

C. *Classification*

The accuracy results for each classifier are shown in Fig. 7. The maximum classifcation accuracy of 68.5% was achieved with the Linear Discriminant Analysis classifier. Although far from perfect, this classifier's accuracy is much better than random guessing (which would on average yield 20% accuracy for the 5 classes). This suggests that this classifier is able to identify unique trends between the 5 classes just by looking at the 46-dim features used in this project.

IV. Discussion

Even with a limited dataset consisting of only 1 or 2 works from each artist, noticeable differences were identified between each class. These differences allowed a classifier to distinguish between the 5 classes with moderate accuracy. The shapes of the principal components when plotted in a polar graph in the contour angle and curvature domains provide a level of interpretability to the trends used to distinguish between each class.

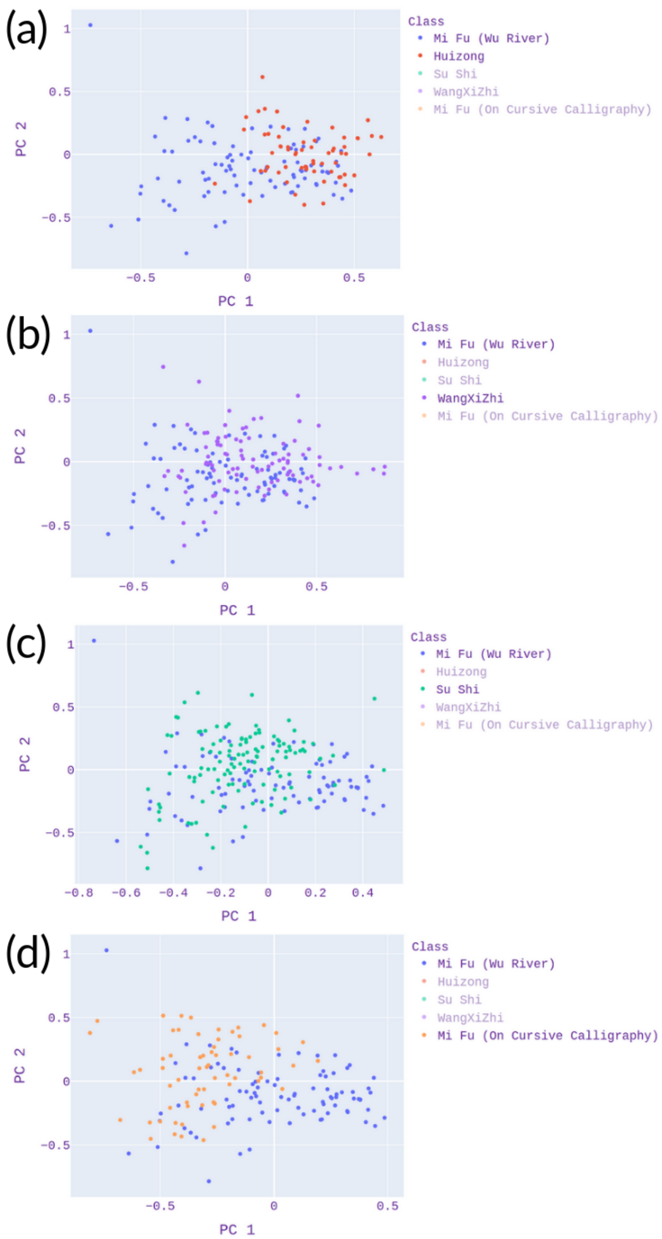

Fig. 6. Visual comparison, in terms of principal components, of Mi Fu's *Poem Written on a Boat in the Wu River* versus (a) Huizong's *Bamboo and finches*, (b) Wang Xizhi's *On the Seventeenth Day*, (c) Su Shi's *Inscription of Hanshi*, and (d) Mi Fu's *On Cursive Calligraphy*.

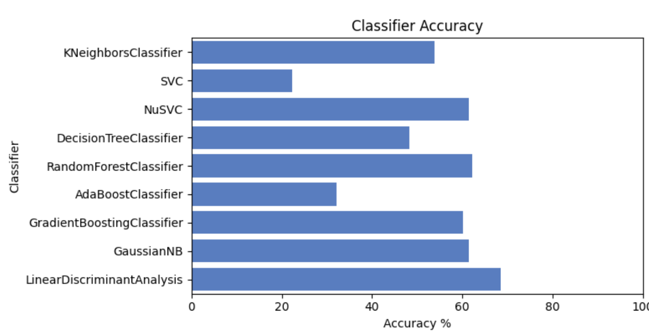

Fig. 7. Classification accuracy on the test set for each classification which was trained on the training set.

Each class appears as a cluster of points in the PCA graph, with each character represented by a point. Although the center of each cluster can be seen to be unique for each class, there is a large spread across the points within each cluster. Therefore, the points from different clusters overlap, which makes it challenging for a classifier to distinguish between classes on a single point basis. An improved classifier might use statistical measures, such as mean and covariance, drawn from a group of points, in order to classify the group as a whole, rather than classifying each point independently. In other words, rather than trying to figure out which artist drew a single character, the classifier would look at many or all characters within a work, and then try to figure out which artist executed the work. However, this would require a larger dataset that includes multiple works for each artist, which is out of scope for this project.

An important limitation of this analysis is that the statistics of the contour angles and curvatures may be skewed by the presence of certain characters in one class but not in another class, since certain characters inherently have more straight lines or curves than other characters. Therefore, an apples-to-apples comparison should have a set of equivalent characters in each class, with each the contribution of each character to the class's feature vector being weighted by the frequency of the character. However, the limited number of characters present in the works considered here precludes the possibility of finding many characters with stroke diversity and common to all the classes. As such, a comparison of one or two simple characters which are present in all of the classes would have very limitied utility. A solution to this problem would be to include more works by each artist, thus increasing the likelihood of finding multiple characters used by all the artists.

V. Conclusion

In conclusion, the masterful work *Poem Written in a Boat on the Wu River* by Mi Fu was compared with other famous works of Chinese calligraphy by extracting features such as contour angle statistics, curvature statistics, and mass distribution. A Principal Component Analysis revealed interpretable trends in the preferred angles and amount of curvature that could be used to distinguish each class, and a classifier was able to distinguish between the classes with moderate accuracy. Therefore, the technique described in this project shows promise that it may be extended to a more rigorous analysis with a larger dataset.

Acknowledgment

The author would like to thank David Stork for his advice and guidance with this project.

Code

The code and source images used in this project are available in the Github repository at https://github.com/wlmeng11/ee292fproject.

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