*Design Studies and Intelligence Engineering*
*L.C. Jain et al. (Eds.)*

*doi:10.3233/FAIA231510*

# Computational Interpretation of the Difference Between the 5 Writing Styles of Chinese Calligraphy

Yangzi FU[a], Ruimin LYU[a,1], Guoying YANG[b], Baixi XING[c] and Lekai ZHANG[c]
[a] *School of Artificial Intelligence and Computer Science, Jiangnan University*
[b] *Goldsmiths College, University of London*
[c] *Zhejiang University of Technology*

**Abstract.** Visual art works contain a lot of tacit knowledge that is difficult to accurately express in words. If they are expressed quantitatively in a computable form, it helps to apply this part of tacit knowledge to a wider field. Chinese calligraphy style carriers have tacit knowledge of Chinese cultural characteristics, which our research quantitatively interprets. In our study, 33 interpretable features were designed and summarized, and the random forest classification was adopted. As a result, we found that only 8 computational features with concise mathematic form were needed to interpret the differences between the five writing styles of Chinese calligraphy with an accuracy of 66.7 %. Based on these features and the evaluation of five calligraphy styles, we find that some combination of features can cause people's perception of a particular style and establish the relationship between objective features and people's subjective feelings. The results can provide inspiration for the creation of artists and designers, and have potential applications in the fields of psychology, design, and human-computer interaction.

**Keywords.** Visual perception, Chinese calligraphy, Interpretable features, Computational aesthetics

## 1. Introduction

Language cannot fully capture all knowledge, and many researchers argue that artistic works often contain implicit knowledge that far surpasses the explicit knowledge described in language[1]. This is particularly true for the vast reservoir of visual knowledge embedded within visual art, which remains largely untapped and underutilized[2]. Visual art serves as a crucial medium for recording the perceptual facets of these concepts. Human society has evolved numerous forms of visual art, such as sculpture, painting, animation, calligraphy, and more. These art forms coexist in an irreplaceable ecological balance due to their unique strengths in capturing and expressing visual knowledge. How to transform unique visual knowledge from a culturally specific art category such as calligraphy into an interpretable quantitative form is the main thrust of this study.

Chinese calligraphy contains a rich reservoir of visual knowledge and appreciation materials that have evolved and accumulated throughout the history of Chinese cultural

[1] Corresponding Author: Ruimin Lyu, ruiminlyu@jiangnan.edu.cn

development, and some scholars believe that it contains the unique gene of Chinese culture[3]. The usability of calligraphy has been validated in certain studies[4], If we could transform this knowledge from experiential expression into a quantitative form, it may allow this knowledge to transcend cultural barriers and be applied more widely.

The development of emerging fields such as empirical aesthetics, computational aesthetics, and self-explanatory models has brought about possibilities for exploring visual knowledge within various art forms. Existing research categories include: color composition[5], low-level visual features[6], visual complexity[7], web design[8], packaging design[9].

In recent years, machine learning plays a very important role in the quantitative research of calligraphy style. However, the existing work mainly attempts to train artificial intelligence models to achieve style classifications[10][11], rather than explaining calligraphy styles. Only a few studies have discussed the interpretability of calligraphy style. Sun et al. [12] proposed a calligraphy scoring model, SRAFE, which combines calligraphy aesthetic features with deep learning and discusses the correlation between these aesthetic features and subjective human aesthetics. Rongju Sun et al. [13] proposed certain aesthetic features based on classical calligraphy rules, unveiling the relationship between these aesthetic features and human aesthetic preferences. Kaixin Han et al. [14] proposed some computational features related to the visual complexity of calligraphy and discusses the connection between visual complexity in calligraphy and subjective human aesthetic perceptions. However, these studies did not delve into specific stylistic impressions within calligraphy. Kaixin Han et al. [15] introduced the stylistic impressions of squares and circles in calligraphy, explaining how the objective features of calligraphy fonts impact human perceptions of squares and circles' aesthetic appreciation. Based on the above-mentioned research, it is evident that establishing a relationship between interpretable features and calligraphy styles is feasible, though relevant research remains scarce.

In view of this, this study aims to provide a quantitative explanation of calligraphy style, rather than improving the style discrimination ability of AI models. As a result, the following two contributions have been made:

- We built a new calligraphy database, which contains five styles of calligraphy, and extracted 1600 characters from 130 calligraphy works. Then we extract 33 interpretable features from morphology, structure, and contour, which cover the features proposed by previous studies, and we propose some new ones.
- We examined the interpretability of these features for five calligraphy styles using random forest classification and found that only eight simple, intuitive interpretable features, such as aspect ratio, contour entropy, etc., were needed to interpret the differences between the five styles with an accuracy of 66.7%. In the end, we delved into the relationship between calligraphy styles and these features, uncovering that certain combinations of features can influence how people perceive specific styles. This not only validated existing calligraphy knowledge but also established a connection between objective features and individuals' subjective aesthetic experiences.

## 2. Dataset For Experiment

This experiment selected a total of 130 works, including five basic calligraphy styles: seal script, official script, regular script, running script, and cursive script, and then randomly selected about 6 to 18 characters from each work as original materials.

Before extracting features, it is necessary to perform data normalization on the materials. Firstly, we convert the artwork images into binary format, which results in black characters on a white background. Many historical books contain varying levels of noise. To address this issue, we first apply median blur to reduce some of the noise. After the initial computer-based processing, we proceed with manual adjustments.

To ensure uniform character size, we use the outer rectangle of the font to split the characters, scale the longer sides of the split character image to 200 pixels equally, and finally align the center of each word to a 260×260 canvas.The processed character samples are shown in Figure 1.

**Figure 1.** Processed character samples

## 3. Feature Extraction

In this section, based on the aesthetics of calligraphy, we have summarized 33 interpretable objective features from three perspectives: morphological features, structural features, and contour features. Subsequently, we applied these features to the character materials processed in the previous section. Finally, we calculated the average feature value of individual characters in each artwork to describe the characteristics of each piece.

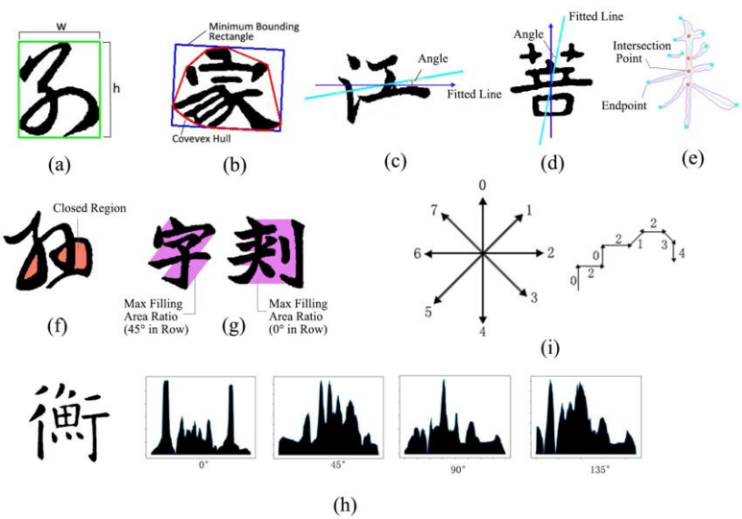


**Figure 2.** Illustrations of some features

### 3.1. Morphological features

This section presents several fundamental morphological features derived from convex hull, skeleton, and other basic geometric shapes.

f1: Aspect ratio. It is used to describe the width and narrowness of a character, as shown in Figure 2(a), where w represents the width of the character's bounding rectangle, and h represents the height of the character's bounding rectangle. The calculation method for f1 is as Eq. (1).

$$f1 = w / h \tag{1}$$

f2: Rectangularity. It is used to describe the degree of approximation between a character and a rectangle. As shown in Figure 2(b), we introduce the convex hull to describe the basic shape of the character. $P_{con}$ represents the perimeter of the character's convex hull, and $P_{min}$ represents the perimeter of the character's minimum bounding rectangle. The definition of f2 is as Eq. (2).

$$f2 = P_{con} / P_{min} \tag{2}$$

f3: Roundness. This metric assesses how closely a character's convex hull approximates a circle, with C denoting the character's area. The calculation formula is as Eq. (3).

$$f3 = 4\pi C / P_{con} \tag{3}$$

f4: Eccentricity. It is used to calculate the eccentricity of the character's minimum bounding rectangle. Eccentricity values range from 0 to 1, with 0 indicating the minimum eccentricity for a circle, and 1 indicating the maximum eccentricity for a straight line. Here, a represents the semi-major axis, b represents the semi-minor axis, and the formula for calculating eccentricity is as Eq. (4).

$$f4 = \sqrt{1 - (b / a)^2} \tag{4}$$

f5, f6: The inclination angle of the fitted line and slope, which describes the character's tilt degree. We employ the least squares method to calculate the optimal fitted line, where k represents the slope of the line and b is the intercept. The Angle denotes the minimum angle between the fitted line and the x-axis, defined as Eq. (5).

$$\text{Angle} = |180 \sec k \ / \pi| \tag{5}$$

If Angle is less than 45°, f5 measures the angle between the fitted line and the x-axis, as shown in Figure 2(c). However, when Angle exceeds 45°, f5 determines the angle between the fitted line and the y-axis, as illustrated in Figure 4(d). The definitions of f5 and f6 are as Eqs. (6) and (7).

$$f5 = \begin{cases} \text{Angle}, & \text{Angle} < 45 \\ |90 - \text{Angle}|, & \text{Angle} \geq 45 \end{cases} \tag{6}$$

$$f6 = k / w \tag{7}$$

f7, f8: Skeleton Endpoint Count and Intersection Point Count. As shown in Figure 2(e), the font's skeleton is extracted, removing short skeleton branches. Then, the skeleton is traversed, with endpoint pixels being defined as black pixels with only one adjacent black pixel, and intersection pixels as black pixels with three adjacent black pixels. The counts of these endpoints and intersection points are recorded.

f9, f10: Average Width and Variance. The average width and thickness variation of strokes can be obtained from the medial axis of the character.

f11, f12: The Count and Area Proportion of Enclosed Regions. While writing characters, a multitude of enclosed areas is generated, as shown in Figure 2(f). We quantify the number of these enclosed regions within the character as f11. Furthermore, f12 provides insights into the size of these areas, where Cn signifies the area of enclosed regions, and A represents the convex hull area. This is defined as Eq. (8).

$$f12 = Cn / A \tag{8}$$

### *3.2. Structure features*

From the perspective of calligraphy aesthetics, we introduce some structural features.

f13: Space Utilization. It describes the relationship between ink usage and the space occupied by the font. C represents the character area, and it is defined as Eq. (9).

$$f13 = C / A \tag{9}$$

f14~f17: Pixel Projection Variances. Illustrated in Figure 2(h), these metrics provide insights into the stroke distribution characteristics of the character. They compute the variances of the character's vertical projections at 0°, 45°, 90°, and 135° angles, respectively.

f18~f22: Ink Distribution. Create a new coordinate system with the center of the convex hull as the origin. Then, calculate the convex hull area to ink ratio for the four quadrants. f22 is the variance of f18~f21.

f23: Fitted Line Segmentation Area Ratio. The fitted line divides the convex hull into two regions, calculating the ratio between the smaller area Cmin and the larger area Cmax.

$$f23 = Cmin / Cmax \tag{10}$$

f24, f25: Maximum GAP Proportion and Average GAP Proportion. Utilizing a straight-line scan through the character, it traverses the character and fills the spaces between characters, as shown in Figure 2(g). These areas are instrumental in characterizing the spacing between characters. *gap(i)* represents the gap when characters are scanned with a line at an angle of i degrees.

$$f24 = \max\{\mathrm{gap(i)}/\mathrm{gap(i)} + \mathrm{C}\}, i=1,2,3,....,90 \quad (11)$$

$$f25 = \sum_{i=0}^{90} \mathrm{gap(i)}/\mathrm{gap(i)} + \mathrm{C} \;/\; 90 \quad (12)$$

f26~f31: Elastic Mesh Layout. To achieve this, we uniformly divide the ink strokes of the font into four equal parts in both the vertical and horizontal directions using four lines, and then calculate the relative positions of these four lines.

### *3.3. Contour Features*

This section extracts some features from the outline of the character.

f32: Corner Count. Utilizing the Shi-Tomasi algorithm, we detect and quantify the sharper regions within the character contours.

f33: Contour Entropy. Illustrated in Figure 2(i), we utilize Freeman encoding to traverse the font's contour, generating a sequence based on the relative positions of the current pixel and the next pixel, and subsequently calculate its contour information entropy.

## 4. Feature Selection

To validate the interpretability of font styles, we employed these interpretable features to classify five calligraphy styles (Seal Script, Clerical Script, Regular Script, Running Script, and Cursive Script). We initially standardized the data through z-score normalization and used 90% of the original dataset as our training set. We compared the performance of various classifiers and found that the random forest classifier had the best performance, with an accuracy of 73.6% on the five-fold cross-validation model, indicating that these features we introduced could distinguish the five calligraphy styles to a certain extent.

Table 1 lists the features and meanings that are also in the top ten of MeanDecreaseAccuracy and MeanDecreaseGini, and a total of 8 features are screened. The random forest classifier trained on only eight features can achieve 66.7% accuracy on the five-fold cross-validation model, indicating that these eight features can interpret most of the style differences.

**Table 1.** Eight features that influence the differences in calligraphy styles.

| Feature | Definitions | MeanDecreaseAccuracy | MeanDecreaseGini |
|---|---|---|---|
| f1 | Aspect ratio | 26.90 | 9.86 |
| f16 | Pixel projection variance at 90° | 19.48 | 5.72 |
| f33 | Contour entropy | 17.77 | 6.04 |
| f7 | Skeleton endpoint count | 17.31 | 4.96 |
| f32 | Corner count | 11.01 | 3.59 |
| f11 | Area proportion of enclosed regions | 12.27 | 3.76 |
| f12 | The count of enclosed regions | 5.38 | 2.22 |
| f5 | The inclination angle of the fitted line | 10.48 | 3.89 |

## 5. Analysis

Based on the eight interpretable features selected, we correlate existing calligraphic evaluations to these features and discuss the characteristics of each style and the differences between styles.

### *5.1. Analysis of the characteristics of five calligraphy styles*

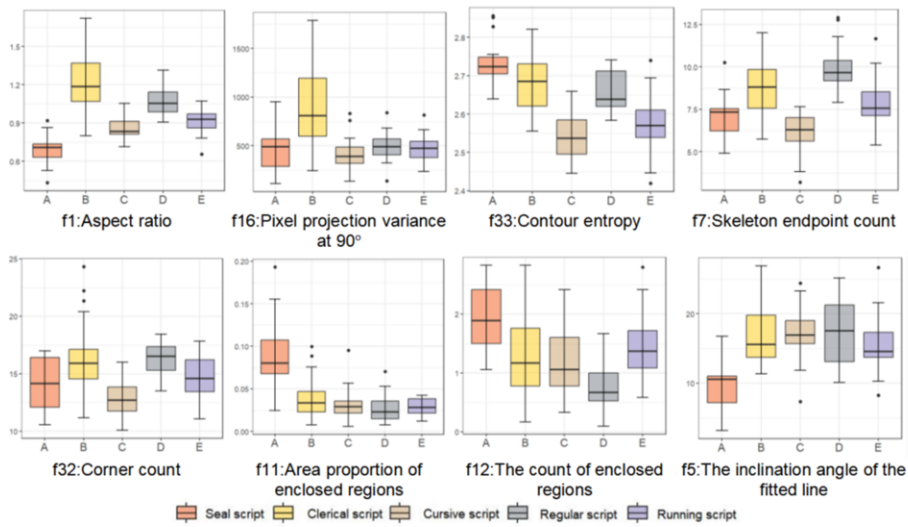


**Figure 3.** The presentation of how the five calligraphy styles are distributed across various features. A corresponds to Seal Script, B to Clerical Script, C to Cursive Script, D to Regular Script, and E to Running Script.

The distribution of the five calligraphy styles in different characteristics is shown in Figure 3.Seal Script exhibits higher values in features f33, f11, and f12, suggesting greater shape complexity with strokes often concealing their endpoints, forming closed areas. In contrast, features f1 and f5 have lower values, indicating Seal Script's characteristic slender shapes and even ink distribution, aligning with its description of elongated forms, uniform lines, and symmetrical complexity.

Clerical Script displays elevated values in features f1, f16, and f33, indicating its characteristic wide characters with a substantial variation in the 90° projection and a high level of complexity in its outlines. This aligns with the typical evaluation of Clerical Script, known for its broad, flat characters, emphasis on horizontal strokes, and diverse stroke patterns.

Cursive Script typically exhibits lower values in features f33, f7, and f32, suggesting fonts in this style tend to have simpler outline shapes with fewer endpoints and corners. This aligns with the general impression of Cursive Script, characterized by its fluidity, abundance of connected strokes, and a high degree of simplification.

In Regular Script, the values of feature f1 tend to cluster around 1. Additionally, there are elevated values for features f7 and f32, while feature f12 exhibits lower values. This indicates that fonts in this style tend to have square and well-defined shapes, with more endpoints and corners and fewer enclosed areas. This corresponds to the typical view of Regular Script, known for its regular, clear characters with distinct edges.

Running Script, which is a type of font that falls between Regular Script and Cursive Script. Our results indicate that the majority of feature values for Running Script are distributed between those of Regular Script and Cursive Script.

### 5.2. *Analysis of the characteristics of five calligraphy styles*

To further discuss the unique characteristics of each calligraphy style, we paired them up and used random forest classification to distinguish their characteristics. We then visualized these differences in Figure 4.


**Figure 4.** The visualization of feature importance obtained through random forest classification for each pair of script styles, with feature importance determined by MeanDecreaseAccuracy. A corresponds to Seal Script, B to Clerical Script, C to Cursive Script, D to Regular Script, and E to Running Script. Accuracy represents the classification accuracy obtained after five-fold cross-validation

Seal Script (A) showed distinct differences in features f1, f11, and f5 when compared to other styles, highlighting its slender character shapes, balanced structures, and consistent line thickness. Clerical Script (B) stood out from most other styles in features f1 and f16, emphasizing its elongated character shapes and exaggerated horizontal strokes. Cursive Script (C) differed in features f33 and f7 from most other styles, underscoring its simplified character shapes. Regular Script (D) showed significant differences in feature f7, primarily characterized by clear and distinct brushstrokes. Semi-Cursive Script (E) did not display pronounced feature differences when compared to other styles. However, Cursive Script and Running Script (CE) had similar features, resulting in lower accuracy in binary classification, primarily differing in feature f32.

Traditionally, people describe calligraphy features using language, but our research provides strong, objective evidence for distinguishing the unique traits of different calligraphy styles.

## 6. Discussion

Figures 3 and Figures 4 illustrate the unique characteristics of each script style based on these objective features. These five script styles have well-established guidelines for style appreciation. By mapping these features to how people perceive calligraphy styles, we can establish a link between interpretable features and individuals' subjective style perception. The corresponding relationships are explained as follows.

In terms of subjective evaluations, Seal Script is characterized by elongated character forms, smooth and consistent strokes, and a balanced, stable structure. It conveys a sense of refinement and solemnity, appealing to a careful and serious impression. This can be interpreted by the high values on features f33, f11, and f12, along with low values on features f1, f7, and f5 is easy to cause people's delicate and solemn style perception.

The Clerical Script is flat and criss-crossed, emphasizing horizontal stroke fluctuations. It conveys a natural and somewhat casual impression with a rustic quality. This may suggest that patterns with high values on features f1, f16, f7, f32, and f5 are likely to evoke simplicity and rusticity.

Cursive Script, the most unique style, features a simple structure, continuous brushwork, and a sense of free-spiritedness. It exudes a feeling of freedom and unbridled expressiveness. This can show that the pattern that gives people a free look and feel will take lower values at f1, f16,f7, f33, and the value of f5 is clustered at a relatively high value.

Regular Script has well-proportioned character forms with a precise and open structure, giving a sense of regularity and dignity. This may indicate that the value of f1 tends to 1, and takes higher values on f33, f16, f32, f5, and lower patterns at f11 and f12, which is easy to cause people to feel regular style.

Running Script features fluid brushwork and a flexible character structure, creating a dynamic and graceful visual effect. Most of its feature values are distributed between Cursive Script and Regular Script, with only feature f5 having lower values, indicating that no matter how the lines vary in Running Script, the ink distribution tends to balance. This provides evidence for the perception of stability and liveliness in Running Script. This indicates a pattern that gives a stable but lively impression, with moderate eigenvalues and low f5.

## 7. Conclusions and future work

Calligraphy is not only a form of subjective expression but also a graphic art. In this study, we aim to extract unique visual information from calligraphy, select 1600 characters from 130 works as experimental datasets, summarize 33 interpretable features, and finally screened out 8 interpretable features that have a significant impact on people's visual perception. Additionally, we have revealed the relationship between objective features and people's subjective perception of style. This contributes to a better understanding of how humans perceive information and can be used to guide artists in their creative process. Furthermore, it offers new perspectives for the study of other forms of art. In the future, the dataset and features obtained in this paper can be used to develop style and emotion recognition models. How to specifically apply these models in design and psychology will be a significant focus of future research.

## Acknowledgement

This work was supported by the 2022 Open Project of Jiangsu Key Laboratory of Media Design and Software Technology (Jiangnan University), and Humanities and Social

Sciences Foundation of Ministry of Education of China (18YJC760123), and the National Natural Science Foundation of China (72304249), and Fundamental Research Funds for the Provincial Universities of Zhejiang (GB202003008).

## References

[1] P.J, and Silvia, Emotional Responses to Art: From Collation and Arousal to Cognition and Emotion, *Review of General Psychology* **9** (2005), 342-357.
[2] G.E. Myers, and R. Arnheim, Art and Visual Perception: A Psychology of the Creative Eye. *Philosophy and Phenomenological Research* **16** (1956), 425-426.
[3] R. Li, X.F. Jia, C.l. Zhou, and J.S. Zhang, Reconfiguration of the brain during aesthetic experience on Chinese calligraphy—Using brain complex networks, *Visual Informatics* **6** (2022), 35-36.
[4] W. Hou, and G. Festi, Cultural Dynamics of Chinese Calligraphy from a Semiotic Gaze. A Design-Oriented Platform to Valorize Cultural Heritage, *Design in the Era of Industry 4.0* **3** (2023), 61-72.
[5] D. Kang, H. Shim, and K. Yoon, A method for extracting emotion using colors comprise the painting image. *Multimedia Tools and Application*s **77** (2018.), 1-18.
[6] J.L. Liu, E. Lughofer, X.Y. Zeng, Could linear model bridge the gap between low-level statistical Features and aesthetic Emotions of Visual textures, *Neurocomputing* **168** (2015), 947-960.
[7] Dai, L., Zhang, K., Zheng, X.S. et al., Visual complexity of shapes: a hierarchical perceptual learning model, *Vis Comput* **38** (2022), 419–432.
[8] J.Kim, J.Lee, and D. Choi, Designing emotionally evocative homepages: an empirical study of the quantitative relations between design factors and emotional dimensions. *International Journal of Human-Computer Studies* **59** (2003), 899-940.
[9] C. Spence, and G.V. Doorn, Visual communication via the design of food and beverage packaging, *Cognitive Research: Principles and Implications* **7** (2022), 42.
[10] Y.B. Wen, and S. Juan, Chinese Calligraphy: Character Style Recognition based on Full-page Document, *In Proceedings of the 2019 8th International Conference on Computing and Pattern Recognition* (2019), 390-394.
[11] P.C. Gao, G. Gu, J.Q. Wu, and B.G. Wei, Chinese calligraphic style representation for recognition. *International Journal on Document Analysis and Recognition* **20** (2017), 59-68.
[12] M.W. Sun, X.Y. Gong, H.T. Nie, Iqbal, M. Minhas, and B. Xie, SRAFE: Siamese Regression Aesthetic Fusion Evaluation for Chinese Calligraphic Copy, *CAAI Transactions on Intelligence Technology* (2022), 1077-1086.
[13] R.J Sun, Z.H. Lian, Y.M. Tang, and J.G. Xiao, Aesthetic visual quality evaluation of Chinese handwritings. *In Proceedings of the 24th International Conference on Artificial Intelligence* ( 2015), 2510-2516.
[14] K.X. Han, W.T. You, S.H. Shi, H.H. Deng, and L.Y. Sun, The Doctrine of the Mean: Chinese Calligraphy with Moderate Visual Complexity Elicits High Aesthetic Preference, *International Journal of Human-Computer Interaction* (2022), 1-14.
[15] K.X. Han ,W.T. You, S.H. Shi , and L.Y. Sun, The Impression of Round and Square: Chinese Calligraphy Aesthetics in Modern Type Design. *International Journal of Human-Computer Interaction* (2023), 1-14.