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A Computational Approach to Chinese Calligraphy: Data-Driven Feedback Through Pixel-Based Stroke Segment Analysis

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Abstract

The complex aesthetic and structural conventions of Chinese calligraphy pose significant challenges for instructors in developing reliable, actionable assessment frameworks and in providing precise, actionable feedback. The lack of standardization and evaluative subjectivity could obscure students' learning capability and limit their ability to efficiently identify and address areas in need of technical improvement. This study aims to address this issue by establishing an evaluative body of quantifiable features as a foundation to implementing an AI-based learning instrument. Designed to provide specific and objective feedback for side-by-side copying, this mechanism is established by benchmarking expert-written samples through digitized, statistical analysis of pixel optics distributions in individual brushstrokes. Using the traditional Chinese character 永 as a case study, results show student-written leftward slants and pressing strokes demonstrate consistently significant deviation from the instructor model, which pinpoints where the students need further training. More importantly, while preliminary, consistent agreement across multiple analytical tests demonstrates the feasibility of the study's methodological approach, illustrating its promising potential for developing future AI-assisted feedback instruments.

Keywords
Chinese calligraphy, digital handwriting analysis, assessment and feedback.

1. Introduction

Despite rapid advancements in technological modernization of traditional arts, Chinese calligraphy education stalls due to the lack of effective, structured objectives and efficient feedback mechanisms for students and teachers alike. Once recognized as an art form that flourished only after the development of the written language, archeological evidence now points to its emergence as early as the Neolithic period (Zeng 1993). Considering its long-lived heritage, one cannot deny that Chinese calligraphy is a substantial representation of the cultural legacy and identity of the Chinese people.

However, the artistic nature of calligraphy may turn pursuits of artistic beauty into a prolonged struggle to meet invisible aesthetic standards. This combined with the structural complexity of characters makes objective feedback and assessment a difficult task. Huang and Qiao (2024) shed light on the heavy grading workloads that hinders tailored feedback, resulting in “a monotonous grade or a rank,” which proves insufficient for student improvements. With aim to tackle the limitations, this study highlights the importance of directional feedback in improving calligraphy through AI-driven instruments.

This study devises a preliminary methodology for developing a statistical, AI-based instrument that conducts stroke-based analysis on students’ side-by-side (SBS) copied calligraphy characters. To guide evaluation, this study adopts a set of expert-advised structural and visual criteria that reflect essential characteristics of stroke execution. The two main benchmarks evaluated in this study are angle of segment slope and proportion, which together serve as the basis for assessing deviations from the model character and offer visual diagnostics that support more consistent and actionable feedback for learners.

1.1 Objectives

This study has three main objectives: (1) demonstrate how statistical analysis of segment data can support objective, targeted evaluation, (2) help instructors identify segments where students deviate from the model, through both collective and individual student assessments.

2. Literature Review

Three major perspectives will be examined in the following review: kinematic and biomechanical principles of Chinese calligraphy, image processing and analysis of calligraphy characters, and past artificial intelligence (AI) implementations for analytical use.

2.1 Kinematic and Biomechanical Principles of Chinese Calligraphy

While evaluation is often dominated by aesthetic conventions in traditional Chinese calligraphy instruction, instructors can move beyond stylistic criticism to provide more constructive feedback by recognizing how impression-based deviations often stem from kinematic and biomechanical factors.

2.1.1 Biomechanical Implications of Finger-Grip Techniques

A defining characteristic of calligraphy is the brush-tipped pen, with control stemming from the writer's finger grip and wrist position. In Chinese calligraphy, there are multiple grip methods, including single-hook grip, double-hook grip, three-finger grip, etc. As this study uses digital writing equipment, the three-finger and five-finger grip methods are most relevant for their similarity to hard-tipped pen holding techniques in terms of finger positions. The three-finger grip— uses the thumb, index, and middle fingers— offers greater stability and agility compared to the five-finger grip (Lee and Lee, 2021). Since fewer fingers are in contact with the brush handle, the brush moves with a looser pivot, thus allowing for greater mobility, leading to superior hand flexibility and stability (Murata and Gotoh, 2020).

2.2 Image Processing and Analysis of Calligraphy Characters

Existing works exploring the integration of technology with Chinese calligraphy predominantly aim to preserve or present calligraphy arts through digital mediums, may they be through generating replicas of— often archaic— texts or uploading them to online databases. While there is no standard methodology for digitizing visual and spatial characteristics in image-based pre-processing of individual characters, past publications have discussed a range of techniques capable of serving various processing goals— some reflecting biomechanical implications within strokes, and others overall stylistic and aesthetic features (Woolf et al., 2021; Bi et al, 2025).

2.2.1 Raster and Vector Digital Stroke Analysis

Scientific analysis of calligraphic characters fundamentally depends on stroke segmentation to detect definitive errors and enable targeted feedback (Ip and Leung, 2025). As a result, the digital representation of characters must be made to fit model-specific parameters: commonly divided into two distinct yet complementary graphical techniques—

rasterization, consisting of fixed-resolution pixel matrices; and vectorization, relying on parametric equations for stroke definition (Research Guides 2025).

Between the two, raster-based approaches have proven superior in showcasing authenticity and providing quantitative measurements, whereas vectors were applicable for flexible scaling and geometric analysis (Gong et al., 2024; Liu and Lian, 2024; Wang et al., 2016). Recognizing the benefits of each model, hybridized analytical frameworks have been introduced to train computerized character replication and generation models, retaining presentation clarity while resolving pixel noise through mathematical and geometric analysis (Chen and Qian, 2022; Ip and Leung, 2025). However, few have been adapted to train and quantify improvement in human learners, leaving a gap in pedagogical applications.

2.2.2 Grayscale and RGB Colorimetric Image Segmentation

In existing studies, grayscale and RGB analysis have been fundamental in determining ink and brush stroke compositions. Grayscale, in particular, has been applied to resolve ink absorptions and diffusion in physical writing. However, with the popularization of digital writing, it has been most notably used to analyze stylus kinematics in strokes, whereas the RGB scale has been used in a complementary manner, often to analyze colorized archaic texts (Hanif et al., 2023). However, when used in contingency with the pixelated composition of rasterized characters, RGB colorization has been proven useful in stroke segmentation (Woolf et al., 2021; Hanif et al., 2023).

2.3 AI Implementation on Chinese Calligraphy

The emergence of AI has introduced novel pathways to the analyses and presentation of Chinese calligraphy, many of which explore innovative approaches to the aesthetic qualities of characters. These approaches demonstrate promising capabilities in automating classification, replication, and evaluation, bypassing traditional manual analytical principles (Yan et al., 2024; Cai, 2022; Wong et al., 2008). Nonetheless, present limitations, such as in capturing human intentionality or understanding aesthetic regulations, restrict applications to surface-level aesthetic replication rather than nuance analysis.

2.3.1 Learning-Based AI Systems in Chinese Calligraphy

The emergence of AI introduces a shift from rule-based analytics to learning-based, incorporating deep learning models to recognize and generate calligraphy writings. A majority of past studies use Generative Adversarial Networks (GANs)— a generative AI for producing and imitating realistic data— to learn and replicate calligraphy writing styles (Bi et al., 2025, Chen et al., 2024, Wang and Gong, 2023). However, given that machine-learning AIs generally struggle to comprehend stroke purpose and variability, they are comparatively inadequate for supporting pedagogical feedback.

3. Method

The aim of the present study is to analyze and compare a model character written by the instructor and 11 replicas written using side-by-side copying by student volunteers. Feedback is made through comparison of the model and student-written characters, quantifying their similarity and deviation through regression modeling and principal component analysis.

The character「永」is used for its nearly symmetrical structure. Due to the goal of constructing a preliminary foundation for the feedback model, symmetrical and simplistic characters are preferred as they minimize the variability in shape distortion and disproportionate spacing between strokes. Moreover, the character 永 offers a variety of 8 stroke types: dot, horizontal, vertical, turning point, ticks, slant, hook, and pressing (捺), which allows for an immediate understanding of the writer's technique.

All 12 versions of 永 are written in the Notability app using an iPad Air 6th generation and Apple Pencil Pro, each within a standardized 10 x 10 centimeter square area. Written characters are then processed colorimetrically into a total of 15 segments. To clarify terminology: color-coded sections would be referred to as 'segments', and their directional flow as 'strokes'.

The resulting images were unitarily output in rasterized format, then resized to 650 x 650 pixels to minimize pixel interference during analysis. Pixel-level data— including x and y coordinates, grayscale, and RGB values— were extracted using custom Python code and saved into Comma Separated Value (csv) format for segment-level analysis (Figure 1 and 2).

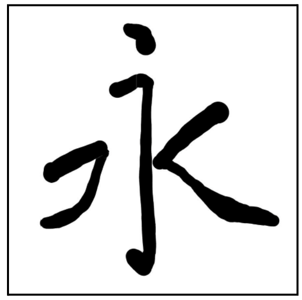


Figure 1 and Figure 2. Colorized image of teacher-written 永, showing multi-colored segments; bivariate x by y fit of pixel-level data from teacher-written 永.

As supported by prior literature, segmenting brushstrokes is necessary for targeted feedback, whereas individual colorization of segments reduces unintended pixel overlap. Rasterized imaging was chosen for the quantifiability of pixels to provide specific feedback. At current stages, vector-relevant curvature analysis methods are unsupported by data analytical tools.

3.1 Segment Data Analysis — Angle of Slope and Proportion

After RGB and grayscale data are filtered to isolate specific segments, two main segment analysis methods are applied: angle of slope, and proportion analysis (Figure 3).

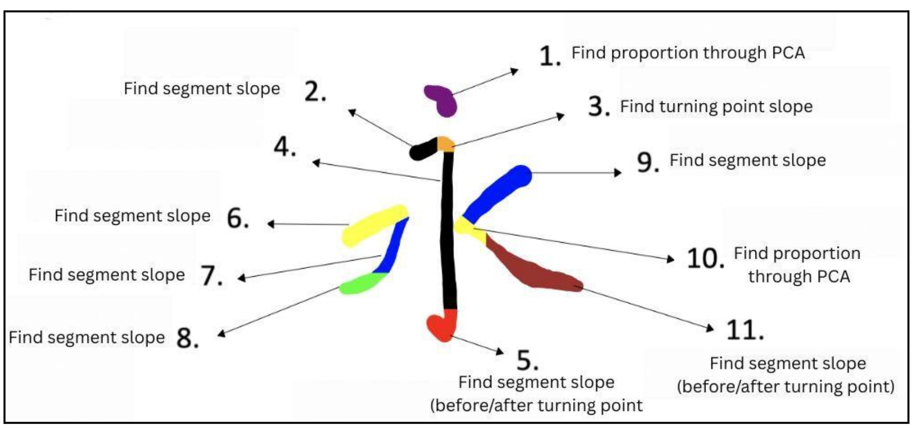


Figure 3. Annotation for colorized segment-specific analysis of 永.

3.1.1 Angle of Slope

Slope is primarily used to analyze segments in linear form. After the desired segment is isolated colorimetrically, its pixel data will be used to find the regression line that models the trajectory of the segment (Figure 4).

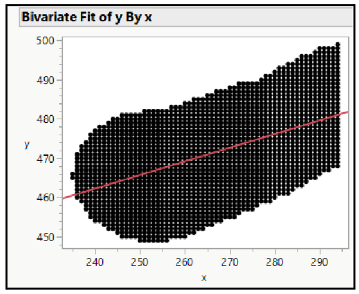


Figure 4. Regression analysis for bivariate fit of a segment that has high linear correlation.

Given the linear form of the regression model, slope can directly be extracted from the equation:

$$y = mx + b.$$

The angle is then determined using the equation below:

$$\theta = tan^{-1}(m)\times 180/\pi$$

By comparing the slope values of the segments in student-written and teacher-written characters, the degree of structural similarity between the samples can be quantified, thus enabling the delivery of potential segment-specific feedback.

Anomalies: Shorter Segments and Directional Shifts

Post-separation, some segments— in particular those wider or shorter— tend to lose their directional coherence. Other possibilities include segments— such as the pressing stroke (捺) or the hook— that contains shifts in direction, making them incompatible to linear fit. In these cases, the boundary of the segment will be found by isolating pixel data that are only partially colored (Figure 5).

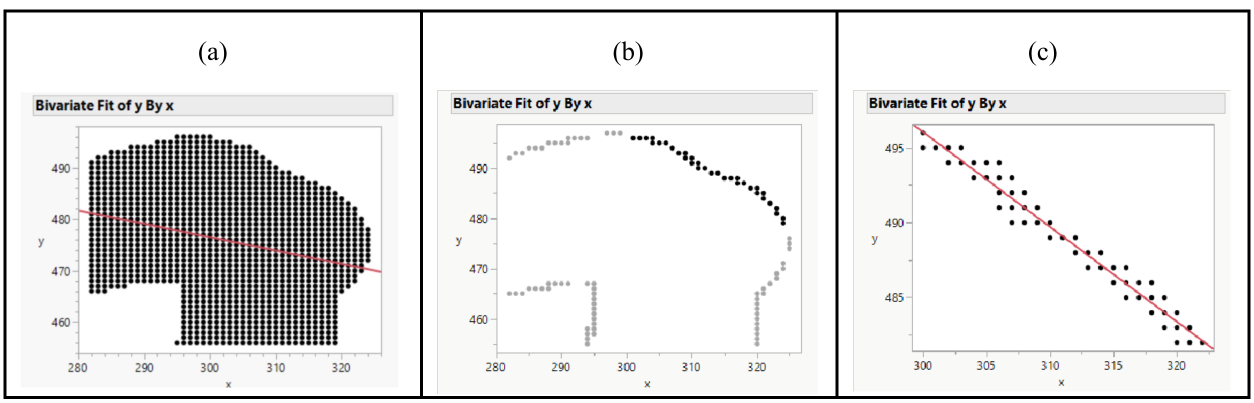


Figure 5. Bivariate fit of a shorter segment that shows a shift in direction. (a) Regression analysis of the segment. (b) Selection of slope determination section using manual selection of boundary pixels. (c) Regression analysis of selected pixels.

To mitigate manual error, multiple trials were run across 2 members, and the mean angle of slope was extracted. Notably, deviations between trials were consistently within the +/- 2 degrees range, of which were taken into consideration when devising the tolerance spec for later data analysis (Figure 6).

3.1.2 Proportion & Principal Components Analysis (PCA)

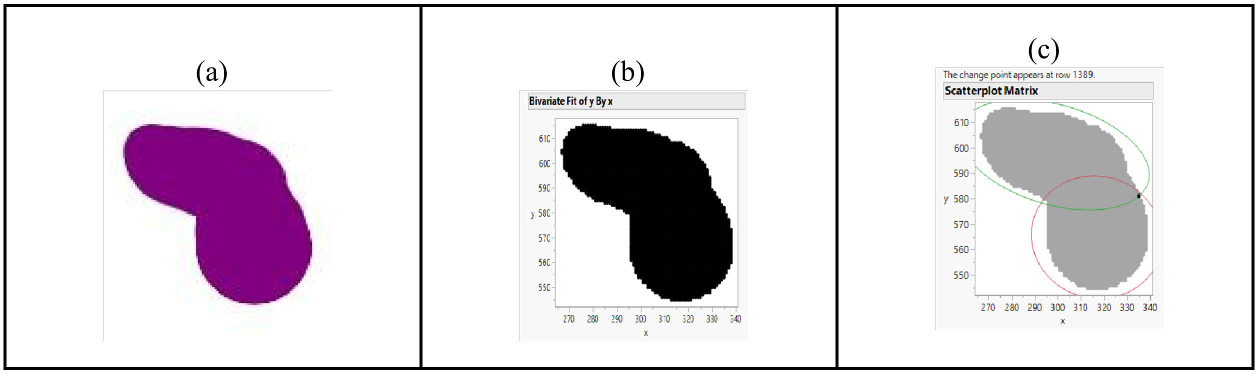


Figure 6. (a) Colorized image of dot from instructor-written 永. (b) Bivariate fit of the dot. (c) Detection of turning/change point using Principal Component Analysis (PCA).

Proportion is used to determine how dots and turning strokes are written. The structure of these strokes can be technically demanding due to the specific size and width each segment of the stroke is expected to maintain. Principal Component Analysis (PCA) is performed to find the turning point of the segment. In doing so, the percentage of pixel data before and after the turning point can be calculated.

Not all strokes that are stockier in presentation or contain a change in direction are analyzed via proportion. For some segments, manual detection of turning points deviates largely between operators, resulting in a mix of methods being adopted to define segment statistics.

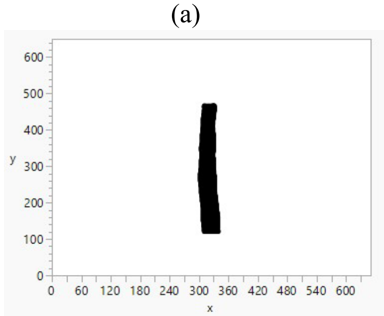
Anomaly: Vertical Segment Proportion

The vertical segment is analyzed differently than all others due to the fidelity of its slope angle— being undefined in optimal circumstances. The angle of the segment was determined through the proportion ratio of the total x coordinates the segment occupies as opposed to those the widest region of the segment occupies (Figure 7). The equation functions as below:

$$\text{Total X / Widest X by Y} = (\text{MaxX} - \text{MinX}) / \text{Max}(\text{MaxXByY} - \text{MinXByY})$$

throughout the segment. (c) Distribution of x coordinates occupied across each y coordinate.

(a)



(b)

Distributions

x

Quantiles

100.0%	maximum	339
99.5%		338
97.5%		335
90.0%		330
75.0%	quartile	326
50.0%	median	319
25.0%	quartile	313
10.0%		309
2.5%		306
0.5%		304
0.0%	minimum	303

(c)

Distributions

WidthByY

Quantiles

100.0%	maximum	29
99.5%		29
97.5%		29
90.0%		28
75.0%	quartile	27
50.0%	median	26
25.0%	quartile	22
10.0%		19
2.5%		19
0.5%		18
0.0%	minimum	18

Figure 7. (a) Isolated bivariate fit of teacher-written vertical stroke segment. (b) Distribution of x coordinates

The ratio of total x coordinates to maximum x coordinates per y coordinate uses proportions to identify segment angle variability. A higher ratio could reflect more extreme angular variation from the optimal slope, whereas a lower one could indicate less variation, thicker strokes, and local bulging.

4. Data Analysis & Results

To effectively provide objective scoring and stroke-based feedback, it is necessary to evaluate the extent of which student sample measurements deviate from those of the model instructor. Directed from an instructor's perspective, this study adopts two approaches:

1. Determining collective student error across segments, to identify which segment students' communally have difficulty with. Meant for multiple students, this approach allows instructors to give class-wide feedback based on trends seen in the majority (>50%) of the student body.

2. Determining individual student deviations across segments, and providing exemplary scoring criteria. Meant for personalized feedback, this approach allows both the student and instructor to know segment-based strengths and weaknesses.

4.1 Addressing Collective Student Deviations Across Segments

Collective student error across segments was determined by one-sample t-tests of student sample means against the instructor model. By examining the t-ratio and p-value, knowledge of the level of deviation between the two, and thereby of which segments students have an average tendency to struggle with the most can be attained. Prerequisite to t-test application, sample interdependency and normality factors were evaluated to validate test suitability (Table 1).

Table 1. Evaluations of segment measurements: autocorrelation, normality test goodness of fit, t-ratio, two sided p-value, and percentage of students exceeding spec across 11 student samples against model instructor sample measurements.

Segment	Autocorrelation	Normality Goodness of Fit p-value	t-ratio	Two-Sided p-value	Percentage of Students Exceeding Spec
		Angle of Slope (degrees)			(± 5°)
2	0.0978	0.5012	-2.6626	**0.0238**	0.455
3	-0.1832	0.7352	-0.5943	0.5655	**0.818**
5-1	-0.2051	0.2248	-0.9071	0.3857	**1.000**
5-2	**0.4414**	0.2132	-0.6553	0.5270	**0.909**
6	0.1284	**0.0072**	-3.3227	**0.0077**	**0.636**
7	-0.2742	0.8512	**-7.5723**	**<.0001**	**1.000**
8	**0.5497**	0.2868	**12.0863**	**<.0001**	**1.000**
9	0.0149	0.3228	3.3425	**0.0075**	**0.727**
11-1	-0.1145	0.1572	-1.2640	0.2349	0.455
11-2	0.1683	0.4496	**-6.3884**	**<.0001**	**0.909**
		Ratio (Turning Point Proportions)			(± 0. 1)
1-1	0.1889	0.9056	-2.5818	**0.0273**	0.091
1-2	0.1880	0.8812	2.5581	**0.0285**	0.091
10-1	-0.0182	0.0664	-1.2548	0.2381	**0.545**
10-2	-0.0184	0.0728	1.2526	0.2389	**0.545**
		Ratio (Vertical Stroke X-Coordinate Proportions)			(± 0. 1)
4	-0.1718	0.3400	1.3984	0.1922	**0.727**

4.1.1 Autocorrelation, Normality, and Non-Normal Benchmarking

Acting on the standard ±0.3 border for managing autocorrelation, all segments except 5-2 and 8 demonstrate sufficient independence. That said, given the low effect size, it could be argued that some leniency may be granted to the correlation margin. Normality is supported for all measurements but segment 6, of which deviation was driven by an extreme outlier. The existence of outliers highlights limitations of relying solely on measurement mean, given their vulnerability to extremities. To address this, an alternative method is proposed: assessing the percentage of individual students demonstrating significant deviation from the model sample, given a set of exemplary specs. While this novel method offers a more robust indicator of performance consistency, it is examined jointly with t-tests for the purpose of maintaining statistical reliability through standardized inferences.

As no prior studies have proposed a similar solution, the tolerance limits were provided by calligraphy advisor Mr. Lee. Though these benchmarks may not be reflective of communal structural and artistic standards, they align with this study's objective of supporting individual instructors in their pedagogical evaluations. By allowing instructors to develop their own specs, not only could they rapidly identify and filter work based on their own instructional boundaries and stylistic preference, they become more critically aware of their own evaluative practices. Given that there were three types of measurements with varying units (angle of slope, turning point ratio, and X-coordinate ratio), independent specs were developed around the instructor's sample: a ±5 degree tolerance for angle of slope, and ±0.1 for turning point proportion and vertical stroke x-coordinate proportion ratios.

The consistency in high t-ratio, low p-value, and tolerance fail proportions for segments 7, 8, and 11-2 demonstrate divergence in both average and individual student performances, highlighting areas where students exhibit the greatest shared difficulty. Thus, it can be concluded, preliminarily, that students typically struggle to master leftward slanting strokes (segments 7 and 8) and the pressing technique (segment 11-2) (see figure 3). However, it must be noted that all three segments were subject to manual separation before measurement, which poses undeterminable influence on individual results.

4.1.2 Validation of Analysis through Equivalence and Sample Size Tests

Considering the limited sample size and existence of extremities, secondary-level examination is necessary to support t-test inferences. For segments where no significant difference is found between instructor and student mean measurements ($p>.05$), a sufficient sample size is necessary to validate this conclusion, as small samples lack the statistical power to make meaningful inferences. Whereas if assuming a statistically significant difference ($p<.05$), practical significance must be assessed through equivalence testing— using the tolerance limits previously applied in individual filtering (Table 2).

Table 2. Evaluations of segment sample size sufficiency (with minimum required sample size given α 0.05, and power 0.90) and practical significance given p-value.

Segment	Two-Sided p-value	Sample Size Sufficiency (p>.05)	**Practical Significance (p>.05)**
		Angle of Slope (degrees)	
2	**0.0238**	-	Unconfirmed
3	0.5655	No (71)	-
5-1	0.3857	No (73)	-
5-2	0.5270	No (106)	-
6	**0.0077**	-	Unconfirmed
7	**<.0001**	-	Yes
8	**<.0001**	-	Yes
9	**0.0075**	-	Unconfirmed
11-1	0.2349	No (52)	-
11-2	**<.0001**	-	Yes
		Ratio (Turning Point Proportions)	
1-1	**0.0273**	-	No
1-2	**0.0285**	-	No
10-1	0.2381	No (15)	-
10-2	0.2389	No (15)	-
		Ratio (Vertical Stroke X-Coordinate Proportions)	
4	0.1922	No (116)	-

For segments with mean p>0.05, the general consensus is that the given sample size (11) is insufficient to conclude whether or not a statistically significant difference exists. As for those with mean p<0.05, previously mentioned segments with the highest t-ratios (7, 8, and 11-2) also demonstrate practically significant differences between student sample means and instructor measurements, reinforcing the inference of substantial average divergence in these segments.

4.2 Addressing Individual Student Deviations Across Segments

Individual student deviation was calculated using the relative error between student and instructor measurements for each segment. This approach normalizes variation across different measurement scales (angle of slope, ratios), allowing fair comparisons. As a result, it supports unbiased, targeted assessment of student work and helps instructors identify student strengths and weaknesses. Below is a scoring sheet of the first student using relative error, using exemplary guidelines as below in Table 3:

1. Each measurement weighs 100 ÷ 15 = 6.667% of total score.
2. Measurement score is found using the formula: (1 - error) = 6.667%.
3. Relative error is found using the formula: (student - instructor measurement) ÷ instructor measurement.
4. If the error is greater than 1, then the measurement score automatically goes to 0.

Table 3. Scoring sheet of student 1 using relative error.

Student 1	Relative Error	Measurement Score
1-1	0.1444	0.0570
1-2	0.1783	0.0548
2	0.5604	0.0293
3	0.3376	0.0442
4	0.6204	0.0253
5-1	0.1295	0.0580
5-2	0.2921	0.0472
6	0.0763	0.0616
7	0.0899	0.0607
8	**2.0261**	**0.0000**
9	0.1694	0.0554
10-1	0.2799	0.0480
10-2	0.4140	0.0391
11-1	0.6611	0.0226
11-2	**4.0523**	**0.0000**
Sum		**60.3113%**

With regards to the results above, the student performed most poorly in segment 8 and 11-2. A similar trend was observed collectively across the majority of students, as previously concluded in collective deviation analysis. While instructor-set tolerance limits offer familiarity by building upon instructor artistic and structural standards, they are inherently shaped by subjectivity. Thus, by using relative error, fairness is prioritized by minimizing instructor-introduced assessment bias.

5. Discussion

5.1 Root-Cause Analysis of Data Variation

While using partial pixel-based filtering to collect slope and proportion data has proven effective for most segments in 永, some segments— such as 8 and 11-2— demonstrate extreme deviations across the student average and majorities. Citing past literature approaches to Chinese calligraphy analysis through hand motor control of brushstroke execution, it is plausible that segment data variability may be an outcome of inconsistent control of hand motion. In particular, directional shifts like those found in the two segments require wrist movements that may be challenging for novel calligraphers (Granek et al., 2013). Additionally, manual segmentation and selection of segment boundaries introduce uncontrolled systematic errors, adding to data variability.

5.2 Future Directions for Model Method Improvement

While the present framework provides objective insights into calligraphy writing, some limitations suggest directions for future works. In doing so, the model can benefit from analytical coherence and alignment with artistic standards in Chinese calligraphy practices. The current system strives to capture measurable parameters but, in turn, omits the broader artistic standards such as spatial harmony, stroke continuity, and visual coherence. As stroke segmentation allows for more personalized and detailed analysis, this current framework prioritizes granularity, conflicting with the holistic nature of Chinese calligraphy. The current model may benefit from incorporating more integrated analysis methods that preserve the harmony of the entire character while capturing nuanced deviations. These analyses may include stroke skeletonization, which obviates the need for stroke segmentation but was not implemented due to methodological limitations, and heat-mapping, providing information on pressure control.

6. Conclusion

This study proposed a preliminary framework for an AI-assisted feedback instrument specifically developed for Chinese calligraphy work assessment and feedback. By quantitatively analyzing slope-based and proportion-based segment data for the character 永, the current framework facilitates an evaluation of student calligraphy performance based on structural conformity to instructor sample. Through statistical analysis, this system is able to provide diagnostic feedback on calligraphic execution, pinpointing where students struggle with the most.

This model, though in its preliminary stages, offers valuable implications to calligraphy education, presenting a potential quantified solution to a longstanding limitation that both instructors and students suffer from: the absence of actionable and objective feedback on calligraphy writing. Instructors, who struggle to give objective and actionable feedback, can incorporate this system to supplement traditional subjective evaluation, as it can identify segment-level deviation based on consistent, instructor-defined benchmarks. Students can benefit from segment-specific feedback that guide their technical executions without having to decode vague, or subjective, commentaries. Hopefully, future adaptations of this model support various artistic and pedagogical fields in standardizing evaluation frameworks, bridging scientific and artistic gaps by solidifying aesthetic subjectivities into data-driven disciplines.

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