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Learning the Traditional Art of Chinese Calligraphy via Three-dimensional Reconstruction and Assessment

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Abstract—The traditional art of Chinese calligraphy, reflecting the wisdom of the grass-roots community, is the soul of Chinese culture. Just like many other types of craftsmanship, it is part of the historical heritage and is worth conserving, from generation to generation. Since the movements of an ink brush are in 3D style when Chinese calligraphy is written, they embody "The Power of Beauty", comprising various reflectance properties and rough-surface geometry. To truly understand the powerful significance and beauty of the art of Chinese calligraphy, in this paper, a 3D calligraphy reconstruction method, based on Photometric Stereo, is designed to capture the detailed appearance of the calligraphy's 3D surface geometry. For assessment, an Iterative Closest Point (ICP) algorithm is applied for registration of 3D intrinsic shapes between the Chinese calligraphy and the calligraphy fans' handwriting. Through matching the two sets of calligraphy characters, the designed system will give a score to the handwriting of a user. Experiments have been performed on Chinese calligraphy from different historical dynasties to evaluate the effectiveness of the proposed scheme, and experimental results show that the developed system is useful and provides a convenient method of calligraphy appreciation and assessment.

Index Terms—Image quality assessment, Chinese calligraphy, 3D surface geometry, 3D surface heightmap, Photometric Stereo

I. INTRODUCTION

The calligraphy of Chinese characters, which is a pearl of Chinese culture, is also an appreciated aspect of East Asian

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culture. In oriental culture, traditional Chinese calligraphy is not only considered as the first of the ancient Chinese arts, but also expresses a unique spirit and artistic value. Just like the saying goes, "Handwriting reveals the essentials of personality and character."

The definition of calligraphy is literally "the way of writing" or "the art of writing" [1]. Traditional East Asian handwriting (for example, Chinese, Japanese, Korean, and Vietnamese) uses the *Four Treasures of the Study*: the ink brushes to write Chinese characters, Chinese ink, paper, and an inkstone. Although Chinese calligraphy is written by using ink brushes, it conveys an infectious feeling of beautiful strength. Fig. 1 illustrates the work considered most representative of Chinese calligraphy, which is deemed to be the greatest masterpiece in the history of Chinese calligraphy.



Fig. 1. A masterpiece of traditional Chinese calligraphy: "Lanting Xu", created by a well-known calligraphist - Wang Xizhi, is regarded as the greatest work in the traditional art of Chinese calligraphy.

To preserve this heritage of traditional culture, in this paper, we propose a 3D Chinese calligraphy reconstruction and assessment method based on integrating Photometric Stereo (PS) with an iterative Closest Point (ICP) algorithm. First, with the aid of PS, 3D details with surface geometry can be used to realistically represent the genuine surface structure of Chinese calligraphy, under various illuminations and viewing angles. In the meantime, a 3D surface heightmap can express the beauty of strength and richness of personality in the work of the calligraphist, running through the whole writing process. Then, the ICP algorithm is employed to align and match the 3D surface heightmaps between the traditional Calligraphy and the users' handwritings, for which a similarity function is designed for evaluating and grading a score for each calligraphy-handwriting input. Experimental results show that our designed system is effective and useful.

The rest of this paper is organized as follows. In Section II, we present the state-of-the-art work for Chinese calligraphy analysis and evaluation. Section III will briefly introduce the designed framework for 3D Chinese calligraphy reconstruction

and assessment, which is independent of the prior knowledge of calligraphy content. Experimental results are provided in Section IV, and a conclusion and discussion are given in Section V.

II. RELATED WORK

In the past few decades, many calligraphy analysis and evaluation methods have been proposed [2-4, 41-46]. Strassmann [5] designed a 2D brush tool to generate calligraphy by using four virtual parts, namely brush, stroke, dip, and paper. Later, Wong and Ip [7] also presented a virtual brush model for synthesizing vivid Chinese calligraphic characters. In their virtual brush model, several typical calligraphy styles are simulated effectively. For Chinese character recognition, Liu et al. [7] described a model-based stroke extraction and matching algorithm. In their method, the structural matching contains the reference strokes and the candidate's strokes, compared via a heuristic search. In [8], a stroke extraction method based on Gabor filters for Chinese character analysis was proposed. For Chinese calligraphy creation and generation, Xu et al. [9] designed an automatic system based on training examples of calligraphic styles, while Dong et al. [10] proposed a Chinese calligraphy generation model based on a stroke-reforming method. In [11], by estimating the ink model and 3D geometric parameters, Chinese calligraphy characters can be generated using different brush styles. To assign a score for calligraphic characters, Han et al. [12] designed an interactive calligraphic system based on fuzzy inference techniques. In [13], a calligraphic style discovering model for recognizing the style of Chinese calligraphy, based on a latent style model, was designed. Later, Xu et al. [14] proposed an approach for evaluating the quality of Chinese calligraphy handwriting regarding its aesthetic level. In [15], a global feature descriptor and a SVM classifier were integrated to tackle the Chinese calligraphy style recognition issue. In order to express and reflect the geometric properties of Chinese calligraphy, Sun et al. [16] proposed a novel method to extract strokes using the geometric properties of the contour(s) of a character. Wang et al. [17] proposed a quality assessment system for Chinese calligraphy characters based on disk B-spline curves vectorization and an iterative closest point method. In [38], Nakamura et al. designed a useful tool, named beautifying font, to help Chinese calligraphy fans to learn how to write it. Recently, a robotic Chinese calligraphy system [39], based on aesthetics evaluation, was proposed to evaluate the aesthetics level of calligraphy writing. In this method, aesthetics of the overall calligraphy effect are assessed by the weighted sum of three indices – the coordination, balance, and distribution indices. In [40], Ma and Su proposed a stroke reasoning strategy for robotic Chinese calligraphy based on complete feature sets. For modeling 3D calligraphic surfaces, in [48], in order to obtain 3D Chinese calligraphy on stone, a region-detection based model with a Gaussian filter was proposed to compute 3D calligraphic surfaces. Recently, Zhang et al. [49] designed an effective Laplacian-based inflation method to produce Chinese calligraphy reliefs from height fields.

In this paper, in order to display, learn, and evaluate traditional Chinese calligraphy, an effective and novel model for 3D Chinese calligraphy reconstruction and assessment is proposed, by combining Photometric Stereo and the ICP algorithm. In contrast to previous research, for the sake of reflecting the ink brush's movements in 3D style and Chinese calligraphy's intrinsic characteristic - "the beauty of strength", 3D surface heightmap reconstruction based on PS is utilized to represent the 3D details of the Chinese calligraphy's surface geometry, which makes the virtual reality of digital Chinese calligraphy more realistic and vivid. Moreover, the ICP algorithm is employed for the registration of 3D surface heightmaps of traditional Chinese calligraphy and users' handwriting, which can afterwards be graded a calligraphy handwriting score by means of a devised similarity function. So far, most of the existing Chinese calligraphy assessment methods are based on 2D images. The merit of the proposed model is that it works on the 3D surface heightmap so as to take advantage of the intrinsic surface characteristics of Chinese calligraphy. Experimental results show that our proposed system is valid and achieves promising performances. With this effective computer-assisted system, calligraphy fans can study, appreciate, evaluate, and enhance the level of writing Chinese calligraphy on their own.

The contributions of the designed model for 3D Chinese calligraphy reconstruction and assessment are twofold, and are summarized as follows:

- 1) We exploit PS to reconstruct a 3D surface heightmap precisely, which can effectively highlight the inherent properties of the Chinese calligraphy's surface geometry.
- 2) The ICP algorithm is applied to match the 3D surface heightmaps of traditional Chinese calligraphy with the users' handwriting, so as to generate a handwriting score based on a similarity function.

III. THE PROPOSED METHOD

In this paper, we propose a novel approach for 3D Chinese calligraphy reconstruction and assessment. In the first stage of the designed framework, the 3D surface heightmaps of the Chinese calligraphy in a Gallery set are reconstructed with geometric details by means of the PS technique, which can make the Chinese calligraphy more impressive and realistic, under different illuminations and viewing angles. In addition, with the virtual display of the 3D surface geometry of calligraphy characters, calligraphy fans, students, and academic researchers can appreciate, investigate, learn, and follow the style of Chinese calligraphy more easily, and make calligraphy learning more efficient and effective. Furthermore, 3D surface heightmaps not only can be used to reflect the beauty of strength, but also provide 3D intrinsic characteristics, independent of the prior knowledge of Chinese calligraphy's content, for Chinese calligraphy assessment in the next phase. In the second stage, for evaluating and scoring each user's calligraphy handwriting (probe input), the ICP algorithm is utilized to register and match the 3D surface heightmaps between the reference calligraphy in the Gallery set and the

users' handwriting. In this framework, the proposed scheme contains two consecutive stages to fulfill the purpose, as shown in Fig. 2.

A. Photometric stereo based on uneven lighting rectifying system

Compared to other 3D image-reconstruction models, PS owns the advantage that it is an efficient and expediently realized 3D image-reconstruction ways of capturing the information about 3D surface images [18-22]. In this part, we will give an introductory description of the PS model for reestablishing 3D surface heightmaps in the wild.

For the 3D imaging apparatus, by fastening the camera and the object simultaneously, we can shoot three images from the object lit at three different tilt angles, 0° , 90° , and 180° . The three images are denoted as "a" image, "b" image, and "c" image, respectively. The intensity at the spatial position (x, y) is expressed by using eq. (1), under the assumption of Lambertian surface [23, 28].

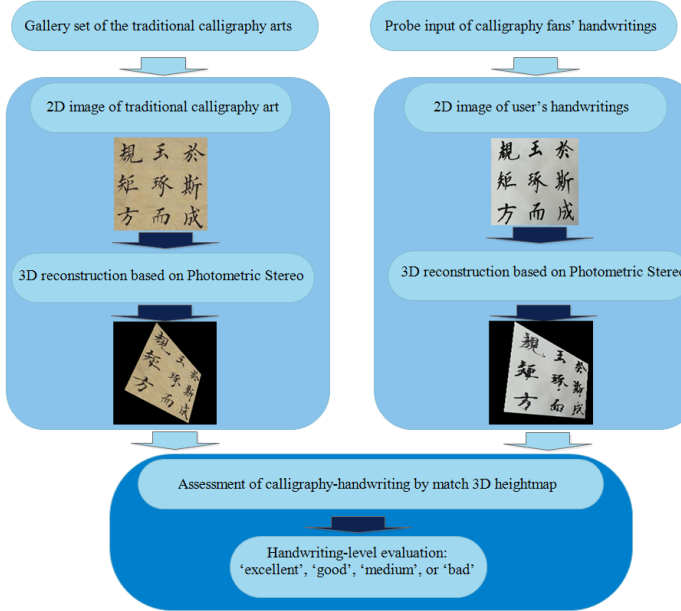


Fig 2. The proposed framework for traditional Chinese calligraphy, via three-dimensional reconstruction and assessment.

$$I_{\tau,\sigma}(x, y) = \lambda\rho \frac{-p \cos \tau \sin \sigma - q \sin \tau \sin \sigma + \cos \sigma}{\sqrt{p^2 + q^2 + 1}}, \quad (1)$$

where λ is the density of incident light to the object surface; ρ is the albedo of the Lambertian reflection; τ is the tilt angle of lighting; σ is the slant angle of lighting; p is the surface derivative image along the x -axis direction expressed as

$$p(x, y) = \frac{\partial z(x, y)}{\partial x}, \text{ and } q \text{ is the surface derivative image along}$$

the y -axis direction represented as $q(x, y) = \frac{\partial z(x, y)}{\partial y}$, where

$z(x, y)$ is the surface function.

In this paper, we will present the designed approach in detail, which is based on the Lambertian reflection model and the three images lit at 0° , 90° , and 180° , respectively, for reconstructing 3D heightmaps [23, 28] of Chinese calligraphy.

By holding on the slant angle a constant and setting the tilt angle at 0° , 90° and 180° , we have the respective images as follows:

$$a = I_0(x, y) = \lambda\rho \frac{-p \sin \sigma + \cos \sigma}{\sqrt{p^2 + q^2 + 1}}, \quad (2)$$

$$b = I_{90}(x, y) = \lambda\rho \frac{-q \sin \sigma + \cos \sigma}{\sqrt{p^2 + q^2 + 1}}, \text{ and} \quad (3)$$

$$c = I_{180}(x, y) = \lambda\rho \frac{p \sin \sigma + \cos \sigma}{\sqrt{p^2 + q^2 + 1}}. \quad (4)$$

From eq. (2) and eq. (4), we obtain

$$\lambda\rho \frac{\cos \sigma}{\sqrt{p^2 + q^2 + 1}} = \frac{I_0(x, y) + I_{180}(x, y)}{2}. \quad (5)$$

In the same way, by using eq. (5), eq. (3) and eq. (4), we can deduce the following two expressions:

$$\lambda\rho \frac{-p \sin \sigma}{\sqrt{p^2 + q^2 + 1}} = \frac{I_0(x, y) - I_{180}(x, y)}{2}, \text{ and} \quad (6)$$

$$\lambda\rho \frac{-q \sin \sigma}{\sqrt{p^2 + q^2 + 1}} = I_{90}(x, y) - \frac{I_0(x, y) + I_{180}(x, y)}{2}. \quad (7)$$

Thanks to the slant angle is a constant, we can rewrite eq. (1) as follows:

$$\begin{aligned} I_{\tau}(x, y) &= \lambda\rho \frac{-p \cos \tau \sin \sigma - q \sin \tau \sin \sigma + \cos \sigma}{\sqrt{p^2 + q^2 + 1}} \\ &= \left[\frac{I_0(x, y) - I_{180}(x, y)}{2} \right] \cos \tau + \left[\frac{I_{90}(x, y) - I_{180}(x, y)}{2} \right] \sin \tau \\ &\quad + \left[\frac{I_0(x, y) + I_{180}(x, y)}{2} \right] \\ &= \frac{1}{2} [(\cos \tau - \sin \tau + 1) \cdot I_0(x, y) + 2 \sin \tau \cdot I_{90}(x, y) + (1 - \cos \tau - \sin \tau) \cdot I_{180}(x, y)]. \end{aligned} \quad (8)$$

From eq. (8), it can be observed that $I_{\tau}(x, y)$ is a linear combination of the input images "a", "b", and "c". That is to say, the original images "a", "b", and "c" can be utilized to generate a 3D image under any arbitrary lighting conditions by relighting [26, 27, 28]. The palpable benefit of this rendering method consists in the linear combination scheme, which can be directly applied to multimedia and virtual reality applications.

In PS, a 3D surface heightmap $h(x, y)$ can be integrated through the x -axis and the y -axis surface-derivative images [26-28]. However, uniform and even illumination is a crucial requirement for reconstructing 3D surface heightmaps based on PS in the wild. Uneven illumination usually produces distorted surface heightmaps during the reconstruction process [29, 30, 31, 32]. In order to extend the PS to reconstruct 3D surface heightmaps in the wild, a self-adaptation method is required for rectifying non-uniform illumination. Based on inverse-square law, lighting offset can be predicted in terms of the distance between the object surface and the point light source [31]. Suppose that a small surface patch is at a distance r from a light source and a pixel in the patch has the value I_1 . If the light source is shifted a distance s away from the patch, the attenuation of the surface irradiance is $((r+s)/r)^2$. Consequently, the image intensity I_2 updated with the new distance can be expressed as follows:

$$I_2 = I_1 (r/(r+s))^2. \quad (9)$$

As the illumination offset s is obtained, the distance r can be solved by utilizing the two intensities as follows:

$$r = ks/(1-k), \quad (10)$$

$$\text{where } k = \sqrt{\frac{I_2}{I_1}}.$$

However, in real circumstance, if the slant angle is changed, both the distance offset s and the original distance r will be varied. As a result, changing the position of the light source will result in the need to gauge these distances personally every time. For this reason, Jian et al. [32] proposed an algorithm for correcting and rectifying non-uniform lighting automatically. Figure 3 illustrates the abridged general view for rectifying uneven lighting. The white arrows illustrate the illuminant directions of the light source, where G^1 or G^2 represents the region containing n columns or rows in the original input. Our experiments have shown that reasonably good results can be achieved when n is set between 5 and 11. Therefore, we set the region size at $n = 7$ for the inputs of traditional Chinese calligraphy.

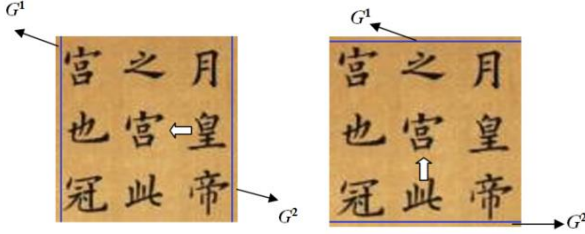


Fig 3. A diagrammatic sketch illustrates uneven lighting rectifying system. The white arrows show the illuminant directions of the light source.

The main idea is explained in the following. Presume that there exist $M = n \times l$ pixels (l is the width or length of an input image) in G^1 and G^2 , and $p(x, y)$ denotes the pixel's intensity at the position (x, y) located in the region G^1 or G^2 . Suppose I_1' and I_2' express the average intensities of the regions G^1 and G^2 , correspondingly, and they are computed as:

$$I_1' = \frac{1}{M} \sum_{p(x,y) \in G_1} p(x, y), \text{ and} \quad (11)$$

$$I_2' = \frac{1}{M} \sum_{p(x,y) \in G_2} p(x, y). \quad (12)$$

Afterwards, we can calculate the parameter K' as follows:

$$K' = \sqrt{\frac{I_2'}{I_1'}}. \quad (13)$$

The size of the regions G^1 and G^2 is determined by the parameters n and l [32]. According to the Retinex theory, the image intensity $I(x, y)$ can be expressed as the product of illumination $L(x, y)$ and surface reflectance $R(x, y)$ [33]. Overall, the k leading eigenvectors of an image primarily manifest the condition of illumination fluctuations.

By applying singular value decomposition to an input image, the diagonal matrix W can be separated [47], as follows:

$$\begin{aligned} W &= \text{diag}(w_1, w_2, \dots, w_i, \dots, w_n) \\ &= \begin{pmatrix} w_1 & & & & & & \\ & w_2 & & & & & \\ & & \dots & & & & \\ & & & & w_i & & \\ & & & & & \dots & \\ & & & & & & w_n \end{pmatrix} \\ &= \text{diag}(w_1, \dots, w_k, 0, \dots, 0) + \text{diag}(0, \dots, 0, w_{k+1}, \dots, w_n) \\ &= \begin{pmatrix} w_1 & & & & & & \\ & \dots & & & & & \\ & & w_k & & & & \\ & & & & 0 & & \\ & & & & & \dots & \\ & & & & & & 0 \end{pmatrix} + \begin{pmatrix} 0 & & & & & & \\ & \dots & & & & & \\ & & 0 & & & & \\ & & & & w_{k+1} & & \\ & & & & & \dots & \\ & & & & & & w_n \end{pmatrix} \\ &= W_1 + W_2 \end{aligned} \quad (14).$$

By using eq. (14), the input image can be decomposed into two individual components [33, 47]:

$$\begin{aligned} I_i(x, y) &= UWV^T = U(W_1 + W_2)V^T \\ &= UW_1V^T + UW_2V^T \\ &= L'(x, y) + R'(x, y) \end{aligned} \quad (15)$$

where $UW_1V^T = L'(x, y)$, with the first k leading eigenvectors, basically represents the variations in the illumination conditions, while $UW_2V^T = R'(x, y)$ refers to the intrinsic property of the object surface, which is called the surface-reflectance-representation matrix. The range of k can be $2 \leq k \leq 19$, because the inherent surface-reflectance component $R(x, y)$ is close to zero if $k \geq 20$ [33, 38]. In our experiments, setting $k = 7$ results in the best performance.

Analogous to eq. (13), K' can be evaluated by using L_2' and L_1' , instead of I_2' and I_1' . Hence, we can compute the parameter K' efficiently, as below:

$$K' = \sqrt{\frac{L_2'}{L_1'}}. \quad (16)$$

In the practice of 3D surface reconstruction, image rendering can be produced by using (1), with the slant angle τ and tilt angle σ of the light source varied. The proposed method can eliminate the distortion and aberration caused in the 3D surface heightmap reconstruction phase. In the next section, we will provide, in detail, the quantitative assessment of reconstructed heightmaps. For similarity measurement in the assessment stage, each reconstructed heightmap $h(x, y)$ is normalized to have its values between 0 and 1, as follows:

$$h'(x, y) = \frac{h(x, y) - \min(h(x, y))}{\max(h(x, y)) - \min(h(x, y))}. \quad (17)$$

Furthermore, a 3D virtual exhibition of Chinese calligraphy is a good learning experience for visitors, calligraphy fans, students, and researchers. Our proposed 3D surface reconstruction technique is novel, and can make the virtual reality and digital calligraphy masterpieces more vivid and realistic, as is shown in Fig. 4. With the display of the 3D surface geometry of calligraphy, people can learn and research the style of Chinese calligraphy more efficiently.

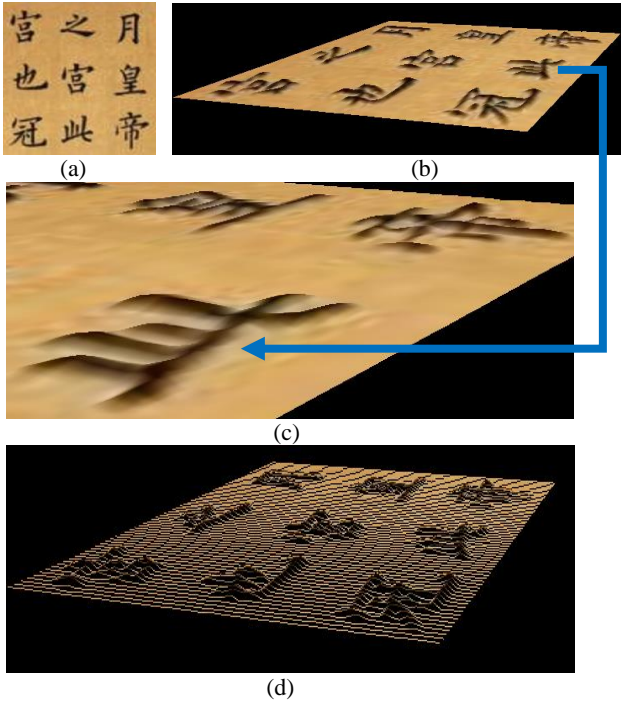


Fig. 4. A 3D example of the art of traditional Chinese Calligraphy using our 3D surface reconstruction technology. (a) A 2D image piece of the traditional Chinese calligraphy art written by a famous ancient calligraphist, Xun Ouyang. (b) Photorealistic appearance based on 3D surface heightmap reconstruction, with texture-mapping, using our proposed method. (c) 3D geometrical details of single Chinese character. (d) 3D surface reconstruction analysis with meshmap [32].

B. Assessing calligraphy-handwriting based on 3D heightmap and ICP

As the calligraphy-handwriting brush is soft, its movements are in a 3D style, rather than in the modern 2D hard-tipped way. Chinese calligraphy expresses its aesthetic through this 3D movement, which has practical and charming significance in carrying forward the strong spirit of traditional Chinese culture. Due to this intrinsic 3D-movement characteristic, in this section, in order to evaluate and score calligraphy handwriting, the widely used Iterative Closest Point (ICP) algorithm [34-37] is utilized to register and match the 3D surface heightmaps of traditional calligraphy arts in a Gallery set, with the input of a user's handwriting, as illustrated in Fig. 2. We will briefly introduce the ICP algorithm employed in our strategy.

An ICP algorithm aims to match two sets of 3D points. One of these sets is taken as a reference, while the other is the set of data points describing the ranges of certain points on an object's surface. The goal of an ICP registration algorithm is to find the optimal rotation and translation to align the model's shape and the data shape, such that the distance between the two point sets is minimized [34-37].

Quaternions are utilized to compute the 3D rotations. According to the quaternion algebra, a quaternion \mathfrak{q} is made up of one real part and three imaginary parts, as follows:

$$\mathfrak{q} = [q_0, q_1, q_2, q_3]^T, \quad (18)$$

where the real part $q_0 > 1$, $\{q_1, q_2, q_3\}$ are the imaginary parts, and $q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1$. A quaternion rotation matrix can be

written as follows [34-37]:

$$R_{or} = \begin{pmatrix} q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_0q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\ 2(q_1q_2 + q_0q_3) & q_0^2 + q_2^2 - q_1^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\ 2(q_1q_3 - q_0q_2) & 2(q_2q_3 + q_0q_1) & q_0^2 + q_3^2 - q_1^2 - q_2^2 \end{pmatrix}. \quad (19)$$

Let the translation vector be $\mathbf{r}_T = [q_4, q_5, q_6]^T$, which can be appended to the unit vector \mathfrak{q} to obtain the complete registration vector $\mathbf{r} = [q_0, q_1, q_2, q_3, q_4, q_5, q_6]^T$. Suppose that $P = \{P_i\}$ is a set of measured data points to be registered with a set of model points $X = \{X_i\}$, where the number of model points N_x and the number of data points N_p are the same, and each data point P_i corresponds to the model point X_i , with the same index. The optimal rotation will produce the smallest mean-squared error in the following objective function [34-37]:

$$f(\mathbf{r}) = \frac{1}{N_p} \sum_{i=1}^{N_p} \|\mathbf{r}_i - R_{or}(\mathfrak{q}P_i - \mathbf{r}_T)\|^2. \quad (20)$$

The centers of mass μ_p and μ_x of the measured data point set P and the model point set X , respectively, can be expressed as follows:

$$\mu_p = \frac{1}{N_p} \sum_{i=1}^{N_p} P_i, \text{ and } \mu_x = \frac{1}{N_x} \sum_{i=1}^{N_x} X_i. \quad (21)$$

To measure the similarity between the measured point set P and the model point set X , their cross-covariance Σ_{px} can be utilized:

$$\Sigma_{px} = \frac{1}{N_p} \sum_{i=1}^{N_p} [(P_i - \mu_p)(X_i - \mu_x)^T] = \frac{1}{N_p} \sum_{i=1}^{N_p} [P_i X_i^T] - \mu_p \mu_x^T. \quad (22)$$

Let the anti-symmetric matrix be $A_{ij} = (\Sigma_{px} - \Sigma_{px}^T)_{ij}$. The column vector $\Delta = [A_{23}, A_{31}, A_{12}]^T$ is then formed, which is employed to form of a symmetric matrix $Q(\Sigma_{px})$ using quaternion mathematics, as follows:

$$Q(\Sigma_{px}) = \begin{bmatrix} \text{tr}(\Sigma_{px}) & \Delta^T \\ \Delta & \Sigma_{px} + \Sigma_{px}^T - \text{tr}(\Sigma_{px})I_3 \end{bmatrix}, \quad (23)$$

where I_3 is the 3×3 identity matrix. The unit eigenvector of the symmetric matrix $Q(\Sigma_{px})$, with the largest eigenvalue, is selected as the optimal rotation, and the optimal translation vector is given as follows:

$$\mathbf{r}_T = \mu_x - R_{or}(\mathfrak{q}\mu_p). \quad (24)$$

The least-squares quaternion operation is:

$$(\mathbf{r}, d_{ms}) = 1(P, X), \quad (25)$$

where d_{ms} is the mean-squared point matching error, and $P = \mathbf{r}(P)$ denotes the point set P registered by the vector \mathbf{r} . Therefore, the ICP algorithm in [34], which terminates the iteration when the change in the mean-squared error falls below a dimensionless threshold $\tau\sqrt{\text{tr}(\Sigma_x)}$, with $\tau > 0$, can be applied to register a data shape P (3D surface of a probe input) so as to align with the model shape X (the 3D surfaces in a

gallery set, i.e. the reference point set), as shown in Figure 2.

We define a similarity function, denoted as SIM , to measure the similarity between the probe calligraphy-handwriting input (i.e. the user's handwriting) P and the calligraphy art in the gallery database (i.e. the ground truth) X as follows:

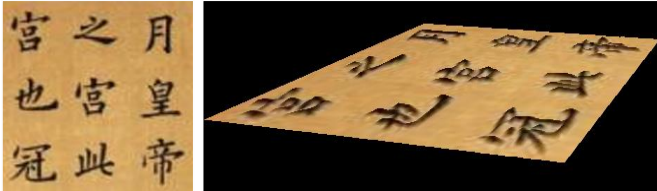
$$SIM(P, X) = (1 - \frac{d_{ms}(P, X)}{\|X\|_F})100\% = (1 - \frac{d_{ms}(P, X)}{\sqrt{\text{tr}(X^T X)}})100\%, \quad (26)$$

where $\|A\|_F$ is the Frobenius norm of the matrix A , which is defined as the square root of the sum of the squares of all its entries. The larger the SIM value is, the more similar the calligraphies are.

IV. EXPERIMENTAL RESULTS

A. 3D Chinese calligraphy reconstruction based on Photometric Stereo

In order to verify the effectiveness of the proposed strategy, a Gallery set is built by collecting 30 masterpieces of traditional Chinese calligraphy art from different historical periods, including the Qin, Han, Jin, Tang, Song, Yuan, Ming and Qing dynasties. First, we apply the Photometric Stereo method to construct 3D surface heightmaps of Chinese calligraphy with surface geometry, which can make the Gallery set information more impressive and vivid by considering multi-viewing angles and different illuminations.



(a) Tang Dynasty



(b) Tang Dynasty



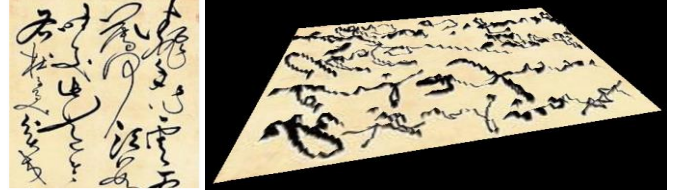
(c) Song Dynasty



(d) Song Dynasty



(e) Yuan Dynasty



(f) Ming Dynasty

Fig 5. 3D examples of some traditional Chinese calligraphy from different dynasties. The left shows the 2D images of calligraphy arts of different dynasties, and the right shows the corresponding 3D reconstructed result with texture mapping.

A Virtual Gallery is a convenient way for calligraphy fans, students and researchers to appreciate and enjoy the artistic beauty of Chinese calligraphy. We can inherit, conserve and carry forward the traditional art of Chinese calligraphy from generation to generation through this Virtual Gallery. Figure 5 illustrates some 3D examples of typical traditional Chinese calligraphy art with surface geometry from different dynasties in Chinese history. Experimental results show that the reconstructed 3D Chinese calligraphy results provide an attractive way and distinctive perception of the masterpieces for the calligraphy fans, students, calligraphy-history researchers, and other academic investigators.

B. Assessment of Chinese calligraphy

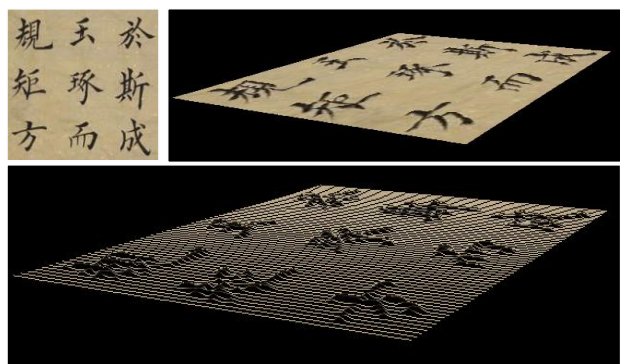
To objectively measure the robustness and effectiveness of the proposed method, we consulted three Chinese calligraphy experts and asked them to score various people's handwriting, and the mean score was used as the ground-truth score (reference score) for each person's handwriting. Meanwhile, we have also utilized the mean scores as a reference to grade the handwriting into four levels, namely, 'excellent', 'good', 'medium', and 'bad', for evaluation and comparison. **In addition, the mean runtime required by our method to score an image of Chinese calligraphy with a size of 512×512 is 1.25 seconds. This provides convenient access to a wide variety of contents according to the users' interests.**

With the aid of ICP registration, we utilize the similarity function SIM in eq. (26) to quantitatively assess the quality of each user's handwriting (i.e. probe inputs). Figure 6 shows an assessment example based on a traditional Chinese calligraphy masterpiece, done by a famous ancient calligraphist - Xun Ouyang, and four individual user's handwriting. Based on the proposed method, the handwriting of the four users was correctly assessed, and graded into one of the four levels, which coincide precisely with the ground truth. In terms of this calligraphy assessment, calligraphy fans and students can find out how well they have written, in terms of the 3D surface structure and geometrical shape of their calligraphy.

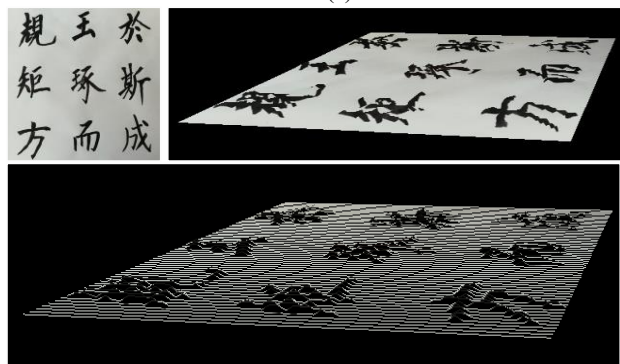
Generally speaking, Chinese calligraphy, according to the basic structure and diversity of calligraphy, can be divided into five styles: seal script, clerical script, regular script, running script, and cursive hand. In the experiments, the 30 masterpieces of Chinese calligraphy art from different historical dynasties are equally divided into five types (6 pieces per category) for further evaluation. Table 1 tabulates the statistical accuracy of handwriting-level evaluation ('excellent', 'good', 'medium', or 'bad') of the five different styles. Although calligraphy is an integrative art style, which is inclined to express subjective spirit and feeling, it can be seen from Table 1 that the proposed approach can still achieve satisfactory results, except that handwriting in the cursive-hand style is wrongly assessed. This is because this style is created freely, as well as randomly, without any restraining regulations. Therefore, it is harder to assess, and still a difficult and challenging issue to be solved, compared with the other four more regular styles (seal, clerical, regular, and running scripts).

Table 1. The statistical accuracy of handwriting-level evaluation of the five different types.

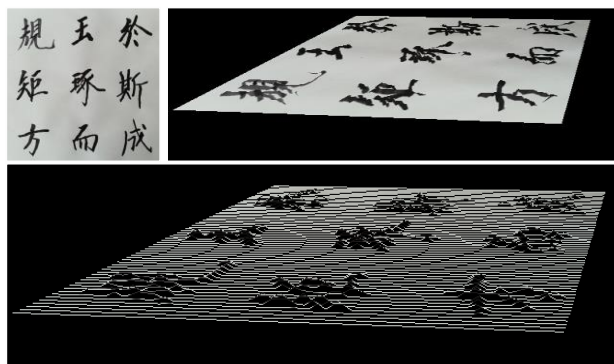
Calligraphy styles	Seal Script	Clerical script	Regular script	Running script	Cursive hand
Accuracy	100%	100%	100%	100%	83.33%



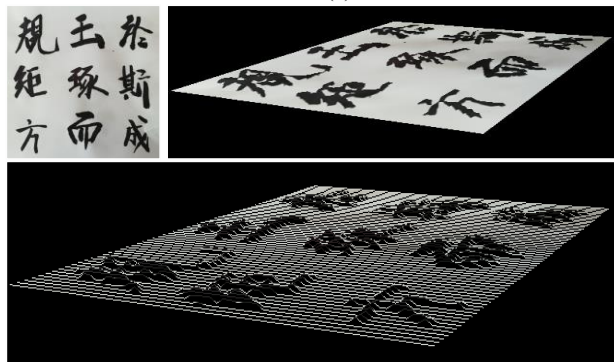
(a)



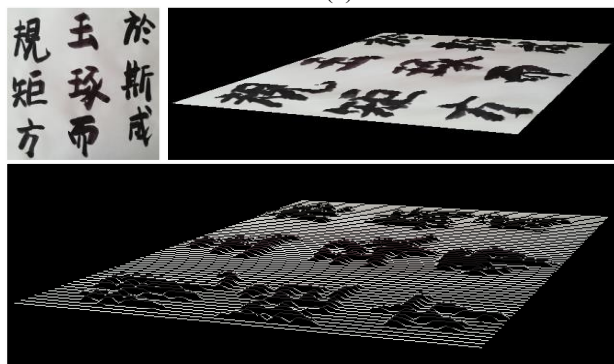
(b)



(c)



(d)



(e)

Fig. 6. Assessment of an example of traditional Chinese calligraphy using our 3D surface reconstruction and assessment technology. The left of the first row shows the handwriting, the right shows the corresponding photorealistic appearance based on 3D surface heightmap reconstruction using our proposed method, and the second row shows the corresponding 3D surface reconstruction analysis with meshmaps. (a) The 2D image of a work of traditional Chinese calligraphy art written by a famous ancient calligraphist, Xun Ouyang. (b) Handwriting assessed as excellent. (c) Handwriting assessed as good. (d) Handwriting assessed as medium. (e) Handwriting assessed as bad.

In addition, we also quantitatively evaluate the effectiveness of the proposed approach, compared with the other five state-of-the-art methods. Two typical stroke-based methods are compared: the Model-Based Stroke Extraction (MBSE) algorithm based on the pseudo-reference image [4] for handwritten Chinese character matching, and the Gabor-Filter-based Stroke Extraction (GFSE) method [5] for Chinese character evaluation. The Calligraphy generation-based algorithm proposed in [9], namely, Interactive Grading and Learning System (IGLS) for Chinese calligraphy, is also selected for comparison. Moreover, two more state-of-the-art methods, namely the disk B-spline curves

Vectorization and ICP Algorithm (VICP) [14] for Chinese calligraphy evaluation and the geometric Aesthetics-based method (AEST) [16] for robotic Chinese calligraphy assessment, are used for comparison.

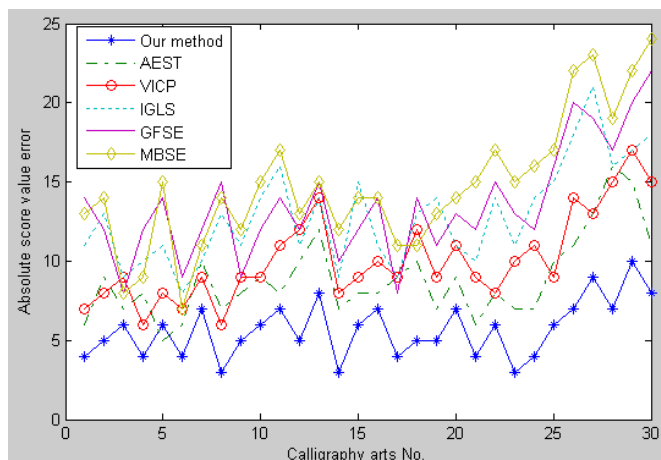


Fig 7. The absolute score-value errors of the six different state-of-the-art algorithms.

We use the absolute score-value error, defined as the absolute difference between the “automatic marked score value” and the “ground-truth score value”, to quantitatively assess the validity of different state-of-the-art algorithms. Figure 7 shows the performance of the six different methods in terms of their absolute score-value error curves, which evaluate the calligraphy assessment capability of each of the approaches. From the results, we can see that our proposed algorithm outperforms the other state-of-the-art algorithms. The reason for this is that the proposed method can reflect the intrinsic characteristics of the 3D surface geometry of Chinese calligraphy more effectively than the other state-of-the-art methods.

Table 2 shows that our proposed scheme is superior, in terms of the average and standard deviation of the score-value errors, to the other state-of-the-art algorithms. These results prove that our approach is promising, and can help users improve their calligraphy study effectively and efficiently.

Table 2. The mean and standard deviation of the score-value errors of different state-of-the-art methods.

Methods	MBSE	GFSE	IGLS	VICP	AEST	Our method
Mean score error	14.7± 4.16	13.5± 3.48	12.9± 3.16	10.1± 2.79	8.9± 2.59	5.7± 1.78

V. CONCLUSIONS

In this paper, an effective Chinese calligraphy reconstruction and assessment method is proposed, based on Photometric Stereo and the ICP algorithm. Aiming to grasp the inherent nature of 3D surface geometry of traditional Chinese calligraphy and calligraphy fans’ handwriting, Photometric Stereo is utilized for 3D surface reconstruction. During the assessment stage, the ICP algorithm is employed to align the

3D shapes of the calligraphy in a Gallery set and the user’s handwriting (probe input). Then, the proposed similarity function can evaluate a score and rank a level (‘excellent’, ‘good’, ‘medium’, or ‘bad’) to the probe input handwriting. Experiments have been conducted on a collected set of traditional Chinese calligraphy from different dynasties, and the assessment results show that the proposed method is plausible and provides a convenient method of calligraphy evaluation.

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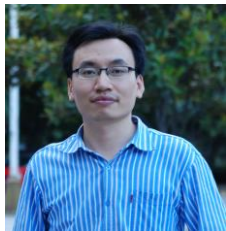
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