Classification Method of Traditional Art Painting Style Based on Color Space Transformation

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***Abstract*—In order to improve the accuracy and efficiency of traditional art painting style classification, a classification method of traditional art painting style based on color space transformation is proposed. This method preprocesses the traditional artistic painting style, improves the contrast of the image, makes the color and details of the image more vivid, and provides the basis for the subsequent color space conversion. After the traditional artistic painting style is stretched by automatic contrast stretching method, the color space is transformed. The purpose is to transform the image from one color space to another, so as to better extract the features of the image. Based on the traditional artistic painting style image after color space conversion, the traditional artistic painting image is balanced by the adaptive histogram equalization method with limited contrast, and an enhanced traditional artistic painting image is obtained, which further enhances the contrast of the image, makes the details in the image more prominent, and also enhances the overall visual effect of the image. Taking the enhanced traditional art painting images as input, the fuzzy C-means method is used to classify the traditional art painting styles, and the images are effectively divided into different categories according to the characteristics of the images. The experimental results show that this method can effectively enhance the image of traditional art paintings and effectively classify traditional art paintings with different styles, which has strong application effect.**

***Keywords*—Color space; traditional art; painting style; classification method; fuzzy c-means**

I. INTRODUCTION

In the development of human civilization, culture, and art play a very important role. Painting is an important form of culture and art [1]. It is an important part of a nation's culture. Rooted in the soil of national culture, it reflects a wide range of real-life content through beautiful art forms, thus reflecting the cultural outlook and aesthetic taste of all nations. It is a unique and important way for human beings to observe and express the world. For thousands of years, a large number of paintings have been produced. The study of these paintings is an important means for people to understand the history of human history, culture, art, and the development of science and technology to promote the development of human civilization further. It has been in the ascendant for many years. In reality, painting samples as research materials are often not easy to obtain, which has brought various inconveniences to the research work of art researchers for a long time. With the development and wide application of digital technology, more and more paintings are digitized [2] and saved in various forms such as images, videos, 3D models, multimedia documents, etc. The development of the network makes it possible for anyone to obtain digital works of art through the Internet, which brings great convenience to the majority of art researchers. The acquisition of large quantities of painting images has become a reality, which also makes large-scale art analysis possible. While digital technology has brought researchers a wealth of research materials [3], it has also provided them with many new research topics. For example, after the digitization of the murals in Mogao Grottoes in Dunhuang, art researchers need to process a large amount of data on the flying frescoes in order to study the comparison of different styles of different dynasties and classify them according to the styles of the dynasties before conducting research. Such a huge amount of data, if only classified manually by researchers, obviously requires huge and repeated work, which is undoubtedly feasible and has lost the significance of digitization [4]. In recent years, it has become an important research direction in the field of computer image processing to combine computers with art and use the powerful storage and computing power of computers [5] to realize the processing of large-scale digital painting images [6]. It is one of the research hotspots to study the classification of painting works of art according to the unique artistic style characteristics of painting images.

The artistic style of painting works generally refers to the artistic style, characteristics, style, style, and style shown in the painting works [7], which is a relatively stable and overall artistic feature presented by the interaction between the personality shown by the artist in the creation process and the semantics and context of the art works. The evaluation of the artistic styles and similarities of different paintings [8] is an important means for art researchers to classify paintings. At present, there are also many scholars studying painting image style classification methods, such as Hassanzadeh, T et al. [9], who proposed an evolutionary depth convolution neural network for image classification, input painting images into the evolutionary depth convolution neural network, and output painting image style classification results through the network model. Phasinam, K et al. [10] proposed a framework for real-time image classification. From IoT cameras to mobile applications to machine learning methods, there is everything. Arduino Uno, sensors, and Wi-Fi devices make up the hardware. The computer can "learn" from previous examples and use the machine to detect patterns from noisy or complex data sets, input the painting image into the frame, and then output its style classification results. Arco J et al. [11] proposed a feature space block sparse coding method for image classification. The image in this method is first divided into different tiles, and a dictionary is constructed after PCA is applied to these tiles. Then, the original signal is transformed into a linear combination of dictionary elements. Then, refactor each component by iteratively activating its associated elements.Finally, the subsequent reconstruction error is used as the feature for classification. Ciga, O et al. [12] proposed the method of learning to use classification labels to segment images, which realizes the style classification of painting images by annotating a few regions of interest. Fernandes, J et al. [13] proposed an end-to-end depth learning method for table detection and table image classification in data table images. This method first learns basic feature representations, such as different types of edges and contours, through the convolution layer of the basic network. Then, using the long-term memory mechanism of the Long Short-Term Memory Network (LSTM), the spatial correlation is modeled in both horizontal and vertical directions. Finally, the spatial correlation features learned are used to construct a classifier for classification.

Although these methods can realize the classification of painting styles, they are affected by the clarity and contrast of painting images. These methods have defects in practical applications. Color space conversion is a method of exchanging different color spaces to obtain texture details and image enhancement in the image [14]. This paper proposes a traditional art painting style classification method based on color space conversion based on color space conversion, so as to improve the level of painting style classification technology. The advantage of this method is to transform the image from one color space to another, so as to better extract the features of the image, further improve the contrast of the image, make the details in the image more prominent, and at the same time enhance the overall visual effect of the image. The technical route of this paper is as follows:

1) This method preprocesses the traditional artistic painting style, improves the contrast of the image, makes the color and details of the image more vivid, and provides the basis for the subsequent color space conversion.

2) After the traditional artistic painting style is stretched by automatic contrast stretching method, the color space is transformed. Based on the traditional artistic painting style image after color space conversion, the traditional artistic painting image is balanced by using the adaptive histogram equalization method with limited contrast, and the enhanced traditional artistic painting image is obtained.

3) Taking the enhanced traditional art painting images as input, the traditional art painting styles are classified by fuzzy C-means method, and the images are effectively classified into different categories according to the characteristics of the images.

II. Classification Method of Traditional Art Painting Style

A. Image Enhancement Processing of Traditional Art Painting based on Color Space Conversion

1) Automatic contrast stretching: Before classifying the style of traditional art painting images [15], it is necessary to enhance them to make their image features more obvious. Automatic contrast stretching is a point operation [16] whose purpose is to change the pixel gray value of the current image so that the pixel value distribution of the resulting image covers all available ranges of pixel gray value. This algorithm maps the current darkest and brightest pixel gray values to the minimum and maximum values in the range of available gray values. Then, it makes the middle gray values linearly distributed. In the classic automatic contrast stretching algorithm, the gray value of each input pixel is calculated using the following formula:

$$f_{ac}(e) = e_{min} + (e + e_{low}) \times \frac{e_{max} - e_{min}}{e_{high} - e_{low}} \tag{1}$$

Where: e_{max}、e_{min} represents the maximum and minimum values of pixel grayscale, e_{low} and e_{high} are the minimum and maximum values of pixel gray values in the current image, and the range of image pixel gray values can be $[e_{max}\ ,\ e_{min}]$.

The mapping function in Formula (1) is only strongly affected by several extreme values, which may not represent the main content of the image. Therefore, this scheme adopts the modified automatic contrast stretching algorithm, and the formula of the modified automatic contrast stretching algorithm is:

$$f_{mac}(e) = \begin{cases} e_{min} & e \le \hat{e}_{low} \\ e_{min} + (e - \hat{e}_{low}) \times \frac{e_{max} - e_{min}}{\hat{a}_{high} - e_{low}} & \hat{e}_{low} < e < \hat{e}_{high} \\ e_{max} & e \ge \hat{e}_{high} \end{cases} \tag{2}$$

In the above formula, $\hat{e}_{low}$、$\hat{e}_{high}$ represent two thresholds respectively. These two thresholds depend on the content of the image and can be represented by the cumulative histogram of the image $H(i)$ calculated:

$$\hat{e}_{low} = M \times N \times f_{ac}(e) \tag{3}$$

$$\hat{e}_{high} = M \times N \times f_{mac}(e) \tag{4}$$

Where: $M \times N$ is the number of pixels in the image. All pixel values can be derived from the formula $\hat{e}_{low}$ and $\hat{e}_{high}$ values other than (including) are mapped to extreme values respectively e_{min} and e_{max}, intermediate values are linearly mapped to $[e_{max}\ ,\ e_{min}]$. It can be seen that the mapping function is not only affected by several extreme values but also depends on a group of representative pixel values. In this algorithm, the contrast stretching of gray image Eq. (2) is applied to the R, G, and B color channels of the color image, respectively, to complete the automatic contrast stretching of traditional art painting images.

2) Color space conversion of traditional art painting based on polynomial regression: Based on the traditional art painting image after automatic contrast stretching [17], the color space is converted by polynomial regression.

Polynomial regression belongs to linear regression. In practical application, the independent variable is constructed by selecting the number of polynomial terms x and dependent variable y in the polynomial regression model, the dependent variable y and multiple arguments $x_1, x_2, \cdots, x_M$ with linear relationship, where is the number of independent variables, there are:

$$X_{DF} = (x_{t1}, x_{t2}, \cdots, x_{tN}), t = 1,2, \cdots, N \tag{5}$$

Where, N indicates the number of dependent variables. The relationship between the dependent variable and independent variable can be described as:

$$\begin{gathered} y_1 = \alpha_0 + \alpha_1 x_{11} + \alpha_2 x_{12} + \cdots + \alpha_M x_{1M} + \varepsilon_1 \\ y_2 = \alpha_0 + \alpha_1 x_{21} + \alpha_2 x_{22} + \cdots + \alpha_M x_{2M} + \varepsilon_2 \\ y_N = \alpha_0 + \alpha_1 x_{N1} + \alpha_2 x_{N2} + \cdots + \alpha_M x_{NM} + \varepsilon_N \end{gathered} \tag{6}$$

Among them, $\alpha_0, \alpha_1, \cdots, \alpha_M$ represents the coefficient to be determined $\varepsilon_0, \varepsilon_1, \cdots, \varepsilon_N$ represents an independent random variable.

If the parameter $b_0, b_1, \ldots, b_M$ is estimated by the least squares method β the regression formula obtained by fitting is:

$$\hat{y} = b_0 + b_0 x_1 + \cdots + b_M x_M \tag{7}$$

According to the principle of least squares, the coefficient $b_0, b_1, \ldots, b_M$ all measurements shall be obtained y_t, and regression value $\hat{y}$ minimum sum of residual squares of Q:

$$Q = \sum_{i=1}^{N} (y_t - \hat{y}_t)^2 \tag{8}$$

The polynomial regression method can describe not only linear problems but also nonlinear problems [18]. When describing nonlinear problems, the dependent variable needs to be y and arguments x a selected polynomial model is constructed, which can be correctly applied to the actual color signal processing system. Build the conversion between RGB color space and CMYK color space as fixed K. The polynomial of the conversion between RGB and CMY in the case of value is as follows:

$$C = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{p=0}^{n} \alpha_C R^i G^j B^p \tag{9}$$

$$M = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{p=0}^{n} \alpha_M R^i G^j B^p \tag{10}$$

$$Y = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{p=0}^{n} \alpha_Y R^i G^j B^p \tag{11}$$

where, α is a polynomial coefficient, n is the order of a polynomial, and $i + j + p \leq n$, the polynomial is represented by a matrix as follows:

$$\begin{bmatrix} \boldsymbol{X} & \boldsymbol{Y} & \boldsymbol{Z} \end{bmatrix}^{\boldsymbol{T}} = \boldsymbol{B_{3L}} \times \boldsymbol{\rho_L} \tag{12}$$

where, B_{3L} represents the coefficient matrix, ρ_L represents a polynomial matrix.

After the above steps, the traditional art painting image RGB color space and CMYK color space can be converted.

3) Adaptive histogram equalization with limited contrast: The Histogram equalization (HE) method has the advantages of fast speed and an obvious effect in enhancing image contrast. Histogram equalization can improve the overall image contrast [19]. Still, after processing, the image will appear "too bright or too dark," and local details cannot be processed, resulting in a loss of details and poor effect. Considering this, adaptive histogram equalization (AHE) based on the idea of block processing has been proposed to solve the problem of local highlight or too dark. Still, these two methods also amplify noise while enhancing contrast. Based on the advantages of the AHE algorithm, the concept of limiting contrast is proposed to solve the problem of amplifying noise. CLAHE algorithm not only effectively improves the contrast but also suppresses the generation of noise.

The specific steps of the CLAHE algorithm are as follows:

1) Divide the image into $n \times n$ there are rectangular sub blocks of the same size and non-overlapping each other. As the number of sub blocks increases, the enhancement effect of the image becomes more significant, but more details are lost [20].

2) Calculate the sub-block histogram.

3) Solve restricted values η.

$$\eta = \chi \times \frac{n_x n_y}{\hat{K}} \tag{13}$$

where:$n_x$represent Subblock x number of direction pixels; n_y express y number of direction pixels; $\widehat{K}$ is the gray level; χ is the limiting factor.

4) Crop the histogram and reassign the pixels. Cut sub-block histogram $h(x)$ restricted value η constraints, the exceeding part of the number of pixels is evenly distributed to other gray levels, and the pixel points are cut and reallocated, as shown in Fig. 1.

5) Sub block histogram equalization.

6) The bilinear difference reconstructs the gray value.

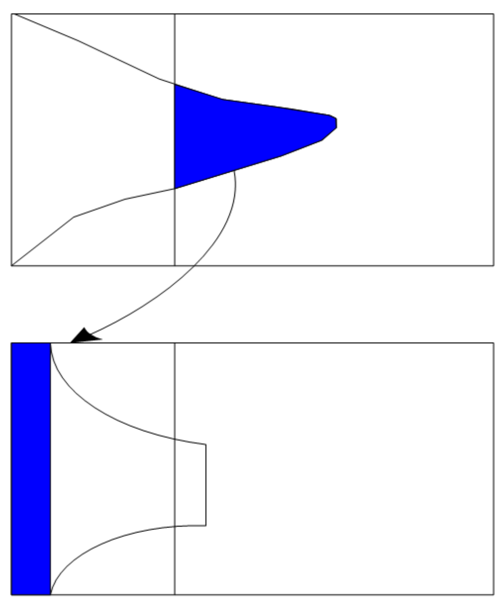


Fig. 1. Pixel cropping and reassigning.

The pixel value obtained only by mapping function transformation will cause the image to be blocky, and the bilinear difference processing for each point of the image can effectively avoid blocky.

The bilinear difference is only for the area surrounded by the center points of four blocks. The center of each sub block is taken as the reference point and recorded as $\theta_{11}(x_1, y_2)$、$\theta_{12}(x_2, y_2)$、$\theta_{21}(x_1, y_1)$、$\theta_{22}(x_2, y_1)$. Points to be calculated: The pixel value of P is determined by four adjacent reference points.

After the above steps P, after pixel reconstruction, traditional art painting image enhancement is realized.

B. *Extraction of Salient Information from Traditional Art Painting Images*

After the enhancement of traditional art painting images, extract its significant information to prepare for classification [21]. In the traditional art painting image, the image edge is usually used as the image background area, away from the image center of the target and surrounded by the position where the image's prominent target exists. The image background area is used as the super pixel block of the image edge, and the background area is compared with the remaining area from the perspective of color space to obtain the significance information of different areas [22].

The acquisition process of prior significance information of digital painting image background is as follows:

1) Get image manifold sorting: Set the background area of the traditional art painting image as the super pixel block at the image edge, and compare the color space of all the super pixel blocks with that of the background super pixel block to obtain the significance information of all parts of the image [23]. The manifold sorting algorithm is used to calculate the salient information of traditional art painting images. The algorithm obtains the sorting function by setting the correlation between fixed nodes and other nodes. It sets the correlation between nodes and other nodes according to the obtained sorting function measurement [24]. The correlation of each point is obtained by using the sorting method of the internal manifold structure of the data. Set data vector $M = [m_1, m_2, \cdots, m_n]^T$, assign the sorting value to each point in the data vector m_i, and get the final output of the function $g = [g_1, g_2, \cdots, g_n]^T$. Set up $p = [p_1, p_2, \cdots, p_n]^T$ as a marker vector, when $p_i = 1$ as well as $p_i = 0$ respectively m_i set query nodes and non set query nodes for. Set existence diagram $Q = (U, R)$ in the dataset, where U and R represent data node set and image edge set respectively, and use weighted similarity matrix $Q = \left[q_{ij}\right]_{n\times n}$ the above parameters can be obtained.

Using an optimization problem to express the optimal ordering of nodes $g*$, the calculation formula is as follows:

$$g* = (B - \alpha Q)^{-1} p \tag{14}$$

where:B represents a diagonal matrix; α represents the Plath coefficient.

2) Significant information calculation: The input digital drawing image is converted to the diagram structure representation according to Formula (14). Select the super pixel segmentation method to represent the image graph structure with multiple super pixel blocks [25], where each super pixel and node $U_i (1 \le i \le |U|)$ correspondingly set the query node as the super pixel node at the edge. The regular graph is used to represent the graph structure of the image [26]. That is, each node in the image is connected to the adjacent node, and the graph is connected to the adjacent node. The weight formula of the image edge is as follows:

$$k_{ij} = exp\left(-\frac{\sqrt{(L_i - L_j)^2 + (A_i - A_j)^2 + (B_i - B_j)^2}}{\delta^2}\right) \tag{15}$$

Where: L_i, A_i, B_i represent super pixels in color space i average of LAB value; δ indicates the node edge coefficient. The significance information of each node in the image is represented by the ranking value obtained by Formula (15). The query node is set as the upper boundary, and the ranking vector is obtained by using the significance information of the upper boundary and the significance information of other nodes $g*(i)$, using $\bar{g}*(i)$ indicates the significance information obtained by normalization to $[0,1]$ interval, set $\bar{g}*(i)$ use 1 as a difference to obtain the foreground significance information map.

Obtain saliency information map through image upper boundary $O_t(i)$. The formula is as follows:

$$O_t(i) = 1 - \bar{g}*(i) \tag{16}$$

Repeat the above steps to obtain the significance information map of the left, right, and lower boundaries $O_t(i)$, O_r, O_d means that the four saliency information maps obtained are multiplied to obtain the saliency information map of the final digital painting image, and the formula is as follows:

$$O\ \ (i) = O_t(i) \times O_d(i) \times O_r(i) \times O_l(i) \tag{17}$$

After the above steps, the salient information of traditional art painting images is obtained.

C. *Traditional Art Painting Image Style Classification Method based on Improved Fuzzy C-Means Algorithm*

The salient information of traditional art painting images obtained in the above sections is used as input, and the improved fuzzy C-means algorithm is used to realize the classification of traditional art painting styles.

The fuzzy C-means algorithm is a local search algorithm that mainly constructs the Lagrange function and iteratively calculates the minimum of the sum of squares of the global weighted distances from each sample to the cluster center to obtain the optimal cluster center. If the sample set is U, the cluster center set is V, the objective function can be expressed as:

$$min\, J\,(U, V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{ik}) m (d_{ik})^2 \tag{18}$$

where: n and c are the number of samples to be classified and the number of clusters; m is the fuzzy degree coefficient, which is responsible for controlling the sharing degree between fuzzy classes; u_{ik} is a sample pair k clustering i and has $0 \leq u_{ik} \leq 1$, $\sum_{i=1}^{c}(u_{ik}) = 1$; d_{ik} is a sample k to clustering i the Euclidean distance of the center.

Because the fuzzy C-means algorithm is prone to the local optimal solution, slow convergence, and poor classification effect under high-dimensional data, we use the differential evolution algorithm to improve the fuzzy C-means algorithm and use the improved fuzzy C-means algorithm to classify the traditional art painting image style.

The differential evolution algorithm is used to improve the fuzzy C-means algorithm. First, a group of initial centers is randomly generated, and the non-center points are grouped into the center point area one by one according to the principle of minimum distance. Then, the differential evolution algorithm is used to carry out parameter adaptive adjustment, mutation, crossover, and selection operations for the current partition so that the search process changes from an unsupervised state to a dynamic information-guided optimization and performs the second assignment operation on the current part of non-optimal individuals to enhance the small range of the later stage of the algorithm fine search capability. The specific steps are as follows:

Step 1: Initialize the parameters. Determine various control parameters required by the algorithm and make the number of iterations $T = 0$.

Step 2: Initialize the population. The cluster center is used as a population individual to code. First, the initial cluster center is randomly generated, and the individual coding method is as follows:

$$\boldsymbol{X_i = (x_{1,1}, x_{1,2}, \cdots, x_{1,s}, x_{2,1}, \cdots, x_{2,s}, \cdots, x_{c,s})} \tag{19}$$

where: s is the dimension of the cluster center; c is the number of individuals. Then, the differential evolution algorithm is used to generate a random initial population:

$$x_{i,j} = xi, jmini, jmax_{i,jmin} \tag{20}$$

where: $x_{i,j}$, $x_{i,jmax}$, $x_{i,jmin}$ individual set of population X_i of j components and their upper and lower bounds; r is a random number in the range of [0,1].

Step 3: Formula (18) is taken as the objective function, and the adaptability evaluation function, so the objective function value is the population fitness evaluation result. The smaller the objective function value, the higher the quality of the population of individuals. Calculate the fitness of the current population and determine whether the maximum number of iterations of the algorithm is reached T_{max}.

Step 4: Adaptively adjust the mutation factor F and hybridization factor C. The variance of population fitness can effectively reflect the individual distribution of the contemporary population and dynamically adjust the control parameters in a targeted way, thus having good results. The variance of group fitness σ^2 can be expressed as:

$$\boldsymbol{\sigma^2 = \sum_{I=1}^{n}\left(\frac{\delta_i - \delta_{av}}{\delta_b}\right)^2} \tag{21}$$

where: N is the population size; δ_i is for i individual fitness; δ_{av} is the average fitness of the population; δ_b is the best fitness of the group.

Based on the above calculation σ^2, the adjustment parameter changes from a fixed value to the following dynamic form:

$$F_k = F_{\min} + (F_{\max} - F_{\min} - \frac{\sigma_k^2(F_{\max} - F_{\min})}{N} \tag{22}$$

$$\hat{Z}_k = \hat{Z}_{\min} + (\hat{Z}_{\max} - \hat{Z}_{\min})1 - \frac{\sigma_k^2(\hat{Z}_{\max} - \hat{Z}_{\min})}{N} \tag{23}$$

where: F_{max} and F_{min} are the upper bound and the lower bound of the variation factor; $\hat{Z}_{max}$ and $\hat{Z}_{min}$ are the upper bound and lower bound of hybridization factors respectively; σ_k^2 is for k generation population fitness variance.

Step 5: Conduct mutation and crossover operations on the population, generate a trial offspring population, recalculate the fitness, and use the "greed" strategy for selection operations to form a new generation of population.

Step 6: Secondary assignment. Randomly select some individuals from the non-optimal individuals of the current population according to the previously specified probability distribution function for secondary assignment:

$$X_{i,re} = X_i(1 - \delta_{rand}) + O\delta_{rand} \tag{24}$$

$$O = \frac{\lambda_{ad} I X_{optimal} + rX_{r1} - rX_{r2}}{\lambda_{ad} I} \tag{25}$$

where: X_i is the individual value of the current population; δ_{rand} is a binary random decision variable; O is the local search adjustment operator defined in this paper; $X_{optimal}$ is the best individual in the contemporary population; λ_{ad} is an adjustment factor, which is used to adjust the local search sensitivity of the differential evolution algorithm. The larger the value, the stronger the local search ability of the algorithm; I is the number of iterations; X_{r1} and X_{r2} are from a new population of randomly selected individuals and meet $X_{r1} \neq X_{r2}$.

As the number of iterations increases, the optimization scope of the algorithm gradually shrinks, and finally, the optimal clustering division result is obtained, which is the classification result of traditional art painting image style.

III. Experimental Analysis

With 5000 traditional art paintings of different styles as experimental objects, including comics, sketches, ink paintings, watercolors, and other painting styles, this paper uses this method to classify the 5000 traditional art painting styles and analyzes and verify the practical application effect of this method.

Set the parameters needed for the experiment, as shown in Table I.

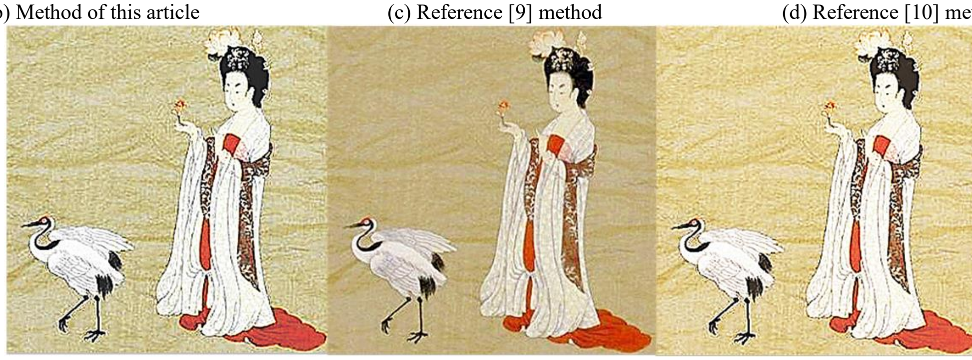
Taking a traditional art painting as the experimental object and contrast stretching as the measurement index, the enhancement ability of this method to the traditional art painting image is tested. To make the experimental results more sufficient, the literature [9] method, literature [10] method, literature [11] method, literature [12] method, and literature [13] method are used at the same time. The test results are shown in Fig. 2. Analysis of Fig. 2 shows that the overall color of the original traditional art painting image is dark, and the internal details of the image are not clear enough. After using six methods to enhance the traditional art painting image, the clarity and contrast of the traditional art painting image enhanced by this method have been significantly improved. Although the contrast of the traditional art painting image enhanced by the literature [9] method, literature [11] method, and literature [13] method is effectively prompted, the contrast is too large, which leads to the disappearance of the internal details of the traditional art painting image, while the traditional art painting image enhanced by the literature [10] method and literature [12] method has a low lightness and darkness. The details in traditional art painting images cannot be clearly presented. To sum up, this method can effectively stretch the traditional art painting image and has a strong traditional art painting image enhancement effect.

TABLE I. CONFIGURATION TABLE OF PARAMETERS REQUIRED FOR EXPERIMENTS

Serial number	Parameter	Content
1	Color space conversion parameter	From RGB color space to HSV color space, it is necessary to convert the coefficients in the formula.
2	Automatic contrast stretching parameter	Relates to parameters such as tensile strength or tensile ratio.
3	Adaptive histogram equalization parameters with finite contrast	Parameters such as contrast limit threshold and the number of histogram partitions are involved.
4	Fuzzy c-means clustering parameters	When using fuzzy C-means method to classify styles, it is necessary to set parameters such as the number of clusters (that is, the number of styles) and fuzzy factors.
5	Relevant parameters of training and testing data sets	Including the ratio of training set to test set, data enhancement parameters (such as rotation angle, cutting size, etc.), batch size, learning rate, etc.

(a) Primitive traditional art painting images

(b) Method of this article (c) Reference [9] method (d) Reference [10] method



(e) Reference [11] method (f) Reference [12] method (g) Reference [13] method

Fig. 2. Test results of image enhancement in traditional art painting.

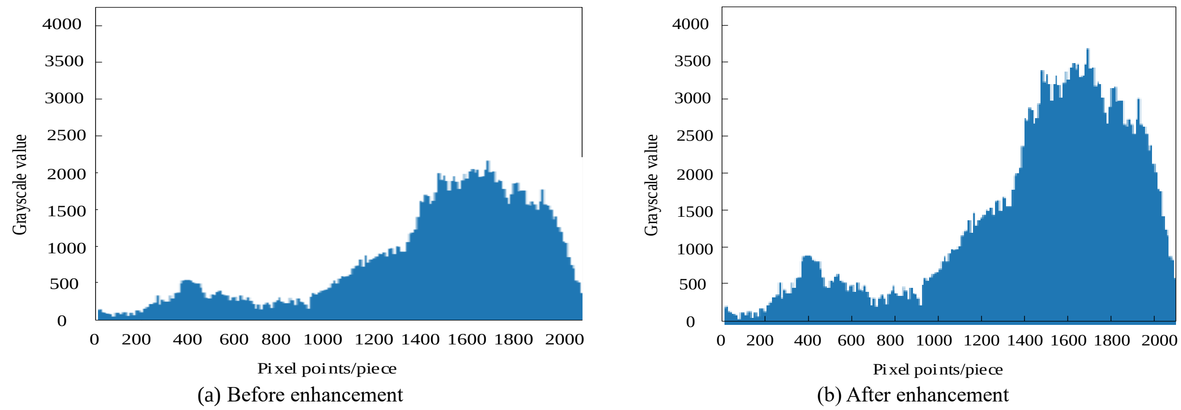


Fig. 3. Test results of image enhancement in traditional art painting.

To further verify the enhancement effect of this method on traditional art painting images, take a traditional art painting image as the experimental object and use this method to enhance it. Additionally, the histogram is employed to showcase the grayscale values of the traditional art painting image both before and after undergoing enhancement processing. The test results are shown in Fig. 3.

According to the comprehensive analysis of Fig. 3, after applying the method in this paper to enhance the traditional art painting image under the same pixel situation, the pixel gray value can be effectively improved. This result further verifies that the method in this paper has a good enhancement effect on the traditional art painting image.

The color space conversion accuracy is taken as a measure to test the color space conversion ability of the method in this paper for traditional art painting images under different color space lightness and color saturation. The test results are shown in Table II.

According to the analysis of Table II, when using this method to convert the color space of traditional art painting images, the separation accuracy value is higher than 0.9 under the conditions of different color space lightness and color space saturation. This value shows that this method can effectively convert the color space of traditional art painting images and also confirms from the side that this method has a strong ability to classify traditional art painting styles.

Take a large number of traditional art painting images as experimental objects and use the method in this paper to classify their styles. In order to make the verification results more sufficient, the style classification is carried out respectively under the conditions of no rotation, 30-degree rotation, and 70-degree rotation of traditional art painting images. The results are shown in Fig. 4 to Fig. 6, respectively.

TABLE II. PRECISION VALUES OF COLOR SPACE CONVERSION IN TRADITIONAL ART PAINTING IMAGES

Color space brightness	**Color space conversion accuracy**	**Saturation**	**Color space conversion accuracy**
5	0.95	50	0.98
10	0.95	55	0.95
15	0.96	60	0.96
20	0.94	65	0.93
25	0.95	70	0.98
30	0.97	75	0.94
35	0.92	80	0.97
40	0.96	85	0.92
45	0.93	90	0.95
50	0.95	95	0.94
55	0.94	100	0.96

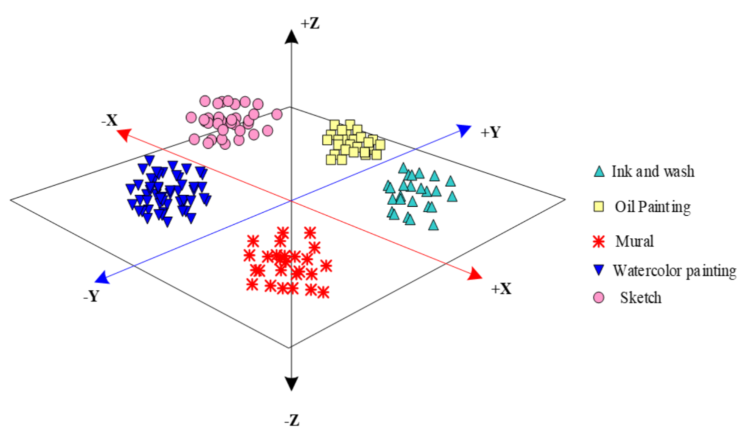


Fig. 4. No rotation.

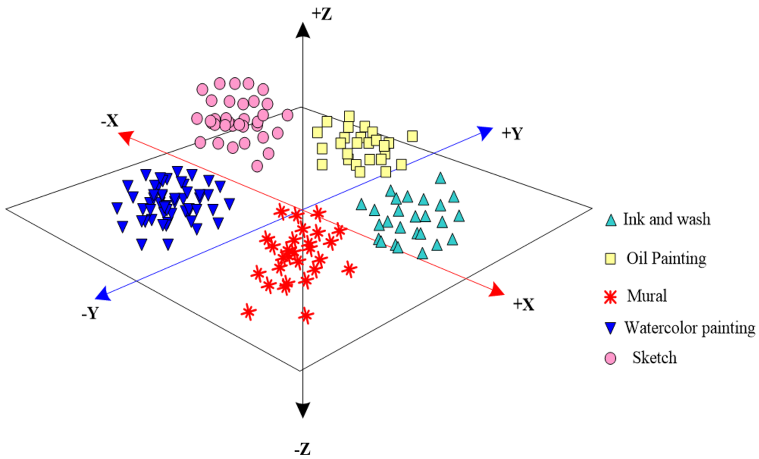


Fig. 5. Rotate 30 degrees.

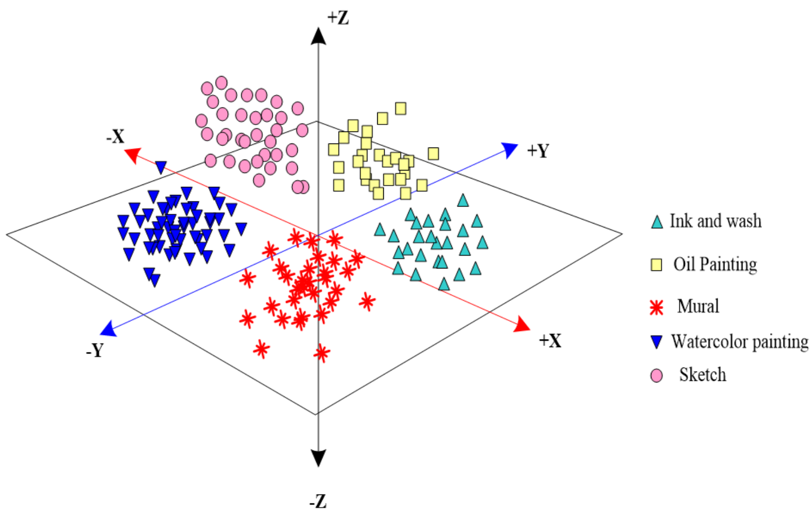


Fig. 6. Rotate 70 degrees.

From the analysis of Fig. 4 to Fig. 6, it can be seen that when the traditional art painting images are not rotated, the distance between different clusters is far when this method classifies their styles, and the distribution of traditional art painting images in the same cluster is relatively dense. When traditional art painting images are rotated 30 degrees and 70 degrees, respectively, the distribution distance of different clusters is shortened when the method in this paper is applied to classify traditional art painting styles, and the distribution of traditional art painting images within the same cluster becomes sparse, but the differences between different clusters are still obvious. The aforementioned findings indicate that the utilization of this approach leads to an efficient classification of traditional art painting styles. When classifying, the density between class clusters is better, and the classification of traditional art painting styles is more accurate, which is not affected by the rotation of traditional art painting images.

The Xie Beni (XB) index is used to measure the classification accuracy of traditional art painting styles. The smaller the value, the higher the classification accuracy of traditional art painting styles. With 15 traditional art painting images as the experimental objects, this paper analyzes the changes in the Xie Beni index when classifying the magnification of traditional art painting images by this method and sets the threshold value of the Xie Beni index to 0.4. The test results are shown in Table III.

TABLE III. CLASSIFICATION OF TRADITIONAL ART PAINTING STYLES BY XIE BENI INDEX

Traditional Painting Image Coding	**Magnification**		
	1	***1.5***	***2***
1	0.12	0.21	0.32
2	0.11	0.23	0.33
3	0.19	0.25	0.31
4	0.08	0.19	0.28
5	0.07	0.19	0.24
6	0.12	0.25	0.26
7	0.15	0.29	0.27
8	0.09	0.31	0.31
9	0.14	0.24	0.33
10	0.16	0.25	0.35
11	0.08	0.26	0.28
12	0.17	0.22	0.29
13	0.15	0.21	0.31
14	0.16	0.27	0.25
15	0.11	0.18	0.24

Analysis of Table III shows that with the increase of magnification of traditional art painting images, the Xie Beni index when classifying traditional art painting styles in this method shows an upward trend, but the increase is not significant. When the magnification of the traditional art painting image is 2, the maximum value of the Xie Beni index when this method classifies the traditional art painting style is only 0.35, which is lower than the preset threshold value of the Xie Beni index. The above results show that the method in this paper has a high accuracy in classifying traditional art painting styles and has a relatively significant application effect.

IV. Discussion

1) The traditional art painting style classification method based on color space transformation has obviously improved the clarity and contrast of the traditional art painting images, which can effectively stretch the traditional art painting images and has strong traditional art painting image enhancement effect.

2) After the traditional art painting style classification method based on color space transformation is applied to enhance the traditional art painting image, the gray value of each pixel is effectively improved under the same pixel, which further verifies that the method in this paper has a good enhancement effect on the traditional art painting image.

3) When the traditional art painting style classification method based on color space conversion is used to convert the color space of traditional art painting images, the separation accuracy values are all higher than 0.9 under different color space lightness and color space saturation, which shows that the method in this paper can effectively convert the color space of traditional art painting images, and also proves from the side that the method in this paper has strong ability to classify traditional art painting styles.

4) The traditional art painting style classification method based on color space transformation is far away between different clusters, and the traditional art painting images in the same cluster are densely distributed. The application of this method can effectively classify the traditional art painting styles, and the density between clusters is good, and the classification of traditional art painting styles is more accurate, which is not affected by the rotation of traditional art painting images.

5) With the increase of the magnification of traditional art painting images, the Xie-Beni index of the traditional art painting styles classified by this method shows an upward trend, and the classification of traditional art painting styles by this method has a high accuracy and a remarkable application effect.

V. Conclusion

The classification of traditional art painting styles is one of the more efficient applications of deep learning methods in the field of traditional art painting. It can effectively enhance the performance of both classification and imitation of traditional art painting styles. This paper studies the classification algorithm of art-style images and proposes a traditional art painting-style classification method based on color space conversion. The salient information contained in traditional art painting images can effectively reflect the image's salient features, improve the accuracy of style classification, and combine the salient information with the fuzzy C-means algorithm. According to the characteristics of traditional art painting images, the salient features contained in different styles of painting images are extracted. Then, the extracted features are passed on to the fuzzy C-means algorithm in order to accomplish the classification of traditional art painting styles. Through the actual verification of the method in this paper, based on the verification results, it is evident that the approach presented in this paper exhibits a high level of effectiveness in categorizing traditional art painting styles, yielding notable practical applications.

Although the traditional art painting style classification method based on color space transformation has certain effectiveness, it also has some limitations.

1) Dependence on color space transformation: One of the core of this method is color space transformation. However, the conversion of color space may be influenced by many factors such as lighting conditions, pigment types and painting techniques. For some special cases, the transformation of color space may not accurately capture the essential characteristics of painting style, which leads to the error of classification results.

2) Limitations of feature extraction: This method mainly relies on image features such as color and contrast for classification. However, the traditional artistic painting style is not limited to color and contrast, but also includes many characteristics such as texture, composition and brush strokes. These methods fail to fully consider other features, which will limit the accuracy and comprehensiveness of classification.

3) Requirements of data set: The method based on color space conversion has higher requirements for training data set. It needs enough diverse and representative samples for training in order to obtain an accurate classification model. If the data set is small or the samples are not rich enough, the generalization ability of the model will be insufficient, and the new paintings cannot be accurately classified.

To sum up, the traditional art painting style classification method based on color space transformation has achieved certain results, but it still faces some limitations. Future research can further combine advanced technologies such as deep learning to improve the accuracy and efficiency of classification.

Data Availability

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation."

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work."

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