

Retraction

Retracted: Design of Artistic Creation Style Extraction Model Based on Color Feature Data

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] W. Yao and M. Sohail, "Design of Artistic Creation Style Extraction Model Based on Color Feature Data," *Mathematical Problems in Engineering*, vol. 2022, Article ID 4811191, 9 pages, 2022.

Research Article

Design of Artistic Creation Style Extraction Model Based on Color Feature Data

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In order to improve the style extraction and extraction ability of works of art, a color extraction method based on color features is proposed. The color feature extraction method is used to extract the style of visual works of art. The color feature region of works of art is segmented combined with a sparse scattered point reorganization method. Texture tracking and matching method is used for information fusion of works of art, combined with corner detection, three-dimensional edge contour feature detection method to realize texture filling and automatic rendering of art color extraction to improve art graphics' color visual feature expression ability. The color feature data method is used for visual feature sampling and equalizing works of art. According to the equilibrium configuration results, the fuzzy clustering method is used to extract the color style of works of art to improve the style extraction and extraction identification ability of works of art. The simulation results show that this method has high accuracy in color extraction of works of art. It has a good effect on the extraction of art creation style and improves the ability of three-dimensional extraction and automatic extraction of art.

1. Introduction

Color feature data processing technology has been used in style extraction and automatic extraction of works of art, extracting the three-dimensional color information feature of works of art, and extracting works of art according to the color feature information of works of art as work of art processing technology has progressed. It can increase the capacity to accurately identify and rebuild works of art [1]. Color feature segmentation and texture information feature extraction of works of art are used to create three-dimensional extraction. The RGB color feature decomposition approach is utilized to extract the style of works of art, as well as the color features, sparse point characteristics, and texture features of works of art. The color extraction of works of art and accurate identification of works of art are accomplished using the feature extraction findings paired with the color visual analysis approach. The color feature extraction technique is employed to extract the visual image style of works of art. The color feature area segmentation of the

image of works of art is processed by combining the sparse dispersed point reorganization method [2]. Texture tracking and matching method is used for image information fusion of work of art. Combined with corner detection and 3D edge contour feature detection method, texture filling and automatic rendering of artwork color extraction are realized to improve artwork graphics' color visual feature expression ability.

2. Artistic Creation Style Extraction Model

2.1. Color Feature Region Segmentation of Works of Art. To create digital artworks with high levels of color accuracy, you will need color feature acquisition equipment. A color digital camera and a series of optical filters are used to build a multispectral acquisition system. Following the gathered multispectral works of art [3], we extract the spectral reflectance of each pixel. Then, using spectral reflectance, it will be possible to faithfully replicate the color information contained inside artwork. Color restoration techniques are

provided based on the distinct ageing and fading processes and the degree of rice paper or painting pigment in the carrier material. A physical experiment is used to mimic rice paper ageing to create an accurate ageing model. In terms of pigments, the pigment composition of the repaired area is computed and a set of alternative pigments are offered based on the concept of computer color matching [4]. Finally, a comprehensive art restoration paradigm is developed. The works of art are color layered based on spectral reflectance similarity, and the new color is determined based on the distinct color information of each layer. Color is the sense of color generated by external stimuli on the human eyes, which is then analyzed and judged by the brain. It is not a physical quantity in its purest form. The International Lighting Commission (CIE) has established a series of standard chromaticity systems to assess the color impact uniformly. [5]. CIE colorimetry system uses tristimulus values to quantitatively describe color. To measure the tristimulus values of object color, spectral tristimulus values must be measured first. The visual characteristics of different observers are different, but the difference between normal color observers is not very large [6]. Therefore, CIE determines a set of data "standard chromaticity observer tristimulus values" through color experiments on some observers. To sum up, the relationship between the relative spectral powers of the light source, the object's spectral reflectance, the standard observer data, and the CE tristimulus value of the object color is shown in Figure 1.

The object's reflectance spectrum value is shown on the left, with the wavelength range represented by the abscissa and the reflectance of the corresponding wavelength represented by the ordinate. The spectral distribution of the light source is shown in the center image, with the abscissa representing the wavelength range and the ordinate representing the relative radiation strength corresponding to that wavelength [7]. The standard chroma observer data is shown on the right, with the abscissa representing the wavelength range and the ordinate representing the tristimulus values of the corresponding wavelength. When light shines on the surface of an opaque media, except for a little portion that is reflected, the majority of the light enters the interior of the medium and is absorbed and dispersed, resulting in a variety of colors [8]. The relationship between the object's spectral reflectance and the absorption and scattering of the medium is derived. The incident light R_g is irradiated on a medium with a thickness of S_x , parts of which are scattered b and absorbed a . Therefore, the spectral reflectance R of the medium with thickness h can be expressed by the following formula:

$$R = \frac{1 - R_g(a - b \coth bS_x h)}{a - R_g + b \coth bS_x h}. \quad (1)$$

In the above formula, $b \coth bS_x$ is the hyperbolic cotangent of bS_x . If K is the spectral reflectance of the base, Q is the absorption coefficient, S is the scattering space, and R is the spectral reflectance of the sample. If the thickness x reaches infinity, formula (1) can be simplified to the following formula:

$$R = 1 + \frac{K}{S} - \left[\left(\frac{Q}{S} \right)^2 + 2 \left(\frac{K}{S} \right) \right]^{1/2}. \quad (2)$$

For the extraction of digital works of art, firstly, multispectral works of art are obtained through a group of optical filters in different bands. Due to camera vibration and other factors during shooting, there may be displacement image registration methods between works of art to eliminate the displacement caused by jitter and other reasons [9]. In addition, spectral artworks may exhibit localized unsmooth phenomena because of the camera's noise. Therefore, noise filtering is used to smooth out the art. Finally, each pixel's spectral reflectance is computed via spectral extraction. A flow diagram is given in Figure 2 showing how spectral color is used to display the artwork.

In the preservation process of art, the carrier materials and pigments are affected by aging factors. Therefore, they need to be layered according to the color of works of art and then make different color restoration places for each layer [10]. Artwork segmentation and clustering may identify pieces with similar color characteristics. It is the technique and practice of splitting works of art into distinct areas and then extracting the regions of interest from these segments. Grayscale, color, texture, and other elements may be used in an artwork. It is possible to target a single region or a group of places at once [11]. The segmentation of works of art can be defined by collection, so that I represents all the pixels of works of art. Different areas $\{S_1, S_2, S_3, \dots, S_i\}$ can be defined by applying the segmentation method. The relationship between them can be as follows:

$$\bigcup_{i=1, n}^n S_i = I, \quad (3)$$

where S_i is a connected region and satisfies certain similarity conditions, as shown in the following formula:

$$P(S_i) = TURE. \quad (4)$$

This paper selects the color space model and histogram for the color feature descriptor. The color space model includes RGBISI, HSV, and Lab. The histogram is divided into gray and color histograms (red R , green G , and blue B histogram). This paper selects the gray level cooccurrence matrix and five texture feature parameters for the texture feature descriptor. According to the direction, the gray level cooccurrence matrix is divided into 0° , 45° , 90° , and 135° according to the direction [12]. The five texture feature parameters are energy, entropy, moment of inertia, correlation, and local stationarity. Finally, for the shape feature descriptor, this paper selects wavelet transform and seventh-order moment, and the wavelet transform is distinguished according to the transformation times and direction. The image descriptor is shown in Table 1.

Different subregions have different characteristics, and there is no similarity between regions. There is no ideal work of art segmentation system that can partition every pair of works of art according to people's preferences. It is often separated into two schemes in early study on the segmentation techniques of works of art: the boundary technique,

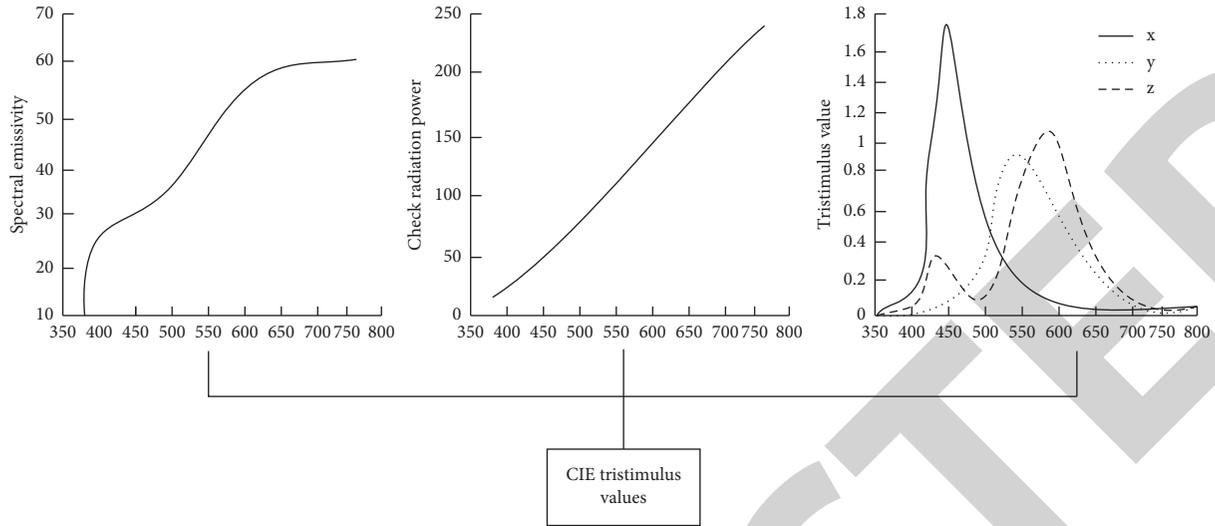


FIGURE 1: Tristimulus values of image color features.

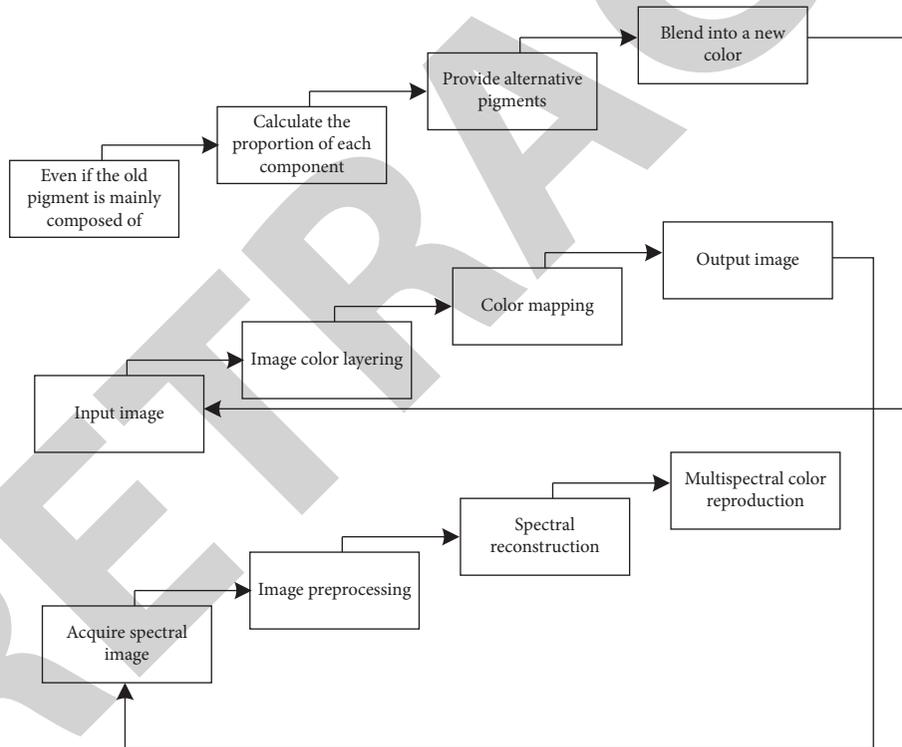


FIGURE 2: Color feature extraction model.

TABLE 1: Image descriptor.

Features	Descriptor
Color	Color space model
Texture	Gray level cooccurrence matrix
Shape	Seventh moment

for example, presupposes that edges exist in the pre-segmented region of works of art [13]. The other is based on the fact that the segmented region must have similar

characteristics, the region method. For the segmentation of color works of art, the choice of color space is also an important factor affecting the segmentation effect.

2.2. Feature Information Fusion of Works of Art. To realize the art color extraction of color features and the style extraction of works of art, the feature points are segmented and fused in combination with the contour extraction method of works of art, and the color feature area of works of art is segmented and processed in combination with the sparse

and scattered point reorganization method. The texture tracking and matching method is used for the information fusion of works of art. Firstly, the feature analysis model (x, y, z) of works of art with color features is constructed [14]. Then, the local quadric surface P is fitted by grid model matching method, and the uniformly distributed grid vertex model of works of art with color features is constructed $(H + t \times I)$. The significance judgment method is used for color feature imaging O analysis for the collected original works of art. According to the cross-sectional principle, the threshold g of color visual feature points of works of art is determined. According to the threshold judgment results, the color visual features of works of art are separated w , and the correlation fusion processing method is used to form the color visual feature point set q of works of art.

$$\begin{pmatrix} x & y & z \\ 0 & 0 & 0 \end{pmatrix} = \begin{pmatrix} (H + t \times I) & P \\ & O \end{pmatrix} \begin{pmatrix} g & q & w \\ a & b & c \end{pmatrix}, \quad (5)$$

where x , y , and z are the color visual feature points corresponding to the three primary colors of the works of art: red, yellow, and blue. a , b , and c are the visual features corresponding to the three primary colors of red, yellow, and blue of the artistic work; $L(x, y, \sigma)$ is the correlation factor. $I(x, y)$ is the fusion coefficient. $G(x, y, \sigma)$ is the fusion error; $G(x, y, k\sigma)$ are the threshold values of visual feature points for the color of works of art. In the three-dimensional shape model of artwork, the three-dimensional key feature points of visual artwork are extracted, the color weak convex components of artwork are combined, the significance judgment method is used to extract the texture surface of artwork, and the Harris corner detection method is used to fuse and filter the color features of artwork [15]. The filtering function is

$$\begin{aligned} D(x, y, \sigma) &= (G(x, y, k\sigma) - G(x, y, \sigma) \times I(x, y)) \\ &= L(x, y, k\sigma) - L(x, y, \sigma). \end{aligned} \quad (6)$$

If $I(x, y)$ is the clustering gray value of feature points at (x, y) of art color features, it explains about the fusion filter factor of artworks.

$$L(x, y, \sigma) = G(x, y, \sigma) \otimes I(x, y). \quad (7)$$

Judging the color characteristics of works of art, the current seed point of works of art is the weak convex decomposition and three-dimensional model segmentation method. As a result, the color characteristics of works of art are obtained [16]. The sparse point cloud distribution feature set of works of art is (x, y) . Furthermore, the spatial neighborhood decomposition is carried out, and the spatial neighborhood decomposition coefficient is

$$F_d - \frac{d}{dx}F_{d_x} - \frac{d}{dy}F_{d_y} = 0, \quad (8)$$

where dx is the decomposition scale of the approximate convex decomposition part of works of art, the texture tracking and matching method is used for works of art

information fusion, and the corner detection method is used for color component dy detection. The edge points are determined as feature points, the color features of works of art are processed by fuzzy clustering, and the distance between the clustering centers is L . The smaller prominent part is selected for voxel feature segmentation, and the visual feature segmentation output of works of art is described as

$$N_1 = \begin{cases} 1, & l = 0, L, \\ \left[2\pi \frac{D}{2} \sin \frac{\eta}{l} \right], & l = 1, L - 1, \end{cases} \quad (9)$$

where η is the division angle of the protruding part. D is the division width of the protruding part. L is the maximum distance from the color feature point of the obtained artwork to the clustering center [17]. According to the above analysis, the vector quantization feature quantity of the artwork is set with the color feature of the artwork, the texture information on the surface quantized as the art component is detected, and the color feature of the artwork is obtained. The first k -dimensional feature template of the artwork is described as

$$P(\varphi) = \int \frac{1}{2} (|\Delta\varphi| - 1)^2 dx, \quad (10)$$

where φ is the color feature of the work of art and $\Delta\varphi$ is the local template volume feature component of the work of art. For the volume similarity feature component, the concave point is 1 and the convex point is 0. The sparse linear programming method is used for the regional fusion of works of art. The weighted feature segmentation method is used to obtain the initial weak bump color feature distribution function as

$$\text{Data}(x, y, d(x, y)) = |u(x, y) - \bar{u}(x, y)|^2. \quad (11)$$

According to the above analysis, the detected color feature artwork point cloud data is fused, and the artwork color feature is constructed according to the mutual visibility between adjacent blocks. Therefore, the decomposition process equation of artwork color feature is

$$\frac{\langle \tau_d u', \bar{u} \rangle_{\phi_{x_0}}}{\|\tau_d u'\|_{\phi_{x_0}} \|\bar{u}\|_{\phi_{x_0}}} = \frac{\langle \sigma_d u, \bar{u} \rangle_{\phi_{x_0}} \langle \tau_d u', \tau_d \bar{u} \rangle_{\phi_{x_0}}}{\|\tau_d u'\|_{\phi_{x_0}}^3 \|\bar{u}\|_{\phi_{x_0}}} \cdot \frac{\|\tau_d u'\|_{\phi_{x_0}}^2}{\langle \tau_d u', \tau_d \bar{u} \rangle_{\phi_{x_0}}}, \quad (12)$$

where $\|\tau_d u'\|_{\phi_{x_0}}$ is the feature quantity of weakly convex components combined for the three-dimensional works of art to be reconstructed. R is the consolidation coefficient of works of art. φ is mutual visibility between adjacent blocks. The art color extraction technique is enhanced based on the style extraction of works of art, and a color extraction approach based on color characteristics is provided. The color feature area of works of art is segmented using the sparse dispersed point rearrangement method [18]. Within the search radius of R , the works of art with color characteristics are block segmented, and the appearance texture

information feature is retrieved. The texture feature component for the output is

$$L(a, b_m) = \sum_{V_m \in Pmv_n \in P^{i+nx}} \frac{|V_m \cap V_n|}{|V|} \log \left(\frac{|V| |V_m \cap V_n|}{|V_m| |V_n|} \right). \quad (13)$$

If the texture feature quantity of works of art within the R search range. V_m is the texture feature quantity of works of art within the m search range. V_n is the amount of texture features of works of art within the n search range [19]. Combining corner detection and 3D edge contour feature detection methods, the texture filling and automatic rendering of art color extraction are realized, and the matching points of mesh model of art are obtained.

$$F = \hat{p}(x, y) = p(x, y) \left(\frac{v(x)}{v(y)} \right)^{1/2}. \quad (14)$$

The statistical shape model of works of art with color features is established. Combined with the correlation filter detection method, the two adjacent pixel sets of color vision of works of art are obtained.

$$\begin{cases} p(x, y) = \frac{k(x, y)}{v(x)}, \\ v(x) = \sum_y k(x, y), \end{cases} \quad (15)$$

where v is the color extraction function of works of art. The background color is reconstructed; the color space of works of art with the color characteristics of works of art is enhanced, and the output color RGB component is

$$d = \frac{1}{n} \sum_{i=0}^{n-1} |v_i - v_{i-1}|. \quad (16)$$

Combined with corner detection and three-dimensional edge contour feature detection, the texture filling and automatic rendering of art color extraction are realized to improve the color visual feature expression ability of works of art.

2.3. The Realization of Style Extraction of Artistic Works.

For a given work of art, the self-similarity descriptor of the work of art can be obtained. Based on the self-similarity descriptor of works of art, the similarity between different types of works of art is calculated. It is assumed that the two types of problems have Q training samples $\{x_1, y_1\}, \dots, \{x_i, y_i\}, \dots, \{x_0, y_0\}$. Among them, the self-similarity descriptor corresponding to $X_i \in x$ is $SSD_i = 1, \dots, Q$, y is the sample identification, $y \in \{2, \dots, D\}$, and there are l classes. Suppose that X_i and X_j are similar samples, and X_i and X are heterogeneous samples; $I, JK \in \{1, \dots, Q\}$. According to the similarity rules 2 and 3, the similarity coefficient between sample X and similar samples and heterogeneous

samples can be obtained: sample x is a homogeneous sample (intra-class), and sample X is marked as l , and the similarity coefficient is calculated as

$$SM_i = \begin{bmatrix} G_{i1} & G_{i2} & \dots & G_{iM} \\ \vdots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ \dots & \dots & \dots & G_{iMN} \end{bmatrix}. \quad (17)$$

Sample XK is a heterogeneous sample, and the sample identification is I , and the similarity coefficient is calculated as

$$\beta_{(i,k)}^l = e \left(-\frac{d(x_i, x_k)^2}{\sigma^2} \right). \quad (18)$$

According to the similarity rules, there may be

$$\alpha_{(j)}^l > \beta_{(k)}^l. \quad (19)$$

The inherent ability of the human brain, namely, visual attention, is used to classify painting works of different artistic styles, as shown in Figure 3.

The points of interest are gathered according to the saliency map related to the art piece, and then the classification based on probability model is carried out and more points of interest are collected, all based on the feature map at the sampling place. Our technique is comparable to the agile framework method, but our method is entirely different in many ways, such as the feature and importance graph model. We get the art piece saliency map and sample the focus set t times at random [20]. For each sampling T , position P is selected according to the significance map (the position coordinates are first regularized according to the width and height of the artwork), and then s is extracted on position $P \times S \times n$ filter responses. Considering the computational efficiency, using the pyramid model for spatial downsampling, C reduces the number of dimensions on the region heap. The classification method is based on elegant framework and uses kernel density estimation to model $(L_t | C = j)$, where l represents the feature vector obtained at time t , and j represents the category of the sample in the training. Assuming that all focus sets are statistically independent, all the information from the 1st to t times is combined.

$$P(\{L_t\}_l^T | C = j) = \prod_{t=1}^T P(L_t | C = j). \quad (20)$$

Then, Bayesian rules are used to obtain

$$P(C = j | \{L_t\}_l^T) \propto P(C = j) \prod_{t=1}^T P(L_t | C = j). \quad (21)$$

Here $P(C = J)$ is the a priori category, it is adjusted as main distributed pair in the experiment $P(L_t | C = j)$ which is set uniform and its calculation is not an easy thing. We use 1-

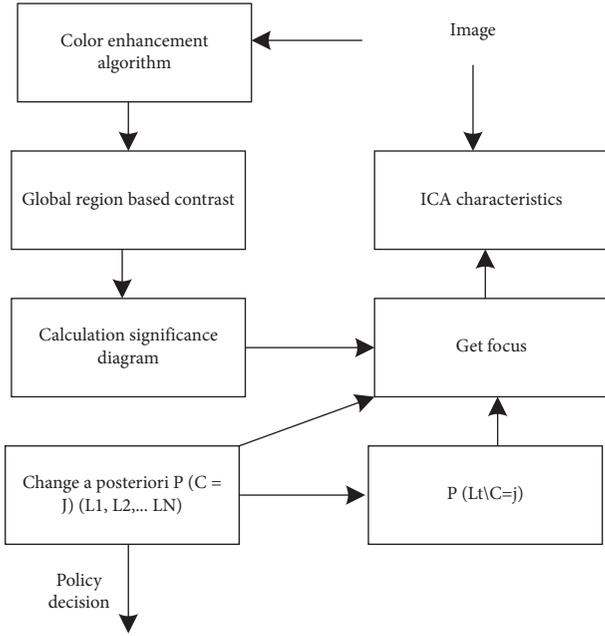


FIGURE 3: Frame diagram of art style research and painting image classification method based on saliency.

nearest neighbor KDE for calculation. Specifically, through the joint feature sample distance and the distance between their positions, we have

$$P(L_t | C = j) \propto \text{Max} \left(\frac{1}{\left(\|f_{j,i} - L_t\|^2 + a \|w_{j,i} - p_s\|^2 + \varepsilon \right)} \right). \quad (22)$$

Here, s (PO) is a small number to prevent $P(L_t | C = j)$ from infinity, and $f_{j,i}$ represents the feature of the concern in category j . FL is a constant value used to control the weight of the position item. $f_{j,i}$ is the regularized coordinate, and l is the corresponding coordinate. In the experiment, R iterations are performed, and the maximum a posteriori category is finally selected as the category of the test sample. The contour of the art color feature image is extracted using the above model, the global color equalization configuration method is used for the visual feature sampling and equalization of the art, and the fuzzy clustering method is used to extract the color style of the art based on the equalization configuration results, improving the three-dimensional reconstruction, extraction, and identification ability of the art.

3. Analysis of Experimental Results

In order to test the effect of this method on realizing style feature extraction, a simulation experiment was carried out. The experiment was designed with MATLAB simulation tool. For the color features of works of art, the pixels collected by works of art are 24 million, the error coefficient of the surface extracted by art color extraction is 0.23, and the edge pixel intensity is 100 dB. The pixels are 200×400 , and the number of mesh points for texture rendering is set to

1080 and 2000, respectively. 100 surface points are collected for sparse texture reconstruction of art representation, and the color of art is extracted according to the above simulation environment and parameter settings [21–23]. The category and attribute prediction benchmark is used as the dataset in this experiment to test the impact of the strategy provided in this study. It has around 200000 images of 50 different types of works of art about magnitude. This experiment extracts 60000 training sets, 20000 test sets, and 20000 verification sets from a subset of 30 different types of images. Python is used to build and implement the experiment. The network layer of the PyTorch framework is used to extract the depth features of every work of art in the feature library, and these network parameters are pretrained on the image net dataset. This paper conducted a series of comparative experiments to assess the performance superiority of the artwork retrieval method integrating color features of works of art and deep network features. The network models pretrained on ImageNet, VGG16, GoogleLeNet, and ResNet50 are fine-tuned, and the features of the penultimate full connection layer are extracted. Then, using the ResNet50 network structure, the two characteristics are retrieved and merged. For experimental comparison, four approaches are applied, and color feature clustering is used for retrieval. The first 5, 10, and 20 photos returning from the experimental retrieval are used to determine the accuracy [24, 25]. The experimental results are shown in Table 2.

ResNet50 has a better effect among the selected convolutional neural network models on the dataset of works of art. Therefore, this paper chooses ResNet50 as the basic model, fine-tuning and adding color features. The experimental results of the improved method in this paper are better than those without adding color features. In contrast, the retrieval map increases by 4.45%, 6.85%, and 2.49%, respectively, when $N=5, 10$, and 20 . Because the fused multiple features can better express the image information compared to a single feature, the method proposed in this paper can get better retrieval results. We state that the criterion for determining whether two pieces of art are comparable is whether they belong to the same class to make the experiment more objective. The following is the procedure for experimenting: As query works of art, five works of art are chosen at random from ten subcategories with more than 19 works of art, totaling 50 questions. The matching accuracy rate for each query is calculated using the top 1 to 19 art pieces from the query results (i.e., the first 19 pictures are taken as effective query results). After 50 queries, the corresponding average precision rate is obtained, as shown in Figure 4.

In order to compare the impacts of different features on the classification results, on the premise of 10 training pictures, the classification performances of line, color, and texture are tested on all databases, as shown in Table 3.

It can be seen from the table that different features play different roles in different databases. For example, line features play a decisive role in Chinese and Western painting databases. The classification results of texture features are better in the database of Chinese painters. In the Dunhuang mural database, the classification performances of these three features have little

TABLE 2: Retrieval map comparison of algorithm model percentage.

Algorithm model	$N = 5$	$N = 10$	$N = 20$
VGG16	82.65	78.26	57.62
GoogLeNet	85.69	80.76	65.98
ResNet50	88.39	82.65	68.82
ResNet50 + color	92.89	89.35	75.35

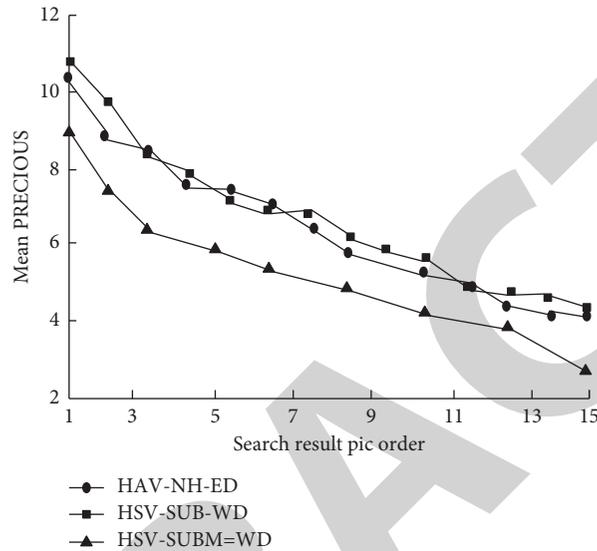


FIGURE 4: Comparison of average retrieval rate of features of works of art.

TABLE 3: Comparison of classification results of different features (accuracy %).

Features	Dunhuang mural database (%)	Chinese and Western painting database (%)	Database of Chinese painters (%)
Line	42.3	63.2	36.5
Color	42.8	55.6	37.8
Texture	41.6	58.8	41.2
All features	47.9	69.8	42.8

difference. It is worth noting that, after the combination of these features, the classification performance has been improved, which shows the completeness of the features used in this chapter. A multispectral acquisition system is built with a CIE standard illuminant D65 light source and a Canon 5D Mark II 3CCD digital color camera. There are eight narrow-band interference filters with different peak center values (405 nm, 409 nm, 447 nm, 470 nm, 506 nm, 532 nm, 650 nm, and 740 nm, respectively). We have used 210 gloss Raul standard color cards and Ral K7 color card data filters in our research. The spectral reflectance of the sample surface of the color card is measured by UV-VIS Spectrophotometer in advance. The measured wavelength range is 380 nm–780 nm, with an interval of 5 nm. In the experiment, 200 color cards were used as training samples, and the remaining 10 were used as test samples. Experiments on spectral extraction and color reproduction were carried out based on VC++. The spectral extraction results of some test color cards are shown in Figure 5.

It is not difficult to find that, compared with the traditional methods, the artistic creation style extraction model based on color feature data proposed in this paper has higher accuracy in practical application and is closer to the actual expected standard. Further, the color difference results of the test samples are compared and analyzed, as shown in Table 4.

The above table shows that the outcome is within 99.5 percent, which is satisfactory. The average color difference result is 4.08, indicating that the extraction accuracy in terms of color difference has to be improved further. The research demonstrates that the color feature data method is used for visual feature sampling and equalizing works of art. The fuzzy clustering method is used to extract the color style of works of art based on the equilibrium configuration results to improve the style extraction and identification ability of works of art, which has a good application value in identifying works of art.

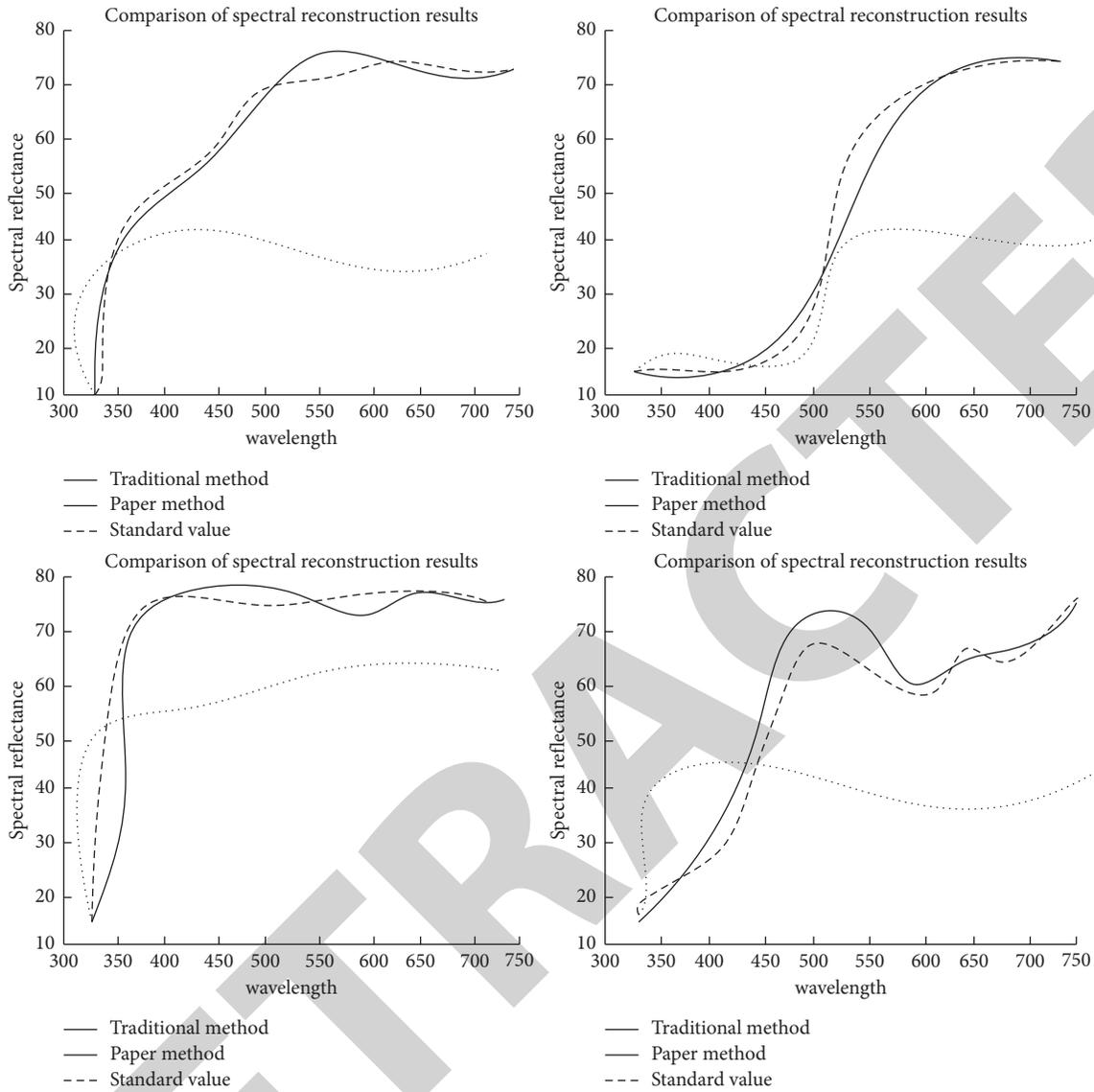


FIGURE 5: Comparison test results of style extraction accuracy of works of art.

TABLE 4: Color difference results of test samples.

Color card number	1	2	3	4	5	6	7	8	9	10
GFC	99.98	99.85	99.87	99.88	99.78	99.91	99.97	99.92	99.78	99.65
ΔE^*_{ab}	2.25	1.45	3.36	2.26	3.06	4.13	6.18	3.18	5.46	7.23

4. Conclusion

The proposed work of art retrieval algorithm combines color and depth features, extracts deep network and color features from work of art pictures using the ResNet50 pretraining network model, connects the two feature vectors in parallel, and clusters the features using color features to improve retrieval efficiency and reduce time overhead. The testing

findings demonstrate that this method's map is substantially higher than the single-feature approach extracted directly using the ResNet50 depth network. The retrieval picture effect style and color similarity are visible. The retrieval time is longer than the single-feature extraction time, but the difference is not significant; therefore, the retrieval time is unaffected. Deep learning needs a significant quantity of data. You may expand the quantity of artwork images or

modify other datasets for experimental verification in the future and tune the network model to enhance retrieval accuracy even further.

Data Availability

The data are available upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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