Research Article

Study on the Performance of Image Color Style considering Brushstroke Control Factors

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To address the issues of high time consumption, low recall rate of image color styles, and poor image color processing outcomes in existing methods, we proposed an image color style performance analysis method that takes brushstroke control elements into account. We investigate the connection between brushstroke control parameters and picture color style performance. Furthermore, assuming that the brushstroke components are completely considered, we evaluate the image's color composition to derive the R, G, and B values and apply the cloning process to prejudge the image's color style. Based on the color style prejudgment, the median segmentation method for color quantization is used to increase the efficiency of image color style extraction, and the cumulative histogram is used to categorize the image color style. The experimental findings reveal that the suggested technique has low time complexity, good picture color accuracy, and recall and does not generate uneven image color brightness.

1. Introduction

Color is present in many aspects of life. Color exists as long as light exists. Color is seen directly and quickly by people [1]. The light source stimulates the retina of the eye, and the associated signal is received and transferred to the brain through the optic nerve [2, 3]. Through analysis and judgment, the brain forms vision. Color is a key aspect of a picture that may significantly influence the image's impression [4]. Color may be used to portray emotions, depict the mood of a tale, and improve visual appeal in photographs, and it is an essential approach to improving image communication [5]. Color is an important factor in picture drawing. Color has a route to follow in the visual creation process as one of the essential aspects [6]. At the moment, predecessors have studied and investigated the issue of picture color style performance, but there are few more systematic and mature ideas [7].

Cao et al. [8] proposed a technique for evaluating image color quality and performance. First, the brightness, hue, and saturation of a color image are extracted based on the characteristics of the human visual system. The brightness component is convoluted with the Scharr operator, the edge features of the image brightness channel are extracted, and the edge features of the part with a strong brightness change are obtained. Simultaneously, the hue and saturation are treated as color features. Secondly, the edge features of the grayed image are extracted to obtain the edge features of the part with slow brightness change. Finally, the edge features of the grayed image are extracted to obtain the edge features of the part with slow brightness change. Finally, an assessment model of color image quality and performance is constructed by combining the criteria mentioned above. To acquire the spectrum of the Fourier transform, the color image is first described by a quaternion matrix. Then the quaternion Fourier transform is performed to produce the spectrum of the Fourier transform. The second step is to determine the threshold of the high-frequency component of the signal. Finally, the number of pixels in the spectrum that are bigger than the threshold value is used to determine the quality of the color image. The testing findings demonstrate that this approach of evaluating the picture color performance ability is consistent with the subjective assessment results. Despite this, the algorithm does not

consider the peculiarities of distinct color styles, and the recall rate for image color styles is not very high. Chen et al. [9] introduced a blind image quality assessment approach based on the complementary color wavelet domain and constructed natural scene statistics, multiscale, and directional energy distribution models of image complementary color domain. The investigation demonstrates that complementary color may effectively describe the information connection between multiple channels of a color image and give a set of efficient characteristics to assess image quality. Statistical features of image distortion can be effectively extracted based on these features. The experimental results demonstrate that the evaluation results of their method are consistent with the subjective evaluation results of human eyes. But that the display results of image color performance are poor when the analysis of image color performance is carried out using our proposed method. It is possible to encounter issues such as picture color loss and uneven brightness.

Using brushstroke control components, we proposed an image color style performance analysis technique that addresses time consumption, low recall rate of image color styles, and poor image color processing outcomes. On the other hand, we look at the relationship between brushstroke control parameters and image color. Furthermore, we use the cloning process to prejudge the image's color style, provided the brushstroke components are fully examined. The cumulative histogram characterizes the picture color style based on the prejudgment color style. The proposed approach has minimal time complexity, excellent picture color accuracy, and recall and does not produce uneven image color brightness.

2. Analysis of the Relationship between Brushstroke Control Factors and Image Color Style Performance

2.1. The Functionality of Image Color

2.1.1. Emotional Expression. Distinct tones may elicit different emotional responses due to the effect of color on human physiology. Color is often a sensory experience of nature and civilization. Each hue has its feeling, and each person's color emotion is likewise unique. When individuals view a given color, they do not simply remain in that color's feeling, but they also make certain associations with that color to develop their own color emotion [10, 11]. Color qualities, processing methods, emotional expression, and stylistic features of works may all be observed in image processing.

2.1.2. Render the Atmosphere Image. Color may be used to explain the material, portray emotions, and improve the ambiance. Colors are used differently in various picture styles. Realistic photos should be founded on objective nature and then handled creatively. Images in the decorative style have a strong formal beauty and may be produced using flat, basic, and subjective color themes. According to the

above-mentioned emotional expression effects of colors, the atmospheric depiction of colors is often dependent on the psychological sensations of colors. The fundamental objective of the picture to be exhibited is more clearly communicated via the use of color, which may increase the comprehension of the image content and emotional substitute and enrich the visual experience.

2.2. Analysis of Control Factors of Brush Strokes. Being one of the image's physical textures, the stroke belongs to the image's most fundamental visual unit. Strokes may also exhibit numerous rhythmic esthetics, such as thickness, falseness, realism, stroke weight, and density. The overlap between strokes and strokes creates a distinct charm and adds tension to the picture. Artists are often motivated by their personal emotions throughout the production process. They incorporate these feelings into their art by using vibrant colors and fluid pen movement. The pieces exude a powerful emotional atmosphere that infects and affects the audience. There are variances in the priority of strokes, the direction of movement, and the emotion directing the velocity of strokes in the process of creation, which not only makes the picture more dynamic and has distinct life and creative expression but also generates images with diverse images styles.

Artists should seek the most honest and expressive creative inspiration. The motorway is often mirrored most naturally in the painter's pen how to utilize it freely and communicate an identity via the rhythm of the brush [12]. Not only is the form interesting, but also is the color, as well as the pen. Because artists may freely pick a hue they want to paint, such freedom can frequently alleviate most of an artist's restraints. Strokes will very definitely be used to coordinate the interaction between perception and illusion. They can communicate supernatural notions exactly because they have broken free from the shackles of copying nature. A stroke is the most fundamental unit of expression for artists in their work. The inner world communicates with the observer to establish visual harmony due to the unintended flow and swing of the stroke. People's affection for a painting is often shown via the expressive technique of a person on the artwork. Some individuals like the simple, expressive form and might be emotionally influenced by it.

3. Image Color Style Performance Analysis

According to the findings of the preceding investigation, the creator's color style will be influenced by stroke elements throughout the picture production process. Taking this aspect into account, the expression form of image color style is further analyzed, and the image color characteristics are mined from the perspectives of image color composition, color style, and color characteristics to produce image color analysis and assessment findings.

3.1. Image Color Composition. The image's hue is determined by the delicate interaction of light and the object's surface material in the actual scenario. The modern computer graphics lighting model includes a complete

description of the interaction between the object material and the light. In both the basic lighting model and the two-color lighting model, incoming light is reflected off the object's surface in two ways as follows: the first kind of reflection is surface reflection. The surface of an object reflects all light to its surface; the second method is known as body reflection. When light strikes an object's surface, it selectively absorbs some of it while releasing some of it. The spectral distribution of incoming light is altered by body reflection. The reflected light is affected not only by the spectral properties of the incident light but also by the object's surface characteristics. Any light's spectral energy distribution (SPD) can be used to characterize it, and $(\lambda_{(t)})$ represents the spectral energy. Suppose the two-color light reflection model characterizes the spectral energy distribution, the spectral energy $(\lambda_{(t)})$ reflected from a point on the object surface can be expressed as a linear combination of two spectral energies such as the spectral energy $(\lambda_{1(t)})$ reflected by the body and the spectral energy $(\lambda_{2(t)})$ reflected by the surface, as shown in the following formula:

$$E(\lambda) = \sum_{-\infty}^{\infty} [\lambda_1(t) + \lambda_2(t)]^2. \tag{1}$$

Because the color perceived by humans is mostly affected by lighting and material qualities, the material substantially influences the color in ordinary natural settings with homogeneous illumination. Distinct materials in a photograph often indicate different places. As a result, the color distribution in the local picture region is generally simpler and more regular.

The region of the item with an evident surface reflection is substantially less in ordinary natural scene photos than the area of the body reflection. The hue of ontology reflection can be seen in most settings, including trees, mountains, sky, people, buildings, and highways. Assume the nonbody reflection region appears in the picture, or appears as a brilliant flare, or reflects and projects the color of the surrounding objects, such as the glass of the lake, sea, and buildings, like a mirror. In such a situation, their color distribution might be seen as a reflection of the color of the surrounding items. As a result of this insight, formula (1) is reduced as follows:

$$E(\lambda) = E(\lambda_1 + \lambda_2). \tag{2}$$

Assuming a digital camera captures the image with three-color linear response, the R, G, and B values recorded by the image for the outgoing light with the spectrum of $\lambda(t)$ are as follows:

$$\left\{ \begin{matrix} R \\ G \\ B \end{matrix} \right\} = \lambda_i \left\{ \begin{matrix} R_\lambda \\ G_\lambda \\ B_\lambda \end{matrix} \right\}. \tag{3}$$

It can be seen from formula (3) that the rays emitted from the same surface are all along the $(R_\lambda, G_\lambda, B_\lambda)$ vector.

3.2. Prejudgment of Color Style.
After analyzing the basic color composition of the image, the color style of the image is judged. The original image and the target image are set to I_a and I_b, respectively. To calculate the percentage of basic colors in the original and target image, we first determine if the target image is impacted by colored light. A cloning method is required to prejudge the image's color style to tackle this difficulty.

The cloned selection region should retain the same ambient light color when the target image's ambient light is a colored light source. As a result, the target picture's color takes up a higher percentage; the cloned selection and target image pixels in the color gamut space should be united in a compact region. The average boundary color difference $\overline{D}$ is introduced as the translation distance of the cloned selection in the color gamut space. For any pixel k on the boundary of the cloned selection, the displacement is determined by the following formula:

$$\overline{D} = E_\lambda \left(|p_k| - \beta_k \right)_m \tag{4}$$

Among them, $|p_k|$ represents that the pixel corresponds to the color value in the target image; p_k represents that the pixel corresponds to the color value in the original image; m represents the number of pixels on the image boundary.

When the destination image's ambient light is white, the foreground item in the cloned selection area should retain its original color. However, the border must still be consistent with the target image's backdrop color to provide a smooth transition effect. Since the $\overline{D}$ value produces the same amount of color change for all pixels in the selection, in order to control the color of the clone selection, it is necessary to distinguish the translation amount of the foreground area and the background area. Therefore, it is necessary to add a color control variable α on the basis of the color average difference $\overline{D}$ to distinguish the color gamut translation amount. The α value is determined by the Euclidean distance [13] and the color distance between the inner pixel and the boundary pixel. The expression of α is as follows:

$$\alpha = \overline{D} \cos \left[\varphi_i (f_0 + f_1) \right], \tag{5}$$

where φ_i represents the distance constraint parameter. The shortest distance between the current pixel and the boundary of the cloned selection can be set to $\varphi_i(\min)$, and the expression is as follows:

$$\varphi_i(\min) = E \left\{ d_r(t) \times H_r(t)^2 \right\}. \tag{6}$$

Among them, $d_r(t)$ represents the boundary of the cloned selection area; $H_r(t)^2$ represents the light judgment parameter.

It is further restricted by the color distance. When the pixels in the cloned selection meet the color constraints of formula (7), then $\varphi_i(\min)$ is changed to 1.

For any pixel k in the cloned selection, the specific color distance constraint judgment formula is as follows:

$$\frac{D_{\text{color}}(k)}{\partial_{\text{color}}(k)} < \text{color\_threshold}. \tag{7}$$

Among them, color_threshold represents the color threshold; $D_{\text{color}}(k)$ represents the color difference; $\partial_{\text{color}}(k)$

represents the average color of the original image boundary pixels.

3.3. Color Quantization Algorithm.

Color quantization is conducted based on color style prejudgment to increase the efficiency of picture color style extraction. The color quantization algorithm's major purpose is to represent color pictures with rich colors using a limited number of color sets while attempting to retain the vivid display impact of the original color images [5].

In the realm of image processing, the median segmentation method is increasingly commonly employed. The basic idea behind the median segmentation algorithm is as follows: in RGB color space, the three primary colors of R, G, and B correspond to the three coordinate axes of the space, and each coordinate axis is quantized as 0–255, with 0 corresponding to the darkest (black), and 255 corresponding to the brightest to form a color cube with 256 side length, with all possible color values in the original image corresponding to a point in the cube. The cube is made up of 256 tiny cuboids. As seen in Figure 1, each cuboid in the picture includes the same number of color spots.

By removing each little cube's center point, the colors represented by these points are the 256 colors required to depict the image color attributes. The fundamental feature of this technique is that each color in the final color table may represent the same number of color points as in the original image. This algorithm's particular procedure is as follows:

(1) The three fundamental colors of R, G, and B correlate to the space's three coordinate axes. Each coordinate axis is assigned a value between 0 and 255. 0 represents the darkest (black), while 255 represents the brightest. In this manner, a color cube with 256 side lengths is produced. The smallest cube containing all of the original image's color points. The size of the box in R is defined by the color coordinates of the lowest and maximum color points in each of the three directions.

(2) To split the cuboid, we must first determine which color edge to divide. Typically, the cuboid is split along its longest length while attempting to guarantee that an equal number of color spots fall on both sides of the cutting plane. At this stage, we have two cuboids with an equal amount of color points.

(3) The process of step (2) is executed recursively until N cuboids are finally produced, that is, the number of colors that can be contained in the color table.

(4) The representative color of each rectangular parallelepiped after segmentation is selected, which is generally represented by the average value of the original image colors that fall into that rectangular parallelepiped and fill in the n colors in the color table.

(5) And each color point in the original image will be mapped to the representative color value of that area according to the area it falls into in the median segmentation algorithm.

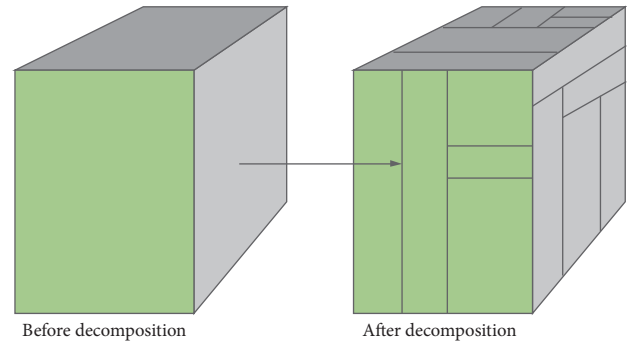Before decomposition   After decomposition

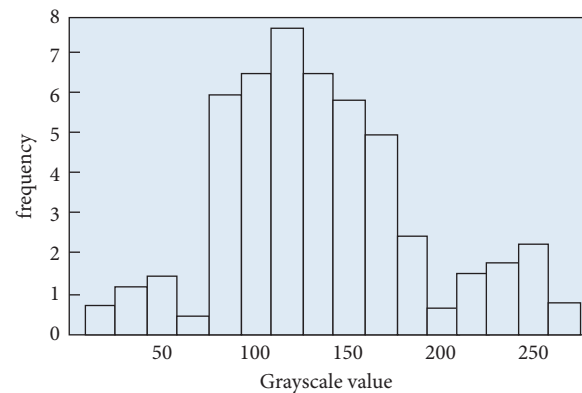FIGURE 1: Decomposition of color blocks in the image area.

FIGURE 2: Image cumulative histogram.

The median segmentation approach distinguishes itself by using the image's color information to segment the color space, and a nonuniform quantization algorithm may provide superior quantization results. The downside of this technique is that it requires complex sorting effort, has a high memory cost, and takes a long time to wait. In response to this issue, the image color style will be improved and categorized using the image color classification technique, which is easy for focused color analysis, to decrease the time consumption of image color style analysis.

3.4. Image Color Style Classification Based on Cumulative Histogram.

The color histogram [14] is a popular picture analysis tool. The histogram retains the image's color information. It is still impossible to characterize the image's overall color style using typical histograms. Traditional histograms make it difficult to capture the image's overall color style. As a result, the cumulative histogram is used in this article to identify the picture color style.

A cumulative histogram is a useful tool for classifying an image's overall color style. It primarily uses the cumulative histogram of several image sections to form a complete judgment on the image's color style. The cumulative histogram is the total number of pixels after counting numerous successive image frames at a certain gray level. It indicates the total of all images to be tallied on a certain gray level. Figure 2 depicts the image's cumulative histogram.

The gray level is the abscissa of the cumulative histogram in Figure 2. The ordinate is the total number of pixels in the

image in the current region and all prior gray level areas. The cumulative function expression of the first j frame sequence frame of the image is as follows:

$$L(j) = \exp\left[-\frac{\sqrt{\left(\sum_{j=1}^{N}\left(\varphi_j \cdot \varphi_j(k)\right)\right)}}{\eta(i)} \times D(i)\right]. \quad (8)$$

Among them, φ_j represents the gray level; $\varphi_j(k)$ represents the gray histogram of the image frame; $D(i)$ represents the image block histogram mapping function.

The function expression of the number $Y(j)$ of pixels corresponding to a certain gray level in the image is as follows:

$$Y(j) = \sum_{j=1}^{N} \mu_{ij} \times \omega_{jk} \times J^2(\omega). \quad (9)$$

Among them, μ_{ij} represents the gray level difference of the background segment; ω_{jk} represents the membership degree of the function; $J^2(\omega)$ represents the image gray level mapping transformation function.

3.5. Image Color Performance Feature Extraction

3.5.1. Image Color Style Extraction. An image's color feature is a global feature that conveys the surface qualities of the picture or scene relating to a specific section of the image. Color features are often dependent on pixel properties, and each pixel in a specific region contributes to the overall color scheme. Histogram intersection, distance, reference color table, cumulative color histogram, and other approaches derive picture color styles. The image color feature extraction method serves as the foundation for image color style analysis and assessment. The impact of image color performance analysis can only be enhanced by using an appropriate color extraction technique to determine the attributes of the image color style.

When extracting picture color styles, the issue of too slow performance is often encountered. This work uses the image color style extraction approach based on the binary value method [15] to decrease the time consumption caused by extracting image color feature values as much as feasible. The following is the workflow:

(1) An appropriate color space is chosen based on the research needs.

(2) The dot matrix is determined in eight directions in the image based on the possible range and proportion of image feature points.

(3) The binary value method is used to select the appropriate feature points in the eight dot matrices, and these feature pixels are doubly weighted.

(4) Finally, more accurate image color style eigenvalues are calculated.

Figure 3 depicts an image color style extraction flow chart.

3.5.2. Image Color Feature Point Extraction. When employing the binary value technique to extract the color feature value of an image, if just a few points at a certain area are retrieved, the derived feature value will be more partial and unfavorable. A single point cannot represent a specific one. Color qualities that are only partially present. When such points are kept in a lattice, the total eigenvalues suffer from greater inaccuracies. As a result, the weighted average approach is applied here to increase the accuracy of the derived feature values. As a result, the derived feature value is no longer the feature value of a single feature point but the feature value of a feature point plus the weighted average of the feature values of its surrounding pixels. The weights are set as specified in Table 1.

The formula for obtaining the average color characteristic value is as follows:

$$\Delta W = \sum_{j=1}^{N} W_j (t_0 + t_1). \quad (10)$$

Among them, W_j represents the color feature value; t_0 represents the feature value of a certain pixel around the pixel obtained by the binary value method; t_1 represents the weight of the intermediate point.

The image feature value acquired via this weighted average process has a certain degree of representativeness. It may represent the color feature value of a specific area of the picture, enhancing the feature value's precision.

3.6. Image Color Style Performance Analysis and Evaluation Realization.

The image's average value and standard deviation [16] are used to quantify the image's color style performance impact based on the image color feature extraction findings. The image's first- and second-order statistical characteristics are linearly transformed. The target picture contains statistics similar to the original image attributes to generate a visually comparable color effect.

The RGB color space of the target image and the original image is transferred to the LAB color space [17, 18], and M, the local area that needs color transfer, is selected.

The local area that needs color transfer is selected in the target image and the original image. Let ∂_i and ∂_j be the corresponding areas in the original image and the target image, and $\ell(i, j)$ is the color channel value of pixel (i, j) in the reference image. We then calculate the color distribution statistics of the corresponding area and calculate the average value and standard deviation of the different color channels in the image [19]:

$$\overline{P} = \frac{\chi_p + t_{kj}}{g_{kj}} \times E_{ij}^k, \quad (11)$$

$$S^2 = J_i \overline{V}_i - d_i^k (J_i V_i).$$

Among them, χ_p represents the color average of the image RGB space; t_{kj} represents the color average; g_{kj} represents the color gain; E_{ij}^k represents the color gamut mapping of different color spaces; J_i represents the dynamic threshold; $\overline{V}_i$ represents the average value of the variance; d_i^k
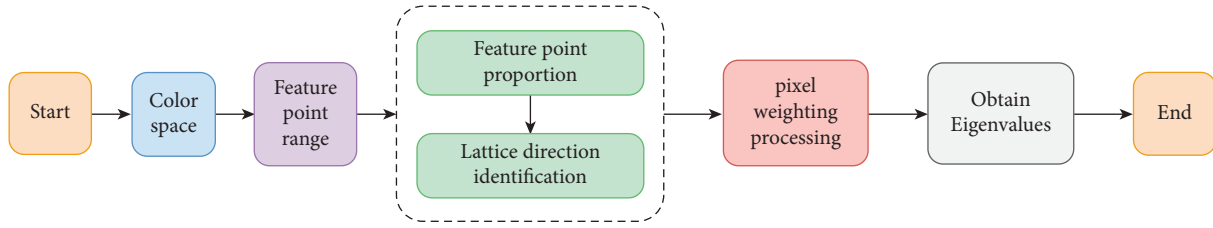
FIGURE 3: Flow chart of image color style extraction.

represents the image color space channel component; V_i represents the image gray mean square error.

The formula as mentioned above, image's average value and standard deviation may assess image color style performance attributes and measure image color performance ability, therefore attaining the preset aim.

4. Experimental Research

Experiments on time complexity, precision, recall, and image color balance will be carried out to verify the effectiveness and feasibility of the proposed image color style performance analysis and evaluation method, considering stroke control factors to verify the method's application effect.

4.1. Experimental Hardware Environment and Settings.
The experiment is run on the Windows 10 operating system, using a 3.2 GHz Intel CPU, 8 GB of RAM, and a Matlab2016a programming experiment. The experiment is validated in this hardware and simulation software environment.

All of the pictures used in the experiment were from the Corel image library. The Corel image library, which comprises numerous CDs, includes a wide range of themes such as vehicles, dinosaurs, and beaches. Each CD includes 100 photos of various sizes that may be translated into various formats. The Corel picture collection is often divided into three sections as follows: 4000 photos for training, 500 images for verification, and the remaining 500 images for testing. In this article's experiment, some images from the image library are arbitrarily chosen as the target image. The method of this article, the image color quality and performance evaluation method, and the nonreference color image quality evaluation algorithm based on quaternion Fourier transform are compared.

The following is an explanation of the experimental method:

> Experiment 1 has 20 image categories (the sun, flowers, butterflies, waves, etc.). There are 100 photographs in each image category for 2000 images. The time complexity is used to assess the quality of the image color performance analysis findings.

> (i) In the second experiment, 10 image categories were chosen such as sunset, aircraft, and rose, and 300 positive examples were retrieved from each image category and distributed to the training and test sets in an 8 : 7 ratio. Images from other categories are added to the training set as counterexamples to each other. The training set's counterexamples additionally

TABLE 1: Feature point extraction weights.

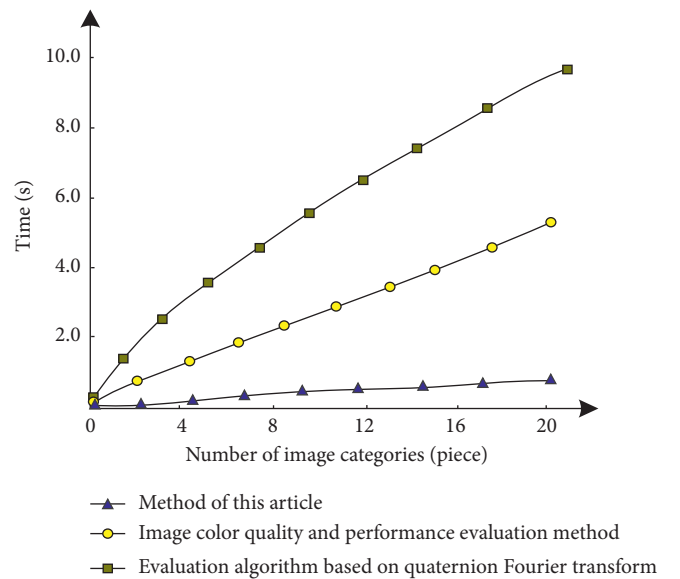| Feature point location	Weight	Significance
Center point	1.0	Reference of eigenvalues
Surrounding pixels	0.7	Reduce eigenvalue error

FIGURE 4: Time complexity comparison results.

comprise 1000 images from other categories in addition to the 10 kinds of images. The recall rate and accuracy rate of image color styles are utilized as comparative indicators to assess the application impacts of the three approaches.

(ii) Experiment 3 chose 300 photos from the Corel image collection at random, including 75 images of individuals, 68 images of autos, 107 images of landscapes, and 50 images of structures. As training examples, ten paintings from each category were chosen at random. The remaining image comprised 65 images of individuals, 58 images of automobiles, 97 images of landscapes, and 40 photographs of structures. These images served as test subjects. To assess the practical application value of various methodologies, picture color balance is used as an experimental indication.

4.2. Analysis of Experimental Results

4.2.1. Experiment 1.
Figure 4 shows the outcome of comparing this approach's image color style analysis impact of

TABLE 2: Comparison results of recall rate.

Image category	Method of this article	Image color quality and performance evaluation method	Evaluation algorithm based on quaternion Fourier transform
1	95.6	78.5	84.2
2	97.3	77.4	86.3
3	98.0	75.2	89.1
4	96.4	78.9	87.2
5	95.2	79.0	75.0
6	97.7	79.6	75.4
7	98.3	81.5	77.6
8	99.0	84.3	79.3
9	98.8	74.6	72.9
10	96.1	72.9	71.1

TABLE 3: Comparison results of precision.

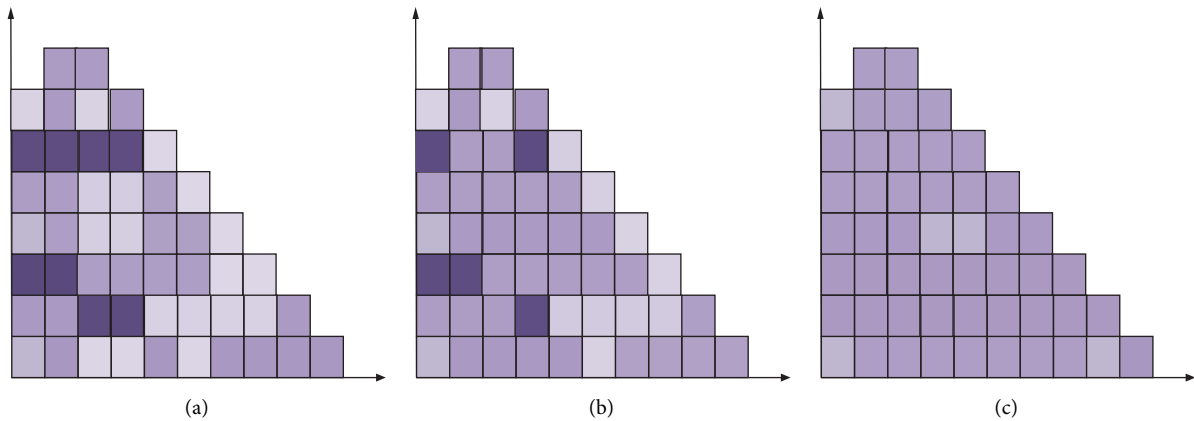| Image category	Method of this article	Image color quality and performance evaluation method	Evaluation algorithm based on quaternion Fourier transform
1	94.5	87.9	84.2
2	93.6	65.9	85.6
3	95.2	76.3	73.4
4	94.1	74.1	72.6
5	97.6	75.2	79.1
6	97.4	77.4	80.0
7	96.5	85.2	84.1
8	97.4	84.3	79.6
9	95.2	75.6	72.6
10	97.4	72.0	73.2

FIGURE 5: Image color block processing effect comparison. (a) Image color quality and performance evaluation method. (b) Evaluation algorithm based on quaternion Fourier transform. (c) The method of this study.

this approach with the standard way using time complexity as an experimental indication.

During the experiment, the time consumption of the three approaches is documented. Figure 4 shows the technique that is used in this study's analysis and that the evaluation time is relatively short. The time consumption of the method in this study does not vary greatly due to different picture types in varied image color analysis. The old process takes a long time, and the time needed for various picture categories varies substantially. It demonstrates that the time complexity of this technique is minimal and that it has clear benefits over previous methods.

4.2.2. Experiment 2. The recall rate and accuracy rate of the image color style are compared as experimental indicators to verify the performance of the technique in this study to assess the analytical impact of the method in this study on the image color expression style. The accuracy and recall rates are stated as follows:

$$A = \frac{U_1}{U_1 + U_2},$$

$$Q = \frac{U_1}{L}. \tag{12}$$

Among them, U_1 represents the number of image color blocks obtained in the analysis; U_2 represents the total number of image color blocks; L represents the overall number of image blocks.

The comparison results of the three methods are listed in Tables 2 and 3.

The experimental results in Tables 2 and 3 show a clear difference between the approach in this study and the old way, whether it is recall rate or accuracy rate. Evaluating Table 2 reveals that this method's maximum recall rate is 99.0%, while analyzing Table 3 reveals that this method's highest accuracy rate is 97.6%. Its benefits are evident, suggesting that it can collect more and more correct image color elements in image color performance analysis, implying that the findings provided by this approach are more thorough and accurate. This is because the approach employs a weighted average method. Therefore, the feature value generated by feature extraction is the feature value of a feature point plus the weighted average of the feature values of its surrounding pixels, rather than the feature value of a single feature point. As a consequence, the image color performance analysis findings are more accurate.

4.2.3. Experiment 3. To study the application performance of the approach in this work, we assess if there are image processing issues such as picture color loss, uneven brightness, and so on, and compare the processing impacts of this method with the old way. Figure 5 depicts the outcome.

According to the above experimental findings, the image processing results of this approach do not have the difficulties of image color loss, uneven brightness, and the image color is reasonably consistent in the analysis of image color expression style. The image processing impact of the two classic approaches, on the other hand, is poor, and the issue of image color unevenness is substantial. It demonstrates that applying the design strategy described in this article may improve image processing effects in real operation.

5. Conclusion

To get accurate and effective picture color style performance analysis, this study proposes a novel method that considers brushstroke control parameters. The proposed method can perform image color preprocessing and execute image color quantization processing, classification, extraction of color style, and other stages. Also, our method uses the average value and standard deviation of the image to assess the impact of the color style of the image. The experimental findings reveal that the approach described in this work successfully overcomes the difficulties of existing methods such as high time complexity, poor picture color accuracy and recall, and uneven image color brightness, indicating that the method's application value is greater.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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