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Article

Quantitative Research and Modern Transformation of Aesthetic Characteristics of Song-Yuan Landscape Paintings from the Perspective of Big Data Analysis

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Abstract: Song Dynasty water painting is the essence of traditional Chinese landscape painting, which has reached unprecedented heights in the development history of landscape painting with its unique aesthetic interest and highly matured brush and ink techniques. In this paper, from the perspective of big data analysis, we quantitatively study the divine aesthetic characteristics of Song and Yuan landscape paintings as well as explore their modern transformation. Firstly, we pre-processed the landscape paintings by image processing methods, extracted the low-level features, high-level features and regional features by using aesthetic feature extraction methods (HSV color model, Fourier description, Circular LBP), and established an aesthetic score assessment model. After quantitative experimental analysis of the aesthetic features of landscape paintings, the mean value of the area proportion of each image element in Song-Yuan landscape paintings is obtained, in which mountains, tall plants, and the sky account for a relatively high percentage, which is 31.28%, 20.36%, and 16.15%, respectively, and secondly, the stylistic changes of Song-Yuan landscape paintings are complex and diverse. Finally, the modern transformation method of Song Yuan landscape painting and its application in jewelry design are explored and analyzed by using perceptual evaluation method, and the results show that the Alpha reliability coefficient is 0.813, which is more than 0.6, and the factors and dimensions of the perceptual imagery evaluation system are established with high reliability. The research enhances the cognition of aesthetic characteristics of Song and Yuan landscape paintings as well as provides a new path in modern inheritance.

Keywords: landscape painting; image elements; Fourier; modern transformation

1. Introduction

Chinese landscape painting is a form of painting that depicts natural scenery as an object, and it has a history of more than a thousand years as an independent painting discipline [1-2]. It was conceived in the Qin and Han dynasties, sprouted in the Wei and Jin dynasties, became independent in the Sui dynasty, matured in the Tang dynasty, and reached its peak in the Song and Yuan dynasties. The Song and Yuan dynasties are the heyday of landscape painting with many famous artists and a variety of genres, which centrally embodies the artistic achievements and aesthetic characteristics of ancient landscape painting [3-4]. Song Dynasty landscape painting is centered on shaping the beauty of landscape, highlighting the artistic and aesthetic concepts of worrying about the country and the people, excelling in expressing people's emotions with brush and ink, and embodying the unity of nature and humanities in traditional Chinese culture [5-7]. In the Yuan Dynasty landscape painting, in terms of expression, it pursues the thoroughness, truthfulness and depth of the picture, and the theme is often the story of the characters with the landscape as the background, by which the author's care and thinking are expressed [8-9].

There are two major schools of Song Dynasty landscape painting, the Northern School and the Southern School. The representatives of the Northern School were Li Si Xun and Fan Kuan, etc. Their works were characterized by the depiction of nature and humanistic backgrounds, valuing traditional painting techniques and focusing on reflecting the times and social realities [10-12]. The Southern Sect, on the other hand, was represented by the Four Southern Song Schools and the Four Yuan Schools, who paid more attention to the combination of nature and humanity, advocated the expression of inner feelings through brush and ink, and pursued the mood of the picture and the vividness and realism of the brush and ink [13-15]. They often used landscape as the background to express their humanistic concern and reflection on society. Yuan Dynasty landscape painting developed and transformed the traditional art style of the Song Dynasty [16-17]. The aesthetics of the Yuan Dynasty advocated the pursuit of "divine resemblance" and emphasized the aesthetic effect and spiritual connotation of paintings. Landscape painters drew on the traditional techniques since the Song Dynasty and developed new expressive techniques and artistic styles [18-20]. The representative works of the Four Yuan Schools (Wang Shishen, Wu Daozi, Wang Meng, and Zhao Boju) emphasized artistic independence and spiritual connotations in terms of composition, brushwork, and color [21-22]. They used many techniques of Yuan dynasty court painting in their paintings and integrated national treasures of calligraphic art forms such as cursive and seal script, focusing on the dynamic effects of brush and ink, which demonstrated the unique artistic charm of Yuan dynasty landscape painting [23-25].

The study conducts a quantitative research on the aesthetic characteristics of Song-Yuan landscape painting from the perspective of big data analysis, and explores its transformation and application in modern society. By using the common methods of graph normalization, image denoising, and image segmentation for image preprocessing, while using the traditional feature extraction methods of basic features, including HSV color space, Fourier descriptive method, Circular LBP algorithm for feature extraction and establishing the aesthetic score assessment model. On this basis, we analyze the distribution of image elements of Song and Yuan landscape paintings as well as the aesthetic characteristics in color, composition, and shape, and then provide theoretical support for their artistic transformation and application in modern society, which promotes the integration and development of traditional art and modern culture.

2. Extraction of Aesthetic Characteristics of Song-Yuan Landscape Paintings from the Perspective of Big Data Analysis

2.1. Song-Yuan landscape painting image preprocessing

2.1.1. Image normalization

In general, the length and width of the acquired images are not all equal, which will not only lead to the lack of uniformity in the extraction results when feature extraction is performed on the regions of the image, affecting the accuracy of the results. At the same time, it will also lead to a more complicated feature extraction process, which is not conducive to the detection of key areas and the extraction of artistic style features of paintings in the later stage.

The image scale normalization of paintings is to convert the image of paintings into a standard pattern, which can prevent the influence of affine transformation, reduce the influence of geometric transformation, improve the standardization of feature extraction of paintings, and improve the accuracy of the description of the painter's artistic style, and at the same time, the reduction of the image to the appropriate scale can also save the computing time and reduce the workload. Usually, the interpolation method is used to normalize the scale of paintings, that is, to reduce the length and width of the original painting image, retain the linear nature of the painting image, and get the painting image with the same scale standard. Common interpolation algorithms include: nearest neighbor interpolation algorithm, bilinear interpolation algorithm and bicubic interpolation algorithm. Among them, the bicubic interpolation algorithm obtains smoother image edges. Bicubic interpolation uses the gray values of 16 points around the point to be sampled to do cubic interpolation. The double cubic interpolation formula is as follows:

$$f_{i+u,j+v} = \mathbf{ABC} \tag{1}$$

$$\mathbf{A} = \begin{bmatrix} S(1+u) & S(u) & S(1-u) & S(2-u) \end{bmatrix} \tag{2}$$

$$\mathbf{B} = \begin{bmatrix} f_{i-1,j-2} & f_{i,j-2} & f_{i+1,j-2} & f_{i+2,j-2} \\ f_{i-1,j-1} & f_{i,j-1} & f_{i+1,j-1} & f_{i+2,j-1} \\ f_{i-1,j} & f_{i-1,j} & f_{i+1,j} & f_{i+2,j} \\ f_{i-1,j+1} & f_{i,j+1} & f_{i+1,j+1} & f_{i+2,j+1} \end{bmatrix} \tag{3}$$

$$\mathbf{C} = \begin{bmatrix} S(1+v) & S(v) & S(1-v) & S(2-v) \end{bmatrix}^{\mathrm{T}} \tag{4}$$

where $f_{i,j}$ denotes the pixel value at (i, j) of the source image. The basis function $S(x)$ used is as follows:

$$S(x) = \begin{cases} 1 - 2x^2 + x^3, & x < 1 \\ 4 - 8x + 5x^2 - x^3, & 1 \le x < 2 \\ 0, & x \ge 2 \end{cases} \tag{5}$$

2.1.2. Image denoising

Image noise is the interference information in the image data, if there is noise in the painting, it will seriously affect the quality of the image of the painting, so it is very important and necessary to denoise the painting before operation, image noise can be classified into different types according to different characteristics, such as according to the composition of noise can be classified into quantization noise, additive noise and multiplicative noise, etc., according to the density of the noise can be classified into gamma Noise, Rayleigh noise, pretzel noise, uniform noise and instructional noise, etc., denoising methods are also varied, such as wavelet denoising, Gaussian filtering, Wiener filtering, median filtering and mean filtering.

Median filter [26] is a nonlinear smoothing technique, when dealing with paintings, median filtering is used to set the grayscale value of a pixel at a point in a painting to the median of the grayscale values of all pixels in the neighborhood window of the point, and the advantage of median filtering is that it can eliminate isolated noise points in the image of paintings, especially for the pretzel noise in the image of paintings, the median filtering filtering effect is very good, in addition, median filtering and Wiener filtering can protect the edge part of the image of paintings, and it is more satisfactory to restore the painting, and its calculation is convenient, and it does not need to count the characteristics of painting images. In addition, median filter and Wiener filter can protect the edge part of the painting image, get rid of the noise in the painting, and recover the painting more satisfactorily, moreover, it is easy to calculate and does not need to count the characteristics of the painting image, but it is not suitable for dealing with the painting image which has more details of the points, lines, and spikes, which is its disadvantage. Mean value filtering is a method of filtering using the average method. When processing paintings, the mean value filter and neighborhood averaging method are used to replace each pixel value in the original painting image with the mean value. The processing is done in four steps. The first step is to first select the pixel point (x, y) as the pixel point to be processed. The second step is to select a number of pixels in the neighborhood of the pixel point and form a template from these pixels. The third step is to find the mean value of the template. The fourth step is to assign that mean value to the pixel point (x, y), which is processed to have a gray scale of $g(x, y)$, i.e., $g(x, y) = 1/m \sum f(x, y)$, and m is the total number of pixels in the selected template. Mean value filtering has the advantage of effectively suppressing noise, but it also has the disadvantage of causing blurring of the painting.

2.1.3. Image segmentation

Image segmentation is crucial for contour extraction and the segmentation of the image has a great impact on the final artistic style extraction. Image segmentation is the key to transforming the processing of images of paintings into image analysis of paintings, which divides each part of a painting into a number of disjointed but unique regions and extracts a number of targets of interest.

The image segmentation of paintings will directly affect the effect of extracting the features of paintings, and then affect the recognition and classification of paintings, so it is crucial to ensure the effect of image segmentation of paintings. The images of paintings have rich colors, so it is most appropriate to use the method of color space clustering. When segmenting color images, the color space clustering method is intuitive and easy to implement, and K-means is one of the commonly used algorithms. The original K-means algorithm is to randomly select k pixels in the image of a painting and take the pixel as the center of clustering, while K-means ++ can select k pixels as the center of clustering according to the principle of farthest first. If $n(0 < n < k)$ initial clustering centers have been selected, when selecting the $n+1$ clustering centers, the further away from the current n clustering centers, the higher the probability of the point being selected as the $n+1$ clustering center. And a similar random approach is used in selecting the first clustering center $(n = 1)$.

2.2. Aesthetic Feature Engineering Extraction Methods for Song and Yuan Landscape Paintings

2.2.1. HSV Color Space Model

The visual representation of an image's color is primarily controlled by three factors of color, namely, hue, saturation, and brightness. Hue (H): represents the state of the color, i.e. the position of the color in the spectrum. The wavelength of the color has a decisive role in this, the same wavelength, the same color, and vice versa. Saturation (S): reflects the vividness of the color, the saturation level, you can use to increase, reduce the black and white and gray components of the three colors to adjust. Brightness (L): represents the degree of brightness and darkness of the color. HSV model of the three channels has a strong independence between the three channels, which helps to sub-channel image processing. HSV color space model for the cylinder, the model details are shown in Figure 1.

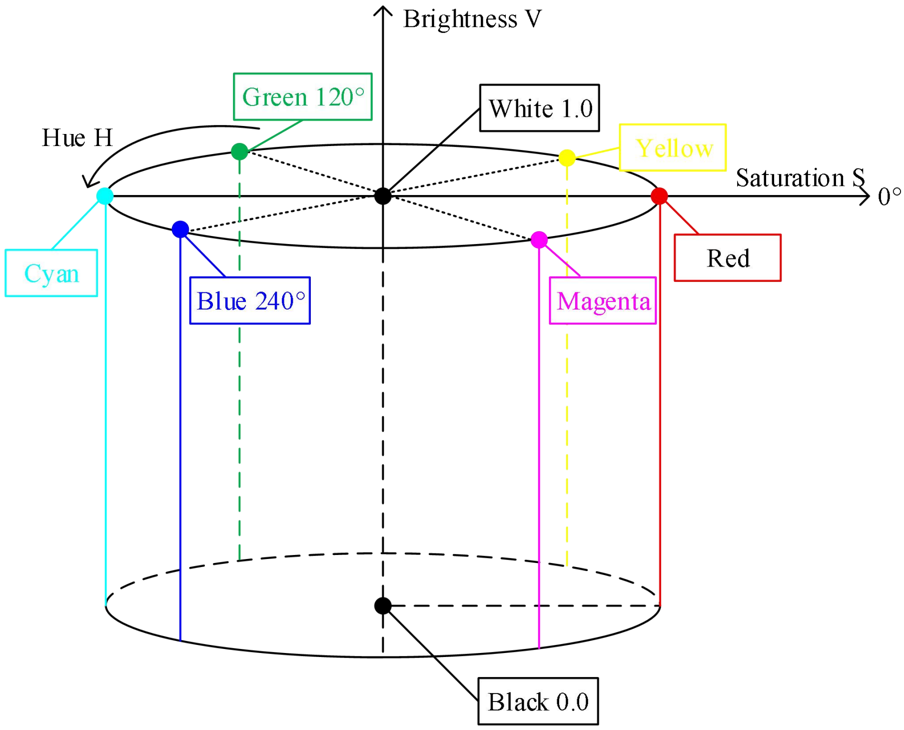

Figure 1. HSV Color Space Model.

However, in the classification task, the processed image data are usually of RGB channels, and compared with the RGB model, the HSV color space is more integrated, global, compact, and natural, and the HSV color space can be closer to the way of human's visual aesthetic cognition. Therefore, in order to conform to the human eye's habit of paying attention to the similarity and distribution of colors when observing an image, it is necessary to convert the color values of the image from the RGB space to the HSV space. The formula for converting a read-in color image from RGB color space to HSV color space is as follows:

r,g,b are the color product coordinates of a color in the RGB color model, respectively, and the coordinate value interval is (0,1) and real. First, take:

$$\begin{aligned} C_{\max} &= \max(r,g,b) \\ C_{\min} &= \min(r,g,b) \end{aligned} \tag{6}$$

Then:

$$H=\begin{cases} 0°, C_{\max}=C_{\min} \\ 60°\times\dfrac{g-b}{C_{\max}-C_{\min}}+0°, C_{\max}=r, g\geq b \\ 60°\times\dfrac{g-b}{C_{\max}-C_{\min}}+360°, C_{\max}=r, g<b \\ 60°\times\dfrac{b-r}{C_{\max}-C_{\min}}+120°, C_{\max}=g \\ 60°\times\dfrac{r-g}{C_{\max}-C_{\min}}+240°, C_{\max}=b \end{cases} \tag{7}$$

$$S=\begin{cases} 0, C_{\max}=0 \\ 1-\dfrac{C_{\min}}{C_{\max}}, \text{Other} \end{cases} \tag{8}$$

$$V=C_{\max} \tag{9}$$

where $H\in\left[0,360^{\circ}\right]; S\in[0,1]; V\in[0,1]$. Then the coordinates (r,g,b) can be calculated from equation (10)

$$\begin{cases} r=R/(R+G+B) \\ g=G/(R+G+B) \\ b=B/(R+G+B) \end{cases} \tag{10}$$

R, G, and B represent the values of a pixel in the red, green, and blue channels, respectively, and the range of values is generally between 0 and 225.

2.2.2. Fourier descriptive methods

Generally, the region where the shape is recognized consists of a closed curve as the outer contour, and a point on the closed curve is set as the initial point, which moves along the boundary of the closed region with the closed curve as the movement path, and the coordinates of the moving point are dynamically changed according to the periodic function. The form of the periodic function is transformed into a Fourier series by normalizing the manipulation of the periodic function. Because, the value of each coefficient of the Fourier series changes with the change of the edge of the curve, the Fourier series can be used as the shape description operator of the closed region. The basic idea of the method is as follows:

Assume that the boundary curve of the closed region in the plane is C and that C is a closed, continuous and smooth curve. A moving point $P(l)$ on the curve starts from the starting point and moves along the closed curve with a certain speed, then the complex form of the coordinate change of the moving point can be expressed as:

$$P(l)=x(l)+jy(l) \tag{11}$$

The above equation is a periodic function whose period is the perimeter of the closed curve and can be expressed using Fourier series. Each coefficient in the Fourier series is directly affected by the shape of the curve, and these coefficients are denoted as $z(k)$, i.e. the Fourier descriptor. When the coefficient term is taken to a certain order, the Fourier descriptor can extract the shape information. Representing the curve C as a sequence of discrete coordinates $\{x(n), y(n) \mid n=0,1,\ldots,N-1\}, n=0,1,\ldots,N-1$ with total length N, we have Eq:

$$z(n)=x(n)+jy(n), n=0,1,\ldots,N-1 \tag{12}$$

At this point, the closed curve C can be represented in one dimension. Since N points are taken to represent the curve C, the curve period $T=N$. The sequence of curve coordinates is Fourier transformed to have:

$$z(n)=\sum_{n=0}^{N-1} z(n)\exp\left(-\frac{j2\pi kn}{N}\right), (0\leq n\leq N-1) \tag{13}$$

The inverse transformation of the coordinates yields Eq:

$$z(n)=\frac{1}{N}\sum_{k=0}^{N-1}z(k)\exp\left(\frac{j2\pi kn}{N}\right),(0\le n\le N-1) \tag{14}$$

After normalization, the Fourier description operator phase information is eliminated from the calculation, at which point the Fourier description operator can be rotationally invariant, translationally invariant, and not subject to changes in the initial point of the contour.

2.2.3. Circular LBP Algorithm

The Circular LBP algorithm [27] allows for any number of pixel points within a circular neighborhood of radius R. This yields an LBP operator with P sampling points within a circular region of radius R, denoted LBP_p^R . Encoding neighboring pixels using a circle of variable radius yields a neighborhood as shown in Fig. 2:

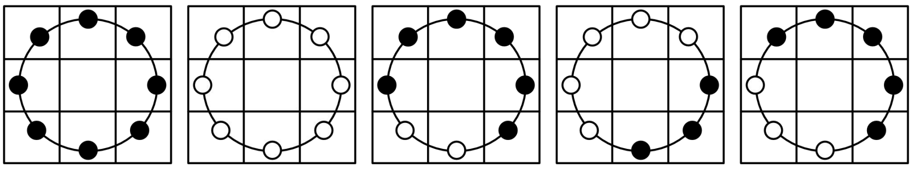

Figure 2. Encodes adjacent pixels using circles with variable radii.

For a given center point $\left(x_c, y_c\right)$, its neighborhood pixel position is $\left(x_p, y_p\right), p\in P$, and its sample point $\left(x_p, y_p\right)$ is computed using equations (15) and (16):

$$x_p=x_c+R\cos\frac{2\pi p}{p} \tag{15}$$

$$y_p=y_c-R\sin\frac{2\pi p}{p} \tag{16}$$

where R is the sampling radius, p is the pth sampling point, and P is the number of samples. Since the computed values may not be integers, in order to use the computed pixel points fall on the coordinate positions of the integer values, the pixel values on the diagonal in the neighborhood are derived using linear interpolation. For non-integer coordinate values, rounding up and down is denoted as x_0,x_1,y_0,y_1 , which gives $\left(x_0,y_0\right),\left(x_1,y_0\right),\left(x_0,y_1\right),\left(x_1,y_1\right)$ four coordinates. The bilinear interpolation points are shown in Eq. (17):

$$f\left(x_p,y_p\right)=\begin{bmatrix}x_1-x_p & x_p-x_0\end{bmatrix}\begin{bmatrix}f\left(x_0,y_0\right) & f\left(x_0,y_1\right)\\ f\left(x_1,y_0\right) & f\left(x_1,y_1\right)\end{bmatrix}\begin{bmatrix}y_1-y_p\\ y_p-y_0\end{bmatrix} \tag{17}$$

Since the landscape painting image dataset is a color image, when using circular LBP in this study, the features are acquired in each of the three channels of the color image.

2.3. Eigenvalues of Song-Yuan landscape painting images with computable aesthetics

2.3.1. Lower Level Visual Characteristics

The low-level visual features can independently and objectively describe the image content, and have the meaning of intuitive visual expression. The low-level visual features extracted in this paper are color features, including a 128-dimensional color histogram $f_1\sim f_{128}$ based on the non-uniformly quantized HSV color space, and the first-, second-, and third-order moments of the H, S, and V3 components (9 dimensions) $f_{129}\sim f_{137}$.

Finally, a 137-dimensional low-level visual feature vector was extracted from each image.

2.3.2. High-rise aesthetic features

Combining the knowledge related to human aesthetic perception such as aesthetic metrics, aesthetic psychology and aesthetic standards of watercolor paintings, we summarize the high-level aesthetic features of images such as image complexity features and image color balance features from previous studies.

(1) Image complexity characteristics

The degree of complexity of some distributional characteristics of the image itself, such as color distribution, shape distribution, and structural distribution, is called image complexity, which is considered to be one of the measures highly related to aesthetics.

The aesthetic metric (AM) formula, as shown in equation (18):

$$AM = \frac{O_O}{O_C} \tag{18}$$

Where O_O and O_C denote the intrinsic order of things and the intrinsic complexity of things, respectively. This paper takes the basic knowledge of image processing and so on, Kolmo gorov complexity, information theory, physical entropy and so on as the background, combines with the current research results on complexity, categorizes and calculates the image complexity characteristics.

(2) Image color balance

Color balance refers to the balance of image color strength, weakness, weight and lightness. As another form of formal beauty, color balance can make people's visual physiological and psychological feelings relatively stable. Among them, the balance of lightness refers to the balance of heavy and light colors, which is expressed as the symmetry of the sense of color weight.

In this paper, we use 2 kinds of metrics to measure the image color balance, namely, color full distribution and color visual balance. Color Entropy Distribution. In this paper, the way to define the color distribution is defined by calculating the Shannon entropy of the image through the color distribution information, which is based on the perspective of information entropy, as shown in equation (19):

$$M_B = \left(H_{\max} - H_p\right) / H_{\max} \tag{19}$$

In Eq. (19), H_p is the average information entropy of each color component of the HSV, $H_{\max}$ is the maximum information entropy of the image, and $\left(H_{\max} - H_p\right)$ is obtained as absolute redundancy. The smaller M_B is, the higher the color balance of the image is. In this way, we extracted the watercolor image color balance distribution feature f_{143}.

Color visual balance. The basic idea of solving the minimum transportation cost is used to find the similarity between 2 objects to be matched, which is a similarity measure reflecting the computer visual perception, and is essentially a two-way problem of choosing the optimal path of the network. The color visual balance of an image can be measured by calculating the color EMD between the original image and an ideal image with uniform color distribution.

The RGB color space is uniformly quantized into 64 equal parts, and for the ideal image with uniform color distribution, its 64 color component values are equal. The EMD distance is used to represent the similarity of color distribution between an image and an ideal image as shown in equation (20):

$$\begin{gathered} EMD_{RGB} = emd\left(D_1, D_2, \{d(a,b) \mid 0 \le a, b \le 63\}\right) \\ d(a \cdot b) = \left\| C_a - C_b \right\| \end{gathered} \tag{20}$$

where the computational function of EMD is denoted by emd(), D_1 denotes the color distribution of the ideal image, and D_2 denotes the to-be-seeked image's; a and b denote a histogram of one of the distributions of the D_1 and D_2 distributions respectively intervals; C_a and C_b are the heights of a and b, respectively, i.e., the frequency of occurrence of the corresponding color values; and $d(a,b)$ denotes C_a and the Euclidean distance between C_b, a 64×64 matrix. In this way, we obtain the color visual balance feature $\mathrm{EMD}_{\mathrm{RGB}}$ of the image, namely f_{144}.

2.3.3. Regional characteristics

The most significant information content of an image is concentrated in the key areas of the image. In aesthetic analysis, it is more necessary to study the key area than other areas, because visual psychology research shows that the key area contains more information conveyed by the picture and will attract most of the viewer's interest and attention. Compared with other regions of an image, people tend to pay more attention to the color distribution, compositional rules and shape-size ratio of the key regions. Therefore, in this paper, the features of 10-dimensional key regions, including color moments and shape ratios, are specially calculated: the color moment feature refers to the first-, second-, and third-order moments of the H, S, and V color channels $f_{145} \sim f_{153}$, and the shape ratio refers to the ratio of the number of pixels in the key region to the total number of pixels in the original image f_{154}.

Finally, a total of 154-dimensional feature vectors were extracted for each landscape painting image, including low-level visual features, high-level aesthetic features and regional features.

2.3.4. Compositional aesthetic analysis

Compositional aspects are judged in relation to the rule of thirds and the color saturation-related features of the picture. The formula for calculating the average saturation avg_s1 in the center of the rule of thirds is shown in (21):

$$avg\_s1 = \frac{9}{XY} \sum_{x=X/3}^{2X/3} \sum_{y=Y/3}^{2Y/3} I_H(x, y) \tag{21}$$

Where $I_H(x, y)$ denotes the target image, and X and Y are the length and height of the whole image, respectively.

A watercolor composition with the following two points is excellent:

(1) The larger the difference between the saturation avg_s of the whole image and the saturation avg_s1 of the center, the better, noting avgdis = |avg_s-avg_s1|, and the formula for this part of the score T1 is shown in Equation (22):

$$\mathrm{T1} = \begin{cases} 100, & avgdis > 100 \\ 60 + |avgdis - 50| * 4/5, & 100 > avgdis > 50 \\ avgdis * 6/5, & avgdis < 50 \end{cases} \tag{22}$$

(2) The saturation of the image center should be large enough. The formula for this part of the fraction T2 is shown in equation (23):

$$\mathrm{T2} = \begin{cases} 100, & avg\_s1 > 150 \\ 60 + |avg\_s1 - 50| * 2/5, & 150 > avg\_s1 > 50 \\ avg\_s1 * 6/5, & avg\_s1 < 50 \end{cases} \tag{23}$$

Final Result Composition Score $\mathrm{T} = \mathrm{T1} * 20\% + \mathrm{T2} * 80\%$.

3. Quantitative Experimental Results and Analysis of Aesthetic Characteristics of Song-Yuan Landscape Painting

Among the 100 paintings selected for this paper, there are 64 paintings from the Song Dynasty period. The Song Dynasty was the heyday of landscape painting, and more famous landscape artists appeared, so the number of selected works is on the high side.

3.1. Analysis of the Aesthetic Elements of Song and Yuan Landscape Paintings

3.1.1. The basis for extracting the elements of Song and Yuan landscape images

Regarding the study of image elements in art works, from the perspective of landscape gardening, it is believed that the landscape and architectural elements in the selection of subjects for traditional landscape paintings-mountains, rocks, trees, bridges, pavilions, streams, waterfalls, and grassy knolls-constitute an ideal realm that is pleasant to look at, pleasant to live in, and pleasant to swim in. From these studies, we can see that landscape paintings are composed of various different image elements, and at the same time, the image elements do not exist in isolation, they follow a certain proportion, have a primary and secondary, and are arranged harmoniously on the screen. In this study, by analyzing the main components that constitute the image area and proportion of Song Dynasty landscape paintings in 100 paintings, the image elements in the paintings are classified into 12 categories-mountains, bodies of water, sky, tall plants, flowers and plants, clouds, roads, people, characters, animals, buildings, and shore stones.

3.1.2. Process of Analyzing Image Elements of Song and Yuan Landscape Paintings

The quantification is achieved by reading the painting through scanner, dividing the image elements by AUTOCAD, and analyzing the ratio of image element area by the calculation of SPSS. The specific steps are as follows:

(1) Scan 100 ancient landscape paintings of Song and Yuan dynasties. Select the model of Canon Scan Lide7 0 0 F scanner for advanced color scanning of 100 works of landscape painting, the output resolution of 300dpi, the output size of 210mm×297mm.

(2) A grid of 20 mm x 20 mm was drawn with AUTOC AD software. The network squares drawn can be adjusted according to the size of different screens, and the fixed size of each of its squares is 20 MM × 20 MM modulus, and the modulus size of the squares remains unchanged.

(3) The drawn grid map with be imported into AUTOCAD software and superimposed with the paintings.

(4) Extract 12 image elements from 100 ancient landscape paintings of Song and Yuan and distinguish them with different colors.

(5) The area ratio of each image element in the paintings is calculated, and the calculation results are shown in Table 1.

Table 1. Landscape painting image element ratio calculation table.

Picture element	Massif	Wave	Sky	Tall plants	Flowers and plants	Cloud and mist	Road	Figure	Characters	Animal	Building	Shoreline
Area ratio	28.2%	0.7%	11.0%	38.2%	0	8.4	0	0	5.5%	0	8%	0

The calculation results of 100 works were summarized according to the above process of calculating the area ratio of the image elements of landscape paintings. Taking the proportion of each image element in 10 works as an example, it is shown in Table 2. Overall, it can be seen that the proportion of image elements is relatively high in the landscape paintings of the Song and Yuan dynasties, with mountains, water bodies and plants as the main elements.

Table 2. Proportions of Image Elements in Song-Yuan Landscape Paintings.

Painting	1	2	3	4	5	6	7	8	9	10
Element/%	Li Tang's "Wanhe Song Feng Tu"	Ma Yuan's Treading Song	Xishan Qingyuan Tu by Xia Gui	Huang Gongwang's Dwelling in the Fuchun Mountains	Wang Meng's Summer Mountain Dwelling	Guo Xi's "Xishan Yuanxing Tu"	Wang Ximeng's Thousand Li of Rivers and Mountains	Jiuran's "Layered Rocks and Trees"	Fan Kuan's Travelers in the Mountains and Streams	Dong Yuan's Xiao Xiang Tu
Massif	18.2	19.1	44.3	11.4	35.6	0	34.5	41.4	15.7	32.4
Wave	38.3	26.3	10.5	38.2	28.1	43.5	15.1	0	45.2	35.9
Sky	5.8	15.6	4.4	0	10.6	21.5	20.7	31.2	1.4	10.0
Tall plants	10.5	0	18.5	30.8	0	0	9.7	23.6	11.3	7.2
Flowers and plants	1.1	21.3	1.1	2.3	4.3	12.8	1.5	0	21.2	3.9
Cloud and mist	8.8	2.3	7.2	2.8	1.4	3.4	0.7	0	0	8.0
Road	3.2	8.3	3.8	0	0.5	0.7	11.5	2.3	0	0
Figure	0	0	0	0	0	0	0	0	0	1.3

Characters	2.4	2.6	2.6	0	1.4	0	1.5	1.5	2.4	0
Animal	1.8	0.4	0.1	0.5	0.2	2.1	0.1	0	0.4	0
Building	7.8	1.9	1.1	5.3	5.3	3.8	2.2	0	0	1.3
Shoreline	2.1	2.2	6.4	8.7	10.5	12.2	0.5	0	2.4	0

3.1.3. Analysis of the area proportion of Song and Yuan landscape image elements

The project uses the function of SPSS to analyze the scale characteristics of the elements of 100 landscape paintings. The specific steps are shown as follows:

(1) Enter the area proportion values of 100 landscape painting elements into SPSS.

(2) Frequency analysis: choose Analyze→Descriptive Statistics→Frequency in the toolbar and drag 12 elements into the variables.

(3) The system outputs statistical values and histograms as shown in Table 3. From the table, it can be seen that the mean value of the area proportion of each image element in Song and Yuan landscape paintings, in order, is 31.28% for mountains, 20.36% for tall plants, 16.15% for the sky, 10.45% for water bodies, 6.94% for clouds, 3.37% for buildings and so on. The results show that mountains, tall plants, sky and water bodies are the main elements of ancient landscape paintings of Song and Yuan dynasties, while flowers, plants, clouds and fog, buildings, texts, rocks, roads, figures and animals are the auxiliary elements.

Skewness is an indicator used to reflect the degree of skewness of the variable series of cities. It includes both normal and skewed distributions. When the number of people on the left, the average on the right, known as the right skewed distribution, and vice versa. This subject image element area ratio except for mountains and tall plants, all other right-skewed distribution, the value of the multitude is lower than the average; kurtosis characterizes the probability density distribution curve in the average value of the peak height of the characteristic number. From the kurtosis value, it can be seen that the image element area proportions are excessively kurtotic, with sharp distribution curves, all of which are distributed near the plurality.

Table 3. Landscape painting image element statistics.

Element Statistics	Massif	Wave	Sky	Tall plants	Flowers and plants	Cloud and mist	Road	Figure	Characters	Animal	Building	Shoreline
N	100	100	100	100	100	100	100	100	100	100	100	100
Mean	31.28%	10.45%	16.15%	20.36%	2.87%	6.94%	1.57%	0.68%	2.89%	0.55%	3.37%	2.48%
Mid-value	31.08	8.07%	16.14%	21.09%	0	3.97%	0.17%	0.11%	1.54%	0	1.9%	0
Mode	33% a	0	0	25% a	0	0	0	0	0	0	0	0
Standard error	0.14184	0.11471	0.10937	0.09857	0.06981	0.08589	0.02493	0.01793	0.06294	0.02117	0.04975	0.03952
Variance	0.021	0.015	0.013	0.009	0.005	0.008	0.000	0.000	0.0003	0.000	0.002	0.001
Skewness	-0.038	1.387	0.623	-0.019	4.913	1.927	2.496	4.856	4.921	5.174	4.384	1.673
Kurto Sis	-0.368	1.549	0.492	-0.221	28.093	3.754	7.484	26.811	28.015	27.752	23.573	1.652
Minima	0	0	0	0	0	0	0	0	0	0	0	0
Maxima	62%	50%	54%	48%	50%	38%	12%	13%	47%	14%	37%	16%

3.2. Quantifying the Dimensions of Aesthetic Characteristics of Song-Yuan Landscape Paintings

3.2.1. Color dimension

Coordinate value and meaning: the horizontal coordinate of the chart indicates the time, from

960-1028, reflecting the creation of Song and Yuan landscape paintings in different periods. The temporal evolution of the characteristics of the hue dimension (average gray scale) is shown in Figure 3, with the vertical coordinate indicating the average gray scale value of the hue dimension. As can be seen from the figure, the average gray scale value during the period of 960-996 shows a relatively smooth fluctuating trend of change as a whole, and the fluctuation during the period of 1002-1015 is more drastic, indicating that there is a greater adjustment in the brightness of their works during this period.

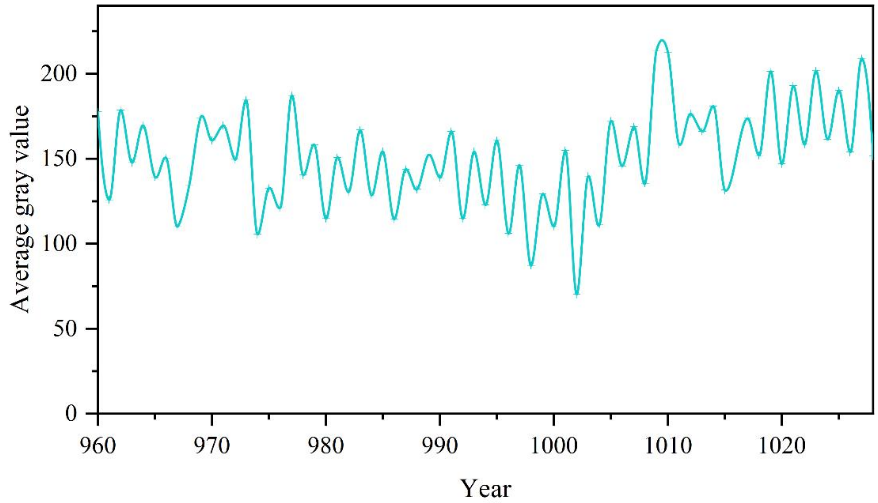

Figure 3. Time series evolution of hue dimension features.

The time-series evolution of the characteristics of the color tone dimensions (standard deviation, skewness, and kurtosis) is shown in Figure 4. The standard deviation is relatively stable during the period 960-994, with occasional small fluctuations, and these fluctuating upward trends indicate richer gray-scale variations in the works of this period. The skewness value has a significant peak around 978, indicating a higher degree of asymmetry in the distribution of image gray values during this period. The kurtosis values fluctuate significantly from year to year, with image gray-scale changes being more gentle in periods with higher kurtosis values and more dramatic in periods with lower kurtosis values.

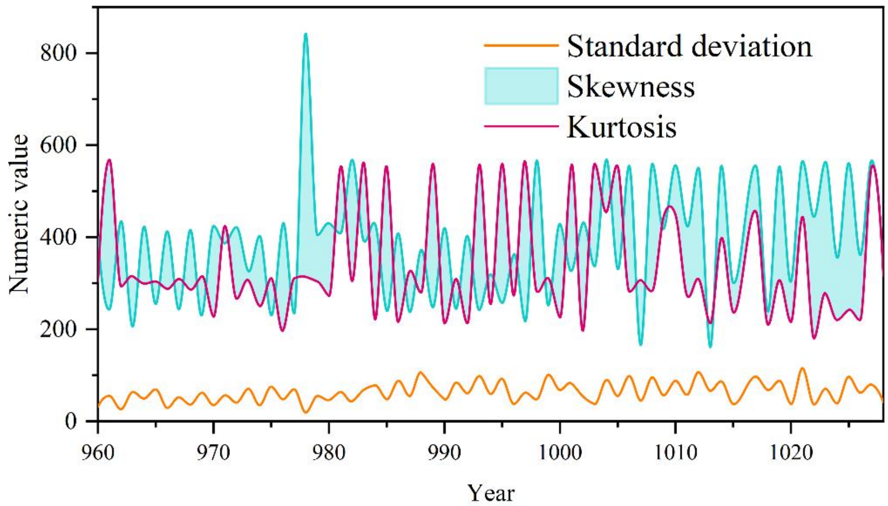

Figure 4. Timeline of hue dimension features.

3.2.2. Compositional dimensions

Center of mass offset can be used to measure the extent to which the center of gravity of the distribution of visual elements in an image deviates from the center of the image, and a large offset implies that the artist intentionally shifted the visual focus to a certain side of the picture, so as to create a specific visual effect and artistic atmosphere. The distribution of visual elements in an image is fitted to an ellipse, which results in an ellipse eccentricity, which reflects the compactness of the image composition and the shape characteristics. When the eccentricity is equal to 0, the ellipse becomes a circle, which indicates that the distribution of elements is more uniform and symmetrical. The larger the eccentricity, the flatter and longer the ellipse becomes, which indicates that the elements are distributed more centrally in a certain direction, or have a specific extension direction. Through the distribution status of the scatter points, the changing characteristics of the compositional features of Song and Yuan landscape paintings at different stages of creation are analyzed to find the relationship between the underlying laws and the evolution of the creative style.

The scatter plot of center-of-mass offset is shown in Figure 5, in which the horizontal coordinate represents the time and the vertical coordinate represents the value of center-of-mass offset, with the value ranging from 60-240, reflecting the degree of the center-of-mass of the visual elements of landscape paintings deviating from the center of the image in different periods. The scatter plot of center-of-mass offset degree has a relatively scattered distribution of scatter points, with no obvious linear trend. In different years, the value of the center of mass offset degree fluctuates greatly, indicating that the location of the center of gravity of the visual elements of landscape paintings varies in landscape painting compositions in different periods.

The ellipse eccentricity scatter plot is shown in Figure 6, in which the horizontal coordinate also represents time, and the vertical coordinate represents the value of the ellipse eccentricity, with the value ranging from 0.65 to 0.7, which reflects the size of the eccentricity of the ellipse fitted to the distribution of the visual elements in the works of different time periods, i.e., the compactness of the distribution of the elements and the shape characteristics. The distribution of scatter points of the ellipse centrifugal rate scatter plot is also more discrete and does not show obvious regular changes. The value of centrifugal rate in 960-990 is concentrated in the higher range of small dispersion, indicating that the distribution of visual elements in the works of this period is more uniform and symmetrical, which may show a more regular composition; the larger range of dispersion in 1000-1028 indicates that the distribution of visual elements in landscape paintings of this period is more concentrated in one direction and has a clear tendency to extend, and the composition is more compact. There is a clear tendency of extension, and the compositions may be more dynamic or directional.

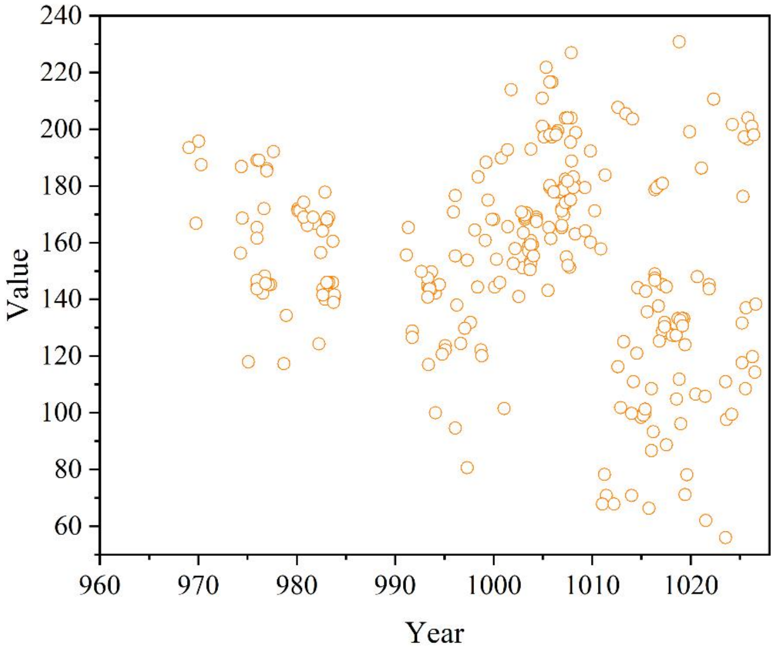

Figure 5. Centroid offset scatter diagram.

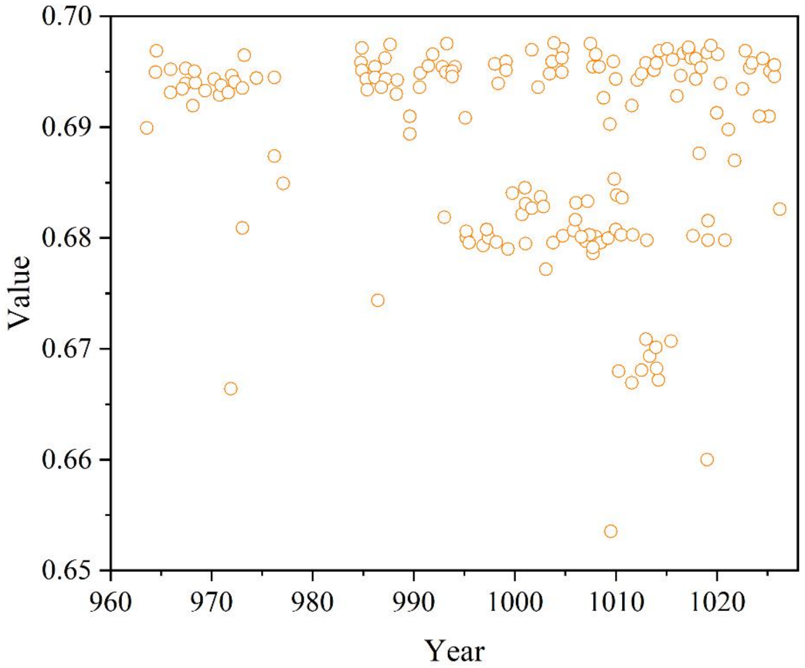

Figure 6. Elliptical eccentricity scatter.

3.2.3. Shape dimension

Shape complexity is used as a metric to measure the complexity of the shape of an object in an image. Different shape description values (e.g. Circ., AR, Solidity) show the complexity of shapes from different perspectives.Circ. (Circularity) AR (Aspect Ratio). Higher cumulative density indicates a denser distribution of image shape elements, and lower cumulative density indicates a sparser distribution of shape elements. By extracting the shape features of landscape paintings from different periods, different data of shape complexity and the values of cumulative density were calculated separately.

The time-series evolution of shape dimension features is shown in Fig. 7, reflecting the landscape paintings created in different periods of the Song Dynasty period from 960 to 1028. The red curve fluctuates less and the values are mostly within a certain range, indicating that the proximity of the shape of the objects in the landscape paintings to the circle varied relatively little from period to period, and that there were no obvious ups and downs in the circular character of the overall shape. The blue curve fluctuates more, indicating that the aspect ratio of the shape of the objects in the images varies more at these points in time, and the shapes differ significantly in the degree of narrowness or regularity. The orange curves are all relatively smooth overall, indicating that the fullness of the object shapes varies less from time to time. The absolute value of the green curve is small and relatively stable, with no obvious upward or downward trend or significant peak, indicating that the density of shape elements in landscape paintings is low overall, and that the distribution sparseness of the shape elements in the image is more stable overall, and that it does not change much in different time periods, with no significant change trend of being too dense or sparse.

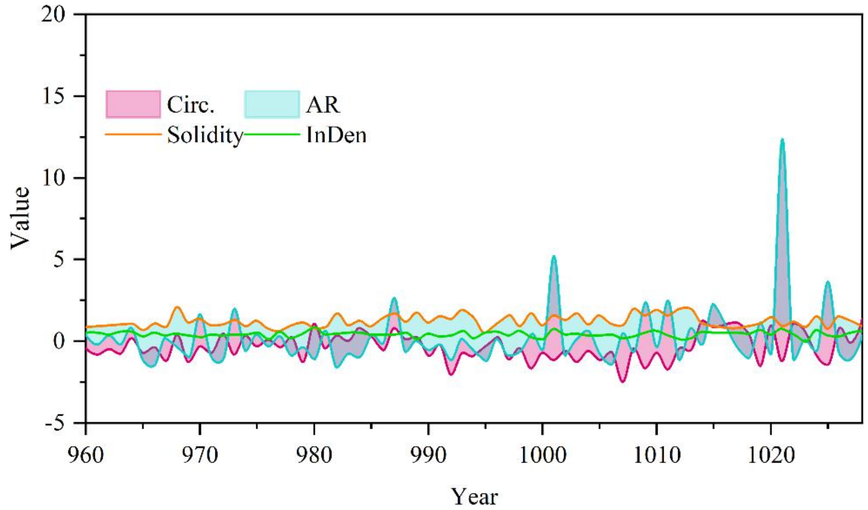

Figure 7. Time series evolution of shape dimension features.

3.2.4. Quantitative style index fitting

Drawing the style index curve fitting mapping to visualize and analyze the change rule of the style characteristics of landscape painting is shown in Figure 8. The black point is used to indicate the data point, which reflects the condition of the actual work characteristics taking values. It can be seen that the standard deviation has different distributions under different years and average gray values. The darker color of the purple area indicates a smaller standard deviation, which means that the gray scale variation of the works is relatively small under the conditions of these years and average gray scale values; the lighter color of the yellow area indicates a larger standard deviation and a richer gray scale variation. The distribution of data points also reflects the situation of the characteristics of the actual works. The data points of 690-1020 are more scattered, indicating that the stylistic characteristics of the works in this period show an unstable state.

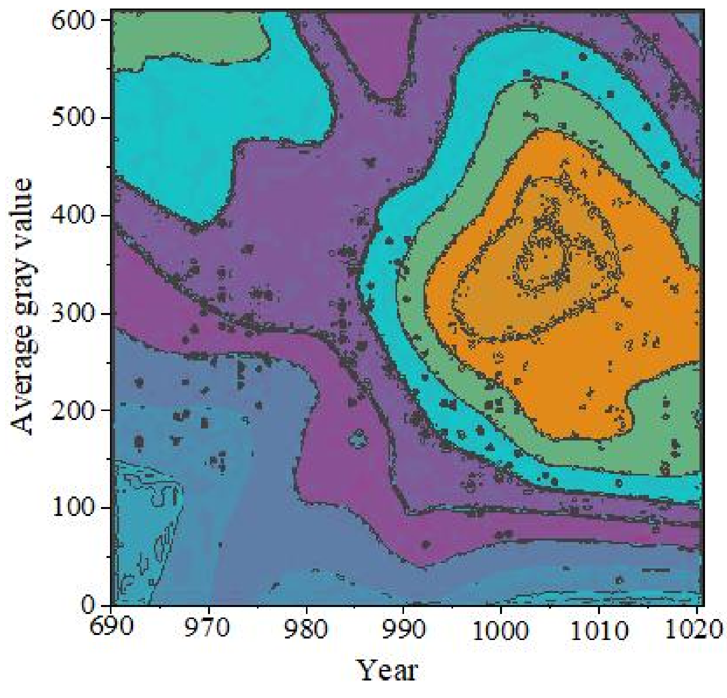

Figure 8. Style index curve fitting.

4. Modern Transformation and Analysis of Aesthetic Characteristics of Song and Yuan Landscape Paintings

4.1. Transformative Forms of Creative Expression in Landscape Painting

4.1.1. Transformation of painting concepts

Landscape painters pay great attention to recognizing and observing the objects in nature, collecting a large amount of materials, brewing ideas, and through their own subjective consciousness, integrating objective objects with their own subjective thoughts and feelings, and then transforming nature into meaningful works of art. Landscape painting's vividness, the shape of God, the mood, writing and other painting concepts precisely for the modern creative design provides from the objective object through the art of modeling to express the spiritual connotation of the design of the creative ideas, so that the modern creation of both artistic aesthetics and can pass the emotion. Through the clever deformation of traditional objects or the abstract treatment of the outline of the lines, or reinterpretation with modern style and create works that can convey personal feelings.

4.1.2. Transformation of Pen and Ink Components

Brush and ink is the most fundamental art language in traditional painting, the basic visual element of its artistic expression, and the most important essence of landscape painting. The beauty of vividness in landscape painting can only be expressed by the art language of brush and ink techniques. In the process of creation, the use of brush and ink to combine different elements of dots, lines and surfaces to express the sense of volume and texture of objects; the use of dots to express the level and depth of objects; the use of lines to express the rhythm and rhythm of interspersions, sparseness, solidity and emptiness, etc., make the objects depicted in the picture become delicate, vivid and lively, and at the same time, they are also endowed with life and feelings.

4.1.3. Transformation of “white space” expressive language

The technique of “white space” in landscape painting refers to the blank space left in the picture. The technique of white space is often used in landscape painting in China, and it is an important technique for the expression of spatial language of reality and emptiness. The virtual and real scenery together create the mood of the picture and form the author's spatial feeling. In landscape painting, in addition to the shape of the ink and brush performance, white space is also an important part of the picture, the blank part of the picture is the spatial extension of the picture, is an indispensable part of the work of the “mood” shaping, there is no blankness in the picture as a support, the specific shape of the ink and brush is no contrast. White space is not a blank space without content, but an artistic language that transforms reality into reality, turning the unintentional into the intentional, and using the less to win over the more.

4.1.4. Transformation of Song and Yuan landscape painting elements in modern design

(1) Application of modeling elements in modern jewelry design

Landscape is the main depiction object of landscape painting and the main component of landscape painting. In the Song Dynasty, the art of landscape painting developed to the peak, the subject matter is more abundant, rocks, grass, trees, pavilions, temples, river fishing boats, sunset swimmers, etc., a stone, a branch, a small river, a weed can become the source of inspiration and the main body of the picture, these vivid elements of landscape can also be applied in modern jewelry design. Modern jewelry designers should first experience the unique way of expression of landscape painting, and then refine, transform and apply the landscape elements in it, incorporate the aesthetics of modern people, and endow the jewelry with cultural connotations and characteristics of the times.

(2) The application of painting techniques in modern jewelry design

Landscape painting with ink and brush as the main means of creation, the application of unique techniques to reflect the landscape mood, the most common is the chapping method. Chapping is a special technique that can produce a unique aesthetic meaning, the use of this method in landscape painting can truly show the texture and texture of rocks and trees. Of course, there are many types of chapping, such as rice point chapping, axe chapping, pima chapping, etc. Different techniques bring different textures and textures.

Landscape painting techniques applied to jewelry design, can better shape the texture of the jewelry, showing the beauty of the strength of different jewelry, the beauty of the line and the beauty of the texture.

4.2. Conducting Perceptual Imagery Evaluation Descriptions

4.2.1. Conducting Perceptual Imagery Evaluation Descriptions

A total of 30 professionals participated in the workshop, mainly from design-related majors, including 5 jewelry designers, 3 product designers, 18 teachers and students of design-related majors, 2 product structural engineers and 2 material engineers. One-on-one interviews were conducted with the professionals, and in the form of video, audio or video phone calls, the professionals evaluated the original perceptual imagery of the jewelry design samples using the main editorial elements and completed the recordings, and then through the organization of the expert group to conduct focus group interview meetings, the expert group consisted of three people who have been engaged in design-related work for a long time, and the content of the seminar revolved around the elements of landscape paintings in the design of jewelry The content of the workshop centered on the extraction of statements for the original evaluation of sensual imagery. After the expert group's organization and screening, a total of 173 effective statements for the evaluation of sensual imagery were obtained.

4.2.2. Refinement of Sensory Imagery Evaluation Entries

A panel of experts comprehensively analyzed the evaluation statements of perceptual imagery, used semantic analysis to merge those with similar expressions and delete those with the same expressions, and finally synthesized 28 evaluation entries of perceptual imagery of landscape painting elements used in jewelry design.

4.2.3. Analyzing the Sensory Imagery Evaluation Entries

The seven levels of evaluation data obtained through the analysis of semantic difference method can be informed of the user's preference tendency, demand characteristics and evaluation imagery, but the dimension range of this evaluation is not clear, which is not conducive to designers to accurately grasp the user's needs. Therefore, the study of the evaluation dimension of the sensual imagery of landscape painting elements needs to be refined and downgraded through the method of factor analysis. Specific analysis steps and analysis results:

First, analyze whether the data can be factor analyzed through the reliability test of the data. In the Bartlett's spherical test test, the observed value is 752.28, and the significance level is close to the value 0. The correlation between the original variables is obvious, which indicates that the data collection is reliable. Meanwhile, the value of KMO is 0.802, which is greater than 0.6 indicating that the original data is suitable for factor analysis.

Second, the principal factors were analyzed using principal component analysis as shown in Table 4. Among them, there are four principal factors with eigenvalues greater than 1 and a cumulative variance of 65.392%, which have represented most of the perceptual imagery evaluation factors. Also, it can be seen that the variance between the remaining factors of the factor has decreased, therefore, the four factors can be established as the main factors. It can be seen from the degree of aggregation of the variance of the first four factors: the first four factors have a significant difference between the rest of the factors the difference between the remaining factors decreases, therefore, it can be established out that the four factors as the main factors.

In the total variance interpretation in the table, the loadings of the four principal component factors are decreasing, in which the percentage of variance of principal factor 1 is 25.194%, which is the most representative factor among the four factors; the percentage of variance of principal factor 2 is 19.259%, and the percentage of variance of principal factor 3 is 12.843%, which is also highly representative, and it is the main in the evaluation of the design and the user's perceptual image as the main Consideration category. However, the percentage of variance of main factor 4 is 8.627%, which is not more than 10%, and it is weak relative to the first three main factors and can be considered as an auxiliary factor.

Table 4. Total variance explained.

Factor	Initial eigenvalues			Extract sum of squares of loads			Sum of Squares of Rotational Loads factor		
	Amount to%	Variance%	Accumulate%	Amount to%	Variance%	Accumulate%	Amount to%	Variance%	Accumulate%
1	3.884	28.842	28.842	3.884	28.842	28.842	3.583	25.157	25.194
2	2.779	20.019	48.519	2.779	20.019	48.519	2.752	19.259	45.773
3	1.364	9.679	58.048	1.364	9.679	58.048	1.682	12.843	56.763
4	1.032	7.478	65.416	1.032	7.478	65.416	1.335	8.627	65.392

Third, according to the characteristics of factor analysis, during the factor analysis process, the obtained results, if not rotated, have larger coefficients of variation of the factors in their component matrices, which is not conducive to obtaining accurate factor definitions. Therefore, the maximum variance method was used to rotate the factors orthogonally during the factor analysis process in order to obtain a more stable factor matrix after rotation. The rotated component matrix is shown in Table 5. From the results of the factor analysis, the main characteristic factors of the main factor 1 can be summarized based on the values of the components as practicality factor, memorable factor, fun factor, moral factor, taste factor, and comfort factor; The main characterizing factors of Master Factor 2 are styling factor, environmental factor, diversity factor, and stability factor; the main characterizing factors of Master Factor 3 are serialization factor, sense of order factor, and innovativeness factor; and the main characterizing factors of Master Factor 4 are value and price factor.

Table 5. Factor analysis results.

Factor Name	Factor			
	1	2	3	4
Useless-Useful	0.831	-0.096	0.128	0.276
No More-Fun	0.772	0.034	0.084	0.026
Vulgar-Elegant	0.754	-0.041	-0.018	0.357
Forgetful-Unforgettable	0.755	0.023	0.069	-0.019
No meaning-Meaningful	0.693	-0.005	0.285	-0.346
Discomfort-Comfort	0.642	-0.194	-0.015	0.346
Small-Thick	-0.015	0.857	0.105	0.048
Natural-Artificial	-0.022	0.839	-0.021	-0.086
Diversity-Singularity	-0.159	0.752	0.179	-0.059
Structural stability-Structural thinness	0.051	0.628	-0.071	-0.005
Non-series-Series	0.153	-0.105	0.789	0.129
Disorder-Order	0.286	0.083	0.668	-0.296
Inherit-Bring forth new ideas	-0.135	0.441	0.657	0.206
Low value-High value	0.336	-0.018	0.079	0.814

Finally, the reliability analysis of the overall study was carried out, and the Alpha reliability coefficient was 0.817, which is more than 0.6, based on the homogeneous reliability statistics of standardized items, which were tested on 151 valid cases, and based on these results, it can be concluded that the factors and dimensions of the evaluation system of perceptual imagery were established with high reliability.

5. Conclusion

This paper quantitatively researches the aesthetic characteristics of Songyuan landscape paintings and explores its modern transformation path through big data analysis technology. Firstly, the aesthetic elements of Song-Yuan landscape paintings are extracted and the area proportion of the elements is analyzed, followed by mapping analysis in four aspects: color, composition, shape and style quantification, and the experimental results show that the mean value of the area proportion of each image element in Song-Yuan landscape paintings is, in order, 31.28% of the mountains, 20.36% of the tall plants, 16.15% of the sky, 10.45% of the water, 6.94% of the clouds, and architectural 3.37%. Meanwhile, from the results of image element area ratio analysis, it is found that except for mountains and tall plants, all other image elements are right skewed and excessively kurtosis distributed. The graphical analysis shows two key mutation periods, the period of 1005-1028, the fluctuation of hue and shape features is obvious, followed by the peaks of AR curves, etc. which represent shape features and texture dimensions, reflecting the complexity and variety of stylistic changes in Song-Yuan landscape paintings.

Based on the above research, the aesthetic characteristics of Song and Yuan landscape paintings have laid the foundation for modern transformation, which is specifically reflected in the concept of painting, the composition of ink and brushwork, and the creation of “white space” to realize the transformation of modern jewelry design. Finally, evaluating the jewelry design with image elements, the Alpha reliability coefficient is 0.813, which is more than 0.6, and the factors and dimensions of the evaluation system of perceptual imagery are established with high reliability.

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