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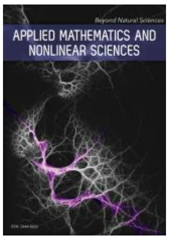

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The Transformation of Traditional Chinese Painting Elements in Modern Design Contexts

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Abstract

To ensure the effective preservation and evolution of traditional painting art, it is imperative to integrate contemporary art design concepts and methodologies. This paper focuses on the reconstruction of traditional Chinese painting elements, distilling and adapting its pattern, ink, and calligraphy components into a modern design framework. Specifically, the features of the pattern elements are identified and transformed using a feature point extraction algorithm combined with K-Means clustering. For ink and calligraphy elements, a fusion of self-attention mechanisms and Generative Adversarial Networks (GANs) facilitates the stylistic migration and conversion of these elements through the construction of distinct discriminators. Subsequent evaluation of the transformed painting elements utilized Importance-Performance Analysis (IPA) within a contemporary design context, aiming to assess the practical value of traditional painting elements in modern design. The findings indicate that the clarity of information (C1) and its accuracy and efficacy (C3) in the context of contemporary design achieved importance scores exceeding 3.6. Furthermore, the satisfaction scores for modeling (C10), color (C11), and imagery (C12) each surpassed 3.5, denoting a high level of satisfaction in the IPA of their conversion. The study enriches traditional artistic methods and conceptualizations, thereby enhancing their cultural depth and significance.

Keywords: K-means clustering algorithm; GAN network; Style migration; IPA analysis; Traditional painting elements.
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1 Introduction

Nowadays, traditional culture is increasingly emphasized, and many designers pay attention to the integration of traditional cultural elements in modern art design, which gives modern art design with contemporary cultural flavor and, at the same time, promotes the promotion of conventional culture [1]. Not only that, the use of ethnic art in diversified modern art design is conducive to the inheritance and promotion of outstanding Chinese traditional culture and enhances cultural self-confidence [2].

From the point of view of the respective characteristics of traditional painting and modern design, traditional Chinese painting focuses on the creation of mood. All kinds of conventional paintings take intention as the priority, and the height of the mood determines the height of the painting's thought, which reflects the high aesthetic quality [3-4]. Traditional painting not only pursues the resemblance of form but also pays attention to the resemblance of God in order to realize both form and spirit [5-6]. Modern art design is bolder and abstract, not confined to forms and ideas, and emphasizes the embodiment of artistic value and ideological connotation [7-8]. Therefore, modern art design prefers exaggerated expression, and through the collocation of multiple elements, it integrates modern fashion elements to reflect the innovation of art design [9].

There are four ways in which modern art design borrows from traditional painting art. The form of composition can be the integration point of conventional painting and modern poetry design. Painters often use different forms of composition to convey different moods and ideas. Contemporary design can also use the composition of traditional painting ideas in order to get a better performance effect [10-11]. Contextual expression is also a common language between the two. The mood of the painting can reflect the painter's thoughts and emotions to convey specific cultural connotations, and modern design can draw on the use of color in traditional paintings to express emotions [12-13]. The art of white space is also an important form of reference. Modern art design pursues simple artistic beauty. Drawing on the traditional painting art of white space can reasonably adjust the spatial layout, prompting the artwork to be sparse and dense, structurally reasonable, and rich in simple artistic aesthetics [14-15]. Line drawing allows traditional painting art to provide new ideas and new ways for the development of modern art, only by virtue of the interspersed use of lines, conveying a kind of smooth flow of ideas [16-17].

In this paper, we define traditional Chinese painting elements and design a reconstruction process in a modern design context, resulting in the refinement of traditional Chinese painting elements from three aspects: pattern, ink, and calligraphy. It first extracts and transforms the feature points and color points of pattern elements using the SIFT algorithm and K-Means clustering algorithm, respectively. The feature representations of ink style and content are decoupled, and an ink style migration model based on a GAN network is proposed to facilitate the transformation of ink elements. An improved Pix2pix network is also proposed, and a spectral normalization and residual module is introduced to achieve the transformation of calligraphic elements. On this basis, the transformation effects of pattern elements, ink elements, and calligraphy elements are analyzed respectively. Finally, through the construction of the evaluation index system for the satisfaction of the transformation of traditional Chinese painting elements in the context of modern design, the IPA analysis of the transformation effect is carried out, and its application value is discussed.

2 Traditional Chinese painting elements in the context of modern design

2.1 Digital representation of traditional painting elements under modern design

2.1.1 Definition of traditional Chinese painting elements

The elements of traditional Chinese painting shape the structure of conventional painting art. The profound and far-reaching traditional history and culture demonstrate the art, techniques, and crafts of traditional Chinese painting to all people around the world. Due to a long period of precipitation and brewing, it has developed a distinctive style and meaning in traditional painting. The elements of traditional Chinese painting are both a characterization of conventional history and culture, as well as an artistic ideology, which is influencing our modern lives all the time.

2.1.2 Expression of traditional Chinese painting elements

The rapid development of science and technology has caused digital media, a new communication medium, to inject fresh blood into Chinese traditional painting and create new means of artistic expression. The application of traditional Chinese painting combined with modern digital technology mainly focuses on digital painting and ink photography, and the results of the survey on digital expression are shown in Table 1. In digital painting, there are two categories of expression: computer-synthesized graphic images and computer-produced vector graphics. In the case of Kan Tai-keung's work "Chinese Characters", for example, the part of the "mountain" in the background is a pen-and-paper drawing, where the image is first drawn on rice paper, then imported into the computer using digital scanning technology, and then post-synthesized using design and drawing tools. In the case of computerized vector graphics, for example, Zhang Yupeng's poster work "Zhimei Xuexue Tang" was created directly on the computer.

Table 1. Digital performance form survey results

Classification	Form	Performance	Instance
Modern design	Digital painting	Use computer to synthesize graphic images	Jin tai-qiang "chinese characters"
		Use a computer to make vector graphics	Zhang yupeng "the aesthetic hall of knowledge"
	Ink photography	Image and later synthesis of digital devices in the real world	Langjingshan "hua pavilion is in the kingspot"

2.1.3 Reconstruction of traditional Chinese painting elements

The reconstruction method of traditional Chinese painting elements summarizes the traditional pattern elements are decomposed into several parts through segmentation and extraction, and the broken pattern elements are combined into new patterns through reconstruction methods such as collocation, replacement and insertion. These divided and extracted graphics are rearranged and combined into a new modeling concept, which both represents the graphic concept and changes the original modeling features. In addition, the design concentrates on the details to achieve the graphic unity of the pattern modeling elements and the visual presentation of the picture as a whole. The reconstruction process of traditional Chinese painting elements is shown in Figure 1. Its reconstruction process is mainly built on the basis of extraction combined with modern innovative design concepts, using design law to design innovative patterns. The pattern reconstruction design is primarily analyzed from two major parts: the extraction of the pattern and the reconstruction of the pattern. Decomposition of the entire pattern element reconstruction process is as follows: selecting the original drawing, extracting the pattern, analyzing the pattern, forming a new pattern element, reconstructing the basis of analysis, pattern composition analysis, completing the reconstruction, and so on.

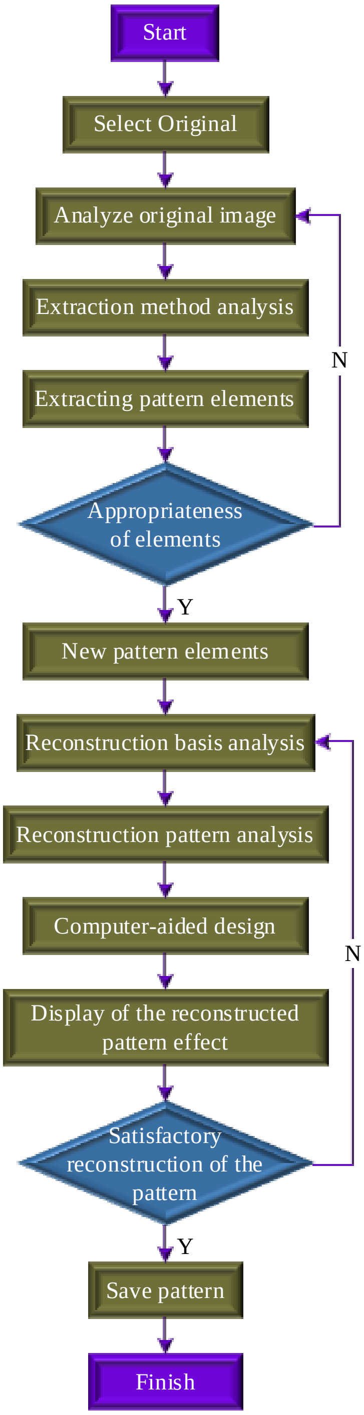


Figure 1. The reconstruction process of traditional Chinese painting elements

2.2 Refinement of traditional Chinese painting elements

Modern design will incorporate traditional Chinese painting patterns, painting, calligraphy, and other elements into it. Chinese traditional painting elements are categorized as shown in Figure 2. Specific elements are classified as follows: 1) traditional patterns: cloud pattern, ruyi pattern, daylily pattern, etc. 2) traditional paintings: ink and wash elements, brushwork elements, fish and insect elements, and pictorial flower and bird painting elements, etc. 3) calligraphy: brushes elements, rice paper elements, and ink elements. From these traditional Chinese painting elements, we extract the cultural elements with strong characteristics, transform these factors into symbols suitable for modern aesthetic value orientation, and apply them in the contemporary cultural context design program.

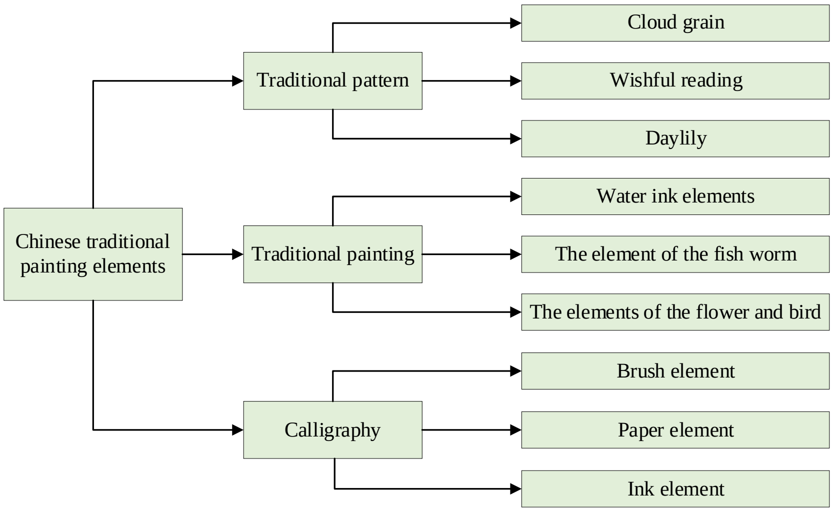


Figure 2. Classification of traditional Chinese paintings

2.2.1 Refinement of Pattern Elements

Chinese traditional patterns were first found in colored pottery of primitive societies and have evolved into many forms since then, with a unique national character. Depending on the motifs, they can be divided into primitive motifs drawn on early primitive pottery, classical motifs with hierarchies and norms in ancient societies, and motifs used by working people in their daily lives or motifs with a certain folklore nature, which are closely related to labor and embody a sense of life. As a multi-ethnic country, each minority group in China also has its unique patterns, which they show through clothing, architecture, and painting, reflecting their unique ethnic attributes. Modern design contexts use pattern elements to embellish and transition between elements, and they can also create auspicious meanings in the design products.

2.2.2 Refinement of Ink Elements

The use of water and ink in Chinese ink paintings is aimed at maximizing the use of water and ink. The dripping of the ink symbolizes the melting of water into a pool of clear water. The carp brush painting swims onto the page. The carp is colorful, and the depiction is detailed and realistic. Carps are often used as a theme in brush painting to signify good luck and a good year. The appearance of the fish makes the page come alive, driving modern development. Writing flowers and birds as the background painting, using special effects to show, makes the contemporary design more ornamental.

2.2.3 Refinement of Calligraphic Elements

Calligraphy, as an art form, often appears alongside painting as a part of the painting, serving as a finishing touch. The calligraphy fonts that appear in modern designs are the fonts of ancient calligraphers synthesized through software to enhance their artistic flavor. Putting the fonts into the scroll and using animation software to create the animation effect of brush-writing fonts makes the overall atmosphere of the design come alive.

3 Transformation of traditional Chinese painting elements

3.1 Transformation of traditional Chinese painting pattern elements

The transformation of traditional Chinese painting pattern elements mainly involves extracting pattern features and pattern colors. Image matching occupies an important position in the field of digital image processing, which can quickly find the image that matches the template in a large amount of image information, and the time spent is much less than searching one by one by using the naked eye. Extracting feature points is done before matching the image. Currently, the SIFT algorithm is commonly used to extract features. This algorithm can match the image with scale transformation, noise interference, rotation, or miscue transformation very well with the original image. As for color extraction, a K-means clustering algorithm is used, which can accurately mine and reconstruct the colors of traditional Chinese painting patterns so as to be applied in modern design contexts.

3.2 Transformation of ink elements in traditional Chinese painting

3.2.1 Ink Elemental Style Generation Model Structure

A feature representation that decouples the content feature representation and the style feature representation is proposed as a generative adversarial network CycleGAN-based ink style image generation model (SWAN). The structure of the ink-style image generation model is shown in Fig. 3. It mainly consists of generator G, generator F, and the overall edge extractor TOM. The generator G of this model is a style-weaving attention network, which contains a content encoder, a style encoder, a self-attention module, nine residual blocks, and a decoder. A new self-encoder has been added to the original generator G model to achieve the decoupled representation of semantic and stylistic features. The content feature mappings and stylistic feature mappings extracted from real photographs and ink paintings by two encoders with the same network structure, respectively, are woven and fused through the self-attention module, where the learning of content features is focused. Subsequently, the output of the attention module is delivered to the decoder through a residual network, where the content and style features are extracted to produce the target ink-style image.

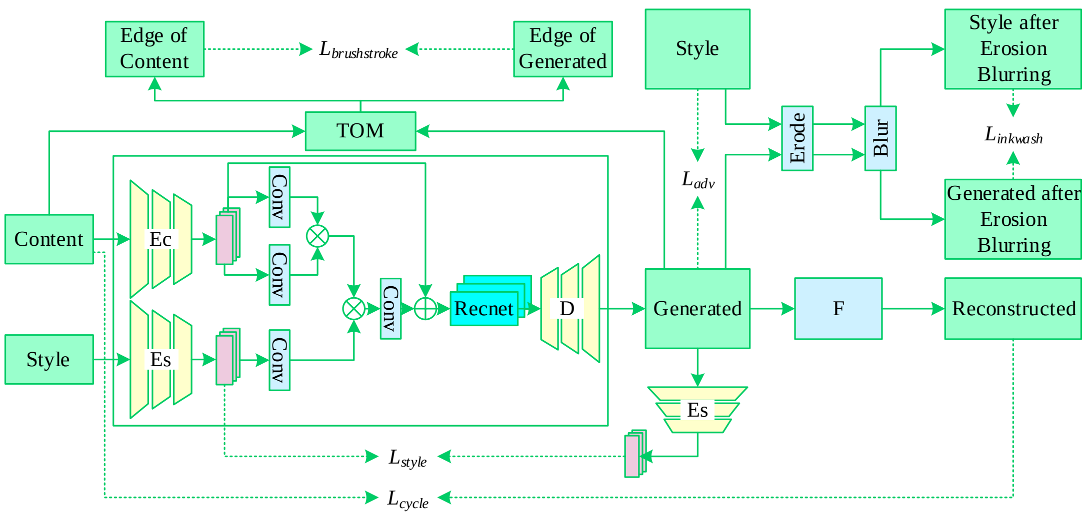


Figure 3. Model structure

To avoid the problem of content information loss, such as object blurring and contour blurring, this paper proposes a stylistic feature weaving method (SA) based on the self-attention mechanism, which spatially rearranges the stylistic features according to the content features, and learns the semantic correlation between the content features and the stylistic features. The normalized content feature mapping F_C and style feature mapping F_S are captured using the self-attention module and then transformed into feature spaces f, h, g to compute the attention F_{CS}^i as shown in Equation (1):

$$P'_{CS} = \frac{1}{\alpha A} \Sigma_{\forall j} \exp\left(f\left(\bar{F}_d\right)^T g\left(\bar{F}_c^i\right)\right) h\left(\rho_S\right) \tag{1}$$

$$C\left(F\right) = \Sigma_{\forall j} \exp\left(f\left(\bar{F}_d\right)^T g\left(\bar{F}_c^i\right)\right) \tag{2}$$

Where $f\left(\bar{F}_c\right) = W_f \bar{F}_c$, $g\left(\bar{F}_c\right) = W_g \bar{F}_c$, $h\left(F_S\right) = W_h F_S$, W_f, W_g, and W_h are weight matrices implemented by 1*1 convolution operations, and $\bar{F}$ denotes the channel normalized version of F.

The network structure of the self-attention mechanism module in this paper is similar to that of existing nonlocal neural networks, but with a different amount of input data (the input feature vector mappings for this network model are F_C and F_S, respectively). The SA module can appropriately embed local style patterns at each position of the content feature map by learning to map the relationship (e.g., affinity) between the content feature map and the style feature map.

3.2.2 Ink Element Feature Labeling Learning Methods

1) Realization of white space

White space is a typical feature of Chinese ink paintings, in which the artist expresses a far-reaching mood and thoughts by "leaving white space" on the canvas. To achieve the real ink and wash style transformation, the inclusion of the white space feature is essential. How to utilize deep learning to simulate abstract artistic expressions is the problem that will be investigated in this subsection.

Generating Against Loss:

Given a set of unpaired datasets from domains X and Y, the model in this paper consists of two mappings $\left(G : X \rightarrow \gamma\right)$ and $\left(F : Y \rightarrow X\right)$. For the first mapping $\left(G : X \rightarrow Y\right)$ and its discriminator D_Y, an adversarial loss description is generated as shown in Equation (3):

$$\begin{aligned} L_{ad_v}\left(G, D_r, X, Y\right) = E_{y\sim\rho_{dota}\ (y)}\left[\log D_Y(y)\right] \\ + E_{x\sim\rho_{data}(x), y\sim\rho_{\cot a}(y)}\left[\log\left(1 - D_Y(G(x, y))\right)\right] \end{aligned} \tag{3}$$

G tries to generate images that are similar to real samples, while D tries to distinguish between real samples and generated results. The goal of this loss is to minimize the gap between the results generated by the generator and the real samples and to maximize the discriminator's ability to distinguish between the real samples and the generated results, e.g., $M_{inG} M_{ax} D_r L_{adv}$. The mapping $(F : Y \rightarrow X)$ and its discriminator D_X have similar goals.

Cyclic consistency loss:

Reconstruction is the process of mapping sample x from domain X through G to domain Y and then from domain Y through F back to domain X. The content features of the reconstructed image and sample x should be highly similar, $F(G(x,y)) \approx x$ and therefore the cyclic consistency loss is shown in Equation (4):

$$\begin{aligned} L_{\text{cycle}}(G,F,X,Y) &= E_{y\sim p_{\text{datat}}(y)}\left[\left\|G(F(y))-y\right\|_1\right] \\ &+E_{x\sim p_{\text{data}}(x),y\sim p_{\text{data}}(y)}\left[\left\|F(G(x,y))-x\right\|_1\right] \end{aligned} \tag{4}$$

Considering the correctly generated blank area, this paper takes into account the characteristics of “brushwork” and “writing” in ink painting, with “brushwork” characterized by straightforward content and precise strokes.

2) Stroke constraints

In order to model the various types of strokes in Chinese ink paintings in a unified way, a stroke constraint is proposed to enhance the consistency between the real photographs and the generated paintings with different levels of edge mapping.

Therefore, this paper introduces a GAN-based domain transfer model called TOM, which stands for “Train Once and get Multiple transfers”. After the source image and the generated image are transferred through TOM, the edge sketch information is extracted and then backpropagated through a brush constraint loss to improve the generation effect of generator G.

The balanced cross-beam loss is computed for the edge image generated from the real photo x and the generated image $G(x,y)$ so that the image generated by the generator has similar contour information as the source image.

The brush constraint loss is shown in equation (5):

$$\begin{aligned} &L_{strokebrush}(G,X,y)= \\ &E_{x\sim p_{dotat}(x),y\sim p_{datat}(y)}\left[-\frac{1}{N}\sum_{i=1}^{N}\mu E(x),\log E(G(x,y))_i\right. \\ &\left.+(1-\mu)\left(1-E(x)_i\right)\log\left(1-E(G(x,y))_i\right)\right] \end{aligned} \tag{5}$$

Where N is the total number of pixels in the edge map of the real photo or the generated image, μ is a balance weight. $\mu = N_-/N$, $1-\mu = N_+/N_0$. N_- and N_+ are the sum of non-edge probabilities and edge probabilities for each pixel in $E(x)$, respectively.

3) Realization of ink diffusion effect

Having correctly simulated the white space and brushes, our final processing is to make the global color tone (e.g., the overall color temperature of the generated ink painting horse should be close to that of the real ink painting) and diffusion effect (e.g., the different shades of gray of the horse’s brushes diffused onto the rice paper) consistent between the real ink painting and the generated ink style image.

Because the ink used for painting melts with the rice paper and produces a special effect of agitated wet penetration, which is an ink diffusion effect (e.g., the horse’s tail appears to have a gradual lightening of grayscale on the rice paper), for this reason, this paper adds an ink constraint to make the generated image look closer to the effect of a real ink painting. The diffusion of ink on rice paper is approximately isotropic, so it can be simulated using an erosion operation and a Gaussian blurring operation while suppressing the display representation of texture and content to make the model more inclined to tonal consistency. Furthermore, a discriminator is taught to differentiate the representation after the erosion operation and the Gaussian blur operation.

The ink diffusion constraint loss is shown in Eqs. (6) to (8):

$$y_{eb}(i,j) = \Sigma_{k,1}(y!\ \ B)_{i+k,j+1} \cdot G_{k,l} \tag{6}$$

$$G(x,y)_{eb}(i,j) = \Sigma_{k,1}(G(x,y)!\ \ B)_{i+k,j+1} \cdot G_{k,1} \tag{7}$$

$$\begin{aligned} L_{inkwast}\left(G, D_1, X, Y\right) = {} & E_{y\sim p_{data}(y)}\left[\log D_1\left(y_{eb}\right)\right] \\ & + E_{x\sim p_{dotat}(x), y\sim p_{data}(y)}\left[\log\left(1 - D_1(G(x,y)_{eb})\right)\right] \end{aligned} \tag{8}$$

3.2.3 Optimization objectives

The optimization objective consists of six parts in total: generative adversarial loss, the core idea in generative adversarial networks; loop consistency loss between the reconstructed image and the original image of the generated result after forming the shape of the loop; and three constraint losses of whiteout constraints, brush constraints, and ink diffusion constraints, respectively, for the features of ink painting; Finally, in order to let the style encoder learn the ink style features better, this paper enables the style to the image, and the generated image passes through the style encoder and adds a style loss between them to constrain the realization of the ink style, and the loss is shown in Eqs. (9) and (10):

$$Gram_{ij} = \Sigma_k P_k^i P_k^j \tag{9}$$

$$L_{style} = \left\| Gram\left(E_s(y)\right) - Gram\left(E_s(G(x,y))\right) \right\| 2 \tag{10}$$

Therefore, the overall objective of the model is shown in equation (11):

$$G^*, F^* = \arg\min_{G,F} \max_{D_X, D_\gamma, D_l} L\left(G, F, D_X, D_Y, D_l\right) \tag{11}$$

The total loss function is shown in equation (12):

$$\begin{aligned} L\left(G, F, D_X, D_Y, D_l\right) = {} & L_{adv}\left(G, D_Y, X, \eta\right) + L_{adv}\left(F, D_X, X, \eta\right) \\ & + aL_{cycle} + \beta L_{strokebrush} + \gamma L_{inkwash} + \eta L_{style} \end{aligned} \tag{12}$$

3.3 Transformation of Chinese traditional painting and calligraphy elements

3.3.1 Pix2pix network

A Pix2Pix network consists of a generative network and a discriminative network. The structure of the generative network is generally composed of two parts: encoding and decoding.

1) Spectral Normalization

The core idea of spectral normalization is to do spectral decomposition (singular value decomposition) on the weight matrix and then use the largest singular value obtained to scale the weight matrix to ensure Lipschitz continuity. In contrast to other normalizations, spectral normalization can be used directly on the weight parameters. In contrast to methods that prune and thus destroy the coefficients, spectral normalization can be applied directly to the matrix to create K-Lipschitz constraints that limit the variation of the weights within the interval. This also preserves the characteristics of the trained parameter distributions. For the purpose of enhancing the robustness and generalization of the model, the spectral normalization can be added to the quantized network by applying the quantized network in a convolutional network. Where the restriction of Lipschitz can improve the stability of the model training, which in turn speeds up its training speed with better robustness and generalization ability.

Only when the discriminator function satisfies the 1-Lipschitz constraint can the parameter changes be made relatively stable when optimizing the neural network, and the gradient explosion is less likely to occur. In short, the Lipschitz constraint is the requirement that Eq. (13) is satisfied over the entire domain of definition of $f(\cdot)$:

$$\frac{\left\| f(x)-f(x)\right\|_2}{\left\| x-x\right\|_2} \le M \tag{13}$$

Where M represents a constant. A function $f(\cdot)$ that satisfies Eq. then implies that the function will not change too fast and its gradient will be limited to below M even at its most drastic. For the N -layer neural network input-output relationship is shown in Eq. (14), where D_N represents the diagonal matrix for the action of ReLu and W_i represents the network parameter matrix. Namely:

$$f(x)=D_N W_N \cdots D_1 W_r x \tag{14}$$

Satisfying the Lipschitz constraint is the requirement imposed on the gradient of $f(x)$. The formula is shown in equation (15):

$$\left\|\nabla_x\left(f(x)\right)\right\|_2 \le \left\|D_N W_N \ldots D_1 W_1\right\|_2 \le \left\|D_N\right\|_2 \left\|W_N\right\|_2 \cdots \left\|D_1\right\|_2 \left\|W_1\right\|_2 \tag{15}$$

Where $\|W\|$ represents the universal paradigm of matrix W as shown in equation (16):

$$\sigma(A) := \max_{\|h\|\neq 0} \frac{\|Ah\|_2}{\|h\|_2} = \max_{\|h\|=1} \|A\|_2 \tag{16}$$

$\sigma(W)$ is the largest singular value of matrix W, and for diagonal matrix D, there is $\sigma(D)=\max(d_1,\cdots,d_n)$. Then equation (15) can be changed to equation (17):

$$\left\|\nabla_x\left(f(x)\right)\right\|_2 \le \prod_{i=1}^{N} \sigma(W_i) \tag{17}$$

The spectral paradigm of the diagonal matrix corresponding to the ReLU function is maximized to 1. To make $f(x)$ satisfy the Lipschitz constraint, Eq. (15) is normalized to:

$$\left\|\nabla_x\left(f(x)\right)\right\|_2=\left\|D_N\frac{W_N}{\sigma(W_N)}\dots D_1\frac{W_1}{\sigma(W_1)}\right\|_2\leq\prod_{i=1}^{N}\frac{\sigma(W_i)}{\sigma(W_i)}=1 \tag{18}$$

As shown in Eq. (18), in order to satisfy the Lipschitz = 1 constraint, the parameters of each layer of the network are divided by the spectral paradigm of the parameter matrix of that layer. Spectral normalization is thus achieved.

2) Perceptual loss

Perceptual loss is a fixed network (usually using pre-trained VGG16 or VGG19), respectively, the real image, the network generation results as its input, to get the corresponding output features: feature_gt, feature_pre, and then use feature_gt and feature_pre to construct the loss (usually L2 loss) The loss (usually L2 loss) is then used to approximate the deep information between the real image and the network-generated result, i.e., the perceptual data, which enhances the detail information of the output features compared to the ordinary L2 loss.

In order to make the details of the generated calligraphic image information better, this experiment introduces perceptual loss to improve the image quality. The perceptual loss uses the trained VGG16 model to extract the deep abstract features of the image and then, after removing the feature information of the generated image and the original image, compares the difference between the computations, which is used to enhance the detail information of the image. As shown in equation (19):

$$L_{pl}=\frac{1}{dwh}\left\|\phi\left(G(x,c)\right)-\phi(x)\right\|_2^2 \tag{19}$$

Where, d represents the depth, w represents the width, h represents the height, φ represents the feature extraction function, $G(x,c)$ represents the generated data while x represents the input and c classifies the label of the input.

3.3.2 Generator and discriminator models

In this paper, the generator network part is improved and optimized, and the residual network and attention mechanism are introduced in the generator part to extract more features so that the quality of the generator network on the generated images is greatly improved, the images are more realistic, and the details of the photos are more perfect. Unlike the original generator model, the improved generator adds a transcoder to the original. The encoder of the enhanced network consists of a VGGNet16 network, the converter is composed of a self-attention mechanism with an eight-residual network and a linear layer is added to the last layer of the transcoder to perform a dimensionality transformation of the encoder's output, which is used to match the input dimensions of the encoder. The decoder has a network that is similar to that of the encoder.

This paper utilizes the PatchGAN model to differentiate between the generated image and the real image. The model of the discriminator network is shown in Fig. 4. After the input image is fed into the discriminator, the Patch GAN divides the image into size blocks of 70×70 size and then evaluates the segmented blocks as true or false. The value of each element in the output matrix indicates the probability that each image block is a true sample, and the average of the probabilities for each image block is the result of the final global image decision. The high resolution and image detail can be maintained to a great extent by this network. In order to mitigate gradient vanishing and improve model stability, spectral normalization is added after the convolutional layer of the discriminator in this paper.

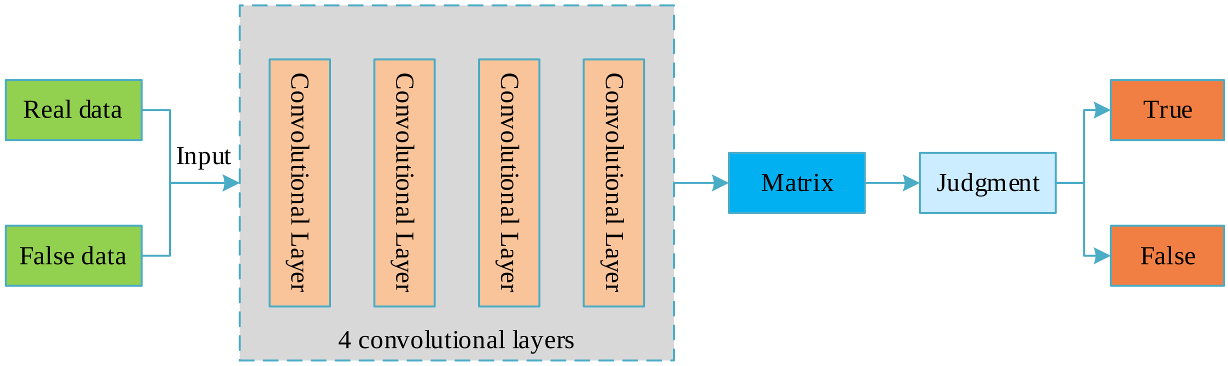


Figure 4. Discriminator model structure

3.3.3 Model Loss Functions

Compared to image style migration, calligraphy style migration is more complex and requires more details, which requires better fluency of the stroke structure of the generated text. The common method of evaluating generated results by pixel matching is not quite compatible with the style migration of calligraphy. Therefore, this experiment will use three kinds of losses, namely the adversarial loss, the pixel loss, and the perceptual loss, to make a comprehensive evaluation in terms of style, content, and details, respectively. The loss function of the generator model is as follows:

$$L_{nakal} = L_{ofversarial} + L_{pisel} + L_{perecptaral} \tag{20}$$

4 Analysis of the transformative effect and value of painting elements

4.1 Transformation effect of traditional Chinese painting elements

4.1.1 Color element transformation effect and analysis

In this section, we use the common image of the Fengxiang clay tiger in Chinese traditional paintings as an example to analyze the transformation effect of its pattern color elements. The RGB color extraction results in the image of the Fengxiang clay tiger in painting elements are shown in Figure 5. It can be seen that the color of the Fengxiang clay tiger is mainly distributed in the warm color system and the use of red, orange, and yellow accounts for a large proportion. Red is the most prominent, accounting for 25.0%, occupying almost a quarter of the overall proportion of all the colors, which can be seen in the drawing of clay tiger is especially favored red, and because in folk red, red, hot, joyful and encouraging symbolism, loved by the people. The Fengxiang clay tiger image color background content can be seen. Fengxiang clay tiger painting commonly used green, red, yellow, white, and black as the main colors, and all appear in the form of color blocks, but due to the artist's hand-colored pigment uniformity, different non-heritage artists coloring different preferences and other issues, so that the final extracted color hue across the relatively large.

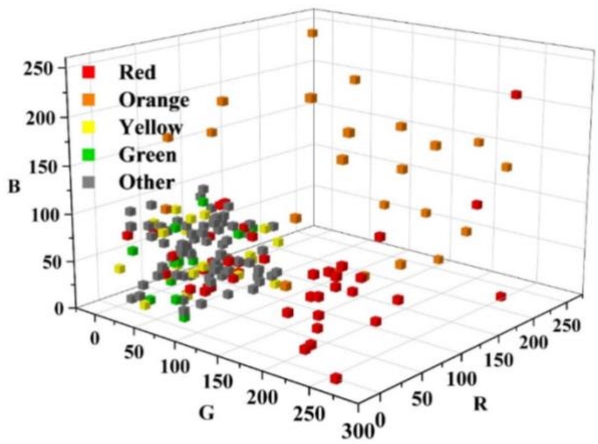


Figure 5. RGB color extraction results

Further, the saturation and brightness composition of the Fengxiang clay tiger image were analyzed, and Table 2 shows the color extraction results of the Fengxiang clay tiger image. The overall color of the Fengxiang clay tiger image is 58%, 19%, and 23% of high saturation, medium saturation, and low saturation, respectively. Fengxiang clay paintings works are very infectious in terms of the use of color, often using contrasting and complementary colors to make the works produce a strong stimulating visual effect, coupled with the psychological implication of folklore on people, so a large number of works in the use of highly saturated colors. Fengxiang clay tiger image has a preference for high-brightness colors, occupying 61% of the overall brightness of colors, with red, yellow, and green being the three most obvious basic colors. Medium brightness and low brightness colors accounted for 18% and 21%, respectively. The overall view of uniformity, in coordination with the sitting tiger color, plays a great role. A comprehensive analysis of Fengxiang clay tiger color data shows that the image of the Fengxiang clay tiger often appears in fuchsia, with a probability of brightness above 82% and saturation above 99%. The ratio of high saturation of red is 66%, and the ratio of high brightness is 75%, which shows the preference of Fengxiang artists for high saturation of red and precision of color control. Therefore, it is necessary to pay attention to the color characteristics of the image of the Fengxiang clay tiger in the above painting elements in modern design and grasp the key to the image of the Fengxiang clay tiger in the painting elements.

Table 2. The color extraction result of Fengxiang clay tiger image

Saturation degree		Brightness	
Low saturation	**23%**	Low brightness	**18%**
Fullness	**19%**	Medium brightness	**21%**
High saturation	**58%**	Brilliance	**61%**
Red interval High saturation:66% Brilliance accounted:75%	Orange interval High saturation:62% Low medium high brightness proportion	Yellow interval High saturation:65% Brilliance accounted:71%	Yellow green interval High saturation :64% Superior color ratio:61%
Green interval High saturation:62% Superior color ratio:55%	Green color interval Low saturation:59% Brilliance accounted:69%	Green range Low saturation:51% Brilliance accounted:83%	blue and green interval Low saturation:51% Brilliance accounted:82%
Blue interval Low saturation:75% Brilliance accounted:55%	Purple interval Low saturation:69% Brilliance accounted:69%	Magenta interval High saturation :68% Superior color ratio:51%	Purple range Above 82% probability Saturation is greater than 89%

4.1.2 Ink element transformation effect and analysis

The dataset used in this section is the ChipPhi dataset provided by the ChipGAN model. This dataset contains real-scene photos and painting images collected from the Internet and art studios. The dataset mainly consists of two main parts: the horse dataset and the landscape dataset, the horse dataset consists of 908 paintings by Xu Beihong and 1,635 images of horses. The landscape dataset includes 1522 paintings of Huang Binhong and 1957 pictures of world-famous landscapes, and these datasets are divided into training sets and testing sets in the ratio of 8:2. Subjective and objective evaluation methods were used for the images after the migration of styles. To evaluate the advantages and disadvantages of the model-generated images from a subjective perspective, 50 art students majoring in Chinese painting were tasked with scoring the ink effect of the model-generated images. Next, the quality of the images was evaluated by quantitatively analyzing the images, using peak signal-to-noise ratio (PSNR), structural similarity (SSIM), Frechette distance (FID), and cosine similarity (CosSim) as the metrics. PSNR is used to measure the generation quality of the image, FID is used to measure the similarity of the two images in terms of feature vectors, CosSim is used to measure the similarity of the two images in terms of pixels, and SSIM is a measure of the structural similarity of the two images.

The traditional GAN model (Method 1), ChipGAN model (Method 2), ChipGAN model based on residual dense network RDN (Method 3), ChipGAN model based on multiscale discriminator (Method 4), ChipGAN model based on residual dense network RDN and multiscale discriminator (Method 5), and this paper's model (Method 6) are selected. The results of the subjective and objective evaluation of the style migration of ink elements in Chinese paintings are shown in Table 3. According to the subjective assessment, Method VI's ink-style image is the most successful in terms of white space and style expression, with a selection rate of 48%. Using this paper's model for contextualizing traditional Chinese painting elements, Method VI increases SSIM and PSNR indices by 46.79% and 41.98%, FID by 15.08%, and CosSim by 3.24% relative to Method I. Table 3 demonstrates that adding the ink style constraint function is the most effective method for contextualizing traditional Chinese painting elements, as shown by the results of Method VI. The results prove that adding the ink style constraint function is helpful for image quality improvement, and the overall improvement of this paper is still a great improvement compared to the GAN model, which can accurately migrate and transform the ink elements in traditional Chinese painting elements.

Table 3. The objective evaluation results of the migration of Chinese painting ink elements

Subjective evaluation	Evaluation index	Method 1	Method 2	Method 3	Method 4	Method 5	Method 6
	Selectivity	22%	26%	31%	34%	41%	**48%**
Objective evaluation	SSIM	0.5548	0.6789	0.7028	0.7622	0.7981	**0.8144**
	PSNR	11.2686	13.5564	14.4269	15.0125	15.4468	**15.9986**
	FID	185.4423	172.4611	168.8523	165.4439	162.2269	**157.4832**
	CosSim	0.9581	0.9622	0.9774	0.98002	0.9858	**0.9891**

4.1.3 Effectiveness and Analysis of Calligraphic Elements Transformation

This section crawls the calligraphic character libraries of four calligraphers from the web as our dataset. The specific amount of data, as well as the training set test, is divided as follows: 750 training set data and 250 test set data for Liu Gongquan, a Tang Dynasty calligrapher; 800 training set data and 200 test set data for Ouyang Xun, a Tang Dynasty calligrapher; 740 training set data and 260 test set data for Zhao Zhiqian, a calligrapher in the late Qing Dynasty; and 600 training set data and 400 test set data for Shen Yinmo, a calligrapher in the modern era. We crawl the images of Chinese characters, all of which are preprocessed into single-channel images of size 256 × 256. This section investigates the conversion effect of calligraphic elements from three aspects: quality of generated calligraphic images, model stability, and time spent.

1) Quality Assessment of Calligraphic Image Generation

We choose structural similarity (SSIM) and cosine similarity (CosSim) as quantitative assessment metrics here. In this paper, the SSIM and CosSim values of the results generated by our model and the results generated by CycleGAN are counted separately, using the same model parameters and input samples as in the previous experiment. Ten characters are randomly selected from each dataset, and the average value is taken, and the results of the model generation quality are shown in Table 4. It can be seen that among the above two IQA methods, this paper's model achieves higher scores compared to CycleGAN, with SSIM and CosSim values of 0.482 and 0.939, respectively. SSIM reflects that our model is able to successfully retain the structural information of the Chinese characters and improve overall readability. Cossim reflects that the quality of Chinese characters generated by our model is higher than that of CycleGAN overall, indicating that our model generates higher quality Chinese characters than that of CycleGAN, indicating that the model in this paper is able to learn the style of the target calligrapher and migrate this style to the input font while retaining the structure of the input font, so as to be able to generate any Chinese character we want in the target style, and to realize the transformation of the calligraphic elements of traditional Chinese paintings in the modern design context.

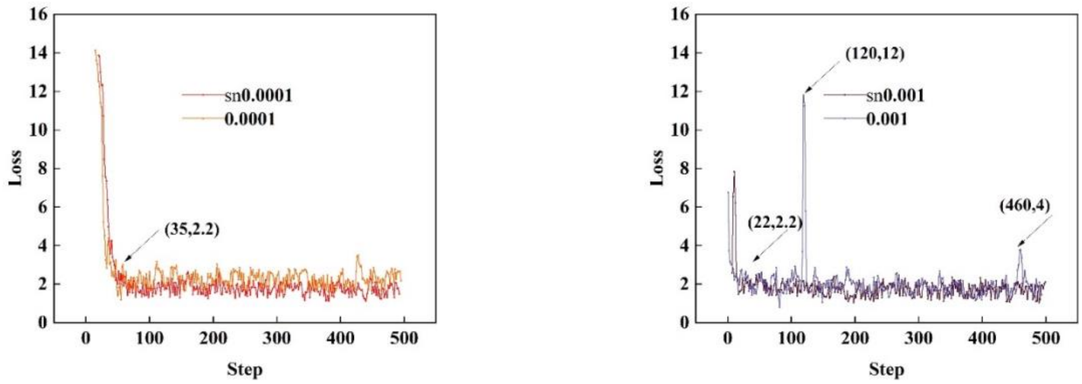
Table 4. Model generates quality results

Models	SSIM	CosSim
CycleGAN	0.312	0.911
CycleGAN+SN	0.322	0.917
Our(without $L_{percetaul}$)	0.445	0.931
Our	0.482	0.939

2) Training stability analysis

The stability of the overall network, as well as the convergence speed, is analyzed using the generator loss during the training process, where the generator network loss with and without the addition of spectral normalization is recorded at a learning rate of 0.001 and 0.0001, respectively. Figure 6 shows the comparison of the generator loss cases during training (a) and (b) for learning rates of 0.0001 and 0.01, respectively. At a learning rate of 0.0001, the generator loss with the addition of spectral normalization decreases more smoothly. Its generator loss variation is more stable, and the average loss is smaller than that of the network without the addition of spectral normalization. In the network without spectral normalization, although the loss function at the beginning of the decline is a little faster, the decline to about 2.2, the loss function began to become difficult to converge, the oscillation is obvious, and the loss of the average loss is higher than that of the network with the addition of spectral normalization. Using a learning rate of 0.001, both models start with a faster rate of descent. Then, we look at them separately. The network with the spectral normalization removed has more pronounced oscillations during training, and there is even a very high upward pulse in the middle, indicating that the whole network is very unstable during training. After adding the spectral normalization, the model's loss decreases faster compared to before. The loss changes very smoothly in the subsequent training process, and the average loss value is lower than that of the network with the spectral normalization removed.

The performance of the loss function also matches the intuition in our experiments. Before adding spectral normalization, even after 250 iterations, there are still many generation failures in the results, and 350 iterations are needed to generate the calligraphic Chinese characters stably. After adding spectral normalization, 250 iterations are enough to output the Chinese character images stably.



(a) Learning rate=0.0001 (b) Learning rate=0.001

Figure 6. Comparison of generator loss in training process

3) Training and generation time analysis

Theoretically, the addition of a spectral normalization layer to the discriminator network may increase the training time of the network to some extent due to the increase in computation when normalizing the discriminator network by solving the spectral paradigm using the power iteration method. We recorded the average time used to train a batch and the average time used to train an iteration. The total training time during the training process for this purpose to analyze and the generation time was recorded (the time used to generate 20 images at once was recorded). The results of the model training and generation time are shown in Table 5. Adding a spectral normalization layer to the model does increase the average training time of the network. Each round of batch training adds an average of 0.014 seconds, each iteration adds an average of 31.83 seconds, and training through 250 iterations adds 1.42 hours. However, the addition of spectral normalization stabilizes the training process. It allows for a faster convergence state, and without spectral normalization it takes 305 iterations to stabilize the output results, so it seems that although the average training time increases, the total training time decreases significantly. The spectral normalization layer in the model is only added to the discriminator network, which theoretically has little impact on the generation time, and this is true from the results of the performance on the four datasets. The impact of spectral normalization is on the order of 0.01 seconds, and the impact is sometimes positive and sometimes negative, which can be regarded as an almost negligible error.

Table 5. Model training and generated time results

	Record type	Our Model	Our Model without SN
Training time	Batch	0.172s	0.158s
	Epoch	512.48s	480.65s
	250epoch	27.20h	25.78h
Generation time	Dataset	Our Model	Our Model without SN
	Liu gongquan	1.4485s	1.4259s
	Ou Yangxun	1.4492s	1.4802s
	Zhao Zhiqian	1.4141s	1.3895s
	Shen Yinmo	1.4669s	1.4278s

4.2 IPA Analysis of the Transformation of Painting Elements in Design Contexts

4.2.1 Construction of evaluation indicator system

The transformation of traditional Chinese painting elements into modern design contexts led to semantic evaluations of contemporary design being conducted on 55 interviewees using the user interview method to identify universally common perceptual key factors. The collected semantic evaluations were then analyzed in terms of utterances, and 150 valid assessments were obtained by removing repetitive and meaningless comments. The Delphi method was used to classify the above evaluations according to the experts' suggestions, to organize the various factors affecting the assessment of consumer satisfaction, and combined with the design factors extracted from the literature research to finally determine the modern design satisfaction evaluation index system that contains 18 measurement indexes in 5 dimensions. The contemporary design satisfaction evaluation index system is shown in Table 6. The five dimensions in the evaluation index system are information communication degree B1, recognition degree B2, functional usability degree B3, creative attractiveness degree B4, and user experience degree B5.

Table 6. Modern design satisfaction evaluation index system

Target	Dimension	Secondary indicator
Modern design context conversion satisfaction	Information communication B1	Clear view C1
		Intelligibility C2
		Accurate information C3
	Recognition B2	Consistent design image C4
		Values C5
		Suitability C6
	Functional availability B3	Protective design C7
		Easy to use C8
		Easy to store C9
	Creative attraction B4	Molding C10
		Colour C11
		Image C12
		Fonts C13
		Material C14
	User experience B5	Emotional resonance C15
		Aesthetic preference C16
		Environmental protection C17
		Personalization C18

4.2.2 Materiality and Satisfaction Analysis

The constructed index system was distributed in the form of a questionnaire, and the evaluation scale used a five-level standardized Likert scale. A total of 350 questionnaires were distributed, and 350 valid questionnaires were retrieved, with an effective recovery rate of 100%. The satisfaction and importance scales were analyzed by SPSS software for mean and standard deviation respectively, and the results of IPA analysis were obtained as shown in Table 7.

A higher mean value indicates the index’s degree of agreement with the test subjects, while the standard deviation reflects the difference between the test subjects. Among them, information can be clearly viewed (C1), and information is accurate and effective (C3) have higher importance scores, both exceeding 3.6, indicating that the test subjects value this more. On the other hand, design contextualization reflects values (C5) and appropriateness (C6) scored lower, both not exceeding 2.5, indicating that the respondents did not value these aspects. The satisfaction scores of modern design contextualization of shape (C10), color (C11), and image (C12) are higher, indicating that the respondents are most satisfied with these aspects of modern contextualization of traditional Chinese painting elements. In comparison, the satisfaction scores of packaging embodying personalization (C18) and environmental friendliness (C17) are lower, suggesting that there is still room for improvement in these aspects. The standard deviation is generally around 1.3, which indicates that the shock amplitude of the degree of scoring by the subjects is not high and has a certain degree of stability.

The IPA index was employed to objectively measure the distinction between the significance of each indicator and satisfaction. The IPA index values that are lower indicate higher levels of satisfaction. The IPA index values were categorized into five grades: “very dissatisfied” (less than 5.00), “dissatisfied” (5.01~10.00), “average” (10.01~20.00), “More Satisfied” (20.01~30.00), and “Very Satisfied” (>30.01). After analyzing the I-P mean difference and IPA index values, it was found that the satisfaction level of the 18 indicators could be divided into three levels: 10, 1, and 5, respectively.

Table 7. IPA analysis results

Index	Importance			Satisfaction			I-p MD	IPA index	Evaluation
	Mean	SD	Sort	Mean	SD	Sort			
C1	3.704	1.173	1	3.068	1.301	7	0.636	17.189	General
C2	3.420	1.362	3	3.000	1.310	8	0.420	12.341	General
C3	3.607	1.294	2	2.964	1.318	9	0.643	17.688	General
C4	3.302	1.39	4	3.201	1.309	6	0.101	2.723	Satisfaction
C5	2.185	1.161	18	2.781	1.272	10	-0.596	-26.791	Satisfaction
C6	2.248	1.188	17	2.627	1.251	12	-0.379	-17.158	Satisfaction
C7	2.341	1.214	16	2.572	1.214	14	-0.231	-9.81	Satisfaction
C8	2.976	1.305	10	2.514	1.232	16	0.462	15.49	General
C9	2.394	1.221	14	2.558	1.246	15	-0.164	-7.088	Satisfaction
C10	3.165	1.193	5	3.596	1.218	1	-0.431	-13.74	Satisfaction
C11	3.121	1.295	6	3.570	1.269	2	-0.449	-14.583	Satisfaction
C12	2.449	1.218	13	3.563	1.264	3	-1.114	-45.782	Satisfaction
C13	2.359	1.197	15	3.459	1.318	4	-1.1	-46.832	Satisfaction
C14	3.054	1.322	8	3.333	1.329	5	-0.279	-9.363	Satisfaction
C15	3.017	1.298	9	2.587	1.198	13	0.43	14.343	General
C16	2.914	1.282	12	2.689	1.265	11	0.225	7.536	Still can
C17	3.06	1.309	7	2.498	1.204	17	0.562	18.04	General
C18	2.965	1.288	11	2.494	1.229	18	0.471	15.923	General

4.2.3 Overall IPA Matrix Analysis

Based on the above analysis to construct the IPA quadrant matrix, Figure 7 shows the distribution of audience satisfaction in the IPA quadrant, and the evaluation factors of the indicator layer are analyzed as a whole. Taking the mean value of importance and satisfaction (x=2.90, y=2.97) as the intersection point, where importance is the x-axis and satisfaction is the y-axis, the overall IPA matrix is built, and the mean values of 18 indicators are placed in it, which are analyzed as follows.

1) Quadrant I (H, H): the dominant region. This region is distributed with seven indicators, including a clear view of information (C1), easy comprehensibility (C2), accurate and effective information (C3), consistent design image (C4), styling (C10), color (C11) and material (C14). This quadrant is an indicator of high importance and satisfaction, which needs to be maintained and continuously improved.

2) Quadrant II (L, H): Maintenance area. This quadrant is for indicators with low importance and high satisfaction, which need to be moderately regulated. The distribution indicators in this region are context-switched images (C12) and fonts (C13). For the indicators in this quadrant, the image and font design of traditional Chinese painting elements transformed in modern design contexts can maintain the existing advantages.

3) Quadrant III (L, H): Opportunity Area. The distribution indicators in this region are value (C5), appropriateness (C6), protection design (C7), and easy storage (C9). This quadrant is a low-importance and low-satisfaction indicator, and it is an opportunity area for future enhancement related to the transformation of modern design contexts, which needs to be actively expanded.

4) Quadrant IV (H, L): Improvement area. Indicators distributed in this area include ease of use (C8), emotional resonance (C15), aesthetic preference (C16), environmental friendliness (C17), and personalization (C18). This quadrant is designed for indicators that have high importance but low satisfaction. These indicators are important to respondents but are not highly effective. This results in a psychological gap between consumers and a relatively low level of satisfaction and should be a key area for future improvement and enhancement.

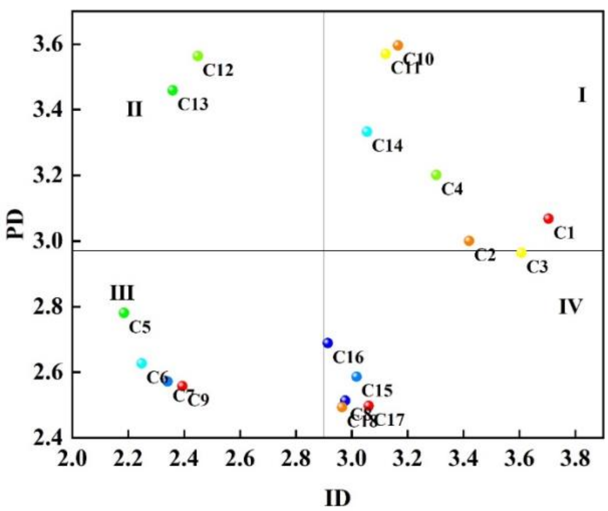


Figure 7. Audience satisfaction IPA quadrant distribution

4.3 Application value of traditional painting elements

1) The application of graphic design: traditional Chinese painting is mainly based on ink, rice paper, and brush as the painting material. The picture effect is full of spirit full of flavor that will be used in the graphic poster design. The traditional flavor is full and can play a very good effect.

2) The application of landscape design: traditional Chinese painting elements have long been used in Chinese landscape design, and strive for every landscape can be like a complete painting. The Suzhou Garden is a good use of some of the classic elements of traditional Chinese painting. Pavilions, flowers, and trees. Everywhere is a beautiful painting, as if you were walking in the painting.

5 Conclusion

This paper explores the conversion of pattern elements, ink elements, and calligraphy elements in traditional painting elements in a modern design context and studies their application value in contemporary design through the evaluation of the importance and satisfaction of their conversion by the audience.

Modern design contexts pay attention to the color characteristics of pattern elements and colors in painting elements while also grasping the key of pattern images in painting elements. Applying the method of this paper in the converted ink element images in the best effect in terms of white space and style performance, the selection rate of 48%, and the value of SSIM and CosSim of the converted calligraphy element images are 0.482 and 0.939, respectively, which can effectively convert the traditional Chinese painting elements.

The importance scores of information being able to be clearly viewed (C1) and information being accurate and effective (C3) in modern design contextualization are high, both exceeding 3.6. In contrast, the scores of design contextualization embodying values (C5) and appropriateness (C6) are low, neither exceeding 2.5. The level of satisfaction for the 18 indicators can be classified into three grades. There are 10 satisfied, 1 more satisfied, and 5 average, respectively, and the elements of painting in the contextual transformation still have room for improvement.

Culture is the backbone of a nation. Suppose a nation wants to flourish and stand in the forest of the world’s nations. In that case, it must have and hold on to the unique cultural heritage of its country, and the integration of modern design with traditional Chinese painting elements brings novel concepts to the design.

References

[1] Gao, H. (2019). The value and a preliminary study of the integration of traditional chinese painting and calligraphy & modern and contemporary art in primary school art teaching. International Education Studies, 12(6), 75.

[2] He, Y. (2020). Analysis of the application of the modern graphic design and the traditional art design elements under the background of the multivariant integration. Basic & clinical pharmacology & toxicology.(S1), 127.

[3] Chen, S. (2020). Exploration of artistic creation of chinese ink style painting based on deep learning framework and convolutional neural network model. Soft Computing, 24(9).

[4] Fu, F., Lv, J., Tang, C., & Li, M. (2020). Multi-style chinese art painting generation of flowers. IET Image Processing.

[5] Liang, Y. (2022). Analysis of the integration of chinese painting techniques in watercolor painting. Arts Studies and Criticism, 3(1), 37-40.

[6] Wen, R., Zhang, Y., Wang, D., & Wang, L. (2017). The compositional characterization and painting technique of chinese red and white porcelain by edxrf and sr-μxrf mapping analysis. Analytical Methods, 9(30).

[7] Lintel, A. V., & Roos, B. (2018). Expanding abstract expressionism: elaine de kooning, action painting, and the american west. American Art(2).

[8] Chang, Y. W. E. (2022). Space-age aesthetics in modern art inspired by space exploration: a brief study on installation, painting and music art. Acta astronautica.

[9] Zhong, C. (2020). A study of environmental visual art design in modern technological vision. Basic & clinical pharmacology & toxicology.(S1), 127.

[10] Dietrich, N., & Dietrich, N. (2015). Figure and space in vase painting and in architectural sculpture: on the (ir-)relevance of the medium. Tempo, 21.

[11] Souleles, & Nicos. (2017). Ipad versus traditional tools in art and design: a complementary association. British Journal of Educational Technology, n/a-n/a.

[12] Park, & Eunwha. (2017). Poems by ancient worthies: figure painting expressing poetic ideas by du jin. Art History, 33(33), 63-63.

[13] Fugui, L., & Zubrilin, K. M. (2020). Methods of teaching traditional chinese painting style "mogufa" in the moscow institute of arts (china). Science and School(2, 2020), 217-221.

[14] Wang, G., Shen, J., Yue, M., Ma, Y., & Wu, S. (2021). A computational study of empty space ratios in chinese landscape painting from 618–2011. Leonardo, 1-10.

[15] Zhen-Bao, F., Yi-Na, L., Kang, Z., Jinhui, Y., & Lin, H. M. (2021). Measuring and evaluating the visual complexity of chinese ink paintings. The Computer Journal(8), 8.

[16] Jiang, W., Wang, Z., Jin, J. S., Han, Y., & Sun, M. (2018). Dct-cnn-based classification method for the gongbi and xieyi techniques of chinese ink-wash paintings. Neurocomputing, 330.

[17] Zou, Q. (2021). The role of sketching in figure creation of modern chinese painting. Clausius Scientific Press.