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International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Application Research of color collocation and space Layout based on numerical optimization Algorithm in modern painting art creation

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SUMMARY: *In order to solve the problems of strong subjectivity of color collocation, insufficient efficiency of spatial layout optimization and unclear coordination mechanism of the two in modern painting art creation, this paper constructed an optimization method of modern painting creation based on numerical optimization algorithm. Through digital image processing, color space transformation, saliency detection and region segmentation technology, the digital representation of comprehensive color features and the parametric description of spatial layout structure are realized, and a multi-objective optimization model is established with the joint constraints of color harmony, composition balance, coupling consistency and style preservation. The experimental results show that the scores of comprehensive color harmony, light contrast and saturation balance of the proposed method reach 0.91, 0.87 and 0.89 respectively, and the comprehensive color score reaches 0.90. The score of layout balance, spatial rhythm and whitespace rationality reaches 0.92, 0.89 and 0.88, respectively, and the score of comprehensive layout reaches 0.90. The comprehensive score of the complete model reached 0.91. The results show that the proposed method can effectively improve the comprehensive color unity, composition stability and visual order in modern painting creation, which provides a feasible path for computer-aided art creation and intelligent painting optimization.*

KEYWORDS: *Numerical optimization algorithm; Modern painting art creation; Color matching; Spatial layout*

1 Introduction

The creation of modern painting art is not an aesthetic activity relying solely on perceptual experience. Color collocation and spatial layout jointly determine the visual balance, emotional tension, subject focus and narrative rhythm of the picture. With the development of digital image processing, computer vision, parametric design and intelligent generation technology, the traditional color matching and composition process, which relies on the long-term experience of artists, is gradually shifting to a new mode driven by the collaboration of "art rules, data representation and algorithm optimization". Especially in modern painting creation, there is a significant coupling between comprehensive color relationship, local lightness organization, primary and secondary spatial hierarchy and visual flow direction, and it is difficult to balance creation efficiency, style consistency and form order only by manual trial and error. Therefore, numerical optimization algorithm is introduced to solve color collocation and spatial layout jointly. It has become an important

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https://doi.org/10.65102/is2026747
Published: 30 April, 2026

research direction of computer aided art creation.

From the existing research, the related achievements are mainly developed along three paths. One is color generation, color transfer and harmony constraint modeling. Liu et al. proposed an image-driven harmonious color palette generation method [3], Tan et al. carried out research on color palette harmony [4], Chao et al. implemented palette-aware brightness control and color editing based on sparse optimization [9], Wang et al. constructed a language-driven image re-colorization framework [10]. Lin et al. further applied color palettes and harmony templates to vector icon coloring [13]. In addition, Lv et al. and Gao et al. systematically reviewed color transfer and color palette generation respectively [15, 16], and Zhao et al., Hu et al., and Liu et al., expanded the implementation path of intelligent color design from color palette transfer, cue-driven color matching, and knowledge-data fusion color matching [17-19]. The second is layout generation and structure optimization. Kong et al. improved graphic design aesthetics from the perspective of design principles and human preferences [1], Qiao et al. studied layout optimization of visual notes [2], Hu et al. proposed a structured layout generation model [6], Yang et al. emphasized element order learning in graphic design generation [11], etc. Shen et al. further used optimized post-processing to weaken the problem of misalignment, overlap and inclusion imbalance [14]. The third is style transfer and computer aided art creation. Song et al. focused on visual style transfer [5], Zhou et al. systematically evaluated arbitrary style transfer methods [7], Wang et al. studied realistic portrait style transfer [8], Zhang et al. unified the arbitrary style transfer framework through adaptive contrastive learning [12]. The Stroke-GAN Painter proposed by Wang et al is directly oriented to the generation of brushstroke style paintings [20]. These studies show that computer technology has been able to effectively model color, style, layout and visual preference, but most of the work is still focused on graphic design, interface design, information visualization or image style transfer scenarios, and the research on the collaborative optimization of "color collocation, spatial layout and style expression" in modern painting art creation is still insufficient. In particular, there is a lack of a multi-objective numerical optimization framework for the context of painting creation. The comparison between references and this paper is shown in Table 1.

Table 1: Comparison between some references and this paper

Reference	Research Object	Main Techniques	Existing Limitations	Distinction from This Study
[1] Kong et al., 2023	Aesthetic optimization for graphic design	Design principle modeling, preference learning	This study mainly focuses on aesthetic refinement in graphic design and does not deeply address the coupling between color and spatial arrangement in painting	This study targets modern painting creation and emphasizes the joint optimization of color matching and spatial layout
[2] Qiao et al., 2023	Visual note layout optimization	Layout sequence modeling, layout optimization	This study mainly concerns information arrangement, while the semantic characteristics of artistic creation are relatively weak	This study incorporates compositional balance and visual flow in painting into the objective function
[3] Liu et al., 2024	Image-driven palette generation	Color harmony modeling, palette generation	This study mainly focuses on palette recommendation and lacks constraints on spatial structure	This study simultaneously optimizes color matching and layout
[4] Tan et al., 2025	Palette harmonization	Palette-driven color coordination	This study emphasizes color-level optimization and does not consider the layout relationships among painting subjects	This study constructs a dual-variable optimization model integrating color and space
[11] Yang et al., 2025	Graphic design layout generation	Element sequence learning, layout generation	This study is oriented toward the ordering of design elements and does not directly address color organization in painting	This study introduces the collaborative optimization of color parameters and compositional parameters
[14] Shen et al., 2025	Graphic layout post-processing	Optimization-based post-processing, alignment and overlap correction	This study is more suitable for repairing generated layouts and shows limited capability in artistic style expression	This study emphasizes style consistency and overall aesthetic objectives
[20] Wang et al., 2023	Painting generation	Brushstroke-style GAN	This study mainly focuses on stylized generation and lacks an explicit numerical optimization framework	This study highlights an interpretable multi-objective numerical optimization process

Based on the above shortcomings, this paper focuses on the joint optimization problem of color collocation and spatial layout for modern painting art creation scenes. The research contents include: constructing the modern painting image sample set and its color-space feature representation system; Computer technologies such as color space transformation, saliency analysis and regional relationship modeling were used to extract the comprehensive color distribution, dominant color proportion, visual center of gravity, spatial hierarchy and white space structure of the screen. On this basis, a multi-objective function considering color harmony, layout balance, visual guidance and style consistency is established. Then the color parameters and spatial layout parameters are solved by genetic algorithm, particle swarm optimization or hybrid numerical optimization strategy. The effectiveness of the model is verified by a case study. The corresponding technical route can be summarized as "sample construction, image preprocessing, color and space parametric representation, coupled objective function design, numerical optimization solution, creation result evaluation". The innovation of this paper is mainly reflected in three aspects: first, the color relationship and spatial order in modern painting creation are incorporated into a unified computing framework; Secondly, a numerical optimization algorithm is introduced to realize the joint iteration of comprehensive color and composition structure. The third is to extend computer-aided art creation from single style transfer or local color matching to systematic optimization for the overall visual organization of modern paintings.

2 Computational representation of color collocation and spatial layout in modern painting art creation

2.1 Digital representation of color collocation features in modern paintings

The color collocation in the creation of modern painting art is not an isolated visual decoration factor, but a core variable that directly participates in the emotional transmission of the picture, the intensification of the subject, the shaping of the spatial level and the unified construction of the style. The comprehensive hue distribution, lightness contrast, saturation organization and dominant color ratio in the original painting image should be transformed into a computable set of parameters with the help of digital image processing and computer vision technology in order to make the color relationship enter the subsequent numerical optimization algorithm. The digital representation process of color matching features in modern painting art creation is shown in Figure 1.

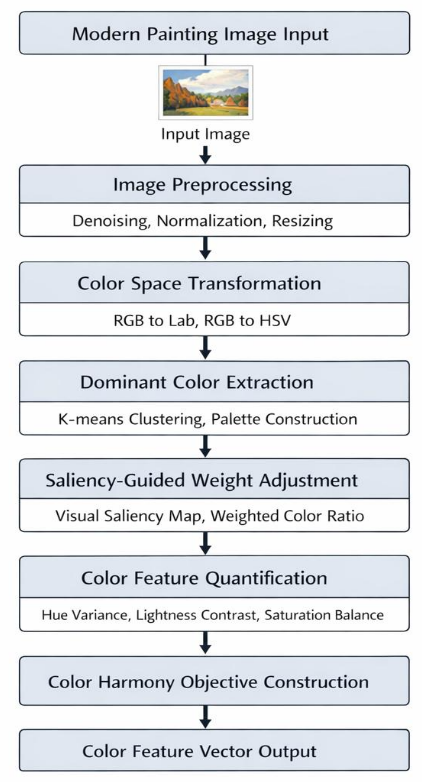

Figure 1: Flowchart of the digital representation of color collocation features in modern paintings

The process includes five key steps: image preprocessing, color space transformation, dominant color extraction, saliency weighting and comprehensive color evaluation. Finally, the color feature vector suitable for the optimization model is output.

Let the input painting image be:

$$I = \{p_{ij} \mid 1 \le i \le H, 1 \le j \le W\}, \quad p_{ij} = (R_{ij}, G_{ij}, B_{ij}) \tag{1}$$

where H and W represent the height and width of the image respectively, and p_{ij} is the RGB color value of the ith and JTH pixel. Due to the weak consistency between RGB space and human eye's comprehensive color perception, this paper first maps the image from RGB space to CIE Lab space, and the transformation process can be expressed as follows.

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = M \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{2}$$

$$L^* = 116f(Y/Y_n) - 16, \quad a^* = 500[f(X/X_n) - f(Y/Y_n)], \quad b^* = 200[f(Y/Y_n) - f(Z/Z_n)] \tag{3}$$

Where M is the color transformation matrix, X_n,Y_n,Z_n are the reference white points, and $f(\cdot)$ is the nonlinear correction function. After this step, each pixel is represented as follows.

$$c_{ij} = (L^*_{ij}, a^*_{ij}, b^*_{ij}) \tag{4}$$

Thus, a base representation that conforms to the law of comprehensive color difference perception is established.

In order to extract the dominant color structure of the picture, this paper uses K-means clustering to cluster the pixels in Lab space. Let the set of dominant color centers be:

$$C = \{\mu_1, \mu_2, \dots, \mu_K\} \tag{5}$$

Then the clustering objective function is as follows.

$$\min \sum_{k=1}^{K} \sum_{c_{ij} \in S_k} \| c_{ij} - \mu_k \|_2^2 \tag{6}$$

Here, S_k represents the KTH color cluster. After clustering, the area of the KTH dominant color is defined as follows.

$$w_k = \frac{|S_k|}{HW}, \quad \sum_{k=1}^{K} w_k = 1 \tag{7}$$

From this, w_e can construct the main color palette representation of the screen:

$$P = \{(w_k, \mu_k) \mid k = 1,2, \dots, K\} \tag{8}$$

This representation can compress the comprehensive color composition in modern painting into a small number of dominant color parameters, which provides the basis for subsequent optimization variable design.

Considering that the effective color matching in modern painting is not completely determined by the global pixel proportion, and the comprehensive color distribution of the main area and the visual focus area has more artistic significance, we introduce saliency detection to modify the weight of the main color. Let the saliency map be $M_s(i,j) \in [0,1]$, then the color proportion weighted by saliency can be expressed as follows.

$$\tilde{w}_k = \frac{\sum_{c_{ij} \in S_k} M_s(i,j)}{\sum_{i=1}^{H} \sum_{j=1}^{W} M_s(i,j)} \tag{9}$$

This formula can enhance the contribution of the comprehensive color of the visual center region in the overall color matching evaluation, and make the color representation more in line with the aesthetic attention mechanism in modern painting creation.

In the stage of feature construction, this paper further quantizes from three levels: hue dispersion, lightness level and saturation equilibrium. After converting the image to HSV space, the comprehensive hue mean and dispersion are defined as follows.

$$\bar{h} = \sum_{k=1}^{K} \tilde{w}_k h_k, \quad \sigma_h = \sqrt{\sum_{k=1}^{K} \tilde{w}_k (h_k - \bar{h})^2} \tag{10}$$

Here, σ_h reflects the comprehensive color variation amplitude. Comprehensive color lightness contrast is defined as follows.

$$D_L = \sqrt{\sum_{k=1}^{K} \tilde{w}_k (L_k - \bar{L})^2} \tag{11}$$

Among them, L is the average brightness of comprehensive color. Comprehensive color saturation equilibrium is defined as follows.

$$B_S = 1 - \frac{1}{K} \sum_{k=1}^{K} | s_k - \bar{s} | \tag{12}$$

Among them, $\bar{s}$ is the average saturation of comprehensive color. The above indicators correspond to the comprehensive hue richness of the picture, the light and dark organization ability, and the comprehensive color stability degree.

In order to embed comprehensive color features directly into the numerical optimization model, this paper constructs a comprehensive color harmony objective function:

$$F_c = \alpha_1 H_c + \alpha_2 D_L + \alpha_3 B_S - \alpha_4 E_c \tag{13}$$

Among them, H_c represents the comprehensive hue harmony, D_L represents the brightness level contrast, B_S represents the saturation equilibrium, Ec represents the comprehensive color conflict penalty term, $\alpha_1,\alpha_2,\alpha_3,\alpha_4$ are the weight coefficients. The comprehensive color conflict item is defined as follows.

$$E_c = \sum_{m=1}^{K} \sum_{n=m+1}^{K} \tilde{w}_m \tilde{w}_n \cdot \frac{1}{\|\mu_m - \mu_n\|_2 + \varepsilon} \tag{14}$$

Here, ε is a tiny constant that prevents the denominator from being zero. This item is used to suppress the phenomenon that the dominant color is too close to each other, the comprehensive color competition is too strong, or the comprehensive color level is confused.

Finally, the color matching characteristics of modern paintings are expressed as follows.

$$f_{color} = [\mu_1, \dots, \mu_K, \tilde{w}_1, \dots, \tilde{w}_K, \sigma_h, D_L, B_S, F_c] \tag{15}$$

This vector not only retains the main aesthetic information of color organization in modern painting, but also has good numerical computability and optimization adaptability. It can be directly used as the input of subsequent spatial layout coupling modeling and multi-objective numerical optimization solution. Therefore, the color matching process of modern paintings, which originally relied on empirical judgment, is transformed into a computational representation problem that can be measured, constrained, and updated iteratively.

2.2 Parametric description of the spatial layout structure of modern paintings

The computational representation of spatial layout in modern paintings is not a simple record of the position of screen elements, but by means of image segmentation, saliency detection, region connectivity analysis and geometric relationship modeling, the main body, accompany body, background and white space organization are transformed into structural variables that can be used for numerical optimization algorithms. In this paper, the input image I is first semantically segmented to obtain the set of regions R={r_1,r_2,... ,r_N}, where the area proportion of the KTH region is defined as follows.

$$a_k = \frac{|r_k|}{HW} a \tag{16}$$

where, H and W are the image height and width respectively. Further compute the region centroids:

$$(x_k, y_k) = \left(\frac{1}{|r_k|} \sum_{(i,j)\in r_k} j \, , \frac{1}{|r_k|} \sum_{(i,j)\in r_k} i \right) \tag{17}$$

To represent the subject position and the spatial center of gravity. In order to depict the balance of the overall composition, the visual center of gravity of the picture is defined as:

$$G = \left(\sum_{k=1}^{N} a_k x_k, \sum_{k=1}^{N} a_k y_k \right) \tag{18}$$

The balance index is constructed by its offset relative to the frame center C=(W/2,H/2) :

$$B = 1 - \frac{\|G - C\|_2}{\sqrt{(W/2)^2 + (H/2)^2}} \tag{19}$$

The larger B is, the more stable the overall layout of the picture is.

Considering the hierarchical and guiding relationship between regions in modern painting, this paper uses the adjacency matrix A=[a_{mn}] to describe the spatial topology. When the region rm and rn are adjacent or have significant visual connection, the following is taken:

$$a_{mn} = \exp(-d_{mn}/\sigma) \tag{20}$$

Here, dmn is the centroid distance between two regions and σ is the scale parameter. Further define the spatial rhythm index:

$$R_s = \frac{1}{N(N-1)} \sum_{m \neq n} |a_m - a_n| \tag{21}$$

It is used to measure the density contrast brought by the change of regional area. Whitespace is defined as:

$$\eta = \frac{|R_{blank}|}{HW} \tag{22}$$

To depict the influence of non-physical space on the sense of visual breathing in modern painting. Thus, the spatial layout structure can be expressed as follows.

$$f_{layout} = [a_k, x_k, y_k, B, R_s, \eta, A] \tag{23}$$

Its core parameters and functions are shown in Table 2. The parametric results can transform the empirical composition organization into computable, constrainable, and optimized spatial variables, and provide a structural basis for the subsequent collaborative optimization of color matching and spatial layout.

Table 2: The main parameters and meanings of the spatial layout structure of modern paintings

Parameter	Definition	Computational Meaning
a_k	Area ratio of region r_k	Describes visual weight
(x_k, y_k)	Centroid of region r_k	Describes spatial position
G	Global visual centroid	Reflects overall composition center
B	Layout balance index	Measures composition stability
A	Adjacency matrix	Represents spatial topology
R_s	Spatial rhythm index	Measures density variation
η	Blank-area ratio	Reflects negative space structure

2.3 Computational Modeling of Coupling relationship between color collocation and spatial layout

Color collocation and spatial layout in modern painting art creation are not independent of each other. The dominant color distribution will change the visual center of gravity and spatial hierarchy, and the regional position and area change will negatively affect the comprehensive color perception intensity and emotional orientation. Therefore, it is necessary to construct a unified coupling calculation model. Based on the color feature vector fcolor and spatial feature vector flayout obtained above, the screen is represented as a region map in this paper:

$$G = (V, E), \quad V = \{r_1, r_2, \ldots, r_N\} \tag{24}$$

where the node r_k represents the KTH spatial region and the edge emn represents the adjacency or visual association between regions. Figure2 shows the coupling modeling framework of color collocation and spatial layout.

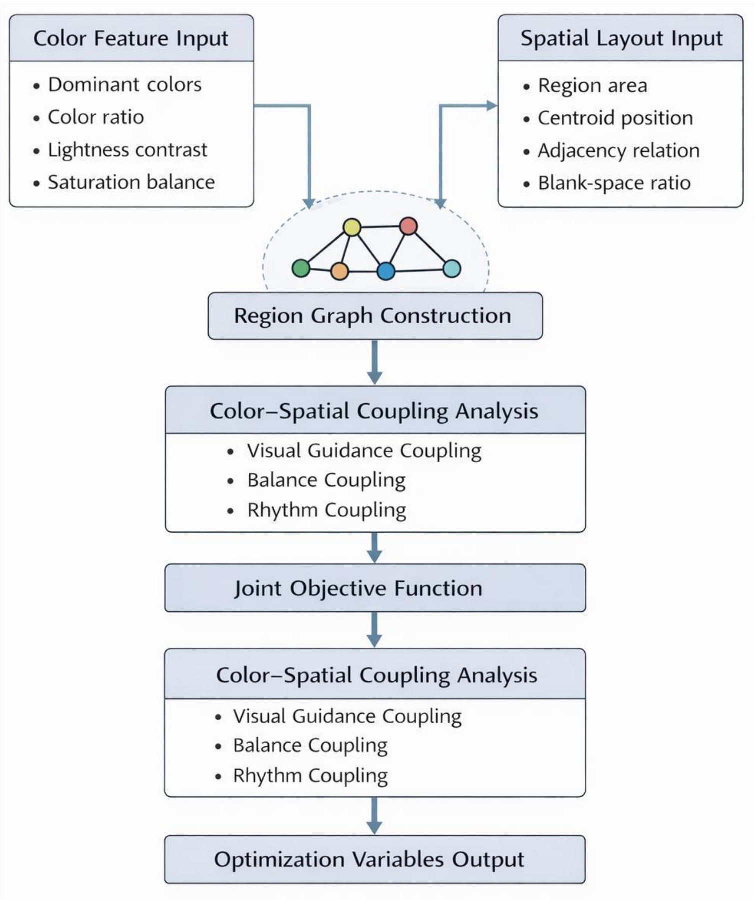

Figure 2: Computational modeling structure diagram of coupling relationship between color collocation and spatial layout

For each region rk, define its integrated color center as follows.

$$\bar{c}_k = \frac{1}{|r_k|} \sum_{(i,j)\in r_k} c_{ij} \tag{25}$$

where c_{ij} is the Lab space color vector. Furthermore, the region area proportion, position coordinates and comprehensive color information are concatenated as node features:

$$z_k = [a_k, x_k, y_k, \bar{c}_k] \tag{26}$$

In order to describe the "color difference-space distance" coupling relationship between adjacent regions, the edge weight is defined as follows.

$$w_{mn} = a_{mn} \cdot \|\bar{c}_m - \bar{c}_n\|_2 \tag{27}$$

where amn is the neighboring weight in Section 2.2. This equation is used to measure the integrated color tension between regions due to their close location.

On this basis, this paper constructs three types of coupling terms. One is the visual guidance coupling term:

$$E_1 = \sum_{k=1}^{N} a_k \; s_k \, \|\bar{c}_k - \bar{c}_g\|_2 \tag{28}$$

where sk is the regional saliency weight and $\bar{c}_g$ is the global average color. This item is used to enhance the comprehensive color discrimination between the visual focus area and the overall picture. The second is the spatial balance coupling term:

$$E_2 = \sum_{k=1}^{N} a_k \cdot \|(x_k, y_k) - G\|_2 \cdot L_k \tag{29}$$

where G is the global visual center of gravity and L_k is the regional average lightness. This term is used to limit the imbalance of the composition caused by high brightness or high saturation areas too far away from the center of the frame. The third is the rhythm coordination coupling term:

$$E_3 = \sum_{m \neq n} w_{mn} \; \exp(-d_{mn}/\sigma) \tag{30}$$

where dmn is the region centroid distance. This term reflects the degree of synchronization between the comprehensive color change and the spatial density change.

Based on the above relations, the joint color-space objective function is constructed as follows.

$$F = \lambda_1 F_c + \lambda_2 B + \lambda_3 E_1 - \lambda_4 E_2 + \lambda_5 E_3 \tag{31}$$

where F_c is the comprehensive color harmony objective in Section 2.1, B is the spatial balance index, and λ_i is the weight coefficient. Finally, the optimization variables can be uniformly written as follows.

$$\Theta = \{P, (x_k, y_k), a_k\} \tag{32}$$

That is, the dominant color ratio, region location and area allocation are solved jointly at the same time. This model maps the comprehensive color organization, composition order and visual guidance mechanism in modern painting into a computable graph structure optimization problem, which provides a clear mathematical foundation for subsequent numerical optimization algorithms.

3 Optimization method of modern painting creation based on numerical optimization algorithm

3.1 Modern Painting Sample Data Construction and Image preprocessing

In order to ensure that the color collocation optimization and spatial layout solution have a stable data basis, this paper constructs a sample set for modern painting creation:

$$\mathcal{D} = \{(\mathrm{I_n}, \mathrm{y_n^c}, \mathrm{y_n^l}, \mathrm{M_n})\}_{\mathrm{n}=1}^{\mathrm{N}} \tag{33}$$

Here, In represents the NTH painting image, ync represents the comprehensive color annotation vector, ynl represents the spatial layout annotation vector, and Mn represents the salient region or main region mask. The sample sources include digital collection images, public modern painting image databases and high-resolution scanned works. After eliminating duplicate samples, filtering low-definition samples and correcting abnormal color cast samples, a standardized data set for numerical optimization modeling is formed. The flow of modern painting sample data construction and image preprocessing is shown in Figure3.

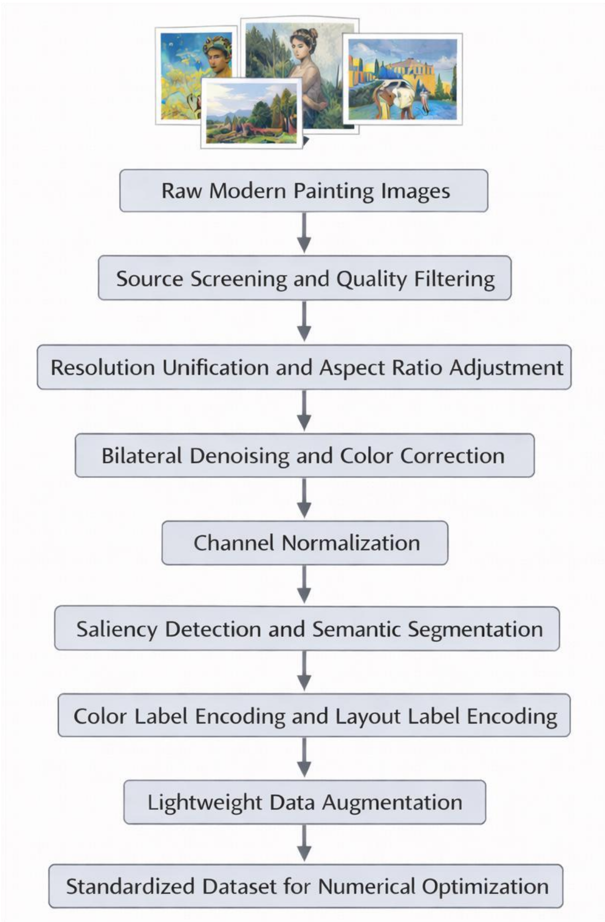

Figure 3: Flowchart of modern painting sample data construction and image preprocessing

Considering that the original images have obvious differences in resolution, aspect ratio, lighting conditions and scanning noise, we adopt a uniform size mapping function to normalize the image to H0×W0:

$$I_n^r = \mathcal{R}(I_n; H_0, W_0) \tag{34}$$

Here, R(·) represents the scaling and edge-filling operations that preserve the scale of the main structure. In order to reduce the interference of scanning particles, compression noise and local artifacts on comprehensive color feature extraction, bilateral filtering is used for denoising:

$$\hat{p}_{ij} = \frac{1}{W_{ij}} \sum_{(u,v)\in\Omega} \exp\left(-\frac{\|(i,j)-(u,v)\|^2}{2\sigma_s^2}\right) \exp\left(-\frac{\|p_{ij}-p_{uv}\|^2}{2\sigma_r^2}\right) p_{uv} \tag{35}$$

Here, Ω is the neighborhood window, and σs and σr control the attenuation intensity of spatial distance and color distance, respectively. This operation can suppress high-frequency noise while preserving the boundary structure, and avoid the distortion of subsequent region segmentation and dominant color extraction.

In order to eliminate the comprehensive color offset caused by different acquisition devices, this paper uses a combination of channel normalization and gray-world correction to complete color calibration. The pixel channel value x is normalized:

$$\tilde{x} = \frac{x - \mu_x}{\sigma_x} \tag{36}$$

Here, μ_x and σ_x are the corresponding channel mean and standard deviation, respectively. The comprehensive color correction coefficient is defined as follows.

$$g_c = \frac{\bar{I}}{\bar{I}_c}, \quad c \in \{R, G, B\} \tag{37}$$

Among them, $\bar{I}$ is the overall mean of the three channels, Īc is the mean of the CTH channel, and the pixel value after correction is $\bar{I}_c$=gcIc. This process can improve the consistency of samples from different sources in the comprehensive color space, so that the comprehensive color harmony objective function has better comparability.

At the annotation level, we combine saliency detection, semantic segmentation and manual review to construct structural labels. Let the segmentation result be:

$$S_n = \{r_1, r_2, \dots, r_K\} \tag{38}$$

Here r_k denotes the KTH functional region, which corresponds to the subject, companion, background, or blank unit. The region area, centroid, adjacency, and dominant color ratio are further encoded as follows.

$$y_n^l = [a_k, x_k, y_k, A, \eta], \quad y_n^c = [w_k, \mu_k, D_L, B_S] \tag{39}$$

Thus, the unified mapping of "image samples-comprehensive color parameters-spatial layout parameters" is realized. In order to enhance the robustness of the model to scale changes and local disturbances, this paper only uses lightweight enhancement strategies that do not destroy the semantics of the composition, such as brightness perturbation, contrast perturbation and small rotation. The transformation form can be expressed as follows.

$$I_n^a = T(I_n^r; \theta) \tag{40}$$

Here, θ is the set of enhancement parameters. After the above processing, the original modern painting image is transformed into the standard input suitable for the subsequent numerical optimization solution, which provides a high consistency and high computability data basis for the collaborative optimization of comprehensive color and spatial layout.

3.2 Multi-objective optimization model construction of color collocation and spatial layout

In order to realize the collaborative optimization of color collocation and spatial layout in modern painting art creation, a multi-objective optimization model for creation result evaluation is constructed based on the aforementioned color feature vector fcolor and spatial layout feature vector flayout. The core idea of the model is to integrate comprehensive color harmony, composition balance, visual guidance and style consistency into a unified objective space, and jointly solve the dominant color proportion, regional position and regional scale by numerical optimization algorithm. The overall modeling framework is shown in Figure4.

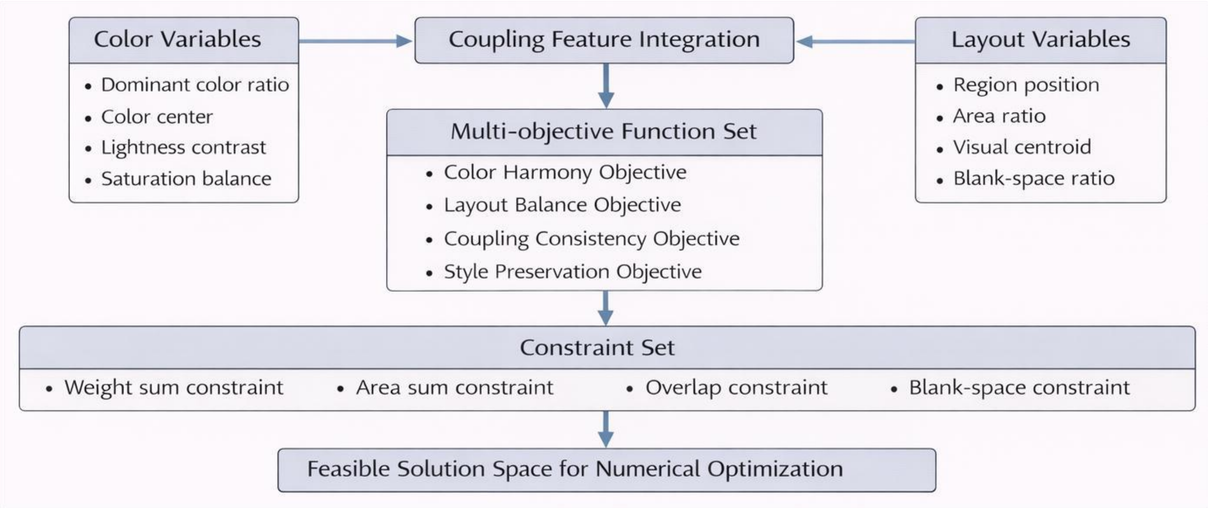

Figure 4: Frame diagram of multi-objective optimization model construction for color collocation and spatial layout

Let the set of decision variables be:

$$\Theta = \{w_k, \mu_k, x_k, y_k, a_k\}_{k=1}^{K} \tag{41}$$

Here, w_k and μk represent the proportion of the KTH dominant color and the color center, (x_k,y_k) represents the centroid position of the region, and ak represents the proportion of the region area. The comprehensive color optimization objective is defined as follows.

$$\max F_1(\Theta) = \alpha_1 H_c + \alpha_2 D_L + \alpha_3 B_S - \alpha_4 E_c \tag{42}$$

Among them, H_c represents the comprehensive hue harmony, D_L represents the brightness level contrast, B_S represents the saturation equilibrium, and Ec is the comprehensive color conflict penalty term. This object is used to improve the comprehensive color order and visual unity of modern painting pictures.

The spatial layout optimization objective is defined as follows.

$$\max F_2(\Theta) = \beta_1 B + \beta_2 R_v + \beta_3 \eta - \beta_4 O \tag{43}$$

Here, B is the spatial balance index, Rv represents the intensity of visual rhythm, η is the reasonable blank rate, and O is the area overlap penalty term. To avoid overcrowding or edge imbalance in the main area, the overlapping penalty is defined as follows.

$$O = \sum_{m \neq n} \frac{|r_m \cap r_n|}{|r_m \cup r_n|} \tag{44}$$

This formula can effectively suppress regional conflicts and ensure the clarity of the composition hierarchy.

Considering the synergistic relationship between color and layout in modern painting, the coupled consistency goal is further introduced:

$$\max F_3\,(\Theta) = \gamma_1 E_1 - \gamma_2 E_2 + \gamma_3 E_3 \tag{45}$$

Here, E_1 is the color enhancement term in the visual focus area, E_2 is the imbalance term in the high brightness area away from the visual center, and E_3 is the color change and spatial rhythm consistency term. The introduction of this objective makes the dominant color distribution no longer adjusted in isolation, but jointly optimized with the subject position, spatial density and visual flow direction.

In order to maintain the stability of the work style, this paper adds a style constraint term. Let the sample style prototype vector be $s*$ and the current scheme style code be s(Θ), then the style deviation is defined as follows.

$$F_4(\Theta) = \|s(\Theta) - s^*\|_2^2 \tag{46}$$

The corresponding optimization direction is as follows.

$$\min F_4\,(\Theta) \tag{47}$$

This item can prevent the problem of excessive deviation of comprehensive color and layout in the process of numerical optimization, which destroys the original artistic style of modern painting.

Based on the above goals, the multi-objective optimization model is finally obtained as follows.

$$\max F(\Theta) = [F_1(\Theta), F_2(\Theta), F_3(\Theta), -F_4(\Theta)] \tag{48}$$

$$\text{s.t.} \sum_{k=1}^{K} w_k = 1, \quad 0 \leq w_k \leq 1, \tag{49}$$

$$\sum_{k=1}^{K} a_k = 1, \quad 0 \leq a_k \leq 1, \tag{50}$$

$$0 \leq x_k \leq W, \quad 0 \leq y_k \leq H, \tag{51}$$

$$O \leq \varepsilon_o, \quad \eta_{min} \leq \eta \leq \eta_{max} \tag{52}$$

where ε_o is the maximum allowable overlap threshold, η_{min} and η_{max} are the lower and upper limit of the blank rate, respectively. Therefore, the comprehensive color organization, composition structure and style preservation in modern painting creation are uniformly mapped into a multi-objective optimization problem with constraints. The model not only retains the aesthetic rules in art creation, but also has a good numerical solution interface. It can be directly connected with genetic algorithm, particle swarm optimization and hybrid evolution strategy, which lays a mathematical foundation for the generation and optimization of subsequent creation schemes.

3.3 Authoring solution flow and computer implementation based on numerical optimization algorithm

After the multi-objective optimization model of color collocation and spatial layout is constructed, the problem of modern painting creation can be transformed into a high-dimensional nonlinear optimization task with constraints. The core of the algorithm is to adjust the dominant color proportion, comprehensive color center, regional centroid position and spatial area allocation at the same time, so as to achieve the optimal comprehensive color harmony, composition balance, visual guidance and style preservation. Let the set of decision variables be:

$$\Theta = \{w_k, \mu_k, x_k, y_k, a_k\}_{k=1}^{K} \tag{53}$$

Here, w_k represents the KTH dominant color weight, μ_k represents the comprehensive color center, (x_k,y_k) represents the location of the region, and ak represents the proportion of the region area. The comprehensive objective function is written as follows.

$$\max F(\Theta) = [F_1(\Theta), F_2(\Theta), F_3(\Theta), -F_4(\Theta)] \tag{54}$$

Among them, F_1 corresponds to the comprehensive color harmony goal, F_2 to the spatial layout goal, F_3 to the color-space coupling consistency goal, and F_4 to the style deviation term.

In the solving process, firstly, the comprehensive color feature vector fcolor and the spatial layout feature vector flayout are extracted from the preprocessed painting samples, and the initial solution set is generated according to the dominant color clustering results, region segmentation results and saliency distribution.

$$\mathcal{P}^{(0)} = \{\Theta_1^{(0)}, \Theta_2^{(0)}, \dots, \Theta_M^{(0)}\} \tag{55}$$

where M is the population size. To ensure that the solution space is feasible, a normalized projection is required after initialization:

$$w_k' = \frac{w_k}{\sum_{j=1}^{K} w_j}, \quad a_k' = \frac{a_k}{\sum_{j=1}^{K} a_j} \tag{56}$$

Thereby satisfying:

$$\sum_{k=1}^{K} w_k = 1, \quad \sum_{k=1}^{K} a_k = 1 \tag{57}$$

And further constrain the region locations to satisfy$0 \le x_k \le W, 0 \le y_k \le H$.

Since the optimization problem contains both continuous variables and structural variables, and the objective function is non-convex and there are many terms that cannot be analytically derived, we adopt a hybrid strategy of "multi-objective evolutionary search + local numerical correction". The global search phase uses the improved particle swarm for updating. For the ith candidate solution, the velocity and position are updated as follows.

$$v_i^{(t+1)} = \omega v_i^{(t)} + c_1 r_1 \left(p_i^{best} - \Theta_i^{(t)}\right) + c_2 r_2 \left(g^{best} - \Theta_i^{(t)}\right) \quad (58)$$

where ω is the inertia coefficient, c_1,c_2 are the learning factors, r_1,r_2 are the random disturbance terms, pibest and G I best represent the individual historical optimal solution and the non-dominated optimal solution in the external archive, respectively. To avoid premature convergence, Gaussian mutation is introduced after each iteration:

$$\Theta_i^{(t+1)} = \Theta_i^{(t+1)} + \delta_t \cdot \mathcal{N}(0,1) \quad (59)$$

The δ_t decreases with the number of iterations to achieve enhanced search in the early stage and stable convergence in the later stage.

In the fitness evaluation stage, the comprehensive color harmony degree, layout balance degree, coupling consistency and style deviation are calculated for each candidate scheme, and a penalty function is constructed to deal with constraint violation:

$$F^{(}\Theta) = F(\Theta) - \lambda p P(\Theta) P(\Theta) = Po(\Theta) + Pb(\Theta) + P\eta(\Theta) \quad (60)$$

Here, P_o represents the region overlap penalty, P_b represents the boundary transgression penalty, P_η represents the margin violation penalty, and λ_p is the penalty weight. Then, Pareto non-dominated sorting and crowding distance are used to retain candidate solutions with better diversity to avoid the optimization results only biased towards a single objective.

In the local numerical correction stage, the coordinates of the optimal solutions in the current non-dominated solution set are fine-tuned. If the perturbation of a variable θm satisfies:

$$\Delta F = F(\Theta^{new}) - F(\Theta^{old}) > 0 \quad (61)$$

Accepts updates; Otherwise, it is revoked. This process focuses on fine-grained adjustment of the comprehensive color center μk, the location of the visual focus area (x_k,y_k) and the dominant color ratio wk, so as to improve the accuracy of the final solution in the local structure.

At the computer implementation level, the whole process is integrated and developed using Python. OpenCV is used for image reading, scaling, denoising, color space transformation, and region segmentation, NumPy and SciPy are used for matrix operations, feature encoding, and numerical updates, and PyTorch is used for style feature embedding and parallel tensor computation. The system first reads the input image and performs feature parsing, then generates a population of candidate solutions, then performs multiple rounds of fitness evaluation, population update, non-dominated sorting, and local correction, and finally outputs the Pareto optimal solution set:

$$\mathcal{P}^* = \{\Theta_1^*, \Theta_2^*, \dots, \Theta_Q^*\} \quad (62)$$

where Q is the optimal number of candidate solutions. Each optimal solution corresponds to a set of comprehensive color configuration and spatial layout schemes that can be directly used as an aid to modern painting creation. Different from a single deterministic solution, this implementation can not only output a single optimal result, but also retain multiple groups of alternative solutions with their own advantages in comprehensive color style and composition method, so as to better meet the actual needs of "coexistence of multiple solutions and aesthetic screening" in modern painting creation.

4 Experimental Results and application analysis of modern painting creation based on numerical optimization algorithm

4.1 Experimental environment, evaluation index and comparison scheme

In order to verify the effectiveness of the modern painting creation method based on numerical optimization algorithm in color collocation optimization and spatial layout reconstruction, the experiment is completed in a unified software and hardware environment. The computing platform uses Intel Core i9 processor, 64 GB RAM and NVIDIA RTX 4090 GPU. The operating system is Ubuntu 22.04, and the development environment is Python 3.10. The image processing and feature extraction module is implemented based on OpenCV 4.8, the numerical calculation and matrix operation are completed by NumPy and SciPy, and the style feature embedding and parallel evaluation module is implemented by PyTorch 2.1. In order to ensure the repeatability of the experiment, the number of dominant color clusters K is set to 5, the population size is set to 80, the maximum iteration number is set to 200, the initial value of inertia weight ω is set to 0.8, the learning factor c1=c2=1.6, and the mutation disturbance coefficient δt is decreased by linear annealing. The sample data was divided into training set, validation set and test set according to 7:1.5:1.5, and all input images were uniformly scaled to 512×512 resolution. The experimental environment configuration is shown in Table 3.

Table 3: Experimental Environment Configuration

Item	Configuration
CPU	Intel Core i9
GPU	NVIDIA RTX 4090
Memory	64 GB
OS	Ubuntu 22.04
Programming Language	Python 3.10
Image Processing Library	OpenCV 4.8
Numerical Computing Libraries	NumPy, SciPy
Deep Learning Framework	PyTorch 2.1
Input Resolution	512 × 512
Number of Dominant Colors	5
Population Size	80
Maximum Iterations	200

The evaluation system focuses on three levels: color quality, spatial composition quality and joint optimization effect. Comprehensive color quality is measured by comprehensive color harmony Hc, brightness contrast DL and saturation equilibrium BS, where the comprehensive color comprehensive score is defined as:

$$Q_c = \alpha_1 H_c + \alpha_2 D_L + \alpha_3 B_S \tag{63}$$

The spatial composition quality is evaluated by the layout balance degree B, the spatial rhythm index Rs and the whitespace rationality degree ηs. The comprehensive composition score is written as follows.

$$Q_l = \beta_1 B + \beta_2 R_s + \beta_3 \eta_s \tag{64}$$

In order to measure the consistency of color collocation and spatial layout in joint optimization, the coupling coordination index is further defined as follows.

$$Q_{cl} = \gamma_1 E_1 - \gamma_2 E_2 + \gamma_3 E_3 \tag{65}$$

Here, E_1 represents the visual guidance coupling term, E_2 represents the imbalance penalty term, and E_3 represents the rhythm consistency term. Considering that modern painting creation still needs to maintain the original style characteristics, the experiment also introduces style preservation error:

$$L_s = \|s(\Theta) - s^*\|_2 \tag{66}$$

A smaller value indicates that the optimization result is closer to the original artistic style. The final comprehensive evaluation function is expressed as follows.

$$Q = \lambda_1 Q_c + \lambda_2 Q_l + \lambda_3 Q_{cl} - \lambda_4 L_s \tag{67}$$

The meanings and functions of each index are shown in Table 4.

Table 4: Evaluation Metrics for Modern Painting Creation Optimization

Metric	Definition	Function
Hc	Color harmony score	Measures color coordination
DL	Lightness contrast	Reflects tonal hierarchy
BS	Saturation balance	Measures color stability
B	Layout balance index	Evaluates compositional equilibrium
Rs	Spatial rhythm index	Reflects density variation
ηs	Blank-space rationality	Measures negative-space organization
Qcl	Color-layout coupling score	Evaluates collaborative consistency
Ls	Style preservation loss	Measures style deviation
Q	Overall optimization score	Comprehensive performance index

The comparison scheme setting follows the three-level structure of "traditional method-single objective optimization method-joint optimization method". The first baseline method is an empirical color matching and composition adjustment method, which only modifies the proportion and position of the main color according to the rule base. The second baseline method is a single comprehensive color optimization method, which only optimizes the dominant color center and the comprehensive color ratio, and does not adjust the regional layout. The third baseline method is a single spatial layout optimization method, which only adjusts the main body position, area ratio and white space distribution without changing the original color structure. The fourth baseline method is a joint optimization method based on genetic algorithm, which is used to verify the differences of different numerical optimization strategies. The baseline method five is a single layer joint optimization method based on particle swarm optimization, which is used to compare the advantages of the proposed hybrid solution mechanism in terms of convergence speed and result quality. The proposed method achieves collaborative optimization under the constraints of four objectives of comprehensive color harmony, composition balance, coupling coordination and style preservation. Through this experimental design, the comprehensive color control ability, spatial organization ability and overall aesthetic improvement effect of the proposed method in modern painting art creation can be systematically tested.

4.2 Results and analysis of color collocation optimization

The results of color collocation optimization for modern paintings are shown in Figure5. The empirical adjustment method, layout optimization method only, color optimization method only, and joint optimization method based on genetic algorithm are compared with the proposed method around the four indexes of comprehensive color harmony, brightness contrast, saturation balance and comprehensive color comprehensive score. The corresponding scores of the empirical adjustment method are 0.71, 0.64, 0.69, and 0.68, respectively, and the corresponding scores of the layout optimization method are 0.73, 0.66, 0.70, and 0.70, respectively, indicating that without explicit modeling of comprehensive color variables, the dominant color relationship of the screen, the level of light and dark, and the comprehensive color stability are difficult to materially improve. The scores of the four items of the color optimization method only increase to 0.82, 0.78, 0.80 and 0.81, indicating that the comprehensive color order of the screen is significantly improved after incorporating the dominant color ratio, comprehensive hue distance and saturation constraints into the optimization. The joint optimization method based on genetic algorithm further reaches 0.86, 0.81, 0.84 and 0.85, which indicates that the local comprehensive color conflict and visual fragmentation are further suppressed after the cooperation of comprehensive color adjustment and spatial structure. The proposed method achieves 0.91, 0.87, 0.89 and 0.90 on the four indicators respectively, which achieves the best results, and increases by 0.05, 0.06, 0.05 and 0.05 respectively compared with the joint optimization method based on genetic algorithm. The results show that the multi-objective numerical optimization model constructed in this paper can more effectively coordinate the relationship between the dominant color distribution, lightness level, saturation stability and the comprehensive color weight of the salient region, so that the modern painting can achieve a better state in terms of comprehensive color unity, hierarchical expression and visual appeal, which verifies the effectiveness of the proposed method in color collocation optimization.

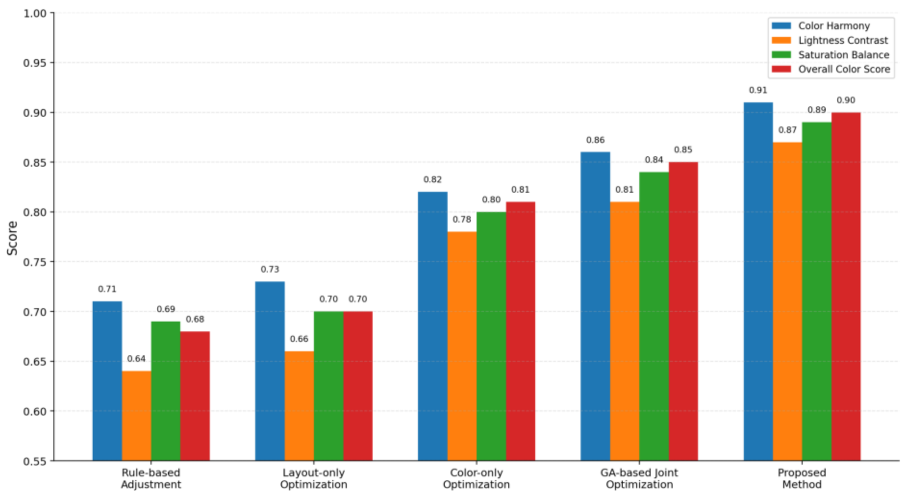

Figure 5: Comparison of Color Matching Optimization Results

4.3 Spatial layout optimization results and analysis

The results of spatial layout optimization for modern paintings are shown in Figure6. The empirical adjustment method, color only optimization method, layout only optimization method, and joint optimization method based on genetic algorithm are compared with the proposed method by focusing on four indicators: layout balance degree B, spatial rhythm index Rs, whitespace reasonable degree ηs and comprehensive layout score Ql. The corresponding scores of the empirical adjustment method are 0.68, 0.65, 0.66 and 0.67, respectively, indicating that the overall composition stability is weak, and only the color optimization method is improved to 0.70, 0.67, 0.68 and 0.69, indicating that the improvement effect of simple comprehensive color adjustment on the subject distribution, regional scale and negative spatial structure is limited. The scores of the layout optimization method only increase to 0.83, 0.80, 0.81 and 0.81, indicating that the subject migration, local crowding and spatial looseness problems can be effectively alleviated when the region position, area proportion and boundary relationship are explicitly solved. The joint optimization method based on genetic algorithm further achieves 0.87, 0.85, 0.84 and 0.86. The visual flow continuity and spatial hierarchical organization are enhanced after the integrated color information is displayed. The proposed method achieves 0.92, 0.89, 0.88 and 0.90 on the four indicators respectively, which achieves the best results, and increases by 0.05, 0.04, 0.04 and 0.04 respectively compared with the joint optimization method based on genetic algorithm. The results show that the multi-objective numerical optimization model constructed in this paper can more effectively coordinate the relationship between the main area distribution, the migration of visual center of gravity, the control of white space and the transition of rhythm, so that the modern painting can achieve a better state in terms of composition balance, hierarchical advancement and spatial order.

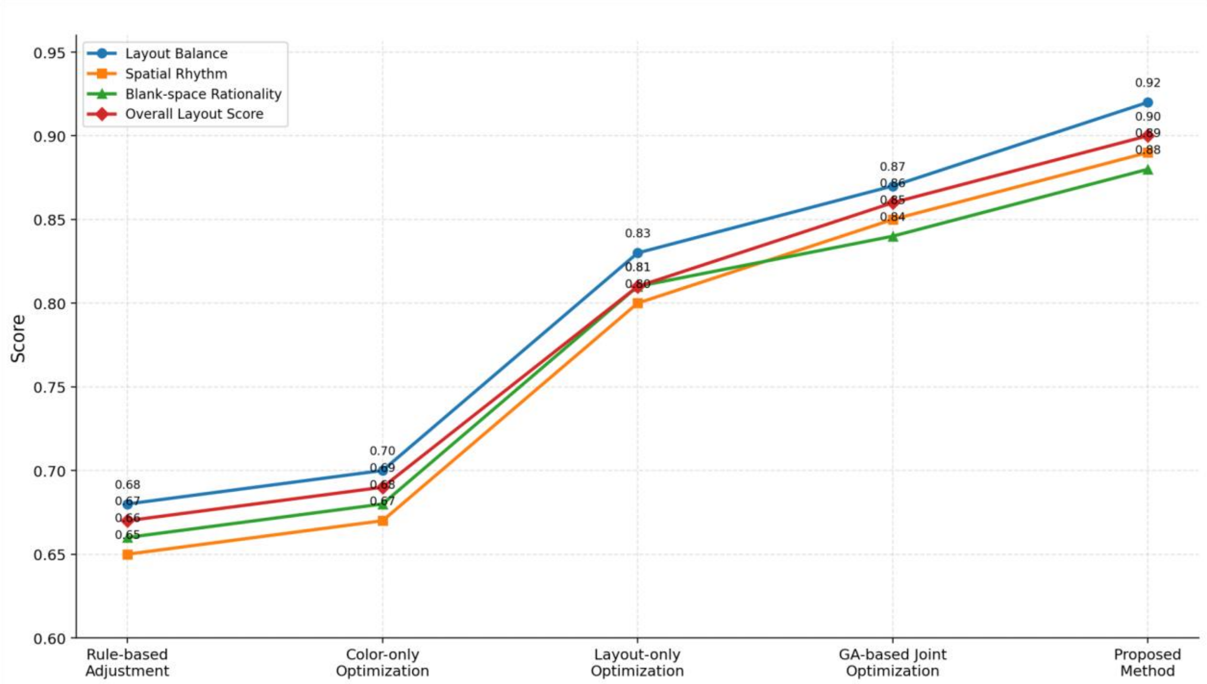

Figure 6: Comparison of Spatial Layout Optimization Results

4.4 Ablation Experiment and Case Study of Modern Painting Creation

In order to verify the contribution of each module to the optimization effect of modern painting creation, this paper sets up four ablation schemes: removing color module, removing layout module, removing coupling constraint and removing local finishing, and compares them with the complete model. The results are shown in Figure7.

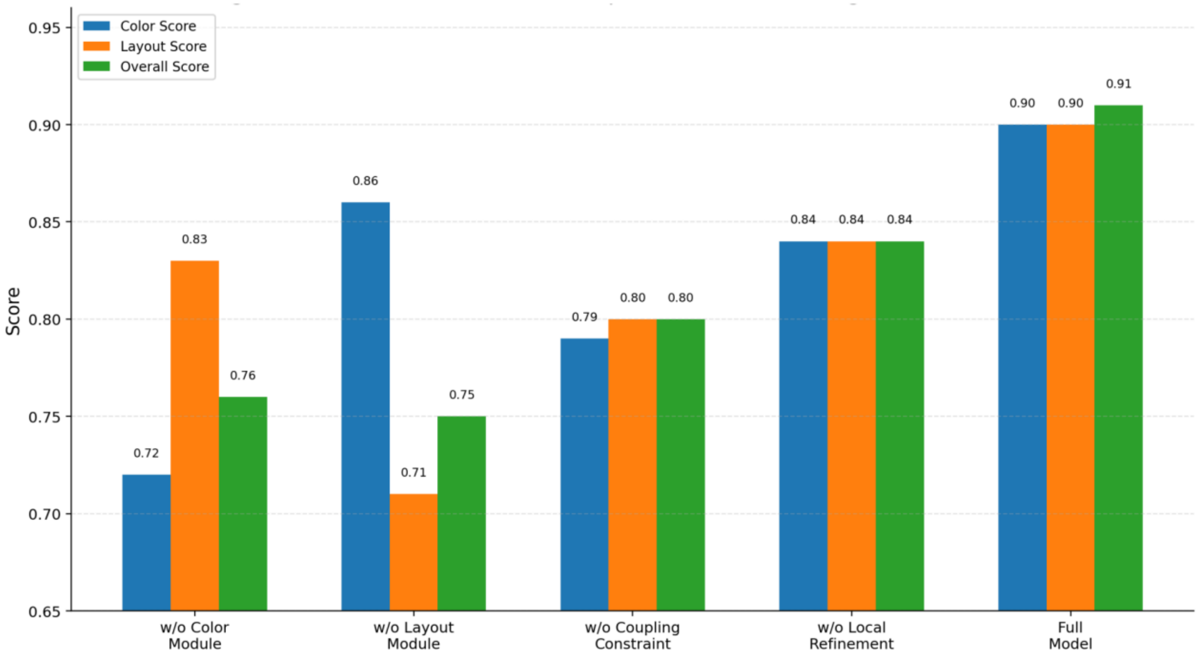

Figure 7: Ablation Results of the Proposed Modern Painting Creation Method

The comprehensive color score, layout score and overall score of the complete model reach 0.90, 0.90 and 0.91, respectively, which are the best. After removing the color module, the comprehensive color score is reduced to 0.72, and the comprehensive score is reduced to 0.76, indicating that the dominant color proportion control, light and dark level constraints, and saturation equalization modeling play a key role in the comprehensive color unity of the picture. After removing the layout module, the layout score is only 0.71, indicating that the stability of the composition will be significantly reduced without explicit optimization of the main body position, region scale, and white space structure. After removing the coupling constraints, the comprehensive color and layout scores are 0.79 and 0.80, respectively, indicating that color collocation and spatial layout cannot be treated separately. After removing the local finetuning, the overall score is 0.84, indicating that local finetuning still plays an important role in boundary transition, visual focus stability, and detail balance.

In order to further test the applicability of the method in different modern painting creation scenes, this paper selects two kinds of representative works as case analysis objects. Case A belongs to the modern painting dominated by high saturation and strong contrast colors, and its typical problems are strong comprehensive color conflict, excessive visual focus, and crowding in local areas. Case B belongs to the modern painting with low saturation and weak contrast spatial hierarchy, and its main problems are manifested as insufficient comprehensive color variation, weak composition rhythm and unclear organization of white space. The two cases are used to verify the optimization effects of the proposed method in two aspects of "strengthening the comprehensive color coordination ability" and "improving the spatial structure order ability" respectively. The results of typical modern painting creation cases are shown in Table 5.

Table 5: Optimization results for the modern painting creation case

Case	Painting Type	Color Score Before	Color Score After	Layout Score Before	Layout Score After	Optimization Focus
Case A	High-saturation and strong-contrast modern painting	0.74	0.90	0.69	0.89	Reduce color conflict and stabilize visual focus
Case B	Low-saturation and weak-contrast modern painting	0.77	0.88	0.72	0.90	Enhance spatial rhythm and improve blank-space organization

After optimization, the comprehensive color score of case A is improved from 0.74 to 0.90, and the layout score is improved from 0.69 to 0.89, indicating that the model can effectively alleviate the comprehensive color conflict and improve the subject focus effect. In case B, the comprehensive color score is improved from 0.77 to 0.88, and the layout score is improved from 0.72 to 0.90, indicating that the model can enhance spatial hierarchy, rhythm continuity, and whitespace rationality. It can be seen that the proposed method is not only suitable for the creation scenes with strong comprehensive color tension, but also suitable for the modern painting scenes with higher spatial order requirements, and has good adaptability and promotion value.

5 Conclusion and Prospect

5.1 Research Conclusions

Focusing on the cooperative optimization problem of color matching and spatial layout in modern painting art creation, a joint modeling and solving framework supported by computer vision, digital image processing and numerical optimization algorithms is constructed. This paper completed the construction of modern painting sample data, the digital representation of comprehensive color features, the parametric description of spatial layout structure, and the computational modeling of color-space coupling relationship. On this basis, a multi-objective optimization model considering comprehensive color harmony, composition balance, coupling consistency and style retention was established. The experimental results show that the proposed method is superior to the empirical adjustment method, the single optimization method and the general joint optimization method in the core evaluation indexes of comprehensive color harmony, light contrast, saturation balance, layout balance, spatial rhythm index and white space rationality. The comprehensive color comprehensive score reaches 0.90, and the comprehensive layout score reaches 0.90. The comprehensive score of the complete model in the ablation experiment reached 0.91. The results show that there are significant coupling characteristics between color organization and spatial composition in modern painting, and it is difficult to obtain stable and high-quality optimization effects by dealing with either dimension alone. By integrating the dominant color proportion control, regional position adjustment, area allocation, visual focus guidance and style constraints into the numerical optimization process, the empirical aesthetic judgment in modern painting creation is further transformed into a solution mechanism that can be calculated, compared and updated iteratively. Therefore, it provides an operational technical path for digital art creation, intelligent aided design and modern painting scheme optimization, and also provides a new method support for computer technology to intervene in art creation research.

5.2 Research deficiencies and future prospects

Although the existing research has achieved relatively stable results in the co-optimization of color collocation and spatial layout of modern paintings, there is still room for further deepening. The sample source is still mainly static digital painting images. Although it covers typical scenes such as high saturation and strong contrast and low saturation and weak contrast, the adaptability of cross-genre, cross-media and composite material painting works still needs to be verified in a larger scope. The model construction level mainly relies on explicit feature extraction, parametric representation and multi-objective numerical optimization solution, which is still insufficient for the depiction of deeper symbolic meaning, emotional projection, cultural semantics and creative intention in modern paintings. Especially in works with stronger abstraction and fuzzy style boundaries, the existing evaluation indicators are still not sufficient for the expression of aesthetic quality. In terms of computational implementation, although local finishing and style constraints improve the optimization accuracy, there is still a certain amount of computational overhead in large-scale candidate generation, interactive adjustment of complex scenes, and real-time creation feedback. Further research can be carried out in three directions: first, to expand the sample database of modern paintings and build a more diverse data base; Second, deep representation learning, multi-modal semantic modeling and generative models are combined to improve the understanding of art semantics and creation preferences. Thirdly, the human-computer collaborative interaction mechanism and explainable optimization strategy are introduced to form a modern intelligent painting creation system with real-time feedback, multi-scheme recommendation and personalized adjustment, which further improves the application depth, generalization ability and practical value of the method.

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