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# Color and Material Matching Space Effect Optimization in Soft Decoration Design Based on Computer Image Processing Algorithm

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**Abstract**

This study introduces an intelligent optimization method based on computer vision to solve the problem that color and material matching in soft decoration design is highly subjective and lacks quantitative standards. ConvNeXt (Convolutional Next Network) is used to extract the color-material features of the interior space, and a GMM (Gaussian Mixture Model) color database is constructed to quantify the coordination of different color distributions. The PSO (Particle Swarm Optimization) algorithm is used for multi-objective optimization to ensure the balance and visual beauty of color matching. The design scheme is realistically rendered in the Unity platform to simulate the visual effects in the actual environment, and CHI (Color Harmony Index), ECS (Emotional Color Similarity) and MCI (Material Conflict Index) are used to quantitatively evaluate the design effect. The results show that the proposed method is superior to traditional manual design and feature extraction combined with manual design in terms of color harmony, consistency of emotional expression and material adaptability. The average CHI of the proposed design method reaches 0.92, the average ECS is 0.93, and the average MCI is reduced to 0.12, which significantly optimizes the visual coordination and overall aesthetic effect of the soft decoration scheme. The design method in this paper can improve efficiency while ensuring the aesthetics of the design, and provides a feasible quantitative optimization strategy for intelligent soft decoration design.

**Keywords**: Soft Decoration Design, Color and Material, Space Effect, Computer Image Processing, ConvNeXt Model.

## 1. Introduction

With the continuous improvement of modern living standards, interior environment design [1-2] has become an important part of people's pursuit of high-quality life. As an important part of interior design, soft furnishing design [3-4], with its color [5-6] and material matching, directly affects the visual effect and emotional experience of the overall space. Traditional soft furnishing design [7-8] mainly relies on the designer's rich experience and subjective aesthetics, and there are strong individual differences and uncertainties, resulting in the lack of unified quantitative standards and replicability in the design results in terms of color [9-10] and material matching. The rapid development of computer vision [11-12] and deep learning technology has provided new ideas and technical means for quantitative color and material matching. This paper uses GMM to perform probabilistic modeling on the extracted color information, accurately distinguishes the primary color from the secondary color, and constructs a dedicated color database for different space types. This study introduces the PSO algorithm into the multi-objective optimization process, comprehensively consider-

ing the color harmony index, material compatibility, and user preference. It achieves the transformation and optimization of the design scheme from perceptual to rational by constructing multi-dimensional evaluation indicators including ΔE (the degree of difference between the extracted color and the original image color in the CIELAB color space), SSIM (Structural Similarity Index Measure), CHI, ECS, and MCI. By building a virtual scene on the Unity platform and integrating advanced rendering technologies such as global illumination and physical rendering, the study not only verified the actual effect of the optimization algorithm in a virtual environment, but also provided an intuitive and interactive evaluation tool for future designers. This study has achieved breakthroughs in algorithm innovation, data-driven design, and realistic rendering, bringing new theoretical perspectives and practical tools to the field of soft furnishing design.

## 2. Related Works

With the rapid development of computer vision and deep learning technology, image processing [13-14] is increasingly widely used in the field of interior design. A large number of studies have focused on using convolutional neural networks [15-16] and their variants to automatically analyze the color, material, and spatial layout of indoor scenes. Researchers have achieved accurate capture of the main color tone [17-18] and secondary colors of indoor scenes through deep feature extraction methods, and quantified color matching and differences using CIELAB color space [19-20] conversion calculations. In order to solve the problems of strong subjective judgment of designers and lack of unified quantitative standards in traditional soft furnishing design, Gaussian mixture model [21] and cluster analysis technology [22] were introduced to statistically model the color information extracted from the image and build a color database, which initially realized data-driven design assistance. Regarding material feature extraction [23-24], related studies not only focus on physical properties such as texture, glossiness and roughness, but also use structural similarity index to evaluate the similarity between material textures, providing quantitative support for material matching. Existing work has made significant progress in image feature extraction [25-26], color space modeling and material recognition. However, there are still many shortcomings in how to integrate these technical systems to achieve comprehensive soft decoration design optimization. This provides a theoretical basis and improvement direction for this study in the construction of an automated soft decoration design system.

In terms of optimization design methods and multi-objective decision-making, researchers have also conducted a lot of explorations to make up for the shortcomings of strong subjectivity and low efficiency in traditional design. Research based on intelligent optimization algorithms such as genetic algorithms [27-28] and particle swarm optimization [29-30] provides an effective way to solve the problem of balancing multiple objectives in design. Many scholars have proposed multi-dimensional evaluation indicators, such as using the color wheel theory [31] to construct a color harmony index, using semantic segmentation and the Pantone color psychology database to construct emotional color similarity, and combining gloss difference with SSIM to construct a material conflict index. These methods have laid a theoretical foundation for the quantitative evaluation of automatic design solutions. At the same time, with the development of virtual reality [32-33] and rendering technology, building highly realistic virtual scenes using platforms such as Unity [34-35] has become a research hotspot. By integrating technologies such as global illumination and physical rendering, it not only intuitively demonstrates the optimization design effect, but also further verifies the practical applicability of the algorithm. Although existing work has achieved remarkable results in data collection, feature extraction and optimization algorithms, there are still shortcomings in the full-process integration of soft decoration design, expansion of data set scale and response to user personalized needs. These issues provide a direction for further innovation in this study, that is, on the basis of inheriting and improving the previous work, a more complete soft decoration design optimization system is constructed by combining ConvNeXt deep

network, Gaussian mixture model and PSO multi-objective optimization algorithm. This can realize the transformation of design schemes from perceptual experience to quantitative analysis, and verify the realistic rendering in virtual scenes, promoting the intelligent development of soft decoration design theory and practice.

Researchers have also conducted extensive exploration in optimizing design methods and multi-objective decision-making to compensate for the shortcomings of traditional design, such as strong subjectivity and low efficiency. The generation and evaluation of soft decoration design schemes essentially constitute a complex multi-objective optimization problem, with non-linear or even conflicting relationships between its objectives (such as color harmony, emotional expression, material compatibility). The research based on metaheuristic algorithms such as genetic algorithm and particle swarm optimization provides an effective approach to solving multi-objective balancing problems in design. This type of method does not rely on gradient information of the problem, and is particularly suitable for global exploration in non convex, multi-modal high-dimensional solution spaces, which can effectively approximate the Pareto optimal solution set and provide designers with a series of solutions that achieve different trade-offs between multiple criteria. Many scholars have proposed multidimensional evaluation indicators, which have laid a theoretical foundation for the quantitative evaluation of automated design schemes.

# 3. ConvNeXt Extracts Image Features

## 3.1 Data Collection

The data source of this study is mainly based on public soft furnishing design data, and a total of 167 design images from the Houzz platform were selected. As an internationally renowned interior design and decoration communication platform, Houzz covers a wide variety of design cases and styles, providing representative and diverse image resources for this study.

Although the dataset used in the current research is relatively limited in scale, it covers various types of indoor spaces and typical soft decoration objects, with good representativeness and structural diversity, which can effectively support the validation of core tasks such as color and material feature extraction, probability modeling, and multi-objective optimization. By using a pre trained ConvNeXt model combined with transfer learning strategy, high feature expression ability and optimization performance were achieved even with limited samples, indicating that the current data scale is sufficient for verifying the feasibility and effectiveness of the method.

The acquired design object information is shown in Table 1.

**Table 1. Acquired design object information**

| Space type | Design object | Number of images |
|---|---|---|
| Living room | Sofa | 20 |
| | Coffee table | 23 |
| | TV cabinet | 18 |
| Bedroom | Bed | 24 |
| | Lamp | 15 |
| Kitchen | Dining table and chairs | 15 |
| | Tableware | 13 |
| Bathroom | Mirror | 18 |
| | Shower curtain | 21 |

The living room design objects mainly include sofas, coffee tables and TV cabinets, of which 20, 23 and 18 images were collected respectively; the bedroom part mainly includes beds and lamps, with a total of 24 bed images and 15 lamp images collected; the kitchen design covers dining tables and chairs and tableware, with 15 and 13 images obtained respectively. The bathroom focuses on mirrors and shower curtains, collecting 18 and 21 images re-

spectively. Through the quantitative statistics and spatial distribution analysis of various design objects, the characteristics and style differences of various space types in soft decoration design can be more carefully reflected, providing detailed data support and basis for subsequent feature extraction, color and material matching, and multi-objective optimization.

The obtained image display is shown in Figure 1.




**Figure 1. Display of acquired images. a) Sofa; b) Coffee table; c) TV cabinet; d) Bed; e) Lamp; f) Dining table and chair; g) Tableware; h) Mirror; i) Shower curtain**

The acquired images have been strictly screened and sorted to ensure the authenticity and practicality of the data. In order to facilitate subsequent feature extraction and model training, the image data is classified according to the space type, including four categories: living room, bedroom, kitchen and bathroom. Such classification helps to reveal the differences in color, material and layout of different spaces, and also provides more detailed scene description and data support for the optimization algorithm.

## 3.2 Image Preprocessing

The acquired image data is preprocessed, including image size normalization, color space conversion and denoising, so as to reduce the impact of environmental factors on color and material feature extraction and improve the robustness of the analysis. Image size normalization ensures that all input images meet the neural network model input requirements. Since images from different sources have different resolutions and scales, direct input may cause the neural network to be unable to process efficiently.

All input images are uniformly resized to a fixed size of 512×512 to improve computational efficiency while preserving details. The bilinear interpolation method is used for scaling, and the formula is:

$$I'(x', y') = \sum_{i=0}^{1} \sum_{j=0}^{1} w_{ij} I(x + i, y + j) \quad (1)$$

In formula 1, $I'(x', y')$ is the target image pixel value, and $w_{ij}$ is the interpolation weight, which is calculated from neighboring pixels.

Color space conversion is to reduce the impact of illumination changes on color analysis. This study uses the CIELAB color space, which is designed based on human eye perception, where the L channel represents brightness, and the a and b* channels represent color information, which helps to process brightness and color information independently.

The formula for conversion to CIELAB is:

$$L^* = 116 \cdot f(Y/Y_n) - 16 \tag{2}$$

$$a^* = 500 \cdot (f(X/X_n) - f(Y/Y_n)) \tag{3}$$

$$b^* = 200 \cdot (f(Y/Y_n) - f(Z/Z_n)) \tag{4}$$

In formula 2-4, $X_n$, $Y_n$, and $Z_n$ are the reference white points of the D65 standard light source. $f(\cdot)$ is the nonlinear transformation function:

$$f(t) = \begin{cases} t^{1/3}, & t > 0.008856 \\ (7.787t) + \frac{16}{116}, & t \le 0.008856 \end{cases} \tag{5}$$

This study uses Gaussian filtering to smooth the image and reduce high-frequency noise. Gaussian filtering is a smoothing method based on normal distribution. The calculation method of its two-dimensional convolution kernel is as follows:

$$G(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{6}$$

In formula 6, $\sigma$ controls the standard deviation of the filter and determines the degree of smoothing. The convolution calculation of this filter on the image can be expressed as:

$$I'(x,y) = \sum_{i=-k}^{k} \sum_{j=-k}^{k} G(i,j) \cdot I(x+i, y+j) \tag{7}$$

Through Gaussian filtering, random noise in the image is effectively removed, while the basic structure of edge features is maintained to ensure the accuracy of subsequent feature extraction. This study uses three steps: image size normalization, color space conversion, and denoising to make the input image more consistent and stable in the process of structural, color, and material feature extraction, thus providing a high-quality data foundation for subsequent color harmony index calculation, material compatibility analysis, and deep learning model training.

## 3.3 Feature Extraction

In soft furnishing design analysis, color distribution features are crucial for the evaluation of spatial aesthetics. This study uses the ConvNeXt pre-trained model and its deep convolutional feature extraction capabilities to accurately model the color information in the image. The ConvNeXt network architecture design is inspired by Transformer and combines standard convolution with a more powerful normalization strategy to improve feature extraction capabilities.

The ConvNeXt model structure is shown in Figure 2.

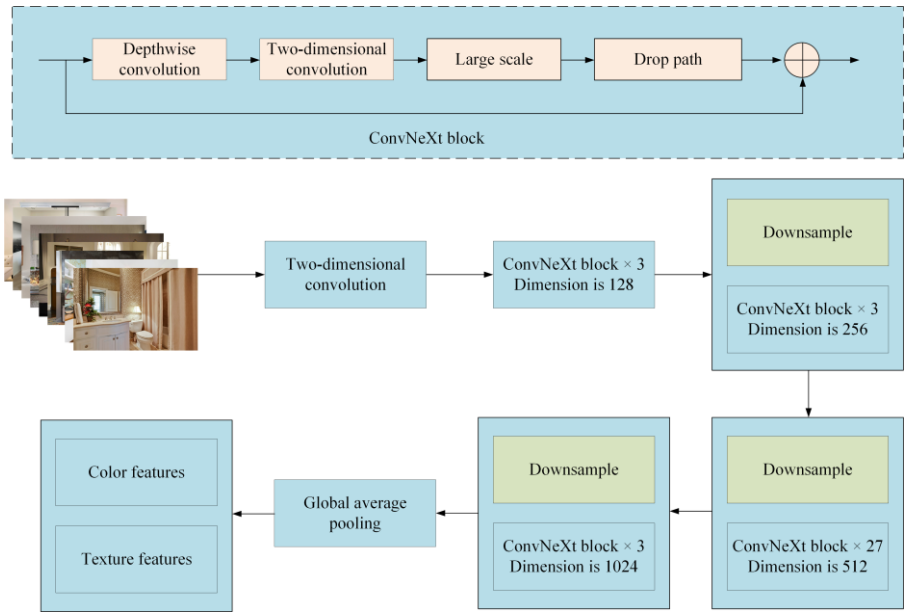



**Figure 2. ConvNeXt model structure**

The ConvNeXt block uses Depthwise convolution for feature extraction, forms the initial feature map through two-dimensional convolution, and uses the Drop path mechanism to enhance training stability. This paper gradually extracts features through multiple layers of ConvNeXt blocks.

The first stage consists of 3 ConvNeXt blocks (feature dimension 128). The second stage uses 3 ConvNeXt blocks (feature dimension 256) to further extract high-level color features. The third stage uses 27 ConvNeXt blocks (feature dimension 512) for deep learning. In the fourth stage, three ConvNeXt blocks (feature dimension 1024) are used to maximize the model's ability to express complex material characteristics, and global average pooling is combined to calculate global color and texture features.

ConvNeXt-Large is used as the backbone network to focus on high-dimensional feature mapping. After ConvNeXt processing, the obtained feature mapping is expressed as:

$$F = f_{\text{ConvNeXt}}(I) \in \mathbb{R}^{h \times w \times c} \tag{8}$$

In Formula 8, $h$ and $w$ are the spatial dimensions of the feature map, and c is the number of channels. The feature map covers the local color information of each region in the image and enhances the ability to capture color patterns through the self-attention mechanism.

In order to further quantify the color distribution characteristics, this study converts the feature map extracted by ConvNeXt into the CIELAB color space. The color distribution of each image region is statistically analyzed, and the pixel ratio in each interval is calculated:

$$H(i) = \frac{\sum_{x,y} \delta(L^*(x,y) \in B_i)}{h \times w} \tag{9}$$

In formula 9, $H(i)$ is the normalized histogram value of the i-th color interval, and $B_i$ is the pixel set of the interval.

ConvNeXt extracts rich local texture patterns through multi-scale convolution kernels. It is difficult to capture texture structures with strong periodicity and directionality using convolution features alone. This study further combines Gabor filters to calculate frequency responses in different directions. The formula for Gabor filtering is:

$$G(x, y; \lambda, \theta, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \cos\left(2\pi \frac{x'}{\lambda}\right) \tag{10}$$

In formula 10, $\lambda$ is the wavelength, which determines the texture frequency. $\theta$ is the filter direction angle, which controls the extracted texture direction. $\sigma$ controls the scale of the Gaussian envelope. $\gamma$ is the spatial aspect ratio, which is used to adjust the filter shape.

The formula for rotating coordinates $x'$ and $y'$ is:

$$x' = x\cos\theta + y\sin\theta \tag{11}$$

$$y' = -x\sin\theta + y\cos\theta \tag{12}$$

Through Gabor filtering at different angles, direction-sensitive texture features are obtained. The Retinex algorithm is used to extract brightness information and calculate glossiness. The formula is:

$$G = \frac{I_{max} - I_{min}}{I_{max} + I_{min}} \tag{13}$$

In formula 13, $I_{max}$ and $I_{min}$ represent the brightness of the highlight area and the shadow area respectively.

Texture entropy is used to measure the complexity of the material surface, and the formula is:

$$H = -\sum_{i=1}^{N} p(i) \log p(i) \tag{14}$$

In formula 14, $p(i)$ is the probability distribution of Gabor texture features. The larger the entropy value, the more complex the material.

## 3.4 Constructing Color and Material Data

In the process of color feature modeling, GMM is used to fit the color histogram of each image to estimate the probability distribution of the color in the image. Assuming that the color distribution of the image conforms to the mixture model of K Gaussian components, its probability density function is expressed as:

$$p(x) = \sum_{i=1}^{K} \pi_i \cdot \mathcal{N}(x|\mu_i, \Sigma_i) \quad (15)$$

In formula 15, $\pi_i$ is the weight of the i-th Gaussian component.

$\mathcal{N}(x|\mu_i, \Sigma_i)$ is the i-th Gaussian distribution, and its parameters include the mean vector $\mu_i$ and the covariance matrix $\Sigma_i$:

$$\mathcal{N}(x|\mu, \Sigma) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right) \quad (16)$$

In formula 16, $d = 3$ corresponds to the three dimensions of the CIELAB color space, and the GMM parameters are optimized by the expectation maximization algorithm.

In order to extract the dominant and secondary colors of the image, based on the mixing weights calculated by GMM, the Gaussian component with a larger weight represents the dominant color, while the second largest component represents the secondary color.

During the image analysis process, the extracted material area is analyzed for features and key material properties are recorded. The surface light reflection characteristics are calculated using the formula:

$$G = \frac{R_{\text{specular}}}{R_{\text{diffuse}} + R_{\text{specular}}} \quad (17)$$

In formula 17, $R_{\text{specular}}$ represents the specular reflection component, that is, the brightness of the highlight area. $R_{\text{diffuse}}$ represents the diffuse reflection component, that is, the overall light reflection of the surface.

In order to analyze the compatibility of different materials, a material compatibility matrix is constructed based on physical properties. The formula is:

$$MCM_{i,j} = h(G_i, R_i, T_i, G_j, R_j, T_j) \quad (18)$$

$G_i, R_i, T_i$ are the glossiness, roughness and texture characteristics of material i. $G_j, R_j, T_j$ are the corresponding attributes of material j.

The formula for calculating similarity is:

$$S_{i,j} = \frac{G_i G_j + R_i R_j + T_i T_j}{\sqrt{G_i^2 + R_i^2 + T_i^2} \cdot \sqrt{G_j^2 + R_j^2 + T_j^2}} \quad (19)$$

In formula 19, the closer $S_{i,j}$ is to 1, the more compatible materials i and j are in terms of physical properties. This matrix can be used to recommend material combinations. High-gloss metal combined with low-roughness glass has high compatibility and is suitable for modern style design. Rough fabric combined with low-gloss wood has moderate compatibility and is suitable for warm atmosphere. High-roughness concrete combined with high-gloss plastic has low compatibility and is not recommended.

# 4. Multi-objective Optimization and Three-Dimensional Scene Construction

## 4.1 Objective Function Design

In the PSO-based method, the color matching and material combination are optimized through the objective function. The objective function covers the color harmony index, emotional color similarity, material conflict index, and user preference matching to ensure that the optimization results meet both the design specifications and the personalized needs of users.

The Color Harmony Index (CHI) is used to measure the coordination of the primary and secondary colors in the CIELAB color space. The formula is:

$$CHI = 1 - \frac{\sum_{i=1}^{n} w_i \cdot \Delta E_{ij}}{n \cdot \Delta E_{max}} \quad (20)$$

In formula 20, $\Delta E_{ij}$ is the color difference between the primary color and the secondary color calculated according to the CIEDE2000 standard, and $w_i$ is the area ratio of the color in the design area. $\Delta E_{max}$ is the theoretical maximum color difference. The closer CHI is to 1, the more harmonious the color matching is.

Emotional color similarity (ECS) reflects the degree of match between the color expression in the design scheme and the target emotion. Its calculation formula is:

$$ECS = \frac{\sum(P_c \cdot S_e)}{\sum P_c} \tag{21}$$

In formula 21, $P_c$ is the pixel ratio of a specific color area, and $S_e$ determines the emotional intensity of the color based on the Pantone color psychology database.

The Material Conflict Index (MCI) is used to evaluate the possible conflicts between different materials during the matching process. The formula is:

$$MCI = \sum_{i \neq j} \left| \frac{R_i - R_j}{R_{max}} \right| \cdot SSIM(T_i, T_j) \tag{22}$$

In order to further enhance the personalization of design and user experience, user preference matching is introduced as an additional goal. By using historical user feedback data to establish a user preference model, an evaluation index for user aesthetic matching is constructed. User preference matching is calculated through collaborative filtering, and the formula is:

$$UAM = \frac{\sum_{k=1}^{m} W_k \cdot S_k}{\sum_{k=1}^{m} W_k} \tag{23}$$

In formula 23, $W_k$ is the user's preference weight for historical design solutions, and $S_k$ is the similarity between the current design solution and the historical solution in terms of multi-dimensional features.

The objective function is expressed as a weighted sum:

$$J = \alpha \cdot (1 - CHI) + \beta \cdot (1 - ECS) + \gamma \cdot MCI + \delta \cdot (1 - UAM) \tag{24}$$

## 4.2 Optimization Process

The pseudo code of the PSO optimization process is shown in Figure 3.

```
Input:
   N          ← Population size
   max_iter   ← Maximum number of iterations
   w          ← Inertia weight
   c1, c2     ← Cognitive and social acceleration constants
   DesignSpace ← Bounds of design variables (color combinations, material parameters)
Output:
   g_best     ← Best design solution found
   f(g_best)  ← Fitness value of the best solution
```

```
Begin
   // Initialization
   For each particle i = 1 to N do
      Initialize position x_i randomly within DesignSpace
      Initialize velocity v_i randomly
      Evaluate fitness f(x_i) using the multi-objective function J (incorporating CHI, ECS, MCI, and User Preference Matching)
      Set p_best_i ← x_i
   EndFor

   g_best ← particle with the best fitness among {p_best_1, p_best_2, …, p_best_N}

   // Iterative Optimization Process
   For iteration k = 1 to max_iter do
      For each particle i = 1 to N do
         // Update velocity
         v_i ← w * v_i + c1 * r1() * (p_best_i − x_i) + c2 * r2() * (g_best − x_i)

         // Update position
         x_i ← x_i + v_i

         // Boundary Check: Ensure x_i remains within DesignSpace
         x_i ← AdjustToBounds(x_i, DesignSpace)

         // Evaluate fitness for the new position
         f_current ← f(x_i)

         // Update personal best if current fitness is better
         If f_current < f(p_best_i) then
            p_best_i ← x_i
         EndIf
      EndFor

      // Update global best based on updated personal bests
      g_best ← particle with the best fitness among {p_best_1, p_best_2, …, p_best_N}

      // Check for convergence (e.g., minimal improvement or reaching maximum iterations)
      If ConvergenceCriteriaMet() then
         Break
      EndIf
   EndFor

   Return g_best, f(g_best)
End
```

**Figure 3. Pseudocode of PSO optimization process**

In this study, the PSO algorithm is used to search for the optimal soft decoration design scheme. In the initialization stage, a certain number of design schemes are randomly generated. Each scheme consists of a set of color combinations and material configurations. The scheme variables include the main color, auxiliary color and corresponding material parameters of each area. In this way, each particle represents a feasible design solution, forming the initial population. In the fitness evaluation phase, each particle is evaluated according to a predefined objective function, which comprehensively considers CHI, ECS, MCI and user preference matching indicators. The comprehensive fitness value of each design solution can be calculated. The evaluation results can serve as the "fitness" feedback of the particle in the search space, guiding the optimization process towards the design goal.

The particle update formulas are as follows:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (p_{best,i} - x_i^k) + c_2 r_2 (g_{best} - x_i^k) \quad (25)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (26)$$

In formula 25-26, $v_i^k$ and $x_i^k$ represent the velocity and position of particle i at the kth iteration, respectively. $\omega$ is the inertia weight, which controls the inertia of the particle. $c_1$ and $c_2$ are acceleration constants, which guide the particle to its historical optimal position $p_{best,i}$ and the global optimal position $g_{best}$, respectively. $r_1$ and $r_2$ are random factors used to increase the randomness and diversity of the algorithm, thereby preventing it from falling into the local optimum.

By repeating the steps of fitness evaluation and particle update, the PSO algorithm enters an iterative process until the stopping criterion is met: reaching a predetermined number of iterations or the fitness value converges.

## 4.3 Virtual Scene Construction and Realistic Rendering Based on Unity

In virtual soft furnishing design, three-dimensional scenes are built to simulate different types of home spaces, such as living rooms, bedrooms, kitchens, bathrooms, etc. Unity is used as a rendering and interaction platform, and professional modeling tools are used for detailed modeling to ensure the true restoration of the spatial structure. After the model is built, it is imported into Unity and the geometry, textures, and material mapping are optimized to ensure rendering quality and computational efficiency.

The 3D scene construction process is shown in Figure 4.

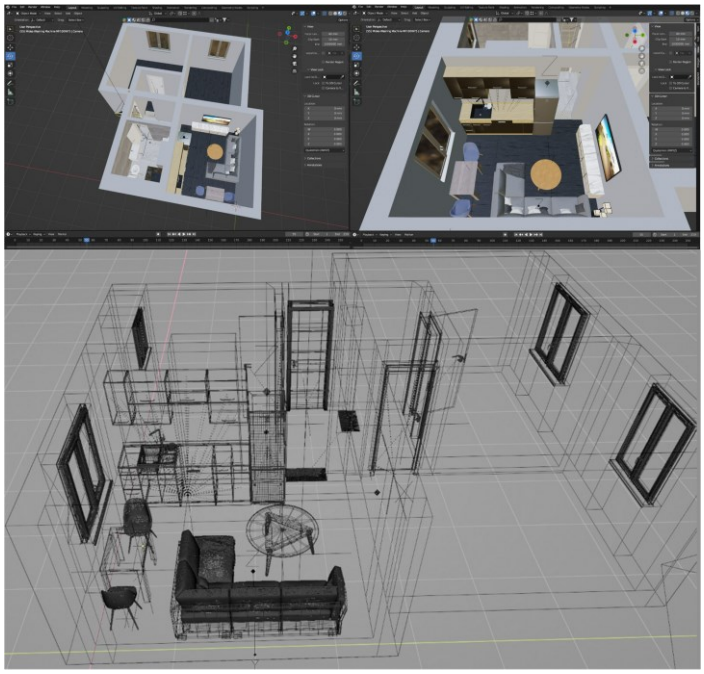


**Figure 4. 3D scene construction process**

Figure 4 shows the construction process of the 3D scene, including modeling, material mapping, and visualization of the structural wireframe. The two pictures in the upper part show the scene rendering view completed in the 3D modeling software. From a bird's-eye view, people can see the complete interior layout, including room structure, furniture placement, and material application. The right window provides rendering results from different perspectives, showing texture and lighting effects. The wireframe view in the lower part shows the geometric structure of the scene, highlighting the boundaries and vertex relationships of the model. This process combines modeling, material mapping, and rendering techniques to ensure the authenticity and aesthetics of the three-dimensional scene.

Based on the optimal soft furnishing design generated by the PSO algorithm, the calculated color matching and material parameters are accurately mapped to each soft furnishing element in the scene, such as sofas, coffee tables, curtains, TV cabinets, etc. Through Unity's material system and Shader processing, different materials can be realistically presented. Combined with color mapping rules, the color matching of each element is ensured to conform to the PSO calculation results to achieve optimal visual harmony.

Unity's built-in physically based rendering provides a material modeling method that conforms to real physical properties. By defining parameters such as glossiness, roughness, normal map, and reflectivity, soft furnishings can present realistic physical performance under lighting conditions. Smooth metal surfaces have high reflectivity, while the surface of fabric sofas presents a high-roughness diffuse reflection effect.

In order to improve the lighting effect of virtual scenes, global illumination is used to calculate indirect lighting, and real-time lighting and shadow technology is combined to enhance the interactive effect of light on different material surfaces. With the support of high-performance hardware, ray tracing technology is introduced to enhance the softness of shadows, the realism of light refraction and reflection, and make the overall vision more natural.

In order to further optimize the rendering output and make it conform to the laws of human visual perception, color management and Tonemapping technology are used for post-production adjustments. It ensures that colors remain consistent across different devices and lighting conditions, improves color expression by adjusting highlight compression and contrast, and enhances the visual beauty of the final rendered image.

# 5. Design Effect Evaluation

## 5.1 Feature Extraction Accuracy Evaluation

In order to study the accuracy of color feature extraction, ConvNeXt is compared with ResNet-50 (Residual Network-50), EfficientNet-B3, and ViT (Vision Transformer), and the color difference between the extracted color features and the original image color is calculated. The results are shown in Figure 5.

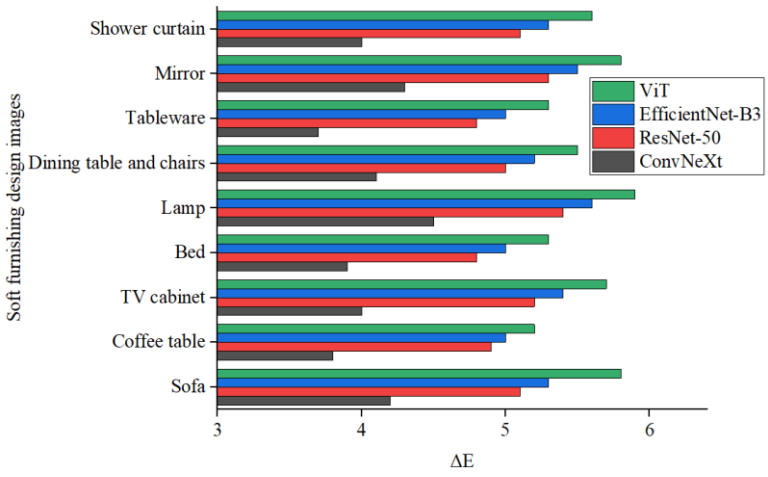



**Figure 5. Color extraction color difference**

The horizontal axis ΔE in Figure 5 represents the difference between the extracted color and the original image color in the CIELAB color space. The larger the value, the more obvious the color difference is. It is used to evaluate the accuracy of color restoration and matching. In the comparison of color feature extraction accuracy of soft furnishing design images, the ConvNeXt model has lower color difference than the ResNet-50, EfficientNet-B3 and ViT models in all categories (sofa, coffee table, TV cabinet, bed, lamp, dining table and chair, tableware, mirror, shower curtain). Taking the sofa as an example, the color difference obtained by ConvNeXt is 4.2, while ResNet-50 and EfficientNet-B3 are 5.1 and 5.3 respectively, and the color difference of ViT is up to 5.8; similar situations are reflected in other design objects. This shows that the ConvNeXt model has higher accuracy in capturing subtle color changes in images and can more accurately extract the color distribution information between the main color and the auxiliary color. The possible reason is that ConvNeXt introduces an improved convolution module and normalization strategy in the network structure, which makes it more sensitive to capturing low-level color features. At the same time, its deeper feature layer is also better at extracting global color information, thus gaining an advantage in color feature modeling.

In contrast, although ResNet-50 performs well in classic image classification tasks, its residual connection design is slightly insufficient in capturing color details; EfficientNet-B3 strikes a balance between computational efficiency and accuracy through a compound scaling strategy, but its accuracy in color feature extraction is slightly lower than ConvNeXt. Since ViT relies on the self-attention mechanism to model global information, it may have certain deficiencies in processing local subtle color changes, resulting in generally higher color difference values. The ConvNeXt model showed lower color difference values in this comparison, indicating that the difference between its extracted color features and the original image color is minimal, which is of great significance for the subsequent construction of color databases and optimization of soft furnishing design. The lower color difference value indicates the model's advantage in color restoration, which also means that it can provide more accurate data support in the automatic generation of color matching schemes.

The SSIM index is used to measure the texture similarity between the extracted material texture and the corresponding area of the original image. The results are shown in Table 2.

**Table 2. Texture similarity results**

| Soft furnishing design images | ConvNeXt | ResNet-50 | EfficientNet-B3 | ViT |
|---|---|---|---|---|
| Sofa | 0.92 | 0.89 | 0.88 | 0.87 |
| Coffee table | 0.93 | 0.90 | 0.89 | 0.88 |
| TV cabinet | 0.91 | 0.88 | 0.87 | 0.86 |
| Bed | 0.92 | 0.90 | 0.89 | 0.87 |
| Lamp | 0.93 | 0.91 | 0.90 | 0.88 |
| Dining table and chairs | 0.91 | 0.89 | 0.88 | 0.87 |
| Tableware | 0.90 | 0.88 | 0.87 | 0.86 |
| Mirror | 0.92 | 0.90 | 0.89 | 0.88 |
| Shower curtain | 0.91 | 0.89 | 0.88 | 0.87 |

In Table 2, for the texture similarity evaluation of different objects in soft furnishing design, the ConvNeXt model achieved the highest SSIM value in all test items, with the data ranging from 0.90 to 0.93, indicating that the material texture features extracted are highly consistent with the texture of the corresponding area of the original image. ResNet-50, EfficientNet-B3, and ViT have slightly lower SSIM values. SSIM is an indicator for measuring the consistency of local structure, contrast, and brightness of an image. The closer its value is to 1, the more similar the two images are in texture and structure. ConvNeXt can achieve a higher SSIM value, probably due to its improved convolution module and deeper feature expression

capabilities, which makes it more robust and accurate in extracting subtle texture features of images. In addition, ConvNeXt uses a more advanced normalization strategy and fine-grained feature fusion method when processing color and texture information, thus performing well in restoring the texture details of the original image.

Although ResNet-50 has achieved certain advantages in deep feature extraction by relying on residual connections, its original design focuses more on semantic information, and its ability to capture local texture details is slightly insufficient compared to ConvNeXt. EfficientNet-B3 has made better adjustments in the balance of network width, depth and resolution, but it still fails to surpass ConvNeXt in high-precision texture feature extraction. As for the ViT model, it has advantages in global feature modeling based on the self-attention mechanism, but its sensitivity to local texture information may be limited by the patch segmentation strategy, resulting in the retention of subtle texture information not being as delicate as that of traditional convolutional networks. A higher SSIM value indicates that ConvNeXt retains more original texture information in material texture feature extraction, and also reflects that it attaches more importance to local structure, contrast and edge details.

## 5.2 Color Matching Effect

This paper uses a fully automatic design method constructed by ConvNeXt, GMM and PSO to quantify the color and material features in the image. Feature extraction combined with manual design takes into account the aesthetic experience of data-driven and traditional design, and combines the extracted features with Munsell color harmony theory for design. Traditional manual design relies on the designer's experience and intuition. Comparing these three design methods, the color matching effect is shown in Figure 6.

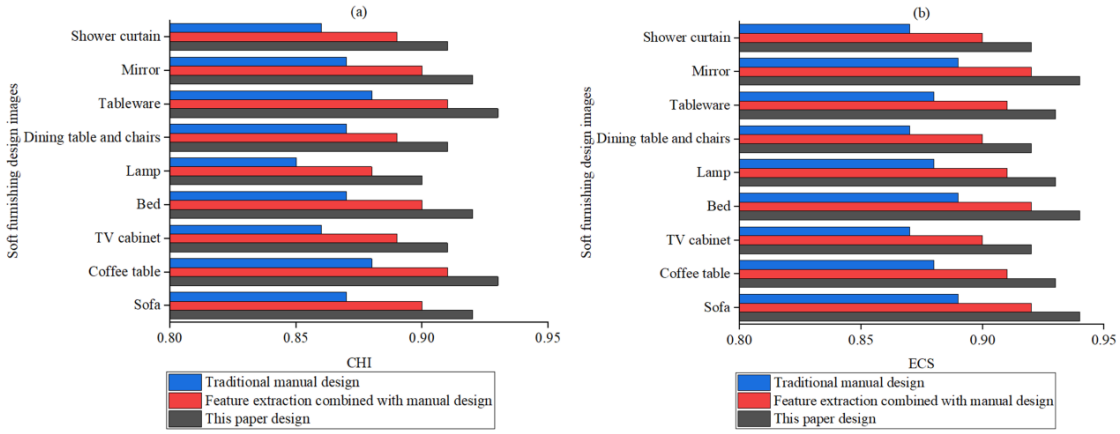



**Figure 6. Color matching effect. a) CHI result; b) ECS result**

In Figure 6 (a), the fully automatic design method constructed using ConvNeXt, GMM and PSO shows the highest CHI value on all kinds of soft decoration design images. The method of feature extraction combined with manual design is second, with a slightly lower CHI value, and the traditional manual design has the lowest CHI value. This shows that the design method in this paper can achieve more precise quantification and optimization in color matching, and make full use of deep learning models to capture tiny color differences in images. The color database can be established through the Gaussian mixture model to accurately distinguish the primary color and the secondary color, and then the PSO algorithm can be used to perform global optimization under multiple design objectives to obtain a matching solution with minimal color difference. In contrast, although the feature extraction combined with manual design method introduces Munsell's color harmony theory and corrects the automatically extracted features based on traditional aesthetics, it is still affected by the subjectivity of manual experience, making the color harmony slightly lower than that of the fully automatic method. Traditional manual design relies entirely on the designer's experience and intuition, and it is difficult to achieve precise quantitative adjustment in color matching. It is

easily restricted by personal style and aesthetic bias, and thus performs the weakest in the CHI index. This difference shows that data-driven fully automatic design has obvious advantages in color harmony evaluation. Its quantitative algorithm can more accurately grasp the color balance and proportion distribution in the design, and improve the overall matching effect and consistency.

The ECS index in Figure 6(b) also reflects the performance of different design methods in color emotional expression. The ECS values of the fully automatic design method on each category of images are maintained between 0.92 and 0.94. This method has advantages in color difference control and is closer to the expected emotional intensity in emotional expression, thanks to its fine extraction of color features and full use of color psychology data. Although the feature extraction combined with manual design method introduces the emotional intensity of Pantone color psychology as an auxiliary evaluation in emotional expression, its ECS value is slightly lower than the design in this paper, ranging from 0.90 to 0.92, because it still partially relies on manual experience in the later color and material matching design process. Traditional manual design is limited by the designer's subjective judgment and intuition in emotional color expression, and its emotional color matching often lacks a unified quantitative standard, resulting in ECS values generally lower than the automated method, maintained at a level of 0.87 to 0.89. The design method in this paper achieves the minimization of objective color difference through data-driven and intelligent optimization, and can accurately convey the emotional atmosphere required by the design by combining the emotional model. However, due to the lack of quantitative support, traditional manual design is easily affected by personal subjective factors, resulting in unstable emotional expression.

## 5.3 Material Matching Effect

The material conflict index is used to measure the material matching effect. The comparison results of this paper's design, feature extraction combined with manual design, and traditional manual design are shown in Table 3.

**Table 3. MCI comparison results**

| Soft furnishing design images | This paper design | Feature extraction combined with manual design | Traditional manual design |
|---|---|---|---|
| Sofa | 0.12 | 0.16 | 0.21 |
| Coffee table | 0.11 | 0.15 | 0.20 |
| TV cabinet | 0.13 | 0.17 | 0.22 |
| Bed | 0.12 | 0.16 | 0.21 |
| Lamp | 0.14 | 0.18 | 0.24 |
| Dining table and chairs | 0.13 | 0.17 | 0.22 |
| Tableware | 0.11 | 0.15 | 0.20 |
| Mirror | 0.12 | 0.16 | 0.21 |
| Shower curtain | 0.13 | 0.17 | 0.22 |

The lower the MCI value, the smaller the conflict between different materials in the matching process, and the more harmonious the overall matching effect. From the data in Table 3, it can be seen that the MCI value of the design method in this paper is significantly lower than that of feature extraction combined with manual design and traditional manual design in each design object. For sofas, the MCI of this design method is 0.12, while feature extraction combined with manual design is 0.16, and traditional manual design is 0.21; for lamps, the MCI of this design method is 0.14, while the other two design methods are 0.18 and 0.24 respectively. This trend is consistent in all test objects, indicating that the fully automatic design method shows higher compatibility and consistency in material matching. The design method in this paper is based on advanced technologies such as ConvNeXt, GMM and PSO. It

can accurately extract material properties (such as glossiness and texture features) in images and minimize the physical property differences between materials globally through data-driven optimization strategies. This method uses quantitative indicators to accurately capture the subtle differences between each material, achieves the best balance of material combinations through optimization algorithms, and significantly reduces the material conflict index. In contrast, although feature extraction combined with manual design draws on the guidance of traditional design theory on color and material, there are still certain subjective factors in the quantification and optimization of specific parameters, resulting in material matching accuracy slightly inferior to that of fully automatic methods. Traditional manual design relies entirely on the designer's intuition and experience. Its design results lack strict quantitative standards for material matching, which is prone to imbalance or conflict, and thus the MCI value is relatively high. In general, the design method in this paper has obvious advantages in material matching optimization. It can not only better balance the physical properties of different materials, but also achieve detailed global optimization, thus providing more scientific, accurate and efficient technical support for virtual soft decoration design.

## 5.4 Design Efficiency Analysis

The purpose of design time analysis is to quantify the time cost of the design process. The time comparison between the design, feature extraction combined with manual design, and traditional manual design in this paper is shown in Figure 7.

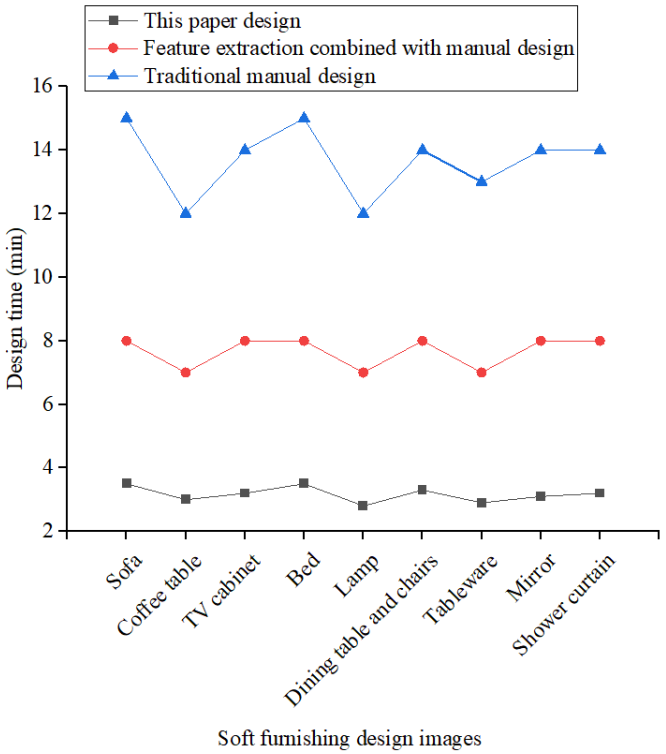



**Figure 7. Design time**

The design time of this paper is kept between 2.8 and 3.5 minutes, which is significantly lower than feature extraction combined with manual design and traditional manual design. This difference reflects that the design method of this paper greatly reduces the time of manual intervention in the design process through algorithm automation and data-driven methods, thereby achieving an efficient design process. The average design time for this design, feature extraction combined with manual design, and traditional manual design were 3.2 minutes, 7.7 minutes, and 13.7 minutes, respectively. Although feature extraction combined with manual design uses advanced image processing and intelligent optimization methods, and is guided by traditional design theories (such as Munsell's color harmony theory), it still

requires designers to manually calibrate and optimize the automatically generated solutions, so it takes nearly twice as long as fully automatic design. Traditional manual design completely relies on the designer's intuition and experience, and requires repeated discussions, experiments and adjustments, which significantly prolongs the design time. The design method in this paper has a relatively consistent time advantage on various design objects, and the time fluctuation is small, indicating that its process is highly standardized and automated, which is conducive to large-scale application and rapid iteration. The improvement in efficiency can shorten the project cycle, reduce labor costs, and enable the design solution to quickly respond to market and user needs in multiple optimization iterations, thereby enhancing the competitiveness of the design. Through this data comparison, it can be further proved that the data-driven fully automatic design method has significant advantages in improving design efficiency and reducing project costs, providing strong support for the intelligent development of soft decoration design.

## 5.5 Soft Decoration Design Display

Taking the kitchen space as an example, the soft decoration design effects of different design methods are shown in Figure 8.




**Figure 8. Soft furnishing design display. a) Original kitchen; b) Design in this paper; c) Feature extraction combined with manual design; d) Traditional manual design**

In the comparison of soft decoration design of kitchen space, the three design methods are optimized on the basis of the original kitchen color, but show different design styles and effects. The design of this paper uses intelligent algorithms to accurately extract color and material characteristics. Under the main tone of light yellow-white, the lighting design enhances the sense of space hierarchy and optimizes the placement of kitchen utensils to make the overall space more tidy and orderly. In addition, the design of this paper emphasizes the coordination of colors, and the matching of various materials is optimized through the material conflict index to ensure visual harmony and unity. In contrast, although the feature extraction combined with manual design method also uses lighting, the black main color of the selected lighting is somewhat inconsistent with the overall space, making the visual center of gravity more dispersed and affecting the overall aesthetics. Traditional artificial design focuses more on practicality, and the tableware and kitchen utensils are placed compactly, which makes the space utilization rate higher, but lacks in aesthetics and comfort. Overall, the design in this paper shows great advantages in color matching, space utilization, material coor-

dination, etc., achieving a good balance between functionality and aesthetics, and providing an optimization solution for the intelligent soft decoration design of kitchen space.

## 6. Conclusions

This paper studies and constructs an intelligent soft decoration design method based on ConvNeXt, GMM and PSO, which optimizes the matching scheme by accurately extracting the color and material characteristics of the space. The research results show that compared with traditional manual design and feature extraction combined with manual design, the proposed method shows better performance in multiple key indicators such as color harmony index, emotional color similarity and material conflict index, achieving higher color coordination, visual beauty and spatial adaptability. This paper combines deep learning and swarm intelligence optimization technology to provide a quantifiable evaluation system for intelligent design. By introducing a framework that combines data-driven and design aesthetics, it breaks through the limitations of traditional design that relies on experience and subjective judgment. This study promotes the development of intelligent soft decoration design, improves design efficiency, and provides technical support for personalized space optimization. However, this study still has some limitations, such as only conducting experiments on specific indoor spaces, not considering the applicability of more complex environments, and the ability to adapt to user personalized preferences still needs to be improved. Future research can further expand the scope of application of this method, combine augmented reality and virtual reality technology, improve the interactive experience of design solutions, and explore the application of deep reinforcement learning in soft furnishing design to achieve more intelligent and personalized optimization strategies.

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