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INTERIOR SCENE COLORING DESIGN MODEL COMBINING IMPROVED K-MEANS AND SAA

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Abstract. Due to technological progress and changes in people's aesthetic standards, traditional design models need to be constantly broken through, seeking more efficient and accurate design methods. Seeking effective design models to improve design efficiency and prediction accuracy is an important task. Therefore, this study proposes an indoor scene coloring design model that combines improved K-means clustering and simulated annealing algorithm for this important task. Based on the analysis of indoor scene coloring, particle swarm optimization algorithm is used to optimize K-means clustering to achieve color classification. Combined with simulated annealing algorithm, adaptive adjustment of lighting conditions is achieved to enhance the naturalness and realism of coloring. These results confirmed that the proposed method had the highest average F-value, with an average F-value of 92.524 and 143.601 on both datasets, respectively. The average ARI values were 0.361 and 0.897, respectively. The designed algorithm performed the best and converged faster than other three. Therefore, the proposed method can effectively ensure the consistency between the distribution of data objects after clustering and the actual situation. For indoor scene coloring design, it has important practical significance and provides new possible paths for improving design efficiency and prediction accuracy.

Key words: Scene coloring; K-means; SAA; Interior design; Color compatibility

1. Introduction. In the current digital era, Indoor Scene Coloring Design (ISCD) plays a crucial role in architectural design, film production, game development, and more [1]. With the rise of virtual reality technology and consumers' high requirements for visual experience, interior scene coloring design has become more complex and the demand has increased [2]. The color design of indoor scenes can not only affect the visual perception of viewers, but also to a certain extent affect their emotions and psychological states [3]. Traditional ISCD usually requires designers to invest a lot of time and energy, and requires rich color knowledge and good artistic aesthetics [4]. Studying an effective ISCD has important research value and practical significance, in order to reduce the workload of designers, improve design efficiency and quality [5]. With the growth of visual experience requirements, the demand for interior scene design also rises. The double pressure on designers is to quickly master emerging tools and technologies and build on them to increase productivity without sacrificing design aesthetics. This challenge has led to the need for an efficient interior scene coloring design model, which aims to reduce the burden on designers and improve the efficiency and quality of the design, which has far-reaching implications for research and practice. Based on this background, this study proposes an ISCD that combines improved K-means Clustering Algorithm (K-means) with Simulated Annealing Algorithm (SAA). The aim is to cluster colors using K-means to determine the main colors of scene, and then optimize colors using SAA to achieve better visual effects. This study innovatively combines two color processing techniques, taking into account both the distribution characteristics of colors and the visual effects of colors. In addition, the model also considers the characteristics of indoor scenes and can effectively design colors for different scenes. This design model not only provides a new ISCD method and new tools for designers, but also provides a new research direction for color processing technology research. The article hopes to have an important impact on interior design, movies, and games, and promote further development in these fields. The research will be conducted in four parts. The first is an overview of indoor scene coloring analysis. Next is the study of indoor scene coloring models that integrate Particle Swarm Optimization (PSO) to optimize K-means and SAA. The third part is experimental verification. Finally, there is a summary and outlook on the research methods and results of this study.

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2. Need of the Study. Interior scene coloring design is of great significance to enhance the aesthetic sense of space and functional practicability. In the existing research, K-means algorithm is widely used in color clustering because of its simplicity and efficiency, but it is sensitive to the initial cluster center and is easily affected by local optimal solutions. In contrast, SAA shows great potential in optimization problems with its global search capability, but the computational cost is high. Therefore, for interior scene color design, there is a need to improve the combination of K-means algorithm and SAA, aiming to improve the accuracy and efficiency of color clustering through hybrid algorithms, and provide a new color optimization tool for the field of interior design. Research in this area aims to address the limitations encountered when applying existing single algorithms to interior scene coloring design and explore the potential advantages of algorithm fusion for design results and performance.

3. Objectives of the Study. A coloring design model of indoor scene based on improved K-means algorithm and SAA is proposed. This paper aims to improve the selection mechanism of initial clustering center of K-means algorithm, reduce its dependence on random initial value, and improve the stability and accuracy of the algorithm. Secondly, SAA optimization process is introduced to overcome the limitation that traditional K-means algorithm is easy to fall into local optimal, and to enhance the optimization ability of the model in the global search space. Through the application of mixing algorithm, the color matching scheme of indoor scene is optimized to achieve uniform and harmonious color distribution. Finally, it is expected that the model can effectively improve the generation efficiency and quality of interior design color scheme, and provide a scientific decision support tool for interior designers in the development of color scheme. Through this research, we explore the application value and practical significance of algorithm mixing in the field of interior design.

4. Related works. The core of indoor scene layout design is the synthesis of indoor home scenes, which includes optimization of object selection, object placement, and style matching within the scene. Numerous scholars have actively studied indoor spatial layout. A Fahim et al. were committed to finding suitable k-values or improving the selection method of initial centers, using density-based strategies to obtain initial clusters. This strategy did not require predicting the clusters, but calculated the average value of each cluster object and used this information for k-means to improve the results quality. The preprocessing step adopted a density-based noisy application spatial clustering method, which could converge the results to the global minimum and improve the results quality [6].

Rezaee et al. explored a new k-means variant to cluster data through a bargaining game model. The competition between cluster centers attracted as many similar targets or entities as possible to their respective clusters. These experiments confirmed that it exhibited higher clustering accuracy based on eight evaluation indicators such as f-measure, Dunn, and Rand index [7].

Hu et al. proposed a K-means based on slimy flight trajectory. These experiments confirmed that LK-means had better search results and a more uniform distribution of cluster centroids, significantly improving global search capabilities and big data processing capabilities [8].

Zhao et al. proposed an iterative difference de-blurring algorithm based on LCL. The keys were to remove the contribution of OFL from the projection data, eliminate the blurring of IFL, and then use SAA to reconstruct the corrected projection. These experiments confirmed that this algorithm could achieve PLO reconstruction of LCL systems under extremely sparse sampling conditions and effectively reduce inter chip aliasing and blur [9].

M Ehsani et al. studied the multiple variables to predict the fracture failure of jointed plain concrete pavement. Four feature selection methods were developed by combining Multi-objective PSO (MPSO) with decomposition-based multi-objective evolutionary algorithm. These experiments confirmed that the model had the best performance and could identify 17 input variables that affect faults [10].

Indoor spatial layout is a key part that reflects the details of indoor scenes and has been widely used in various fields. In computer vision, indoor scene synthesis and layout design have overall color style compatibility. Numerous scholars have actively studied indoor scene synthesis. S Guo et al. proposed a representative view selection method using visual attention. A progressive method of integrating user preferences through eye tracking was used to support innovation and make convergent thinking possible. The validation experiment confirmed the effectiveness of this proposed view selection method, preference inference model, and innovation support mechanism [11].

Table 4.1: Symbol table

Symbol table	
$E_1E_2E_3$	Constraints on the target scene palette
$\lambda\ \mu$	Balance the corresponding weights of the three energy terms
C_i	Every furniture theme color
C_j	The fourth color of the target scene palette
P_j	The percentage of the corresponding color in the color palette extracted from the target scene
N_f	The total number of furniture in the scene
P_i	Furniture i category
P_j	Furniture j category
m_i	Furniture i color
m_j	Furniture j color
$C(P_i, P_j)$	The number of times furniture i and j simultaneously assign all colors in the color database
$C(P_i, P_j, m_i, m_j)$	The number of times furniture i and furniture j are simultaneously assigned to m_i and m_j colors
$C(m, n)$	Furniture i has the number of specific colors n in the color database
$C(n)$	The number of all available colors in the color database
T_0	Initial temperature
i	Current iterations
ρ	Temperature drop for each iteration
x_i	Coordinates for each signal sample
N	The number of samples of the signal
ω	Inertia weight
c_1c_2	Learning factor
r_1r_2	Represents random numbers between
$d(x_jC_i)$	The distance from particle x_j to particle swarm centerC_i
x_iz	The z component of the i sample point
x_ip	The p component in the i th sample point

Park et al. proposed a framework based on object detection and so on to derive furniture pairing principles. These experiments confirmed that images with high fidelity values matched existing style descriptions, proving that this framework could be used for indoor style image retrieval [12].

Solah et al. proposed an automatic adjustment of the texture and color of virtual indoor scene objects to match target emotions. Extracting features through deep learning could assist in the optimization process of automatically coloring virtual scenes based on target emotions. This method was tested in four different indoor scenarios and its effectiveness was demonstrated through user research and statistical analysis [13].

Ren et al. proposed a new digital lighting design framework that enabled users to automatically obtain visually pleasing lighting layouts and indoor rendered images. These experiments confirmed that the framework effectively learned guidelines and principles, and generated lighting designs that were superior to rule-based baselines [14].

Xie et al. analyzed 284 complete questionnaires using a mixed effects model. Compared to the baseline, biophilic design had improved people's perception of the office, especially in designs with daylight and visibility. This made the perceived office space brighter, more comfortable, and spacious, superior to indoor plant spaces [15].

In summary, this study delves into ISCD and provides a new perspective for understanding and solving color selection issues in interior design. There may be some computational pressure when processing large-scale data. Further optimization and adjustment may be required for specific types of indoor scenes. Therefore, the study proposes an ISCD that combines improved K-means with SAA, aiming to improve the efficiency and accuracy of processing complex color matching and distribution. The article aims to achieve more automated and personalized scene color design, improve design efficiency and quality.

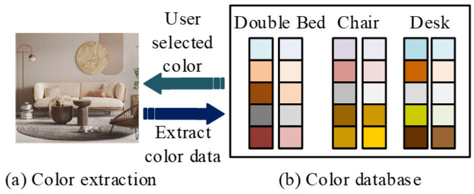


Fig. 6.1: Interior design furniture category color data extraction

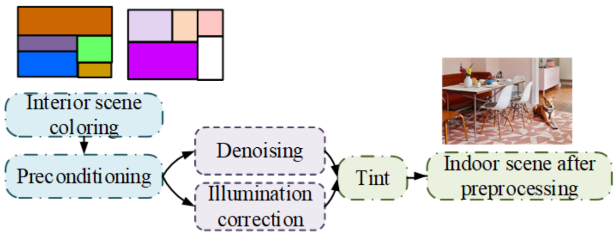


Fig. 6.2: Pre-processing of indoor scene coloring

5. Research Methodology. In the research methodology of indoor scene coloring design model, firstly, the improved K-means algorithm is adopted for color classification, and the initial clustering center is optimized by Particle Swarm Optimization (PSO) to enhance the stability and accuracy of the classification process. Then SAA algorithm is used to adjust the classification results to simulate the color changes under natural light, so as to improve the naturalness and realism of coloring. Through quantitative analysis of the visual effects of each color category and illumination conditions, the index of the algorithm optimization process can be quantified. Statistical methods such as cross-validation were used to evaluate the robustness of the model in order to ensure the scientific and reliability of the research results.

6. An indoor scene coloring model that integrates improved K-means and SAA. Deepening the analysis of indoor scene coloring can construct efficient and accurate coloring models. The indoor scene coloring model that integrates improved K-means and SAA emerges in this context. This model consists of two main parts. Firstly, the improved K-means is responsible for color classification, ensuring that various parts of scene can be reasonably divided, thereby giving more accurate coloring. Secondly, SAA adjusts lighting based on this to achieve a more natural and realistic visual effect. The fusion of these two algorithms aims to improve the rendering effect of indoor scenes by optimizing and improving traditional coloring methods, providing the possibility of achieving higher quality indoor scene coloring.

6.1. Indoor scene coloring analysis. Indoor scene coloring is widely used in the intersection of computer graphics and computer vision, aiming to achieve accurate and natural color rendering of indoor scenes through computer algorithms [16]. Currently, commonly used methods are color classification based on machine learning and lighting adjustment based on physical models. However, these methods often require a large number of computational resources, and their accuracy in processing complex scenes still needs to be improved [17]. Figure 6.1 shows the extraction of color data for interior design furniture categories.

Color data extraction in interior design is a composite study that integrates color theory, computer vision, and furniture design. By using computer algorithms and data analysis techniques, color information can be accurately extracted from different categories of furniture design, to conduct statistical analysis of the application trend of furniture color. Figure 6.2 shows the preprocessing of indoor scene coloring.

The preprocessing operations for indoor scene coloring mainly include geometric structure analysis of the scene, material feature recognition, and preliminary color classification. The application of preprocessing technology in interior scene coloring design involves advanced image analysis and color matching algorithm. Among

Fig. 6.3: Interior scene coloring process

them, image analysis technology subdivides the indoor scene into manageable areas by detecting the geometric structure of the space and object boundaries. At the same time, the color matching algorithm evaluates existing colors and suggests color schemes, taking into account factors such as light conditions and material reflectivity. These pre-processing steps provide the data foundation for the design model, enabling it to quickly identify and adjust the color distribution in the scene, laying a solid foundation for the subsequent design phase. The accuracy of preprocessing directly affects the effectiveness and performance of subsequent steps. By combining deep learning technology with traditional computer vision algorithms, the accuracy and efficiency of preprocessing can be improved. To ensure that the color combination of the entire indoor scene is compatible, energy minimization is used to represent the constraint problem of color satisfaction, and the corresponding energy function is constructed in equation 6.1.

$$E = E_1 + \lambda E_2 + \mu E_3 \tag{6.1}$$

In equation 6.1, E_1 , E_2 , and E_3 respectively represent constraints from the color palette of the target scene. λ and μ represent the corresponding weights for balancing the three energy terms, with a value of 0.5. For each furniture model in the scene, the difference between color theme and target color theme is calculated in equation 6.2.

$$M_k = \sum_{i,j=1}^{5} P_j \min \|\mathbf{C}_i - \mathbf{C}_j\|_2 \tag{6.2}$$

In equation 6.2, C_i represents the theme color of each furniture. C_j represents the j-th color of target scene's color palette. $\|\mathbf{C}_i - \mathbf{C}_j\|_2$ represents the color difference value between two sets of colors obtained by calculating the weighted Euclidean distance. P_j represents the percentage of corresponding colors in the color palette extracted from the target scene, representing the tendency of each color. Deep learning can improve the performance of each step. Figure 6.3 shows the indoor scene coloring process.

Indoor scene coloring usually includes key steps such as preprocessing, color classification, lighting adjustment, rendering, etc. [18]. Through preprocessing for scene analysis, geometric structures and object boundaries can be determined. By using machine learning and other methods to identify the colors of various objects, color classification can be achieved, providing a basis for subsequent rendering steps. Lighting adjustment will simulate the lighting of the scene based on the physical model, further improving the realism of the rendering effect. Equation 6.3 represents the energy term E_1 .

$$E_1 = \begin{cases} 0 & \text{if } N_f = 0 \\ \sum_k^{N_f} M_k & \text{if } N_f \neq 0 \end{cases} \tag{6.3}$$

In equation 6.3, N_f represents the total furniture in the scene. The energy term E_2 can evaluate the rationality of the combination of two furniture colors in indoor scenes, aiming at measuring the correlation between the problem color themes between the two furniture types, and its calculation is shown in equation 6.4.

$$E_2 = \frac{\sum_{i,j} C(p_i, p_j, m_i, m_j)}{C(p_i, p_j)} \tag{6.4}$$

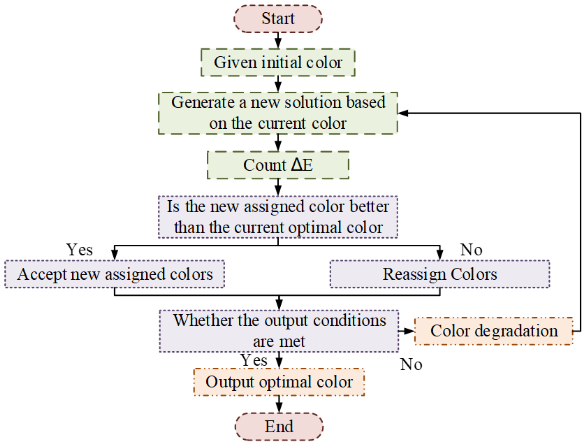


Fig. 6.4: SAA to solve the energy function flow of color allocation

In equation 6.4, p_i and p_j represent the category of furniture i, j . m_i and m_j represent the color of furniture i, j . $C(p_i, p_j, m_i, m_j)$ represents the frequency at which furniture and are simultaneously assigned to colors m_i and m_j. $C(p_i, p_j)$ represents the frequency at which furniture i and j simultaneously allocate all colors in the color database. Each furniture model selects the probability value of the corresponding color theme as the measurement standard. A low probability value indicates that the color is rare. Equation (5) is its calculation.

$$E_3 = \sum_i \frac{C_{(i,n)}}{C_{(i)}} \tag{6.5}$$

In equation 6.5, $C_{(m,n)}$ represents the number of furniture i with a specific color n in the color database. $C_{(n)}$ represents the number of all available colors for furniture i in the color database. This model improves the accuracy and efficiency of design through efficient processing and global search capabilities, providing new technical methods and reference basis for the field of indoor scene coloring.

6.2. An indoor scene coloring model that integrates PSO optimized K-means and SAA. PSO optimized K-means is used for color classification, dividing complex indoor scenes into different color regions to improve the accuracy of subsequent coloring. Combining SAA can achieve adaptive adjustment of lighting conditions, further improving the naturalness and realism of coloring. However, due to the complexity of indoor environments and the computational complexity of PSO and SAA, research has mainly focused on optimizing algorithm performance. So, it can reduce the demand for computing resources and improve algorithm applicability. Figure 6.4 shows the solution energy function of SAA for color allocation.

The energy function solving for color allocation is to use SAA to solve color allocation and achieve optimal color allocation by minimizing the energy function [19]. SAA is based on simulating the human visual system and adapting to different lighting environments to accurately reflect the true colors of the scene by adjusting color allocation. SAA is used in this experiment to find the optimal color allocation result. In the -th iteration, the probability of C_i' being accepted as C_{i+1} is represented by equation 6.6.

$$P_{(C_i' \to C_{i+1})} = \min\left[1, \exp\left(-\frac{(E(C_i') - E(C_i))}{(T_0 - \sigma_T \cdot i)}\right)\right] \tag{6.6}$$

In equation 6.6, T_0 represents the initial temperature. i represents the current iteration. ρ represents the temperature reduction value for each iteration. Clustering algorithm is an unsupervised learning method that can divide all data objects into several clusters without relying on data labels. The schematic diagram of K-means algorithm is shown in Figure 6.5.

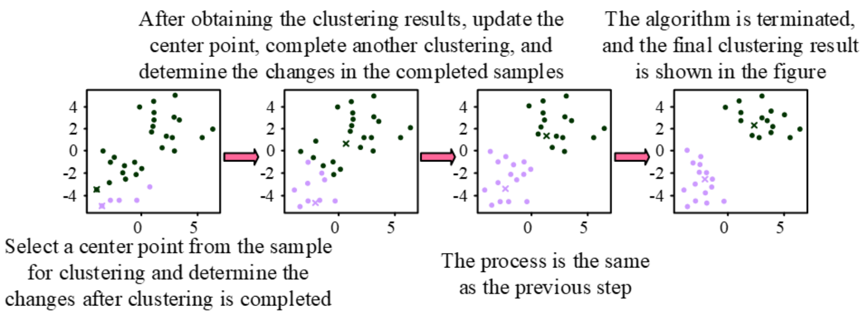


Fig. 6.5: Diagram of the K-means algorithm

K-means can partition a given dataset, making data points of the same category as similar as possible and data points of different categories as different as possible [20, 21]. The basic process includes four stages: initialization, clustering, update, and convergence. During initialization, the algorithm selects K data points as the initial category center according to certain rules. Clustering is the process of assigning each data point to the nearest category center. Update is to recalculate the center of each category based on the new category allocation results. During the convergence phase, if the change in the category center is less than the set threshold or reaches the preset number of iterations, the algorithm stops iteration. The clustering center point is selected using mathematical methods. Equation 6.7 is this algorithm's optimization function.

$$J = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \tag{6.7}$$

In equation 6.7, x_i stands for each signal sample's coordinate. μ stands for the cluster center point. N represents the sample size of signal. PSO is used to optimize it. For PSO population, the optimal location found can be recorded as the optimal location of PSO population, expressed by equation 6.8.

$$G_{\text{best}} = (P_{g1}, P_{g2}, \ldots, P_{gd}) \tag{6.8}$$

In equation 6.8, $g = 1, 2, \ldots, n$. In PSO, it is necessary to obtain the optimal individual position and the optimal group position. Equation 6.9 represents the update of particle swarm velocity and position in PSO.

$$\begin{cases} v'_{id} = \omega v_{id} + c_1 r_1 (p_{id} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \\ x'_{id} = x_{id} + v_{id} \end{cases} \tag{6.9}$$

In equation 6.9, ω represents the inertia weight value. c_1 and c_2 represent learning factors. r_1 and r_2 represent random numbers between [0,1]. To obtain the optimal solution, the sum of squared errors in equation 6.10 is used as the fitness function.

$$f(x) = \sum_{i=1}^{k} \sum_{x_j \in C_i} d(x_j, C_i)^2 \tag{6.10}$$

In equation 6.10, $d(x_j, C_i)$ represents the distance from particle x_j to the swarm's center C_i. If the objective function is small, the algorithm performs well. The indoor scene coloring system combining PSO optimized K-means with SAA is a new type of color rendering strategy [22]. This can achieve high-quality shading rendering of indoor environments through precise color classification and adaptive adjustment of lighting conditions. Figure 6.6 shows an indoor scene coloring system that integrates PSO optimized K-means and SAA.

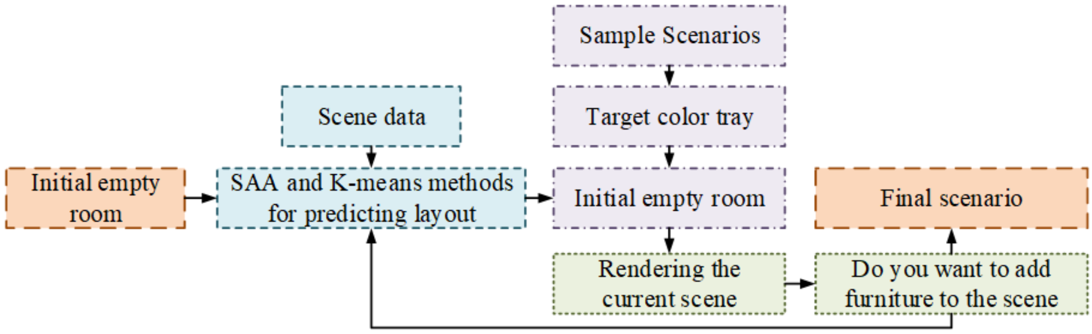


Fig. 6.6: The indoor scene coloring system by combining PSO optimized K-means with SAA

The K-means optimized by PSO is responsible for scene color classification, dividing complex indoor scenes into areas with similar color characteristics [23, 24]. SAA adjusts color allocation based on lighting conditions to achieve approximate simulation of the real environment [25]. The similarity between indoor samples is measured using Euclidean distance, and a small distance indicates sample similarity. Equation 6.11 represents the Euclidean distance between $x_i = (x_{i1}, x_{i2}, \ldots, x_{im})$ and $x_j = (x_{j1}, x_{j2}, \ldots, x_{jm})$.

$$d(x_i, x_j) = \sqrt{\sum_{s=1}^{m} (x_{is} - x_{js})^2} \tag{6.11}$$

In equation 6.11, x_i represents the m dimensional vector. To increase the degree of differentiation between data attributes, equation 6.12 represents the weight values of data from different dimensions.

$$\omega_{ip} = \frac{x_{ip}}{\frac{1}{n}\sum_{i=1}^{n} x_{ip}} \tag{6.12}$$

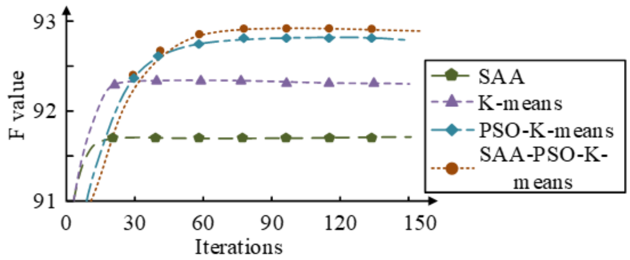
In equation 6.12, x_{ip} represents the p-th component in the i-th sample point. x_{ip} represents the average value of the p-th component of each sample point. This does not change the calculation of Euclidean distance in K-means and increases the differentiation between data features. This system has to some extent improved the effect of indoor scene coloring. It can still improve rendering quality when facing the complexity of the environment and the computational complexity of algorithms.

7. Indoor scene coloring model testing integrating PSO optimized K-means and SAA. To verify the reliability of ISCD and the effectiveness of the algorithm, an indoor scene synthesis system constructed by mixing K-means and SAA was tested and analyzed. The article aimed to assist non-professional users in efficiently completing interior design to meet the needs of layout and style. The hardware configurations required for system operation were processor of Intel®Core™i5-9300h CPU @2.40GHZ, 8GB RAM, graphics card of NVIDIA GeForce GTX1650 (4096MB graphics memory), and screen resolution of 1920*1080 (60Hz). In terms of software, the system was based on Windows 10 Enterprise Edition, using the 3D rendering tool Mitsuba to generate indoor panoramic images. The development tool was Visual Studio Code, and PyQt4 was used to display the system's graphical interface. Table 7.1 showed the experimental parameters.

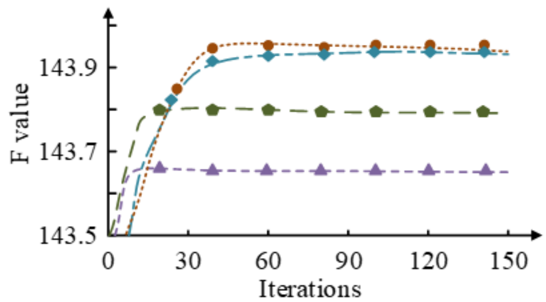
Table 7.1 listed some indoor scene coloring model data for the exploration and analysis of this research system. The experiment mainly tested the proposed SAA-PSO-K-means to obtain the parameters that could achieve the best clustering effect. Then it compared and tested SAA with K-means, PSO-K-means, and SAA-PSO-K-means on two text datasets. Several aspects such as clustering indicators, convergence, and stability were analyzed to verify this proposed algorithm's feasibility and effectiveness. Figure 7.1 showed the iterative results of different algorithms on datasets DS1 and DS2.

Table 7.1: Experimental environmental parameters

Parameter	Specification
Hardware	Intel® Core™ i5-9300h CPU @2.40GHZ processor, 8GB RAM, NVIDIA GeForce GTX1650 graphics card (4096MB VRAM), Screen resolution of 1920*1080 (60HZ)
Operating System	Windows 10 Enterprise Edition
3D Rendering Tool	Mitsuba for generating interior panorama
Development and GUI Tool	Visual Studio Code with PyQt4 for graphical interface



(a) Iterative Results of Different Algorithms on DS1 Datasets



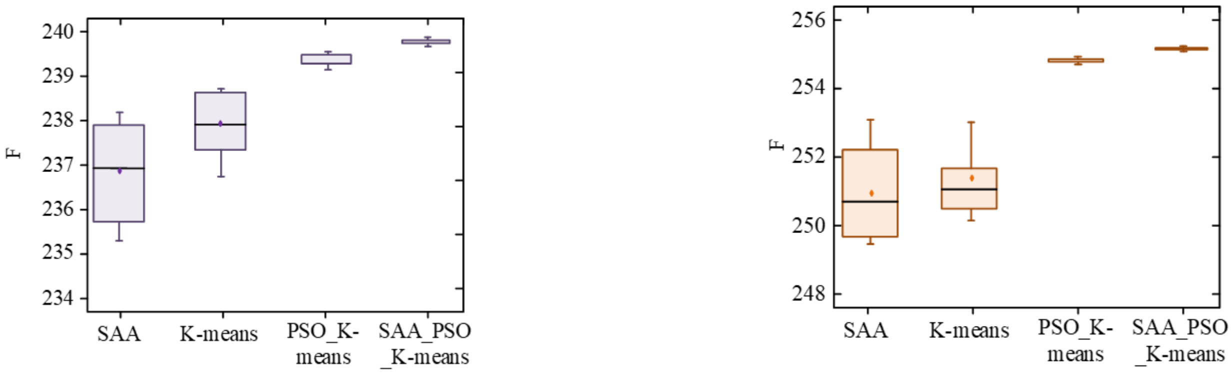
(b) Iterative Results of Different Algorithms on DS2 Datasets

Fig. 7.1: Different algorithms' iterative results on DS1 and DS2

In Figure 7.1, when iterating 30 times, SAA and K-means's convergence curves on two datasets were steep and rapidly tended towards lower stable values. Although they had the fastest convergence speed, their fitness F-values were all low, as low as 91.68 and 143.64. The convergence of PSO-K-means was relatively smooth, and the F-value steadily increased. The convergence curve of SAA-PSO-K-means was close and steep, but the F-value after convergence was high, reaching 92.85 and 143.94. Therefore, these four algorithms could achieve good F-values in the early stages of population evolution. In the 30-60 iterations, SAA and K-means continued to slowly trend towards better F-values. However, PSO-K-means and SAA-PSO-K-means gradually stabilized and almost completely stagnated near the highest F-value, with values of 92.58 and 143.93. After iterating 60 times, GAI-PSO began to stabilize, while other methods had converged completely. Therefore, SAA had obvious advantages in high-dimensional text clustering, and could quickly converge to the approximate optimal solution in the early population updating stage, demonstrating excellent optimization ability and operational efficiency. Figure 8 showed the F-value boxplot of different algorithms on DS1 and DS2.

Figure 7.2 shows a boxplot of F-values calculated after 20 independent runs of four algorithms on four datasets. The performance of SAA and K-means on the dataset was not stable. In Figure 7.2a, it ranged from 235.8 to 237.9, and in Figure 7.2b, it ranged from 249.8 to 252.2. Their F-values varied greatly and exhibited significant fluctuations. Volatility might affect the reliability and prediction accuracy of algorithms. For PSO-K-means and SAA-PSO-K-means, their performance on the four datasets was relatively stable, ranging from 239.3 to 239.4 in Figure 7.2a and 255.1 to 255.2 in Figure 7.2b. The smaller variance of its F-value verified that the performance of these two algorithms was more stable and the optimization effect was more reliable. Therefore, the proposed algorithm had a certain stability and optimization effect. Figure 9 showed different algorithms' ARI values on DS1 and DS2.

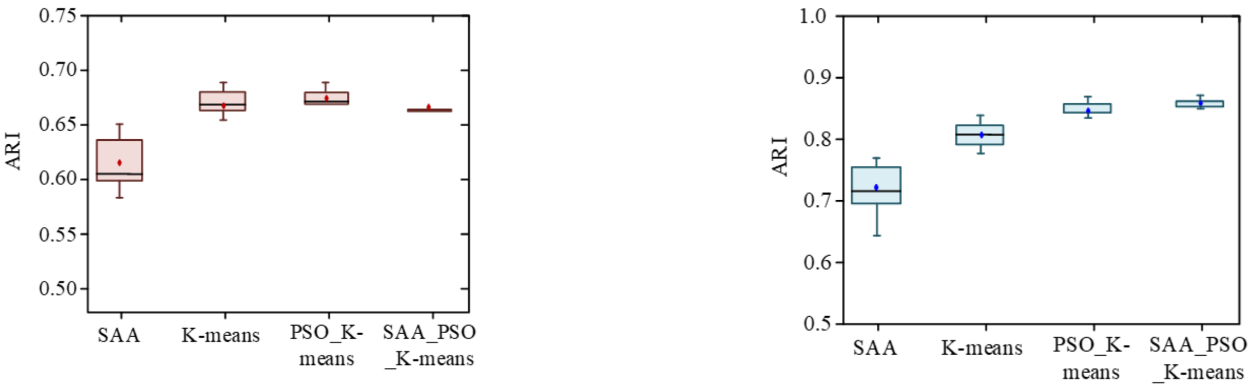
In Figure 7.3, on DS1, SAA-PSO-K-means displayed the most compact boxplot with the smallest variance on the remaining three datasets. The range in Figure 7.2a was 0.66 to 0.665, and the range in Figure 7.2b was 0.85 to 0.856. The result distribution of SAA-PSO-K-means was relatively concentrated, with small fluctuations,



(a) F-box plots of different algorithms on the DS1 dataset

(b) F-box plots of different algorithms on the DS2 dataset

Fig. 7.2: F-value boxplots of different algorithms on DS1 and DS2



(a) ARI Box Graph of Different Algorithms on DS1 Dataset

(b) ARI Box Graph of Different Algorithms on DS2 Dataset

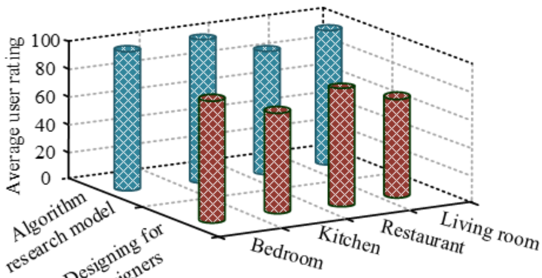
Fig. 7.3: Different algorithms' ARI values on DS1 and DS2

and the stability of this algorithm was good. SAA-PSO-K-means not only performed well in clustering accuracy, but also performed well in consistency between clustering results and real situations. Therefore, SAA-PSO-K-means was a relatively stable and efficient method. They could provide consistent and accurate clustering results in most cases, and had good adaptability to various types and sizes of datasets. Table 7.2 showed the average values of F and ARI for different algorithms in DS1 and DS2.

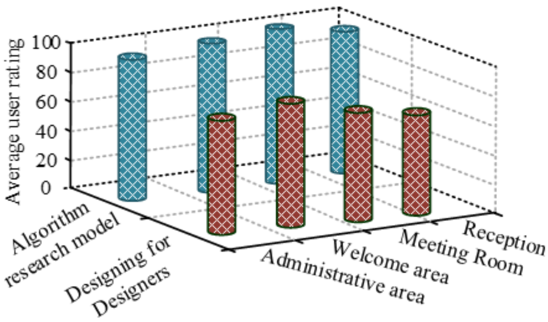
In Table 7.2, the average F-values of SAA, K-means, PSO-K-means, and SAA-PSO-K-means on DS1 were 91.106, 92.241, 92.283, and 92.524, respectively. On DS2, they were 143.437, 143.216, 143.587, and 143.601, respectively. Therefore, whether on DS1 or DS2, the average F-values of SAA-PSO-K-means were higher than other three algorithms. In terms of average ARI values, they were 0.359, 0.374, 0.346, and 0.361 on DS1, and 0.942, 0.914, 0.931, and 0.897 on DS2, respectively. In DS1, SAA-PSO-K-means performed the best, while in DS2, PSO-K-means performed better than other three. Therefore, SAA-PSO-K-means could achieve good fitness F-values and obtain good external clustering indicators. It could effectively ensure the consistency

Table 7.2: Different algorithms' F-values on DS1 and DS2 datasets

Dataset/Algorithm	SAA	K-means	PSO-K-means	SAA-PSO-K-means
Average F				
DS1	91.106	92.241	92.283	92.524
DS2	143.437	143.216	143.587	143.601
ARI average				
DS1	0.359	0.364	0.346	0.371
DS2	0.902	0.914	0.931	0.897



(a) User satisfaction results for living room types



(b) User satisfaction results for office area types

Fig. 7.4: User satisfaction results in different scenarios

between the distribution of data objects after clustering and the actual situation. To verify the effectiveness of the scene coloring algorithm, this study randomly invited 20 users to conduct a user evaluation survey. The spatial layout of living room types and office area types was provided, and some rendering scenes were presented to each investigator. Figure 10 showed users' satisfaction.

In Figure 7.4, the color beauty and richness of the scene are quantitatively evaluated. It is scored on a scale of 0-100, with higher scores indicating greater user satisfaction with the scene. Under this scoring system, the scene colored by the algorithm model gets a high evaluation. In Figure 7.4a, the satisfaction scores of the living room, dining room, kitchen and bedroom after the algorithm color adjustment reached 96.34, 95.58, 93.14 and 97.26 respectively, and the average satisfaction score of the solution provided by the algorithm model was 95.58. The average satisfaction score for hand-designed coloring schemes was 63.66. In Figure 7.4b, the satisfaction scores of the living room, dining room, kitchen and bedroom are 94.89, 95.77, 97.14 and 96.38 respectively, and the average user satisfaction of the algorithm model is further improved to 96.05. In the same scenario, the user satisfaction of the designer's solution was only 60.96 points. The effectiveness of the algorithm model in coloring scheme design is verified [26, 27, 28], and its objective score is better than that of traditional design methods, which shows the potential of the algorithm in improving user satisfaction in scene design.

8. Conclusion. Combining the efficiency of K-means with the global search ability of SAA can achieve higher accuracy and faster speed in completing indoor scene coloring design. Effective ISCD can improve design efficiency and prediction accuracy. Based on this background, this study proposed an ISCD that combined improved K-means with SAA. By combining improved K-means with SAA, the application effects of four algorithms in ISCD were compared and analyzed. These experiments confirmed that when iterating 30 times, the convergence curves of SAA and K-means were steep, but the fitness F-values were both low. Relatively speaking, the convergence of PSO-K-means and SAA-PSO-K-means was relatively smooth, but the F-value after convergence was higher. In the 30-60 iterations, SAA and K-means continued to slowly trend towards better F-values, while PSO-K-means and SAA-PSO-K-means gradually stabilized. After more than 60 iterations, all algorithms converged basically. Therefore, SAA had obvious advantages in high-dimensional text clustering and could quickly converge to the approximate optimal solution in the early population updating stage. SAA and K-means's performance was not stable, and the range of F-values varied greatly, showing significant fluctuations. For PSO-K-means and SAA-PSO-K-means, their performance was relatively stable, and the variance of F-values was smaller. This study provided a new design model for ISCD by combining K-means and SAA, which could effectively improve the accuracy and efficiency of the design. However, there are some shortcomings in this study. The performance of four algorithms is not completely stable, which may affect the reliability and prediction accuracy of the algorithms. Therefore, further research and improvement are needed to improve the stability of this design model combining K-means and SAA, and to further verify the effectiveness and feasibility of this design model.

9. Future Scope of the Study. In the follow-up research on the hybrid improved K-means and SAA indoor scene coloring design model, it is necessary to conduct in-depth analysis on the stability of the algorithm, explore the influencing factors and their internal mechanisms, optimize the parameter setting and structure of the algorithm, and improve the applicability and robustness of the algorithm in different indoor scenes. Secondly, the research focus is extended to the parallel processing of the algorithm, so as to shorten the large-scale data processing time and improve the practical application efficiency of the algorithm. In addition, the future research should also consider integrating more advanced optimization algorithms, such as genetic algorithm, ant colony algorithm, etc., for the comparative study of algorithm performance and further improvement of the model. Through cross-field collaborative research, the application potential of the algorithm in other aspects of interior design, such as material selection, furniture layout, etc., is explored, and the application scope of the model is expanded.

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