



Research on the development of 3D visualization system for indoor display optimization

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SUMMARY: *With the development of smart home, the demand for digital modeling and visualization of indoor space is increasing. To address the demand for indoor display optimization, the study combines WebGL and Unity3D to develop an indoor 3D visualization system. On this basis, in order to effectively annotate the layout relationship of indoor scenes, a coarse-to-fine spatial layout estimation method is proposed, and then the NSGA-II multi-objective genetic algorithm is applied to solve the spatial layout optimization problem of the dormitory with the effective active space utilization rate as the layout optimization index. Experiments show that, relative to other models, the indoor spatial layout estimation model in this paper has advantages in mIoU, MPA and PE global indexes, with results of 78.38%, 87.52%, 7.33% and 79.56%, 87.53%, 8.57% in the LSUN and Hedau datasets, and has good estimation efficiency. The performance of the indoor display optimization model on the dataset is also significantly better than the comparison method, which reflects the superiority of the model in the rationality of indoor space layout. The application of the method can effectively expand the indoor activity area, resulting in an effective activity space utilization rate of 56.3%, which is 1.2% to 4.0% higher than other methods. The proposed method can effectively solve the indoor space layout problem and realize the functional requirements of the 3D visualization system.*

KEYWORDS: *spatial layout estimation model; NSGA-II genetic algorithm; indoor display optimization; 3D visualization system*

1 Introduction

Interior display design, as a crucial component of interior design, directly impacts spatial efficiency and user experience quality [1, 2]. Traditional design primarily relies on designers' professional experience and subjective judgment. The “two-dimensional drawings + renderings” approach to interior design demands high spatial imagination from viewers, struggles to depict complex forms, and faces limitations such as lengthy design cycles, strong subjectivity, and insufficient precision when addressing diverse requirements [3-6]. The rapid advancement of 3D visualization technology has introduced new solutions for display design.

Interior design operates within three-dimensional space. The most intuitive way for designers to convey their intent and evaluate outcomes is through visual representations of this spatial context [7, 8]. Intelligent technologies enable data-driven 3D visualization of interior spaces. Combined with in-depth user needs analysis and automated layout generation, these

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tools provide robust support for enhancing design quality [9-11]. Advancements in software technology have matured and diversified 3D visualization techniques, expanding data from two-dimensional representations into spatial dimensions. This enables designers and clients to comprehend and analyze data more intuitively and realistically, enhances the visual impact of design drawings, and effectively boosts design efficiency while reducing costs and energy consumption. It also facilitates the preservation of documentation for subsequent operations, maintenance, and repairs [12-15].

In the field of interior decoration display design: Reference [16] developed an interactive 3D interior decoration system based on 3D scene modeling technology. This system can generate corresponding 3D scenes from 2D drawings to achieve interior decoration layouts. Reference [17] developed a mathematical model based on composite material properties using computer modeling techniques. It constructed indoor visualization scenes through computer graphics and virtual reality technology, and analyzed tensile test data to evaluate the decorative effects of composite materials in interior spaces. Reference [18] employs augmented reality technology for interior furniture layout design. Users can select desired furniture in stores and visualize its placement within virtual indoor spaces. Customers can review layout effects, enabling efficient and rapid interior furniture purchasing and arrangement. Reference [19] developed a 3D visualization application for indoor furniture using augmented reality within a multimedia development lifecycle methodology. Users can rearrange interior items via a mobile app to achieve ideal furniture layouts.

Regarding material and lighting design: Literature [20] indicates that with 3D visualization technology, interior designers can use 3D sketches to communicate requirements with clients and suppliers, while showcasing material effects to facilitate client material selection. Reference [21] employs generative AI tools, enabling interior designers to instantly search for interior decoration materials, colors, and textures. These can be integrated with 3D scene modeling for material selection and texture mapping. Reference [22] leverages Building Information Modeling (BIM), Virtual Reality (VR), and head-mounted displays to create a lighting design feedback prototype system. This system simulates lighting scenarios, continuously adjusts relevant parameters, and generates design solutions that meet both indoor lighting requirements and energy-saving objectives.

Regarding overall interior display design and decision communication: Reference [23] reconstructs interior landscapes using 3D modeling technology, presenting them as floor plans. Edge matching methods analyze floor plan features to construct 3D visual effects, which are then optimized for visual appeal, landscape color coordination, and spatial utilization through adaptive tracking and rendering techniques. Reference [24] developed an application for architects and interior designers based on home design concepts. It integrates markerless and marker-based augmented reality (AR), 3D modeling, and interactive technologies to visualize 2D drawings in 3D, enabling online design discussions. Reference [25] integrates neural style transfer algorithms, augmented reality, and virtual reality overlay technology to establish an interior design presentation model. Users can conduct visual and auditory virtual inspections of interiors with the model's assistance. Reference [26] employs 3D computer software and virtual reality technology to realistically simulate furniture layout, color schemes, materials, and lighting arrangements in interior design. Clients can engage in immersive virtual experiences to aid decision-making on design proposals. Reference [27] shares a Hippocampus-optimized multi-functional convolutional neural network algorithm for detecting innovative residential interior design data. It performs data preprocessing through image standardization, incorporates virtual reality technology to enhance the virtual environment for interior layout design, and combines deep Q-learning networks to optimize the positioning of display components

including spatial layout, color coordination, decorative item selection and arrangement, and lighting. Reference [28] employs deep convolutional neural networks and image processing techniques to generate three-dimensional panoramas incorporating various components (walls, furniture, decorations) from perspectives including geometric features, lighting effects, and material rendering. Design adjustments are made based on different component parameters.

The study proposes a 3D visualization system for room display optimization, and introduces the relevant technologies for its system implementation. Based on the spatial layout optimization function of the system, a coarse-to-fine spatial layout estimation method is developed, which organically integrates the global features of the depth-aware whole image and the traditional area-level features based on the individual area facets in the spatial layout of the room, in order to optimally select a large number of scene candidate layouts. After obtaining the spatial art layout data of the indoor environment, the indoor display optimization model is constructed to measure the use of personnel activity space in the indoor space through the utilization rate of effective indoor activity space, design the relevant objective function and constraints, and solve the problem by using the NSGA-II multi-objective genetic algorithm. The LSUN dataset and Hedau dataset are selected to carry out experiments on the spatial layout estimation method, and the spatial layout estimation effect of the modeling method is verified by comparing it with other semantic segmentation methods and other indoor spatial layout estimation related research methods, as well as by analyzing the number of parameters and inference time. Then the indoor display optimization model and other models are used to carry out the task of generating bedroom and living room layouts and compare the results of each index. Finally, take a four-room dormitory of a university as an example, use the model to generate its indoor display optimization scheme, explore the space utilization rate of each model-generated scheme, and verify the feasibility and superiority of this paper's method.

2 Three-dimensional visualization system for indoor display optimization

2.1 Overall system design

The research area of this paper is mainly indoor space, focusing on constructing indoor scenes and publishing them as WebGL content so that the system can be run and displayed on the browser side, and the user can observe the indoor space intuitively, interactively, and freely without any limitation. The main functional requirements of the 3D visualization system for indoor display optimization include:

(1) Constructing a realistic virtual indoor scene to simulate the real indoor environment, and constructing the important entities in it, which can be optimized for the display of these important entities.

(2) To be able to realize the human-computer interaction operation of the scene as well as the third-person roaming function through input devices such as mouse and keyboard.

(3) Smoothly run the prototype system in the Web front-end.

The necessary process of experimental realization mainly includes selecting Unity3D development environment as the basic development platform, importing external model data to carry out scene construction based on hierarchical model in Unity, integrating it and publishing it as WebGL content, and debugging and building optimization framework to optimize it, and the specific technical process is shown in Figure 1.

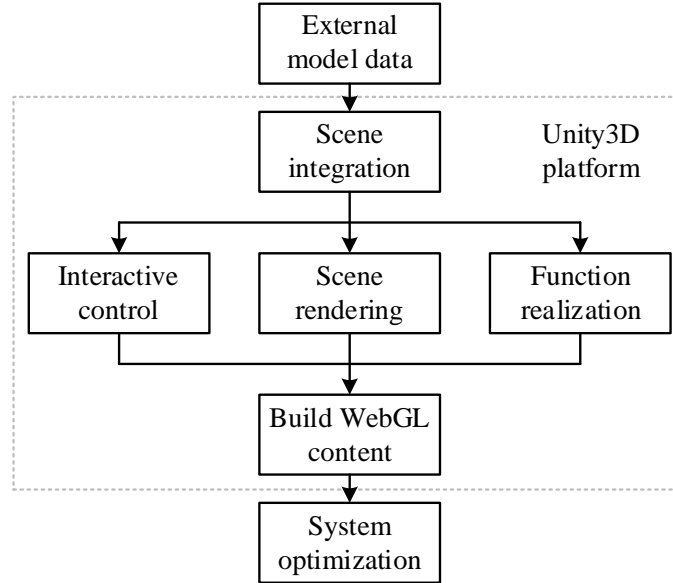


Figure 1: System implementation technology process

2.2 System implementation

2.2.1 Indoor Model Construction and Scene Generation

The indoor scene model is the basis for building the system, which is crucial to the construction and even the performance of the system at runtime. Since there is no mature, stable and efficient solution for image-based 3D reconstruction, we consider using modeling software to construct the 3D geometric model of the scene as well as adding materials and textures to enhance the performance effect. After the 3D model is constructed, it is imported into the Unity development environment for scene integration. Considering the complexity of the indoor 3D scene, the efficiency of the external model imported into Unity is slow, and the distribution of the 3D model after import is scattered, difficult to integrate and so on, it is impractical to directly construct the 3D model of the whole indoor environment. In this paper, by drawing on the industrial base class standard, the standard division of the indoor area, the establishment of the indoor environment framework model, hierarchical 3D indoor scene generation: that is, respectively, the import of important entities of the three-dimensional model, through the hierarchical model in the Unity environment for organization.

After the virtual scene is created, we first need to set the light source according to the specific needs of the scene and calculate the real-time shadows through the light source and the material, so as to make the space get a more realistic display effect. Add a virtual camera to simulate the observation of the real-time scene world, the camera is responsible for the observation of the three-dimensional content of the projection to the two-dimensional screen for rendering, in the experiments to choose closer to the real world, with a sense of disappearance and the sense of distance of the perspective camera for the rendering of the indoor three-dimensional scene.

2.2.2 Web indoor 3D scene interaction system

After constructing the basic 3D indoor scene in Unity3D development environment, we utilize various 3D graphic objects encapsulated by Unity3D engine and various graphic interfaces provided by Unity3D engine and combine them with C# scripts to implement the system

function modules. After the realization of the basic functions, we start to build the WebGL standard-based Web terminal project in the development environment.

Combined with the general interactive logic, we use the mouse wheel to pan the scene, the mouse wheel to scroll to zoom the scene, the right mouse button to rotate the angle, double-click the right mouse button to return to the center of the scene, and use the CameraFollow script to complete the above operations and attach the script to the main camera. Third-person perspective by using the keyboard keys to complete the scene roaming function to improve the user's sense of participation, the keyboard keys can generate an event will be converted to the corresponding control commands to control the roaming character, W/S/A/D or up and down, left and right keys correspond to the character's forward, backward, and left, right movement, use PlayerMovement script to complete the above function code and add it to the character. Use PlayerMovement script to complete the above function code and add it to the character. After confirming the functions and passing the debugging, we start to build the WebGL content in the development environment and publish it, the main process is as follows:

Step 1, select WebGL in the platform list of build options, and choose whether to build the project as a release version.

Step 2, streamline the WebGL code by removing some components, native engine code or third-party plug-ins in Unity3D that have nothing to do with the project during the build to streamline the code.

Step 3: Set up the release settings, such as the memory size allocated for the Web project, whether to throw exceptions when the script is running, and so on.

When publishing, Unity will package and publish the finished project into an html file, a folder with template resources and loading toolbars, and a folder with project output files. After publishing, deploy the project in the web server (or local cross-domain call) and access the specified file in the project directory through the browser to open the web system.

3 Interior space layout estimation and display optimization methods

In order to realize the display optimization function of the indoor scene 3D visualization system, this paper first researches the indoor spatial layout estimation method, obtains the basic data of indoor environmental spatial layout, and then constructs the indoor spatial layout optimization mathematical model by using the NSGA-II multi-objective genetic algorithm to realize the indoor display optimization.

3.1 Estimation model of indoor space layout

Before the layout optimization process, with the goal of understanding the current spatial art layout of the indoor environment, this study proposes to apply to deep learning technology to construct a coarse-to-fine indoor spatial layout estimation model.

3.1.1 Coarse Selection of Candidate Layout Items Based on Global Feature Sensing

(1) Candidate layout generation based on improved vanishing rays

First, a number of long straight line segments in the scene are detected using the local discontinuity adaptive thresholding method, and the detected straight line segments are classified into vertical and horizontal categories according to the orientation attributes of the straight line segments. Then, a voting scoring mechanism is used to calculate the contribution score to the vertical vanishing point for the group of straight line segments in the vertical

direction, and the vertical vanishing point p_1 is estimated. Then the group of linear segments in the horizontal direction is estimated according to the orthogonality principle and the voting scoring mechanism, and the horizontal and projection direction vanishing points p_2 and p_3 are obtained, from which the normalized vanishing point estimate $p = \{p_1, p_2, p_3\}$. By p_1 and p_2 respectively, the rays are induced to the room scene image at equal angular intervals and sampled, and the division of the area surface is determined according to the ray intersection result, so as to generate a number of spatial candidate layouts of indoor rooms.

(2) Global feature perception based on fully convolutional neural network

In this paper, the VGG-16 FCNN model is utilized to directly estimate the boundaries of the scene layout. In view of the possible existence of layout boundaries between each area face such as floor, left wall, center wall, right wall and ceiling, the pre-trained and fine-tuned FCNN model is used to predict the informative boundary IE, which is used as a global layout-aware cue to constrain the boundary location of the spatial layout.

Based on the possible existence of the five regional facets in the scene layout and the a priori knowledge of the scene categories in the LSUN dataset, the scene layout can be categorized into 11 types. Thus, the scene layout categories are introduced as another global layout perception cue, and a softmax classifier is used to classify the fc7 fully connected layer features extracted by the FCNN model, and maximize the normalized probability values of each scene layout category to predict the scene layout categories of the image. This estimation process is regarded as a multi-valued problem solving process with a loss function:

$$\begin{aligned} L_{scene-type}(\theta) &= -\sum_{i=1}^k \delta(c-i) \lg p(c=j|x;\theta) \\ &= -\sum_{i=1}^k \delta(c-i) \lg \frac{e^{\theta_j^T x}}{\sum_{l=1}^k e^{\theta_l^T x}} \end{aligned} \quad (1)$$

where x is the fc7 layer feature of the input image, c is the scene category baseline annotation corresponding to the image, k is the total number of scene layout categories, θ is the model parameter of FCNN, and $\delta(\cdot)$ is the impulse function.

(3) Fusing global cues to coarsely select candidate layouts

For any generated candidate layout, let s_1 be the overlap rate between the layout boundary obtained in (1) and the informative boundary obtained in (2), and s_2 be the accuracy of the corresponding probability value normalized with respect to the individual layout categories in section (2), and then the total score of each of its candidate layouts is written as $s = \alpha_1 \times s_1 + \alpha_2 \times s_2$, $\alpha_1 + \alpha_2 = 1$. Due to the strong global sensing ability of FCNN, it is recommended to increase the α_2 weights, and $\alpha_1 = 0.26$ and $\alpha_2 = 0.74$ are selected in the experiment. The total scores of the candidate layouts are sorted from high to low, and a number of higher-scoring layouts are retained to coarsely select the spatial candidate layouts.

3.1.2 Fine-grained regional feature-induced spatial layout estimation

(1) Perceptual extraction of fine-grained area-level features in scene layout

In view of the limited appearance features such as color and texture, geometric information such as normal vector and depth are introduced into the regional features of the scene layout (i.e., straight line segment membership feature f_{lm} , geometric context feature f_{gc} , normal

vector feature f_{nv} and depth feature f_d). A spatial multi-scale convolutional neural network is used to estimate the multi-scale normal vector map and depth map corresponding to the input image based on the length of the estimated vanishing point, and the corresponding normal vector features and depth features are extracted by appropriate transformations.

Assuming that the normal vector map in the image scene with height and width of h and w respectively is a 3-channel $N_{h \times w \times 3}$, to transform it into a 5-channel normal vector feature $F_{h \times w \times 5}$, the pixel point $n = (n_1, n_2, n_3) \rightarrow f_{mv} = (f_1, f_2, f_3, f_4, f_5)$ the mapping relationship is represented by equation (2). The 3-dimensional normal vector of a pixel at any point in the scene represents the normal vector direction of the plane in which it is located. Given that the pixel points with backward direction are occluded by the pixel points with other directions, only the pixel points with valid left, right, front, up and down directions are taken, then:

$$\begin{cases} f_1 = -\beta_1 \cdot n_1, & \text{if } n_1 < 0 \\ f_2 = \beta_1 \cdot n_1, & \text{if } n_1 > 0 \\ f_3 = -\beta_2 \cdot n_2 \\ f_4 = -\beta_3 \cdot n_3, & \text{if } n_3 < 0 \\ f_5 = \beta_3 \cdot n_3, & \text{if } n_3 > 0 \end{cases} \quad (2)$$

where β_i denotes the weight given according to the size of the absolute value of $n_i (i = 1, 2, 3)$, the larger the absolute value means the stronger the corresponding directionality, so it is given a larger weight.

(2) Structured modeling of scene layout and model inference

The maximum angle supported by the vanishing ray induced by the scene vanishing point is used to parameterize the 3D box layout consisting of the ground F_1 , the left wall F_2 , the middle wall F_3 , the right wall F_4 and the ceiling F_5 . The corresponding region-level features of the candidate layout y are aggregated based on geometric integral images, and the parameters of the scene layout model are learned using maximally spaced structured regression method w . Let x be an RGB appearance image and $y_i = \{F_1, F_2, F_3, F_4, F_5\}$ denote the corresponding baseline 3D boxed layouts, the mapping relation $f(x, y; w) = w^T \Psi(x, y)$ denotes that the model parameter w structuring the score of candidate layout y . where $\Psi(x, y)$ denotes the region-level features such as linear segment membership f_{lm} , geometric context f_{gc} , normal vector f_{nv} , and depth f_d corresponding to a single candidate layout y . Training is performed using the cut-plane structured learning method to optimally solve the model parameters w that satisfy Eq. (3). Solving the mapping relation $f(x, y; w) = w^T \Psi(x, y)$ can be transformed into:

$$\begin{cases} \min_{w, \xi} \frac{1}{2} \|w\|^2 + C \sum_i \xi_i & \text{s.t. } \xi_i \geq 0 \\ \forall i, w^T \Psi(x, y_i) - w^T \Psi(x, y) \geq \Delta(y_i, y) - \xi_i \\ \forall i, \forall y \in Y / y_i \end{cases} \quad (3)$$

where ξ_i denotes the slack variables, C denotes the constants, $\Psi(x, y_i)$ denotes the feature vectors generated by the benchmark labeled layout y_i corresponding to the image x , and Y is the state space of all the layouts. Based on the similarity between the candidate layout y and the baseline labeled layout y_i , the measure between any candidate layout y and the baseline labeled layout y_i is quantified by the loss function $\Delta(y_i, y)$.

Given a test image x , the model parameters w are obtained using the training mapping relation $f(x, y; w)$ to maximize its structural prediction score to estimate the spatial layout of the indoor scene:

$$y^* = \arg \max_y f(x, y; w) \quad (4)$$

The best candidate layout is selected as the final indoor scene layout from the set of coarsely selected candidate layouts. The higher the similarity between the scene candidate layout and the baseline layout, the higher the corresponding structured score of the candidate layout.

3.2 Indoor display optimization model

3.2.1 Effective space utilization for activities

The layout of indoor space is essentially a question of the interrelationship between containers (space) and belongings (indoor facilities). The advantages and disadvantages of the layout effect are related to the size of the effective activity space of the personnel on the one hand, and the convenience of the personnel's activities, the comfort of the environment, and the support of the indoor facilities on the other hand. In this paper, the data indicator of effective activity space utilization rate is used to evaluate the use of indoor personnel activity space.

Effective indoor activity space refers to the spacious and continuous activity space after removing the space occupied by furniture and facilities, and the small space around furniture and facilities that cannot be utilized. The larger the indoor effective activity space is, the smoother the activities of the personnel will be carried out, and vice versa, the space will be confined and the activities will be limited. Effective activity space can be expressed by its corresponding ground area. In order to facilitate the comparison of the use of effective activity space under different space layouts, this paper introduces the evaluation index of effective activity space utilization:

$$E = \frac{S}{A} \quad (5)$$

where: S is the ground area corresponding to the indoor effective activity space, and A is the total indoor ground area.

From equation (5), it can be seen that the value of E should be between 0 and 1. The larger the value of E , the higher the utilization rate of the indoor effective activity space, and the better the effect of the program.

The effective indoor activity space area is:

$$S = A - S_1 - S_2 \quad (6)$$

where: S_1 is the sum of the floor area corresponding to the space occupied by the furniture

and facilities, and S_2 is the sum of the floor area corresponding to the narrow space around the furniture and facilities that cannot be utilized. S_2 consists of two parts: (1) the floor area corresponding to the space that cannot be accessed by people, and (2) the floor area corresponding to the space that can be accessed by people but where they are unable to carry out effective activities.

The layout of indoor space includes space, furniture, and their mutual relations and requirements. These relationships and requirements are the constraints of the layout. The convenience of personnel activities and environmental comfort should be considered from multiple perspectives, such as indoor furniture configuration, furniture placement, and personnel's psychological needs. Therefore, this paper adopts NSGA-II multi-objective genetic algorithm to establish a mathematical model for indoor space layout.

3.2.2 Objective function

(1) Furniture that does not interfere with each other and is separated from each other by a larger distance is described by $F_1(x)$:

$$F_1(x) = \sum_{i=1}^n \sum_{j=1}^n (x_i - x_j)^2 \quad (7)$$

where: x_i, x_j is the positional parameter of the furniture with requirements on interference distance, and n is the total number of furniture with requirements on interference distance.

(2) In the case of a certain indoor area, the number and size of furniture, the area occupied by furniture and activity areas are certain. The design is to maximize the utilization of the central area for personnel activities, and $F_2(x)$ is used in this paper to describe the distance of this activity:

$$F_2(x_2) = \sum_{i=1}^n w_i (x_i - x_a)^2 \quad (8)$$

where: w_i is the importance weight coefficient of the area corresponding to each furniture in the interior space layout design, and $\sum_{i=1}^n w_i = 1$, and x_n is the location parameter of the center of the activity area.

3.2.3 Design variables

In this paper, the design variable is defined as the positional parameter $X_i (i = 1, 2, \dots, n)$ of the furniture, viz:

$$\begin{aligned} X &= \langle X_1, X_2, \dots, X_n \rangle \\ &= \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \end{aligned} \quad (9)$$

where: x_i is the x -coordinate ($i = 1, 2, \dots, n$) of the genus i , y_i is the y -coordinate ($i = 1, 2, \dots, n$) of the genus i , and i is the number of the furniture, and in this study we take $n = 16$.

3.2.4 Constraints

The indoor space optimization layout constraints mainly involve the following three categories:

(1) Furniture layout is mainly subject to the constraints of indoor space, which can not exceed the boundaries of the indoor space, but also to meet the positional relationship between neighboring furniture that has requirements on distance, i.e.:

$$\begin{cases} \frac{s_i}{2} \leq x_i \leq L - \frac{s_i}{2} \\ \frac{q_i}{2} \leq y_i \leq W - \frac{q_i}{2} \\ |x_i - x_j| = d_{xij} \\ |y_i - y_j| = d_{yij} \end{cases} \quad (10)$$

where: (x_j, y_j) is the positional parameter ($j=1,2,\dots,n$) of the furniture, s_i, q_i are the dimensions of the furniture i in the direction of x, y , d_{xij} and d_{yij} are the distance requirement between the furniture i and j between the distance requirements in the x and y direction, L and W for the room length and width, respectively.

(2) The furniture in the room do not interfere with each other, can not appear staggered:

$$\begin{cases} |x_i - x_j| \geq \frac{s_i + s_j}{2} \\ |y_i - y_j| \geq \frac{q_i + q_j}{2} \end{cases} \quad (11)$$

where: s_j, q_j are the dimensions of furniture j in the x, y direction, respectively.

(3) Ensure that each piece of furniture does not interfere with the access of people, the constraint is:

$$\begin{cases} |x_i - x_d| \geq \frac{s_i + L_d}{2} \\ |y_i - y_d| \geq \frac{q_i + W_d}{2} \end{cases} \quad (12)$$

where: x_d, y_d is the positioning parameter of furniture relative to the door, and L_d, W_d is the length and width of the door.

The above indoor space layout optimization design model takes the maximum utilization rate of effective indoor activity space as the goal, and at the same time considers the convenience of people's activities, environmental comfort and facility support, and combines with suitable optimization algorithms to carry out the optimization design of indoor space layout.

4 Experimental results and analysis

4.1 Estimated analysis of interior space layout

4.1.1 Introduction to the data set

Currently, in the study of indoor spatial layout estimation, the LSUN and Hedau datasets are mainly used for training and validation of network models. The LSUN dataset is an image scene understanding dataset, which contains image data from eight indoor scene categories such as bedrooms, living rooms, classrooms, dining rooms, and offices, and is one of the important benchmark datasets in the field of computer vision. The Hedau dataset is an image dataset for scene understanding, which is mainly used for the research of object detection and scene segmentation, and covers a total of 10 object categories and 11 room types, including floor, wall, ceiling, door, window, TV, desk lamp, bookshelf, chair, table, bed, bathroom, kitchen, etc.

In this paper, the network is mainly trained by the LSUN dataset, while the Hedau dataset is not involved in the training process and is mainly used to further evaluate the generalization performance of the network model.

4.1.2 Evaluation indicators

In order to fully evaluate the spatial layout estimation performance of the network model in this paper as well as the comparison with other models, this paper adopts the evaluation metrics that are commonly used in the field of image semantic segmentation: intersection and merger ratio (IoU), mean intersection and merger ratio (mIoU), pixel accuracy (PA), mean pixel accuracy of the categories (MPA) and overall pixel error (PE). Compared to MPA, PE relatively ignores the problem of poorer accuracy of some small categories and better reflects the overall spatial layout estimation effect of the model.

Where IoU denotes the ratio of the intersection and concatenation of the set of predicted true values and the set of predicted values for each category, and mIoU denotes the average value of IoU for each category. pa denotes the ratio between the number of pixels predicted to be correctly categorized and the total number of pixels, which can be used as a measure of the categorization accuracy of the dataset, and MPA is the average of the pixel accuracies of all the categories. pe denotes the proportion of the pixels that occupy the total number of pixels in the global prediction error. ratio. The values of the above five evaluation metrics are all in the range of 0-1. For IoU, mIoU, PA, and MPA, the closer their values are to 1, the better the model is, while the closer the PE value is to 0, the better the model is.

4.1.3 Comparative tests

In order to verify the effectiveness of the method proposed in this paper, as well as to compare the performance difference of other methods. This paper focuses on three sets of comparison experiments on LSUN and Hedau data: first, the method model proposed in this paper is compared with the widely used semantic segmentation algorithms, and comparison experiments are done with FCN, PSPNet, and DeepLabV3+, respectively. The second is to compare the method model proposed in this paper with other indoor space layout estimation research methods. Third, the number of parameters and inference time of each model are compared.

(1) Comparison with other semantic segmentation models

The IoU comparisons of each model on LSUN and Hedau datasets are shown in Fig. 2 and Fig. 3, where DeepLabV3+1, DeepLabV3+2, DeepLabV3+3 denote DeepLabV3+ models with different Backbone (ResNet-50, Xception, MobileNetV2). The PA pairs of each model on LSUN and Hedau datasets are shown in Figures 4 and 5. The mIOU, MPA and PE values of

each model on LSUN and Hedau datasets are shown in Table 1.

Compared with other semantic segmentation models, this paper's method is overall better than each comparison method in terms of IoU and mIoU evaluation metrics, and the DeepLabV3+ model is better than the FCN and PSPNet models. Evaluated on the LSUN dataset using the mIoU metrics, this paper's model outperforms the FCN, PSPNet, and DeepLabV3+ (three backbone networks) models by 8.22%, 5.68%, 3.28%, 3.04%, and 2.67%, respectively. Evaluated on the Hedau dataset using the mIoU metric, this paper's model outperforms the FCN, PSPNet, and DeepLabV3+ (three backbone networks) models by 9.99%, 8.09%, 7.14%, 4.26%, and 2.39%, respectively.

On the LSUN dataset, the global evaluation metrics MPA and PE obtained by this paper's model are 87.52% and 7.33%, which are better than FCN, PSPNet, DeepLabV3+ (three backbone networks) models by 8.31%, 7.61%, 6.19%, 3.50%, 2.48% and 55.20%, 44.55%, 38.40%, respectively, 29.38%, and 26.33%. On the Hedau dataset, the MPA and PE obtained by this paper's method are 87.53% and 8.57%, which outperform the FCN, PSPNet, DeepLabV3+ (three backbone networks) models by 8.41%, 7.48%, 6.13%, 3.22%, 2.51% and 40.44%, 29.87%, 21.01%, 14.47%, respectively, 10.82%. In addition, on the evaluation index PA, the segmentation ability of the model proposed in this paper in each specific category is also ahead of the comparison method, and the layout estimation effect on indoor scene space has obvious improvement.

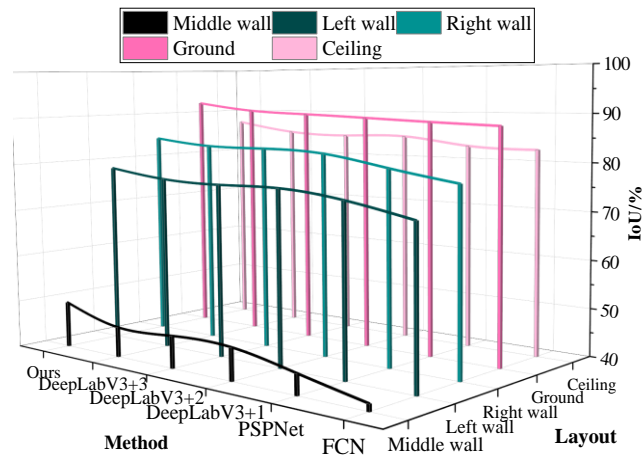


Figure 2: Comparison of IoU of each model on LSUN datasets

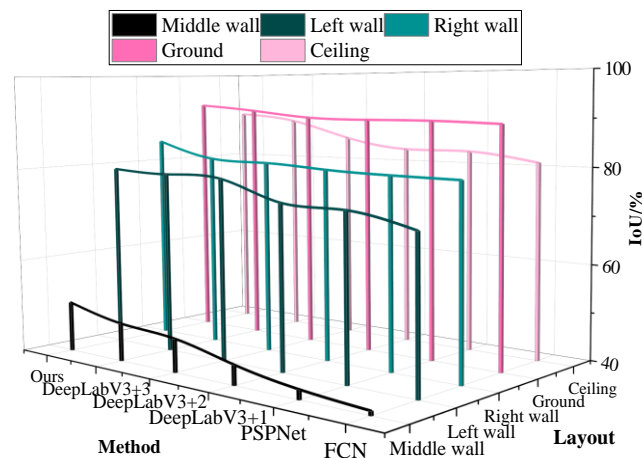


Figure 3: Comparison of IoU of each model on Hedau datasets

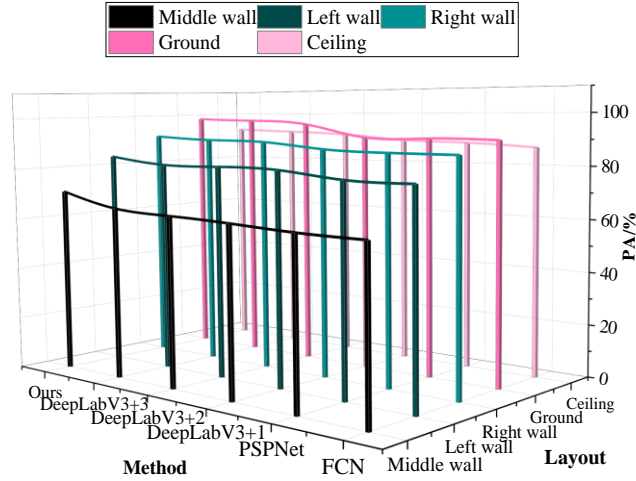


Figure 4: Comparison of PA of each model on LSUN datasets

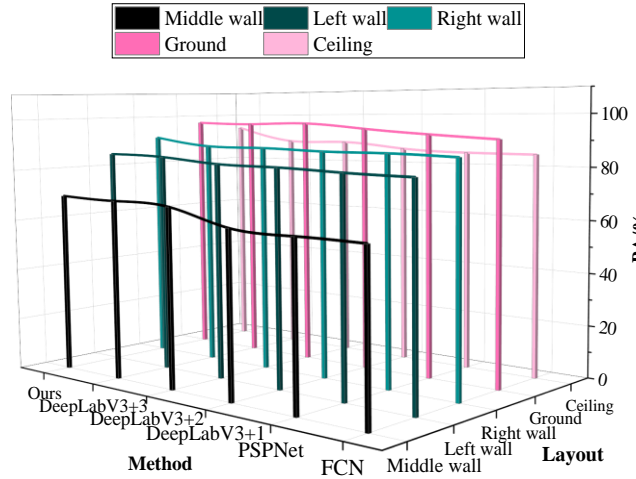


Figure 5: Comparison of PA of each model on Hedau datasets

Table 1: Comparison of mIoU, MPA, PE of each model on 2 datasets

Method	mIoU/%		MPA/%		PE/%	
	LSUN	Hedau	LSUN	Hedau	LSUN	Hedau
FCN	72.43	72.34	80.81	80.74	16.36	14.39
PSPNet	74.17	73.61	81.33	81.44	13.22	12.22
DeepLabV3+1	75.89	74.26	82.42	82.47	11.9	10.85
DeepLabV3+2	76.07	76.31	84.56	84.80	10.38	10.02
DeepLabV3+3	76.34	77.70	85.40	85.39	9.95	9.61
Ours	78.38	79.56	87.52	87.53	7.33	8.57

(2) Comparison with other indoor space layout estimation research methods

In addition, the PE metric was utilized to quantitatively compare this paper's model with other indoor spatial layout related research works, and Table 2 demonstrates the performance of the different methods on pixel errors on the LSUN dataset and the Hedau dataset. The network model proposed in this paper performs the best on the PE evaluation metrics, achieving a pixel-level error rate of 7.85% on the LSUN test set, and on the Hedau dataset, the method of this paper also possesses a good prediction effect, obtaining the lowest pixel error of 7.21%. Therefore, the network model can be applied to different indoor scene datasets, even without

retraining new data, which further validates that the model has good generalization ability as well as scalability.

Table 2: Comparison of this paper's model with other related research methods on PE

Method	PE(%,LSUN)	PE(%,Hedau)
Hedau	22.97	21.39
Mallya	18.87	14.64
Dasgupta	15.21	12.49
CFILF	12.15	10.15
Lee	10.25	9.44
Martin	8.32	8.16
Aopeng	8.01	-
Ours	7.85	7.21

(3) Comparative analysis of the number of parameters and inference time of network models

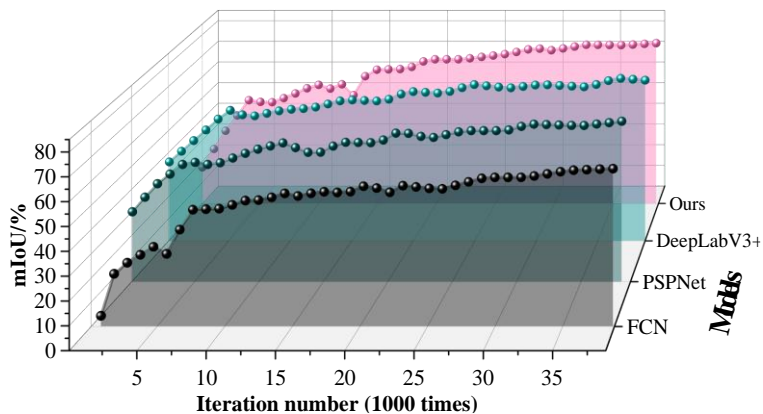
In order to further compare the size of each network model and the speed of indoor layout estimation, the number of parameters and the inference time are chosen as evaluation indexes. The number of parameters (Parameters/M, 10⁶) and the inference time (Prediction Time/ms) calculated by each network model are shown in Table 3. Compared with other network models, the method in this paper has a significant reduction in the number of parameters, the number of parameters is 5.56×10⁶M, and also has a significant improvement in the computing speed, the inference time is 24.36ms.

Table 3: Comparison of the number of parameters and inference time for each network model

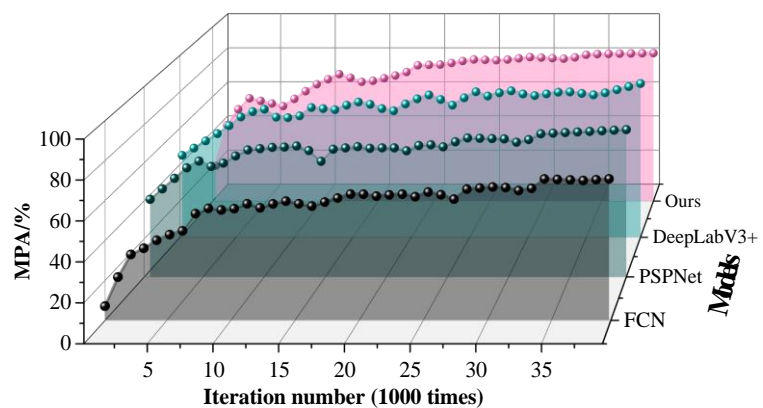
Method	Backbone	Parameters(M,10 ⁶)	Prediction Time(ms)
FCN	ResNet-50	48.41	42.78
PSPNet	ResNet-50	46.34	41.69
DeepLabV3+	ResNet-50	43.19	47.49
DeepLabV3+	Xception	53.03	46.24
DeepLabV3+	MobileNetV2	6.04	25.17
Ours	VGG-16	5.56	24.36

4.1.4 Comparison of training processes

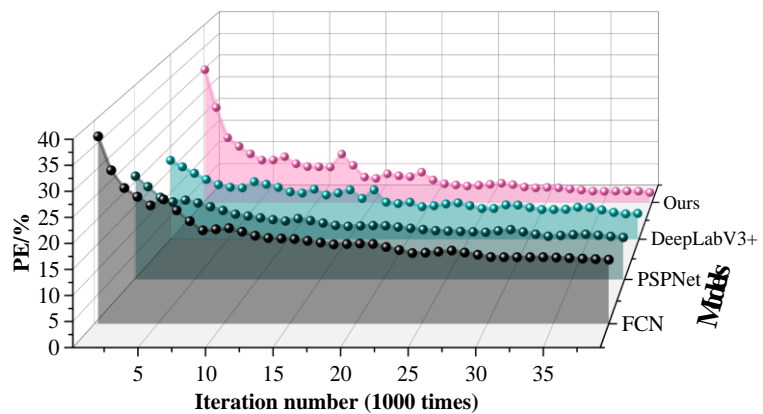
The changes of mIoU, MPA and PE of FCN, PSPNet, DeepLabV3+ and the proposed model in this paper during the training process are shown in Fig. 6(a)~(c), respectively. As a whole, this paper's model performs the best in all three evaluation indexes, and the advantage of PE is the most prominent, which are all ahead of the other methods. mIoU, MPA and PE of this paper's model finally reach 75.93%, 85.02% and 2.23%, respectively, as the number of iterations increases.



(a) mIoU/%



(b) MPA/%



(c) PE/%

Figure 6: Comparison of the mIoU, MPA and PE during the training process for each model

4.2 Indoor display optimization analysis

4.2.1 Data sets

The 3D-FRONT dataset is used as the basic data source for the algorithm implementation, which is a large-scale indoor 3D scene dataset designed for research in the fields of interior design, object recognition and virtual reality. In terms of data partitioning, the dataset is divided

into training, validation and test sets according to the ratio of 7:1:2. The dataset contains more than 10,000 rich and diverse indoor scenes, and each scene is equipped with a detailed 3D model and its related physical information.

4.2.2 Comparative tests

Four representative algorithms, ATISS, DiffuScene, LEGO-Net, and PhyScene, are selected for comparison, and all these methods have achieved remarkable results in the field of indoor 3D scene layout generation. In this paper, the indoor display optimization model based on NSGA-II multi-objective genetic algorithm is comprehensively evaluated on the 3D-FRONT dataset. Considering the dominant position of the bedroom and the living room in the indoor 3D scene dataset, this paper focuses on the two types of high-frequency scenes to carry out in-depth analysis and evaluation.

(1) Bedroom Scene

The comparison test results of the bedroom scene are shown in Figure 7. This paper's method achieves the lowest scores in FID, KID, SCA, COL_{wall} , and COL_{obj} , which are 25.64, 1.69×10^3 , 49.05%, 0.29, and 0.235, respectively, and achieves superior performance in each key index. The indoor scene generated by this paper's method has a more reasonable layout, the furniture can all fit the wall, and the details are optimized in a more appropriate way, which fully demonstrates the reasonable relationship between the nightstand and the bed, the chair and the table, and thus more realistically restores the indoor bedroom 3D scene.

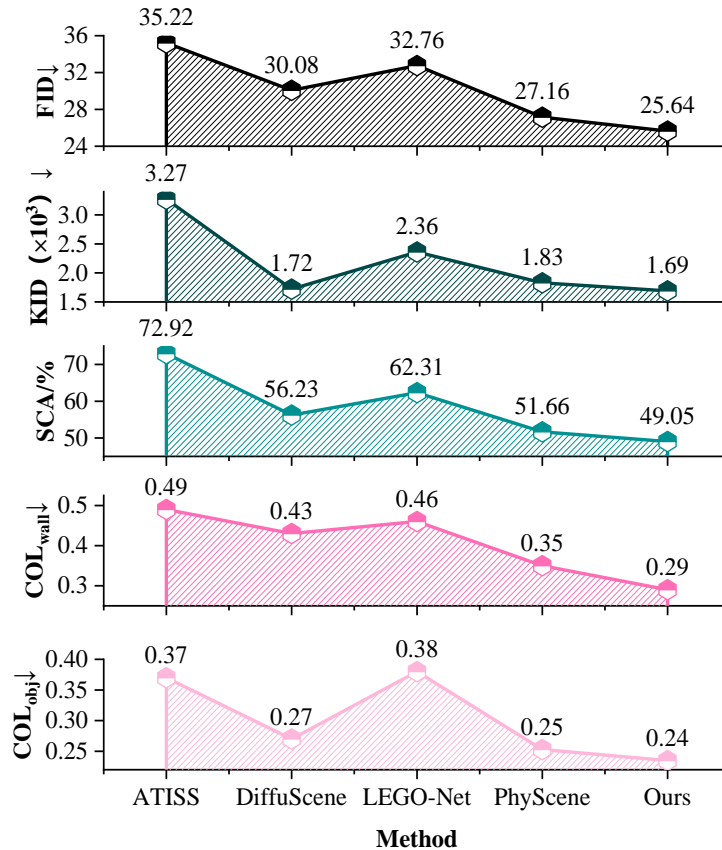


Figure 7: Comparison test results of bedroom scene

(2) Living room scene

The results of the comparison test for the living room scenario are shown in Figure 8. In the

living room scene evaluation, this paper's method performs well in several key indicators and shows a more balanced performance. First, in terms of the FID index, this paper's model achieved 36.73, which is 1.82 lower than the next best method PhyScene (38.55), which indicates that the overall visual quality of the generated indoor scene is closer to the real data. In terms of SCA metrics, the value of this paper's model is closest to 50%, at 50.96%, indicating that its generated scenes are more reasonable in terms of spatial arrangement of furniture and more compact in layout. It reaches 1.34×10^3 , 0.36 and 0.23 on KID, COL_{wall} and COL_{obj}, respectively, which are better than other methods.

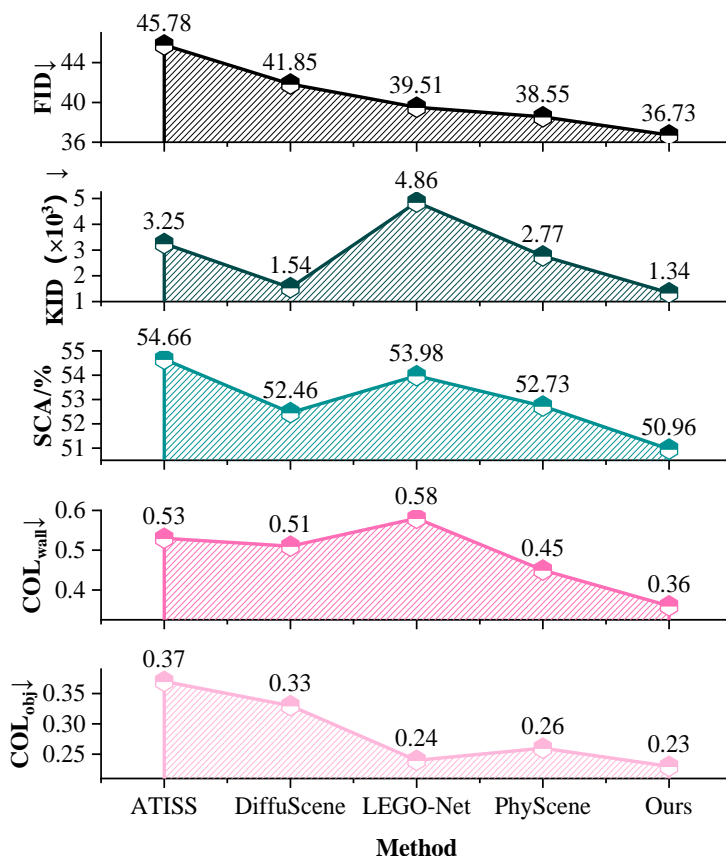


Figure 8: Comparison test results of the living room scene

4.2.3 Optimization examples

In order to test the feasibility of the indoor display optimization method proposed in this study, a four-room dormitory of a university is taken as an example for indoor environmental spatial art layout optimization processing.

After determining the current spatial art layout situation of the indoor environment, the proposed method of this paper is applied to carry out the layout optimization processing. Based on NSGA-II multi-objective genetic algorithm for optimization solution, the iteration curve shown in Figure 9 is obtained. After 50 iterations, the iteration curve stabilizes, representing that the solution result of the Kosei mirror genetic algorithm is at the optimal value at this time. Statistics at this time the output of the indoor environmental space art layout optimization scheme, to get the optimized layout parameters as shown in Table 4. After the layout optimization, the beds, desks, bookcases and closets are unified to make full use of the vertical space area, thus reducing the furniture footprint and expanding the personnel's daily access and interaction activities area. At the same time, the closet and bookcase are placed under the beds,

which is also convenient for students to use at any time without worrying about affecting fellow residents. Overall, the design optimization method in this paper is feasible and can achieve the expansion of effective activity space.

In order to reflect the superiority of the optimization method more intuitively, the dormitory furniture occupancy area is calculated after the optimization of spatial layout, and the indoor effective activity space utilization rate is obtained. ATISS, DiffuScene, LEGO-Net, PhyScene methods were used for layout optimization, calculate the indoor effective activity space utilization rate after the optimization of the five methods, and compare the calculation results with the optimized results of the proposed method, and the spatial activity area and space utilization rate after the optimization of the different methods are shown in Figure 10. After applying the design optimization method in this paper, the indoor effective activity space area is 9m² and the indoor effective activity space utilization rate is 56.3%. While using the other four methods, the layout optimization scheme formed, the indoor effective activity space area was 8.59m², 8.48m², 8.21m² and 8.42m² respectively, and the calculation results of the effective activity space utilization rate were 52.3%, 53.5%, 54.2% and 55.1% respectively. In summary, the design optimization method in this paper can better utilize the indoor space and facilitate the daily life activities of the personnel.

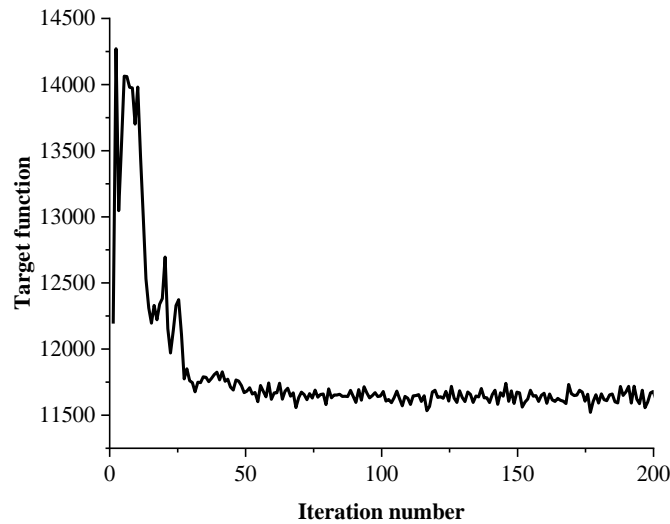


Figure 9: An iterative curve of the NSGA-II-multi-target inheritance

Table 4: Optimize layout parameter statistics

Furniture name	Long/mm	Width/mm	Layout optimization results	
			x/mm	y/mm
Bed 1	2000	900	500	1200
Bed 2	2000	900	2500	1200
Bed 3	2000	900	2500	3500
Bed 4	2000	900	500	3500
Bookcase 1	1500	500	100	450
Desk 1	500	500	500	450
Wardrobe 1	500	800	500	1600

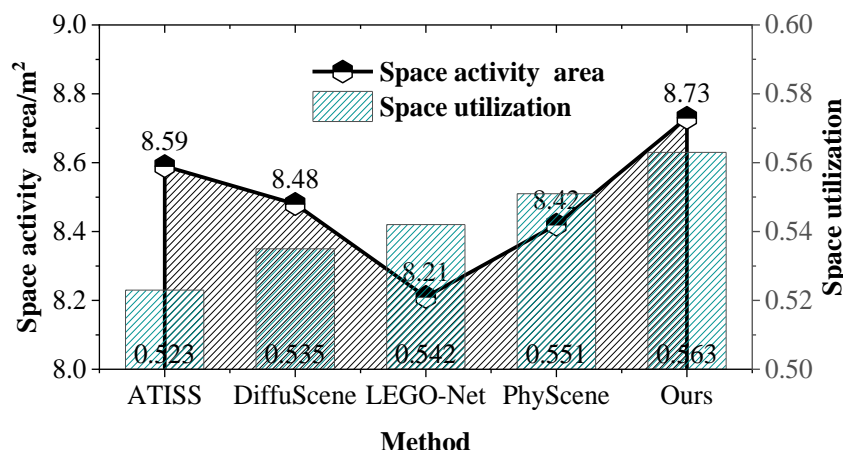


Figure 10: Spatial activity surface product and spatial utilization of different methods

5 Conclusion

This study focuses on the exploration of a 3D visualization system for indoor display optimization. In order to realize the spatial layout optimization function of the system, an indoor spatial layout estimation model and an indoor display optimization model based on NSGA-II multi-objective genetics are proposed, and the performance of the proposed methods is evaluated through experiments, and an arithmetic example analysis of indoor display optimization is carried out. The main results are as follows:

(1) In the comparison test, this paper's indoor spatial layout estimation model achieves 78.38%, 87.52%, and 7.33% on mIoU, MPA, and PE evaluation indexes on LSUN dataset, respectively, and on Hedau dataset, 79.56%, 87.53%, and 8.57% on mIoU, MPA, and PE evaluation indexes, respectively, which are all better than the comparison model. Meanwhile, it has a lower parametric count and a faster computing speed of 5.56×10^6 M and 24.36ms, respectively, indicating that this indoor spatial layout estimation model is able to obtain the accurate layout of indoor display and has a good capability of dividing the layout of indoor scenes.

(2) The values of each index of the indoor display optimization model are optimal in the comparison test, and the FID, KID, SCA, COL_{wall}, and COL_{obj} indexes of the bedroom scene test are 25.64, 1.69×10^3 , 49.05%, 0.29, and 0.235, respectively, and the indexes of the living room scene are 36.73, 1.34×10^3 , 50.96%, 0.36 and 0.23. The effective activity space utilization rate of the layout generated by this paper's model in the calculation example reaches 56.3%, which is higher than that of other methods by 1.2% to 4.0%. The model in this paper can significantly improve the modeling ability of fine-grained spatial relationships between furniture, and the generated indoor 3D scene shows obvious advantages in terms of layout rationality and visual quality.

It should be noted that the influence of indoor physical environment factors (e.g., light effect, temperature, etc.) on indoor spatial layout is not addressed in this study. In future research, we will continue to focus on the functional requirements of indoor spaces and study and explore related issues.

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