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Individualized Interior Design Combining CAD and Data Mining Technologies

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Abstract. The rise of computer-aided design (CAD) technology has brought revolutionary changes to interior design, which can efficiently create, modify, and optimize design schemes and improve design efficiency. This article aims to explore an individualized interior design method combining CAD and data mining (DM) technology. By using the DsNet-1 network for pre-training, we successfully captured the key features of indoor scenes and used these features to guide the subsequent modeling process. This pre-training strategy not only accelerates the convergence speed of the model but also improves its generalization ability. By fusing the feature maps of different levels of Convolutional Neural Network (CNN), the effective combination of local details and global structural information is realized, and a more comprehensive and accurate segmentation result is obtained. By optimizing the algorithm design and adopting an efficient data structure, we successfully reduced the algorithm's computational complexity and shortened the overall time consumption. The indoor scene CAD modeling method proposed in this article improves the accuracy and shows obvious advantages in the time-consuming algorithm, which provides strong support for subsequent individualized design and practical application.

Keywords: CAD; Data Mining; Individuation; Interior Design
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1 INTRODUCTION

As science and technology continue to advance rapidly, people's expectations regarding their living environment have evolved, moving away from a sole functional focus towards a more diverse and personalized approach. As an important means to shape the living environment, the concept and method of interior design are constantly updated and evolved. Building Information Modeling (BIM) is a digital tool used to represent the physical and functional characteristics of buildings, infrastructure, and equipment. BIM is not just a three-dimensional model; it also contains information from multiple dimensions, such as time, cost, and facility management. Through BIM, designers can better understand and manage various aspects of a project, thereby improving design efficiency, reducing

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costs, and enhancing Sustainability. Akin et al. [1] explored an innovative architectural design tool that combines lighting simulation with immersive performance design. It is based on the Building Information Modeling (BIM) method, providing designers with powerful design and visualization tools. This tool can simulate the natural lighting effect of buildings based on factors such as geographical location, season, and time. Designers can optimize the lighting effect and improve the comfort of the indoor environment by adjusting the design scheme and observing in real time how the light is distributed and interacts with the indoor space. Traditional interior design often relies on the designer's experience and intuition, and it is designed by hand drawing or two-dimensional software, but this method is inadequate in dealing with complex and changeable space requirements and individualized customization. With the rapid development of the construction industry, manufacturing and assembly design (DfMA) for outdoor interior design and construction has gradually become a trend. DfMA aims to improve manufacturing and assembly efficiency, reduce costs, and shorten project cycles through standardized and modular methods. In this process, CAD optimization algorithms play a crucial role. Bao et al. [2] explored the specific application and value of CAD optimization algorithms in DfMA. CAD optimization algorithms can divide indoor spaces into different modules based on building requirements and functions. By using parameterization and standardization methods, rapid design and production of modules can be achieved, thereby improving production efficiency and reducing costs. Construction plans can be simulated and optimized through CAD software combined with optimization algorithms. This helps to arrange the construction schedule reasonably, improve construction efficiency, and reduce construction costs. It utilizes CAD software and information technology to achieve digital management and sharing of design information. This helps to promote collaboration and communication among teams, ensuring the accuracy and consistency of the design. The rise of CAD technology has brought revolutionary changes to interior design, which can efficiently create, modify, and optimize design schemes and improve design efficiency. The BIM method can achieve information integration of multiple specialties such as architecture, structure, and electromechanical, which has significant advantages in improving design efficiency, reducing costs, and optimizing construction management. However, traditional architectural studios still face challenges in data integration, information management, and collaborative design when applying BIM methods. Caetano and Leitão [3] proposed an integrated algorithm BIM method that combines CAD and data mining, aiming to solve the problems faced by traditional architectural studios when applying BIM methods. The architectural design project of a large commercial complex adopted an integrated algorithm BIM method that combines CAD and data mining. Through data integration and information management, the project team successfully resolved information conflicts and data inconsistencies among multiple disciplines, improving design efficiency and quality. By mining the association rules and clustering analysis between design elements, the project team quickly identified potential design issues and conflicts, providing designers with timely feedback and suggestions, effectively avoiding rework and delays during the construction process.

CAD (computer-aided design) and data mining technology provide designers with powerful tools to better understand and optimize interior design. Celadyn [4] explores how to combine CAD and data mining techniques to achieve comprehensive environmental sustainability design in interior architectural design. Data mining techniques can extract valuable information from a large amount of data and provide important decision support for interior architectural design. By analyzing historical design data, data mining can help designers understand which design elements have a positive impact on environmental Sustainability. In addition, data mining can also be used to analyze user needs, space utilization, energy consumption, etc., in order to optimize design solutions. Through data mining techniques, designers can track and analyze the actual effectiveness of design solutions in real-time. By monitoring energy consumption and indoor environmental quality, designers can adjust their design plans to achieve better environmental Sustainability. By utilizing CAD and data mining techniques, designers can conduct cost and benefit analyses on different design schemes. This helps designers to maximize economic benefits while meeting environmental sustainability requirements. For beginners in computational design, effectively utilizing CAD tools for architectural design remains a challenge. Empowerment algorithms, as an emerging technology, can provide

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better assistance and support for novice computational designers. Chen et al. [5] explored how to use empowerment algorithms to assist in architectural design in order to facilitate novice computational designers mastering relevant skills more quickly. Parametric design is a design method based on parameters and logic. By empowering algorithms, novice computational designers can more conveniently carry out parametric design, reducing errors and omissions in the design process. Empowerment algorithms can automatically generate common architectural design elements, such as windows, doors, walls, etc. This provides beginners in computational design with more time and energy to focus on innovation and personalization in design. Parametric design is an important trend in modern architectural design. Beginners in computational design need to understand how to use parameters and logic to define and generate architectural design elements in order to improve design flexibility and maintainability. Rendering and visualization are important means of showcasing architectural design achievements. However, CAD technology mainly focuses on the improvement of design tools, but it is relatively weak in excavating and utilizing a large amount of data information knowledge and experience involved in the design process. DM can extract valuable information and knowledge from massive amounts of data and help designers better understand the internal relations among user needs, market trends, and design elements. In the field of interior design, users' preferences, behavior habits, and space usage patterns can be analyzed through DM technology, thus providing strong support for individualized design. How to combine it with CAD technology effectively to realize individuation, intelligence, and automation of interior design is the focus of this article.

With the increasing concern for environmental Sustainability, the interior design industry is also shifting towards more environmentally friendly design practices. Convolutional neural networks (CNN), as a powerful machine learning tool, have significant advantages in image recognition and feature extraction. Dissanayake et al. [6] explored how to utilize the feature extraction function of CNN to guide sustainable environmental practices in interior design. It uses CNN to analyze indoor photos and extract features of natural lighting in order to better utilize these features in design. For example, by adjusting the position and size of windows, indoor lighting can be increased, and artificial lighting can be reduced, thereby reducing energy consumption. It uses CNN to analyze indoor environment photos and extract features related to comfort. In the design process, taking into account human comfort and psychological feelings, create a comfortable and pleasant indoor environment. Analyze the elements and materials of interior design through CNN to extract reusable features. In the design process, follow the principle of circular design and minimize the generation of waste and resource waste as much as possible. Markov decision process is a mathematical model used to describe decision-making problems in uncertain environments. It consists of a set of states, a set of actions, state transition probabilities, and reward and punishment functions. In each state, decision-makers can choose an action and transition to a new state based on the probability of state transition. Based on the feedback of the reward and punishment function, decision-makers can understand the quality of their actions and gradually learn the optimal strategy. Automation and intelligence have become important development directions in the field of interior design. In order to achieve automation in interior design, researchers are constantly exploring new technologies and methods. Among them, the Markov Decision Process (MDP), as an effective decision model, is widely used in various fields.

Individualized interior design combining CAD and DM technology is expected to bring broader application prospects to the design industry. Part of the existing research only stays at the basic application level of CAD technology and has not deeply explored its potential in individualized interior design. The prediction of user behavior patterns based on big data analysis may be limited by data quality and privacy issues. This article aims to explore an individualized interior design method combining CAD and DM technology. Through in-depth analysis of CAD technology and DM technology, this article puts forward a new idea of interior design based on 3D reconstruction (TDR). This method can not only use the powerful modeling function of CAD technology to build a 3D model of indoor space quickly but also deeply excavate and utilize the data in the design process with the help of DM technology to realize the individuation and intelligence of design. The research includes the following innovations:

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(1) Based on the combination of BIM and CAD, this article proposes a more efficient and collaborative interior design process.

(2) This article not only uses CAD for basic modeling but also combines DM technology to analyze users' needs and design trends so as to deepen individualized design.

This article focuses on indoor scene CAD modeling and individualized design and defines the research background and objectives in the introduction. The theoretical and technical overview part expounds on the relevant theoretical basis; The method part expounds on the proposed modeling strategy in detail; The experimental part verifies the effectiveness. Finally, in the conclusion and prospect, the research results are summarized, and the future direction is prospected.

2 RELATED WORK

Karan et al. [7] explored how to apply Markov decision processes to interior design automation and build corresponding processes. Based on the choice of action and the probability of state transition, the system will update the designed state. For example, in the layout planning stage, choosing different layout schemes may lead to different spatial utilization efficiency and aesthetics. The system can calculate the probability of state transition based on these factors and update the design state based on the transition probability. In indoor space design, personalized needs are increasingly prominent, and how to use CNN to support personalized design decisions has become an important research direction. Lee et al. [8] proposed a conceptual framework aimed at integrating convolutional neural networks at different levels to achieve more accurate personalized interior space design decisions. CNN can be used to identify indoor space images, extract features such as room size, shape, layout, and decorative style, and provide basic data for subsequent design decisions. By training CNN to learn a large number of interior design style images, automatic style classification and recommendation can be achieved, providing inspiration and reference for designers. By combining user historical behavioral data and preferences, deep learning through CNN can predict user preferences for specific interior designs, providing a basis for personalized design. On the basis of low-level features, further extract more abstract design elements, such as furniture layout, material texture, etc. These features can help designers better understand the usage needs and aesthetic orientation of the space.

The color and material combination of furniture in interior design are key factors that affect the overall atmosphere and style of the space. How to choose and reasonably match furniture colors and materials to achieve ideal interior design results is an important issue faced by designers. Park and Hyun [9] proposed a data-driven framework for analyzing furniture color and material combinations in interior design. It extracts features related to furniture color and material matching from the data, such as color saturation, brightness, hue, material texture, texture, etc. These features can be used as the basis for analysis. Taking the portfolio of an interior design company as an example, a data-driven framework is used for analysis. Firstly, collect the color and material information of the furniture in the portfolio and preprocess it. Then, extract relevant features such as color saturation, brightness, and hue, as well as texture and texture of the material. Data mining technology is playing an increasingly important role in this field, especially in the three-dimensional manufacturing of free-structure-balanced floating bodies. Wang et al. [10] explored how to use data mining techniques to provide strong support for personalized interior design, with a focus on the three-dimensional manufacturing of free-structure balanced floating bodies as an example. In interior design, data mining techniques can be used to analyze data on customer needs, style preferences, space utilization, and other aspects to achieve more personalized design solutions. Free structure balanced floating body 3D manufacturing is an advanced manufacturing technology that can produce floating bodies with complex structures and free shapes according to design requirements. This technology has broad application prospects in personalized interior design. Based on the information obtained from data mining, designers can use free structure balanced floating body 3D manufacturing technology to create various design schemes. Through simulation and optimization algorithms, the design scheme can be optimized to meet the personalized needs of customers. Data-driven internal

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planning of residential buildings means guiding the planning process through the collection and analysis of a large amount of data. These data may include but are not limited to residents' living habits, spatial usage patterns, air quality, lighting needs, etc. Through data analysis, Wu et al. [11] have gained a more accurate understanding of the needs of residents, predicted potential issues, and developed planning plans that are more in line with actual needs. Data-driven planning generation does not completely eliminate human factors. The intuition and experience of designers are still very important. Therefore, in practical operation, data analysis and human factors should be combined to jointly guide the generation of plans. Although data-driven internal planning for residential buildings has many advantages, it still faces some challenges. For example, data collection and processing require a significant amount of time and resources. The results of data analysis may be influenced by multiple factors and require careful interpretation. The preliminary plan generated by artificial intelligence may need further adjustment and improvement to adapt to specific environments and needs. Xing et al. [12] used a Bayesian network model to evaluate the performance of students in indoor space engineering design automatically. By establishing an evaluation model based on Bayesian networks, it is possible to quantify the evaluation of student design works effectively and provide targeted feedback. This method not only improves the objectivity and accuracy of evaluation but also helps students better understand their design strengths and weaknesses, thereby enhancing their design abilities. Interior space engineering design is a highly comprehensive discipline that involves knowledge from multiple fields. Objectively and accurately evaluating the design performance of students is an important part of the teaching process. Automatically evaluate student design works by running Bayesian network models. The evaluation results will be presented in a quantitative form, and specific feedback and suggestions will be provided for each indicator. Students can understand their design strengths and weaknesses based on feedback results and then optimize the design plan. Xing et al. [13] introduced learning analytics techniques to better understand user needs by collecting and analyzing large amounts of data and utilizing CAD technology for precise indoor scene modeling. Learning analysis refers to the use of data mining and machine learning techniques to analyze students' learning behaviors and habits in order to optimize teaching. In interior design, we can use learning and analysis to collect information on users' lifestyle habits, space usage needs, etc. By analyzing this data, we can deeply understand the real needs of users and provide more personalized design solutions. CAD (Computer Aided Design) technology is the key to achieving indoor scene modeling. Through CAD software, designers can create accurate 3D models based on user needs and behavior patterns analyzed through learning. This model not only includes the physical layout of the interior but also the design of details such as furniture, lighting, curtains, etc. In addition, CAD models can also be used to simulate environmental factors such as lighting and airflow in order to optimize design schemes further. 3D computer-aided simulation technology can provide interior designers with a virtual environment, allowing them to preview and evaluate design proposals more intuitively. This technology can simulate real lighting, colors, and materials, helping designers better grasp the overall effect of the design. Meanwhile, 3D simulation technology can also simulate different pedestrian traffic and activity scenes, helping designers better understand the use and function of space. Yang [14] uses 3D computer-aided simulation technology to enable students to engage in design practice in a highly realistic virtual environment. This teaching method can help students better understand the overall effect and details of design and improve their design perception ability. The optimization teaching of interior design based on 3D computer-aided simulation is not limited by time and space. Students can learn at any time and anywhere, improving the flexibility and convenience of learning. 3D vision and data mining techniques have been widely applied in many fields. In the field of interior design, the combination of these two technologies provides designers with a new perspective and method, making the virtual design of interior landscapes possible. Zhang [15] discussed how to use data mining and 3D vision technology for the virtual design of indoor landscapes. 3D visual technology provides intuitive and three-dimensional visual effects for interior design. Through 3D modeling and rendering techniques, designers can create realistic indoor scenes in virtual environments for better spatial layout, color matching, and other aspects of design. In addition, 3D vision technology can also be used to showcase design solutions, making it easier for users to understand and evaluate. Based on the results of data mining,

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create a virtual model of indoor scenes using 3D vision technology. Through 3D visual technology, designers can perform realistic designs in virtual environments. The application of this method not only improves the efficiency and accuracy of design but also makes the design scheme more in line with user needs and enhances user satisfaction.

3 CAD MODELING AND INDIVIDUALIZED DESIGN OF INDOOR SCENES BASED ON DM

With its high efficiency and accuracy, CAD technology has changed the design method of traditional manual drawing and brought revolutionary changes to various industries. In interior design, CAD technology is widely used, from preliminary space planning to detailed material selection to final construction drawing, and CAD technology runs through the whole design process.

The core of CAD technology lies in its powerful modeling ability. Through 3D modeling, designers can create a realistic indoor space model in the virtual environment, which not only helps designers understand the spatial relationship more intuitively but also allows users to preview the design effect more clearly. In addition, CAD technology also supports the simulation of a variety of materials and textures so that designers can experiment with different materials and color combinations in the model to find the best design scheme.

In addition to modeling ability, CAD technology is highly editable and reusable. Designers can easily modify any element in the model, whether it is size, shape, or position, which can be updated in real time and reflected in the whole design. This flexibility greatly improves the design efficiency and provides designers with more creative space.

DM technology involves extracting valuable insights from extensive datasets through a meticulous process. These data can be structured, such as tabular data in a database, or unstructured, such as text, images, or videos. The goal of DM technology is to find patterns, trends, and correlations by analyzing these data so as to provide support for decision-making.

The utilization of DM technology in interior design is primarily evident in the following areas: user behavior analysis, market trend prediction, and design element optimization. First of all, by collecting and analyzing user behavior data, such as browsing records, purchase history, and social media interaction, DM technology can help designers understand users' preferences and needs more deeply. Secondly, DM technology can also analyze market trends and historical data and predict popular design styles and material selection in the future. Finally, DM technology can also be used to optimize design elements, such as furniture layout, lighting settings, and color matching. By analyzing a large number of design cases and user feedback data, DM technology can reveal which design elements are more popular and which combinations are more harmonious, thus providing a strong reference for designers.

The combination of CAD technology and DM technology in interior design provides new possibilities for individualized interior design. The 3D model created by CAD technology not only provides designers with intuitive design tools but also provides rich data sources for DM. Designers can embed various parameters and attributes in the model, such as material type, color, size, and so on. These data can be used by the DM algorithm to find hidden rules and potential optimization points in the design.

In the early stage of design, designers can quickly construct a number of different spatial layout schemes through CAD technology and analyze and compare these schemes by using DM technology. In the design process, DM technology can also be used to optimize material selection and decoration style. By analyzing a large quantity of design cases and user assessment data, DM technology can recommend to designers the design reference that best conforms to user preferences and market trends. In the process of individualized interior design, CAD modeling based on DM is a key link in combining user needs with design concepts. This section will explore how to use DM technology to construct CAD models for indoor scenes and implement specific algorithms for individualized design. Firstly, it is necessary to collect relevant data from users, including their basic information, historical purchase records, online browsing behavior, social media interactions, etc. These data can be

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obtained through various methods such as questionnaire surveys, web crawlers, API interfaces, etc. Next, preprocess the collected data, including data cleaning, feature extraction, and labeling, for use in subsequent model construction.

When constructing a CAD model for indoor scenes, first, a series of parameters and variables are defined based on the structure and layout of the indoor space, such as the length, width, and height of the room, the position and size of doors and windows, and the placement of furniture. Then, using the programming interface or script language provided by CAD software, write an automated script program to achieve the process of parametric modeling. These script programs can automatically adjust the elements and attributes in the CAD model based on the parameter values provided by the user preference model, thereby generating individualized indoor scenes that meet user needs. The optimization algorithm framework for feature point processing in indoor scenes is shown in Figure 1.

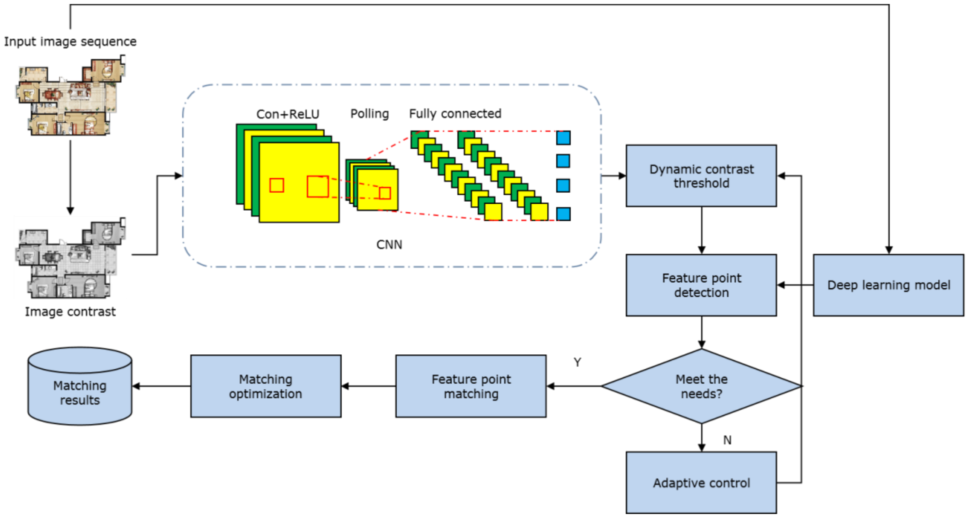

Figure 1: Framework of feature point processing optimization algorithm.

Indoor scene understanding refers to a comprehensive and in-depth analysis and interpretation of the indoor environment, including identifying the types of rooms, detecting indoor objects and their attributes, and analyzing indoor spatial structure and layout. On the basis of understanding the indoor scene, we can extract the key features of the indoor environment, such as the shape, size, and height of the room, the type, quantity, and location of furniture, and the style and color of interior decoration. Layout estimation refers to the automatic or semi-automatic inference and prediction of the spatial layout of indoor scenes. The objective of layout estimation is to produce a precise model that depicts the configuration and arrangement of indoor environments, encompassing the locations and interactions of room perimeters, floors, ceilings, walls, and additional components. The results of layout estimation can be directly applied to CAD modeling and individualized design. By combining the estimated layout with CAD software, we can quickly generate an indoor model that conforms to the actual scene. On this basis, we can carry out individualized operations such as furniture placement, color matching, and lighting design. The process of indoor scene understanding and layout estimation is shown in Figure 2.

In the CAD modeling and individualized design of indoor scenes based on DM, TDR is a key link that can transform real indoor scenes into 3D models that computers can understand and operate. First, we need to get the 3D data of the indoor scene. This is usually done by using 3D scanning equipment such as a depth camera, laser scanner, or structured light equipment. These devices can capture the geometric shape, surface texture, and spatial relationship between objects in indoor space and generate original 3D data such as point cloud data or depth images.

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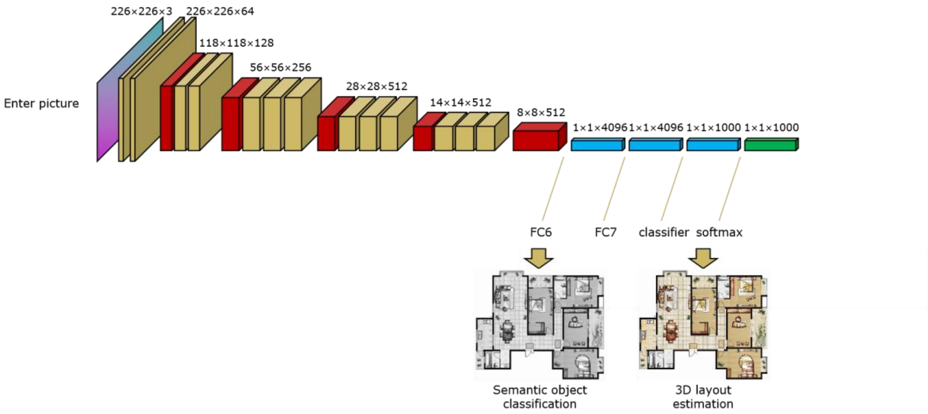

Figure 2: Indoor scene understanding and layout estimation.

The collected point cloud data often contains noise and outliers, so it needs preprocessing to improve the data quality. Preprocessing steps include filtering, denoising, and down-sampling so as to reduce data redundancy and improve calculation efficiency. The preprocessed point cloud data can be used for surface reconstruction, that is, to generate a continuous 3D surface model. In order to make the reconstructed 3D model more realistic, it is necessary to map the texture information of the indoor scene to the model surface. This is usually achieved by texture mapping technology, which corresponds the collected two-dimensional texture image with the 3D model so that the surface of the model presents a visual effect similar to the real scene. Figure 3 illustrates the fundamental procedure for sparse point cloud reconstruction utilizing incremental TDR. This process is primarily segmented into two components: image feature matching, along with camera pose recovery and spatial structure recuperation.

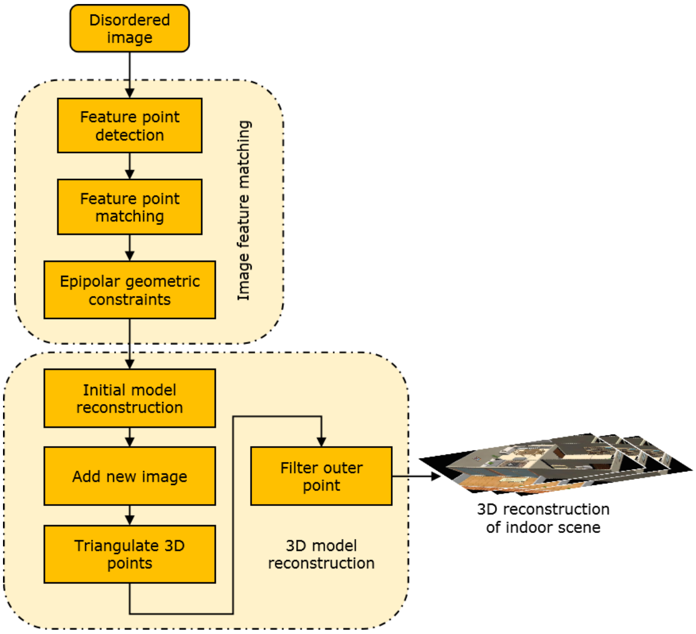

Figure 3: Basic flow chart of sparse TDR.

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Assigning the gray function of the indoor color design image $f(x,y)$, we define the (i,j) domain of the pixel located r $(r>0)$ as the subsequent set:

$$N_r(i,j) = \{(k,l) \mid \max(|i-k|,|j-l|) \le r\} \tag{1}$$

The following defined values are known as the interest of (i,j) bit pixels:

$$I(i,j) = \frac{1}{(2r+1)^2 - 1} \sum_{(k,l)\in N_r(i,j)} \left(f(i,j) + w(k,l,\sigma) f(k,l)\right) \tag{2}$$

Among them:

$$w(k,l,\sigma) = \psi(i-k, j-l, \sigma) \tag{3}$$

Supposing that the number of images involved in TDR is denoted as n while C_i representing the internal and external parameters associated with the i-th image. Assuming further that m 3D spatial points are reconstructed, with the j-th 3D point's coordinate labeled as X_j. In this context, the objective function optimized via the beam adjustment approach is formulated as follows:

$$g(C,X) = \sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij} \left\| q_{ij} - P(C_i, X_j) \right\|^2 \tag{4}$$

In this context, w_{ij} it serves as an indicator variable that determines whether a point appears in an image i. Specifically, if the point j is present in the image i, w_{ij} it is assigned a value of 1; otherwise, it remains 0. Additionally, $P(C_i, X_j)$ represents the coordinate of the point j on the image i following a projection transformation while q_{ij} denoting the actual image coordinate of the point j on the image i.

During practical computations, the Levenberg-Marquardt algorithm is employed for iteratively minimizing the re-projection error through optimization:

$$\Delta = -\left(J_f^T J_f + \lambda I\right)^{-1} J_f^T f \tag{5}$$

The given formula λ represents the weight parameter. Depending on its value, the formula's behavior varies: with a large λ, it mimics the gradient descent method with cautious step size, whereas a small λ, nearing 0, aligns it with the Gaussian Newton method. The procedure to determine the optimum value involves iterative adjustments λ. If, after an iteration, the objective function registers a successful decrease, λ it is reduced; if not, λ it is increased, and the process repeats. The iterations continue until the error falls below a preset threshold, at which point the refined parameter variables are deemed ready for output.

Image assessment of indoor scenes is a process of comprehensive assessment of the image quality of indoor scenes. This assessment not only pays attention to the technical aspects of the image, such as clarity and color reproduction, but also pays attention to the indoor environment atmosphere, design sense, and whether it meets the expectations of users. When quantitative analysis of image contrast is required, the calculation typically involves the use of the root mean square:

$$RMS = \left[\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2\right]^{\frac{1}{2}} \tag{6}$$

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Where n represents the number of pixels, x_i represents the gray value of the ith pixel, and $\bar{x}$ represents the average of the gray values of the image pixels.

To derive the spatial relationships and 3D configurations of planes, we incorporate point cloud data and estimate its normal vectors. Utilizing both the point cloud data and associated labels, we can ascertain the connectivity and closure of individual plane entities. The likelihood of a given point x being part of plane p is determined as follows:

$$P(x|p) = \frac{N(dist(x,p);0,\sigma_d^2)}{N(0;0,\sigma_d^2)} * \frac{N(|N_x * N_p|;1,\sigma_n^2)}{N(1;1,\sigma_n^2)} \tag{7}$$

To enhance computational efficiency, this article discretizes the transfer gradient $x_s^{ij} - x_s^{ji}$, aligning it with the normal vector S of the Woolf shape. Consequently, the correlation between the probability distribution $P_s(n)$, which corresponds to the direction of the normal vector $n \in S$ per unit length of voxel S, and the Woolf shape distance d_s^n can be expressed as follows:

$$P_s(n) = e^{-\varphi^{ij}(n)} = e^{-\max_{p \in W_{H_s}} (p^T n)} = e^{-d_s^n} \tag{8}$$

So, satisfy:

$$d_s^n = \text{-}\log(P_s(n)) \tag{9}$$

A histogram can be created using the input method vector to approximate where the corresponding surface area serves as the weight. The histogram's x-axis represents the direction of the normal vector $n \in S$, while the y-axis denotes the weighted frequency for each direction.

$$d_s^n = \text{-}\log(P_s(n)) \tag{10}$$

Assuming that $\{P_i | P_i \in R^3, i = 1, \cdots, N\}$ and $\{Q_i | Q_i \in R^3, i = 1, \cdots, M\}$ denote the first and second point sets, respectively, the task of aligning and registering these two point sets is equivalent to minimizing the function value expressed by the subsequent formula:

$$f(R,T) = \sum_{i=1}^{n} \left\| Q_i^k - (RP_i + T) \right\|^2 \tag{11}$$

4 RESULT ANALYSIS AND DISCUSSION

In the CAD modeling of indoor scenes, in order to achieve efficient model training and accurate segmentation results, we adopt a pre-training method based on the DsNet-1 network, combined with a multi-scale feature fusion strategy. Firstly, the NYU-V2 data set is selected as the training data source. NYU-V2 is an open data set widely used for indoor scene understanding and segmentation, which contains rich RGB images and corresponding depth information. In the first stage of training, the DsNet-1 network is used for segmentation training. DsNet-1 is a deep segmentation network with strong feature extraction and segmentation capabilities. Through iterative training on the NYU-V2 data set, the DsNet-1 network gradually learned the key features of indoor scenes, such as the boundary and texture information of walls, floors, and furniture. In the second stage of training, the pre-training model obtained in the first stage is used, and the experiment is completed by combining the multi-scale feature fusion method. Multi-scale feature fusion is an effective image processing strategy that can fuse feature information of different scales, thus obtaining more comprehensive and accurate segmentation results.

Layer name	*Convolution kernel size*	*Step length*	*The total quantity of*	*Feature map size*

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			feature maps	
Conv1	12×12	6	96	128×128
Pool1	4×4	3	96	56×56
Norm1	0	0	96	56×56
Conv2	6×6	1	256	56×56
Pool2	4×4	2	256	28×28
Norm2	0	0	384	28×28
Conv3	4×4	1	384	28×28
Conv4	4×4	1	384	28×28
Add3	0	0	384	28×28
Pool5	3×3	2	256	16×16
Fc6	6×6	1	4096	9×9
Fc7	1×1	1	4096	9×9
Score_fr	1×1	1	16	9×9
Upscore	64×64	32	16	318×318
Score	0	0	16	256×256

Table 1: Network parameters.

Table 1 shows the structural parameters of the CNN we proposed. The CNN model adopted in this article includes several convolution, pooling, and fully connected layers. The fully connected layer is responsible for mapping the final feature map to the label space of the segmentation result. The model can achieve efficient feature extraction and accurate segmentation tasks by reasonably designing the network structure and parameter configuration. The network weights are randomly initialized, and other specific training parameters are shown in Table 2.

Parameter	*Set up*
Initial learning rate	0.001
Learning rate update strategy	Learning rate every 5 Epoch transformations
Attenuation weight	5×10-4
Batch size	3
quantity of cycles	80
Momentum	0.6

Table 2: Model training parameter settings.

Figure 4 shows the loss results during the training of indoor scene CAD modeling models. The loss function serves as a crucial metric for assessing the disparity between a model's predicted and actual outcomes, with its varying trend offering a direct insight into the model's training efficacy and convergence.

As the quantity of training iterations increases, the loss value of the model gradually decreases. In the early stages of training, due to the random initialization of model parameters, the loss value is relatively high. During the training process, there may be some fluctuations in the decrease in loss values. This may be caused by noise in the training data, large update steps of model parameters, or the model falling into local optima. However, overall, the loss value still shows a significant downward trend, indicating that the model has strong robustness and learning ability. After completing the training of the indoor scene CAD modeling model, multiple models were tested using test samples to assess their performance. Figure 5 shows the root mean square error (RMSE) of different models. RMSE is a commonly used error measure that reflects the accuracy of model predictions. Compared with other models, the RMSE value of our model is at a lower level. This indicates that the model in

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this article has higher accuracy in predicting indoor scenes and can better capture details and features in the scene.

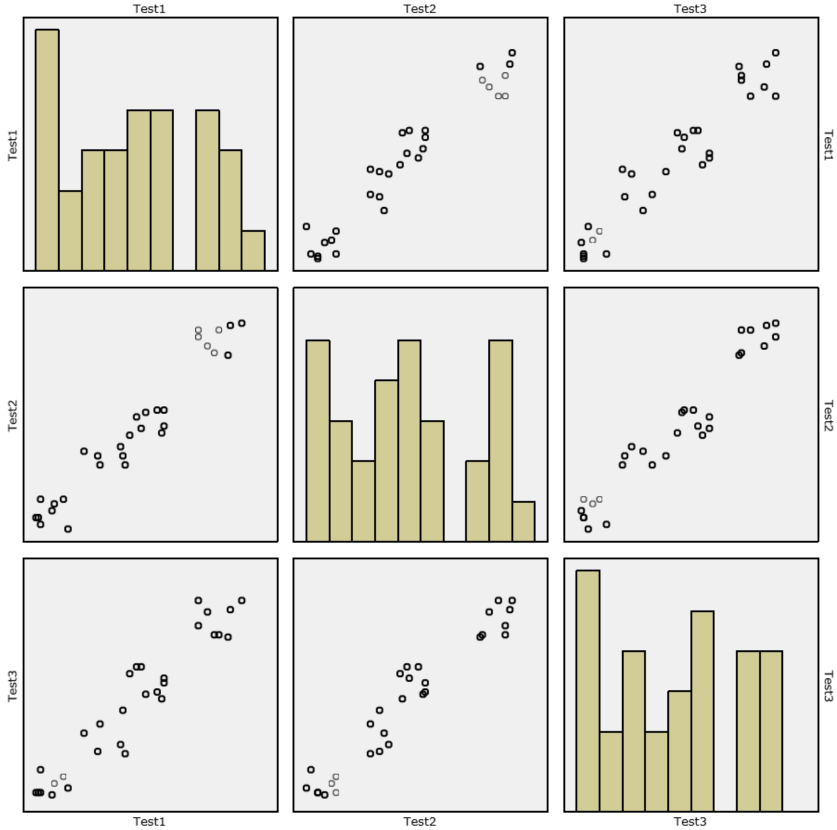

Figure 4: Model training Loss curve.

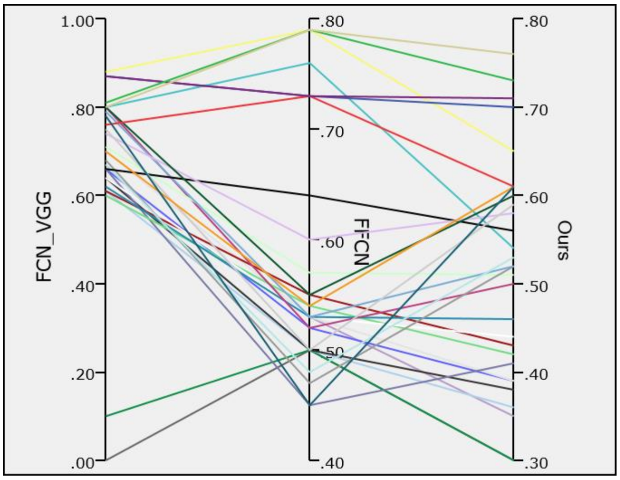

Figure 5: RMSE of different models.

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Figure 6 shows the mean absolute error (MAE) situation of different models. MAE is another commonly used error measure, which calculates the average absolute error between the predicted results of the model and the actual results. The results show that the MAE value of the model in this article is also at a relatively low level. This indicates that the model in this article not only has high accuracy in predicting indoor scenes but also has a relatively uniform error distribution without significant deviation.

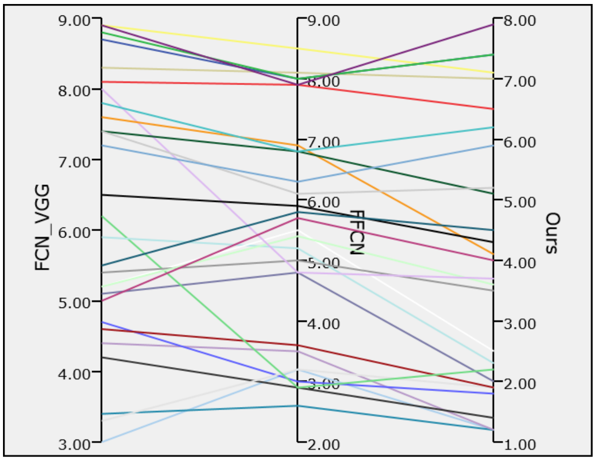

Figure 6: MAE situation of different models.

In the process of indoor scene CAD modeling, the execution efficiency of algorithms is equally crucial. In order to assess the performance of the algorithm in terms of time consumption, we screened some datasets in the experiment and counted all optimization times and corresponding optimization times. Figure 7 shows the comparison of different algorithms in terms of time consumption, which clearly demonstrates the advantages of this method.

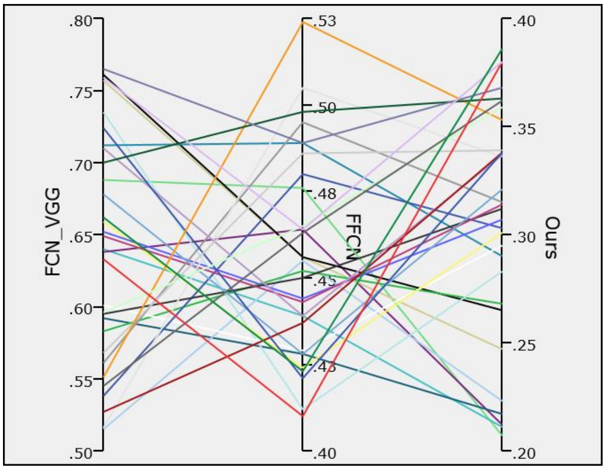

Figure 7: Time-consuming comparison of the algorithm.

From the perspective of optimization times, this algorithm requires relatively fewer optimization times while achieving the same or better performance. This means that the algorithm is more

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efficient in searching for the optimal solution and can converge to a satisfactory solution space faster. This not only reduces the waste of computing resources but also improves the practicality and scalability of the algorithm.

5 CONCLUSION

As an important means of shaping the living environment, interior design concepts and methods are constantly being updated and evolved. Traditional interior design often relies on the experience and intuition of designers, using manual drawing or two-dimensional software for design. However, this approach is inadequate in dealing with complex and ever-changing space needs and individualized customization. After a detailed exploration of CAD and DM technologies, this article innovatively proposes a new interior design strategy centered on TDR. This strategy can fully leverage the excellent modeling ability of CAD technology to quickly build a 3D model of indoor space and rely on the in-depth analysis ability of DM technology to meticulously mine and efficiently utilize the data generated during the design process, thereby promoting the growth of design towards individuation and intelligence. By comparing and analyzing the output results and error situations of different models, the effectiveness and superiority of our model in indoor scene CAD modeling tasks were verified. This algorithm has higher execution efficiency when dealing with indoor scene CAD modeling tasks and can complete complex computational tasks in a shorter time.

Future research can explore more lightweight network structures to reduce the consumption of computing resources and storage space while maintaining or improving the performance of the model. In addition, more efficient optimization algorithms can be studied to accelerate the training process and inference speed, meeting the real-time requirements in practical applications.

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