www.cad-journal.net
Computer-Aided Design
AND APPLICATIONS

Implementation of Object-oriented Design Technology and Deep Learning Algorithm in Interior Design CAD System

Ting Ma[1] and Cun Shang[23]

[1]College of Planning and Design, Xinyang Agriculture and Forestry university, Henan 464000, China, 2009230026@xyafu.edu.cn
[2]College of Planning and Design, Xinyang Agriculture and Forestry university, Henan 464000, China, leadnat@163.com
[3]School of Art and Design, Wuhan University of Technology, Wuhan 430000, China, leadnat@163.com

Corresponding author: Ting Ma, 2009230026@xyafu.edu.cn

Abstract. People's means of interior design are no longer limited to hand painting, but more are carried out by computer software. The emergence of deep learning (DL) promotes the application and growth of 3D data, and with the help of 5G Internet technology, it is possible to generate 3D models and visualize the cloud. With the continuous growth of DL, many researches on 3D modeling based on DL algorithm have emerged. In this article, the application of object-oriented design technology and DL algorithm in interior design CAD system is studied. Convolutional neural network (CNN) is trained by DL to realize 3D reconstruction of interior scene based on object-oriented design, and the reconstructed 3D model is rendered. The model is rendered based on different texture information when its 3D structure is known, which gives full play to the advantages of many samples and wide types of image data and the powerful representation ability of DL, and provides a new solution for the 3D reconstruction and 3D rendering of interior design CAD system.

Keywords: Object-Oriented Design; Deep Learning; Interior Design; Cad System
DOI: https://doi.org/10.14733/cadaps.2024.S1.175-189

1 INTRODUCTION

With the continuous expansion of urban area, a large quantity of urban houses are completed in civil buildings every year. In addition, the current stock of residential houses periodically enters the maintenance period, and the scale of residential decoration market will continue to expand. In architectural and interior design CAD, parametric and intelligent design using object-oriented technology is a key research topic in the field of CAD design in the world. Because the indoor scene is disturbed by many human factors, a large quantity of artifacts in the scene add to the difficulty of reconstruction. On the other hand, the indoor scene is concentrated, the size difference of objects is not big, and the influence caused by occlusion is more serious than that caused by outdoor environment. Therefore, the task of 3D reconstruction of indoor scene has great research value but is also more challenging. 3D reconstruction refers to the reconstruction or recovery of geometric, appearance and semantic information of objects in a 3D scene according to the 2D observation results of targets. If the depth camera can be used to reconstruct the 3D model of the object, the 3D positioning of the workpiece, the volume measurement of the logistics package and the 3D reconstruction of the indoor scene can be completed. With the blessing of big data, artificial intelligence (AI) promotes a new round of technological innovation. With data-driven deep modeling learning technology, with enough data sets, the designed network model is used for training, which makes the task of 3D reconstruction simple and vivid from the original complexity. Object-oriented design technology and deep learning algorithm have certain applications in interior design. Object-oriented design technology is a software development method, which encapsulates the data and operations in the software system in an object to facilitate management and maintenance. In interior design, Object-oriented design technology can be used to design furniture, lamps, decorations and other items, which can be easily modified and extended by encapsulating them in an object. Deep learning algorithm is a machine learning algorithm that uses neural networks to simulate the learning process of the human brain. In interior design, deep learning algorithm can be used to analyze the data of light, temperature, humidity, etc. in the indoor environment, so as to design a more comfortable and energy-saving indoor environment. In general, both Object-oriented design technology and deep learning algorithm have certain applications in interior design, but their application fields are different. Object-oriented design technology is mainly used to design furniture, lamps and other items, while deep learning algorithm is mainly used to analyze data in indoor environment.

People's means of interior design are no longer limited to hand painting, but more are carried out by computer software. 3D models and 3D model scenes can express more visual information and have a stronger sense of reality, which is a data form that is more in line with human visual perception. If we can directly form the construction drawings for the realization of the design scheme from the design scheme of 3D modeling, automatically complete the drawing of statistics and various charts, and automatically verify and adjust the collision situation of existing structural entities repeatedly, it will greatly save design time, improve design efficiency and reduce design cost. The interior design CAD system is committed to assisting designers to create in the process of interior design, effectively integrating different levels and aspects of resources in the design field, optimizing design processes and methods, and improving creativity in the design process. Using CAD to design the interior can not only make the picture simple and beautiful, but also facilitate modification and high reuse rate. In this article, the application of object-oriented design technology and DL algorithm in interior design CAD system is studied. CNN is trained by DL to realize 3D reconstruction of interior scene based on object-oriented design, and the reconstructed 3D model is rendered.

As an important branch of 3D reconstruction, 3D reconstruction of indoor scenes is closely related to its development. At present, some methods of 3D model generation based on DL have been able to recover the structural and geometric information of 3D model from single or multiple images by learning. Hao et al. proposed a method of extracting 3D object features based on multi-view CNN, which rendered 3D objects into multiple contour maps from multiple angles, and fused their features by CNN to get richer high-dimensional feature information for segmentation and classification tasks, but this method relies more on the rationality of perspective selection. Charles and others extracted the feature information of 2D projection by using CNN and fused it into 3D voxel information, and finally got high-dimensional features. Song et al. used CNN to extract and fuse the features of the input single depth image, thus restoring the complete voxel expression of the scene. No matter the reconstruction method based on the underlying geometry and color information or the reconstruction method based on the appearance structure, only the geometry and appearance information of the object are reconstructed or recovered, and there is still a certain gap from the semantic information of the scene. In view of the research status in this field, this article mainly does the following work:

(1) Based on DL technology, this article studies the task of 3D model reconstruction of indoor scene based on DL technology, and optimizes the scene layout and the reconstruction results of indoor objects through model rendering, which finally improves the accuracy of 3D model generation.

(2) In the modeling process, the 2D label is migrated to the 3D model by matching the 2D observation result of the target with the prior model in the large-scale CAD model base, and the matched prior model is registered with the point cloud data of the target, so as to determine its size, position and posture in the 3D scene.

2 RELATED WORK

Adão et al. [1] conducted an analysis of the synthetic environment of building filling in a virtual model. By constructing a flat layer on the automatically generated virtual environment, it components augmented reality content under flat graphics. The results show that the multi-stage artificial time Test point of digital settlements and building components have effective stage results. Cui et al. [2] constructed an information model for 3D model navigation. It carries out interactive visual analysis and construction of indoor environmental information model. By constructing automated tasks for environmental complexity, it combines geometric semantic structured courseware elements. The results indicate that the feature cutting function with multiple labels can achieve good spatial integrity. Hossain et al. [3] measured and analyzed a 3D model mesh reconstruction method based on CAD group building. By observing and measuring the object model space in a commercial environment, it is easier to achieve the editability of simulated scenes. In the triangulation method of object separation technology, the customer has addressed the challenges posed by different simulated elements. Jin et al. [4] analyzed the spatial architecture information of the encoder through 3D point cloud data reconstruction. A new perspective two-dimensional prediction error analysis was conducted by rendering the pose module of the combined camera. It uses a ground based camera synthesis database model to analyze the occlusion robustness of the model's appearance. Karan et al. [5] proposed an automated design process for creating environmental structures based on intelligent AI technology. By constructing the mesh model of triangular surface, it perceives the surface design of Building information modeling. The survey of artificial Intelligent design options shows that the average search improves the satisfaction of participants. Mabrouk et al. [6] used computer-assisted image processing to process and detect the conversion of 2D images to 3D images. The classification of 3D models has been carried out through image limitations, which has improved the development of quantitative technology.

Oniga et al. [7] conducted data source creation analysis for 3D models of urban architecture. By scanning drone images of different building structural objects, a ground point urban control model with open space details was annotated. Using forest learning algorithms and ground point analysis, a 3D model reconstruction with intersecting planar line segments was constructed. Özkan et al. [8] conducted a parameterized 3D modeling of roof structures using automated ground scanning processing. By constructing a point cloud scan of indoor objects, it analyzed the line segment search for region segmentation. A complete cost-effectiveness was constructed based on the results of a customized frontal beam model. This method can perform complete quantitative analysis on the automatically generated thirty models. Ren et al. [9] analyzed the internal virtual information synthesis system in computer vision tasks. Using different databases for different scene 2D images and 3D scene modifications. And designed a programmable pipeline design using a specific language. The geometric structure labels of the images were rendered through different scenes. Computer graphics is an important branch of Computer-aided design system. Through a powerful computer geometric design and analysis system, Velykodniy [10] has constructed a surface level language editing and processing method for forehead models. By analyzing the development graphics experimental results designed by the tool, it summarizes the open-source nature of the source code.

Verykokou and Ioannidis [11] analyzed the 3D model construction technology for the development of computer vision science. By conducting 3D virtual construction on scanners of different target types, real object scenes were restored. By introducing the model types of 3D scanners, this article provides an overview of the image development process of some models. Wang et al. [12] conducted morphological analysis of 3D networks on monochromatic images of deep learning architecture. By constructing a neural network based on the deformed geometry in point cloud shapes, the model vertex attribute format of shape vision was analyzed. Compared with existing technologies, its method not only prioritizes effective network models, but also preserves estimation accuracy. Three-dimensional (3D) reconstruction is the key to link the building information modeling and project schedule with daily construction images. Xue et al. [13] provided an intuitive information model representation for the construction of the constantly changing digital 3D image model. Through the analysis and summary of key technologies in the project schedule of the information model, the homogeneity differences in technology were analyzed. Yang et al. [14] conducted a multi room indoor building model reconstruction analysis. By constructing a scanning system for the semantics of indoor models, it tracks the regularization development parameters of a linear curve complex. The proposed image segmentation function can optimize the Markov model for indoor reconstruction. Yang and Ren [15] analyzed the construction methods of artistic graphics in different educational stages of interior design. The results show that the integration of CAD aided Systems thinking in art education can well construct the system theoretical knowledge. Zhao et al. [16] conducted a document classification on virtual and realistic 3D model information for construction projects. Through research on this document, the geometric shape of geometric textures was analyzed. It uses a complex three-dimensional model image matching structure with multiple data to construct a transformation matrix scene allocation for image matching. The results indicate that the generated 3D model has relatively high accuracy.

3 METHODOLOGY

The world in which human beings live is made up of 3D objects. Compared with 2D images, 3D models have more and richer visual perception details, and human visual nerves have the characteristics of perceiving three dimensions. Therefore, more and more researchers devote their energy to the study of 3D models. The representation forms of 3D data are mainly divided into three types: point cloud, voxel and grid. Because the representation of 3D data is not unique, and each representation has its own advantages and disadvantages, different algorithms and methods need to be designed for different 3D data to obtain a good 3D model. Every link of interior design will use CAD. Designers can use CAD to design and modify the floor plan, 3D plan and section plan of the interior environment. After planning and designing the interior design scheme, they can use CAD to make the renderings. In the method of generating 3D model by using DL technology, most encoders based on self-encoder network extract the feature representation of the target object, and then use decoder network to restore the 3D model of the target object corresponding to the feature. Different from the use of pixels as the minimum unit of 2D images, 3D data has many popular expressions, which also leads to different DL methods based on different 3D data expressions. Using CAD to design and modify the 3D plan of the indoor environment has the following advantages: CAD can provide very accurate measurement and drawing tools to ensure that the designer can accurately draw the size and layout of the room. CAD can visualize designs and display the appearance and feel of rooms through 3D models or rendering. CAD allows designers to perform virtual designs on computers, making modifications and adjustments at any time without the need for physical modifications. CAD files can be easily shared and communicated, allowing team members or customers to collaborate and provide feedback. Use CAD software to create a floor plan of the room, marking the positions and dimensions of elements such as walls, doors and windows, furniture, etc. Add a 3D model to CAD software to represent furniture, decorations, and other elements in the room. Adjust the position and orientation of 3D models in the room by dragging and rotating them. Use rendering tools to simulate the lighting and materials in a room to showcase the design effect of a 3D floor plan. Export 3D floor plans as images or share them as CAD files for team members or customers to view and provide feedback. It should be noted that certain skills and experience are required to use CAD to design and modify the 3D plan of the indoor environment. Therefore, it is recommended to learn basic CAD knowledge and skills before starting, or seek the help of a professional designer.

The CAD system for interior design provides a variety of modeling methods, and designers can build 3D building models conveniently and quickly according to their own needs. Shuran et al. proposed to transform the point cloud of the whole scene into a voxel 3D grid, and use 3D CNN to propose suggested areas and classification categories directly in the 3D scene, so as to detect the target. Su et al. proposed an image-based multi-view CNN. In this method, 2D images are projected from multiple perspectives, and features are extracted from the 2D images by pre-trained network models. Then all features are aggregated by maximum pooling operation; Finally, input the classification network to get the semantic segmentation result. However, this method can not effectively describe the relationship between multi-view features. Wu restored the 3D voxel model of the object with the depth image through the depth belief network. It proposes to encode the 3D shape represented by voxelization into a feature vector, and use this feature vector to restore the 3D model of the object. From the feature point of view, the quality of network feature selection affects the performance of DL-based model, and avoiding the loss of information in the process of feature selection often enhances the richness and robustness of extracted features.

In this article, the DL model of CNN and LSTM will be constructed to extract indoor image features from indoor design CAD images. The overall framework of CNN model for extracting indoor image features from indoor design CAD images constructed in this article is shown in Figure 1.

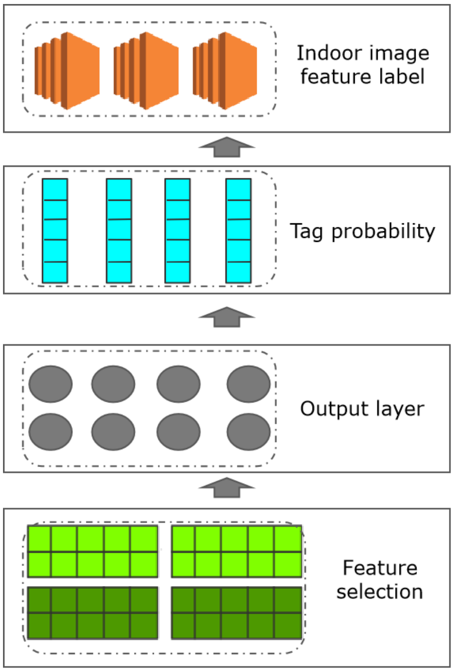

Figure 1: Model framework.

In the aspect of algorithm model, with the growth of machine learning, especially DL, a series of neural networks appear, which provide the support of models and algorithms for the modeling and analysis of 3D scenes. At present, some methods of 3D model generation based on DL have been able to recover the structural and geometric information of 3D model from single or multiple images by learning.

In order to eliminate the influence of data distribution on network training, the data are standardized in batches after convolution operation, and in order to improve the expression ability of the model, nonlinear activation function calculation is added before down sampling, and the modified linear unit activation function is used as the activation function. Select the following exponential loss function during training:

$$L(y, f) = e^{-yf(x)} \tag{1}$$

Where $y \in \{-1,1\}$; f is the output value of the classifier.

The linear truncation activation unit TLU is introduced into the first convolution layer of the network:

$$TLU(x) = \begin{cases} -T, & x < -T \\ x, & -T \le x \le T \\ T, & x > T \end{cases} \tag{2}$$

In CNN, the point cloud transformed by rigid body will be regarded as different point sets. Therefore, if you want to process point cloud data directly, you need to have the invariance of rigid body transformation, which requires the feature information extracted by DL network to represent the same feature information after translation and rotation. Huang et al. used 12 virtual cameras in different directions to render the 3D model and got 12 different images. Kong et al. introduced a measure of similarity. In 2D images, similar pixels were grouped by forcing them to have similar values in their feature space. Li et al. put forward an algorithm for 3D reconstruction based on sonar images, and established a reconstruction method with multi-height features and segmented hierarchical search by using the traditional geometric mapping relationship, so as to realize 3D reconstruction with known rotation and translation parameters. A large quantity of algorithms use DL network to analyze and process 3D objects, and get more general and informative 3D object features, which can be used to solve a series of challenging tasks in 3D field.

Due to the disorder of 3D point cloud data, DL method based on neural network can't directly act on point cloud, but convert point cloud data into voxels. The calculation cost of using 3D convolution method is too high, and it is not suitable for semantic understanding of indoor scenes. Therefore, the DL method directly based on 3D point cloud data came into being. When completing a 2D vision task, the depth of the neural network has a great influence on the accuracy of the task, and the abstract ability of the shallow network is not good. However, with the gradual increase of the depth of the network, the phenomenon of gradient disappearance becomes more and more obvious, and the training effect of the network is not good and it is often difficult to converge. How to weigh the relationship between the depth of the network and the training difficulty has become an important criterion for selecting the network. The indoor design convolution operation process of this model is shown in Figure 2.

In the process of forward propagation, semantic information is gradually formed, but spatial details are gradually attenuated. And the size and quantity of feature maps of a sample passing through different convolution layers are different, so bilinear interpolation and similarity selection strategy are used for each feature map to select the same size and quantity of feature maps of different convolution layers.

x_{avg}^{s} represents the average value of all the characteristic maps in the s convolution layer, and the similarity between the p-th characteristic map and the average value of all the characteristic maps can be calculated as follows:

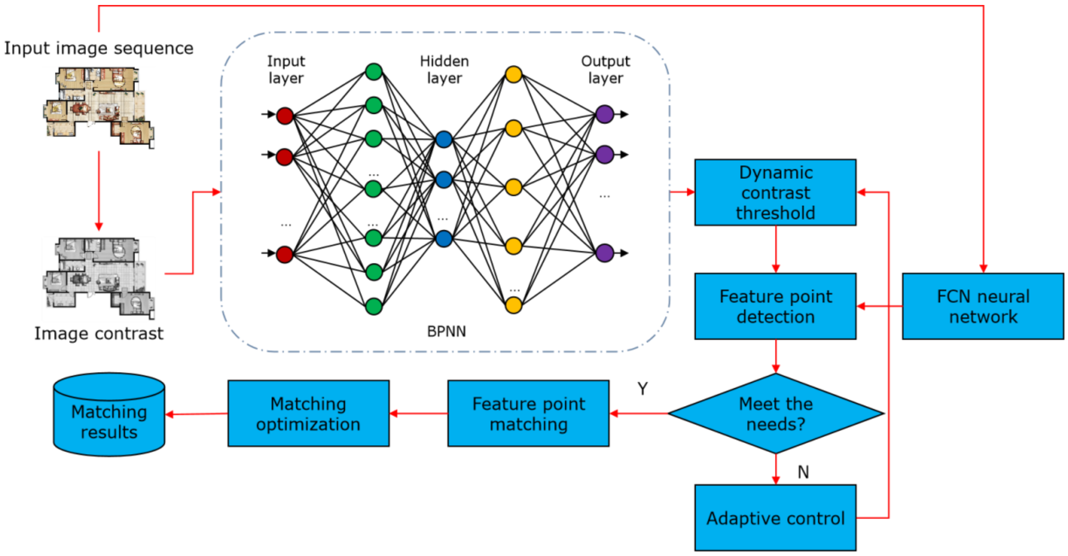

Figure 2: Convolution operation process of interior design.

$$score_p^s = sim\left(x_{avg}^s, x_p^s\right) \tag{3}$$

Where x_p^s represents a sample map; $sim(\ )$ cosine similarity function; $score_p^s$ indicates the similarity of x_{avg}^s, x_p^s. The smaller the value of $score_p^s$, the higher the similarity of x_{avg}^s, x_p^s.

Using the pre-trained CNN, the feature map sequence is formed by extracting the multi-layer convolution feature map, and then the multi-layer RNN generates the hash code by using the multi-layer convolution feature map. It is followed by the tanh function, so the hash code can be defined as:

$$q = \phi\left(W_H^T h_{end} + v_H\right) \tag{4}$$

Where $W \in R^{H\times K}$ represents the weight of the hash layer, $v_H \in R^K$ represents the offset, $q \in R^K$ represents the K-bit binary code, and $\phi(\cdot)$ represents the Tanh function.

Assuming that the mean vector $\{\mu_i | i = 1,\cdots,n\}$ and variance vector $\{\sigma_i^2 | i = 1,\cdots,n\}$ of this batch of samples have been estimated, the weighted average of these statistics is calculated by the following heuristic aggregation rules, and finally the variational posterior distribution based on a certain category of support set is obtained:

$$\mu = \left(\sum_{i=1}^{n} \sigma_i^{-2}\right)^{-1} \left(\sum_{i=1}^{n} \sigma_i^{-2} \mu_i\right) \tag{5}$$

$$\sigma^2 = \left(\frac{\sum_{i=1}^{n} \sigma_i^{-2}}{n}\right)^{-1} \tag{6}$$

The aggregation vector is weighted by the reciprocal of variance statistics of each sample, and the mean statistics of each sample is used as a linear combination of values, which means that the samples with smaller variance statistics will be estimated after classification, and will be weighted more in the process of distributing tests.

Due to the change of network structure, convolution has K convolution kernel for the visible layer node with multiple convolution kernels on one layer, so K hidden layers can be obtained. Then the energy of the whole RBM (Restricted Boltzmann Machine) is:

$$E(v,h)=\sigma\left(-\sum_{n=1}^{k}h^{k}\left(W^{k}*v\right)-\sum_{n=1}^{k}b_{k}\sum_{m=1}^{j}h_{j}-c\sum_{p=1}^{q}v_{ij}\right) \tag{7}$$

The conditional probability formula of the corresponding visible layer node becomes:

$$P(v_i=1|h)=\sigma\left(\sum_{n=1}^{k}c_{sum_k}\left(v_i|K_k\right)+c_i\right) \tag{8}$$

In the supervised training of convolutional belief network, the back propagation algorithm is used to fit the weights, and the formulas and back propagation algorithm in CNN are updated. Different convolution kernels are always used to capture different features, which greatly reduces the weight problem that needs training and improves the generalization ability of the network.

DL transforms the input signal into a new high-level feature representation by layer-by-layer transformation and self-learning the hierarchical feature representation of samples. Compared with traditional perceptron, DL network has not only input and output layers, but also multiple hidden layers. The fully connected layer is generally located behind the pool layer and before the output layer. In the fully connected layer, each neuron uses an activation function to improve the performance of CNN. Because neurons use the fully connected mode, the fully connected layer has the most parameters.

In the retrieval experiment, a state value is set for each object in the generated retrieval sequence. When the class label predicted by the network for the target model is consistent with the known class label in the sequence, the state value is 1, and when it is inconsistent, the state value is set to 0. When it is necessary to quantitatively analyze the contrast of indoor images, the root mean square is generally used for calculation:

$$RMS=\left[\frac{1}{n-1}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2\right]^{\frac{1}{2}} \tag{9}$$

Where n represents the quantity of pixels, x_i represents the gray value of the i th pixel, and x represents the average of the gray values of the image pixels.

In order to obtain the spatial relationship and 3D structure of planes, point cloud information is introduced and the normal vector of point cloud data is estimated. The point cloud data and label information are used to further determine the connection mode and closure of each plane entity. The probability that the defined point x belongs to the plane p is:

$$P(x|p)=\frac{N\left(dist(x,p);0,\sigma_d^2\right)}{N\left(0;0,\sigma_d^2\right)}*\frac{N\left(\left|N_x*N_p\right|;1,\sigma_n^2\right)}{N\left(1;1,\sigma_n^2\right)} \tag{10}$$

Where $dist(x,p)$ refers to the distance from x to plane p, $\left|N_x,N_p\right|$ is the normal vector of point x and plane p respectively, and $N\left(z;\mu,\sigma^2\right)$ refers to the value of the density function of normal distribution with mean value of μ and variance of σ^2 at point z.

In order to overcome the limitation that the algorithm is sensitive to the initial position of the point cloud scene, especially when the initial transformation matrix of the point cloud is particularly unreasonable, which leads to the problem of falling into the local optimum, in the preprocessing stage, the scanning model and the database model are oriented in the same direction, and the corresponding pose parameters are obtained by registering the target object with the database object, and finally the indoor scene modeling process is completed by fusion.

4 RESULT ANALYSIS AND DISCUSSION

The depth map prediction framework proposed in this article, with the assistance of 3D voxel scenes, first uses a perspective generation network to generate depth maps from multiple perspectives. Then, through the perspective fusion network, the depth maps from multiple perspectives are fused and predicted for depth values. The use of depth information from adjacent perspectives can help infer the depth information under the current perspective. Compared to directly predicting color images end-to-end, the perspective generation method can utilize a wider range of information to complete the prediction task of depth maps. When the Autoencoder has a strong 3D feature selection capability and the robustness of the intermediate feature representation is enhanced, this article uses a phased optimization strategy to approximate the 2D image features to the 3D voxel model features, and improve the accuracy of the final single view 3D voxel model generation. Based on the above analysis, this article constructs a CNN model with different network layers. After multiple comparative experiments, it was determined that setting the quantity of hidden layers in the CNN model to 3 resulted in the best classification performance. The comparison is shown in Table 1.

Hidden layer number	*Overall accuracy/%*
1	95.776
2	92.314
3	97.886
4	93.55
5	93.691
6	95.65
7	93.718

Table 1: Comparison between the quantity of different hidden layers and accuracy.

It can also be found that when the quantity of hidden layers is greater than 4, the overall accuracy of network classification is improved, which shows that it is more appropriate when the quantity of hidden layers of CNN is set to 3, and the overall accuracy of the obtained classification reaches the highest of 96.008%. After the corresponding features are obtained through the feature selection network, the object to be replaced gets the most similar model set through feature matching and retrieval with the database model, and the most similar model is artificially selected for the next registration.

The goal of feature fusion is to effectively fuse the feature information obtained by multiple CNN, eliminate the redundancy among them, and provide a basis for future data processing and analysis. The image detection technology based on DL can obtain high-level feature vectors with semantic similarity, which makes it possible to solve the problems of intra-class differences and inter-class overlap of images. On the platform of Matlab, the effectiveness of various methods is verified by experiments, and the recognition effect is evaluated by running time. Different feature dimension reduction methods are tested, and the specific test results of the two methods are shown in Figure 3 and Figure 4. In addition, the test results of training samples and test samples are statistically analyzed, as shown in Table 2.

In the case of video data source, it is necessary to convert video data into the format available for CNN model to identify indoor scenes through DL. The results of LSTM-CNN and the comparison method's indoor spatial feature classification model are shown in Table 3.

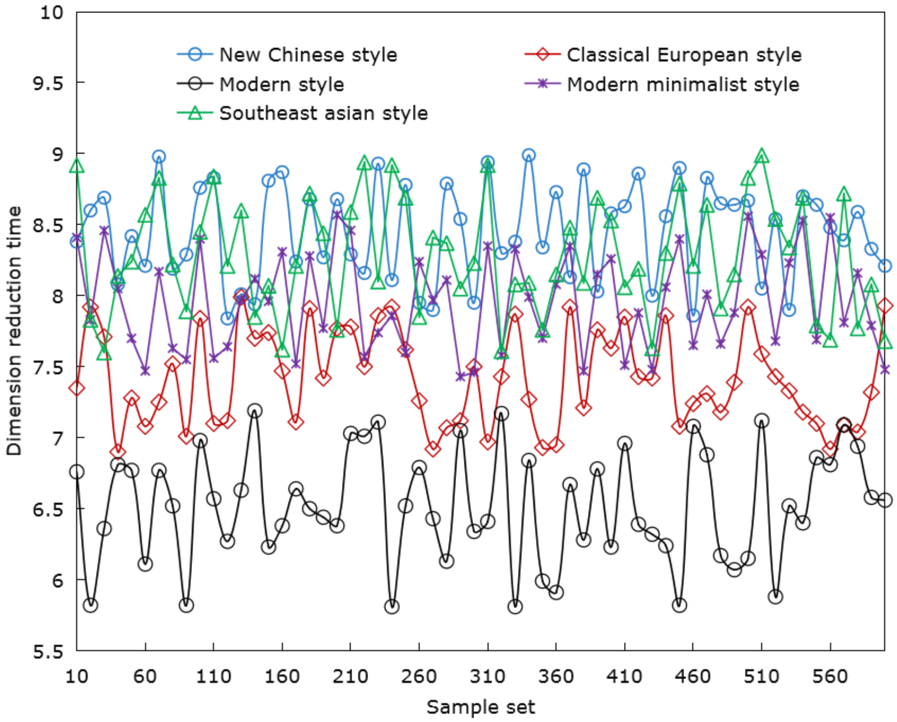

Figure 3: Dimension reduction time of LPMR +Single-stream model.

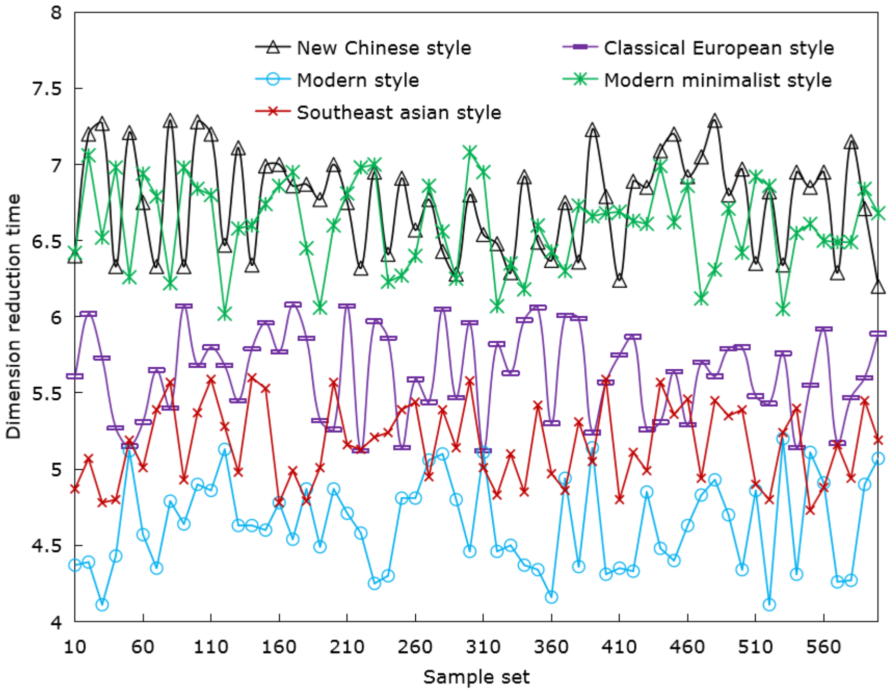

Figure 4: Dimension reduction time of LSTM-CNN model.

Scenario Type Neoclassical style	*Training sample*		*Test sample*	
	LPMR +Single-stream	*LSTM-CNN*	*LPMR +Single-stream*	*LSTM-CNN*
New Chinese style	7.61	6.17	8.55	6.97
Classical European style	8.29	6.57	7.68	5.97
modern style	7.69	6.55	6.68	4.92
Modern minimalist style	6.75	4.55	8.11	6.66
Southeast asian style	6.38	5.25	8.25	5.25

Table 2: Dimension reduction time of indoor spatial feature classification model.

Scenario Type Neoclassical style	*Training sample*		*Test sample*	
	LPMR +Single-stream	*LSTM-CNN*	*LPMR +Single-stream*	*LSTM-CNN*
New Chinese style	89.25%	93.69%	84.42%	93.26%
Classical European style	85.33%	94.35%	85.39%	94.47%
modern style	84.45%	96.38%	86.28%	94.38%
Modern minimalist style	88.67%	94.21%	80.46%	95.49%
Southeast Asian style	89.81%	94.26%	83.99%	94.44%

Table 3: Correct rate of indoor spatial feature classification model

After the data collection is completed, the designer can edit the 3D information of interior design according to the actual requirements of interior design, combining with the actual needs of quantity and variables, and construct a visual and intuitive 3D data model library by using DL-based CAD technology. Figure 5 shows the comparison of modeling accuracy of different algorithms.

When the task to be completed needs a more refined modeling effect, and it requires high authenticity or is sensitive to location information, the modeling framework based on template replacement will cause a big deviation between the retrieved model and the real object due to the limitation of database capacity. After convolution operation, the data are standardized in batches, which can eliminate the influence of data distribution on network training. At the same time, the nonlinear activation function is added before down-sampling operation, which is the modified linear unit activation function, thus improving the expression ability of the model. In order to prevent over-fitting, this article adds the Dropout layer after the full connection layer. Compare the mean absolute error (MAE) of different algorithms for indoor environmental information feature detection, as shown in Figure 6.

The detection results show that the error of this algorithm for indoor environment information feature detection is lower, which is more than 20% lower than that of the traditional algorithm, and the edge contour of indoor environment image can be located more accurately. The indoor CAD modeling method in this article can effectively maintain the local structure of indoor design images and enhance the contrast and stereo degree of images.

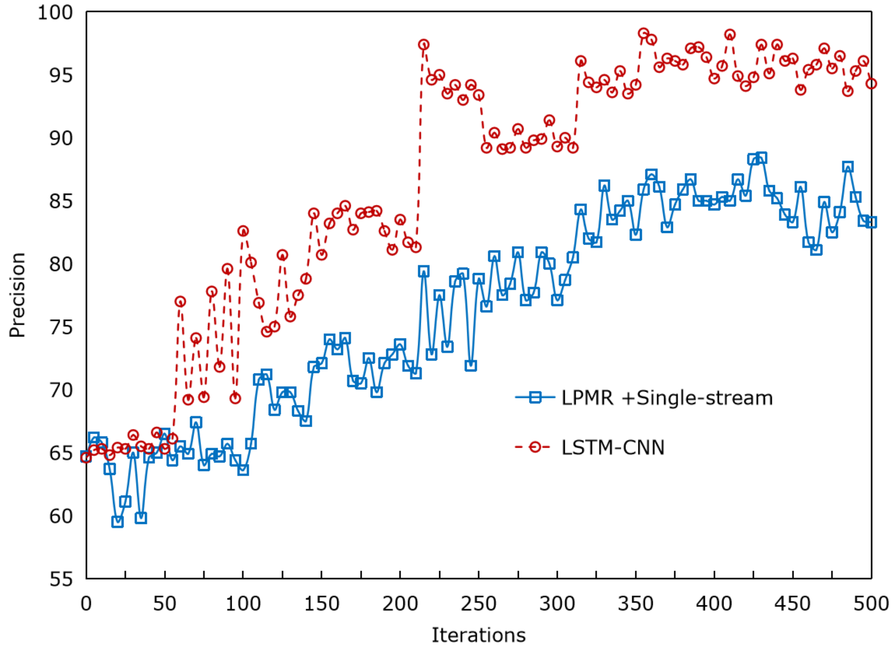

Figure 5: Accuracy results of different algorithms.

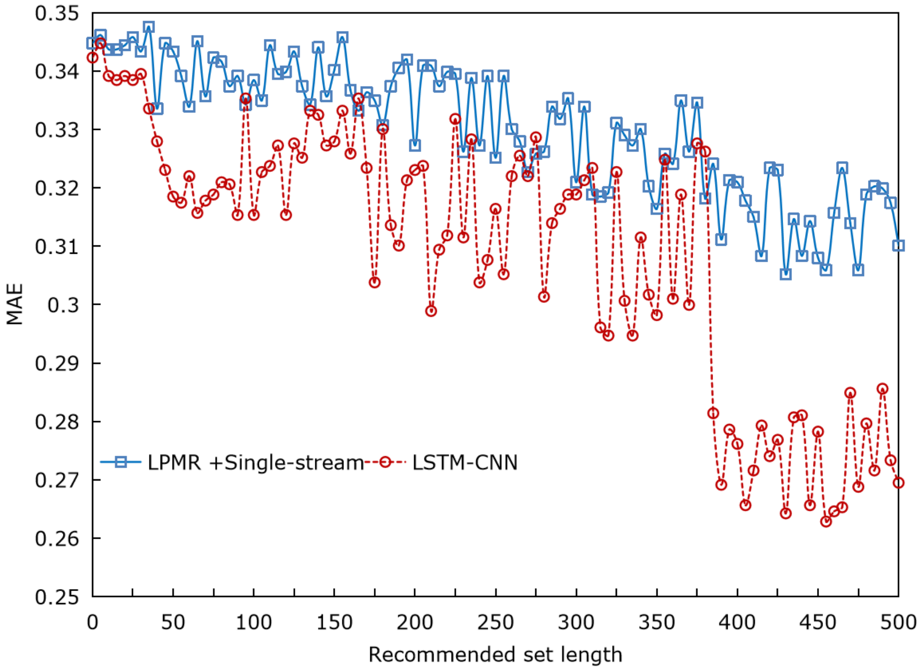

Figure 6: MAE comparison of indoor environmental information feature detection.

The process of interaction between designers and users is actually the essence of interior design activities. In the process of adjusting interior design scheme, users' evaluation of design effect on the basis of strengthening their participation in design effect is an important reference for designers to adjust design scheme. Figure 7 shows the subjective evaluation test results given by the observers on the interior design CAD images.

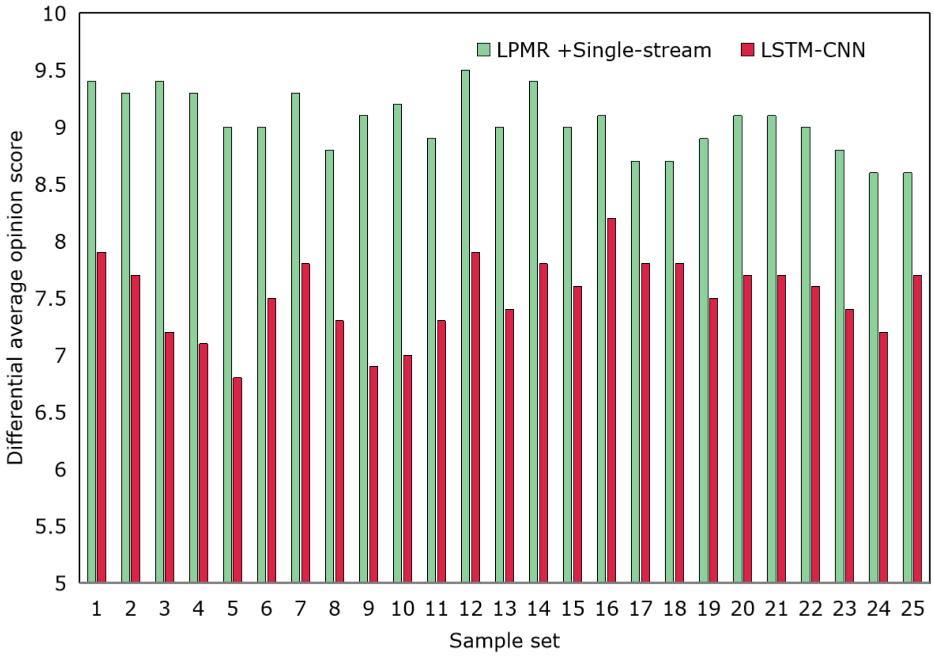

Figure 7: Observer's subjective evaluation of interior design CAD images.

Multi-view 3D model generation network uses transfer learning method to extract the features of multi-view images, and fuses the features by pooling them according to the view dimensions. Combining with the traditional 3D reconstruction algorithm, the ideas of space matching and beam adjustment are integrated into the training of network structure, which can make the designed generated network more interpretable. Parameterization of interior design will greatly strengthen the connection between interior design and other design categories, and various categories of design can jointly create more detailed and regular comprehensive design services.

Multi view 3D model generation network is a deep learning technique that utilizes multi view images to generate 3D models. To achieve this goal, the network needs to extract useful features from multi view images and use these features to reconstruct the 3D model. Transfer learning is a machine learning technology, which can accelerate the learning process of new tasks by transferring the knowledge learned in one task to another. In the multi view 3D model generation network, Transfer learning can be used to extract the features of multi view images. Specifically, the multi view 3D model generation network can use the trained Convolutional neural network (CNN) model to extract the features of multi view images. These CNN models may be pre trained, such as those trained on the ImageNet dataset or those trained in other related tasks. Through Transfer learning, the multi view 3D model generation network can use these pre trained CNN models to extract the features of multi view images. These features can be used to represent objects and scenes in multi view images, thereby assisting in network reconstruction of 3D models.

It should be noted that Transfer learning is only a feature extraction method, and it cannot directly solve the problem of multi view 3D model generation. Therefore, after using the Transfer learning method to extract the features of multi view images, other technologies need to be used to generate 3D models, such as stereo vision matching, triangulation, etc.

5 CONCLUSION

In this article, the application of object-oriented design technology and DL algorithm in interior design CAD system is studied, and CNN is trained by DL to realize 3D reconstruction of interior scene based on object-oriented design. In order to prevent the degradation of feature information caused by too many convolution layers, the encoder is designed by adding jump connections between convolution layers, so that the features of high-level convolution layers and low-level convolution layers are fused with each other, and a multi-level feature fusion 3D voxel model feature selection network is constructed. The test results show that the error of this algorithm for indoor environment information feature detection is lower, which is more than 20% lower than that of the traditional algorithm, and it can locate the edge contour of indoor environment image more accurately. In this article, the input and output of the convolution layer of the self-encoder network and the quantity of convolution layers are improved and optimized. The features of the 3D voxelized model are extracted through the full convolution coding network, and the 3D voxelized model is recovered from the features by using the deconvolution network, which achieves good reconstruction effect.

The single-view modeling framework based on view generation proposed in this article relies on the structural information provided by the voxel scene to generate the depth map. When the prediction effect of the voxel scene is not good, it will interfere with the generation of the depth map and lead to inaccurate scene reconstruction details. In the real world, the indoor environment contains not only one room, but also many rooms, corridors, staircases and so on. Therefore, how to expand the modeling method of indoor 3D scene from one room to the modeling of the whole indoor scene is the next step.

6 ACKNOWLEDGEMENT

This work was supported in part by the Xinyang Key Research and Promotion Special Project: Research on Innovative Development of Integration of Traditional Village Landscape and Tourism Environment in Dabie Mountainous Area of Southern Henan Province (No. 0046); Training Program for Young Backbone Teachers of Xinyang Agriculture and Forestry University and the Innovative: Research Team of Traditional Village Conservation and Regional Culture Research in Xinyang Agriculture and Forestry University (No. 2022KICX021).

Ting Ma, https://orcid.org/0009-0006-2048-8287
Cun Shang, https://orcid.org/0009-0001-3503-7458

REFERENCES

[1] Adão, T.; Pádua, L.; Marques, P.; Sousa, J.-J.; Peres, E.; Magalhães, L.: Procedural modeling of buildings composed of arbitrarily-shaped floor-plans: background, progress, contributions and challenges of a methodology oriented to cultural heritage, Computers, 8(2), 2019, 38. https://doi.org/10.3390/computers8020038

[2] Cui, Y.; Li, Q.; Yang, B.; Xiao, W.; Chen, C.; Dong, Z.: Automatic 3-D reconstruction of indoor environment with mobile laser scanning point clouds, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(8), 2019, 3117-3130. https://doi.org/10.1109/JSTARS.2019.2918937

[3] Hossain, M.-R.; Tasmin, N.; Golder, S.; Mahmud, M.-P.: Environment and object design for 3D simulation in context of commercial vehicles, International Journal on Interactive Design

and Manufacturing (IJIDeM), 16(3), 2022, 969-985. https://doi.org/10.1007/s12008-022-00876-3
[4] Jin, P.; Liu, S.; Liu, J.; Huang, H.; Yang, L.; Weinmann, M.; Klein, R.: Weakly-Supervised Single-view Dense 3D Point Cloud Reconstruction via Differentiable Renderer, Chinese Journal of Mechanical Engineering, 34(1), 2021, 1-11. https://doi.org/10.1186/s10033-021-00615-x
[5] Karan, E.; Asgari, S.; Rashidi, A.: A markov decision process workflow for automating interior design, KSCE Journal of Civil Engineering, 25(9), 2021, 3199-3212. https://doi.org/10.1007/s12205-021-1272-6
[6] Mabrouk, M.-S.; Afify, H.-M.; Marzouk, S.-Y.: 3D reconstruction of structural magnetic resonance neuroimaging based on computer aided detection, International Journal of Bio-Inspired Computation, 17(3), 2021, 174-181. https://doi.org/10.1504/IJBIC.2021.114881
[7] Oniga, V.-E.; Breaban, A.-I.; Pfeifer, N.; Diac, M.: 3D Modeling of Urban Area Based on Oblique UAS Images—An End-to-End Pipeline, Remote Sensing, 14(2), 2022, 422. https://doi.org/10.3390/rs14020422
[8] Özkan, T.; Pfeifer, N.; Styhler, A.-G.; Hochreiner, G.; Herbig, U.; Döring, W.-M.: Historic Timber Roof Structure Reconstruction through Automated Analysis of Point Clouds, Journal of Imaging, 8(1), 2022, 10. https://doi.org/10.3390/jimaging8010010
[9] Ren, H.; Zhang, H.; Zheng, J.; Zheng, J.; Tang, R.; Huo, Y.; Wang, R.: MINERVAS: Massive interior environments virtual synthesis, In Computer Graphics Forum, 41(7), 2022, 63-74. https://doi.org/10.1111/cgf.14657
[10] Velykodniy, S.: Reengineering of open software system of 3D modeling BRL-CAD, Innovative Technologies and Scientific Solutions for Industries, 3(9), 2019, 62-71. https://doi.org/10.30837/2522-9818.2019.9.062
[11] Verykokou, S.; Ioannidis, C.: An Overview on Image-Based and Scanner-Based 3D Modeling Technologies, Sensors, 23(2), 2023, 596. https://doi.org/10.3390/s23020596
[12] Wang, N.; Zhang, Y.; Li, Z.; Fu, Y.; Yu, H.; Liu, W.; Jiang, Y.-G.: Pixel2Mesh: 3D mesh model generation via image guided deformation, IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(10), 2020, 3600-3613. https://doi.org/10.1109/TPAMI.2020.2984232
[13] Xue, J.; Hou, X.; Zeng, Y.: Review of image-based 3D reconstruction of building for automated construction progress monitoring, Applied Sciences, 11(17), 2021, 7840. https://doi.org/10.3390/app11177840
[14] Yang, F.; Zhou, G.; Su, F.; Zuo, X.; Tang, L.; Liang, Y.; Li, L.: Automatic indoor reconstruction from point clouds in multi-room environments with curved walls, Sensors, 19(17), 2019, 3798. https://doi.org/10.3390/s19173798
[15] Yang, Y.; Ren, H.: The Teaching Method Combining Art Design and CAD Design, Computer-Aided Design and Applications, 19(S8), 2022, 157-167. https://doi.org/10.14733/cadaps.2022.S8.157-167
[16] Zhao, L.; Zhang, H.; Mbachu, J.: Multi-Sensor Data Fusion for 3D Reconstruction of Complex Structures: A Case Study on a Real High Formwork Project, Remote Sensing, 15(5), 2023, 1264. https://doi.org/10.3390/rs15051264