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Application Analysis of Particle Swarm Optimization Convolutional Neural Network in Industrial Design

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Abstract. As an important design resource, the quantity of computer-aided design (CAD) models has increased dramatically with the popularization of 3D CAD technology. In order to solve the problem of 3D reconstruction of CAD model and make it serve for industrial design and modeling, this article studies the application of deep learning (DL) algorithm and computer aided industrial design (CAID) in industrial design, and proposes a 3D reconstruction and rendering model based on particle swarm optimization convolutional neural network (PSO-CNN). This model uses mutual attention mechanism to establish long-distance correlation between source domain and target domain, and uses attention-driven modeling, so that the source domain image can directly learn the key features in the target domain. On this basis, for large-size images, the mutual attention mechanism is further improved to a multi-head mutual attention mechanism to save more computer memory costs. The simulation results show that the model can not only reconstruct the 3D structure of an object based on a single-view image, but also render the 3D structure of the object, giving full play to the advantages of many samples and wide types of image data and the powerful representation ability of DL, realizing the 3D reconstruction of an object based on a single-view image and rendering the reconstructed 3D model.

Keywords: Industrial Design; Deep Learning; CAD; 3D Modeling
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1 INTRODUCTION

With the increasingly fierce market competition, consumer demand segmentation is becoming more and more obvious, but from the first day of the birth of industrial design, the design stage of most products is in a relatively closed environment. The reform of manufacturing production and operation mode puts forward higher requirements for all links, especially the upstream design link will directly affect the subsequent production quality and efficiency. Classical 3D reconstruction methods need to scan all the surfaces of the reconstructed object, but in practical application, it is not always possible to completely scan the surface of the object, which may lead to the collapse and cavity of the reconstructed 3D structure. Moreover, processing multi-view images needs more computing resources, which can not meet the requirements of real-time in practical applications. In the design stage of industrial products, in order to obtain a perfect and reliable design scheme, designers need to search and integrate past design experience and knowledge for design reference through various channels.

The key to the implementation of industrial design lies in the rational organization, management and reuse of enterprise design resources. Its core is to produce products that meet the market demand through the optimization and reorganization of design resources on the condition that no new design is produced. Although collaborative design based on computer digital technology has been widely used, manual analysis and integration of design experience is still the core work of designers. Through advanced technologies such as artificial intelligence, further improving the integration and analysis of data in product design and manufacturing, such as the understanding and reuse of product structure, modeling and other knowledge, and promoting the early design of manufacturing big data, will greatly promote the intelligent level of industrial product design. The reconstruction and rendering of the 3D structure of the object can make the computer realize the mutual perception of the 2D and 3D space, analyze the posture, shape, appearance, texture and position of the object in different dimensions, and then recognize, describe, learn, understand and store the real world. Mechanical CAD is a kind of computer software that can help mechanical engineers design and manufacture Machine element, components and entire machines. They are typically used to optimize the design process, helping designers achieve better results in reducing costs, improving quality, and accelerating production speed. Utilize deep learning algorithms to optimize the design process, for example, by predicting the results of different design schemes to accelerate design speed, and by identifying weaknesses in the structure to optimize the behavior and performance of the predicted structure. At the same time, deep learning algorithms can also be used to identify and analyze objects and features in images and videos, for example, by automatically detecting defects on the production line to improve production efficiency. In this article, the application of DL algorithm and mechanical CAD in industrial design is studied, and a 3D reconstruction and rendering model of CAID based on PSO-CNN is proposed, which can quickly establish the product family needed by mature industrial design system, effectively shorten the development cycle of mature industrial design system and realize the industrial design optimization of CAD model.

With the wide application of 3D CAD system, 3D CAD system has gradually become the mainstream tool of product design, and CAD model has become the core medium to express product design information. As the core and source of mass customization, product design technology for mass customization has become a key technical problem to be studied and solved. The features of artificial design have good feature description ability in some fields. However, the scenes in real life are complex and changeable, and the method based on artificial design features is inefficient. Some design features can not describe the original objects well. With the growth of computer technology, most steps in this process are replaced by computers, and a large quantity of design data and design schemes are stored in computers, which can be easily accessed through the Internet. Traditional 3D rendering solutions use discrete operations such as rasterization and visibility calculation in the rendering pipeline, which leads to that the relationship between rendering parameters and projection images is not clearly established in the rendering equation, so reverse rendering cannot be realized. This article studies the application of DL algorithm and mechanical CAD in industrial design. The main contributions of this study are as follows:

(1) This article studies the data exchange method of heterogeneous CAD system integration based on features, establishes the framework of this method, and analyzes its implementation mechanism. It analyzes the information composition of CAD model from the feature level, proposes a feature information description method based on feature classes, constructs a 3D reconstruction and rendering model of CAID based on PSO-CNN, and realizes the industrial design optimization of CAD model.

(2) In order to meet the requirements of the growth of mature industrial design system, the product family structure model for industrial design is established by using the modular design idea, and its modeling method and process are given.

This article first introduces the necessity of applying CAID technology to industrial design, and then proposes to apply CNN model improved based on PSO algorithm to CAID 3D modeling of industrial design. Then, the superiority of the model is verified by simulation and sample measurement, and its application value in industrial design is proved. Finally, the main work and limitations of this article are summarized, and the future research direction of CAID modeling is put forward.

2 RELATED WORK

Abad et al. [1] carried out the manufacturing system analysis of cell Computer-aided design. Evaluated the fracture resistance of 3D impressions and fixed dentures under additive technology. The results show that the strength of the temporary restoration in the milling group under Computer-aided design is higher than that in the Rapid prototyping group. Alidoost et al. [2] constructed aerial images of building RGB images and 3D shapes. It proposed a standardized digital surface model with linear elements and analyzed its coarse features. By evaluating the normalized median absolute deviation measurement of the 3D model of a building in a single image, the accuracy of reconstructing the 3D model of the building from the image was summarized. Almonti et al. [3] conducted additive manufacturing analysis on the production process of complex geometric 3D products. The problem of high raw material process cost is reduced through Business analysis on the production process of additive manufacturing of melt resin metal. Chang et al. [4] succeeded in the prediction and decision-making of the Temporal database for in-depth learning. Through the integration and fusion of the Internet of Things of artificial intelligence, it analyzes the network model architecture infrastructure under edge computing. Solved the transmission delay and destructive impact caused by network infrastructure. Chen et al. [5] carried out the detection of 3D laser scanning point cloud scene of building element points from the depth learning edge computing classifier. Model types that are linked to each other by selecting points from the same object, using fixed cloud converted drawing boundary points. Use entity objects in context specific spaces for corresponding matching.

Henderson et al. [6] proposed a unified framework to solve the weak supervision problem of shape samples in 3D reconstruction of a single image. By comparing parameter information during training and analyzing coloring information, the model trained the reconstructed convex and concave objects in a multi object view. The results indicate that the shape generated by the model captures smooth surfaces and fine details better than voxel based methods. Ilie [7] conducted computer-aided spatial distribution of multivariate shape repair for composite materials. The influence of the measurement performance of the material was determined through the filler under Scanning electron microscope and multivariate linear model analysis. When identifying the distribution of regional differences, it can quickly and sensitively determine the indentation modulus. Kim et al. [8] constructed a detailed image model quantitative standard reconstruction method for microvascular structures. By comparing the image field of view of deep convolutional networks with deep analysis, the problem of missing field of view and bandwidth is avoided. Koch et al. [9] conducted path planning analysis for the 3D model of unmanned aerial vehicles. By reconstructing the environmental model of drone flight trajectory in 3D, a multi view stereo method for constructing high-quality image models was developed. This method solves the path problem of model flight by utilizing the correlation heuristic of the model. Kuś et al. [10] conducted angle range analysis of human depth holographic imaging tomography for illumination. By visualizing the dataset that describes the theoretical framework in detail, the optimal reconstruction process for path calculation, hardware configuration, and fault reconstruction were constructed. Lalegani et al. [11] carried out the filling pattern and density analysis of Computer-aided design. Its research used sedimentary modeling for extensive parameter partitioning and designed a material allocation program. Through finite element analysis of CAD samples, the differences between the printed and simulated models were identified.

Liu et al. [12] conducted an image-based Iterative reconstruction analysis of cracks in UAV flying bridges. Due to the excellent spatial processing of perspective distortion and non planar structural surface distortion by drones, good crack width features can be obtained for sequences and 3D surface models. Nguyen et al. [13] carried out Iterative reconstruction of Structured light with multi frequency fringe contour technology. By predicting pixel differences in dense computing through deep learning analysis, the content of the high-quality sample dataset of the 3D shape of the image was determined. At the same time, the effectiveness and robustness of the technical methods proposed in the experiment were verified. Villalba et al. [14] conducted high-resolution optical quality combination detection analysis of deep learning software sensors. It completes the self-learning process of sensor quality control by reducing the performance of automated high defect detection. The developed deep learning sensor network has achieved high fully automatic resolution accuracy. The traditional 3D image reconstruction requires the analysis and construction of medical Grayscale with dose. At present, there is no single vector deformation technology that can describe 2D image information. Wang et al. [15] conducted a deep network learning method and conducted quality analysis and reconstruction of medical image reconstruction techniques. It obtained synthetic prototypes and real patient datasets from the online learning environment. Xie [16] conducted a vertical difference analysis between the left and right views of 3D frames. It proposes a multi view multi view photometric stereo fusion algorithm Iterative reconstruction technology. By estimating the average depth during the iteration process, the surface depth is projected into physical coordinates. This method can obtain more accurate surface normals and better Iterative reconstruction quality. Zheng et al. [17] conducted an analysis of the generalization ability of multi-parameter freeform topology scenes in 3D images. By combining the parametric volume model with the free form deep Implicit function, the accuracy of the estimation of the parametric model is constructed, and the consistency between the parametric model and the Implicit function is enhanced. The results show that the proposed image 3D model has high performance.

3 NECESSITY OF APPLYING CAID TECHNOLOGY TO INDUSTRIAL DESIGN

CAID technology, also known as computer-aided industrial design technology, relies on computer technology and industrial design theory. In the era of increasingly fierce product market competition, shortening product development cycles and enhancing product innovation have become the key to enhancing the competitiveness of enterprises and product markets. Computer-aided design is characterized by improving product design efficiency, optimizing product shape and predicting product performance. Therefore, it is necessary for Computer-aided design and industrial design to cross disciplines. Industrial design is a comprehensive design of the functions, materials, structures, forms, colors, surface treatments, decorations, and other elements of industrial products produced in bulk from various perspectives such as society, economy, technology, art, etc., creating new products that can meet people's growing material needs. Industrial design itself contains potential requirements for technological innovation, and the degree of product innovation directly affects market share. The importance of industrial design for the manufacturing industry is becoming increasingly prominent. In an era of increasingly fierce market competition, not only do enterprises need to enhance their competitiveness, but university students also need to improve their own competitiveness. In terms of understanding industrial design, it is not limited to product appearance design. The work of industrial designers cannot end with appearance design and rendering of drawings.

Due to the continuous growth of sci & tech and the continuous expansion of product diversification demand, the product functions are more perfect, the structure is more complex, the product update speed is faster, and the market competition increases sharply. Enterprises must constantly innovate and introduce new products that can meet the needs of users and have market competitiveness if they want to gain a foothold in today's high-speed development society.

CAID technology, namely CAID technology, relies on computer technology and industrial design theory. Features, geometric elements and topological relations all show the structural characteristics of CAD model, which are characterized by clear structural levels, regular and structured correlation between different levels of data and within each level of data. This is conducive to further processing and analysis of CAD models, and provides a basis for further information extraction, mining and reuse of CAD models.

Industrial design itself contains the potential requirements of technological innovation, and the degree of product innovation directly affects the market share, and the significance of industrial design for manufacturing industry is becoming more and more prominent. In order to speed up the product design process and shorten the design cycle and delivery time of new products, it is necessary to use rapid design methods and formulate rapid design systems. Among many rapid design methods, the most intuitive method is to use existing resources as much as possible. CAID technology not only provides a platform for industrial design communication in the information age, but also enables it to cope with complicated market demands because of its unique advantages.

Design is a creative activity, and the obtained design results are usually not tested by many conditions for a long time, so the reliability of a completely new design is usually not optimistic. Traditional CAD technology simulates product design through computer and network technology. CAID itself is the combination of computer technology and CAD technology, which is based on industrial design theory and goes deep into all aspects of industrial design. Most of the design resources provided by information reuse technology have been tested for a long time in actual production and use, and the reliability of this part can improve the reliability of the whole design to some extent. CAID technology helps products to occupy the market quickly by grasping consumer demand and market demand. Both traditional CAD technology and CAID technology pay attention to the simulation of product design appearance, assist industrial design through computer technology, and constantly change the appearance through simulation to meet the needs of the market and consumers.

4 CAID ITERATIVE RECONSTRUCTION AND RENDERING MODEL BASED ON PSO-CNN

The CAID iterative reconstruction and rendering model based on Particle swarm optimization Convolutional neural network (PSO-CNN) is a deep learning model for computer aided industrial design (CAID). This model uses particle swarm optimization to optimize CNN to obtain more accurate reconstruction and rendering results. Preprocess 2D views and 3D model data in the CAID dataset, including image enhancement, data cleaning, and annotation. Extract features from 2D views using pre trained CNN models (such as VGG, ResNet, etc.) and obtain feature vectors of the image. Input feature vectors into the optimized CNN model to predict the depth information in each view, that is, the distance of the object in space. Based on the depth information of multiple views, use methods such as triangulation to reconstruct the 3D model of the object. Then, algorithms such as lighting models and texture mapping are used to render the 3D model into a 2D view, and post-processing such as color adjustment and depth of field effects are performed. The use of particle swarm optimization algorithm to optimize the CNN model further improves the accuracy and generalization ability of the model. Repeat the above steps until the expected reconstruction and rendering results are achieved. This model can be applied to fields such as industrial design and architectural design, helping designers complete design tasks faster and more accurately. In the stage of traditional mechanical product design, designers mainly rely on design experience to achieve a transformation from abstract thinking to visual thinking through brain thinking. In the stage of mechanical product design, traditional design methods mainly use the brain to represent and process information, which is based on experience and knowledge. These two representations are mainly described by databases: establishing a text database to describe abstract representations based on characters and symbols; Establish a graphical database based on patterns to describe image representation; The information processing process is mainly achieved through computer algorithms and manual optimization.

In traditional CAD design technology, although industrial design and product appearance design simulation are carried out using computer technology, fundamentally, the design data of CAD technology is still stored in the design scheme. In specific product manufacturing, due to actual conditions, design data may not be fully represented as production data. A feature information description method based on feature classes is proposed, and a Iterative reconstruction and rendering model of CAID based on PSO-CNN is constructed. The CNN structure of CAID Iterative reconstruction is shown in Figure 1.

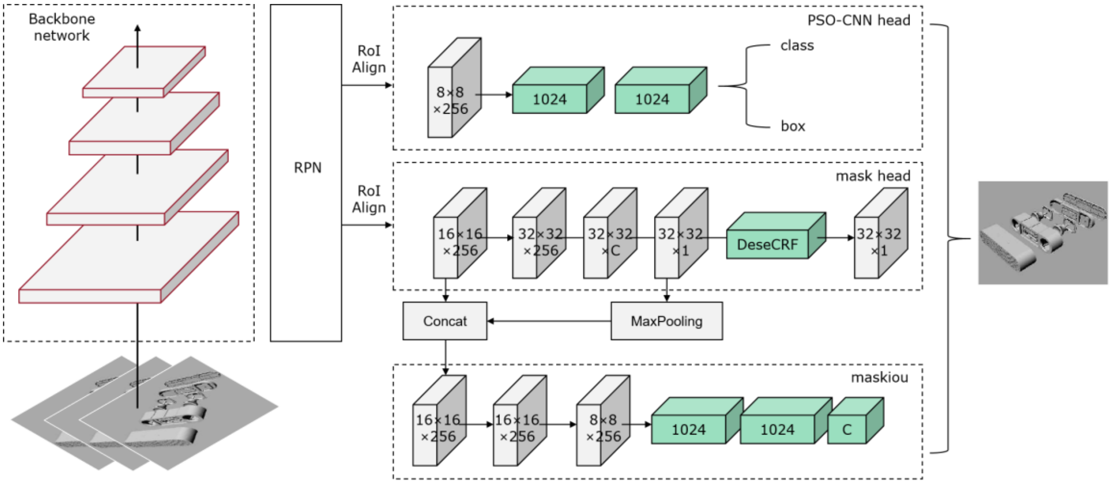

Figure 1: CNN structure of CAID 3D reconstruction.

Image x_i represents the information of all pixels in a picture, and the category it represents is y_i. Through the scoring function (neuron) and activation function $f(x_i, W)$, the scoring s_j of different categories to which x_i belongs can be obtained. Then, the loss function of x_i for category prediction can be expressed as:

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + \Delta) \tag{1}$$

$\max(0,-)$ function is a threshold function about zero, and it is usually also called the loss function of broken leaves. The goal of using the loss function of support vector machine (SVM) in neural network is to make the score of the correct prediction result significantly higher than that of the wrong prediction result, that is, the difference is at least Δ. If this requirement is met, the loss value is zero, that is, the prediction is correct, otherwise, the loss is calculated. In Softmax, the score mapping function is unchanged, and the corresponding loss function is defined as:

$$L_i = -\log\left(\frac{e^{f_{y_i}}}{\sum_j e^{f_{y_j}}}\right) \tag{2}$$

In a one-dimensional function, the slope is the instantaneous rate of change of the function at a certain point. Gradient is a generalized expression of function slope, which represents a vector, not a scalar. In the input space, gradient (or derivative) is a vector of slopes in various dimensions. The derivation formula of one-dimensional function is as follows:

$$\frac{df(x)}{dx}=\lim_{h\to 0}\frac{f(x+h)-f(x)}{h} \tag{3}$$

When a function has multiple parameters, the derivative is called a partial derivative. Gradient is a vector formed by the partial derivative in each dimension, which represents the slope of the loss function in each dimension. Because the network wants the loss function value to decrease rather than increase, the parameters in the network can be updated along the negative direction of gradient.

Through technical innovation, CAID technology can directly convert design data into production data. 3D simulation can reproduce the assembly stage of product parts and transmit design data to the processing and manufacturing departments after assembly through the network to complete the production process from design to manufacturing. Chen et al. studied the problem of product knowledge representation and reuse of heterogeneous 3D CAD models, and proposed a hierarchical representation method of product data based on ontology. On this basis, they proposed a semantic layer heterogeneous 3D CAD model transformation method, a multi-level retrieval method and a CAD/PDM integration method. Gu et al. proposed an incremental data exchange framework based on implicit feature expression, established a standard feature library, and discussed the feature elements, feature structure, feature history and the representation of coordinate system in detail.

The image contains abundant structural and texture information. With the powerful representation ability of the DNN, the feature information in the image can be extracted and stored with potential vectors. The massive image information can assist the neural network to train, learn and extract the image content more accurately, and increase the robustness and robustness of the model, so that it can adapt to different application scenarios. The optimization stage of CAD 3D images is shown in Figure 2.

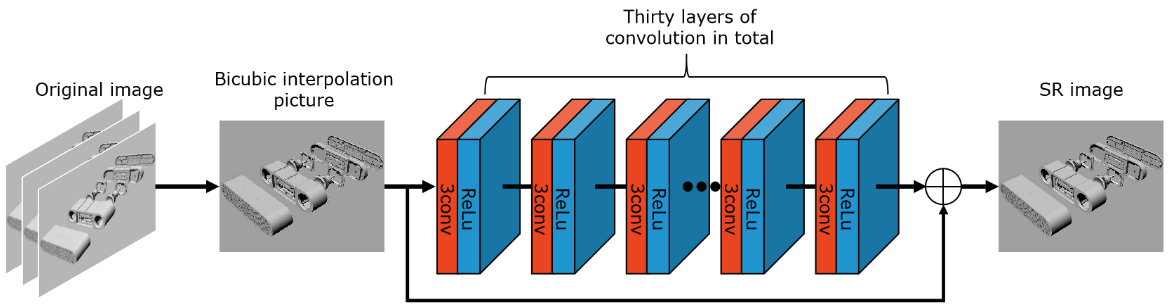

Figure 2: Optimization stage of CAD 3D images.

The layout generation algorithm in this article needs to segment the original 3D object before training the algorithm model, and give the position, size information and connection relationship of the segmented parts as the layout features to be learned. The BPNN improved by adaptive learning rate adjustment method is adopted:

$$\Delta X = lr\cdot\frac{\partial E}{\partial X} \tag{4}$$

$$\Delta X(k+1)=mc\cdot\Delta X(k)+lr\cdot mc\cdot\frac{\partial E}{\partial X} \tag{5}$$

Where lr is the learning rate and mc is the momentum factor. The added momentum term is essentially equivalent to the damping term, which reduces the oscillation trend of the learning process, thus improving the convergence and finding a better solution.

Because the linear relationship between the input vector $X(x_1, x_2, \ldots, x_n)$ and the output vector is not satisfied, the unipolar sigmoid function is selected as the excitation function:

$$f(x) = 1/(1+e^{-x}) \tag{6}$$

The image of Sigmoid function and its derivative function is shown in Figure 3. Sigmoid function curve on the left and Sigmoid function derivative curve on the right. Sigmoid function is usually not used as the activation function of the middle layer of the network, but is only used when the last layer of the network needs probability output.

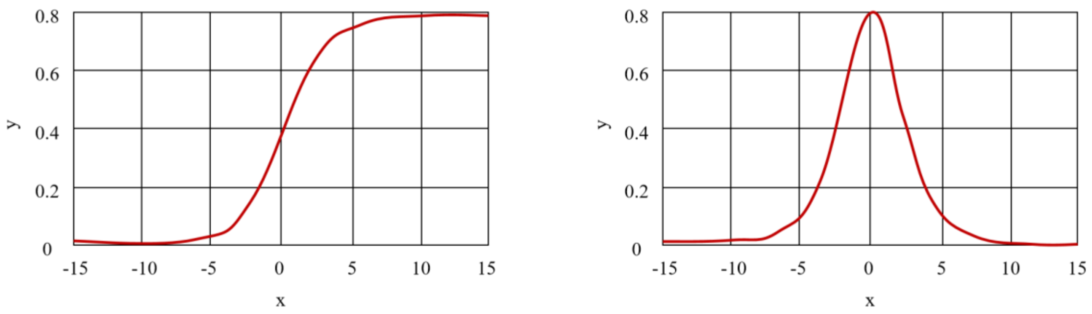

Figure 3: Sigmoid function and its derivative function image.

In computer processing, a digital image is actually a 2D array, and the elements in the array are called pixels. Because each pixel does not exist independently, but has a great correlation with each other, this characteristic ensures that image processing technology has great development potential. PSO algorithm is used to optimize the image processing stage of CNN model. Each particle has its own current velocity, which is recorded as:

$$V_i = \{V_{i1}, V_{i2}, \ldots, V_{il}\} \tag{7}$$

Remember $Xbest(t)$ as the optimal position experienced by the current particle swarm, that is, the particle with the best fitness. Each particle updates its speed according to the following formula:

$$V_k^d(t+1) = V_k^d(t) + c \cdot rand \cdot \left(X_{best}^d(t) - X_k^d(t)\right) \tag{8}$$

Where $V_k^d(t+1)$ is the velocity component of the d feature after the k particle is updated; l is the characteristic quantity of the solution; $X_{best}^d(t)$ is the component of the d feature of the currently searched optimal solution; $X_k^d(t)$ is the d characteristic component of the current position of the k particle; c is a constant; $rand$ is a random number between $(0,1)$. Each particle updates its position according to the following formula:

$$X_k^d(t+1) = X_k^d(t) + V_k^d(t+1) \tag{9}$$

Where $X_k^d(t+1)$ represents the d feature component after the k particle updates its position. The particle copies itself, adds a random disturbance in its neighborhood to reach a new position, and then finds the point with the highest fitness as the position point to which the particle will move according to the fitness function. The location update function of its copy is:

$$X_k^d(t+1) = X_k^d(t) + X_k^d(t+1) \cdot \left(srd \cdot (rand * 2 - 1)\right) \tag{10}$$

Where: $srd = 0.2$, that is, the range of eigenvalue variation on each particle is controlled within 0.2, which is equivalent to searching in its own neighborhood.

A complex product design task will be divided into a large quantity of design sub-task modules, and it will be a very inefficient process if one person or a small team completes these sub-task modules one by one. Therefore, collaborative design becomes an inevitable choice for modular design. According to the principle of information processing, the stage of mechanical product design is a process from demand to concept, from abstract expression of concept to image expression of concept, from functional carrier of structure to performance confirmation of structure, and finally to confirmation of manufacturing information of mechanical product.

5 RESULT ANALYSIS AND DISCUSSION

Through depth perception, spatial positioning, Iterative reconstruction, 3D rendering and other technologies, we can realize mutual perception of 2D and 3D space, so as to better understand and present the 3D structure of objects. Depth perception refers to perceiving the distance or depth of an object in space. This can be achieved by using devices such as depth cameras or laser scanners. A depth camera can capture multiple perspectives of an object, thereby calculating its distance and position. Laser scanners can scan the surface of an object and generate point cloud data, thereby reconstructing the three-dimensional structure of the object. Spatial positioning refers to determining the position and attitude of an object in space. This can be achieved by using positioning devices such as GPS, IMU, visual positioning, etc. These devices can provide information such as the position, velocity, and acceleration of objects, thereby helping to determine their position and posture when reconstructing and rendering them. Iterative reconstruction refers to the process of converting multiple 2D views of objects into 3D models. This can be achieved by using computer vision algorithms, such as stereo vision, Structured light scanning, etc. These algorithms can fuse information from multiple views together to reconstruct the three-dimensional structure of the object. 3D rendering refers to the process of converting 3D models to 2D views. This can be achieved by using computer graphics algorithms, such as lighting models, texture mapping, and so on. These algorithms can convert 3D models into 2D views and present them on the screen, thereby achieving mutual perception of 2D and 3D spaces.

The reconstruction and rendering of the 3D structure of the object can make the computer realize the mutual perception of the 2D and 3D space, analyze the posture, shape, appearance, texture and position of the object in different dimensions, and then recognize, describe, learn, understand and store the real world. The data set used in the experiment is Shape Net Voxels. Shape Net data set itself contains 55 different kinds of 51300 3D shapes. In this experiment, Shape Net industrial product data set is used. Besides being the category with the largest data capacity, the category of industrial products also has great intra-category changes, which will bring more challenges to feature extraction. In this chapter, the proposed 3D reconstruction and rendering network is analyzed, and the functions and concrete realization of each part in the reconstruction network and rendering network are introduced in detail, including the arrangement of layer organization, the architecture and operation within the layer, and the input and output signals of each layer.

In PSO-CNN, the shape and color of industrial products are taken as input parameters. When the training sample size is small, the setting of graphics and color parameters will cause weak correlation. In the feedback stage, PSO method is to train CNN to meet the reasonable functional requirements of industrial design, and then find the best design scheme. During the test, five objects are reconstructed at a time, and each object is randomly selected from five angles for rendering, and then the results are verified and analyzed to assess the performance of the 3D reconstruction and rendering network proposed in this article on different tasks and the generalization ability of the model. Several arithmetic units at all levels are regarded as a set of image filters, and each filter extracts the feature quantity of an image, and the result is the feature quantity of the image. The test results of the first-stage automatic encoder are shown in Figure 4 and Table 1.

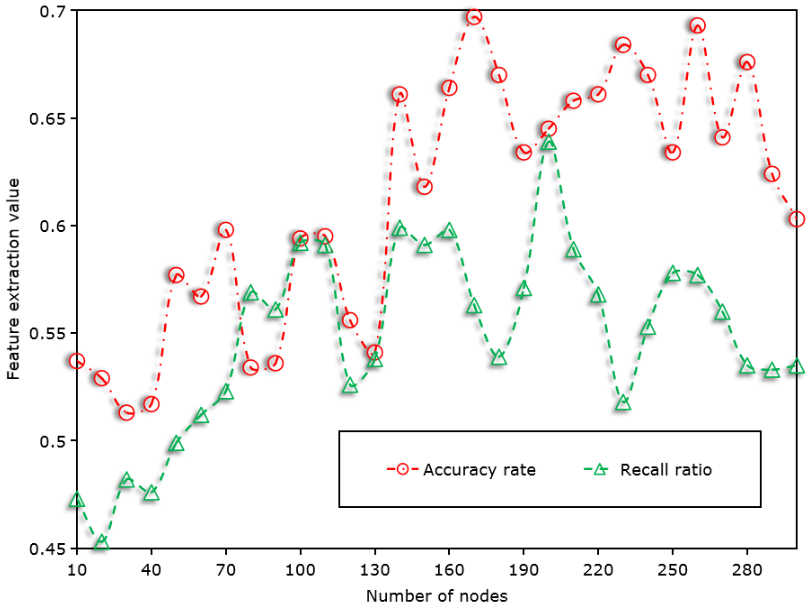

Figure 4: Test results of the first-stage automatic encoder.

Number of hidden layer nodes	*Average precision*	*Average recall*
25	54.6%	57.1%
50	57.7%	49.9%
100	59.4%	59.2%
150	61.8%	59.1%
200	64.5%	63.9%
250	63.4%	57.8%
300	60.3%	53.5%

Table 1: Results of feature extraction of industrial product modeling image by the first layer Autoencoder.

As can be seen from Figure 4 and Table 1, when the quantity of hidden nodes in the first layer of self-encoder is 200, the average precision and recall of image retrieval are 64.5% and 63.9%, which is the highest among all self-encoders, indicating that the encoder at this time has the strongest expressive ability. Therefore, 200 nodes are set as the first layer self-encoder, and the second layer self-encoder is trained. The test results of the second-stage automatic encoder are shown in Figure 5 and Table 2.

As can be seen from Figure 5 and Table 2, when the quantity of hidden nodes of the second layer self-encoder is 150, the average precision rate and average recall of image retrieval are 60.9% and 60.4%, which are the highest among all self-encoders, indicating that the encoder at this time has the strongest expressive ability. Set the quantity of nodes of the layer 2 self-encoder to 150, and then train the layer 3 self-encoder. The test results of the third-stage automatic encoder are shown in Figure 6 and Table 3.

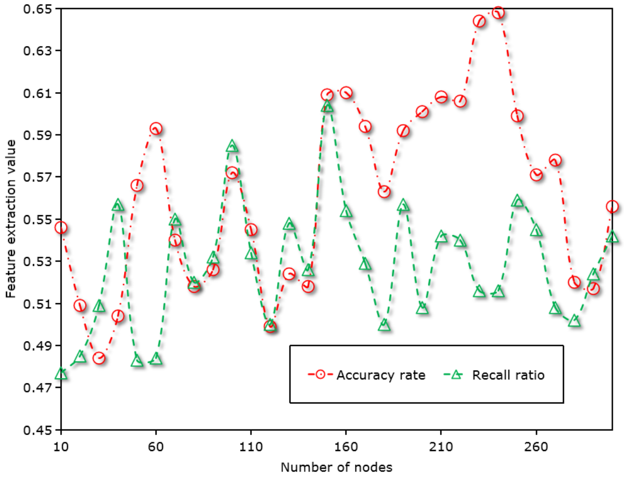

Figure 5: Test results of the second-stage automatic encoder.

Number of hidden layer nodes	*Average precision*	*Average recall*
25	54.8%	56.2%
50	56.6%	48.3%
100	57.2%	58.5%
150	60.9%	60.4%
200	60.1%	50.8%
250	59.9%	55.9%
300	55.6%	54.2%

Table 2: Results of feature extraction of industrial product modeling image by the second layer Autoencoder.

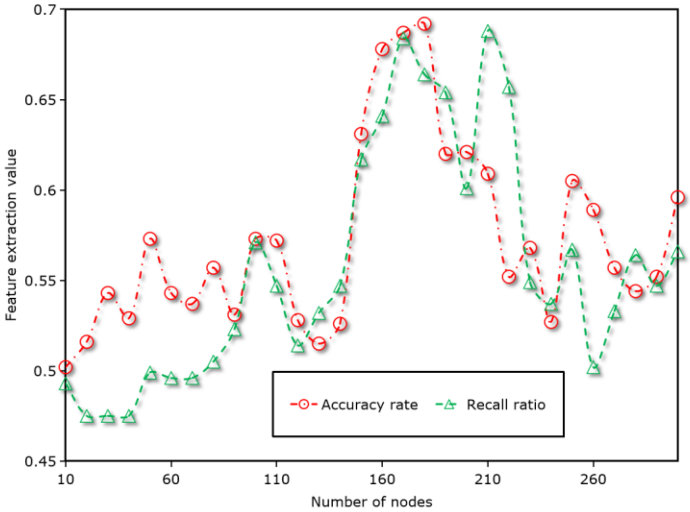

Figure 6: Test results of the third-stage automatic encoder.

Number of hidden layer nodes	Average precision	Average recall
25	57.4%	57.8%
50	57.3%	49.9%
100	57.3%	57.1%
150	63.1%	61.7%
200	62.1%	60.1%
250	60.5%	56.7%
300	59.6%	56.6%

Table 3: Results of feature extraction of industrial product modeling image by the third layer Autoencoder.

As can be seen from Figure 6 and Table 3, when the quantity of hidden nodes of the third-layer self-encoder is 150, the average precision rate of image retrieval is 63.1% and the average recall is 61.7%, which is the highest among all self-encoders, which shows that the encoder at this time has the strongest expressive ability. Fix the quantity of nodes in the third layer automatic encoder to 150.

By fusing and down-sampling the 3D voxel model and texture representation model, the feature information of the model is extracted, and then the 3D model is converted into a low-resolution 2D image by using the mapping unit to realize the rendering operation. Because the region with high sensitivity has greater influence on the decision-making of the target model, the weight of adding disturbance to the corresponding position in the countermeasure sample is greater. On the contrary, the smaller the sensitivity, the smaller the weight of adding disturbance at the corresponding position. Using PSO algorithm to process the 3D image in CAD, the total data of the 3D image in CAD is equal to the original image, that is to say, PSO algorithm itself does not have compression ability. Compared with the original image, the obtained CAD 3D image is characterized by more low-frequency energy and less horizontal, vertical and diagonal energy, so it is applied to image compression. The results show that this method has high recall and accuracy (Figure 7 and Figure 8).

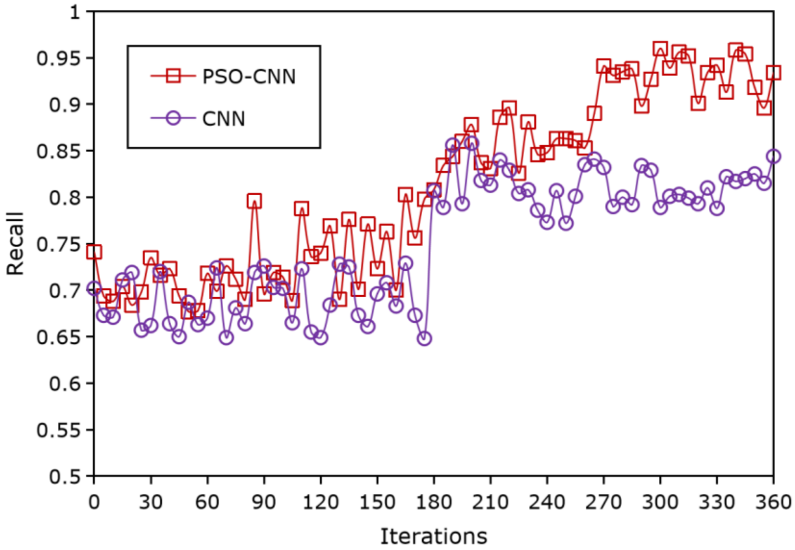

Figure 7: Comparison of recall of industrial product modeling image feature recognition.

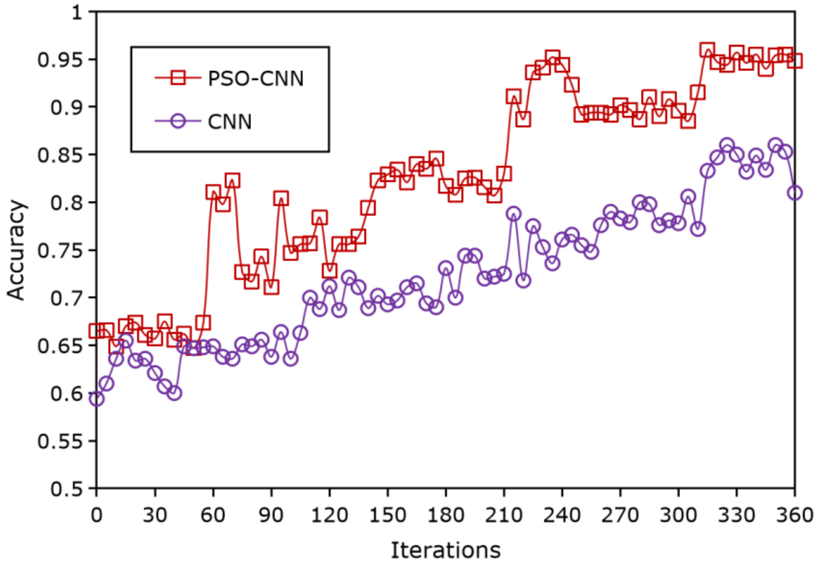

Figure 8: Comparison of feature recognition accuracy of industrial product modeling images.

From the detection results, the algorithm has high accuracy in feature recognition of industrial product modeling images, and its accuracy is more than 20% higher than that of traditional algorithms, and it can accurately locate the edge contour of industrial product modeling images. PSO algorithm can decompose an original image into components with different sizes, directions and positions, and adjust the coefficients of components in different positions according to the needs of practical application, so as to remove useless components and highlight useful components. Generally speaking, the modeling process based on PSO-CNN proposed in this article can meet the generation task, and the generated model provides reference for the construction of CAD model in industrial design.

6 CONCLUSION

With the wide application of 3D CAD system, 3D CAD system has gradually become the mainstream tool of product design, and CAD model has become the core medium to express product design information. The classical 3D reconstruction method needs to scan all the surfaces of the reconstructed object, but in practical application, it is not always possible to completely scan the surface of the object. This article studies the application of DL algorithm and mechanical CAD in industrial design, and puts forward a 3D reconstruction and rendering model of CAID based on PSO-CNN to realize the optimization of industrial design of CAD model. From the detection results, the algorithm has high accuracy in feature recognition of industrial product modeling images, and its accuracy is more than 20% higher than that of traditional algorithms, and it can accurately locate the edge contour of industrial product modeling images. The model can not only reconstruct the 3D structure of an object based on a single-view image, but also render the 3D structure of the object, giving full play to the advantages of many samples and wide types of image data and the powerful characterization ability of DL, realizing the 3D reconstruction of an object based on a single-view image and rendering the reconstructed 3D model. Through synchronous training of convolutional neural network by DL, the operation of reconstructing its 3D structure based on a single image and rendering it can be realized. The trained network can be used modularly, which can not only reconstruct its 3D structure by using the image of the object alone, but also render it by using different texture information under the known 3D structure, thus achieving the expected effect.

In this study, when rendering the reconstructed voxels, the visual angle information is directly taken as a constant as the input. In practice, the observed visual angle is often unknown, so in the future, the visual angle information of the objects in the input pictures can also be taken into account as the target to be learned, so that the reconstruction and rendering network can learn all the parameters.

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