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Computer-Aided Design AND APPLICATIONS

Discussion on the Application of Deep Learning Algorithms and CAD Systems in Industrial Design

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Abstract. The traditional industrial product design process relies on manual modeling, which has some problems, such as high cost, and the knowledge of internal geometry and relationship of the model has not been reused. Based on this, this article discusses the application of DL (Deep Learning) algorithm and CAD system in industrial design, and proposes a 3D modeling algorithm based on DL model. In order to improve the training effect of the model, the training set is preprocessed, including algorithm detection and data enhancement. The depth model obtained by transfer learning training is used in industrial design. The test results show that DNN (Deep Neural Network) can meet the accuracy requirements after 19 iterations, and the network training time is relatively short. And the training value is in good agreement with the target value. Compared with the traditional modeling methods, the 3D modeling algorithm based on DL model learns the layout and dimension features of previous 3D models through graph automatic encoder, generates the layout features of parts of 3D objects, then synthesizes the details of parts, and gradually completes the 3D generation task from coarse to fine. The research in this article provides a new idea for the application of DL algorithm and CAD system in industrial design.

Keywords: Deep Learning; Deep Neural Network; CAD System; Industrial Design
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1 INTRODUCTION

The rise of industrial product design indicates that the production of industrial product models has become a professional industry. In the design process 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. Modern industrial products, whether from design or mass production, are a very complicated process, which requires not only a large number of technical personnel to work together to complete, but also an optimization process of design and modification. Moreover, the change 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. In the early stage, the process of information collection, screening and integration relies heavily on the mental work of designers, which has the problems of low efficiency and easy omission. Due to the growth of computer technology, 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. Obviously, the traditional design technology can no longer meet the needs of the modern market. The effective application of CAD technology can perfectly replace the shortcomings of traditional design technology in all aspects, and at the same time, it can achieve remarkable economic and social benefits, which can have a far-reaching impact on modern industry. As the fourth generation of multimedia information, 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. Moreover, with the growth of virtual multimedia, computer storage technology, computer graphics and hardware upgrade, 3D models and 3D scenes have been widely used in industrial product design, virtual reality, 3D games and other fields. In order to obtain the 3D structural information of the scene through computer processing, it is often necessary to generate the 3D image of the scene through acquisition. Different from two-dimensional images, 3D images contain not only height and width information, but also depth dimension information.

CAD mainly includes product analysis, digital control of process design and so on, which is widely used in various industrial production. For modern industrial product design, the growth of additive manufacturing technology has broken many limitations of traditional manufacturing mode, provided a perfect and reliable way from 3D model to physical object, shortened the period from design to production delivery, and put forward higher requirements for the modeling quality of 3D model. Due to the rapid growth of modern industrialization, the application of CAD technology tends to be standardized. CAID (Computer Aided Industrial Design) is committed to assisting designers to create in the process of industrial 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. However, in the real industrial field, there are still a lot of model resources that have not been effectively reused, and the process of customizing and acquiring 3D models is complicated, which has a high time cost. DL is one of the hottest technologies in machine learning algorithm research in recent years. By simulating the way of human brain analysis and learning, it constructs NN (Neural Network) composed of multiple nonlinear structures, and automatically extracts high-dimensional abstract features from data to complete specific tasks. The driving forces to promote the rapid growth of DL include the increasingly large-scale trainable data sets, the upgrading of computer hardware, the proposal of different types of NN and optimization algorithms. Compared with the traditional hard-coded rules, DL is a completely data-driven algorithm, which can generalize the problems with similar basic feature distribution, which is in sharp contrast with the previous pattern recognition architecture based on specific problems. In the field of 3D intelligent modeling, AI technology provides powerful feature extraction and learning ability. In the field of AI, the rapid growth of DL technology has promoted technological changes in natural language processing, computer vision and other fields. DL method counts the geometric shape, texture, size and other information of 3D data by means of feature engineering, and trains machine learning algorithm to learn relevant features to complete modeling tasks, which has achieved good results in large-scale scene modeling, human posture and other tasks. Based on DL algorithm and CAD system technology, this article makes a relatively in-depth discussion on industrial design. Its innovations and main contributions are as follows:

① This article discusses the related contents of DL algorithm and CAD system; On this basis, a 3D modeling algorithm based on DNN is proposed. It provides a new idea for the follow-up industrial design related work.

② The 3D modeling algorithm based on DNN proposed in this article learns the layout and dimension features of previous 3D models through graph automatic encoder, generates the layout features of parts of 3D objects, then synthesizes the details of parts, and gradually completes the 3D generation task from coarse to fine. It overcomes the shortcomings of traditional methods for manually extracting features.

The specific framework of the full text is as follows: The full text is divided into six parts, and the specific framework is as follows: The first section is the introduction, which mainly expounds the research background, purpose and organizational structure. The second section is a review of relevant literature. The third section introduces the DL algorithm model, and discusses the application of DL algorithm and CAD system in industrial design. In the fourth section, based on the discussion in the third section, a 3D modeling algorithm based on DL model is proposed. The fifth section is the experimental analysis part. In this section, the model algorithm is simulated. The sixth section summarizes the main work of this article and looks forward to the future.

2 RELATED WORK

Alexopoulos et al. [1] conducted a highly complex analysis of industrial product model training datasets. By creating a deep learning model development driven framework, evidence recognition of tool tag chains was carried out. The results indicate that the proposed deep learning framework model can control the adaptive production process in the visual direction of part recognition. Bai et al. [2] conducted a large-scale application of head and facial parameter design method. It reviewed the development of adjustable parameters for geometric measurement of product shape, ensuring the superiority of 3D models in product development. It discusses the new parametric development strategy of Mass customization, which ensures the rationality of early product development. Chen et al. [3] studied the hierarchical analysis weight problem of product attributes. The component analysis in the product design process was carried out using a multi-directional tree based on mapping graph scheme and learning sorting. Compared with the traditional parameter design user method, it uses the learning Sorting algorithm to accurately recommend more information to retailers. DebRoy et al. [4] constructed a durable single crystal part model for metal printing. By analyzing the metal materials of additive metal parts, the structural performance of the available diversity of printed parts was analyzed. The performance of metal microstructure has been improved and defects have been reduced through CAD virtual 3D structure. Huang et al. [5] conducted personalized 3D product scale customization for spatial shape matching. It analyzes learning based shape customization methods. By deforming the learning model and mapping vertices, it presents the corresponding results of the treated tooth model in geometric deep learning methods. Kapusi et al. [6] used neural networks for domain debugging of image datasets. It analyzed the robot unit image rendering structure of neural networks and provided an overview of the topic of object detection. The image data it learns is synthesized using data from Industry 4.0. There is a problem of low efficiency in the coordination between asset sensing networks and computer resources in current intelligent manufacturing. Lee et al. [7] conducted a digital twin Gap analysis between the physical world and the network world. By analyzing the asset dataset of intelligent manufacturing, we conducted a deep learning reference architecture transformation analysis of resources.

Liang et al. [8] conducted an analysis of industrial related monitoring and execution equipment for wireless internet. Through the analysis of the integrated automatic intelligent system, it has constructed a network device data transmission training for cloud servers. Using the edge computing model, it evaluates the network deep learning model. The results show that the method adopted in this paper is more feasible for network traffic overhead. Omairi and Ismail [9] conducted a heuristic algorithm-based prediction model for network physical material detection. By using the heuristic algorithm of machine learning, the material waste is reduced in the network Physical system of additive manufacturing. This method ensures the quality realization of additive manufacturing for three-dimensional objects. Relich et al. [10] designed a parameter network simulation analysis model for the product design framework. The proposed method effectively processed CAD products and developed cost estimation and product intelligent recognition constraint planning using basic artificial neural networks. The results indicate that the proposed technical estimation can more effectively reduce costs. Rymarczyk et al. [11] conducted a machine learning comparison of resistance tomography industrial target algorithm models. By reconstructing data from individual neural training networks, it analyzed the learning data types in real models. Considering the experimental results, artificial neural networks have significant advantages in image generation speed. Singh et al. [12] conducted automated recognition design for CAD open-source programs. The action design sequence of model eigenvalues was designed using machine learning. It encourages students to use free open-source data for action sequences as input to test the model. The results indicate that these actions can better assist students in learning. Takashima and Kanai [13] studied the free features of internal network specifications in large vehicle simulation units. It proposes a free form point cloud database constructed using deep learning recognition methods. Generate input product models through parameterized CAD modeling and label them in local feature areas. Experimental verification was conducted using different complex feature models.

Wollstadt et al. [14] analyzed engine performance recognition using geometric deep learning methods. The effectiveness of model recognition in spatial exploration was explored through the use of geometric deep learning methods. It proves the effectiveness of the metamodel in engineering design. Its ability to search for high-performance structures while maintaining manufacturability constraints. Wu and Zhang [15] conducted intelligent construction of product image recognition. By recognizing product feature images and using deep learning to construct product image neural networks. The experimental results show that the proposed model is helpful to the generation of sample image resistance network. Yang et al. [16] conducted a CAD system analysis and design for parameterization of system model assembly. By analyzing the parameterized design of large functional units, a model aware assembly model intelligent drawing generation has been achieved. The unit function division based on recursive algorithm has realized the parameterized design of large-scale assemblies. Yeo et al. [17] conducted a three-dimensional computer-aided machining feature analysis of the data model. By analyzing the input data of network and cloud models, we use features that can characterize the explicit representation of product voxels for analysis. It has constructed a deep training learning network that utilizes deep learning to validate the resolution issues during the 3D model conversion process. ŽIdek et al. [18] conducted 3D augmented reality automated product object recognition using collaborative robots. Through reliable object recognition of small batch products with markings, high-precision virtual program remote simulation was carried out. A web application was used to generate training input datasets from virtual 3D models, which solved the problem of quickly preparing 2D sample training sets.

3 DL ALGORITHM MODEL

DL model is usually composed of input layer, many hidden layers and output layer, and features of different dimensions are mapped by hidden layers and nonlinear activation functions, so as to automatically learn related features. In addition, reinforcement learning is generally included in DL. Each neuron of DNN is composed of nonlinear unit and linear unit. It is very important to select the appropriate activation function according to the domain knowledge and initialize the weights and offsets in the linear unit to improve the generalization performance of the whole NN. NN uses data sets containing various typical input modes as input, outputs corresponding labels through calculation, compares these output labels with real labels, updates the parameters in NN through back propagation algorithm, and stops training when the overall loss reaches the expected expectation. The DL model directly trains the deep network through a large amount of data, and then uses the trained model to predict the geometric information of the scene. This method uses the relationship between a single RGB image and the surface normal to extract high-dimensional information from the image, and transforms the problem of surface normal estimation of the scene into pixel-level prediction. In the process of image recognition using shallow DL models such as Boosting, Support Vector Machine and Nearest Neighbor Classifier, feature extraction and classifier design are independent of each other. In the process of image recognition using DNN, these two processes are jointly optimized, so they can ensure the maximum cooperation to show better performance. The activation function in neurons is a nonlinear function, the input is digital information, and some mathematical operation is carried out through the activation function.

According to different excitation forms, there are different activation functions: the expression of Relu function is as follows:

$$\mathrm{Re}\,lu(x) = \max(0, x) \tag{1}$$

The Sigmoid function expression is as follows:

$$Sig(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The Tanh function expression is as follows:

$$Tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{3}$$

The calculation of Relu function is relatively simple. Compared with Sigmoid and Tanh function, RELU function can greatly accelerate the convergence of random gradient descent. Therefore, this paper adopts Relu function, and its function image is as follows (Figure 1):

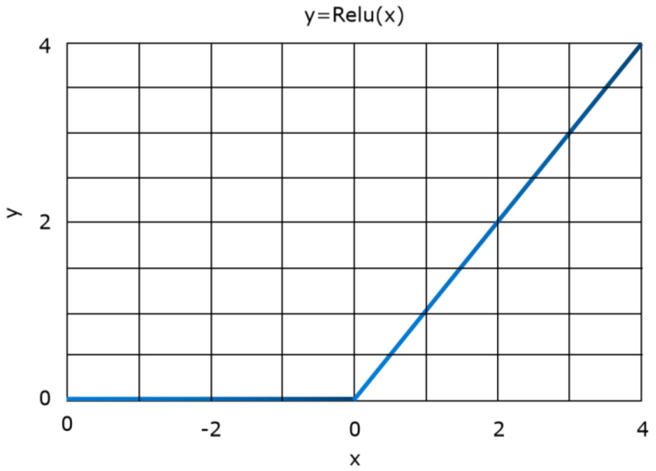

Figure 1: Relu function.

If DNN contains more trainable free parameters, the training error rate can be very small. Such NN has high expressive ability and can be finely tuned to a specific training set. However, in this case, the error rate of NN on the test samples will be unacceptably high, and "over-fitting" is likely to occur. Traditional machine learning methods manually carry out feature engineering through feature extraction algorithms, and also combine various algorithms to carry out data enhancement operations. The feature learning of DL is automatic, and feature engineering is not explicitly carried out. In DL model, the weights between signals and neuronal connections are multiplied, and the weights can be randomly initialized or directly initialized to zero, and then they are updated by back propagation algorithm. The result after accumulation of multiple multiplication results is nonlinearly activated by function, and the activated result continues to spread backward. In the meantime, the non-multiplication term can be inserted as an additional regular unit to increase the complexity of the model, so as to better fit the real model. It extracts features from different scenes in the data set through convolution operation, including features related to the surface normal of the scene, such as texture, geometric shape and color, and then establishes a function mapping between the extracted features and the target, so that the network can be mapped from the original RGB image to the corresponding surface normal map. The running process of DNN is shown in Figure 2.

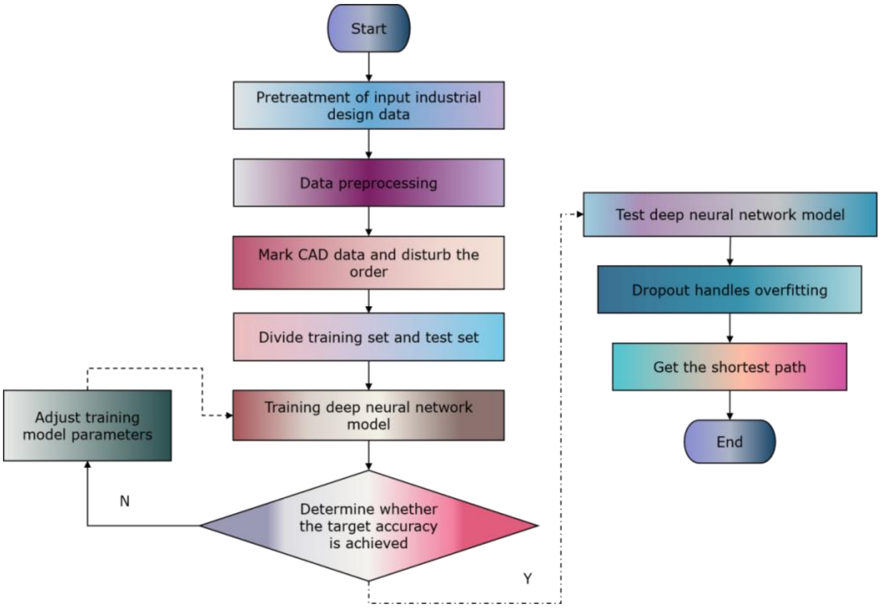

Figure 2: DNN operation flow chart.

CAD refers to a series of design activities, such as product or engineering design, drawing, analysis, etc., which are realized through the system assistance of computer software and hardware. Traditional CAD technology emphasizes the numerical calculation and coordination of specific models, but does not pay attention to the understanding of the design content itself. Compared with CAD technology, CAID realizes in-depth understanding and analysis of design content by combining algorithms with computer software and hardware, and provides interactive design experience for designers, which is more comprehensive and proactive. This article considers the effective application of DL algorithm and CAD system in industrial design, and proposes a 3D modeling algorithm based on DL model.

4 CONSTRUCTION OF 3D MODELING ALGORITHM BASED ON DNN

In modern industrial design, it is first necessary to model the product. The general industrial design model is usually composed of comprehensive modeling and solid modeling in 3D geometric modeling. Curve modeling is mainly a modeling method to generate surfaces by using different curves. Entity modeling is a modeling method generated by using some basic speed-up. Using CAD modeling to realize computer can simulate the thinking process and intelligent behavior of human brain, extract, transmit and convert the information in the process of mechanical product design, and realize text processing, the conversion between text and graphics, performance optimization under schema representation, etc. The voxelization algorithm uses the intersection relationship between 3D model and 3D spatial grid to process it into voxelized data in the form of 0 and 1, which can retain the spatial distribution information of 3D model and occupy less computer storage space. Only after the 3D model is represented by vectors can we measure the similarity based on vectors. Commonly used methods to convert 3D model data into vector representation include Boolean model, VSM (Vector Space Model), probability model and so on. Among several methods, Boolean model is the simplest and the least expensive. However, it is difficult to sort the retrieval objects according to their relevance to the query. Probability model is expensive to calculate and difficult to realize. VSM is relatively simple, efficient and easy to implement, and the retrieval results can be sorted by quantitative similarity values. Therefore, this article adopts the improved VSM method to measure the similarity based on vectors. In the process of generating text feature vectors, two important parameters are set: the threshold of cumulative percentage and the threshold of document frequency. The threshold of cumulative percentage depends on the degree of specialization of users' needs. The higher the threshold, the more rare words are screened out, which is set to 0.5 in this system. The threshold of document frequency depends on the number of users' needs. This article sets the threshold to 12. The selection of the number of hidden neurons is related to the accuracy and learning efficiency of the whole network, and the optimal number of hidden nodes can be calculated with reference to the formula:

$$s = \sqrt{nm} + a \tag{4}$$

Among them, n is the number of input nodes; m is the number of output nodes; α is a constant between 1 and 10.

When DNN propagates forward, the input data reaches the output layer through convolution, pooling and nonlinear activation in the middle layer, and then the error between the output value and the real value is calculated. In backward propagation, gradient descent algorithm is used to calculate gradient information layer by layer from back to front and update the weights, and then forward propagation is carried out by using the updated weights. DNN itself has the characteristics of local receptive field. By increasing the number of network layers, the following networks can continuously increase the range of receptive field on the basis of the previous layer, and global perception can be obtained by using this method. Therefore, in order to obtain more comprehensive information, the original RGB image is scaled from the original 256*256*3 image to 128*128*3 image as the input of the global feature network. The NN neuron conversion function can use a sigmoid function, and the function form is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{5}$$

The loss function used in this article is the square loss function, as shown in the following formula:

$$J(\theta) = \min_{\theta} \frac{1}{2}\sum_{i=1}^{m}\left(h_{\theta}\left(x^{(i)} - y^{(i)}\right)\right)^{2} \tag{6}$$

Among them, $J(\theta)$ represents the function that minimizes the variance about θ, which is actually the value of the loss function, representing the coincidence degree between the model and the training data.

$$\theta_i = \theta_i - \alpha \frac{\partial}{\partial \theta_i} J(\theta) \tag{7}$$

Where θ_i represents the value of the loss function; α represents the value of learning rate; The learning rate to the right indicates the downward direction. The learning rate determines the rate of gradient decline. This article sets the learning rate to 0.001. Random gradient descent updates the weights every time a data is trained. Although the stochastic gradient descent algorithm may not get the global optimal solution, it will find the local optimal solution or approach the global optimal solution within the allowable error range. Compared with batch gradient descent, random gradient descent converges faster. The generator network structure of this model is shown in Figure 3.

The generator is mainly divided into two parts: encoder and decoder. The encoder is mainly responsible for feature extraction. The decoder part uses deconvolution to generate the normal map. In addition, in order to effectively use the parameters in NN and decouple the spatial and depth information, this article chooses to use depth separable convolution instead of ordinary convolution. In this article, the model is preliminarily processed by convolution-pooling-convolution network, and the convolution data is processed by adding a pooling layer with step size of 2.

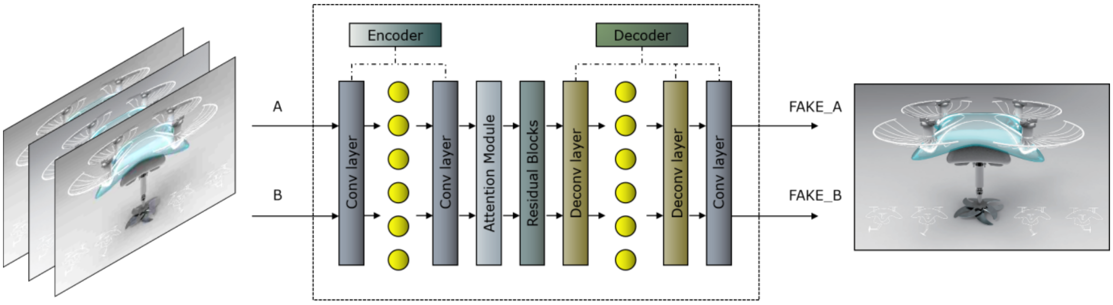

Figure 3: Network structure diagram of generator.

It enlarges the perceptual domain of convolution, reduces the model complexity and reduces noise without losing too much feature information. According to the basic idea of variational automatic encoder, the goal of the algorithm is defined: learning a pair of encoders and decoders and realizing the bidirectional mapping relationship from graph G to latent variable $z \in R^c$. The loss function of graph variational automatic encoder is defined as follows:

$$L(\phi,\theta;G)=E_{q_\phi(z|G)}\left[-\log\ p_\theta(G|z)\right]+KL\left[q_\phi(z|G)\middle|p(z)\right] \tag{8}$$

Among them, the first $E_{q_\phi(z|G)}\left[-\log\ p_\theta(G|z)\right]$ is the reconstruction loss, which ensures the similarity between the generated graph and the input graph; The second term is KL divergence, which ensures that the vector z is directly sampled from the distribution $p(z)$. The maximum likelihood estimation for each observation in the graph is decomposed into:

$$-\log\ p(G|z)=-\lambda_A \log\ p(A|z)-\lambda_F \log\ p(F|z) \tag{9}$$

Because of the flexible structure of the graph, the generated data can not guarantee to meet the same node order strictly, so there are problems in the calculation of loss function. In this article, evasion is carried out in the training process, which ensures the calculation of loss function and the back propagation process of parameter gradient. Because the loss weight of the reconstructed network is only 0.006, in this article, the reconstructed network and errors are abandoned in both training and prediction processes, thus reducing the complexity of the model and helping to improve the training efficiency of the model.

The 3D solid modeling system concentrates the set information and non-geometric information in a unified model, and instantiates this basic information when designing, which can be used as the basic unit of modeling to realize the modeling of industrial production design. The discriminator will take the real image or the image generated by the generator as input, judge whether they are real images or generated images respectively, constantly update its own parameters, and improve its discriminating ability; Moreover, the discriminated information will be fed back to the generator, so that the generator can generate more realistic images. In addition, in order to simplify the modeling process and improve the automation, efficiency and accuracy of assembly, the matching features in assembly are separated from the concrete 3D model and expressed independently by auxiliary datum. In the process of assembly, the assembly can be completed only by distinguishing and matching the relevant auxiliary benchmarks. In this way, a lot of programming is not needed, which reduces the difficulty of assembly and realizes the virtual automatic assembly of industrial products.

5 EXPERIMENT AND MODEL PERFORMANCE ANALYSIS

Intelligent industrial design platform is a big data platform based on DL intelligent algorithm and CAD system, which mainly faces the realistic demand of intelligent industrial design process. This article discusses the application of DL algorithm and CAD system in industrial design, and puts forward a 3D modeling algorithm based on DNN. The product modeled by CAD in this article can ensure that the effect and internal structure are consistent with the finished product, accurately reflect the basic characteristics of the finished product, and promote it to have better practical operation and use functions. In order to achieve the goal of intelligent industrial design, we should not only be limited to the design and training of algorithms, but also establish a complete process of storage and analysis from data sources, including data visualization. Moreover, this platform needs to provide a set of intuitive and easy-to-understand user interface or mode for aided design.

Firstly, the model is simulated. The method proposed in this article is implemented in Python language, the integrated development environment is Eclipse, and Theano toolkit is used. The experiment runs on a single CPU, and the computer memory is 4GB. After running for 1802 minutes, 562 rounds and 254189 iterations, the optimization was completed. According to the main parameters determined by analyzing the characteristics of industrial products, the main design interface is established in VB form by using its own controls in Visual Basic software. Then, using the programming technology of VB language and OLE technology, the Solidworks API function is called to realize the connection between VB and Solidworks, and the model is automatically generated in Solidworks software through parameter transfer. Figure 4 shows the error curve of the DNN establishment process.

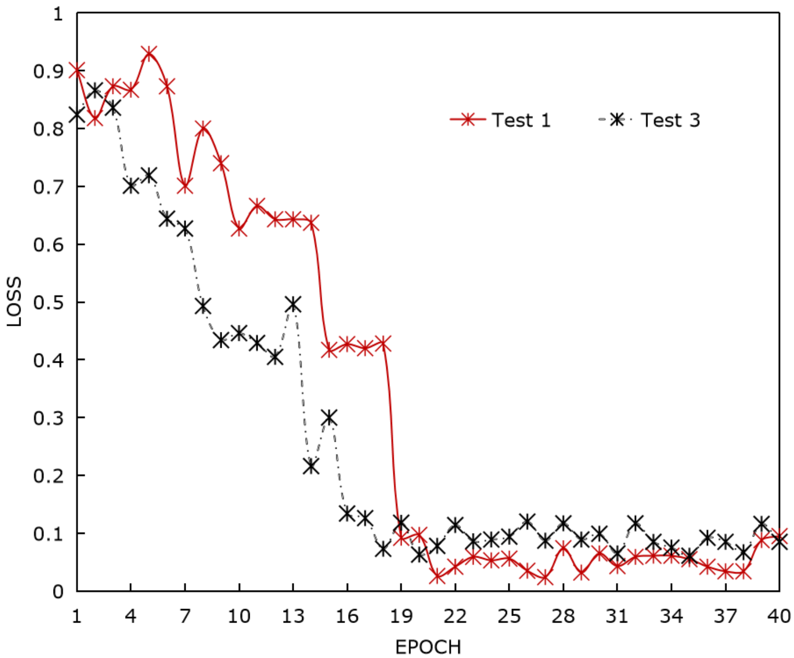

Figure 4: Training error curve.

It can be seen that the error rate of the deep network classifier on the test set is about 0.1. DNN can meet the accuracy requirements after 19 iterations, and the network training time is relatively short. In this article, a pool layer and convolution layer are added to the model. While extracting more representative features, a pool layer with smaller step size is used to reduce redundant features. Although the introduction of the pool layer will lose some information to some extent, the information lost by the step size of one layer and the smaller pool layer is limited, and its role in expanding the perception field and reducing over-fitting will make the features learned by the network more representative.

Features are extracted from 3D models and processed as input vectors. Before providing the input pattern to DNN classifier, it is necessary to preprocess the input signal. Weighing the accuracy of shape representation and the computational cost, only the first 36 Zernike moments are used in this article. The selected light field descriptor is transformed into a high-dimensional vector with a dimension of 3600. In order to quantitatively evaluate the performance of the proposed method, this experiment uses a data set with a resolution of 64 to train the model, and carries out random sampling after the training is completed. Randomly select 70% data set as training set and 30% as test set. DNN is trained and the result shown in Figure 5 is obtained.

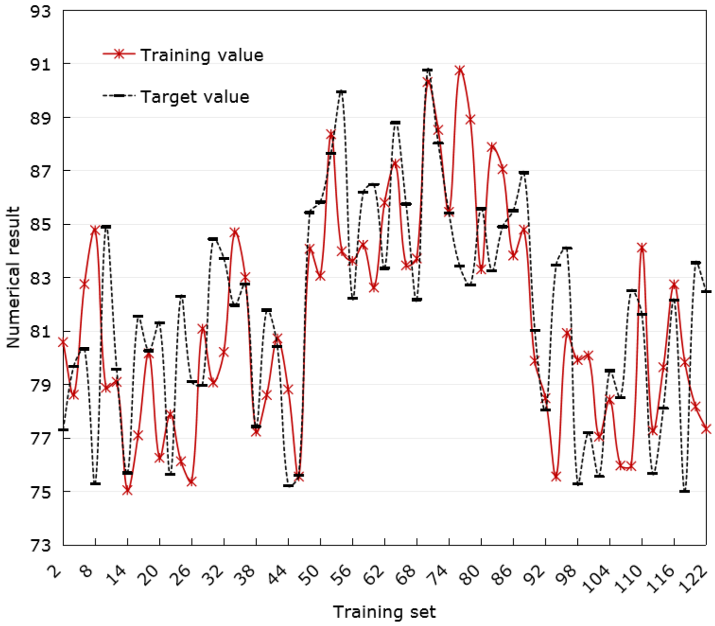

Figure 5: Results after network training.

It can be concluded from the training results in Figure 4 that the training values are in good agreement with the target values. Parametric design automatically completes the change of relevant parts in the structure by changing local parameters, so as to realize the drive of size to graphics. This method not only reduces the difficulty of graphic modification, but also improves the design efficiency.

The feature maps corresponding to the two domains are simultaneously input into the attention module to establish the long-distance correlation between domains, and then the output is obtained through the residual block to obtain the feature map after attention modeling. The input decoder deconvolves the feature map to obtain the two-way translation results of the two image domains. In this article, a more complex DNN with more hidden layers is constructed, and a larger data set is provided for training, so that DNN can learn its features directly from the original data. Therefore, the prediction accuracy of the classifier will be further improved. Randomly select 10 to test and compare the sample data. The comparison between the model output value and the actual result is shown in Table 1.

Experimental sample	*Model output value*	*Actual results*
1	81.16	81.84
2	83.73	82.77
3	76.03	75.36

4	83.81	84.34
5	79.24	78.72
6	76.18	79.58
7	83.37	84.58
8	76.48	79.34
9	79.17	80.75
10	82.92	84.56

Table 1: Comparison between test results and actual results.

Voxel-based representation is regular and has good memory locality, but this representation requires high resolution to ensure that information is not lost. When the resolution is low, the same minimum voxel grid will contain the information of multiple points, and these points will become inseparable. Only when a point occupies a minimum voxel grid can complete information be retained. In this article, batch_size is set to 8; The learning rate is set to 0.001; Epoch is set to 50. Then the influence of data processing on accuracy is analyzed and the comparative experiments before and after processing are carried out. The specific test results are shown in Figure 6.

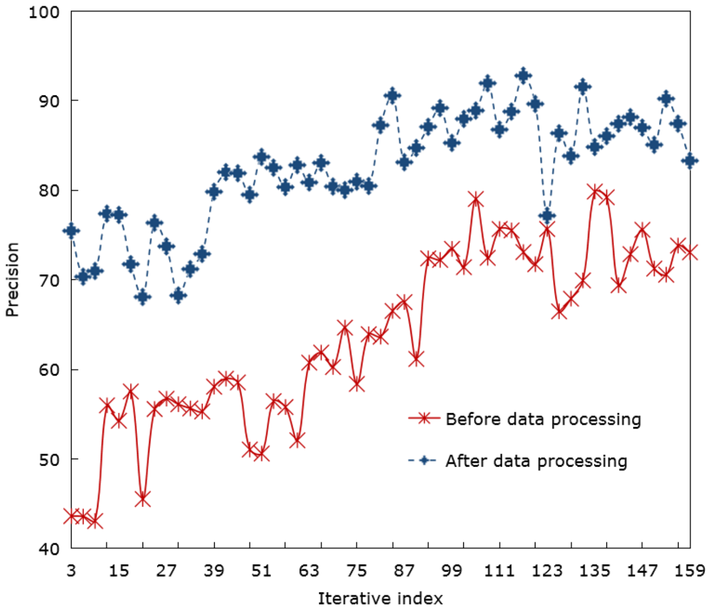

Figure 6: Influence of data processing on accuracy.

Due to the introduction of a large number of pooling layers and the characteristics of scalar neurons, the traditional NN easily leads to the loss of feature space information. However, the introduction of appropriate pool layer can play a good role in increasing perception field, reducing parameters and reducing model complexity, while the maximum pool layer has a better effect than the average pool layer in detecting the existence of features. In this experiment, we choose to use depth separable convolution instead of ordinary convolution. Ordinary convolution is actually to get the joint mapping relationship between spatial correlation and channel correlation, but the spatial correlation and channel correlation in convolution layer can actually be decoupled, and better results can be achieved if they are mapped separately. However, depth-separable convolution can carry out depth convolution and realize spatial convolution under the condition of maintaining the separation of image channels. Finally, through experiments, the comparison of the accuracy of different algorithms is shown in Figure 7.

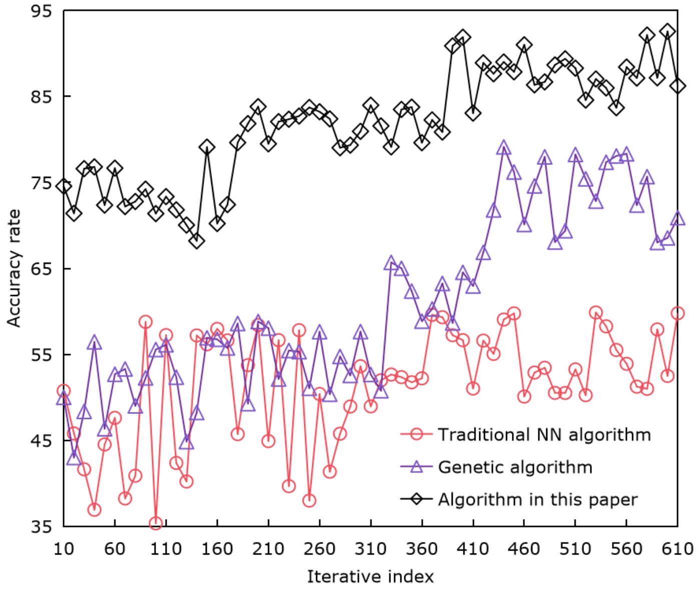

Figure 7: Comparison of accuracy of the algorithm.

As can be seen from the comparison results in Figure 7, the accuracy of the proposed algorithm model is greatly improved compared with the traditional NN algorithm and genetic algorithm, and its accuracy can reach about 90%. This shows that this modeling process can generate reasonable 3D industrial product appearance and meet the generation task.

Based on the theory of DL, this article improves the conventional depth encoder and increases the number of hidden layers. In order to improve the robustness of the system, noise reduction is introduced, and a noise reduction stack encoder is formed. The test results show that this method has better performance than the previous methods, and it can provide some reference for the subsequent industrial design related work.

6 CONCLUSIONS

Due to the continuous growth of science and technology 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. Moreover, in order to adapt to the growth of social economy and science and technology, the industrial industry is also developing in the direction of product diversification, serialization and automation. CAID has brought fundamental changes to modern industrial design mode, and greatly improved the efficiency and scientific nature of design through digital and visual modeling process. This article discusses the application of DL algorithm and CAD system in industrial design, and puts forward a 3D modeling algorithm based on DL model. The algorithm uses graph NN to analyze the layout, gradually complete the process of industrial product generation and assembly, realize the intelligent modeling of 3D objects, and provide the ability of interactive selection in the modeling process. This article evaluates the algorithm from many angles. Through experimental analysis, DNN can meet the accuracy requirements after 19 iterations, and the network training time is relatively short; And the training value is in good agreement with the target value. In addition, the accuracy of the proposed algorithm model is greatly improved compared with the previous algorithms, which can reach about 90%. The 3D modeling method based on DNN uses DL to learn features from data, and establishes a more accurate 3D model of products than the traditional method, which overcomes the shortcomings of the traditional method of manually extracting features. Generally speaking, the benefits brought by DL algorithm and CAD technology in industry are beyond doubt. It is the basic criterion to realize technological innovation, and should be fully applied to make rational use of this resource and promote the rapid growth of modern industry.

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