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

The Combination and Application of CAD Data and Deep Learning Algorithms in Industrial Design

Qianqian Wen[1] and Huizhi Liao[2]

[1]Academy of Art, Jingchu University of Technology, Jingmen, Hubei 448000, China, 201107007@jcut.edu.cn
[2]College of Computer Science, Liaoning University, Shenyang, Liaoning 110036, China, liaohuizhi1036@163.com

Corresponding author: Qianqian Wen, 201107007@jcut.edu.cn

Abstract. Industrial design is a complex process involving multiple disciplines and fields. With the increasing complexity of products and the diversification of market demand, design methods that rely on the experience and intuition of designers are no longer able to meet the needs. In order to promote the intelligence and automation of industrial design, this article proposes a DL-based CAD data processing method to optimize the product design stage. By introducing DL technology, this study successfully achieved automation and intelligence in the design stage, reducing the workload of designers. The convergence speed is compared to traditional algorithms when processing complex CAD data. In addition, the algorithm presented in this article performs better than traditional algorithms in terms of recall and accuracy, demonstrating the excellent ability of DL to handle large-scale and complex data structures. The DL-based CAD data processing method can effectively improve data processing performance and provide strong support for technological innovation in the field of industrial design.

Keywords: Industrial Design; CAD Data; Deep Learning; Automation
DOI: https://doi.org/10.14733/cadaps.2024.S18.306-321

1 INTRODUCTION

Industrial design involves many disciplines and fields, including engineering, aesthetics, psychology, marketing, and so on. Traditional design methods mainly. With the increase in product complexity and the diversification of market demand, traditional design methods have changed. Visual directional guidance technology is one of the keys to achieving precise control of industrial robots. Binocular vision, as a common visual directional guidance technology, has advantages such as high precision and stability and is widely used in the field of industrial robots. The binocular vision system is composed of two cameras, which calculate the pixel difference when two cameras capture the same object to obtain the stereo information of the object. The principle of the binocular vision system is based on the geometric principle of similar triangles; by calculating the pixel difference when the left and right cameras capture the same object, the depth information of the object is obtained. The advantages of binocular vision systems are simple structure, high stability, and high accuracy. Ben and Cengziz [1] explored the application of binocular vision in industrial robot visual orientation guidance, mainly studying visual positioning and pose estimation methods based on CAD models. Firstly, the principle and composition of the binocular vision system were introduced, followed by a detailed explanation of the visual localization and pose estimation method based on CAD models. Finally, the feasibility and practicality of this method were verified through experiments. The visual localization and pose estimation method based on CAD models is a method that utilizes computer-aided design (CAD) models and binocular vision systems to achieve object localization and pose estimation. This method first imports the CAD model into a binocular vision system and then obtains the position and pose information of the object by matching the feature points in the images captured by left and right cameras. The advantages of this method are high accuracy, good stability, and wide applicability. With the growth of AI, the field of industrial design is facing unprecedented challenges and opportunities. In order to meet these challenges and seize the opportunity, more and more researchers began to explore the possibility of combining DL technology with industrial design. When programming welding robot teaching, it is necessary to manually operate the robot for teaching. This process is very time consuming, especially for complex welding workpieces, and teaching programming takes longer, which directly affects production progress and efficiency. The welding process usually requires multiple movements in different directions and angles, but teaching programming can only be one-way, which makes the programming process complex and prone to errors. To address this issue, Fang et al. [2] proposed a method that combines CAD data. Using Convolutional Neural Networks (CNN) for feature extraction of CAD data and Recurrent Neural Networks (RNN) for sequence modelling of welding paths. The deep learning model trained can automatically identify welding points and generate the optimal welding path. Significantly improving welding quality and efficiency. Meanwhile, the application of deep learning algorithms enables robots to handle complex geometric shapes and welding tasks adaptively, which has broad application prospects.

The research topic of this article is the combination and application of computer-aided design (CAD) data and deep learning (DL) algorithms in industrial design in order to promote the intelligence and automation of industrial design and optimize the product design stage. By introducing DL technology, the design stage can be automated and intelligent. Therefore, studying the automated manufacturing method of industrial design castings based on CAD has important practical significance. Favi et al. [3] used CAD software for product design and model construction and established accurate mathematical models based on the structural characteristics and usage requirements of castings. At the same time, the model is optimized through optimization algorithms to improve the mechanical properties and service life of the castings. Based on the mathematical model of the casting, use CAD software for mould design. Optimize the mould structure through intelligent algorithms to improve the manufacturing accuracy and service life of the mould. At the same time, CAM technology is used to process moulds and achieve automated manufacturing of moulds. Using non-destructive testing technology for quality inspection and control of castings. Real-time monitoring and analysis of product quality are carried out through online detection systems and data analysis techniques to promptly identify and address quality issues. To intelligently analyze and predict detection data, improving the level of product quality control. DL-based CAD data processing method can help designers better understand and process CAD data, thus optimizing the product design stage. The process design of industrial molecular products is gradually developing towards digitalization and intelligence. However, in actual process design, there are many random variables and uncertainty factors, such as raw material quality, environmental temperature and humidity, which have a significant impact on the stability of the process and product performance. Therefore, how to deal with these property uncertainties and improve the robustness and optimization of process design is currently a hot research topic. Frutiger et al. [4] The effectiveness and practicality of this strategy were verified through a specific industrial molecular product process design case. Taking a specific industrial molecular product process design case as an example, illustrate the application of a Monte Carlo-based optimization strategy. In this case, the objective function is product yield, and random variables include raw material quality, environmental temperature, and humidity. Firstly, based on actual data and experience, determine the distribution function of the random variable. Then, the Monte Carlo method was used to generate sample points, and process simulation and objective function calculation were performed for each sample point. Finally, by conducting statistical analysis on the objective function values of all sample points, the probability distribution and expected value of the objective function are obtained.

In industrial manufacturing, seam tracking is one of the key factors in improving product quality and efficiency. Traditional seam tracking methods mainly rely on manual operation or simple machine vision technology, making it difficult to achieve accurate seam tracking. Hanh et al. [5] explored a method for tracking three-dimensional complex curve seams in industrial robots based on CAD models and computer vision. Firstly, the geometric information of the object is obtained using CAD models, and the image is processed and analyzed using computer vision technology to identify the position of the seam. Then, using the kinematic model and optimization algorithm of industrial robots, precise tracking of complex curve seams is achieved. Then, feature extraction algorithms are used to identify the position of the seam. By processing and analyzing images, the position and direction information of seams can be obtained. Design a control system based on the kinematic model and optimization algorithm of industrial robots to achieve precise tracking of complex curve seams. The control system includes hardware and software parts, with the hardware part mainly including the robot body, sensors, and other equipment. The software mainly implements functions such as control algorithms and human-computer interaction. Through the design of the control system, precise tracking of complex curve seams by robots can be achieved. Hu [6] introduces the characteristics of AutoCAD 3D modelling function and combines it with the actual needs of industrial intelligent modelling design; this article analyzes the advantages and potential. The 3D modelling function of AutoCAD has strong flexibility, making it easy to create and modify various shapes and structures, and can adapt to complex design requirements. The 3D modelling function of AutoCAD can exchange data with other CAD software, facilitating data sharing and collaborative design by designers. The AutoCAD 3D modelling function can exchange data with other CAD software, facilitating designers to share data and collaborate on design and promoting team collaboration. In summary, the 3D modelling function of AutoCAD has broad application prospects in industrial intelligent modelling design. Its high precision, flexibility, and efficiency enable designers to better control; the 3D modelling function of AutoCAD can facilitate scheme optimization and team collaboration, which helps industrial intelligent modelling design. The 3D modelling function of AutoCAD will play a greater role.

The traditional design methods for industrial processing machines have high manufacturing costs and uncertain market launch times. Therefore, studying the design method of rapid industrial machining beds based on 3D CAD systems has important practical significance. Liu [7] combines modern computer-aided design technology and innovative design concepts, aiming to improve design efficiency, reduce manufacturing costs, and shorten time to market. Through practical application cases, this article verifies the effectiveness and practicality of this method. The design and manufacturing of industrial processing beds are facing increasingly high requirements and challenges. Using 3D CAD software for machine tool model design, including 3D modelling of parts such as the bed, spindle, feed system, fixture, etc. Through computer simulation analysis technology, analyze and optimize the static and dynamic performance of machine tools to improve design quality and performance. After optimization, key parameters such as spindle speed and feed rate of the machine tool are determined. Based on the optimized 3D model, generate engineering drawings, including assembly drawings, part drawings, etc., to provide a basis for subsequent manufacturing and processing. A user review-driven industrial nut optimization design method based on CAD data and deep learning algorithms has been proposed. By collecting and analyzing user review data, combined with deep learning algorithms, the design of nuts is optimized to improve their performance and user satisfaction. Among them, nuts are widely used as fasteners in mechanical equipment, and their design quality directly affects the safety and service life of the entire equipment. Therefore, optimizing the design of nuts to improve their performance and user satisfaction has become an important issue faced by the manufacturing industry. It uses deep learning algorithms to optimize the design of nuts further. Specifically, Lu et al. [8] used a convolutional neural network-based classification algorithm to classify and evaluate different nut design schemes. In this process, we used a large amount of training data to train the model and improve its accuracy in classification and evaluation. By using the method proposed in this article, we have successfully optimized the design scheme of an industrial nut. Specifically, while maintaining the basic functionality of the nut, we have adjusted and optimized its appearance, size, material, and other aspects to improve its performance and user satisfaction.

A method of CAD data processing based on DL is proposed, described, and implemented in detail. Finally, the superiority of this method is verified by experiments, and the experimental results are analyzed and discussed. The research has the following innovations and contributions:

(1) This research applies DL technology to CAD data processing in industrial design, which provides a brand-new data processing and analysis method for designers.

(2) By introducing DL technology, this study successfully reduced the work intensity of designers.

(3) The DL-based CAD data processing method proposed in this study can help designers better understand and process CAD data, thus optimizing the whole process of product design.

This study explores the application of the DL algorithm in industrial design. A method of CAD data processing based on DL is proposed. Experiments verify the superiority of this method. It provides a new idea for the intellectualization and automation of industrial design.

2 DL ALGORITHM AND INDUSTRIAL DESIGN

Niet and Lin [9] proposed an autonomous trajectory planning method for industrial complex surface spraying based on CAD data and deep learning algorithm point cloud models. This method utilizes CAD data to establish a point cloud model of the spraying object and uses deep learning algorithms for feature extraction and surface analysis to achieve autonomous spraying trajectory planning. While reducing costs and risks, using algorithms to process and the point cloud model of spray-painted objects. Firstly, use Convolutional Neural Networks (CNN) to perform dimensionality reduction and filtering on point cloud data, reducing noise and redundant information. Then, the processed data is sequentially modelled using a recurrent neural network (RNN) to extract surface features and geometric shape information. Finally, the extracted features are mapped back to the original point cloud space using upsampling operations to obtain a dense representation of surface features. Based on the processed point cloud model and surface feature information, combined with the kinematic constraints of the robot, spray trajectory planning is carried out. Traditional laser cleaning path planning methods often require a lot of manual intervention and experience accumulation, making it difficult to adapt to complex and changing cleaning environments and surface shapes. Pan et al. [10] utilize high-precision geometric information provided by CAD data, combined with deep learning algorithms for robot cleaning path planning and posture correction, to achieve efficient and accurate cleaning operations. At the same time, they are reducing cleaning costs and risks and utilizing sensors to collect robots' posture information during motion and training and learning the data through neural networks to obtain a posture correction model. This model can predict the robot's posture in real-time and correct it, ensuring accurate cleaning. The industrial robot laser cleaning path planning and posture correction method based on CAD data and deep learning algorithms can achieve efficient and accurate automatic programming, significantly improving cleaning quality and efficiency. Meanwhile, this method can reduce the degree of manual intervention, adapt to different cleaning environments and part types, and have broad application prospects.

Racz et al. [11] studied the incremental forming operation of industrial robots by combining CAD data with deep learning algorithms. Firstly, use CAD data to establish a robot model and use deep learning algorithms for trajectory planning and kinematic analysis. They are using Convolutional Neural Networks (CNNs) for feature extraction from CAD data and Recurrent Neural Networks (RNNs) for sequential modelling of robot operation processes. The deep learning model obtained through training can automatically recognize processing features and generate the optimal operation path. Path generation based on deep learning models, combined with robot kinematic constraints for trajectory planning. An interpolation algorithm is used to achieve a smooth transition between each machining point, ensuring the stability and accuracy of robot motion. At the same time, kinematic analysis is conducted to verify the motion performance and accuracy of the robot. Utilize sensors to collect robots' joint torque data during motion, train and learn the data through neural networks, and obtain a joint torque estimation model. This model can predict the joint torque values of robots in different motion states in real-time. Industrial welding robots are important equipment in automated welding production, and their motion trajectory directly affects welding quality and efficiency. In practical applications, the motion trajectory of welding robots is limited by various constraints such as kinematics and dynamics. Therefore, how to generate optimized trajectories that meet constraint conditions is an important issue in industrial welding robot trajectory planning. Rout et al. [12] introduce kinematic and dynamic constraints, establish a trajectory optimization model for the robot, and use appropriate optimization algorithms for solutions. The experimental results meet the constraint conditions, improving welding quality and efficiency. Establish a trajectory optimization model for industrial welding robots based on kinematic and dynamic constraints. Optimization algorithms based on gradient descent. According to the established optimization model, use appropriate optimization algorithms for solving. Adjust the robot's motion trajectory until an optimized trajectory that meets the constraint conditions is obtained.

Industrial robots have been widely used in many fields. Among them, welding robots are an important industrial robot mainly used for automated welding production. Wang and Arora [13] Firstly, the basic concepts and principles of CAD technology and welding robots were introduced, and then the methods and steps of continuous trajectory planning were elaborated in detail, including path optimization, speed planning, collision detection, etc. It mainly includes path optimization, speed planning, collision detection, and other steps. Firstly, design the welding path based on the CAD model and optimize it to avoid singularity and collision issues. Secondly, speed planning is carried out based on the path to ensure that the robot has good stability and accuracy during its movement. Finally, collision detection is performed to avoid collisions between the robot and other objects during motion. Path planning and speed planning while also having good stability and applicability. Traditional robot machining trajectory planning methods often require a lot of manual intervention and experience accumulation, making it difficult to adapt to complex and ever-changing machining environments. Wang et al. [14] proposed CAD data and deep learning algorithms for measuring point clouds. This method utilizes CAD data to establish a robot model and processes and extracts features from point cloud data through deep learning algorithms, achieving automatic planning and optimization of robot machining trajectories. At the same time, reducing machining costs and risks. Use equipment such as laser scanners to obtain measurements. Using deep learning algorithms to process and extract features from point cloud data, obtaining a dataset that can reflect the surface features of parts. This dataset will be used to guide the planning and optimization of robot machining trajectories. Based on processed point cloud data and combined with robot kinematic constraints for trajectory planning. An interpolation algorithm is used to achieve a smooth transition between each machining point, ensuring the stability and accuracy of robot motion. At the same time, iterative optimization of the planned trajectory is carried out through optimization algorithms to improve machining efficiency and accuracy further.

Traditional arc welding robot systems often rely on manual programming and experience to adjust welding parameters, making it difficult to adapt to complex and changing welding environments and welding needs of different materials. Wang et al. [15] data and deep learning algorithms to achieve digital twin and complex system modelling and simulation of arc welding robot systems. Firstly, establish a digital twin model of the robot system using CAD data, and then use deep learning algorithms for autonomous path planning and welding parameter optimization. Import CAD data into digital twin modelling software and establish a digital twin model of the robot. This model can reflect the actual operating status and environmental changes of the robot, providing a basis for subsequent path planning and welding parameter optimization. Establish a dynamic model of the arc welding robot system using mathematical modelling methods, including robot kinematics, dynamics, and the impact of environmental factors on system performance. Import the established digital twin model and system model into simulation software for simulation experiments. By adjusting welding parameters and environmental factors, observing changes in system performance, and verifying the effectiveness of the digital twin model and path planning algorithm. Additive Manufacturing (AM) technology is a method of manufacturing solid parts by stacking materials layer by layer, which has the advantages of a short manufacturing cycle, high material utilization, and the ability to manufacture complex structures. However, path planning in additive manufacturing has always been one of the key factors restricting its application and development. Traditional path-planning methods are mainly based on rules or experience, making it difficult to achieve efficient and high-precision manufacturing of complex structural parts. Yaseer and Chen [16] reviewed the research progress of path planning for line arc industrial additive manufacturing design based on CAD data and deep learning algorithms. Firstly, the background and significance of additive manufacturing technology and path planning were introduced, and then the application of CAD data and deep learning algorithms in online arc additive manufacturing path planning was elaborated in detail, including data preprocessing, feature extraction, path generation, and optimization. Key information, such as surface shape and structural features of the parts, can be obtained. This feature information can be used to guide path planning and optimization operations, improving the accuracy and efficiency of the manufacturing process. Common path generation methods include neural network-based path planning and genetic algorithm-based path optimization. These methods can generate reasonable paths based on the structural characteristics and manufacturing requirements of the parts, providing a foundation for subsequent optimization operations.

Traditional welding methods, due to their large errors and low efficiency. Zhao et al. [17] introduced a spot welding path planning method for white-body curved workpieces based on CAD data and deep learning algorithms. Firstly, use CAD data to establish a digital model of the white body surface workpiece, and then use deep learning algorithms to extract features and identify welding points from the model. Finally, based on the recognition results, optimization algorithms are used to plan a reasonable welding path. Use CAD software to design a geometric model of the curved workpiece of the white body, including feature information such as shape, size, thickness, etc. Export CAD data into a standard format file and import it into a digital model-building software to create a digital model of the white body surface workpiece. They are using deep learning algorithms to extract features and identify welding points from the digital model of the curved workpiece of the white body. Firstly, select the appropriate Convolutional Neural Network (CNN) model to preprocess and segment the digital model. Then, from the segmented workpiece surface, the extracted features are classified using a fully connected layer (FC) to identify the points that need to be welded. The application of deep learning algorithms has significantly improved the accuracy of welding point recognition, providing a reliable basis for subsequent spot welding path planning. Zhou et al. [18] collaboration and traditional computer-aided design (CAD) in mechanical design. Firstly, we outlined the characteristics of collaborative design and the basic elements and processes of traditional CAD systems. Then, a detailed analysis was conducted on the application of collaborative design and traditional CAD in mechanical design, including the complexity of design, optimization of the design process, and verification and confirmation of design. Finally, we discussed the advantages, disadvantages, and future development trends of collaborative design and traditional CAD in mechanical design. Collaborative design refers to the process in which multiple designers or teams work together to complete a design task by sharing design information, coordinating design processes, and integrating design resources. It has the characteristics of information sharing, collaborative cooperation, and multi-level decision-making. Traditional CAD is a tool for mechanical design based on computer software and hardware environments, which has powerful functions such as modelling, analysis, and optimization. In mechanical design, the complexity of design is often high, and multiple factors, such as structure, materials, mechanical properties, etc., need to be considered. Collaborative design can break down complex design problems into multiple sub-problems through the collaboration of multiple designers or teams and have professionals solve them separately, thereby reducing the complexity of the design. Traditional CAD, due to its powerful modelling and analysis capabilities, can also reduce the complexity of design to a certain extent.

3 DATA PROCESSING METHOD OF CAD BASED ON DL

3.1 Characteristics and Processing Requirements of CAD Data

With the continuous growth of AI, DL, as its main branch, has made remarkable achievements in many fields. Compared with the traditional machine learning algorithm, DL has stronger learning and presentation ability, especially when dealing with complex data such as images, voices, and natural languages. In addition, GAN also provides a new idea for image generation and style transfer. The continuous growth of these models and technologies has laid a solid foundation for the application of DL in industrial design. Industrial design is a complete process from requirement analysis, conceptual design, and detailed design to product manufacturing. At each stage, designers need to engage in a lot of creative thinking. As product complexity increases, the challenges faced by traditional design methods are becoming increasingly prominent:

(1) The amount of data increases: With the use of 3D scanning, simulation, and other digital tools, the amount of data that designers need to process has greatly increased. Extracting useful information from this data and carrying out efficient design are huge challenges.

(2) Design complexity: Modern industrial products often involve knowledge and technology from multiple disciplines, such as machinery, electronics, materials science, etc. How to effectively integrate this knowledge into design is a complex problem.

(3) Personalized demand: Consumers have increasingly high demands for personalized products, and quickly responding to these demands and designing satisfactory products are important tasks faced by designers.

In view of the challenges faced in the field of industrial design, DL provides a new solution:

(1) Data-driven design: Using DL helps designers understand user needs and market trends so as to carry out more targeted design. Through the emotional analysis of users' comments and feedback, we can understand users' real feelings about products and provide guidance for product iteration.

(2) Intelligent aided design: DL can be used to assist designers in creative design. For example, using GAN can automatically generate a variety of design schemes for designers to choose and refer to according to the conditions input by users. By training models such as self-encoder, the design can be automatically optimized.

(3) Virtual simulation and assessment: Using DL technology to simulate and evaluate the design scheme can greatly improve the design efficiency. By training the DL model to predict the performance, structure and appearance of products, potential design problems can be found and solved in the early stage. In addition, using reinforcement learning and other methods can also simulate the use process of products and improve the user experience of products.

(4) Knowledge fusion and design optimization: DL can help designers integrate knowledge and technology from multiple disciplines into their designs. By training the multi-task learning model, the mechanical properties, electronic properties, and aesthetic appearance of the product can be considered for optimization at the same time. In addition, the knowledge learned in one field can be transferred to the design of other fields, improving product design innovation.

CAD data is one of the main data sources in industrial design, which includes various information such as geometric information, topological structure, and attributes of the product. Compared with traditional image and text data, CAD data has the following characteristics:

(1) Complex data structure: CAD data is usually a three-dimensional model containing a large amount of geometric information, such as points, lines, and surfaces, as well as their topological relationships. This complex data structure makes processing and analysis more difficult.

(2) Large data volume: With the increasing complexity of products, the scale of CAD data is also growing.

(3) Rich information but high redundancy: CAD data contains various detailed information about the product, but at the same time, there is also a large amount of redundant information.

Based on the above characteristics, the requirements for CAD data processing can be summarized as follows:

(1) Data compression and simplification: In order to reduce the difficulty of data processing and improve efficiency, it is necessary to compress and simplify CAD data, remove redundant information, and retain key information.

(2) Feature detection and representation: In order to conduct effective product design and analysis, it is necessary to extract key features from CAD data and make appropriate representations.

(3) Intelligent assisted design: By utilizing DL technology to process and analyze CAD data, designers can be provided with intelligent assisted design functions, such as automatic completion and design optimization.

3.2 Selection and Design of DL Algorithm

When dealing with CAD data processing, the selection and design of DL algorithms are particularly important. Due to the characteristics and processing requirements of CAD data, it is necessary to choose DL algorithms that can handle complex data structures and large-scale data and extract rich information while reducing redundancy in research. For the processing of CAD data, this study first considered autoencoders. Autoencoder is a neural network suitable for unsupervised learning, which can compress and simplify data by learning efficient representations of data. In the processing of CAD data, this feature of autoencoders can be used to remove redundant information from the data, retain key information, and achieve the goal of simplifying the data. Then CNN was introduced to process CAD data. Although CNN was originally designed to process image data, its powerful ability in feature detection makes it equally applicable to the processing of CAD data. Through this approach, various detailed features and overall style information of the product can be extracted, providing support for product design. The data collection model for industrial design is shown in Figure 1.

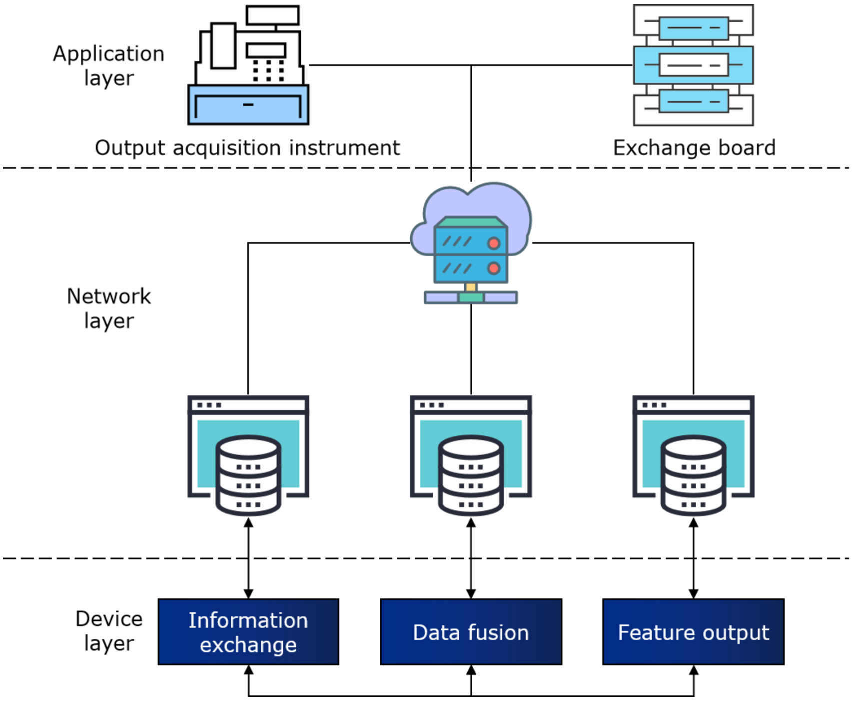

Figure 1: Data acquisition model of industrial design.

The formula for calculating the center of mass of industrial products is:

$$(x_{CM}, y_{CM}, z_{CM}) = \frac{1}{n}(\sum\nolimits_{i=1}^{n} x_1, \sum\nolimits_{i=1}^{n} y_1, \sum\nolimits_{i=1}^{n} z_1) \quad (1)$$

Where (x_i, y_i, z_i) is the coordinate of the i vertex. The centroid of the i triangle is:

$$(x_{cm}, y_{cm}, z_{cm}) = \frac{1}{n}(\frac{x_1 + x_2 + x_3}{3}, \frac{y_1 + y_2 + y_3}{3}, \frac{z_1 + z_2 + z_3}{3}) \quad (2)$$

Where (x_1, y_1, z_1), (x_2, y_2, z_2) and (x_3, y_3, z_3) are the first, second, and third vertices of the i triangle respectively. The inertia tensor of an object is:

$$I = \begin{pmatrix} I_{xx}, I_{xy}, I_{xz} \\ I_{yx}, I_{yy}, I_{yz} \\ I_{zx}, I_{zy}, I_{zz} \end{pmatrix} \quad (3)$$

Where I_{xy} is the moment of inertia of y axis when the object can rotate around x axis. In order to define a coordinate system independent of the direction of the object, the eigenvector of the inertia tensor is calculated as follows:

$$Ia_i = \lambda_i a_i \quad (4)$$

Considering that the geometric information and topological relationships in CAD data can be represented as graph-structured data, this article also chooses graph neural networks to handle this type of data. Graph neural network is a DL algorithm specifically designed for processing graph-structured data, which can effectively capture the relationships and dependencies between nodes, thereby extracting richer information for product design and analysis. The neural network model for CAD data processing is shown in Figure 2.

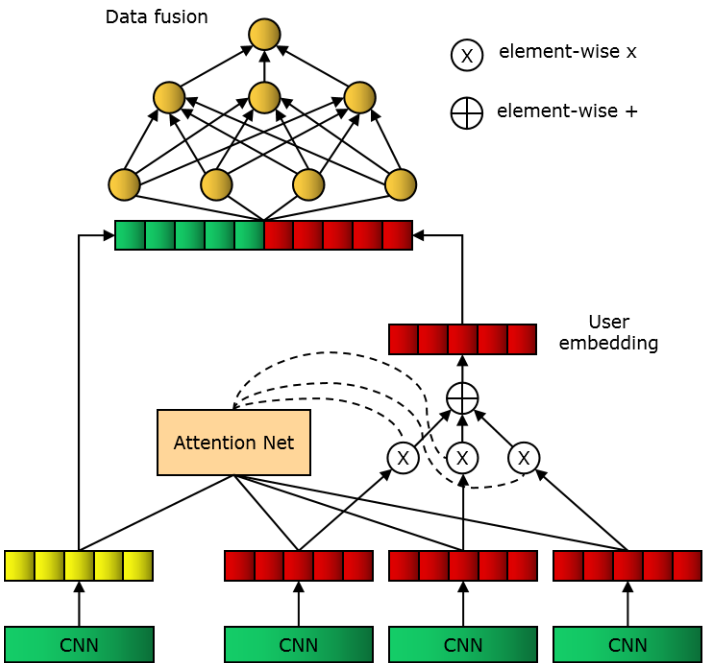

Figure 2: Neural network model of CAD data processing.

$$G_{b1}=\sum_{j=1}^{c}(m_j-m)^T(m_j-m) \tag{5}$$

$$G_{b2}=\sum_{j=1}^{c}p_j(m_j-m)^T(m_j-m) \tag{6}$$

$$J_m=(U,V)=\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ki}^m d_{ik}^2=\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ki}^m\left\|x_i-v_k\right\|^2 \tag{7}$$

3.3 Realization of CAD Data Processing Flow

The DL-based CAD data processing stage can be divided into the following steps:

(1) Data preprocessing: including data cleaning, format conversion, and other operations to ensure the quality and consistency of data. Annotate the data according to the subsequent processing requirements.

(2) Model selection and training: Select the appropriate DL model based on the specific processing task and train it. This study utilizes autoencoders for data compression and feature detection, as well as CNN for image classification and recognition.

(3) Feature detection and representation: Using a trained model to extract and represent features from CAD data, including automatically extracting key features and generating semantic descriptions of products.

(4) Intelligent-assisted design implementation: Based on the extracted features and representation results, realize the intelligent-assisted design function.

(5) Assessment and optimization: Evaluate and optimize the entire processing process to improve processing efficiency and accuracy.

Data fusion is the process of effectively integrating data from different sources. In product CAD visualization, data fusion typically involves associating and corresponding data from 3D models, 2D drawings, and attribute tables. This can be achieved through the use of common data identifiers or spatial alignment. After data fusion is completed, it is necessary to extract key features from the fused data and make appropriate representations. The extracted features can be used for product visualization and analysis. After completing the visualization design, it is necessary to implement and display the visualization. Through visual display, designers can have a more intuitive understanding of product design details and make corresponding adjustments and optimizations. The visualization process of product CAD based on data fusion processing is shown in Figure 3.

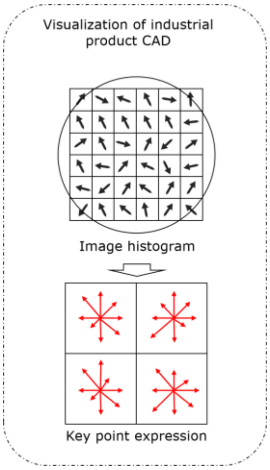

Figure 3: Product CAD visualization.

$$\bar{X}_i = \frac{1}{(n/w)-2}\sum_{\frac{(i-1)n}{w}+2}^{\frac{in}{w}-1} x_i^{'} \quad 1 \le i \le w \tag{8}$$

$$\rho_i = \sum_{j=1}^{N} \phi(d_{ij} - d_c) \tag{9}$$

$$\delta_i = \min_{j:\rho_j > \rho_i} (d_{ij}) \tag{10}$$

δ_i denotes the smallest distance between an attribute and another attribute possessing a local density that surpasses it.

4 EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

4.1 Experimental Environment and Data Set Construction

In order to verify the effectiveness of the product CAD visualization method based on data fusion processing, a series of experiments were conducted in this article.

The experimental environment mainly includes two aspects: hardware and software. In terms of hardware, this study utilized high-performance computer servers configured with multi-core processors and large-capacity memory to ensure efficient operation of DL models and visualization algorithms. In terms of software, Python was used as the main programming language, and DL frameworks such as TensorFlow and PyTorch were utilized for model training and inference.

For the purpose of experimental verification, a product CAD dataset was created in this study. The dataset contains CAD models and related data of multiple industrial products covering different fields and industries. Each product includes data such as 3D models, 2D drawings, and attribute tables to provide comprehensive product information.

The steps for constructing a dataset are as follows:

(1) Data collection: A large amount of industrial product CAD data was collected from publicly available data sources and partners.

(2) Data cleaning: Clean and process the collected data to remove invalid and incomplete data, ensuring the quality and consistency of the data.

(3) Data annotation: For subsequent training and assessment, the data was annotated in the study. The annotated content includes the product category, key features, design parameters, etc.

(4) Data segmentation: Divide the cleaned and annotated dataset into training, validation, and testing sets.

(5) Data statistics: Finally, statistics and analysis were conducted on the dataset, including data volume, data distribution, category balance, and other aspects.

4.2 Display and Analysis of Experimental Results

Figure 4 shows an example of the decomposition of industrial product images, including (a) the original image, (b) the structural part, and (c) the texture part. The original image is the original image of the industrial product to be processed, containing the complete appearance and detailed information of the product. The structural section displays the product structural information separated from the original image. By removing information such as texture and colour, only the geometric shape and topological structure of the product are retained. The texture section displays the product texture information separated from the original image. By removing information such as structure and colour, only the surface details and texture features of the product are retained.

Figure 5 shows the comparison results of the running time of our algorithm under different product parameter complexities. As the complexity of product parameters continues to increase, the running time of the algorithm in this article gradually decreases compared to the other two algorithms, showing higher running efficiency.

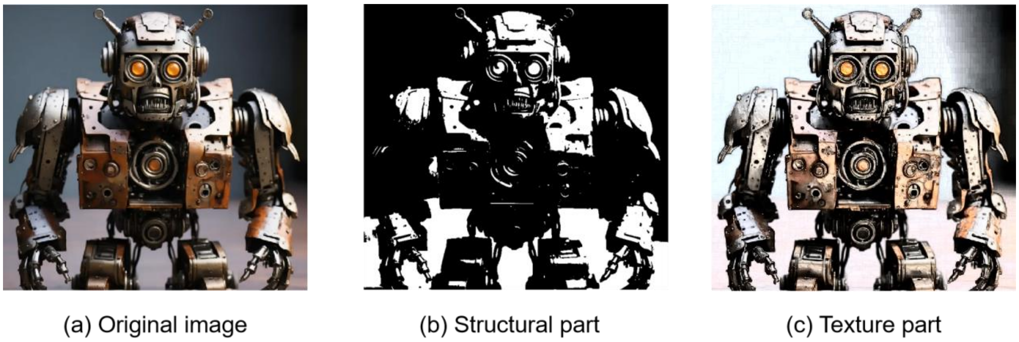

Figure 4: Example of image decomposition based on CAD data processing.

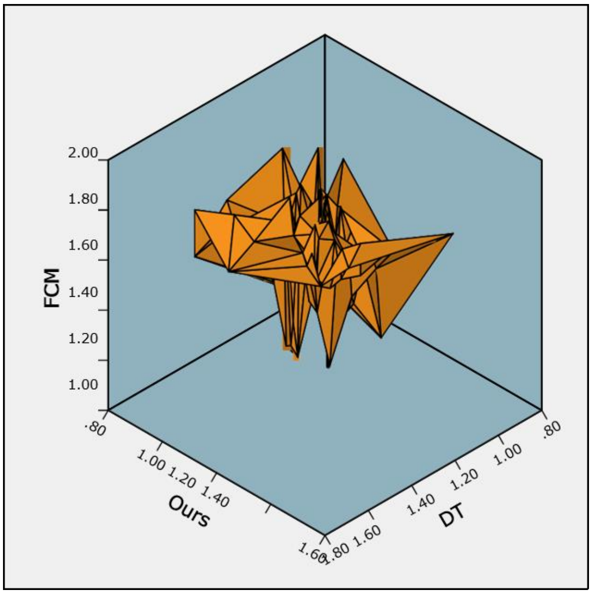

Figure 5: Calculation time comparison of the algorithm.

In the initial stage (when the parameter complexity is low), the running times of the three algorithms are not significantly different, and the algorithm in this article does not demonstrate significant advantages. This is because the initial product parameters are relatively simple, and the processing difficulty between algorithms is not significantly different. As the complexity of product parameters continues to increase, the advantages of the algorithm proposed in this article gradually become apparent. In cases of high complexity, the running time of our algorithm is significantly lower than that of the FCM and DT algorithms. This algorithm adopts DL technology, which can effectively learn and process complex data structures, thereby improving processing efficiency. FCM and DT algorithms may require more computing resources and time to process complex data.

In tackling optimization problems, algorithms with swifter convergence speeds are advantageous as they expedite the discovery of optimal solutions, consequently enhancing processing efficacy. Figure 6 illustrates the comparative results of convergence speeds among this algorithm, the FCM, and the DT. Evidently, the algorithm introduced in this article boasts a notably swifter convergence speed compared to both the FCM and DT algorithms, exhibiting commendable convergence characteristics.

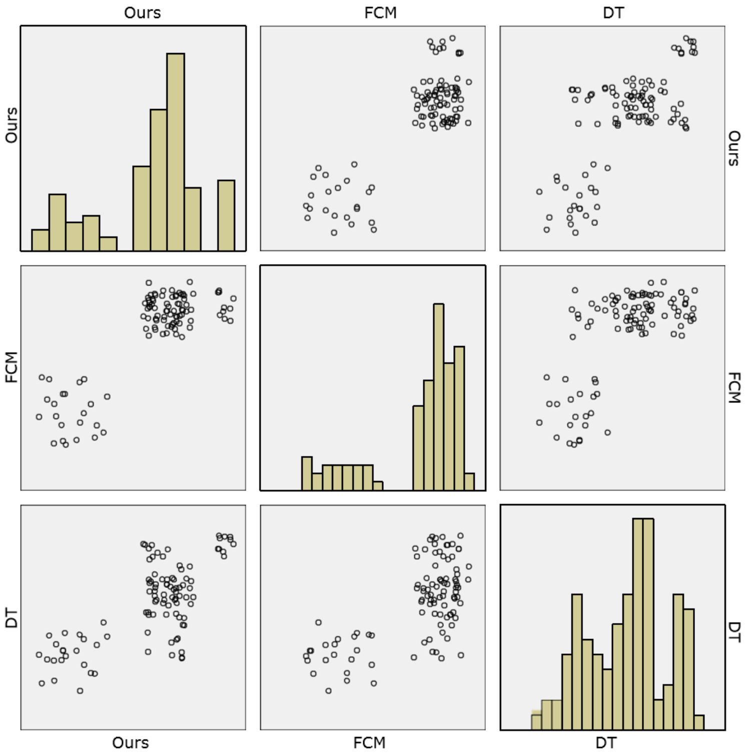

Figure 6: Convergence comparison results.

The FCM algorithm may face computational resource and time constraints when processing large-scale datasets, leading to slower convergence speed. The DT algorithm may require more iterations to find the optimal solution when processing complex data, resulting in slower convergence speed. The algorithm in this article gradually approaches the optimal solution during the iteration process, with small fluctuations. This indicates that the algorithm in this article has good stability when dealing with complex data. This provides strong support for processing large-scale and complex industrial design data in practical applications.

Recall denotes the ratio of correctly identified positive samples by an algorithm out of all the actual positive samples. As depicted in Figure 7, the recall of the algorithm presented in this article is considerably higher than that of conventional algorithms. This indicates that the proposed algorithm is capable of identifying and detecting crucial information and features within CAD data in a more comprehensive manner, thereby minimizing instances of missed and incorrect detections.

Precision signifies the ratio of correctly classified samples out of all the samples by the algorithm. As shown in Figure 8, the precision of the algorithm introduced in this paper is higher than that of traditional methods. This implies that the algorithm put forth in this article is capable of classifying and recognizing CAD data with a greater degree of accuracy, thereby diminishing the incidence of classification errors. The recall and accuracy of the algorithm in CAD data processing in this article have been improved to varying degrees compared to traditional algorithms. This proves the effectiveness and superiority of DL technology in CAD data processing.

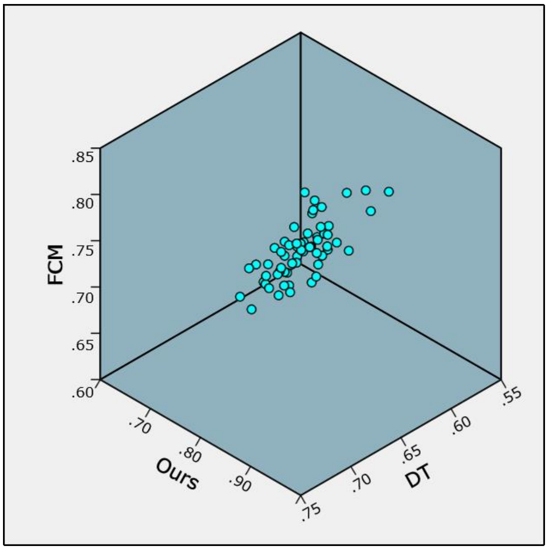

Figure 7: Comparison of recall of CAD data processing.

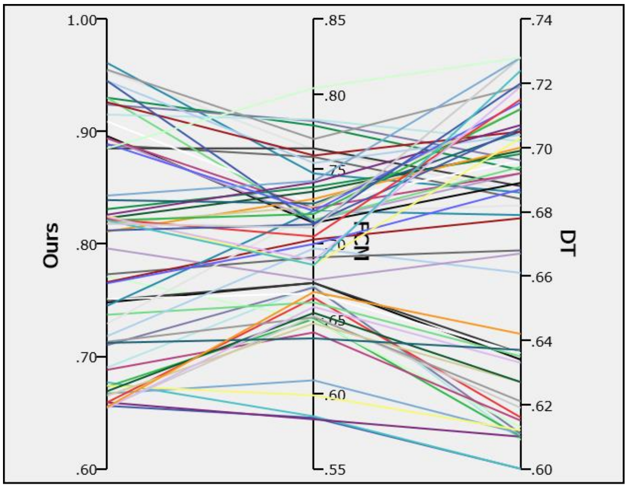

Figure 8: Comparison of accuracy of CAD data processing.

Although the algorithm in this article has shown good performance in terms of recall and accuracy, factors such as algorithm complexity and computational resources still need to be considered in practical applications. At the same time, there may be differences in CAD data in different fields and scenarios, so the performance of algorithms may also vary.

5 CONCLUSION AND OUTLOOK

In the context of the growth of AI, the field of industrial design is facing unprecedented challenges and opportunities. The combination and application of CAD data and DL algorithm can promote the intelligence and automation of industrial design and optimize the product design stage. This article studies a DL-based CAD data processing method and conducts comparative experiments with traditional data processing algorithms. The DL-based CAD data processing method exhibits high operational efficiency and processing power when dealing with complex data. Compared to traditional FCM and DT algorithms, our algorithm has lower runtime and faster convergence speed as the complexity of product parameters continues to increase. By comparing the recall and accuracy of the algorithms, it was found that the performance of our algorithm in CAD data processing is superior to traditional algorithms. DL technology enables algorithms to more comprehensively and accurately identify and detect key information and features in CAD data, thereby improving the accuracy and efficiency of data processing.

It should be noted that although the algorithm in this article has shown good performance in experiments, factors such as algorithm complexity and computational resources need to be considered in practical applications. Therefore, future research can further explore how to optimize CAD data for different fields and scenarios to improve the adaptability of algorithms.

Qianqian Wen, https://orcid.org/0009-0000-8131-0964
Huizhi Liao, https://orcid.org/0009-0005-8982-3066

REFERENCES

[1] Ben, Y.; Cengiz, K.: Research on visual orientation guidance of industrial robot based on CAD model under binocular vision, Computer-Aided Design and Applications, 19(S2), 2021, 52-63. https://doi.org/10.14733/cadaps.2022.S2.52-63
[2] Fang, W.; Ding, L.; Tian, X.; Zheng, F.: A robot welding path planning and automatic programming method for open impeller, The International Journal of Advanced Manufacturing Technology, 124(5-6), 2023, 1639-1650. https://doi.org/10.1007/s00170-022-10415-9
[3] Favi, C.; Mandolini, M.; Campi, F.: A CAD-based design for manufacturing method for casted components, Procedia CIRP, 100(4), 2021, 235-240. https://doi.org/10.1016/j.procir.2021.05.061
[4] Frutiger, J.; Cignitti, S.; Abildskov, J.: Computer-aided molecular product-process design under property uncertainties - A Monte Carlo based optimization strategy, Computers & Chemical Engineering, 122(3), 2019, 247-257. https://doi.org/10.1016/j.compchemeng.2018.08.021
[5] Hanh, L.-D.; Dao, L.-D.; Luan, N.-C.: 3D complex curve seam tracking using industrial robot based on CAD model and computer vision, International Journal on Interactive Design and Manufacturing (IJIDeM), 17(3), 2023, 1039-1046. https://doi.org/10.1007/s12008-022-01043-4
[6] Hu, L.: Application of AutoCAD's 3D modeling function in industrial modeling design, Computer-Aided Design and Applications, 18(S1), 2020, 33-42. https://doi.org/10.14733/cadaps.2021.S1.33-42
[7] Liu, F.: Fast Industrial design method and its application based on 3D CAD system, Computer-Aided Design and Applications, 18(S3), 2020, 118-128. https://doi.org/10.14733/cadaps.2021.S3.118-128
[8] Lu, W.-H.; Ni, Y.-H.; Cai, Z.-B.: User review data-driven product optimization design method, Journal of Computer-Aided Design & Computer Graphics, 34(03), 2022, 482-490. https://doi.org/10.3724/SP.J.1089.2022.19097
[9] Niet, B.-S.; Lin, C.-Y.: Autonomous trajectory planning for spray painting on complex surfaces based on a point cloud model, Sensors, 23(24), 2023, 9634. https://doi.org/10.3390/s23249634
[10] Pan, Z.; Liu, D.; Li, S.; Deng, Z.; Liu, J.; Chen, T.: Path planning and pose correction of robot laser cleaning process for specific surfaces of parts, The International Journal of Advanced Manufacturing Technology, 127(1), 2023, 349-364. https://doi.org/10.1007/s00170-023-11535-6
[11] Racz, S.-G.; Crenganiș, M.; Breaz, R.-E.; Bârsan, A.; Gîrjob, C.-E.; Biriș, C.-M.; Tera, M.: Integrating trajectory planning with kinematic analysis and joint torques estimation for an

industrial robot used in incremental forming operations, Machines, 10(7), 2022, 531. https://doi.org/10.3390/machines10070531

[12] Rout, A.; Bbvl, D.; Biswal, B.-B.: Optimal trajectory generation of an industrial welding robot with kinematic and dynamic constraints, Industrial Robot: The International Journal of Robotics Research and Application, 47(1), 2020, 68-75. https://doi.org/10.1108/IR-06-2019-0137

[13] Wang, G.; Arora, H.: Research on continuous trajectory planning of industrial welding robot based on CAD technology, Computer-Aided Design and Applications, 19(S2), 2021, 74-87. https://doi.org/10.14733/cadaps.2022.S2.74-87

[14] Wang, G.; Li, W.; Jiang, C.; Zhu, D.; Li, Z.; Xu, W.; Ding, H.: Trajectory planning and optimization for robotic machining based on measured point cloud, IEEE Transactions on Robotics, 38(3), 2021, 1621-1637. https://doi.org/10.1109/TRO.2021.3108506

[15] Wang, X.; Hua, Y.; Gao, J.; Lin, Z.; Yu, R.: Digital twin implementation of autonomous planning arc welding robot system, Complex System Modeling and Simulation, 3(3), 2023, 236-251. https://doi.org/10.23919/CSMS.2023.0013

[16] Yaseer, A.; Chen, H.: A review of path planning for wire arc additive manufacturing (WAAM), Journal of Advanced Manufacturing Systems, 20(03), 2021, 589-609. https://doi.org/10.1142/S0219686721500293

[17] Zhao, H.; Zhang, B.; Sun, J.; Yang, L.; Yu, H.: Spot-welding path planning method for the curved surface workpiece of body-in-white based on a memetic algorithm, The International Journal of Advanced Manufacturing Technology, 117(9-10), 2021, 3083-3100. https://doi.org/10.1007/s00170-021-07728-6

[18] Zhou, J.-J.; Phadnis, V.; Olechowski, A.: Analysis of designer emotions in collaborative and traditional computer-aided design, Journal of Mechanical Design, 143(2), 2020, 021401. https://doi.org/10.1115/1.4047685