Optimization of Advertising Design Model Driven by Deep Learning and Interactive VR Display

Fei Li[1] and Rucheng Zhang[2]

[1] Wuhan University of Bioengineering, Wuhan 430415, China, xiaochai717@163.com
[2] China Chinese Antarctic Center of Surveying and Mapping, Wuhan University, Wuhan 430079, China, zrc@whu.edu.cn

Corresponding author: Rucheng Zhang, zrc@whu.edu.cn

Abstract. In today's information-filled era, data processing and presentation are very important. This article explores the optimization of the interplay between computer-aided design (CAD) and virtual reality (VR) through the lens of the Transformer model in information visualization. We introduce an innovative approach to streamline the design and visualization process. Initially, we leverage the Transformer model's robust self-attention mechanism and feature extraction capabilities to handle CAD data efficiently. Additionally, we establish an interactive framework grounded in the Transformer, facilitating seamless data exchange and synchronization between CAD and VR. The outcomes indicate a notable enhancement in design efficiency and a richer immersive VR experience. When juxtaposed with conventional interaction methods, our approach proves its practicality.

Keywords: Information Visualization; Transformer Model; CAD; Virtual Reality
DOI: https://doi.org/10.14733/cadaps.2024.S28.182-195

1 INTRODUCTION

In the era of big data, complex system digital interfaces face severe challenges, and a large amount of information cannot be presented on limited screens. Secondly, Barreto et al. [1] proposed the concept of spatial limitation information and studied the visualization and interaction methods of spatial limitation information. Then, eye-tracking technology is used to evaluate the efficiency of search tasks for multiple schemes presented in information visualization. It proposes five interaction strategies for spatially limited information and, based on this, proposes optimization principles for interaction design based on user experience. Summarized the meaning of spatial limitation information, proposed three visualization methods for spatial limitation information, and, based on this, summarized the design optimization methods for spatial limitation information. Through experimental analysis, the optimal visualization method for geographic information in digital interfaces is obtained. Finally, based on the application of the design method and experimental results proposed in this article, a "daily emergency response system" is designed and optimized to verify the feasibility of the design method proposed in this article. This interactive approach enables designers to have a more intuitive understanding of the actual effects of the design and to identify and solve problems promptly. This step is crucial to ensuring seamless integration between CAD and VR. The effective amalgamation of these two to attain a more intuitive and efficient design process poses a common challenge for researchers and designers. CAD technology significantly enhances design efficiency, minimizes errors, and refines design schemes via precise data analysis. In the development process of smart city concepts, 3D modelling has become an indispensable tool because it can effectively integrate multidisciplinary knowledge and concepts, presenting the blueprint of future cities in a visual way. However, in the process of scene reconstruction to high-performance visualization, platform development faces many challenges, one of which is how to achieve efficient data processing and visualization while maintaining design fidelity. This design method not only improves the accuracy and efficiency of the design but also ensures the feasibility and constructability of the design [2]. Traditional CAD systems primarily rely on a two-dimensional graphical interface for interaction, proving inadequate for complex three-dimensional designs. Combining a three-dimensional computer-aided design (CAD) platform with a power modelling tool of a simulation engine can quickly reflect the detailed situation of a region. Charan et al. [3] conducted a direct impact analysis on energy use in the fields of electricity modelling and urban planning. By intuitively applying CAD information visualization technology, these models can display key information such as energy consumption distribution. This provides the design team with in-depth data insights. The study also demonstrated how the Dragonfly/URBANopt toolset seamlessly integrates with the overall planning workflow. The performance-based iterative design process enables designers to continuously adjust design parameters based on simulation results until the predetermined performance goals are achieved. The results of data research and analysis can allow designers to visually see different design schemes, and then carry out targeted optimization in the early stages of design.

Erdolu [4] are no longer limited to traditional mouse and keyboard operations but interact naturally with visual elements in CAD software through intuitive gestures. It adopts real-time visual feedback and interaction for the technical design integration of a completely virtual 3D environment. In-depth review of how to conduct efficient and accurate design operations in the current work environment. This personalized design support not only enhances the satisfaction and creativity of designers but also helps to reduce errors and rework in the design process. By visually displaying the graphical data images in the data pattern, more accurate and efficient design decisions can be made.

Freitas et al. [5] comprehensively explored the advantages and challenges of the virtual reality-based usability testing and design review industry in in-depth patent and literature reviews. Through virtual reality technology, users can observe complex structures and dynamic effects that are difficult to display on traditional 2D drawings. High-precision tracking ensures that designers and engineers can accurately operate and test in virtual environments. This intuitive and vivid display method greatly improves the efficiency and accuracy of design review. Not only does it help designers better understand design solutions, but it also stimulates their innovative thinking, thereby discovering new design ideas and solutions. This immersive experience further enhances the practicality of virtual reality technology in design reviews. In SSBTN, Gong et al. [6] pioneered the use of two different networks for excuse tasks and downstream tasks and integrated them into a unified framework. Through this approach, it can be ensured that downstream CAD tasks can benefit from carefully optimized features. This not only enhances the coupling between the two networks but also improves the overall performance of the CAD model. When traditional SSL methods share the same backbone network in both pretext tasks and downstream tasks, it is often difficult to fully optimize the pretext network during the pre-training stage if there is a significant difference between these two tasks. Through CAD information visualization, it was observed that SSBTN can learn more precise and targeted feature representations, which play a crucial role in downstream CAD tasks. In the current field of engineering drawing design, CAD technology based on solid models is increasingly valued, especially 3D CAD technology, which has become a hot research and application topic. Hu [7] has successfully established a 3D feature library for injection moulded products using advanced 3D feature modelling and parameterization techniques. In order to more intuitively display and explain various information in the design process, it further proposes an innovative method - using 3D CAD software to establish an "object orthographic projection digital model." Through dynamic display and interactive operation, users can clearly see the entire process of generating orthogonal views of objects, greatly enhancing the visualization and interactivity of the design. This digital model not only displays the three-dimensional form of the physical model but also simulates the orthogonal views of the physical model on multiple projection surfaces through virtual projection technology. With the increasing complexity of design, 3D design has not only become an inevitable trend in the application of CAD technology but also a key means to improve design efficiency and optimize product quality. With the rapid development of digital media technology, universities have taken active measures to strengthen the reform of practical teaching in digital media technology majors. In digital media art, AVG (Adventure Puzzle Game) is an important art form, and the evaluation of its practical teaching reform effect is particularly important. Liu and Li [8] conducted a more in-depth evaluation and analysis of the comprehensive reform effect of AVG digital media art through the combination of fuzzy set theory and CAD information visualization technology. However, traditional fuzzy comprehensive evaluation methods have certain limitations when dealing with indicator weights. CAD information visualization technology can transform complex data and models into easily understandable graphics and images, helping users to understand and analyze problems more intuitively. To overcome this limitation, they processed the indicator weights into interval data and introduced CAD information visualization technology to present the evaluation results in an intuitive and visual form. In the determination of weights, this article adopts an improved entropy weight method to determine the weights of indicators.

The article's objective is to refine CAD-VR interactions by employing the Transformer model, aiming to elevate design efficiency and user satisfaction. With the ongoing advancement of artificial intelligence, this deep learning-based interactive method is poised to play a pivotal role in the design realm. Through this research, we aspire to introduce a novel approach to the integration and advancement of CAD and VR technologies, thereby driving the progress of the design industry.

Highlights:

(1) In this article, the Transformer model is applied to the optimization of interaction between CAD and VR, aiming at solving the limitations of traditional interaction methods.

(2) By introducing a Transformer model to process CAD data, this method significantly improves the interaction efficiency between CAD and VR and enables designers to design in a VR environment more quickly and intuitively.

(3) The optimized interaction mode provides users with a more immersive experience. Through VR technology, users can feel and understand the design scheme more intuitively, which improves user participation.

(4) The effectiveness of the interaction optimization method based on the Transformer model is verified through a series of experiments, and the accuracy of data processing, real-time interaction and other aspects are evaluated.

Initially, this article explores the current utilization of CAD technology and the role of VR technology in the design realm. By gaining a comprehensive understanding of both, we aim to uncover latent synergies and mutual enhancements. Subsequently, we delve into the fundamentals of the Transformer model and showcase its deployments in various domains, laying the groundwork for establishing a CAD-VR interaction paradigm. Through empirical validations, we aim to confirm the efficacy of the Transformer-based CAD-VR interaction. We anticipate that this approach will alleviate the constraints inherent in traditional CAD-VR integrations, thereby elevating design productivity and enriching the user experience. In conclusion, we consolidate our findings and identify areas for further refinement in our research.

2 RELATED WORK

In the operation and maintenance of ensuring the reliability of key infrastructure such as the power grid, safety-centered training is particularly important. Mondragón et al. [9] introduced and evaluated an innovative substation operation training system. Through CAD information visualization technology, these scenes not only accurately reproduce the physical layout of the substation. This system utilizes serious gaming and virtual reality (VR) technology, combined with Building Information Modeling (BIM) and CAD information visualization, to provide a highly realistic simulation environment for substation operators. To evaluate the effectiveness of the training system, we conducted a questionnaire survey using the System Availability Scale (SUS) and Game Participation Questionnaire (GEQ). It also simulates the actual state and potential faults of device operation, allowing students to intuitively understand and learn in a virtual environment. This VR simulator is based on BIM data from a 115 kV substation and has developed a professional training scenario that includes rich technical details. The 16 substation operators participating in the survey generally believe that the system is barely acceptable in terms of usability, but there is still room for improvement.

The application of deep learning technology in the field of design optimization is becoming increasingly widespread, especially in the important field of generative design (or design exploration). Oh et al. [10] emphasized and validated the necessity and effectiveness of deep learning in generative design research. By introducing CAD information visualization technology, they can present these design options in an intuitive way, helping designers better understand the details and characteristics of the design. This visualization not only enables designers to intuitively evaluate the aesthetic value of designs but also enables deeper analysis and comparison. By comparing the differences between newly generated designs and existing designs, unique and innovative design options can be identified. The experimental results show that our framework performs better in aesthetics, diversity, and robustness compared to previous generative design methods. Industry 4.0 is profoundly changing the way design processes are conceptualized, with digital technology making simulation of complex systems, such as human-machine collaboration (HRC), more efficient and cost-effective. To this end, Pellicia et al. [11] explored the potential of 3D factory simulation software that combines information visualization transformer technology in computer-aided participatory design meetings. Information visualization transformer technology can transform complex data into intuitive and easy-to-understand visual expressions, thereby helping users understand the meaning and correlation of data more deeply. They analyzed the applicability of state-of-the-art 3D factory simulation software, supported by information visualization transformer technology, in computer-aided participatory design meetings for developing industrial workplaces and processes. The research results not only define the basic requirements for software tools aimed at effective computer-aided participatory design but also emphasize the key role of information visualization transformer technology in this regard.

Automated design synthesis has enormous potential to completely change the modern engineering design process and provide new opportunities for various industries to obtain highly optimized and customized products. Regenwetter et al. [12] introduced CAD information visualization technology, bringing a new perspective and tool to the design field. AM technology, especially fused deposition modelling (FDM), as an important branch, has received widespread attention and application due to its low cost and relative ease of use. AR technology can create highly realistic virtual environments, allowing operators to perform actual operations within them. Present the design results generated by the digital ground model in an intuitive three-dimensional model form, making the design results easier to understand and communicate. Through CAD models, operators can clearly understand the relationships between various components of the equipment and how they work together. This allows designers to promptly identify potential problems in the early stages of design and make targeted optimizations, thereby avoiding unnecessary modifications and cost waste in the later stages. At the same time, the rapid development of additive manufacturing (AM) technology has brought revolutionary changes to the design field.

In addition, CAD models can provide accurate dimensional and tolerance information, helping operators better grasp the manufacturing accuracy and assembly requirements of equipment. This transformation not only reduces production costs and improves production efficiency, but also makes it easier to achieve customized products [13].

Virtual reality (VR) immersive technology, as a rapidly developing cutting-edge technology in recent years, is gradually changing the way human-computer interaction (HCI) is conducted, providing users with unprecedented augmented reality experiences. Trappey et al. [14] combined VR technology with intelligent chatbot technology to develop and implement a system framework for large-scale customized chatbots for industrial power transformers that support VR. 272 common questions (FAQs) were collected from the knowledge base of power transformer manufacturers. This measure ensures that chatbots can accurately match the questions raised by users and provide corresponding answers. Secondly, a powerful word embedding model was constructed through training on over 1.2 million Wikipedia engineering pages. In recent years, although there have been studies exploring the effectiveness of data narrative expression in the field of information visualization research, these studies still struggle to solve the problem of users having difficulty quickly reading the information conveyed by works in practice. Wang and Yu [15] studied the process of establishing the narrative and visual representation forms of information visualization from the perspective of narrative variables. The strength of this attribute affects whether the information obtained by the subject is consistent with what the narrator conveys. This indicates a lack of research in this field that combines user cognitive structure characteristics with narrative logic methods. Analyze the narrative elements in information visualization through narrative communication structure, and then divide the narrative variables in the cognitive system of information visualization narrative. The expression and combination of spatiotemporal clues and perspective clues, analyzing the visual norms of narrative theme readability, variable perspective relationships, and diverse narrative structures in visualization. It refines the connection between narrative text structure and visual coding in information visualization, improves the conscious narrative process in visual design, and further ensures the transmission of objective information and the expression of subjective consciousness. Therefore, in dynamic interactive teaching scenarios, this technology is crucial for the efficiency and real-time performance of image rendering. Because any delay can affect the learner's experience and learning outcomes.

With the enabling of edge computing technology, the collaboration and collaboration between the central cloud, edge cloud and terminal devices jointly builds a powerful integrated computing ecosystem, which we call cloud edge client architecture. In this article, Wu et al. [16] delved into the integration architecture of cloud edge clients. The prospects of point cloud-based 3D scene modelling and XR representation were analyzed, and the new challenges contained therein were discussed. By combining CAD information visualization technology, the details and complexity of 3D scenes can be presented more intuitively and efficiently, providing designers and users with a richer and more immersive experience. In 3D scene modelling, they use CAD information visualization technology to convert design data into high-quality point cloud data and conduct real-time processing and analysis through edge computing. This demonstration integrates CAD information visualization technology and cloud-edge client architecture to achieve real-time monitoring and data analysis of urban planning, traffic management, and other aspects. Yang and Buehler's [17] research has opened up new applications of Transformer neural networks in the field of cross-modal transformation. Research on the digital interface of the system. In terms of interface, the three characteristics of complex system digital interfaces and the characteristics of information presentation were analyzed, and the process of information visualization, the characteristics and classification of interaction design were studied; In terms of user research, the cognitive process of users was analyzed, and their cognitive characteristics were analyzed from three aspects: human error susceptibility, attention, and fatigue. We have conducted research on the interface and users from a macro perspective, laying a solid theoretical foundation for further research in the following text. The time it takes for users to search for geographic information targets, and through experimental analysis, the optimal presentation of geographic information in the digital interface is obtained. Based on this, research will be conducted on the application of these three visualization methods to propose an optimization method for designing spatial limited information.

3 MATERIALS AND METHODS

3.1 The Application of Transformer Model in CAD Data Processing

In the process of information visualization, filtering and filtering the raw data for the first time is unreasonable. For tasks with a large amount of information, presenting all the information to users is obviously unreasonable. Secondly, the relationship between information itself and information is abstract, so reasonable visual elements are needed to encode information. In the visualization process, key information should be highlighted and non-key information should be hidden according to different design tasks. This can help alleviate perceptual and cognitive load, as well as create a balance between overview and details. Users discover information from the visual presentation and issue operational instructions to interact with the visual presentation, resulting in a new visual presentation. At the same time, a pathway should be retained for users to access deeper levels of information, allowing potential information to be explored and investigated when necessary. This visual element can be simple geometric shapes, icons, photos, etc., but these visual representations must conform to the user's psychological model for the most natural visual presentation. Finally, users need certain operations to interact with the visualization interface. Users can control the transformation of the visualization view, change the visual presentation image, and obtain richer information. This enables the model to better understand the structure and characteristics of CAD data. The information visualization process based on the Transformer model is shown in Figure 1.

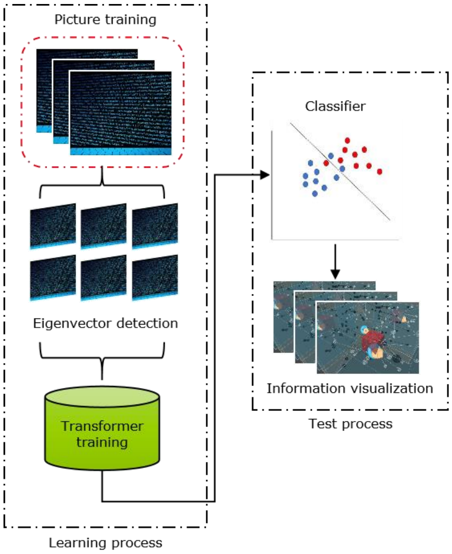

Figure 1: Information visualization process based on Transformer model.

To handle VR interactive tasks, this article introduces a specially designed Transformer model aimed at recognizing key information features. Given that the input layer, denoted as x_p , is a m-dimensional vector, while the output layer is a y_p vector of n dimensions, the structure of the hidden layers can be described as:

$$Z_i, i = 1,2,\cdots,j \tag{1}$$

The output of the k-th hidden layer neuron can be expressed as:

$$y_k = \sum_{i=1}^{j} w_{ik} \cdot \exp\left(-\frac{1}{2\sigma^2}\left\|x_p, Z_j\right\|\right) \tag{2}$$

To determine the sensitivity of the layer Z, an up-sampling operation must be performed on the sensitivity of the corresponding pool layer, assuming the convolution layer count is represented by l and the subsequent pool layer count by $l+1$. Therefore, for the convolution layer l, the sensitivity of the j-th layer is calculated as follows:

$$\delta_j^l = \beta_j^{l+1} \; f' \;\, u_j^l \;\, \circ \, up \;\, \delta_j^{l+1} \tag{3}$$

Where β_j^{l+1} denotes the weight corresponding to the pool layer, $up \cdot$ signifies the up-sampling operation. The selection of the number of hidden layer nodes relies on the empirical formula as follows:

$$N = \sqrt{m+n} + \alpha \tag{4}$$

Let N stand for the number of neurons in the hidden layer, m for the quantity of input neurons, and n for the overall neuron count.

3.2 Interactive Optimization Model Between CAD and VR Based on Transformer

After global pooling operation and nonlinear 1×1 convolution dimension reduction, deep features are extracted from network propagation, and then advanced feature information containing global context is generated. Then, these advanced features and shallow features are weighted and multiplied, and then the weighted shallow features and deep features are superimposed to form a new feature map. The global attention module is used to fuse feature maps of various proportions, thus further enriching the information content of feature maps. To maintain consistency and stability of information throughout the entire process, the generation of shallow feature maps is steered by the deep features procured from the network. Refer to Figure 2 for a depiction of the model's global attention module.

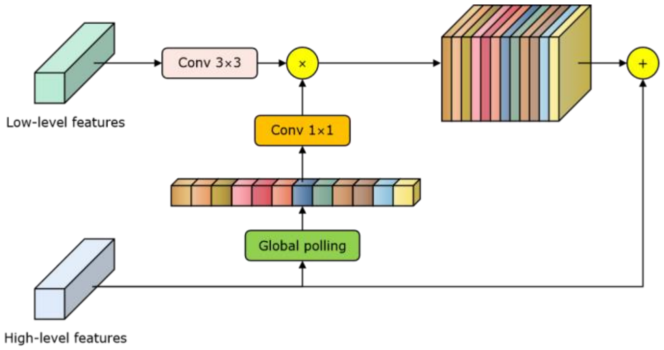

Figure 2: Global attention module.

Before importing CAD data into the Transformer model, it needs to be preprocessed. Pretreatment includes data cleaning, standardization, and feature extraction. This process is represented by the following formula:

$$X_{preprocessed} = f_{preprocess} \;\, X_{raw}; \theta_{preprocess} \tag{5}$$

Where X_{raw} represents the original CAD data, $f_{preprocess}$ is the preprocessing function, $\theta_{preprocess}$ is the preprocessing parameter, and $X_{preprocessed}$ is the preprocessed data.

The preprocessed data will be sent to the Transformer model for training. The training of the Transformer model is usually accomplished by minimizing the loss function. The training process of the model is represented by the following formula:

$$\theta_{model} = \arg\min_{\theta} L\left(Y, f_{model}\left(X_{proprocessed}; \theta\right)\right) \tag{6}$$

Among them, Y is the target of model output, f_{model} the Transformer model θ is the model parameter, L is the loss function, and θ_{model} is the best model parameter obtained through training.

After the training is completed, the interaction efficiency of the model needs to be evaluated. This can be achieved by comparing the model-aided interaction time with the traditional interaction time. The evaluation formula can be expressed as:

$$E = \frac{T_{traditional} - T_{model}}{T_{traditional}} \times 100\% \tag{7}$$

Among them, $T_{traditional}$ are the time required for traditional interaction, T_{model} the interaction time assisted by the Transformer model, and E the percentage of efficiency improvement.

Figure 3 shows the multi-head attention mechanism of the Transformer model. This mechanism can capture the information and dependencies of different positions in the sequence at the same time by processing multiple self-attention heads in parallel, thus effectively improving the model's ability to understand and express complex data characteristics.

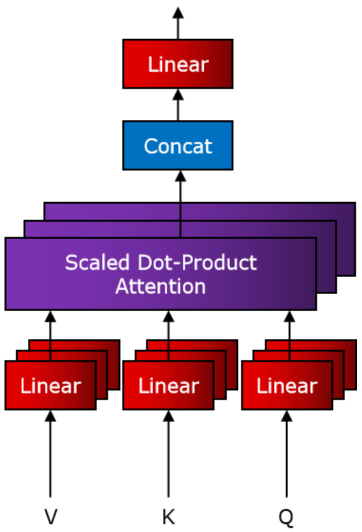

Figure 3: Multi-head attention mechanism.

During the pre-training process, the model will generate a prediction vector based on the input sequence, which includes all possibilities in the sequence. By encoding and decoding the predicted vector, the model can generate a series of generative vectors that contain all possibilities in the sequence and have a certain degree of correlation. In a generative pre-training Transformer, the encoder can generate multiple generative vectors based on the input sequence, which can be used as prediction vectors to generate the output sequence. In the decoder, an output sequence is generated based on the predicted vector. Swin Transformer combines the transformer structure with the idea of CNN and proposes a backbone that can be widely applied in various computer vision fields. The reason why Swin Transformer has such a great influence is mainly because of ViT. On the basis of this interface definition, we need to implement two parts: calling the interface of the backend operator and determining whether it supports local logic. During the execution process of the model, it is better to have fewer operations for game-handling classes, which can maximize the utilization of our

TPU computing power. It has shown good performance on datasets for tasks such as detection, classification, and segmentation, and can be applied to many scenarios that require high accuracy.

Based on this idea, the function of LayerGroup was designed in the main. LayerGroup can divide multiple calculation instructions into a group after calculation. Within a group, each Op can directly use the data stored in Local Memory after the previous Op calculation, which can reduce the moving out and moving in between every two Op data connections, thereby reducing IO time. From the effect of the above group, there is a relatively special situation where AddOp is not combined with other layer groups. The reason here is that one of the inputs to add is weight, so when weight is encountered during segmentation, it is considered that it does not support the group. But for point-to-point operations like add, if the input is weight, theoretically, Op can also be segmented.

In this section, normalization is achieved by utilizing the utilization rate of each resource, and the balanced degree of resource consumption is expressed through the standard deviation analysis method. The formula for calculating the load balance degree is as follows:

$$Degree_m = \left(u_{cpu} - u_{memory}\right)^2 + \left(u_{cpu} - u_{bandwidth}\right)^2 + \left(u_{memory} - u_{bandwidth}\right)^2 \tag{8}$$

Let u_{cpu} denote the utilization rate of the physical machine, u_{memory} signify the utilization rate of memory and $u_{bandwidth}$ indicate the utilization rate of network bandwidth, all determined by the virtual machine's actual operational data. $Degree_m$ signifies the equilibrium level of resource consumption for physical machines m, reflecting the compatibility between the virtual resource consumption it bears and the allocation of physical machine resources.

This scheduling algorithm primarily aims to achieve two goals: firstly, minimizing the system's load balance parameter, and secondly, minimizing the consumption related to virtual machine migration. The objective function for this can be formulated as follows:

$$\begin{aligned} f_1 &= \min(\lambda) = \min\left(\frac{\sum_{i=1}^{n}\left|\bar{W} - W_i\right|}{n \times 0.5}\right) \\ f_2 &= \min(E) = \min\sum E_i \end{aligned} \tag{9}$$

Regarding constraints, the main considerations encompass the following elements:

$$\begin{aligned} &\sum_{i=0}^{k} V_{ij} \le H_j \\ &j \le \max(ID) \end{aligned} \tag{10}$$

In other words, every server must have the capacity to handle the hosts assigned to it, and the number of servers corresponding to a virtual machine should not exceed the maximum allowable server count.

In each training batch, a part of CAD data is randomly selected for training, and the parameters of the model are updated by the gradient descent algorithm. Through an iterative optimization process, the model gradually learns the ability to extract effective features from CAD data and make accurate predictions.

4 SIMULATION EXPERIMENT

4.1 Experimental Preparation

In order to verify the advantages of the Transformer model in image information extraction, a series of simulation experiments are designed. We chose an image set containing various artistic elements and complex scenes as the test data. These images encompass diverse styles, hues, and arrangements, allowing for a thorough assessment of the algorithm's efficacy. In our study, we compare the algorithm that relies on visual comprehension of the scene against the traditional art-aided design approach. Figure 4 displays a selection from the experimental image collection.

Figure 4: Partial experimental image set.

See Table 1 for the experimental environment settings. We chose a server with high-performance computing ability as the experimental platform to ensure the accuracy and reliability of the experimental results. Furthermore, in order to simulate the real design environment, we also configured professional graphics processing software and hardware support.

Item	*Configuration/parameters*
Server	Dell PowerEdge R740XD
Processor	Intel Xeon Silver 4216
Memory	256GB DDR4 RAM
Storage	1TB SSD + 2TB HDD
Graphics card	NVIDIA Quadro P4000
Operating system	Ubuntu 18.04 LTS
Software	Python, TensorFlow

Table 1: Experimental environment configuration.

During the study, rigorous adherence to the aforementioned environmental setup was maintained to guarantee dependable and reproducible results. By conducting comparative tests, we aim to prove the advantage of the art-aided design approach, which relies on visual comprehension of scenes for image data extraction.

4.2 Experimental Result

Visualization aims to realize seamless docking and real-time interaction between CAD design and VR using a Transformer model. After determining this goal, an interactive optimization system based on Transformer is developed, which can understand and transform CAD design data for real-time rendering and interaction in a VR environment. We initially trained a Transformer model capable of comprehending the intricate structure and relationships within CAD design data to accomplish this objective. By exposing the model to an extensive dataset, it progressively acquired the ability to translate CAD data into a VR-compatible format seamlessly. Throughout the training phase, we monitored the model's training loss (illustrated in Figure 5) as a metric to assess its learning progression and proficiency. Our observations indicate that the model steadily converged over several iterations, ultimately attaining the desired training outcome.

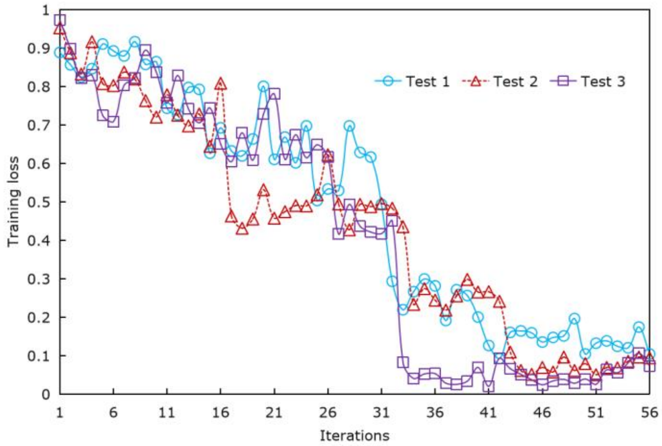

Figure 5: Training loss of algorithm.

Once the model training was finished, we conducted multiple experiments to validate its practical utility. By feeding CAD design data into the model, we successfully achieved high-quality rendering and seamless real-time interaction within the VR setting. This underscores the efficiency of the interactive optimization system rooted in the Transformer model.

Furthermore, our study compares the performance of the conventional CAD-VR interaction approach with the Transformer-based method, focusing on execution time (refer to Figure 6). The findings reveal that the Transformer-based approach significantly outperforms the traditional method in terms of speed, enabling swifter interaction between CAD design and VR.

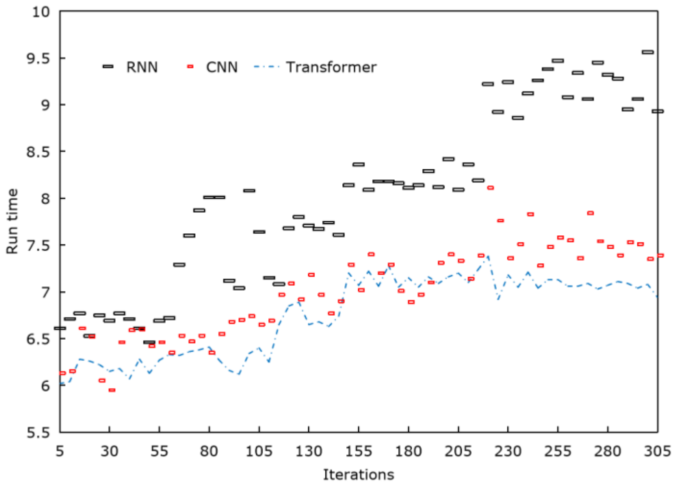

Figure 6: Running time comparison of algorithms.

4.3 Evaluation of CAD Visual Expression

Figure 7 shows some experimental results after interactive optimization between CAD and VR based on the Transformer model. After optimization, the rendering of the CAD model in VR is more delicate and the interaction is smoother, which proves the effectiveness of the Transformer model in the interaction optimization between CAD and VR.

Figure 7: Some experimental results.

Kurtosis is used to describe the sharpness of data distribution, or kurtosis. Here, it is used to measure the stability and concentration of the interactive response of the CAD model in a VR environment.

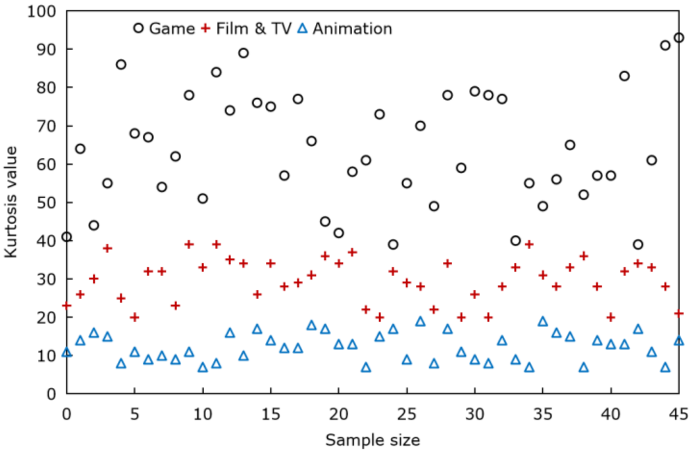

Figure 8: Kurtosis distribution map.

Figure 8 shows the kurtosis distribution of the interactive response of different styles or categories of CAD model data in VR after using the interactive optimization method between CAD and VR based on the Transformer model.

5 DISCUSSION

In the field of information visualization design, the interactive optimization between CAD and VR is a challenging research topic. In this article, the Transformer model is introduced to discuss this problem deeply, and a series of remarkable experimental results are obtained. In the process of information visualization design, designers need to constantly design models in CAD software and preview the effect in a VR environment. Traditional interactive methods often have problems such as slow data transmission, poor rendering effect and unsmooth interaction, which seriously restricts the improvement of design efficiency. In this study, the Transformer model is introduced, which effectively solves these problems, and realizes the real-time interaction between CAD and VR.

From the method point of view, this study adopts the interactive optimization method based on the Transformer model. The transformer model has made remarkable achievements in the field of natural language processing, and its powerful sequential modelling ability enables it to effectively understand and transform CAD design data. Through a large number of training data, the model gradually learned how to generate an understandable format for the VR environment according to the internal structure and relationship of CAD data. The advantage of this method lies in its powerful data-driven ability, which can automatically learn the best interaction mode according to historical data, thus realizing the efficient interaction between CAD and VR.

In terms of experimental results, this study verified the practicability of the interactive optimization method based on the Transformer model through a series of experiments. After a certain number of iterations, the model gradually converges and achieves the expected training effect. From the comparison of running time, the method based on the Transformer model has obvious advantages in running time; After optimization, the rendering of the CAD model in VR is more delicate, the interaction is smoother, and all performance indexes have been significantly improved. These experimental results fully prove the superiority of this research method.

This study bears certain limitations. Primarily, training the Transformer model demands substantial data support, which may pose difficulties in acquiring adequate training data in specific domains or scenarios. This could potentially hinder the widespread application of this methodology. Secondly, despite achieving impressive experimental results, a practical application might still encounter obstacles posed by complex environments and unforeseeable factors. Consequently, future research should prioritize enhancing the model's generalization capabilities and robustness.

6 CONCLUSIONS

In exploring a new field of CAD-VR interaction optimization, this study introduces an innovative method based on the Transformer model. In terms of execution efficiency, it significantly reduces processing time, allowing designers to see design results more quickly. By deeply understanding the internal logic and correlation of CAD design data, efficient data conversion has been achieved. After a series of experimental verifications, this method not only significantly improves the drawing speed of CAD models in VR environments, but also significantly optimizes the user interaction experience. Compared with traditional methods, transformer-based interactive optimization methods have shown significant advantages. These exciting results not only demonstrate the enormous potential of the Transformer model in CAD-VR interaction optimization but also open up new directions for future research. At the same time, our method has reached a new level in terms of rendering quality and interaction performance, providing users with a more realistic visual experience and smoother interaction processes.

Fei Li, https://orcid.org/0009-0005-3876-3374
Rucheng Zhang, https://orcid.org/0009-0000-4908-1188

REFERENCES

[1] Barreto, J.-C.-D.-L.; Cardoso, A.; Lamounier, J.-E.-A.; Silva, P.-C.; Silva, A.-C.: Designing virtual reality environments through an authoring system based on CAD floor plans: a methodology and case study applied to electric power substations for supervision, Energies, 14(21), 2021, 7435. https://doi.org/10.3390/en14217435

[2] Buyukdemircioglu, M.; Kocaman, S.: Reconstruction and efficient visualization of heterogeneous 3D city models, Remote Sensing, 12(13), 2020, 2128. https://doi.org/10.3390/rs12132128

[3] Charan, T.; Mackey, C.; Irani, A.; Polly, B.; Ray, S.; Fleming, K.; Goldwasser, D.: Integration of open-source URBANopt and Dragonfly energy modeling capabilities into practitioner workflows for district-scale planning and design, Energies, 14(18), 2021, 5931. https://doi.org/10.3390/en14185931

[4] Erdolu, E.: Lines, triangles, and nets: A framework for designing input technologies and interaction techniques for computer-aided design, International Journal of Architectural Computing, 17(4), 2019, 357-381. https://doi.org/10.1177/1478077119887360

[5] Freitas, F.-V.; Gomes, M.-V.-M.; Winkler, I.: Benefits and challenges of virtual-reality-based industrial usability testing and design reviews: A patents landscape and literature review, Applied Sciences, 12(3), 2022, 1755. https://doi.org/10.3390/app12031755

[6] Gong, R.; Han, X.; Wang, J.; Ying, S.; Shi, J.: Self-supervised bi-channel transformer networks for computer-aided diagnosis, IEEE Journal of Biomedical and Health Informatics, 26(7), 2022, 3435-3446. https://doi.org/10.1109/JBHI.2022.3153902

[7] 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

[8] Liu, S.; Li, T.: AVG comprehensive practice reform of digital media art based on fuzzy theory, Journal of Intelligent and Fuzzy Systems, 38(1), 2020, 1-10. https://doi.org/10.3233/JIFS-179592

[9] Mondragón, B.-I.-F.; Lozano, R.-N.-E.; Puerto, C.-J.-M.; Valdivia, S.; Muñoz, R.; Aragón, J.; Hernández, G.: An immersive virtual reality training game for power substations evaluated in terms of usability and engagement, Applied Sciences, 12(2), 2022, 711. https://doi.org/10.3390/app12020711

[10] Oh, S.; Jung, Y.; Kim, S.; Lee, I.; Kang, N.: Deep generative design: Integration of topology optimization and generative models, Journal of Mechanical Design, 141(11), 2019, 111405. https://doi.org/10.1115/1.4044229

[11] Pelliccia, L.; Bojko, M.; Prielipp, R.: Applicability of 3D-factory simulation software for computer-aided participatory design for industrial workplaces and processes, Procedia CIRP, 99(11), 2021, 122-126. https://doi.org/10.1016/j.procir.2021.03.019

[12] Regenwetter, L.; Nobari, A.-H.; Ahmed, F.: Deep generative models in engineering design: A review, Journal of Mechanical Design, 144(7), 2022, 071704. https://doi.org/10.1115/1.4053859

[13] Tadeja, S.-K.; Bozzi, L.-O.-S.; Samson, K.-D.; Pattinson, S.-W.; Bohné, T.: Exploring the repair process of a 3D printer using augmented reality-based guidance, Computers & Graphics, 117(1), 2023, 134-144. https://doi.org/10.1016/j.cag.2023.10.017

[14] Trappey, A.-J.; Trappey, C.-V.; Chao, M.-H.; Hong, N.-J.; Wu, C.-T.: A VR-enabled chatbot supporting design and manufacturing of large and complex power transformers, Electronics, 11(1), 2021, 87. https://doi.org/10.3390/electronics11010087

[15] Wang, Q.; Yu, Z.: Deep learning-based scene processing and optimization for virtual reality classroom environments: a study, Traitement Du Signal, 41(1), 2024, 115-125. https://doi.org/10.18280/ts.410109

[16] Wu, H.; Zhang, H.; Cheng, J.; Guo, J.; Chen, W.: Perspectives on point cloud-based 3D scene modeling and XR presentation within the cloud-edge-client architecture, Visual Informatics, 7(3), 2023, 59-64. https://doi.org/10.1016/j.visinf.2023.06.007

[17] Yang, Z.; Buehler, M.-J.: Words to matter: De novo architected materials design using transformer neural networks, Frontiers in Materials, 8(1), 2021, 740754. https://doi.org/10.3389/fmats.2021.740754