Exploration of Optimizing Advertising Design Using CAD and Deep Reinforcement Learning

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Abstract. This article delves into the integrated utilization of CAD (Computer-Aided Design) technology and DRL (Deep Reinforcement Learning) in the realm of advertising design, proposing a novel model for innovative designs. Through an examination of the fundamentals of DL (Deep Learning) and reinforcement learning, along with their potential applications in advertising design, the study formulates a model that fuses CAD technology with DRL. The primary objective of this model is to achieve automation and intelligence in advertising design, thereby enhancing creativity, minimizing costs, and boosting efficiency. To ascertain the efficacy of the proposed model, simulation experiments were conducted, utilizing a comprehensive dataset of advertising. The experimental findings indicate that the advertising design model, which integrates CAD and DRL, exhibits significant advantages in augmenting design creativity, lowering design costs, and elevating design efficiency. Compared with the traditional advertising design method, this model can better understand the needs of users and market trends and generate more creative and attractive advertising design schemes. Its research provides a valuable reference for researchers in related fields and promotes the application research of DRL in creative fields such as advertising design.

Keywords: Computer-Aided Design; Deep Reinforcement Learning; Deep Learning; Advertising Design
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1 INTRODUCTION

Amidst the swift evolution of information technology, the advertising design industry confronts unparalleled transformations. In the design of cultural and creative products, colour imagery and advertising visual aesthetics are two crucial factors. They not only directly affect the attractiveness of the product but also determine its competitiveness in the market and consumer purchasing decisions. Deng et al. [1] analyzed the interactive genetic color-matching design of cultural and creative products that take into account colour imagery and visual aesthetics. In recent years, with the rapid development of deep reinforcement learning technology, it can be applied to the design of cultural and creative products to more accurately grasp colour imagery and advertising visual aesthetics, thereby improving product design quality and market performance. Advertising visual aesthetics refers to the creation of attractive advertising images through visual elements and composition techniques. In the design of cultural and creative products, the visual aesthetics of advertising cannot be ignored. A beautiful and creative advertising image can quickly attract the attention of consumers and stimulate their desire to purchase. Designers need to apply aesthetic principles and creative thinking to create advertising images that are both in line with product characteristics and have a visual impact. Conventional advertising design approaches are becoming inadequate in fulfilling the growing diversification of market demands. There is an imminent need to incorporate cutting-edge technologies and paradigms to elevate design efficiency and quality. With the rapid development of computer technology and the continuous progress of deep reinforcement learning algorithms, the application of graphic processing technology in advertising visual communication design is becoming increasingly widespread. Advertising visual communication design aims to effectively convey information to the audience and stimulate their interest and purchasing desire through visual elements and creative ideas. Computer deep reinforcement learning graphics processing provides new tools and ideas for advertising visual communication design, enabling designers to more accurately control advertising effects and improve the attractiveness and conversion rate of advertisements. Fan and Li [2] analyzed that computer deep reinforcement learning combines the advantages of deep learning and reinforcement learning and can learn and optimize decision strategies in large amounts of data. In the field of graphic processing, deep reinforcement learning can autonomously learn and optimize the process of image generation, editing, and recognition, providing strong support for advertising visual communication design. Computer-aided design technology, as a sophisticated tool, has gained widespread adoption across numerous domains. With the rapid development of the digital advertising industry, the layout and repositioning of advertising banners have become key elements, directly affecting the click-through rate and conversion rate of advertisements. Traditional advertising banner layout methods are often based on experience and fixed rules, making it difficult to adapt to complex and ever-changing user behaviours and environments. To address this issue, Hu et al. [3] utilized advanced technologies such as hierarchical reinforcement learning and variational autoencoder (VAE) for target reorientation. Hierarchical reinforcement learning can learn layout strategies at different levels, from simple element arrangements to complex region segmentation, gradually constructing efficient advertising banner layouts. Through the interaction data between users and advertising banners, hierarchical reinforcement learning can continuously optimize layout strategies to improve the attractiveness and click-through rate of advertisements. VAE can learn the potential distribution of advertising banner layouts and generate diverse layout samples, providing rich candidate solutions for advertising banner repositioning. Concurrently, Deep Reinforcement Learning (DRL), a focal point in artificial intelligence research, showcases remarkable performance in decision optimization and automation. This presents novel opportunities for advertising design.

DRL integrates the strengths of Deep Learning (DL) and reinforcement learning, leveraging DL's exceptional representation learning capabilities to capture state features and reinforcement learning's proficiency in decision optimization to devise strategies. In advertising art design, CAD technology provides designers with powerful tools that enable them to perform precise design, modelling, and rendering in a virtual environment. Deep reinforcement learning is an important technology in the field of artificial intelligence, which combines the advantages of deep learning and reinforcement learning, enabling machines to autonomously learn and make decisions. The application of deep reinforcement learning design software in advertising art design has brought new design ideas and methods to designers. Jin and Yang [4] train deep reinforcement learning models to enable machines to automatically generate design solutions. This greatly broadens the designer's thinking and helps to discover new design inspirations. Deep reinforcement learning models can automatically optimize design solutions based on design goals and constraints. Interactive advertising design in the CAD environment needs to focus on user experience, interactivity, and the combination of creativity and content. Meanwhile, with the help of technologies such as virtual reality, augmented reality, big data, and artificial intelligence, more vivid, interesting, and personalized interactive advertisements can be created. DRL has secured notable breakthroughs in various fields and holds promising potential in advertising design. With the advancement of technology, 3D technology has become an important tool in the field of advertising design. Especially with the application of 3D Convolutional Neural Networks (3D CNN), it is possible to identify features of advertising design from 3D CAD models. Meanwhile, gradient-based visual advertising interpretation technology provides designers with more in-depth and intuitive design feedback. Lee et al. [5] explored how to use 3D CNN for advertising design feature recognition and how to optimize advertising effectiveness using gradient-based visual advertising interpretation. Traditional advertising design feature recognition mainly relies on manual experience and subjective judgment, which is not only inefficient but also easily influenced by personal preferences. The application of 3D CNN provides a new solution for automatic recognition and extraction of advertising design features. Gradient-based visual advertising interpretation technology is an emerging design optimization method. It can intuitively display key regions and features in advertising images by analyzing and processing the gradient information of advertising images. By adjusting these key areas and features, designers can more accurately optimize advertising effectiveness and improve the attractiveness and conversion rate of advertisements.

Specifically, DRL can optimize advertising recommendation strategies, thereby enhancing click-through and conversion rates. Additionally, it can facilitate the automatic generation of advertising concepts and designs, leading to improved efficiency and quality in advertising design processes. With the rapid development of e-commerce and live streaming media, live advertising shopping has become a popular sales model. The multiple challenges faced by dynamic coupon positioning in live advertising shopping. Firstly, user behaviour and interests are diverse, and different users may have different reactions to different coupons. Secondly, the environment of live advertising shopping is dynamic, and the distribution strategy of coupons needs to be adjusted based on real-time user feedback and shopping trends. Finally, the number of coupons is limited, and how to allocate them reasonably to maximize their effectiveness is an important issue. Liu [6] adopts a coupon localization method based on batch deep reinforcement learning. Specifically, it utilizes historical user behaviour data and coupon distribution records to train a deep reinforcement learning model. This model can learn user behaviour patterns and reactions to coupons, thereby predicting the attractiveness of different coupons to different users. Then, based on the predicted results, dynamically adjust the distribution strategy of coupons to meet the interests and needs of users better.

The main focus of this article lies in analyzing the current application of CAD technology within advertising design, exploring the principles of the DRL algorithm and its potential within this field, and ultimately constructing an optimization model that merges CAD and DRL validated through simulation experiments. This research not only aims to facilitate the digital transformation and intelligent enhancement of the advertising design industry, elevating design efficiency, quality, and market responsiveness while reducing costs but also to expand the application scope of CAD technology and DRL, driving further technological advancements.

The objective of this study is to investigate the synergistic integration of CAD and DRL in advertising design, paving the way for innovative approaches in the industry. Its novel contributions are twofold.

Firstly, by fusing CAD technology with DRL, we have established a groundbreaking advertising design model. This model excels in feature extraction and can autonomously generate high-quality advertising designs tailored to user preferences and market trends, injecting fresh perspectives and techniques into the advertising design landscape.

Secondly, traditional advertising design often relies heavily on the designer's expertise and intuition. However, in this study, we leverage the DRL algorithm to autonomously acquire creative components such as layout, colour schemes, typography, and image selection, crafting original and impactful advertising designs.

This article is structured into six distinct sections. The introductory section outlines the research backdrop, significance, scope, methodologies, and overall paper organization. The subsequent section delves into the relevant research landscape. The main body of the paper, spanning the third to fifth sections, delves into the theoretical underpinnings of DRL, the seamless integration of CAD and DRL in advertising design, the design and execution of simulation experiments, as well as a thorough examination and optimization strategies of the experimental outcomes. The concluding section summarizes the key findings and contributions of the study while also acknowledging its limitations and charting a course for future research endeavours.

2 RELATED WORK

With the rapid development of the Internet of Things and big data technology, vehicle data has become a new competitive focus in the advertising industry. Crowdsourcing, as an emerging method of data collection combined with reinforcement learning algorithms, has brought new possibilities for the formulation of advertising strategies. Lou et al. [7] explored how to use crowdsourcing to perceive vehicle data and combine it with reinforcement learning algorithms to develop more accurate and efficient advertising strategies. Through reinforcement learning algorithms, we can accurately locate the target user group and improve the effectiveness of advertising placement based on vehicle data and user behaviour information. Reinforcement learning algorithms can dynamically adjust advertising content based on user feedback and behavioural data, making advertisements more in line with user interests and needs. Through reinforcement learning algorithms, we can choose the appropriate advertising timing based on vehicle data and user behaviour information and improve the exposure and click-through rate of advertisements. Combining crowdsourcing perception of vehicle data with reinforcement learning algorithms can provide us with more accurate and efficient advertising strategies. In the digital age, computer-aided design (CAD) and deep reinforcement learning technologies have permeated every aspect of advertising design. However, with the popularization of these technologies, the problem of advertising encroachment among manufacturers is becoming increasingly serious, and motivating advertising design has become the key to solving this problem. Ma and Hong [8] explore the strategy choices and their impacts on CAD and deep reinforcement learning vendors in advertising design and placement from the perspective of game theory. The introduction of CAD and deep reinforcement learning technology in the advertising market provides more possibilities for advertising design and delivery. However, this also leads to the limitation of advertising space and the scarcity of advertising resources, thereby causing the problem of advertising encroachment. Advertising encroachment refers to the competition between different manufacturers for limited advertising resources in the process of advertising design and delivery, resulting in a decrease in advertising effectiveness and a loss of user experience.

In the new media environment, interactive advertising has attracted a large number of users' attention due to its unique characteristics of interactivity, participation, and personalization, providing new opportunities and challenges for enterprise brand communication and product promotion. Meng and Huang [9] discussed the strategies, technologies, and trends of interactive advertising design in the new media environment. The primary principle of interactive advertising design is user-centered and emphasizes user experience. Designers need to understand the needs and preferences of the target audience and design interactive advertisements that meet user psychological expectations and aesthetic needs. Interactivity is the core characteristic of interactive advertising. Designers need to utilize new media technologies, such as touch screens, voice recognition, augmented reality, etc., to achieve real-time interaction between users and advertisements to enhance user engagement and immersion. Interactive advertising requires breakthroughs in creativity and content. Designers need to uncover the story behind advertisements, closely combining brand concepts, product features, and user emotions to create interesting and informative interactive advertisements. Interactive advertising will place greater emphasis on personalization and customization. The application of technologies such as computer-aided design (CAD) and artificial intelligence (AI) in advertising assembly modelling is becoming increasingly widespread. Especially in capturing design intent and transforming it into concrete product information modeling, these technologies play a crucial role. Mo et al. [10] explored how to utilize these advanced technologies to accurately capture and express the designer's intentions in intelligent advertising assembly modelling. In the traditional advertising assembly modelling process, designers often need to express their design concepts through hand drawing or simple modelling software. This approach is not only inefficient but also difficult to accurately convey the designer's intentions. With the development of computer-aided design and artificial intelligence technology, this problem has been effectively solved. By utilizing CAD and AI technology, we can establish more accurate and comprehensive product information models, providing strong support for subsequent production and assembly.

With the rapid development of machine learning technology, its application in the field of advertising is becoming increasingly widespread. Especially interactive and interpretable machine learning methods provide new perspectives and tools for advertising analysis. Spinner et al. [11] explored how to construct an interactive and interpretable machine learning-based visual advertising analysis framework to optimize advertising effectiveness and improve user experience. Interactive machine learning emphasizes the interaction between users and models, allowing users to optimize model performance through feedback and adjustments. Optimize the recommendation and display of advertising content through user feedback, such as click-through rates, browsing time, etc. Based on the user's historical behavior and preferences, personalized advertising recommendations are made through interactive machine learning. With the rise of new media and the development of digital technology, the advertising industry is undergoing unprecedented changes. In this transformation, CAD visual advertising communication technology and computer-aided interaction of art advertising play a crucial role. They not only enhance the artistic and visual effects of advertising but also enhance its interactivity and attractiveness, making advertising more vivid, interesting, and effective in new media scenarios. Wang [12] analyzed the computer-aided interaction between CAD visual advertising communication technology and art advertising. CAD (computer-aided design) technology has brought revolutionary changes to the advertising industry with its powerful modelling and rendering capabilities. Through CAD technology, designers can create precise 3D models that simulate real scenes and objects, making advertisements more vivid, three-dimensional, and realistic. Meanwhile, CAD technology can also achieve rapid modification and optimization of advertisements, improving design efficiency and advertising effectiveness. In the context of new media, CAD visual advertising communication technology has been widely applied. Computer vision perception systems have been widely applied in various fields, including cultural and creative product design evaluation. The application of this system provides designers with a new perspective, enabling them to have a deeper understanding of the design concept, aesthetic form, practicality, and market acceptance of products, thereby designing products that better meet user needs and are more creative. The system can identify and analyze the color matching, color distribution, etc. of the product, and evaluate whether it meets the aesthetic preferences of the target user. The system can analyze the surface texture of the product to evaluate whether it conforms to the design theme, and whether it has sufficient details and texture [13].

The combination of graphic art design and CAD (computer-aided design) has become a trend in advertising design. This combination can not only improve design efficiency but also make advertising works more creative and attractive. Yang and Ren [14] discussed the design method of combining advertising graphic art design with CAD design, as well as the application of computer-aided design in advertising design. Advertising graphic art design emphasizes creativity and visual effects, conveying advertising information through the combination of elements such as graphics, colours, and text. CAD design provides a precise and efficient design tool that can help designers quickly create and modify design proposals. Combining advertising graphic art design with CAD design can make designers more flexible and efficient in the design process. Designers can first conceptualize and create advertising works in graphic art design software and then use CAD software for precise design and production. This combination can fully leverage the advantages of the two design methods, making advertising works both creative and aesthetically pleasing, as well as precise and practical. The combination of graphic art design and CAD (computer-aided design) has become a trend in advertising design. This combination can not only improve design efficiency but also make advertising works more creative and attractive. Yoo et al. [15] explored the design method of combining advertising graphic art design with CAD design, as well as the application of computer-aided design in advertising design. Advertising graphic art design emphasizes creativity and visual effects, conveying advertising information through the combination of elements such as graphics, colours, and text. CAD design provides a precise and efficient design tool that can help designers quickly create and modify design proposals. Combining advertising graphic art design with CAD design can make designers more flexible and efficient in the design process. Designers can first conceptualize and create advertising works in graphic art design software and then use CAD software for precise design and production. This combination can fully leverage the advantages of the two design methods, making advertising works both creative and aesthetically pleasing, as well as precise and practical.

Scholars and enterprises alike have conducted extensive research and practice in the realm of advertising design. CAD technology, a pivotal tool in this domain, has found widespread application in areas such as layout design, image processing, and animation production. Meanwhile, the burgeoning field of artificial intelligence has propelled the use of DRL in advertising design into the forefront of research. In the coming years, technological advancements and market fluctuations will present both obstacles and prospects for the advertising design industry. The integration of CAD technology with DRL emerges as a significant growth trajectory for this sector. By embracing novel technologies and ideas, we aim to enhance the efficiency and quality of advertising designs, cater to the market's diverse demands, and foster continual innovation within the industry.

3 THEORETICAL BASIS

3.1 Advertising Design

Advertising design is a comprehensive discipline and practical field involving creativity, art, marketing, consumer psychology, technology, and many other aspects. Its main purpose is to convey the advertiser's information, brand values, and the characteristics of products or services through the effective combination of vision, words, and other elements so as to attract, persuade, and motivate the target audience to take some actions, such as buying goods and using services.

In advertising design, the key elements include:

Target audience: Understanding the needs, interests, behaviours, and consumption habits of the target audience is the key to successful design. Designers need to study the target market to determine the most effective way to transmit information.

Creativity: Creativity is the core of advertising design. A good idea can attract people's attention and make advertisements stand out from numerous information. Creativity can be embodied in unique visual expressions, fascinating storylines or unforgettable slogans.

Visual elements: Including colour, shape, image, typesetting, etc. These elements need to be skillfully used to convey the theme and emotion of advertising while ensuring visual appeal and clarity.

Text information: Text plays the role of explanation and persuasion in advertisements. Headlines, subheadings and text need to be carefully written to convey clear, powerful and attractive information.

Brand consistency: Advertising design needs to be consistent with the overall image and style of the brand. This helps to strengthen brand recognition and loyalty.

Technical Realization: With the development of digital technology, advertising design increasingly involves dynamic images, interactive design and multimedia elements. Designers need to master relevant technical tools to ensure the effective presentation of advertisements on various media platforms.

Effect assessment: After the advertisement design is completed, it is necessary to evaluate its effect. This can be achieved through market research, consumer feedback, sales data and other ways. The assessment results can provide a valuable reference for future advertising design.

3.2 CAD Technology and DRL Theory

CAD technology is a technical means to complete the design task by using computer-aided design software. In advertising design, CAD technology can be applied to many links, such as layout design, image processing, animation production and so on. Utilizing CAD technology, designers can streamline the advertising design process, enhancing both accuracy and quality. Additionally, CAD can seamlessly integrate with other design tools, creating a robust design system that offers extensive support for advertising endeavours. Whether it's layout planning, image editing, or animation production, CAD technology proves invaluable, facilitating quick layout planning, effortless image modification, and the creation of dynamic and specialized animations. Furthermore, CAD's support for 3D modelling and rendering enriches designers' toolkits, allowing for more intricate and visually stunning designs.

On the other hand, DRL is a hybrid of DL and reinforcement learning. DL, a subset of machine learning, mimics the human brain's learning processes through neural networks, particularly deep neural networks. It constructs abstract, high-level attributes or features by amalgamating low-level ones, revealing the distributed representations hidden within data. DL's essence lies in its ability to remap raw input data into a fresh feature space via multiple layers of nonlinear transformations, unearthing the inherent patterns and representations of the data. Common neural network structures employed in DL are outlined in Table 1.

Neural network structure	*Application scenario*	*Describe*
CNN	Image recognition, video analysis, target detection	CNN is especially suitable for processing image data, extracting local features of images through the convolution layer, and is often used in image classification, face recognition and other tasks.
RNN	Speech recognition, natural language processing, time series analysis	RNN can process sequence data and capture the time dependence in the sequence through memory cells, which is often used in language modelling, machine translation and other tasks.
LSTM	Natural language processing, speech recognition, time series prediction	LSTM is a variant of RNN. By introducing a gating mechanism and memory cells to solve the problem of long sequence dependence, the ability of sequence modelling is improved.
GAN	Image generation, image style transfer, data enhancement	GAN is composed of a generator and discriminator, which generates realistic new data through confrontation training and is often used in image generation, super-resolution and other tasks.
DBN	Feature learning, dimensionality reduction and classification	DBN is composed of multiple layers of restricted Boltzmann machines, and the weights of deep neural networks are initialized by pre-training layer by layer.

Autoencoders	Data compression, denoising, feature learning	An automatic encoder is composed of an encoder and a decoder. It learns the compressed representation of input data and reconstructs the input for unsupervised learning.

Table 1: Neural network structure classification.

Reinforcement learning is a pivotal branch of machine learning that focuses on teaching agents how to learn optimal strategies through interaction with their environment, aiming to maximize the accumulation of rewards. The fundamental components of reinforcement learning are the agent, environment, state, action, and reward. At each step, the agent selects an action based on the current state, which prompts the environment to respond with a new state and a corresponding reward. This continuous interaction drives the agent to refine its decisions based on the evolving states and rewards. The ultimate objective of reinforcement learning is to devise a strategy that guides agents in maximizing their cumulative rewards throughout their actions. Popular reinforcement learning algorithms include Q-learning, SARSA, and Deep Q-network, among others.

3.3 The combination of CAD and DRL in Advertising Design

CAD technology is extensively employed in advertising design, aiding designers in creating swiftly and precisely. Nevertheless, conventional CAD design procedures still demand manual operation and adjustment, hindering full automation and intelligence. Conversely, DRL, a robust machine learning technique, excels in autonomous learning and decision optimization, making it an ideal complement to CAD technology in pursuing advertising design automation and intelligence. Specifically, the DRL algorithm can acquire the rules and patterns inherent in advertising design, enabling it to generate design proposals and concepts autonomously. Simultaneously, CAD technology's design tools and resources can bolster the DRL algorithm in refining and adjusting designs. Hence, the integration of CAD and DRL in advertising design is both practical and promising.

4 CONSTRUCTION OF ADVERTISING DESIGN MODEL COMBINING CAD WITH DRL

To integrate CAD and DRL in advertising design, a model must be established that encompasses both technologies. This model should have distinct layers: an input layer for receiving advertising design tasks and associated data, a feature extraction layer that utilizes deep learning methods to process this data, a strategy learning layer where reinforcement learning algorithms are employed to learn advertising design strategies, and finally, an output layer that produces the finalized advertising design scheme.

This article defines a reconstruction area $S^{'}$, which is reconstructed from the visual information of 3D images. In this reconstruction process, we pay special attention to the edge contour part of the 3D image in a blurred area and extract the edge feature point $x^{'}, y^{'}$ from it. Next, these feature points are decomposed by texture gradient to further analyze the texture details of the image. Finally, the texture distribution set presented by 3D images in fuzzy areas is calculated, which provides an important database for subsequent image processing and analysis.

$$w\ i,j\ = \frac{1}{Z\ i}\exp\left(-\frac{d\ i,j}{h^2}\right) \tag{1}$$

Where $Z\ i$ is the first-order and second-order texture distribution operator?

After accurate and efficient calculation and analysis, the visual communication constraints of pixels can be parameterized, to understand their image characteristics deeply. In order to further optimize the calculation process and reduce the complexity, the relevant parameters are replaced and transformed, which provides convenience and accuracy for the subsequent image processing work. The formula is as follows:

$$W^{'}=\frac{1}{2}f\ \ x^{'},y^{'},z^{'}\ \ +E \tag{2}$$

The formula $x^{'},y^{'},z^{'}$ stands for 3D coordinate values with visual constraints, which are the key data for our spatial positioning and analysis. E Represents the weighted component of data, which can directly calculate the matching effect through specific formula conversion, thus helping us to evaluate and optimize the matching degree of data. This kind of representation enables us to understand and apply this formula more clearly and then improve the efficiency of calculation and analysis.

The conversion of spatial points between the world and camera coordinate systems involves rotation and translation, which can be precisely represented by a rotation matrix and a translation vector. Given that X_W represents the coordinates of a point in the world coordinate system and X_C represents the same point in the camera coordinate system, the relationship between these two sets of coordinates can be stated as follows:

$$X_W=\ x_w,y_w,z_w,1\ ^T \tag{3}$$

$$X_C=\ x_c,y_c,z_c,1\ ^T \tag{4}$$

Then, the relationship between them is:

$$X_C=\begin{bmatrix} R & -R\tilde{C} \\ 0^T & 1 \end{bmatrix} X_W \tag{5}$$

Among them, $\tilde{C}$ represents the coordinate of the camera center in the world coordinate system, which is a non-homogeneous coordinate and is used to determine the position of the camera in the world space. Through this non-homogeneous coordinate, the camera can be positioned accurately, and various spatial transformations and calculations can be further carried out.

In this model, CAD technology can provide all kinds of design tools and resource support for advertising design. The DRL algorithm takes charge of acquiring the rules and patterns of advertising design while automatically producing design proposals. To implement the aforementioned advertising design model, selecting the suitable DL network structure and algorithm is essential for extracting features from the input data. This article opts for the RNN model to accomplish this task, and Figure 1 illustrates the mask pattern employed within the network.

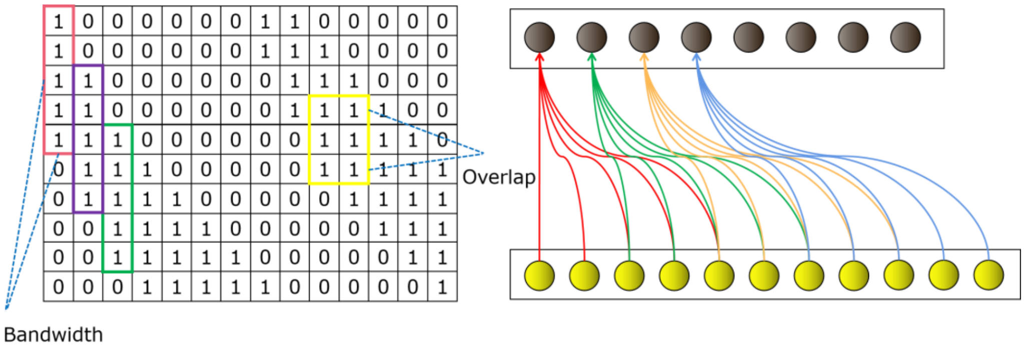

Figure 1: Network mask mode.

In this article, the enhanced 3D point cloud model is used to accurately convert the image boundary lines into spatial boundary lines, and these spatial boundary lines are carefully closed, to extract more accurate feature boundary lines. On this basis, the pixel points with slope values in X direction and

Y direction are further calculated. The following formula is used to calculate the slope values of these pixels one by one, which provides important data support for subsequent analysis and processing:

$$Aspect = a\tan 2\left(-Slope_{we}, Slope_{sn}\right) * 180 / \pi \tag{6}$$

The angle range calculated according to the above formula was originally (−180°,180°], but this does not conform to the commonly understood expression of slope angle. Therefore, it is necessary to transform this range according to the corresponding relationship to ensure that the final expression range of the slope angle is [0°,360°).

In addition, regarding the mapping relationship between 3D model instances and "skeleton" hierarchical structure, this article defines a set M. This collection describes in detail how 3D model instances are mapped to the "skeleton" hierarchical structure, providing a clear framework for subsequent model analysis and processing. It is defined as follows:

$$M = \left(T, D, P\right) \tag{7}$$

Among them T are the "skeleton" set of 3D models, D the corresponding set of 3D model instances, and P the corresponding set of attribute relationships among 3D model structures. Example $d_i \in D$ corresponds to structural connectivity graph F_i.

A relatively direct way to infer the normal direction of a point on the geometric surface is to rely on the vector perpendicular to the surface of the point. Specifically, for point $p\left(x,y\right)$ on surface S, its normal vector can be defined as the vector perpendicular to the tangent plane of surface S at point $p\left(x,y\right)$:

$$n\left(x,y\right) = n / \left|n\right| \tag{8}$$

This definition provides us with a concise and practical way to determine the normal direction of any point on the surface. Among them:

$$N = \frac{\partial \vec{p}\left(x,y\right)}{\partial_x} * \frac{\partial \vec{p}\left(x,y\right)}{\partial_y} \tag{9}$$

In addition, in the process of modelling, we need to pay attention to the following key points: choose the appropriate DL network structure and algorithm to adapt to the characteristics of advertising design; Design reasonable reward function and state representation method to guide the learning process of reinforcement learning algorithm; Make full use of the design tools and resources provided by CAD technology to assist the model design and optimization process; Fully test and verify the model to ensure its correctness and reliability.

5 DESIGN AND IMPLEMENTATION OF SIMULATION EXPERIMENT

This section carries out simulation experiments. In the experiment, the server with high configuration was selected as the experimental platform, and DL frameworks such as TensorFlow and PyTorch, as well as advertising design software such as Auto CAD and PhotoShop, were installed. At the same time, the advertising data set and assessment index are also configured to train and test the model. In the process of setting up the environment, we pay attention to the expansibility of the system. To ensure optimal performance and avoid resource bottlenecks during experimentation, we have optimized the system configuration and adjusted parameters. Additionally, we have designed a flexible experimental architecture and modular code structure to facilitate future expansions and model improvements.

The dataset plays a crucial role in simulation experiments, directly impacting the model's training effectiveness and performance assessment. To acquire high-quality advertising datasets, we have sourced and organized data from various channels, including public datasets, real-world cases provided by partner companies, and self-designed advertising samples. This diverse data covers various advertisement types and design elements. During dataset preparation, we underwent rigorous preprocessing and labelling procedures. Initially, we cleaned and formatted the raw data to eliminate irrelevant information and noise. Subsequently, we defined an appropriate labelling system and label set based on the unique characteristics and task requirements of advertising design. Finally, we labelled the data using a combination of manual and semi-automatic methods.

Following the completion of the environment setup and dataset preparation, we commenced the simulation experiment. This experimental process comprises two primary stages: model training and test assessment. During model training, we utilized the DRL algorithm to train the advertising design model, optimizing its performance through continuous adjustments to model parameters and learning strategies. Figure 2 illustrates the model training process.

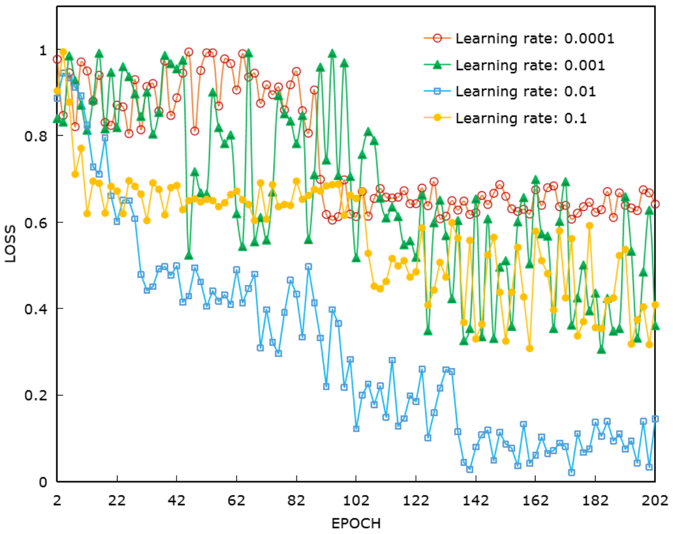

Figure 2: Model training situation.

The experimental results show that the model can converge in a short time when the learning rate is 0.01.

During the test and assessment phase, this study employs a range of assessment metrics such as accuracy, recall, and F1 score to conduct a thorough assessment of the model's performance. These assessment metrics offer insights into various aspects of the model's capabilities, enabling a more comprehensive understanding of its strengths and weaknesses. The accuracy achieved by the model is illustrated in Figure 3. The model recall rate is shown in Figure 4. The F1 score of the model is shown in Figure 5.

Through the detailed analysis of the accuracy, recall and F1 score of the model, we can draw the following conclusions: The advertising design model combining CAD and DRL proposed in this article has excellent performance, high accuracy and recall, and good comprehensive performance. While the F1 score of the model shown in Figure 5 is also at a high level. This means that the model has achieved a good balance between accuracy and recall, which can not only accurately classify advertising designs but also effectively identify examples of target categories. This provides new ideas and methods for the innovative development of the advertising design industry and is expected to promote the technical progress and efficiency of the industry. Comparing the traditional design method with the design scheme of this design method, the design cost and user assessment results of different advertising design schemes are shown in Figure 6 and Table 2.

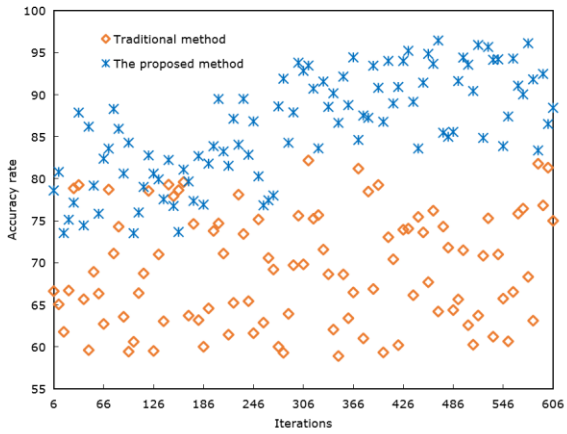

Figure 3: Model accuracy rate.

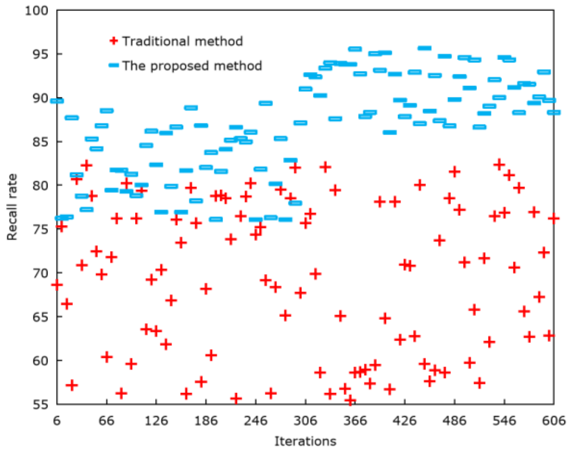

Figure 4: Model recall rate.

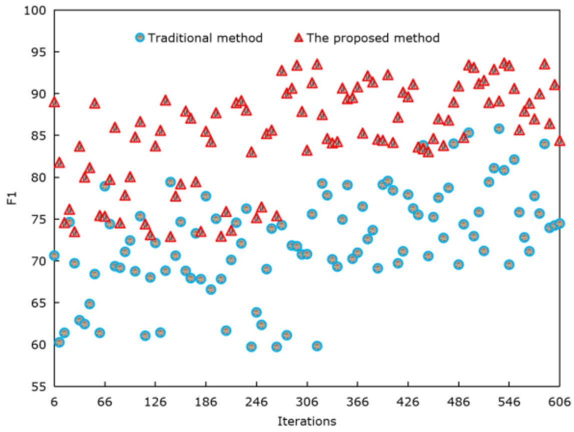

Figure 5: Model F1 score.

Design scheme number	*Type of advertisement*	*Design method*	*Description of design content*	*Number of designers*	*Design cost (yuan)*
A001	Tourist destination advertisement	Traditional design method	Landscape painting style emphasizing natural scenery	2	10,000
A002	Tourist destination advertisement	Traditional design method	Hand-painted city landmarks, highlighting history and culture	3	15,000
A003	Tourist destination advertisement	Traditional design method	The display of photographic works truly reflects the scenery of scenic spots.	2	20,000
B001	Tourist destination advertisement	The proposed design method	Simple style, emphasizing the tranquillity and purity of scenic spots.	1	12,000
B002	Tourist destination advertisement	The proposed design method	Creative illustration design, integrating local cultural elements.	2	16,000
B003	Tourist destination advertisement	The proposed design method	Render renderings in 3D to show the future planning of scenic spots.	3	18,000

Table 2: Design cost comparison.

By comparing and analyzing the results, it is found that the advertising design model combining CAD and DRL is superior to the traditional advertising design method in performance. The model shows good performance in the aspects of creativity, artistry and practicality in generating advertising design. In addition, the model also has fast design speed and low design cost, which can meet the rapidly changing demand of the market.

Using this method to design different types of advertisements, the design results are shown in Figure 7, and the design scoring results are shown in Figure 8.

Through the analysis of the results, it is found that the advertising design model combining CAD and DRL has made significant improvements in many assessment indexes. Compared with the traditional advertising design method, this model can better understand the needs of users and market trends and generate more creative and attractive advertising design schemes. At the same time, the model has good universality and expansibility and can adapt to different types of advertising design and different application scenarios.

Despite achieving promising results in experiments, the advertising design model that integrates CAD and DRL still faces several challenges. One notable concern is the substantial training time and computational resources required, necessitating further algorithm optimization and efficiency improvements. Additionally, the model's performance may be constrained in specific scenarios, necessitating customization and optimization tailored to those contexts. Enhancing the model's interpretability and debugging capabilities is also crucial to empower designers with a better understanding and utilization of the model. To address these challenges, this article proposes several optimization strategies. Firstly, we suggest implementing more efficient deep learning and reinforcement learning algorithms to reduce training time and computational resource consumption. Secondly, we recommend customizing and optimizing the model's structure and parameters based on the unique requirements of specific scenarios. Lastly, we emphasize the importance of enhancing the model's interpretability and debugging design, coupled with the provision of a user-friendly interface and interactive mode.

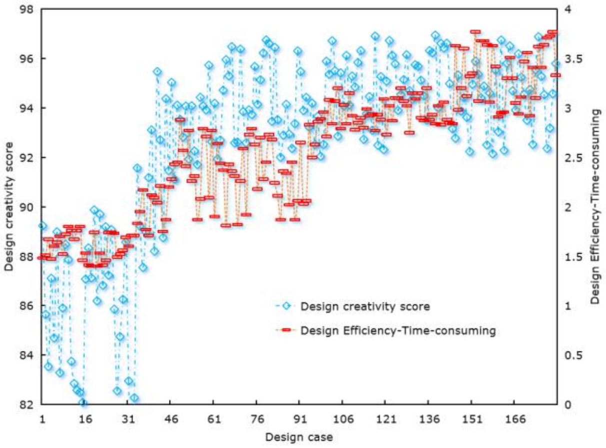

Figure 6: Assessment results of the advertising design scheme.

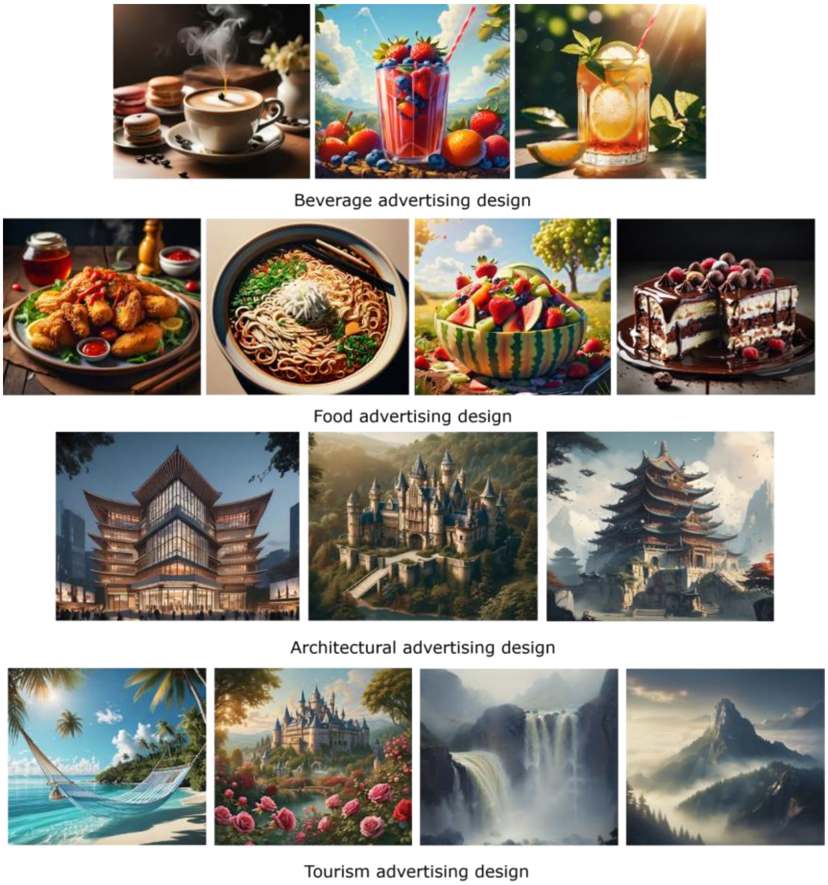

Figure 7: Different types of advertising design cases.

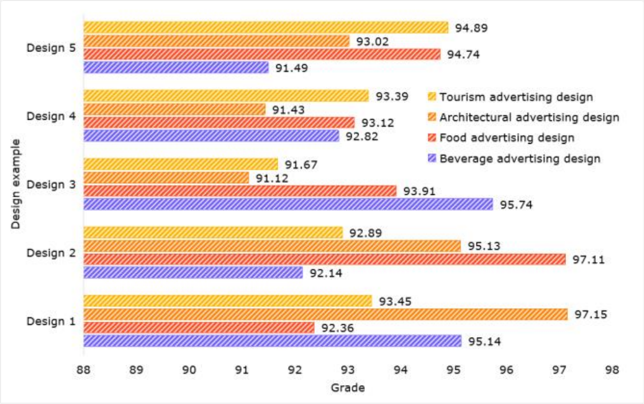

Figure 8: Different types of advertising design scores.

6 CONCLUSIONS

This article delves into the integration of CAD and DRL in advertising design. Initially, it revisits the fundamentals of DL and reinforcement learning, establishing a theoretical backdrop for subsequent explorations. It then elucidates the principles of DRL and its potential to revolutionize advertising design. Leveraging this understanding, an innovative model that fuses CAD technology with DRL is proposed, aiming to automate and enhance the intelligence of advertising design processes.

To validate the model's efficacy, a meticulous simulation experiment is designed and executed within a dedicated experimental environment. A comprehensive advertising dataset is prepared to train and evaluate the model. Detailed analyses of the experimental outcomes reveal that the proposed CAD-DRL integration offers significant advantages in bolstering design creativity, reducing costs, and enhancing efficiency.

Compared to traditional methodologies, this model excels in several ways. DL-extracted features are richer and more precise, reflecting the underlying principles of advertising design. Reinforcement learning enables independent strategy learning and optimization through environmental interactions, resulting in more targeted and personalized designs. Additionally, CAD tools and resources facilitate meticulous and efficient design assistance.

The study's methodology and experimental approach can serve as a springboard for future research, catalyzing the application of DRL in creative domains like advertising design. While notable progress has been achieved, there are still areas for improvement. Specifically, the experimental dataset, though extensive, may suffer from data bias and sample imbalance. Future endeavours should aim to expand the dataset's size and enhance its diversity and representativeness.

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