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User Experience Optimization Strategy of Random Forest Algorithm in Interactive Design of Artistic Systems

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Abstract. Artistic CAD system interactive design can more effectively improve the efficiency, quality, and experience of users using CAD systems. However, many current CAD interactive designs overlook the differences in user operation habits, which invisibly increases the user operation process and learning cost time. Therefore, this article combines the random forest algorithm to construct a user behavior analysis model and mines the actual operational needs of users' behavior data. Meanwhile, based on this, this article constructs a page visual jump model, which improves the smoothness and efficiency of the CAD system interaction design interface and optimizes the user experience. The experimental results show that compared with the other two models, this model can analyze user behavior more accurately and stably and can adapt to situations with a large number of users, providing effective and comprehensive optimization analysis data for future user experience optimization. In addition, the model expands the user's field of view focal length range, allowing users to obtain more information at the same time. Meanwhile, the optimized system can better meet the personalized operational needs of users and provide them with a better user experience.

Keywords: Random Forest Algorithm; Bounce Model; CAD System; Interaction Design; User Experience
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1 INTRODUCTION

Artistic CAD system interactive design can enhance the user experience when using CAD systems, making it intuitive and enjoyable [1]. Through carefully designed interactive interfaces and operational processes, users can more easily understand the system's functions and operating methods, improve design efficiency, reduce operational difficulties, and focus more on artistic creation and design itself, helping users improve their focus on artistic creation and innovation, promote innovative development, and improve design quality [2]. However, there are still some issues that need to be further optimized in the interactive design of existing artistic CAD systems. The richness of tools and functions in artistic CAD systems increases the learning cost for users to use the software, while the complexity of interface layout and the lack of personalized design increase the adaptation time cost for users, increase the steps and complexity of the operation process, and cannot meet the differentiated needs of users in terms of operating habits [3]. Meanwhile, with the development of information technology and communication technology, users have increasingly high demands for information acquisition efficiency, smooth operation, consistency and coherence in the design of CAD pages. However, some artistic CAD interactive designs ignore the issue of personalized user experience needs in the optimization process, and cannot provide users with a better and more convenient user experience based on their behaviour and preferences.

In the field of digital art, artists are increasingly relying on computer-aided design (CAD) tools to create and present their works. However, while CAD tools provide high precision and controllability, they also limit the creativity and intuitiveness of artists [4]. When we try to classify visual art images, we quickly realize that this is not a simple task. This is also the current research direction of many domestic and foreign researchers - they are committed to developing new algorithms and models to more accurately classify and analyze visual art images. For non-art professionals, understanding and appreciating visual artworks may pose certain difficulties. Because the classification of visual art is closely related to its historical background, relying solely on the surface features of images for classification often overlooks the profound influence of history on the development of art. It is worth noting that the recognition of visual art images is not equivalent to general fine-grained image classification [5]. In order to more accurately identify visual art images, researchers usually use deep learning methods, combining global and local features, to extract multi-level information from images, thereby achieving accurate classification of visual art images. Therefore, it is particularly important to use computer methods to provide a more intuitive and easy-to-understand visual art appreciation pathway for these audiences. The determination of its category not only depends on the obvious subject objects in the image, but also is closely related to the artistic tradition, style, and expressive techniques behind the work. With the continuous improvement of people's pursuit of spiritual and cultural aspects, more and more people are beginning to linger in places such as art museums, galleries, and art exhibition halls. Considering the connection between the evolution of art painting styles and the background of art history, this article explores the characteristics of the dimension of art history and summarizes three factors that influence the formation and development of art painting styles, including the place of origin, the time of origin, and the art movement. For different factors, some scholars have designed corresponding knowledge extraction strategies to generate label distributions, provide art history supplementary information for input images, and train models on a multitasking learning framework [6]. We conducted a series of experiments on multiple carefully selected art painting datasets, and the results significantly demonstrated the advantages of this method. In addition, a widely recognized adaptive cross-layer correlated convolutional neural network framework was proposed. Detailed experiments were conducted on three distinct visual art datasets, and the results not only demonstrated the effectiveness of the proposed method but also demonstrated its excellent robustness [7].

Compared to existing classification techniques and traditional network architectures, this method demonstrates significant advantages. This architecture cleverly weights the intrinsic correlations of features at different spatial positions and naturally integrates these correlations into the entire network. It can accurately capture the texture features of images from the visual dimension, providing strong support for the classification of various visual art images. When discussing visual art image classification, we pay special attention to the importance of multidimensional correlations. Therefore, a detailed classification analysis of visual art images was conducted from multiple dimensions [8]. It is not only limited to single-label classification but also adopts an innovative adaptive cross-layer correlation architecture. Through end-to-end training, our model can deeply learn and understand the rich texture information in visual art images. When it comes to the traditional wallpaper design process, we are well aware of the challenges it faces. Designers often rely on hand drawing and constant trial and error, which is not only inefficient but also difficult to ensure consistency and innovation in their designs. New possibilities have been provided for the automatic generation and style transfer of wallpaper textures. As an important component of home decoration, wallpaper's diversity and personalization of texture are crucial for designers and consumers.

Designers can add different artistic styles and emotional colours to wallpapers while maintaining their original texture features [9]. This step not only enriches the visual effect of the wallpaper but also provides designers with more creative inspiration and possibilities. By adjusting the parameters and intensity of style transfer.

Its application in user experience optimization of artistic CAD interaction design can accurately predict user operating habits, preferences, and needs by collecting and analyzing user behaviour data, thereby providing personalized interaction experiences for users. At the same time, it has good robustness and noise resistance, which can improve the accuracy of model prediction in relatively low data quality states, ensuring that users can still obtain a stable interaction experience in the event of accidental touch, improper operation, etc. The random forest algorithm can handle high-dimensional data, which means it can simultaneously consider multiple factors to predict user behaviour or needs [10]. In addition, optimizing the visual flow of the page is an important aspect of user experience optimization in the interactive design of artistic CAD systems. It can improve the smoothness of user CAD system pages and optimize interface layout, color matching, and operation processes. Therefore, this article constructs an artistic CAD interactive design user behaviour analysis model and a jumping model based on the random forest algorithm to achieve the goal of optimizing user experience.

2 RELATED WORK

Artificial intelligence has shown significant capabilities in automation, but its performance in pursuing creative and collaborative design outputs is still insufficient. In the interactive experience of art CAD, users often hope to integrate their ideas and creativity into the design process rather than relying solely on machine-generated automation. They may only have rough sketches or vague concepts, lacking the professional skills and tools needed to transform them into exquisite art. Although existing artificial intelligence methods have made progress in processing images and generating content, there is still room for improvement in transforming user sketches into drawings that preserve both semantic concepts and artistic aesthetics. For most non-professional designers, expressing their creativity in concrete and enjoyable drawings can be a challenge. The training process of SmartPaint relies on the triplets of cartoon images, including the image itself, corresponding semantic label images, and edge detection images. This enables SmartPaint to automatically synthesize corresponding edge maps when receiving user sketches as input for semantic label mapping in response to various styles of sketch inputs. In the interactive experience of art CAD, users can upload their sketches to the system through the intuitive interface provided by SmartPaint. This artwork not only retains the semantic concepts of user sketching but also reaches a delightful artistic level. This training method enables the system to simultaneously understand the visual features of cartoon style and the semantic content of images. To bridge this gap, Liu and Yang [11] developed an algorithm that has been optimized for the interactive experience of art CAD. SmartPaint is not only committed to allowing machines to imitate and understand the style of cartoon landscape paintings, but more importantly, it enables machines to collaborate with human designers in the creative process truly. The experimental results indicate that the SmartPaint system has successfully generated high-quality animations, receiving unanimous praise from users and professional designers. Through collaborative creation with humans, The digital innovation of painting art not only greatly improves the efficiency of design work but also brings users an unprecedented art CAD interactive experience. The SmartPaint system, with its outstanding technology, can accurately generate edge maps based on the semantic content of sketches and further generate creative and detailed paintings. This innovation not only demonstrates the power of technology but also highlights the infinite possibilities of combining art and technology. Looking ahead to the future, with the continuous improvement of technology and the continuous expansion of application fields, SmartPaint is expected to play a more important role in the field of art CAD. We look forward to promoting the deep integration of design and technology, allowing more people to enjoy the unique charm brought by the interweaving of technology and art.

Park et al. [12] proposed a novel semantic perception style transfer method aimed at solving the common semantic mismatch problem in art CAD interactive experience, thereby improving the quality of art style transfer. In addition, it should be noted that the statistical difference between real photos and paintings may lead to inaccurate segmentation of paintings. Domain adaptation technology has been applied to source paintings to more accurately extract their semantic regions, further improving the accuracy and quality of style conversion. To ensure the accuracy of semantic matching, word embedding technology is adopted to obtain the best semantic matching between regions. In art CAD design, users typically wish to combine real-world photos or their own creative sketches with specific artistic styles to create works that are both personalized and aesthetically pleasing. Then, based on the semantic interpretation of each region in the target image, we find the semantically most matching source image region. However, existing style transfer algorithms often overlook the semantic information of images during the processing, resulting in the generated works losing the important content and meaning of the original image during the style transfer process. Sun et al. [13] proposed a style transformation method based on semantic matching. Divide the target photo and source painting image into multiple semantic regions. To address this issue, we will now learn artistic style from the source image region and content and structural information from the target image region. By cleverly integrating these two components, high-quality works can be generated that retain both the original image semantic information and incorporate the target artistic style. User research also indicates that the quality of style transformation is significantly improved after introducing semantic information. Through sufficient experimental analysis and comparison, the effectiveness of the algorithm in the interactive experience of art CAD has been verified.

In the development process of CAD technology, it has evolved from two-dimensional to three-dimensional, gradually popularized from large enterprises specific to small and medium-sized enterprises, and its application has also expanded from the initial automotive design to multiple fields such as architectural design, graphic design, product design, film and animation production. In terms of interactive design in art CAD systems, with the continuous advancement of technology, user interfaces and interaction methods are also constantly evolving. Taking the field of architectural design as an example, modern CAD software can not only help architects complete designs faster and more accurately but also display the appearance and internal structure of buildings through 3D models. Wang et al. [14] used CAD software to draw 3D models and combined lighting, materials, and other effects to achieve realistic rendering, enabling clients to better understand and evaluate design solutions. When appreciating artistic images, adding appropriate explanatory text can undoubtedly reveal the deep meaning of the work to the audience, and also help us manage and organize artistic information more effectively. In this context, the research of Wang et al. [15] is particularly important. They proposed a key technology based on transfer learning aimed at automatically generating readable content descriptions of artistic images. However, compared to the relatively mature general image understanding techniques, research on the understanding and annotation of artistic images is still in its early stages. At the same time, the outstanding performance of artificial intelligence in the field of perceptual intelligence has also shown us its enormous potential in the field of cognitive intelligence, further stimulating our enthusiasm for exploring the intersection and integration of artificial intelligence and art. Based on the existing achievements in the field of image understanding, they have constructed an art image understanding system framework with an image description generation model as the core. The diversity and complexity of the art field bring many challenges to the understanding of art images, and the scarcity of art understanding datasets poses numerous difficulties for the development of this field. The proposal of this framework undoubtedly brings new insights and possibilities for the understanding and annotation of artistic images. By introducing transfer learning into the underlying graph text relationships in general image datasets, and making differential adaptation of content between different datasets.

These tools can automatically adjust and optimize design parameters based on user input and operating habits, greatly reducing user workload. Through automatic and real-time recommendations, users can quickly find suitable design solutions and receive timely help and guidance during the design process. In order to adapt to the popularity of mobile devices, CAD software provides cross-platform support. Users can use the same CAD software on different devices such as mobile phones, tablets, and desktops, and achieve seamless compatibility of design files. Users can access and edit design files anytime, anywhere, greatly improving work efficiency.

In summary, most CAD software currently focuses on improving user experience by optimizing its interface design, functions, and operations, lacking the enhancement of personalized user needs. Therefore, this study has a certain degree of display significance.

3 USER EXPERIENCE OPTIMIZATION MODEL

3.1 User Behavior Analysis Model for Art CAD Interactive Design Based on Random Forest Regression Algorithm

The algorithm is based on decision trees, with significant advantages in its high accuracy and avoiding the potential limitations of a single prediction or classification model by integrating multiple models. In the construction process of random forest regression, each decision tree will extract a training subset from the original dataset through the equal probability random sampling method with replacement (also known as the self-help method). This sampling method ensures that the training data for each tree is independent and distinct, thereby increasing the diversity between models. Each decision tree is trained based on its independent training subset and makes its own predictions. Finally, the algorithm aggregates the prediction results of all decision trees to obtain an overall prediction. For regression problems, this usually means calculating the average of all three predictions to obtain the final predicted value. This aggregation strategy utilizes the prediction results of multiple trees, effectively reducing the prediction error of a single tree and improving the stability and accuracy of the overall model. Therefore, the random forest regression algorithm not only improves the performance of the model through ensemble learning but also ensures comprehensive learning and accurate prediction of data through random sampling and aggregation strategies. The schematic diagram of the principle of the random forest regression algorithm is shown in Figure 1.

Figure 1: Schematic diagram of the principle of random forest regression algorithm.

Let the random forest regression algorithm combine a set of decision subtrees as $\{g(x,\theta_n), n=1,2,\ldots,N\}$ θ_n represents independent and identically distributed random variables, x is the expression of independent variables (1):

$$\overline{g}(x)=\frac{1}{N}\sum_{n=1}^{N}\{g(x,\theta_n)\} \tag{1}$$

Among them $\{g(x,\theta_n)\}$ is the output about x and θ.

Randomly select the training set vector x and the interval function y is shown in formula (2):

$$mg(x,y)=av_n I(g(x,\theta_n)=y)-\max_{j\neq y} av_n I(g(x,\theta_n)=j) \tag{2}$$

In order to overcome the possible overfitting problem in decision tree models, the random forest regression algorithm combines two ideas: bagging and random subspace. The Bagging idea increases the number of randomized regression decision subtrees by randomly sampling multiple training subsets with replacements from the original dataset while ensuring that these subtrees maintain mutual independence. This independence helps to reduce the potential bias of a single decision tree and improve the stability of the model. The idea of random subspaces is reflected in the construction process of each decision tree, which is not only based on different training subsets but also only uses a random subset of the feature set when splitting each node. This means that both the nodes between decision trees and the nodes within the same decision tree use different subsets of features. This randomness further increases the diversity of the model, making the random forest regression algorithm more flexible and random during node splitting, thereby improving the prediction accuracy and robustness of the algorithm.

Randomly select and put back multiple training samples from the original sample with a consistent number of samples.

$$\varepsilon=(1-\frac{1}{M})^M \tag{3}$$

$$\varepsilon=(1-\frac{1}{M})^M\approx\frac{1}{e}\approx 0.368 \tag{4}$$

To quantify this predictive ability, we typically use the output mean square error as an evaluation metric, as described in formula (5). Based on the given formula (4), we can deduce that approximately 36.8% of the samples are unselected during each sample extraction process, which we refer to as "out-of-bag data" (OOB). When evaluating the performance of a model, especially its generalization ability - that is, the model's ability to predict data outside the training set - is a very important indicator.

$$PE^*=E_{X,Y}(Y-g(X))^2 \tag{5}$$

$$g_n(X)=g(X,\theta_n) \tag{6}$$

$$E_{X,Y}(Y-\overline{g}(X,\theta_n))^2\rightarrow E_{X,Y}(Y-E_\theta h(X,\theta))^2=PE_b^* \tag{7}$$

E_θ in the equation represents mathematical expectation and θ_n represents a decision tree random variable with a sequence number of n.

$$PE_c^*=E_\theta E_{X,Y}(Y-g(X,\theta))^2 \tag{8}$$

If the regression decision subtree is unbiased for all random variables θ, as shown in formula (9):

$$EY=E_X g(X,\theta) \tag{9}$$

Then formula (10) can be obtained.

$$PE_c^*\leq\overline{\rho}PE_b^* \tag{10}$$

$$\hat{c}_m=ave(y_i\big|x_i\in D_m) \tag{11}$$

$$D_1(B,s)=\{x\big|x^{(B)}\leq s\} \tag{12}$$

$$D_2(B,s)=\{x \mid x^{(B)}>s\} \tag{13}$$

As shown in formulas (14) and (15), the squared error of the partitioned subset is:

$$SE_1=\sum_{x_i\in D_1(B,s)}(y_i-c_1)^2 \tag{14}$$

$$SE_2=\sum_{x_i\in D_2(B,s)}(y_i-c_2)^2 \tag{15}$$

The optimal splitting attribute and splitting point satisfy formula (16):

$$\min_{B,s}(\min_{c_1}(SE_1)+\min_{c_2}(SE_2)) \tag{16}$$

The output values of the partitioned subset are shown in formulas (17) and (18):

$$\hat{c}_1=ave(y_i \mid x_i\in D_1(B,s)) \tag{17}$$

$$\hat{c}_2=ave(y_i \mid x_i\in D_2(B,s)) \tag{18}$$

Before conducting CAD user behavior analysis, it is necessary to obtain historical behavior records such as user clicks, browsing, searching, editing attributes, movement attempts, and interaction frequencies from existing CAD data, clean the data for missing values outliers, and complete data preprocessing through normalization operations. Due to the impact of the number of user behaviour feature selections on the OOB error and runtime of the random forest regression model, this paper will experimentally test the relationship between the three, as shown in Figure 2. The results in the figure show that there is an overall positive correlation between the number while there is a negative correlation between the number of feature selections and the error of out-of-bag data. In the early stage, the decrease was significant. When the number of feature selections reached 12, it gradually tended to stabilize. The training time will increase significantly when the number of features reaches 12 or more. Taking into account all factors, the number of user behaviour feature selections in this article is 12.

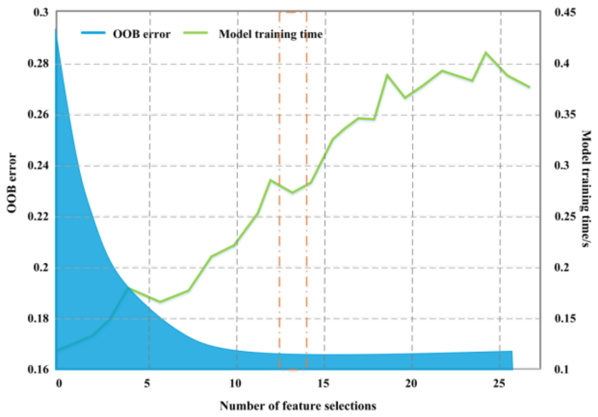


Figure 2: Changes in OOB error and model running time with the number of feature selections.

3.2 A Jumping Model Based on Random Forest

Visual flow is one of the important concepts in CAD interactive design, which involves how users visually interact and communicate with information interfaces. Visual flow refers to a series of focal points and trajectories formed by the movement of the user's gaze when confirming information through visual channels. Due to the characteristics of human vision, line-of-sight movement typically manifests as point-to-point jumping scans rather than smooth movements. Therefore, after continuous attention to the interface, users will leave behind a series of visual focal points, and the trajectory of these focal points constitutes a visual flow. Visual flow mainly plays a role in guiding user vision, highlighting important information, and optimizing user experience in interaction design. Through reasonable visual flow design, designers can effectively guide users' attention, enabling them to quickly find the required information and thus improve interaction efficiency. As shown in Figure 3, the distribution of common visual flow types and elements within the user's field of view in the receptive area is shown.

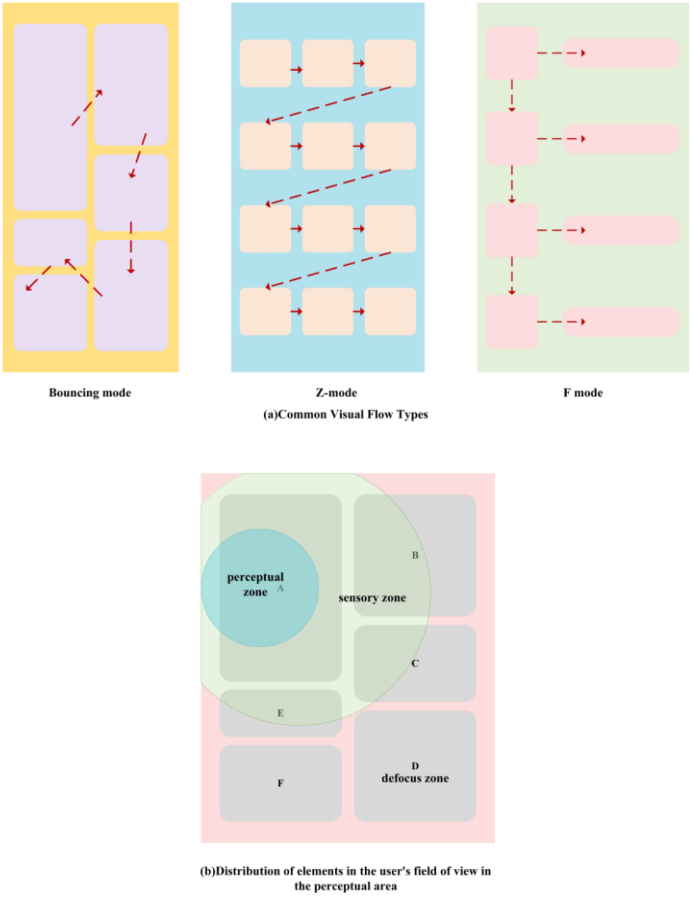


Figure 3: Common types of visual flow and distribution of elements within the user's field of view in the sensory area.

Jumping visual flow mode is an important visual guidance method among common visual flow types. It is based on the jumping scanning characteristics of human vision and attracts user attention by creating a series of visual focuses and dynamic trajectories. Compared with other types, it creates strong visual appeal through dynamic element changes and flows, with good dynamic attraction and quick guidance, improving user interaction efficiency. Its application can make the interface more vivid and interesting, enhancing the user's sense of participation and immersion. At the same time, it can also reduce the cognitive burden on users, making browsing information easier and more enjoyable. At the same time, the jumping visual flow mode can be flexibly adjusted according to different design needs and user habits, which can meet the personalized needs of users for artistic

CAD interactive design. According to Figure 3 (b), it can be seen that when the user's gaze is focused on Area A, the colour and form information of Areas B, C, and D can still be received in their field of view. The elements in these areas form a competitive relationship in their field of view to attract the user's attention. Based on existing literature and experimental results, it is concluded that six factors collectively affect the competition of visual elements. In this paper, a decision tree model for these six factors is obtained through a random forest model, as shown in Figure 4.

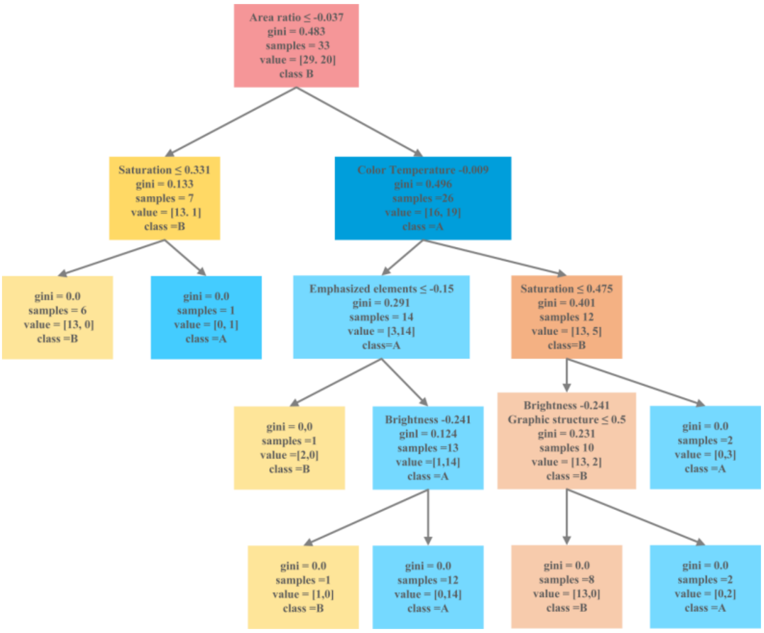


Figure 4: Artistic CAD interactive design jumping visual flow interface element competition decision tree model.

Based on the random forest decision tree model mentioned above, calculate the estimated probability of competition between any factor and then optimize to obtain the attention probability of adjacent factors as close as possible during the competition process. The artistic CAD interactive design interface can arrange similar competitive factors together through changes in the order of arrangement, thereby achieving optimization goals.

4 EXPERIMENTS

4.1 Application Experiment of User Behavior Analysis Model Based on Random Forest Regression Algorithm

In order to test the application of the user experience optimization model based on the random forest algorithm, this paper randomly selected 50 artistic CAD interactive design users for user behaviour analysis and also selected two other user behaviour analysis models for comparison. The horizontal axis in the figure represents the number of user behaviour analyses, and the vertical axis represents the average value of three model indicators. The results showed that both the segmentation clustering algorithm and the decision tree model showed a significant decrease in the average values of the three evaluation indicators as the number of users increased, with the segmentation clustering algorithm having the greatest reduction. The average values of the three indicators in this article's model remain relatively high overall and fluctuate within a small range as the number of users increases. This indicates that the model in this article has good stability and adaptability, and the obtained user behaviour analysis results are more reliable and stable, which can fully reflect the needs of users in the CAD process.

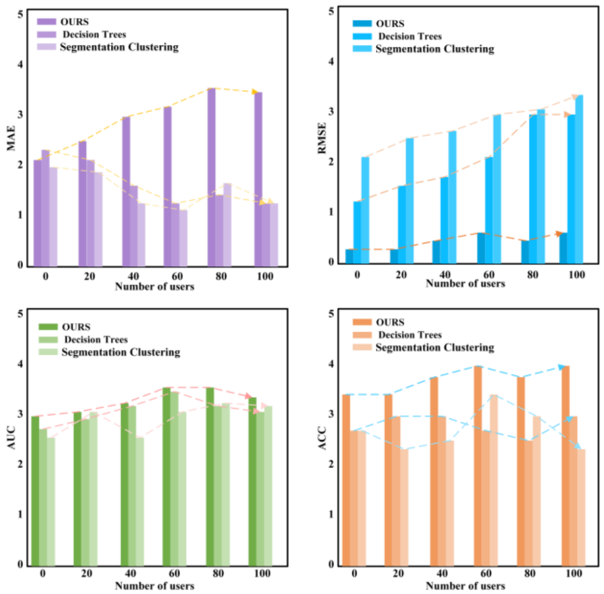


Figure 5: Evaluation index results of three user behaviour analysis models.

Figure 5 shows the evaluation index results of three user behaviour analysis models. The evaluation results of three user behaviour analysis models are shown in Figure 6. The performance of segmentation clustering algorithms and decision tree models in analyzing user behaviour is initially improving with the increase in the number of users. However, when the number of users reaches 35, the analytical performance of both shows a decline, with the segmentation clustering algorithm showing the most obvious downward trend. The model analysis in this article maintains a slow upward trend, demonstrating the best performance in user behaviour analysis. This indicates that compared with the other two models, our model can more accurately analyze the behavioural purposes of users using CAD and deeply explore and analyze the correlation between behavior and requirements. The analysis results are more in line with the actual needs of users and can provide effective, comprehensive, and multi-dimensional basic data support for user behaviour optimization.

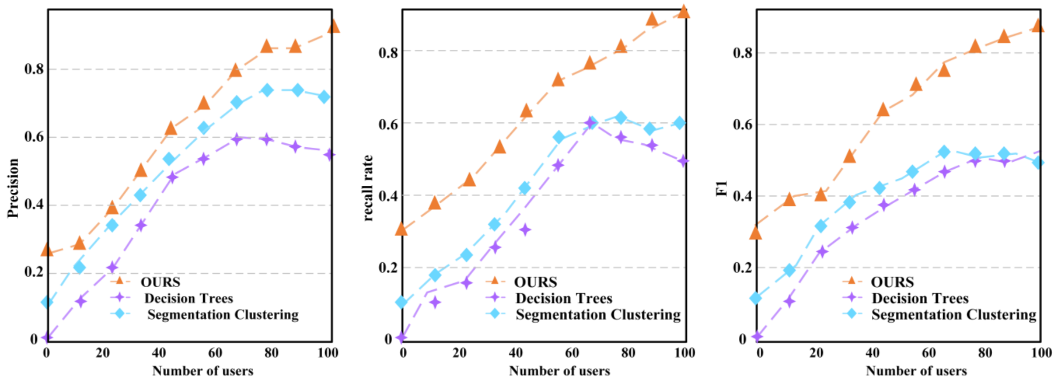
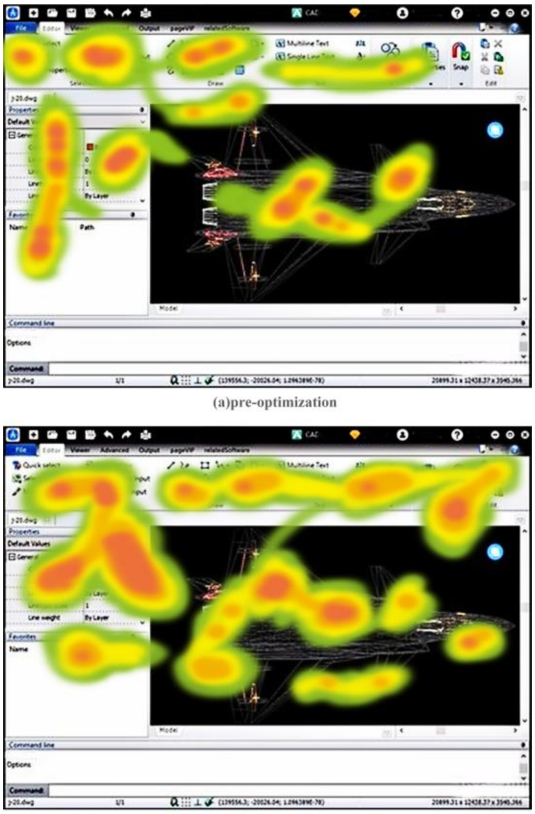


Figure 6: Evaluation results of three user behaviour analysis models.

4.2 Optimization Application, Experiment of Jumping Model, Based on Random Forest

In order to test the optimization application effect of the jump model based on random forest, this paper randomly selected a user of artistic CAD interactive design for the optimization model application experiment; the experiment reflects the user's field of view focus changes by optimizing the CAD interaction interface heatmap before and after optimization. The longer the user stays in a certain area, the darker the colour in that area. The results showed that before optimization, the user's field of vision was relatively focused, with an important distribution in the upper left corner of the interaction interface, indicating that the user's operations were mainly completed through the functions or operations in that area. The centralized operation reflects that the user is highly likely to need multiple multi-level operations to achieve their goals. After optimization, the user's field of view was expanded, and the previously less focused areas in the interaction interface received more attention. This indicates that through user experience optimization, the CAD interface can be sorted and adjusted according to user needs, releasing more third and fourth-level operation functions and simplifying the user's operation process during the use of CAD. At the same time, the expansion of user focus is beneficial for the interaction efficiency of CAD interaction design. Users can set more operation functions in the interaction interface according to their own operating habits. In addition, artistic CAD interactive design can analyze more CAD function operation data based on the settings of different user interface functions, thereby completing corresponding operation optimization. As shown in Figure 7.



(a)pre-optimization

(b)After Optimization

Figure 7: Comparison of user focus heatmaps before and after optimization.

As shown in Figure 8, the statistical results of CAD user function operation entry flow direction are shown. In this experiment, 100 users were randomly selected to operate the entry flow direction before and after optimization. The results in the figure show that the proportion of user CAD basic operations (file management, basic drawing) remains stable before and after optimization. Before optimization, the proportion of editing commands was relatively high except for basic operations, while the proportion of other operations was relatively weak. After optimization, the flow of secondary operations in complex drawing and layer management has increased, and the proportion of auxiliary tools has significantly increased. This indicates that the model in this article can help users set functional operations that are in line with their own habits in the interaction design interface, effectively improving the user experience, and improving the interaction efficiency and usability of CAD use for users. At the same time, the increasing diversity in the use of CAD interactive interfaces has greatly deepened users' understanding of CAD interactive design, promoting further optimization and innovation in CAD.

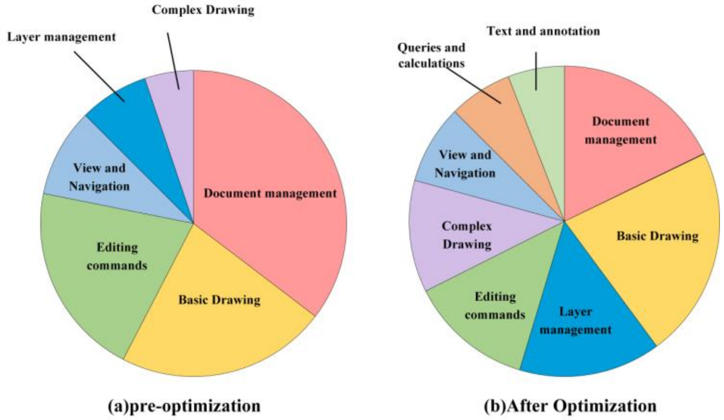


Figure 8: CAD user function operation entry flow statistics results.

5 CONCLUSIONS

Artistic CAD interactive design is aimed at improving the efficiency and quality of user CAD usage and enhancing the user experience. However, current artistic CAD interactive design focuses more on fully showcasing the functionality and operability of CAD, neglecting the personalized operational needs of users, increasing user operation processes and learning costs and time. Therefore, this article constructs a user behaviour analysis model and a page visual jump model based on the random forest algorithm, deepening the analysis of user needs. Based on the analysis results, combined with the page visual jump model, it optimizes the competitiveness of factors within the field of view, improves the smoothness of the CAD interaction interface, and guides users to obtain corresponding information quickly. The experimental results show that the user behaviour analysis model based on random forest in this article has better stability compared to the other two models, and can effectively reduce the error rate of user behaviour analysis, providing more accurate and effective user behaviour and demand data for user experience optimization in a reliable state. In addition, in the application experiment, based on the random forest jump model and user behaviour and needs analysis results, this article optimized the order of competition factors in the CAD interaction design interface, expanded the user's focus range, and enabled users to obtain more information quickly. The optimized CAD can more effectively meet users' personalized operation settings, provide users with a higher and smoother user experience, and effectively improve the efficiency of CAD interaction.

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