Interactive Pattern Recognition and Interface Design Method Based on Image

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Abstract. This article strives to enhance the interactive experience and operational efficiency of the computer-aided design (CAD) system. To accomplish this, we introduce a collaborative image processing algorithm that utilizes multi-light source image thinning and detail enhancement, integrating it into CAD interface design. By combining multi-light source image acquisition with image thinning and detail enhancement techniques, our approach notably boosts the recognition precision of design elements. Moreover, we employ these image processing technologies to refine the CAD interface design. Through enhancements in interface layout, icon symbol design, colour visual style, and the incorporation of interactive guidance and feedback mechanisms, we've significantly elevated user experience and work efficiency. Our findings reveal an exceptionally low error rate of 2.01% in image feature recognition for our algorithm, while the interactive interface demonstrates over 95% accuracy in recognizing user actions and presenting design outcomes. Additionally, the time needed for designers to complete tasks has been considerably reduced, and a user satisfaction survey indicates a comprehensive score of approximately 90.

Keywords: Image Processing; CAD Interface Design; User Experience; Operational Efficiency; Interactive Guidance
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1 INTRODUCTION

Image understanding is the conversion from image to text, which can be seen as a special process of translating image language. It can be assumed that every object present in an image can be transformed into a word in a text through an understanding model. Macroscopically, the encoder-decoder structure is used to achieve the mapping process from images to texts. This includes image and text data modelling, model training, sample extraction, parameter optimization, and effect evaluation [1]. The core of the system is the image understanding model. The encoder for processing images in the system is based on convolutional neural networks, while the decoder is constructed based on sequence models [2]. Adapt feature processing models, image feature correlation enhancement models, sequence search enhancement models based on the characteristics of art data, and debug model parameters based on quantitative evaluation results. The background of the model design here is based on first completing the organization of the publicly available image data description set, as well as constructing an accurate art annotation set. In order to improve the accuracy and specificity of matching, the attention mechanism and feature filtering mechanism are used to capture local objects and features, thereby generating more accurate text. In terms of training, it is necessary to use both public image libraries and art image libraries simultaneously to complete the training [3]. For ease of comparison, the automatic description results obtained from training with a public image library are used as a benchmark for comparing the performance of automatic generation of artistic image descriptions [4]. This real-time feedback mechanism greatly improves user design efficiency, while also increasing the fun and creativity of the design. The software not only focuses on the design of 3D printed clothing but also emphasizes the intuitive and user-friendly user interface, greatly simplifying the design process [5]. Users only need to upload their own flat or design patterns, and the software can automatically convert them into models that can be used for 3D printing. This feature not only simplifies the design process but also lowers the design threshold, allowing more non-professionals to participate in the design of 3D-printed clothing. In terms of software functionality, the advantages of 3D printing technology were fully utilized to achieve rapid conversion from flat patterns to 3D clothing models [6]. This means that users can choose the appropriate printer for production based on their own needs and budget. In addition, we also pay special attention to the interactivity of image interface design. Users can preview and modify their designs in real time through operations such as dragging, zooming, and rotating. It is worth mentioning that our software also supports a variety of 3D printer types, including expensive SLS printers and reasonably priced FDM printers. For users who hope to try 3D printing clothing at a lower cost, this is undoubtedly a huge blessing.

In CAD systems, designers frequently engage with numerous graphic elements, including lines, arcs, polygons, etc. While conventional CAD systems often rely on designers' manual operations and judgments, this approach becomes time-consuming and prone to errors when handling intricate graphics. However, image processing technology, specifically its edge detection and feature extraction algorithms, offers a viable solution [7]. According to Guney's research, computer vision technology effectively aids in CAD target recognition, accurately identifying various shapes and textures through edge and corner detection. Currently, some scholars have studied a fast-sorting image recognition method that integrates deep learning and dual-tree complex wavelet transform. In the image preprocessing stage, dual-tree complex wavelet transform (DTCWT) is used to denoise and optimize the sorted images [8]. From a data perspective, we have comprehensively considered the general public image dataset and the art oil painting dataset and independently constructed an accurately annotated art image dataset, which can provide stable input to the model. In the selection of migration strategies, the development of existing technologies was fully utilized, and the correlation and limitations of the data itself were discussed. Differences in the migration process were also addressed [9]. From the perspective of model architecture, targeted processing has been carried out on text and image data, attention mechanisms have been introduced to enhance training effectiveness, and the potential of the model has been continuously stimulated. Automate the process of identifying and transforming content, style, and other information into corresponding descriptive text. The following content will mainly elaborate on the construction and organizational ideas of this article's model from the perspectives of model and methodology, provide specific definitions for the needs of artistic image description, and propose targeted solutions to related problems [10].

This article explores and introduces an innovative collaborative image processing algorithm that combines multi-light source image refinement and detail enhancement techniques. Through this algorithm that integrates multiple image processing methods, we have successfully improved the recognition accuracy of design elements in CAD (Computer Aided Design) systems and significantly enhanced the intuitiveness of interface design. In traditional CAD systems, the recognition of design elements and the intuitiveness of interface design have always been key challenges. In today's digital design field, with the rapid development of technology, designers have an increasing demand for the accuracy and intuitiveness of CAD (Computer Aided Design) interactive design. The core of this algorithm lies in its utilization of multi-light source image data. In the design process, details often determine success or failure. In this context, we have delved into the potential of image processing technology in CAD interactive design, to provide designers with a better user experience. By collecting and carefully processing light source images from different angles and intensities, our algorithm can capture more detailed information in the design images. This not only significantly improves the clarity of the image, but more importantly, it makes the boundaries between design elements clearer, greatly improving the accuracy of recognition. However, traditional CAD design pattern recognition and interface design methods may seem inadequate in certain situations, especially when dealing with complex images and design elements. To overcome this challenge, we propose an innovative solution by introducing a novel collaborative image processing algorithm.

Initially, this article elucidates the research backdrop and importance, emphasizing the central role of pattern recognition and interface design in CAD interactive design. Then, it presents a collaborative algorithm rooted in image processing to bolster CAD's performance. Ultimately, experiments confirm the algorithm's effectiveness and its potential application in real-world engineering design is deliberated.

2 RELATED WORK

Time consistency demonstrates the enormous potential for reducing shading costs during the rendering process. In Kang and Kim's research [11], it was further recognized that image interface design plays a crucial role in presenting this colouring optimization effect. Traditional colouring optimization methods mainly focus on spatial colouring reuse or lack the ability to adaptively select temporal colouring frequencies. It is feasible to reuse time colouring for a longer time, as it has thoroughly analyzed which specific contexts users may perceive time artefacts. Analysis shows that by approximating colouring gradients, it is possible to effectively determine when and how long colouring can be reused. Through an intuitive and easy-to-understand image interface, users can see the effect of colour reuse and adjust parameters to balance performance and visual quality. But in animation game scenes with advanced shading, typically over 50% of the shading is time coherent. This design can help users better understand the working principle of shading optimization and more accurately control rendering performance. This discovery provides clues for us to further optimize the colouring process. Through image interface design, these time-coherent areas can be displayed and users can choose whether to apply color reuse on these areas. The continuous improvement of industrial production and manufacturing levels has accelerated the updating and replacement of electronic products, thus placing higher requirements on the underlying hardware infrastructure. In recent years, defect detection algorithms based on deep learning have gradually been studied, but traditional convolutional neural networks are focused on PCB image defect detection. Mueller et al. [12] proposed image preprocessing methods such as grayscale, grayscale histogram equalization, and Gaussian filtering to address the unclear feature information in PCB defect images, which contain a lot of noise information unrelated to the features. Based on the reference comparison algorithm, SURF is used to extract feature points from PCB standard images and defect images. Secondly, global defect detection and localization are achieved through machine vision technology on the preprocessed PCB defect image dataset. On the one hand, removing noise interference to highlight feature information, and on the other hand, providing training and validation datasets for subsequent neural network training. By using morphological processing to make defects clearer, preliminary detection and localization of PCB images can be achieved. Match the feature points to achieve image registration, then use threshold segmentation to process the image into a binary image, and then perform image differentiation to obtain the defect information contained in the defect image. It is difficult to balance global and detailed feature information, and the accuracy of detection and labelling is not high. Traditional PCB defect detection relies on manual annotation of defect information, which has low efficiency and accuracy.

Feature extraction of PCB images based on deep learning methods. The traditional residual neural network Resnet101 effectively solves the problem of gradient dispersion caused by too many layers in the network. Pourasad and Cavallaro [13] proposed a multi-scale feature fusion approach to improve the network and enhance the quality of feature extraction, forming the Resnet101 finetune network. Implementing defect target detection in PCB images based on the Faster RCNN algorithm. Improve the efficiency and accuracy of object detection by improving the Faster RCNN algorithm. The experimental results show that the algorithm proposed in this paper achieves an average accuracy of 95.5%, and the mAP values are also higher than other algorithms, verifying the effectiveness of the algorithm proposed in this paper. Qamar et al. [14] trained and validated the network on a PCB image dataset through transfer learning. The experimental results show that the average accuracy of the improved Resnet101 fine-tuning neural network reaches 94.2%, which is significantly improved compared to other neural networks. The universality of the algorithm proposed in this paper has been verified through instance detection results, which can be applied to PCB image defect detection and has high practical value. Compare YOLO, R-CNN, SSD, and the algorithm proposed in this paper on the same PCB image dataset. The low network layer and high resolution have insufficient extraction of image semantic features, while the high network layer and low resolution have insufficient extraction of image detail features. By collecting and analyzing user feedback, continuously optimizing interface design and functional settings, ensuring that users can easily complete image compression and enhancement operations. The experimental results show that our compression technology has higher efficiency and better user experience while maintaining image quality.

In the field of compressive sensing (CS), although deep learning-based CS algorithms have attracted attention for their efficient reconstruction and fast computing speed, existing sampling processes often fail to fully utilize the structural sparsity of image sequences, which limits the further development of CS research. This design allows users to intuitively feel the impact of sparsity on compression perception performance, while also providing professional users with more adjustment options. Therefore, in the design of the image interaction interface, Wei et al. [15] designed an intuitive interface that allows users to view and choose whether to apply sym8 wavelet transform and preview the differences in effect before and after application in real-time. It not only combines the advantages of sparse representation-based sampling networks and deep elastic reconstruction networks but also considers the importance of image interaction interface design to provide a more intuitive and convenient user experience. As an improved version of DR Net, the main innovation of WCS Net is the combination of sym8 wavelet transform and sampling network to better capture sparsity in images. This design allows users to adjust reconstruction parameters according to their own needs and preferences, thereby obtaining better reconstruction results. Through user testing and feedback collection, we continuously optimize interface design and functional settings to ensure that users can easily understand and use these two new compression-aware algorithms. For example, users can select different residual learning scales through the slider or drop-down menu, and view the reconstruction results of different scales in real-time. In addition, considering the advantages of multi-scale residual learning in reconstruction efficiency, Yin et al. [16] further proposed WCS Net+. In terms of experimental verification, in addition to evaluating the performance of algorithms in terms of reconstruction quality, runtime, and robustness to noise, we also paid special attention to the impact of image interaction interface design on user experience.

3 COLLABORATIVE IMAGE PROCESSING ALGORITHM

The performance of image tampering localization algorithms has made a qualitative leap, but more accurate detection techniques and methods are still needed in this field to identify tampering traces between tampered areas and real areas. Due to the variability of tampering methods, there may not be significant differences in semantic information between the tampered and real regions in the image. Many algorithms only pay attention to the importance of local information, but in the field of tampering localization, the extraction of edge information and the fusion of global feature information are indispensable. Most methods overly emphasize the semantic content in images and treat this task as a semantic segmentation task. The current model often utilizes feature information in the spatial domain while ignoring the presence of a large number of forged clues in the frequency domain. Therefore, the algorithm needs to pay more attention to the edge and frequency domain information in the image to locate the forged area. The extraction of multi-scale information is a key context that needs to be supplemented for image tampering localization, but existing methods introduce a large amount of redundant noise, which will seriously affect the sensitivity of the model to feature information. To enhance the recognition of boundary artefacts between the tampered area and the real area. Using adversarial learning to incorporate a small amount of local interference noise into the image, forces the model to undergo more training to identify tampered areas. The CAD fusion attention module aims to integrate spatial and channel correlations in a compatible manner by combining scale and edge information. In this paper, a multi-scale frequency-domain perception enhancement network for image tampering localization is proposed, taking advantage of the phenomenon that the frequency of real and tampered areas in tampered images is different. The global frequency attention module interactively learns each other's feature information to integrate spatial and frequency domain content and improve the overall perception of tampering with physical locations. The experimental results on five commonly used benchmark datasets show that compared to other supervised learning model structures, FP Net has strong robustness and universality. Compared with current mainstream methods, the performance of MB Net on public standard datasets is effective. The frequency separation sensing module determines the high-frequency noise characteristics of the forged area by separating multi-scale frequency domain features and retrieves low-frequency information from the RGB domain.

The rapid development of image editing software allows attackers to quickly forge tampered images that cannot be accurately recognized visually. The tampering clues contained in images are usually very covert, so determining the authenticity of the image and the tampered area in a short period of time is a major challenge. The former is an image generated through post-processing operations such as JPEG compression, size cutting, and adding interference. The widespread dissemination of these images will seriously affect the public's judgment of real events and cause irreversible and enormous harm to society. The types of forged images are mainly divided into content preservation and content alteration. It shows examples of tampered images with content changes. These instances are generated by three operational methods, namely concatenation, copy-paste, and removal. This mainly includes stitching (copying and pasting elements from one image to another), copy-paste (copying and pasting elements from one image to other areas of the same image), and removal (removing elements from the image) operations to tamper with image content. These operations will seriously interfere with the semantic information of the image and will not create a significant sense of disconnection with the content of the source image. It is extremely difficult to directly determine the tampered object with the naked eye. This article uses deep learning algorithms to identify tampering traces. Each downsampling iteration contributes a new layer to this pyramid.

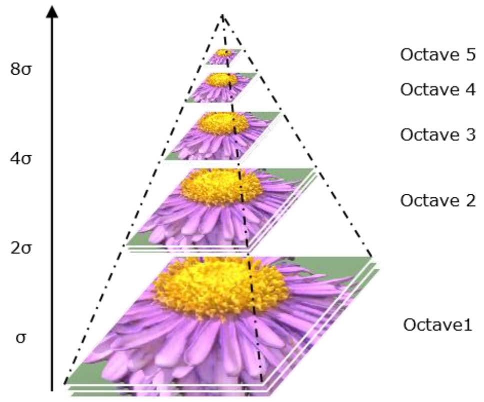

Figure 1: Gaussian pyramid model.

The pyramid model, as illustrated in Figure 1, demonstrates the process of downsampling from the original pattern to the smallest size. This model aids in capturing both global and local image features. When designing CAD interfaces, employing the scale space and pyramid model enhances the precision of design element identification and localization, thereby optimizing the interface's layout and functional divisions.

From the input image I, an undirected graph $G = \ V,E$ is constructed, where V is the set of nodes in the graph and E is the set of edges. For each edge $e_{i,j} \in E$ in the graph, a non-negative cost w_r is given. A Cut of a graph divides the nodes in the graph, which is a set of edges, $C \subset E$. In combinatorial optimization, under normal circumstances, the cost of cutting can be defined as the sum of all edge costs, which is expressed as:

$$\left|C\right| = \sum_{e \in C} w_e \tag{1}$$

Graph Cut needs to minimize the following formula:

$$E\ \ L\ = \sum\nolimits_{p \in P} D_p\ \ L_p\ + \sum\nolimits_{p,q \in N} V_{p,q}\ \ L_p, L_q \tag{2}$$

Where P is a set of pixels and N is an unordered p,q pair in P.

$L = \ L_1, \ldots, L_p, \ldots, L_{|p|}$, which is a binary vector, indicating binary division. D_p is called a region term, which is a penalty term for pixel marking. $V_{p,q}$ is called a smoothing term. Let O represent the set of target pixels and B represent the set of background pixels, then $O \in P$ and N_{new} $B \in P$, that is:

$$\begin{cases} \forall p \in O, L_p = obj \\ \forall p \in B, L_p = bkg \end{cases} \tag{3}$$

The energy function of Graph Cut can be reformulated as:

$$E\ \ L\ = \lambda \cdot \sum\nolimits_{p \in P} R_p\ \ L_p\ + \sum\nolimits_{\ p,q\ \in N} B\ \ p,q\ \cdot\ L_p, L_q \tag{4}$$

Then $D_p\ \ L_p$ becomes a regional term $R_p\ \ L_p$ and $V_{p,q}$ becomes a boundary term $B\ \ p,q\ \cdot \delta\ \ L_p, L_q$. The parameter λ is used to measure the relative importance of regional terms and boundary terms. Among them:

$$\delta\ \ L_p, L_q\ = \begin{cases} 1,\ If\ L_p \neq L_q \\ 0,\ \text{others} \end{cases} \tag{5}$$

$B\ \ p,q\ \geq 0$ contains the boundary information of dividing L, which can be expressed as the punishment of p and q discontinuity. When p and q are similar (such as similar brightness), $B\ \ p,q$ should be very large. When p and q are very different, $B\ \ p,q$ should tend to zero.

After obtaining multi-light source images, these images are processed by a specific algorithm. This step includes image correction, denoising and fusion to ensure image quality and consistency. By undergoing these procedures, a synthetic image of superior quality and intricate detail can be acquired, laying a foundation for future pattern recognition and interface design endeavours.

3.1 Detail Enhancement Technology

In CAD design, the finer points of design elements frequently embody crucial design intents and functional prerequisites. Hence, during image processing, we must give extra attention to extracting and bolstering these specifics. Detail enhancement technology aims to accentuate critical image information, such as line intersections and corners, easing precise editing for designers. To accomplish this, our study employs a detail enhancement algorithm rooted in local feature analysis. This algorithm intelligently tweaks parameters like pixel brightness and contrast by scrutinizing the greyscale and texture attributes of image subsections, thereby emphasizing key details. This not only elevates the image's visual appeal but also aids designers in swiftly pinpointing essential design elements. The process of image enhancement is exemplified in Figure 2.

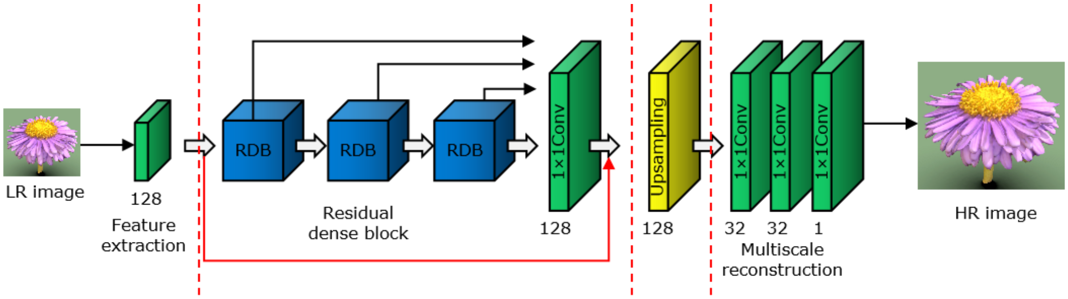

Figure 2: Image enhancement processing.

Assume that N images are captured under the condition of multi-light source illumination, and the input image is converted into model space to obtain its grey information. The grey gradient at the (x,y) pixel of the K input image is denoted as $(\nabla Y_k^x(x,y), \nabla Y_k^y(x,y))$. The maximum gradient $\left[\nabla Y_{\max}^x, \nabla Y_{\max}^y\right]$ is defined as:

$$\nabla Y_{\max}^x(x,y) = \max_k \left|\nabla Y_k^x(x,y)\right| \tag{6}$$

$$\nabla Y_{\max}^x(x,y) = \max_k \left|\nabla Y_k^y(x,y)\right| \tag{7}$$

Because there is usually a large gradient at the shadow edge, $\nabla Y_{\max}$ inevitably contains the gradient at the shadow edge. In order to remove the artifacts caused by the shadow edge, it is also necessary to detect the shadow position and refine the gradient field around the shadow edge pixels. A joint shadow detection scheme is designed because multi-light source images are used. For simplicity, this article uses a histogram-based segmentation algorithm to detect the shadow position of each image independently. An image in the colour space of the model, whose R scale diagram is defined as:

$$R(x,y) = (Q(x,y)+1) / (Y(x,y)+1) \tag{8}$$

Where $Q(x,y)$ is the saturation at the pixel of image (x,y).

In the scale diagram, the value of the umbra area is larger, while the value of the bright area is smaller. Then the scale map is mapped to different regions by a two-level segmentation algorithm. In the first stage of segmentation, it is used to find a threshold T in the whole histogram to separate the umbra from other regions. The threshold T should maximize the function:

$$\sigma_B^2(T) = \frac{\left[\bar{\mu}\omega(T) - \mu(T)\right]^2}{\omega(T)\left[1-\omega(T)\right]} \tag{9}$$

Where

$$\omega \ T \ = \sum_{i=0}^{T} p_i \tag{10}$$

$$\mu \ T \ = \sum_{i=0}^{T} i p_i \tag{11}$$

$$\bar{\mu} = \sum_{i=0}^{255} i p_i \tag{12}$$

p_i is the probability of a pixel with a grey value i in the scale diagram.

In this article, a traditional detail enhancement algorithm-histogram equalization is compared with the method proposed in this article. The comparison result is shown in Figure 3.

Processing effect of histogram equalization method | Processing effect of this method

Figure 3: Detail enhancement contrast.

Shadow areas often occupy a small proportion of the image, but their contribution to the overall visual effect can not be ignored. Because histogram equalization mainly adjusts the image according to the overall contrast, in the process of processing, the details of these shadow areas are likely to be ignored or lost because of the equalization operation. Especially in those shadow areas with low contrast, after equalization, they may become too bright, thus losing the original details and textures.

The approach presented in this article demonstrates evident superiority in addressing such challenges. Our method excels in not just efficiently boosting the local contrast of the image, thereby improving the visibility of all image components, but also restoring lost details in shadowed regions potentially erased due to histogram equalization during enhancement.

During the collaborative processing phase, we initially employ multi-light source image acquisition technology to capture premium-quality original images. Following this, we streamline crucial features within the image using an image-thinning algorithm. Lastly, we utilize detail enhancement technology to accentuate essential specifics. These three stages work in harmony, mutually reinforcing each other, to collectively enhance the precision of design element recognition and ease of operation within the CAD system.

The model trained on MSCOCo can describe simple and commonly used objects in artwork images, but the sentence structure is simple and cannot deeply understand the details in the artwork. In this case, transfer learning between multiple data sources enables the model to improve both in capturing entity relationships and generating more professional artistic descriptions. Afterwards, this article uses the filtered art image dataset SemArt to transfer the model's style, enabling the model to improve its understanding of art images and generate better descriptions of artworks. The model obtained on the ArtWork dataset can generate more professional artistic image descriptions, but due to the small amount of data and the single description data, the model cannot well reflect the entities and relationships between entities in the image. This article first uses the MSCOCO dataset to train the model, enabling it to gain an understanding of common entities and their relationships. Although deep learning models trained on single source datasets can to some extent understand art images and generate corresponding descriptions, these models still have some problems. This simplification overlooks the in-depth exploration of the ability to understand artworks. By comparing the art image understanding abilities of a series of models trained on the large-scale art image dataset SemArt, we further explore the ability of existing deep-learning models to understand art images. In addition, it is also the key to optimising the design of interface interaction logic, including reducing unnecessary interface jump and loading time, optimizing data transmission and processing speed, etc., to ensure that all functions can respond quickly while maintaining fluency.

4 EXPERIMENTAL RESULT

To validate the efficacy and performance of the CAD interface design approach that relies on image processing, this section conducts a sequence of experiments and subsequently analyzes the outcomes.

4.1 Comparison of Error Rate of Image Feature Recognition

Initially, we tested the image feature recognition capabilities of various methods. As illustrated in Figure 4, a comparison of error rates among different algorithms reveals a distinct advantage of our proposed method in image feature recognition. With an error rate of merely 2.01%, our algorithm significantly outperforms the other two comparison methods, which both hover around 10%. This finding demonstrates the precision and reliability of our approach to image processing.

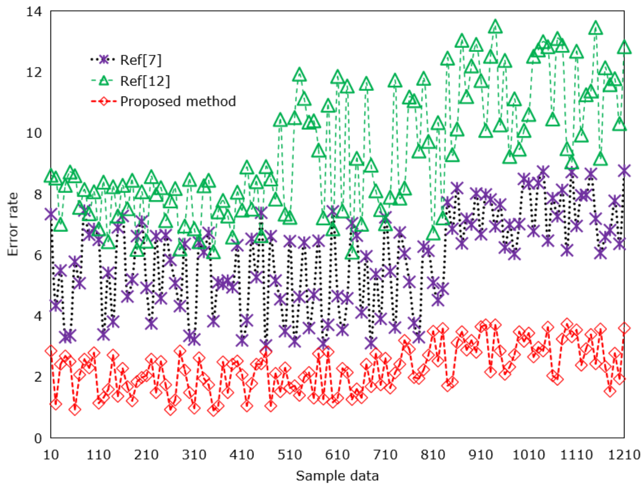

Figure 4: Comparison of algorithm error rates.

4.2 Accuracy of Presentation of Design Results

Furthermore, we evaluated the interactive interface's performance in recognizing user actions and precisely showcasing design outcomes. The experimental findings, depicted in Figure 5, reveal that our interactive interface identifies user operations and displays design results with an accuracy exceeding 95%. This signifies that users can experience exceptional operational precision and result in authenticity while utilizing the CAD interface we have designed.

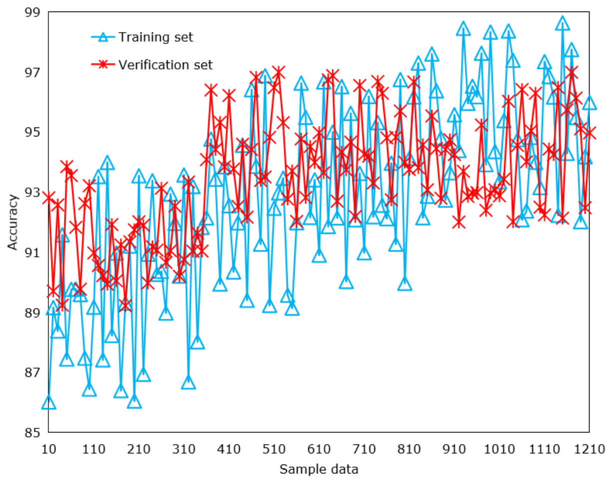

Figure 5: Accuracy of presentation of design results.

4.3 Comparison of the Time Required to Complete the Task

To conduct a comprehensive evaluation of our method, a comparison of the time taken to finish the design task using various methods was also performed. As evident from Figure 6, the experimental data unambiguously demonstrates that our approach significantly reduces the time needed to accomplish the task. This advantage stems from the optimized interface design, intuitive iconography, efficient symbol design, and an effective interactive guidance and feedback system. These factors work together to enable designers to complete design tasks more quickly.

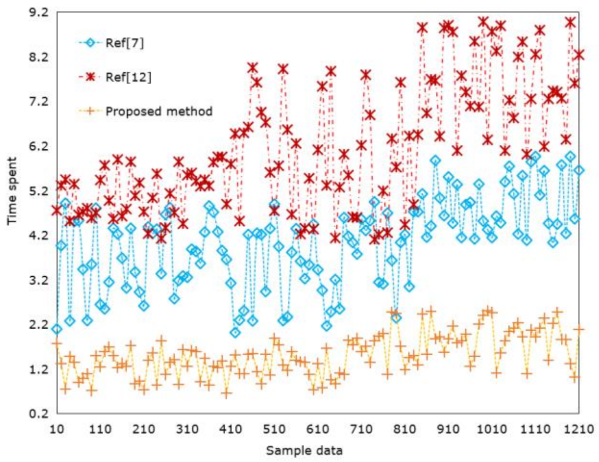

Figure 6: Time required to complete the task.

4.4 User Satisfaction Survey

As shown in Figure 7, this article presents an efficient interface design method for aesthetically pleasing overall functionality. Through a satisfaction survey on the user authenticity of CAD interfaces, an interactive user feedback method was constructed. And allocate resources reasonably to the mapping process, thereby accelerating the training speed of the network. In recent years, numerous scholars have made continuous efforts and proposed various new methods, overcoming many highly challenging problems. Low-resolution image reconstruction provides additional information for high-resolution images and is an important research direction in the field of computer vision image reconstruction. Compared with several existing popular algorithms, this algorithm can achieve convergence in a shorter time and extract rich feature information at a smaller scale.

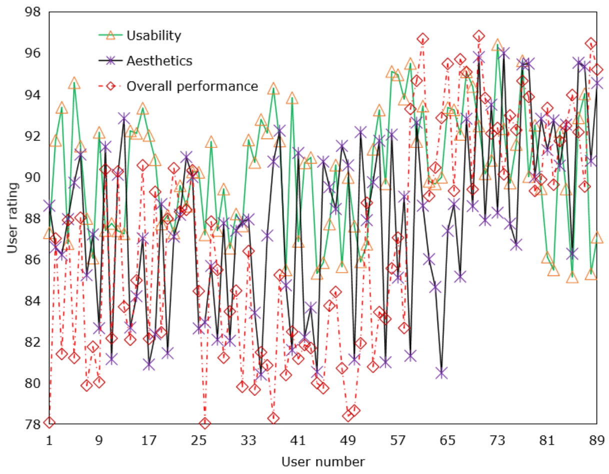

Figure 7: Satisfaction survey.

5 CONCLUSIONS

This article adopts the method of image collaborative processing to enhance the details of image processing applications with multiple light sources. This algorithm can not only fully extract image feature information, but also effectively balance the relationship between performance and model capacity. The experiment shows that the algorithm proposed in this chapter has achieved good performance in both quantitative results comparison and subjective visual effects compared to other advanced algorithms. Rebuild high-quality images with complete edge structures, clear overall contours, and rich details. The integration of multi-light source image feature recognition in the field of interactive image recognition has achieved the completeness and richness of image information. This significantly reduces the error rate of key indicators. Good performance often requires more complex models, which require higher computational power from the device. In reality, images are limited by the surrounding environment and photography equipment. When the degradation mode of the image is unknown, these models for specific operations may experience performance degradation. The images used in the network training process in this article are all obtained from high-resolution images through bicubic downsampling. In order to cope with more complex forms of image degradation and reconstruct better high-resolution images, it is possible to consider designing blind super-resolution methods that are more in line with practical situations to cope with various types of image degradation. This breakthrough provides solid support for accurately capturing design elements in CAD systems.

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REFERENCES

[1] Agarwal, A.; Singh, R.; Vatsa, M.; Ratha, N.: Image transformation-based defense against adversarial perturbation on deep learning models, IEEE Transactions on Dependable and Secure Computing, 18(5), 2020, 2106-2121. https://doi.org/10.1109/TDSC.2020.3027183

[2] Ayas, A.-Y.; Aydin, H.; Çetinkaya, A.; Güney, Z.: Artificial Intelligence (ai)-based self-deciding character development application in two-dimensional video games, Bilgi ve İletişim Teknolojileri Dergisi, 5(1), 2023, 1-19. https://doi.org/10.53694/bited.1247338

[3] Bhattacharjee, S.; Chaudhuri, P.: A survey on sketch-based content creation: from the desktop to virtual and augmented reality, Computer Graphics Forum, 39(2), 2020, 757-780. https://doi.org/10.1111/cgf.14024

[4] Chen, Z.; Dong, R.: Research on fast recognition method of complex sorting images based on deep learning, International Journal of Pattern Recognition and Artificial Intelligence, 35(06), 2021, 2152005. https://doi.org/10.1142/S0218001421520054

[5] Danso, S.; Liping, S.; Hu, D.; Odoom, J.; Quancheng, L.; Mushtag, M.: Security inspection image processing methods applying wavelet transform filters on Terahertz active images, Revista de Investigaciones Universidad del Quindío, 34(1), 2022, 37-51. https://doi.org/10.33975/riuq.vol34n1.853

[6] Dong, H.; Zhao, L.; Shu, Y.; Xiong, N.-N.: X-ray image denoising based on wavelet transform and median filter, Applied Mathematics and Nonlinear Sciences, 5(2), 2020, 435-442. https://doi.org/10.2478/amns.2020.2.00062

[7] 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

[8] Eslami, D.; Angelo, L.; Stefano, P.; Guardiani, E.: A semi-automatic reconstruction of archaeological pottery fragments from 2D images using wavelet transformation, Heritage, 4(1), 2021, 76-90. https://doi.org/10.3390/heritage4010004

[9] Feng, X.; Zhang, W.; Su, X.; Xu, Z.: Optical remote sensing image denoising and super-resolution reconstructing using an optimized generative network in wavelet transform domain, Remote Sensing, 13(9), 2021, 1858. https://doi.org/10.3390/rs13091858

[10] He, C.; Sun, B.: Application of artificial intelligence technology in computer-aided art teaching, Computer-Aided Design and Applications, 18(S4), 2021, 118-129. https://doi.org/10.14733/cadaps.2021.S4.118-129

[11] Kang, M.; Kim, S.: Fabrication of 3D printed garments using flat patterns and motifs, International Journal of Clothing Science and Technology, 31(5), 2019, 653-662. https://doi.org/10.1108/IJCST-02-2019-0019

[12] Mueller, J.-H.; Neff, T.; Voglreiter, P.; Steinberger, M.; Schmalstieg, D.: Temporally adaptive shading reuse for real-time rendering and virtual reality, ACM Transactions on Graphics (TOG), 40(2), 2021, 1-14. https://doi.org/10.1145/3446790

[13] Pourasad, Y.; Cavallaro, F.: A novel image processing approach to enhancement and compression of X-ray images, International Journal of Environmental Research and Public Health, 18(13), 2021, 6724. https://doi.org/10.3390/ijerph18136724

[14] Qamar, I.; Groh, R.; Holman, D.: Bridging the gap between material science and human-computer interaction, Interactions, 26(5), 2019, 64-69. https://doi.org/10.1145/3344943

[15] Wei, X.; Liu, M.; Ling, Z.; Su, H.: Approximate convex decomposition for 3d meshes with collision-aware concavity and tree search, ACM Transactions on Graphics (TOG), 41(4), 2022, 1-18. https://doi.org/10.1145/3528223.3530103

[16] Yin, Z.; Wu, Z.; Zhang, J.: A deep network based on wavelet transform for image compressed sensing. Circuits, Systems, and Signal Processing, 41(11), 2022, 6031-6050. https://doi.org/10.1007/s00034-022-02058-8