International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-12

https://doi.org/10.70917/ijcisim-2026-0104
Article

Analysis of the Use and Effectiveness of Artificial Intelligence-Assisted Creation Tools in Digital Art and Design

Jing Tang *

Communication University of China, Nanjing 211172, Jiangsu, China; jing329084@163.com

Abstract: This paper focuses on the practical application of artificial intelligence-assisted creation tools in digital art design, and establishes a digital art model based on 3D animation special effects production technology. The envelope contour detection method and chunk fusion processing technology are used to optimize the 3D modeling process, and the improved HFRA-SRGAN deep learning model is used to achieve super-resolution reconstruction of digital art images. Through comparative experiments, the proposed method is verified to have significant advantages in peak signal-to-noise ratio, screen resolution, collision performance and reconstruction effect. Based on the results of user emotion annotation for digital art image design, user satisfaction is analyzed. The images reconstructed by this paper's method are more in line with human subjective vision, and the global reconstruction quality and detail reconstruction artistry scores reach 4.82 and 4.38, respectively, which are 23.9% and 29.6% higher than the sub-optimal performance of the control method2. User satisfaction scores at the instinctive, behavioral, and reflective levels all exceeded 4.5.

Keywords: digital art design; 3D animation effects; HFRA-SRGAN model; super-resolution reconstruction

1. Introduction

Traditional digital media art design integrates digital media technology with artistic thinking and design themes. Although the content of these designs varies, they all fall under the category of 2D graphic design [1-2]. As society evolves, people's aesthetic preferences continue to change. 2D graphic design no longer aligns with these evolving tastes, thereby diminishing the value of digital media art design works. As a result, seeking change has become an inevitable trend. Today, various advanced technologies have emerged, greatly enhancing the convenience of people's daily lives and work [3]. Digital media art is a product of the new era, and its importance is self-evident. From a developmental perspective, digital media art possesses characteristics such as interactivity, efficiency, and virtuality [4-6]. It differs from traditional art design in certain ways. Designers can leverage digital technology and digital media to complete design creations more efficiently, and the results can be presented from multiple dimensions [7-9]. From an application perspective, the existence of digital media art enables the secondary development of works [10]. Its editing and replication functions allow original works to be presented in a completely new form. In this secondary creation process, the artistic and aesthetic value of the works is enhanced, and their audience reaches becomes increasingly broader [11-13]. However, in the actual development process, digital art design still faces numerous challenges, hindering further advancement.

Since the advent of the digital age, artificial intelligence has gradually entered the public eye. Integrating artificial intelligence technology into digital media art design can break through the limitations of traditional media, driving design creation toward digitalization and intelligence [14-15]. Additionally, artificial intelligence technology can create new virtual worlds, promoting the deep integration of traditional media and information technology. Incorporating it into digital media art design can provide users with highly realistic experiential sensations, better fulfilling spiritual needs [16-19].

Therefore, to achieve new heights that were previously unattainable in digital media art, many scholars have begun to deeply understand AI technology, viewing it dialectically and applying it to achieve new integration and development between art and AI. Shen, Y. and Yu, F. emphasize that the development direction of digital art design in the AI era is moving toward emerging interactive models, and establishing an interactive art design paradigm within an AI context can bring about new creative thinking and artistic experiences [20]. Wenjing, X., and Cai, Z. clarify that innovative technologies such as AI and deep learning have profoundly transformed the creation, dissemination, and consumption patterns of art design, and point out that the interactive digital art expression effects based on intelligent systems will continue to improve with technological advancements [21]. Tian, H. constructed a digital media art interface design system integrating graphic elements with AI algorithms, fully meeting the requirements of art interface design while providing users with a satisfying experience for direct communication [22].

Additionally, utilizing virtual reality technology to create virtual reality environments is another innovative art design method centered around art design elements. Li, P. explored an art design method based on 3D digital virtual reality, designing more stunning visual art by establishing virtual simulation scenes using computers as a medium [23]. He, L. and Zhu, S. analyzed the application of virtual reality technology in image visualization art design, and achieved dynamic and visual image art products through the use of relevant algorithms to create a complete virtual reality image design model [24]. Qian, J. demonstrated that virtual reality technology, with its unique expression methods and three-dimensional image generation techniques, can create art design scenes tailored to user needs through data modeling and precise data calculations, and has played a significant role in art design across multiple fields [25]. Du, W. and Li, Q. argued that the application of virtual reality technology in art spaces can help address issues such as the monotony of contemporary visual design and visual aesthetic fatigue. Furthermore, the expressive capabilities of this technology in three-dimensional spaces far surpass those of one-dimensional and two-dimensional image art design [26]. However, artificial intelligence technology has not yet been widely adopted in digital media art design, primarily because many designers in this field lack a deep understanding of the technology and struggle to apply it flexibly in their creative work. Therefore, further exploration and practice are still needed.

In this paper, we first analyze the technical path of digital art model construction, 3D dynamic feature volume extraction and chunk fusion processing, and propose an improved HFRA-SRGAN network model. The image super-resolution reconstruction is optimized by multi-scale high-frequency attention mechanism with adversarial loss function. Based on multi-dimensional performance test, systematically evaluate the actual effectiveness of AI tools in technical indexes. Explore the artistic value of AI-assisted creation tools in the use of digital art design from the perspective of user emotional cognition.

2. Artificial Intelligence-Driven Digital Art Design Solutions

As a cross-field of technology and art, digital art design has long been facing challenges such as limited creative efficiency, high cost of realizing complex special effects, and insufficient subjective aesthetic adaptability. Traditional 3D modeling relies on manual experience and step-by-step operation, which is difficult to meet the demand for real-time optimization of dynamic scenes. Image super-resolution reconstruction is limited by the algorithm's ability to capture texture details and the degree of artistic retention. In recent years, the introduction of artificial intelligence technology has provided innovative solutions to the above problems: automated generation of high-frequency details through deep learning models, optimization of physical collision detection, and the combination of 3D dynamic feature extraction technology to enhance the realism and artistry of visual effects.

2.1. Computerized Digital Art Design Based on 3D Animation Special Effects Production

3D animation special effects production is based on computer technology and derived from the new multimedia technology. Three-dimensional animation can also be called 3D animation, its production principle for the computer through a specific software system to establish a virtual world, and to the world of physical objects to set the required movement trajectory. 3D animation virtual three-dimensional world through the way of digital art modeling, the design of virtual three-dimensional special effects. Three-dimensional animation features production applied to digital art design models are character models, animal and plant models and architectural models of three categories. The introduction of 3D animation special effects production technology into computer digital art makes people's daily life colorful. Three-dimensional animation effects technology used in film and television production, through a variety of special effects to enrich the image of the characters or things in the film. Using three-dimensional animation effects first through the computer equipment in the library to screen out the application of three-dimensional special effects effect map; second through the three-dimensional design software in the virtual space for drawing and adjustment; and then through the creation of a virtual camera coupled with simulated reality lighting, you can make the virtual space more realistic. Finally, we will get the smooth and perfect special effects clips as well as more visual effects to enhance the visual impact of the TV screen.

2.1.1. Modeling Digital Art

To establish a digital art model, the first use of traditional animation production techniques to draw the original painting, and then through the computer library of information on the graphic image to transform, and ultimately determine its art model. In the computer transformation process often use software for Flash, Flash software, the first step of the traditional method to get the original painting scanned into a specific preview window; the second step for the drag and drop selection box to select the digital art in the required art model, in order to remove the original painting of the irrelevant content of the screen, but also as far as possible to reduce the picture where the computer memory; the third step of the use of Flash software in the file processing functions The third step is to use the file processing function in Flash software to categorize and name the contents of the image file according to the order of the mirror number in the sub-shot script, to ensure that the image is edited in later stages and quickly called up in the computer gallery; the last step is to carry out basic processing and optimization design for the digital map file, and then design the digital art model.

2.1.2 Extraction of 3D Dynamic Eigenvolumes

In this study, the virtual visual reconstruction method is used to project the features of the landscape environment and collect 3D animated images, and the edge contour detection and binary fitting are implemented on the 3D dynamic images, in which the method used for edge contour detection is the envelope contour detection method, and the model is updated based on the color space fusion of the color space of the 3D animated images to get the iterative formula as shown below:

$$A = C \times \left[\left(l(1-\rho) + \rho k \right) \right] \tag{1}$$

The above equation notates the two distributed fields controlling 3D imaging as ρ , which in turn yields the gray-scale pixel eigenquantities of the 3D animation image. In this study, the Euler-Lagrange equation is utilized to derive the boundary region equation for the observation point of the 3D animated image as shown below:

$$= \frac{d}{dt}\left(\frac{\partial A}{\partial i} \right) - \frac{\partial A}{\partial i} \tag{2}$$

Using the results of edge contour feature detection, the designer is able to enhance the details of the 3D animation image in a targeted manner. Assuming that the 3D animation image is normally distributed, the 3D dynamic feature reconstruction output can be obtained through the continuous reconstruction method as shown below:

$$T_m = \begin{cases} G_v = (v_{\min}, v_{\max}) \\ M_z = (h, w) \\ C_p = (x, y) \\ H_m = (h_1, h_2, \ldots, h_{B-1}, h_B) \end{cases} \tag{3}$$

On this basis the color components of the 3D animation image can be extracted by means of RGB decomposition, which is processed as follows:

$$w = h_{\sigma_s} \times f_{R,G,B} \tag{4}$$

The above equation notates the RGB component as $f_{R,G,B}$, and the 2D Gaussian kernel with standard deviation σ_s as h_{σ_s} , and the output of the 3D animation for edge contour detection is:

$$P = h_{\sigma_f} \times \left(T_m + w \right) \tag{5}$$

The 2D Gaussian kernel with a standard deviation of σ_f is denoted as h_{σ_f} in the above equation, which is used to extract the 3D dynamic feature volume based on the color feature extraction results that have been obtained.

2.1.3. Chunked Fusion Processing

In this study, the Autodesk Maya software is used to optimize the design scheme to extract the color components of the 3D image by means of RGB decomposition, and the expression of the information of the distribution of Harris corner points of the 3D image is as follows:

$$v=\lambda_1+\lambda_2, s=1-\frac{\lambda_2}{\lambda_1}, h=\frac{\theta}{\pi} \tag{6}$$

The above equation notates the elliptic principal direction angle of the 3D image in the feature reconstruction space as θ, the long semi-axis length as λ_1, and the short semi-axis length as λ_1. Thus, the expression for the sequence of pixel distributions of a 3D image is as follows:

$$d=\min\left(e\times\sum_{m=1}^{n}\frac{s\times h}{v}\right) \tag{7}$$

The above equation denotes the weight coefficients of the image feature pixel point distribution sequence in the multilinear fusion model as e, and the total number of iteration steps as m. Let $a=\{a_i\}_{i=1}^{N}$ be the quantized feature decomposition value of the 3D image vector composed of N scalars, based on which the edge pixels are decomposed by means of multi-feature fusion, and then obtain the chunked fusion processing model as shown below:

$$H=g\times a\times d \tag{8}$$

The above equation notates the gray scale pixel level of the 3D image as g, and based on this the chunk fusion process is implemented for the 3D image.

2.2. Deep Learning Based Super-Resolution Reconstruction of Digital Art Images

2.2.1. Loss Function

Super-resolution generative adversarial network proposes a new loss function based on the traditional deep learning using mean square error. The loss function of super-resolution generative adversarial network consists of two parts: generator loss and discriminator loss.

The generator loss focuses on the similarity of the reconstructed images, including content loss and perceptual loss. The content loss is used to optimize the target image of the generator, which is the mean square error between the real image and the target image. Perceptual loss measures the degree of difference between the generated image and the real image, making the generated image more realistic. The total loss function of the generator is shown in equation (9).

$$L_{SR}=\alpha L_{content}+\beta L_{perceptual} \tag{9}$$

where α and β are hyperparameters that control the weights of content loss and perceptual loss, respectively. $L_{content}$ denotes the content loss, defined as the mean-square error between the generated image and the original high-resolution image. $L_{content}$ is shown in Equation (10).

$$L_{content}=\frac{1}{whc}\sum_{i=1}^{w}\sum_{j=1}^{h}\sum_{k=1}^{c}\left(\hat{y}_{i,j,k}-y_{i,j,k}\right)^2 \tag{10}$$

where $\hat{y}$ denotes the generated image, y denotes the original high-resolution image, and w,h,c denotes the width, height, and number of channels of the image, respectively.

The adversarial loss forces the generator to produce a more realistic image, making the discriminator unable to distinguish the difference between the generated image and the real image. Adversarial loss is defined as the sum of the distances between the generated image and the original high-resolution image characterized by certain layers in the VGG network. See equation (11).

$$L_{perceptual}=1/n\sum_{i=1}^{n}\left(\Phi\left(\hat{y}\right)_i-\Phi\left(y\right)_i\right)^2 \tag{11}$$

where $\phi(\cdot)_i$ denotes the feature representation of the i th layer of the VGG network, and n is the number of layers selected.

The discriminator loss is mainly concerned with the realism of the generated image and is defined here as the negative log-likelihood of the probability that the generated image passes the discriminator.

See equation (12).

$$L_{adv} = -\log D(\hat{y}) \tag{12}$$

where D denotes the discriminator. The objective of the generator is to minimize $L_{SR} + \lambda \cdot L_{adv}$, where λ is a hyperparameter to balance the weights of the two loss functions. The goal of the discriminator is to minimize L_{adv}.

2.2.2 Overall Structure

The HFRA-SRGAN network model proposed in this paper is improved based on SRGAN.HFRA-SRGAN is similar to conventional generative adversarial networks and consists of two parts: generator and discriminator.The structure of the HFRA-SRGAN network is shown in Fig. 1.

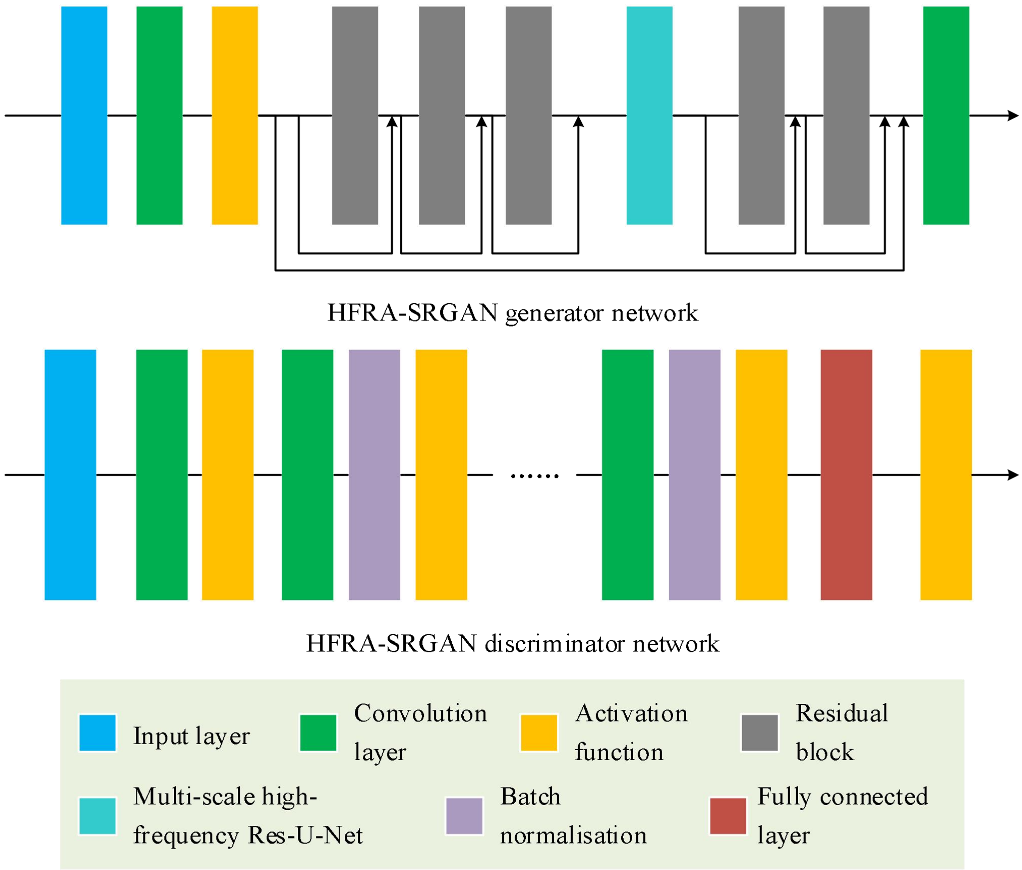

Figure 1. HFRA-SRGAN network structure.

The HFRA-SRGAN generator structure can be divided into the following parts according to the different functions of the convolutional network: input layer, convolutional layer, residual layer, multi-scale HF ResUNet layer, upsampling layer and output layer. In this experiment, digital art images are selected as the dataset and test set for training the model, which all consist of $600 \times 600 \times 4$ RGB images. After the image is input to the generator, it passes through the downsampling layer module in the input layer to obtain the downsampled image. In the residual layer part, since the batch normalization layer may lead to inconsistent performance of the model for different batches of data, the batch normalization layer in the residual layer is removed in HFRA-SRGAN, which reduces the number of parameters during training and makes the model more stable in generating super-resolution images. In HFRA-SRGAN, the residual layer, which consists of continuous residual blocks, is improved by removing a part of the residual blocks and replacing them with the ResUNet module that introduces high-frequency residual attention. In the ResUNet part, the improved ResNet residual block and the U-Net module are combined, which not only better preserves the multidimensional features of the image, but also combines different levels of high-frequency information with the multidimensional features.

The structure of the HFRA-SRGAN discriminator is similar to that of SRGAN, consisting of an input layer, a series of convolutional layers, and a fully connected layer and activation function. Each of these convolutional layers contains a convolutional kernel, batch normalization, and a LeakyReLU activation function. The size of the convolutional kernels is gradually increased, starting with 128 3×3 convolutional kernels and gradually increasing to 1024 3×3 convolutional kernels. At the same time, the step size of each convolutional layer is 2, which can make the size of the feature map reduced by half. Finally, the output of the discriminator is compressed by a Sigmoid activation function to the range of 0 to 1, which indicates the probability that the generated image is a real image.The discriminator network of HFRA-SRGAN receives two kinds of inputs: the original high-resolution image or the super-resolution image after super-resolution reconstruction of the generator.The HFRA-SRGAN discriminator passes the high-resolution image through the convolutional layers for feature extraction, and then the high-resolution image and the super-resolution image are fed together into the binary discriminator to discriminate between real and fake images.

Compared with the SRGAN model, the HFRA-SRGAN model proposed in this paper performs better in the digital art image dataset, and the image obtained after super-resolution reconstruction also retains more textures and details.

3. Analysis of the Effect of the Use of Artificial Intelligence-Driven Digital Art Design Solutions

3.1 Performance Testing

In order to highlight the advantages of the method proposed in this paper in practical applications, the noise point cloud-based digital art design method (control method 1) and the hybrid multi-view digital art design method based on scene graph segmentation (control method 2) are introduced for comparison to test the effects of the three methods. The SeanNet dataset is selected as the test dataset for the experiment, which contains a total of 25,000 art 3D virtual images within the whole dataset.

3.1.1. Dynamic Feature Enhancement

In order to verify the dynamic feature enhancement performance of the proposed method, the peak signal-to-noise ratio and structural similarity are selected as the objective indexes for evaluation, and the higher the values of the two indexes are, the more ideal the enhancement effect is. Three images in the dataset are selected as test samples for the experiment, and the experimental comparison results of the indicators of different methods are shown in Table 1. The peak signal-to-noise ratio and structural similarity of the control method 2 are the lowest, indicating that the image enhancement effect is poor. The values of peak SNR and structural similarity using the method in this paper are significantly better than the sub-optimal performance of the control method 2, with an average peak SNR of 30.31 dB, which can effectively ensure the integrity of the structural information of the dynamic features in the image.

Table 1. Comparison of enhancement Effects of Different methods.

Test indicators	Test image numbering	The proposed	Control Method 1	Control Method 2
Peak signal-to-noise ratio/dB	A1	30.53	25.94	23.06
	A2	30.11	26.11	23.68
	A3	30.28	26.27	24.17
Structural similarity	A1	0.893	0.746	0.703
	A2	0.904	0.799	0.756
	A3	0.921	0.812	0.798

3.1.2. Screen Resolution

Digital art images were designed from the original images and the performance of the three methods was measured using the frame resolution. The results of the comparison of the screen resolution of different methods are shown in Figure 2, with the increase of the number of screen frames, the resolution of the screen is getting higher and higher. When using the 2 control methods, the screen resolution obtained is lower than the method in this paper, and the average screen resolution of the method in this paper reaches 472 dpi, which indicates that the method is able to improve the smoothness, thus ensuring that the quality of the screen has a better performance.

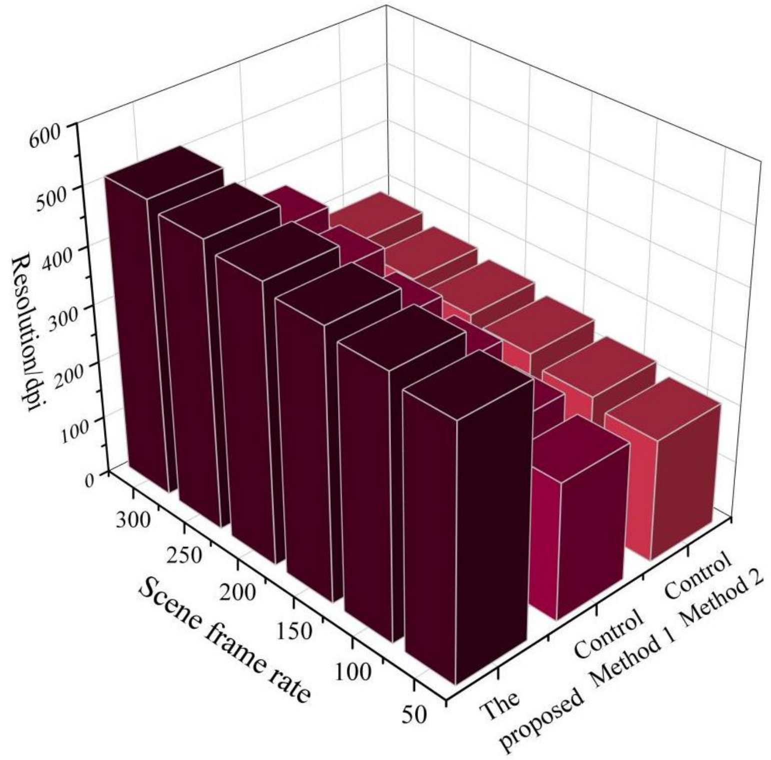

Figure 2. Comparison of picture resolutions by different methods.

3.1.3. Crashworthiness

The collision detection method is used to detect the spatial three-dimensional scene designed by the three-group method on the 3D modeling software. Open the physical collision panel in the editor of the three-dimensional modeling software, add collision effects, set the collision detection properties, and detect the three-dimensional scene designed by the three groups of methods.

Detect 6 times and compare with the actual modeling of the number of collisions, output detection results, different methods of collision detection results comparison shown in Figure 3. The control method 1 produces the highest number of collisions, with an average of about 10 collisions. The number of collisions produced by the control method 2, although less than the control method 2, but the number of collisions is maintained at about 6 times. The proposed method, on the other hand, produces significantly fewer collisions than the control method, with the number of collisions concentrated around 2. It can be seen that the proposed method produces the least number of collisions and is more spatially three-dimensional.

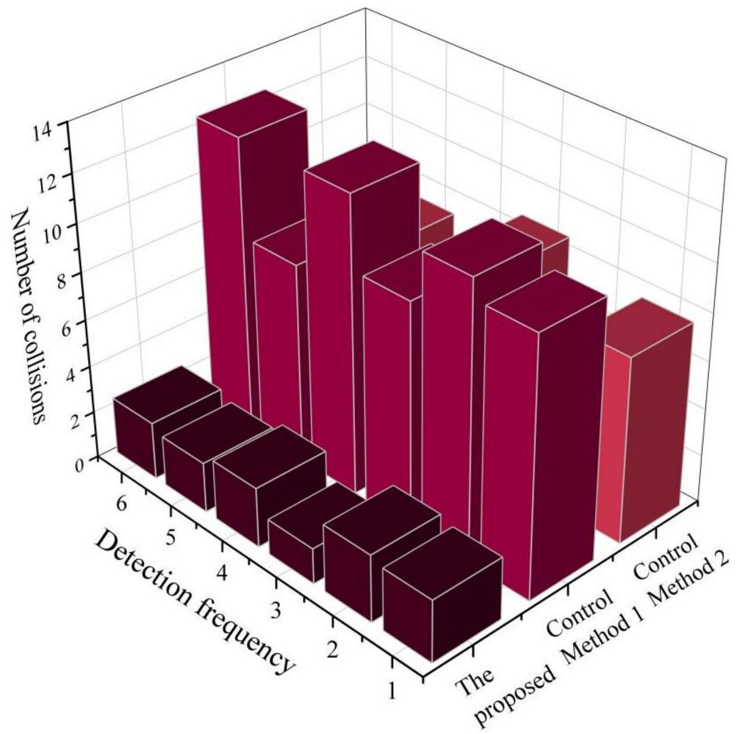

Figure 3. Comparison of collision detection results by different methods.

3.1.4. Evaluation of Reconstruction Effects

Due to the artistic and professional nature of digital art images, the subjective reconstruction quality of images was assessed using the MOS method. Thirty randomly invited industry personnel judged the image reconstruction effect and artistry, and the evaluation criteria were divided into two aspects: global reconstruction quality and detail reconstruction artistry. The global reconstruction quality was evaluated from the color deviation and overall quality of the reconstructed image, and the detailed reconstruction artistry was evaluated from the detailed texture quality, the artistic value of the image at high magnification, and the artistic value of the image at low magnification. Based on the above two aspects, the MOS scoring interval was set to [0,5], and the statistical scoring results were averaged and calculated as the final MOS score respectively. The comparison of subjective evaluation of reconstructed images under different methods is shown in Fig. 4. According to the scoring results, the reconstructed images by this paper's method are more in line with human subjective vision, and the global reconstruction quality and detail reconstruction artistry scores reach 4.82 and 4.38, respectively, which are 23.9% and 29.6% higher than the sub-optimally-performing control method 2. In terms of artistry assessment, industry personnel gave higher evaluation scores to this paper's method for detail texture, image artistic value at high magnification, and image artistic value at low magnification. The overall reconstruction artistry of this paper's method is more in line with human aesthetics as can be seen in the figure. After the discussion of the invited personnel, it is agreed that the reconstructed image of this paper's method is more artistic in terms of texture details.

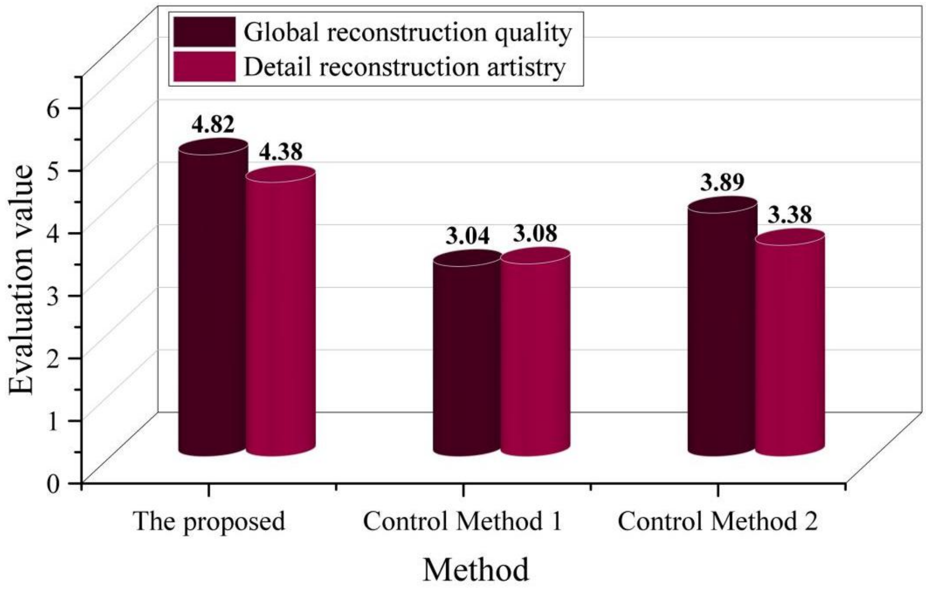

Figure 4. Comparison of subjective evaluations of different methods.

3.2. Analysis of Practical Effects

3.2.1. Emotional Cognitive Feedback

The research population of this study is college students, the target user group of digital art images. The selection of college students as the target users is based on statistical data and market trends. Eight major samples of digital art images were selected for the study, covering different popular content themes. These themes ensured the diversity of the image pool, enabling participants to be exposed to a wide range of visual styles and content for more accurate sentiment labeling in the experiment. A total of 500 questionnaires were distributed and 456 valid questionnaires were returned in this sentiment annotation experiment, with an effective recovery rate of 91.2%.The results of the distribution of basic sentiment labels for the eight samples are shown in Figure 5. Overall, the annotators gave more positive emotional feedback to the digital art images, and the most selected emotion labels were “pleasure” and “awe”, while the least selected emotion label was “fear”.

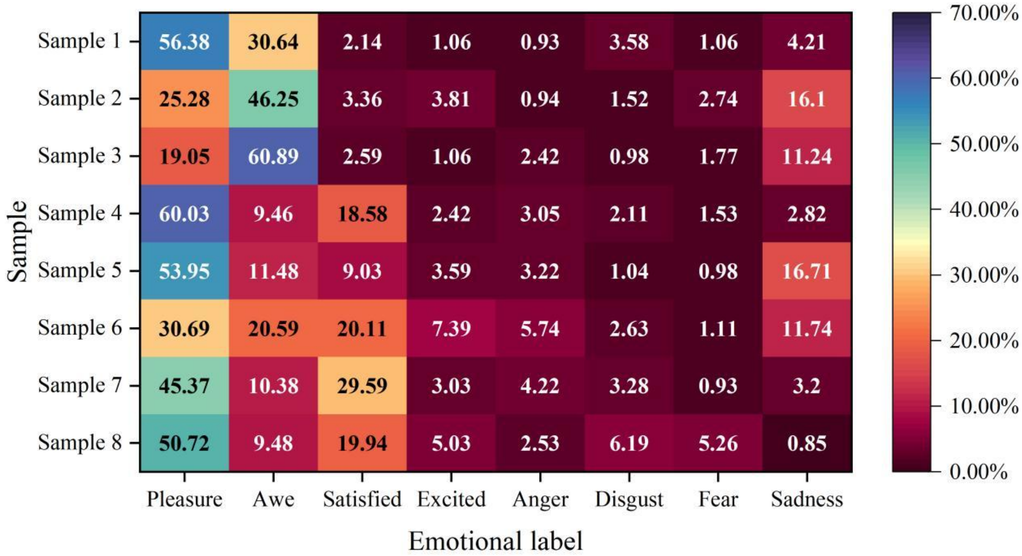

Figure 5. Distribution of basic emotion labels for the eight samples.

Table 2 shows the specific number of sentiment annotations divided by different samples. From the perspective of the classification of eight basic emotional states, "pleasure" is the most popular emotional label, with an average response rate of 42.68%, indicating that digital art images can generally make annotators feel pleasant. The average response rate of "Awe" is 24.90%, which may be related to its deep cultural heritage and unique visual impact. The average response rates of the two emotions of "satisfaction" and "excitement" were low, at 13.17% and 3.42%, respectively, indicating that they were not the main emotional trigger points of digital art images. From the perspective of item specificity, sample 4 had the highest response rate of 60.03% on "pleasant" emotion, indicating that the sample image had a strong positive emotional impact. Sample 3 was outstanding in the emotion of "awe", with a response rate of 60.89%, which may be related to its deep cultural heritage and unique visual presentation.

Table 2. Specific quantity statistics of emotion labeling(%).

Sample	Pleasure	Awe	Satisfied	Excited	Anger	Disgust	Fear	Sadness	Positive	Negative
1	56.38	30.64	2.14	1.06	0.93	3.58	1.06	4.21	90.22	9.78
2	25.28	46.25	3.36	3.81	0.94	1.52	2.74	16.10	78.70	21.30
3	19.05	60.89	2.59	1.06	2.42	0.98	1.77	11.24	83.59	16.41
4	60.03	9.46	18.58	2.42	3.05	2.11	1.53	2.82	90.49	9.51
5	53.95	11.48	9.03	3.59	3.22	1.04	0.98	16.71	78.05	21.95
6	30.69	20.59	20.11	7.39	5.74	2.63	1.11	11.74	78.78	21.22
7	45.37	10.38	29.59	3.03	4.22	3.28	0.93	3.20	88.37	11.63
8	50.72	9.48	19.94	5.03	2.53	6.19	5.26	0.85	85.17	14.83

3.2.2 Satisfaction Analysis

Designing user satisfaction assessment questions from three dimensions, the research is mainly carried out from three dimensions: instinct, behavior and reflection, and 12 assessment questions (numbered Q1~Q12) are summarized for user satisfaction assessment. For user emotional cognition, the method of this paper is used for digital art image design, and 50 target users are invited to score the satisfaction of each index. Each question is full of 5 points, and the scoring results are shown in Figure 6. The user satisfaction at the instinctive level is 4.7 points, the user satisfaction at the behavioral level is 4.65 points, and the user satisfaction at the reflective level is 4.77 points. It can be seen that the overall user satisfaction with the digital art images designed by the method of this paper is high.

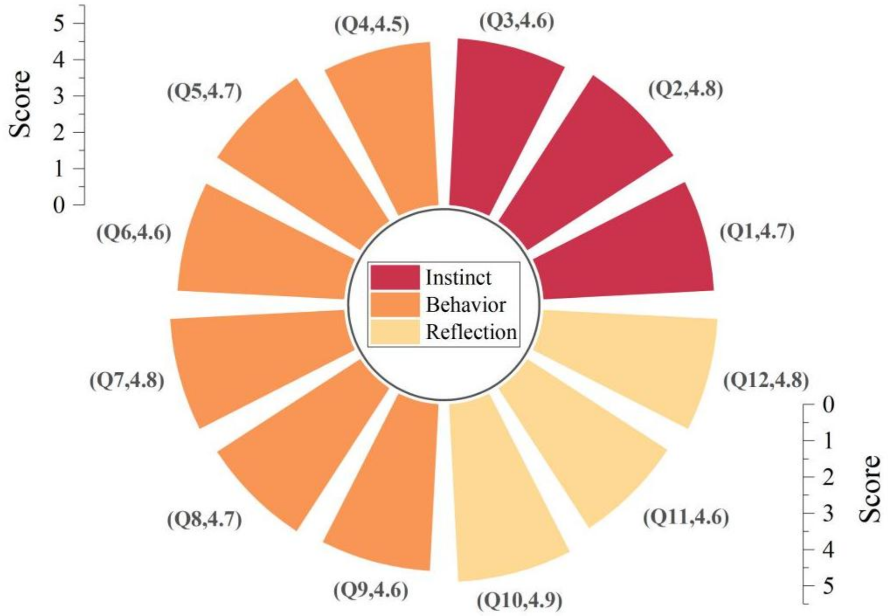

Figure 6. User satisfaction scoring results.

4. Conclusion

Through experimental verification and empirical analysis, this study systematically explains the innovative application and significant effect of artificial intelligence technology in digital art design.

The values of peak signal-to-noise ratio and structural similarity using this paper's method are significantly better than those of the control method, the average screen resolution reaches 472 dpi, and the number of collisions is concentrated at about 2 times. The reconstructed images by this paper's method are more in line with human subjective vision, and the global reconstruction quality and detail reconstruction artistry scores reach 4.82 and 4.38, respectively, which are 23.9% and 29.6% higher than those of the sub-optimal performance control method2.

In practice, annotators have more positive emotional feedback on digital art images, and the most selected emotional labels are "pleasure" and "awe", and the least emotional labels are "fear". "Pleasure" is the most popular emotional label, and the average response rate is 42.68%, indicating that digital art images can generally make annotators feel pleasant. According to the digital art image design for user emotional cognition, the user satisfaction score is 4.7 points at the instinct level, 4.65 points at the behavior level, and 4.77 points at the reflection level. It can be seen that the overall satisfaction of users with the digital art images designed by this method is high.

References

1. Abushawali, M., Lim, Y. P., & Bedu, A. R. (2013, September). The impact of new digital media on graphic designer in Jordan. In 2013 International Conference on Informatics and Creative Multimedia (pp. 274-277). IEEE.
2. Candy, L., & Edmonds, E. (2018). Practice-based research in the creative arts: Foundations and futures from the front line. Leonardo, 51(1), 63-69.
3. Wang, M., Wang, J., & Zhang, C. (2022). Visual Space System Design in Digital Media Art Design. Scientific Programming, 2022(1), 3678090.
4. Kolesnyk, N., Piddubna, O., Polishchuk, O., Shostachuk, T., & Breslavska, H. (2022). Digital art in designing an artistic image. Ad alta, 31(12), 128-133.
5. Wiana, W. (2017). Application design of interactive multimedia development based motion graphic on making fashion design learning in digital format. International Journal of Scientific & Technology Research, 6(5), 102-108.
6. Rocamora, A. (2017). Mediatization and digital media in the field of fashion. Fashion Theory, 21(5), 505-522.
7. Venturelli, S. (2021). Computer art: Software art design. ANIAV-Revista de Investigación en Artes Visuales, (8), 79-91.
8. Ozcan, A., Cidik, E., & Kandirmaz, E. A. (2021). The Effect of Digitalization On Illustration In Graphic Design. Inovacijos Leidybos, Poligrafijos Ir Multimedijos Technologijose, 2021, 39.

9. Romainoor, N. H., & Abdullah, S. (2017). EMBRACING CYBERCULTURE ON GRAPHIC DESIGN. Malaysian Journal of Creative Media, Design and Technology, 1(4).
10. Wang, J., & Hu, C. (2025). Application of Computer-Aided Technology in Digital Graphic Design. Informatica, 49(9).
11. Caydere, O. (2022). Sustainable graphic design in educational environments: sustainable graphic design. International Journal of Curriculum and Instruction, 14(1), 719-727.
12. Jeon, M., Fiebrink, R., Edmonds, E. A., & Herath, D. (2019). From rituals to magic: Interactive art and HCI of the past, present, and future. International Journal of Human-Computer Studies, 131, 108-119.
13. Adeniji, J. B. (2013). The Impact of Digital Arts on Design Problem Solving: Prospects for Creativity in Graphic Design. The International Journal of New Media, Technology and the Arts, 7(1), 25.
14. Zhang, W., & Jia, Y. (2021). Modern art interactive design based on artificial intelligence technology. Scientific Programming, 2021(1), 5223034.
15. Mazzone, M., & Elgammal, A. (2019, February). Art, creativity, and the potential of artificial intelligence. In Arts (Vol. 8, No. 1, p. 26). MDPI.
16. Ornes, S. (2022). Virtual reality helps shape and respond to artistic impulses. Proceedings of the National Academy of Sciences, 119(31), e2210323119.
17. Ruan, Y. (2022). Application of immersive virtual reality interactive technology in art design teaching. Computational intelligence and neuroscience, 2022(1), 5987191.
18. Büttner, S., Mucha, H., Funk, M., Kosch, T., Aehnelt, M., Robert, S., & Röcker, C. (2017, June). The design space of augmented and virtual reality applications for assistive environments in manufacturing: a visual approach. In Proceedings of the 10th international conference on PErvasive technologies related to assistive environments (pp. 433-440).
19. Yang, X., Lin, L., Cheng, P. Y., Yang, X., Ren, Y., & Huang, Y. M. (2018). Examining creativity through a virtual reality support system. Educational Technology Research and Development, 66, 1231-1254.
20. Shen, Y., & Yu, F. (2021). The influence of artificial intelligence on art design in the digital age. Scientific programming, 2021(1), 4838957.
21. Wenjing, X., & Cai, Z. (2023). Assessing the best art design based on artificial intelligence and machine learning using GTMA. Soft Computing, 27(1), 149-156.
22. Tian, H. (2022). Application and analysis of artificial intelligence graphic element algorithm in digital media art design. Mobile Information Systems, 2022(1), 6946616.
23. Li, P. (2021). Research on visual art design method based on virtual reality. International Journal of Gaming and Computer-Mediated Simulations (IJGCMS), 13(2), 1-10.
24. He, L., & Zhu, S. (2022). Virtual reality technology in Visual design of artistic images: Analysis and applications. Scientific Programming, 2022(1), 2527623.
25. Qian, J. (2020, April). Application of VR in art design. In Journal of Physics: Conference Series (Vol. 1533, No. 2, p. 022004). IOP Publishing.
26. Du, W., & Li, Q. (2022). Analysis of the Visual Design and Expression Effect of Virtual Reality and Three-Dimensional Space Technology in Art Space. Mathematical Problems in Engineering, 2022(1), 2065720.