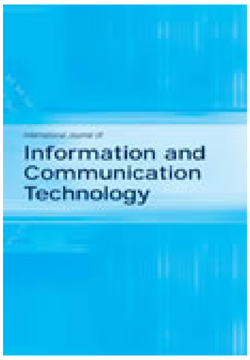


International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642
https://www.inderscience.com/ijict

Analysis of the effect of computer graphics algorithms in reproducing ink painting style in animation

Miaobo Chu, Hao Liu

DOI: 10.1504/IJICT.2025.10070834

Article History:

Received:	11 March 2025
Last revised:	22 March 2025
Accepted:	22 March 2025
Published online:	06 May 2025

Analysis of the effect of computer graphics algorithms in reproducing ink painting style in animation

Miaobo Chu*

School of Design,
Jianghan University,
Wuhan 430056, China
Email: chumiaobo@jhun.edu.cn
*Corresponding author

Hao Liu

School of Artificial Intelligence,
Jianghan University,
Wuhan 430056, China
Email: kyclh411@jhun.edu.cn

Abstract: Modern animation has adopted ink painting as an expressive medium thanks to its original presenting methods and artistic results. A major difficulty in the world of computer graphics is how to replicate the creative style of ink painting in dynamic animation, notably to preserve its brush strokes, halo effect and ink intensity fluctuations. Aiming at duplicating the artistry of ink painting in dynamic situations through image processing and animation generation techniques, we present in this work a method to imitate the style of ink painting based on computer graphics algorithms and introduce graph neural network (GNN). According to the experimental results, the suggested approach can handle style transitions in animation sequences in addition to realising ink painting style migration on stationary images. At last, this work examines the restrictions of the technology and offers recommendations for further paths of ink painting style reproduction.

Keywords: computer graphics; graph neural network; GNN; animation; ink painting style.

Reference to this paper should be made as follows: Chu, M. and Liu, H. (2025) 'Analysis of the effect of computer graphics algorithms in reproducing ink painting style in animation', *Int. J. Information and Communication Technology*, Vol. 26, No. 11, pp.38–52.

Biographical notes: Miaobo Chu received her Master's degree in Wuhan University of Technology in June 2014. She is currently a Lecturer at the School of Design in Jianghan University. Her research interests include computer graphics, animation design, design foundation and art theory.

Hao Liu received her Master's degree in Shenzhen University in June 2014. She is currently an experimenter at the School of Artificial Intelligence in Jianghan University. Her research interests include computer education applications, computer medical applications, artificial intelligence and so on.

1 Introduction

Computer animation production has evolved into one of the fundamental technologies in the world of film, game, virtual reality and so on as computer graphics technology develops rapidly (Li and Li, 2022). Not only is animation production a pile of technologies, but it also combines art and technology to satisfy the visual effect and simultaneously exhibit great artistic expression. Originally a gem of traditional Chinese art, ink painting has progressively evolved into a distinctive technique in modern animation thanks to its unusual expressiveness, changes in intensity, brushstroke representation, mood transmission. With its dynamic qualities, line fluidity, and layer shifts, ink painting offers fresh opportunities for animation production in addition to a form of stationary artistic expression (MacDonald and Wiens, 2019). In the world of computer graphics, how to effectively replicate the visual impact of ink painting in contemporary animation has become a major focus of investigation (Ye, 2021).

High degree of image processing technology is necessary for the reproduction of ink painting style not only for the fundamental duties including texture reconstruction and image style conversion but also for maintaining its artistry in dynamic scenarios (Mao et al., 2022). While transmits emotions through the effects of ink blurring, variations in the weight of the brushstrokes, and the effect of the appropriate shade of light and dark, ink painting lacks clear evidence of brushstrokes like oil paintings or sketches. Past studies have largely concentrated on style conversion of stationary images, investigating how to employ several algorithms to approximate the impression of ink painting since these elements are more difficult to replicate directly using conventional graphics techniques (Ao et al., 2024).

Usually simulating the look of ink paintings by processing the original picture through texture libraries or filtering techniques, traditional ways for duplicating the style of ink paintings mostly depend on image processing and texture mapping methods. When working with complicated photos or movies, these techniques frequently find it difficult to handle dynamic emotion and precise portrayal. Edge detection, colour mapping, and ink texture synthesis, for instance, may readily produce the ink painting appearance on stationary images; nevertheless, their application to dynamic scenarios is more constrained and it is challenging to capture the dynamic changes of ink paints (Liu et al., 2022).

Graph neural networks (GNNs) have been extensively applied in several disciplines recently because their capacity to analyse data with intricate structural linkages (Zhang et al., 2021). GNNs, unlike conventional neural networks (CNNs), record the connections between data by means of graph structure, which is particularly appropriate for feature representation and style reproduction in local areas of images. Especially in animation and dynamic scenes, combining GNNs for ink painting style reproduction can more precisely model the structural information in an image; GNNs can better capture the spatial and structural features in time series, so enhancing the stability and smoothness of style transformation.

While current studies have made some advancement in static picture style transformation, technical difficulties in reproducing ink painting style in animation remain existent. First of all, how can we secure the smoothness and stability of animation while assuring the style replication effect is a pressing issue to be solved since the time and space linkages in dynamic animation are more complicated than those in stationary images. Second, while current style migration techniques mostly depend on deep neural networks, these networks may suffer from high computational complexity and low operational efficiency when handling high-dimensional data and complicated dynamic scenarios.

Thus, using computer graphics techniques and with the advent of GNN, this work suggests an ink painting style reproduction method.

This work has original points of interest as follows:

1 Combining GNN with computer graphics algorithms: The most innovative aspect of this work is the incorporation of computer graphics into the firstly reproducing of the ink painting technique in animation. Computer graphics methods can better process spatial and structural information in images than CNN techniques especially in dynamic scenes and animation sequences demonstrating higher stability and coherence.

2 Dynamic scene reproduction of ink painting styles: While the reproduction of ink painting style in dynamic scenario meets the difficulty of synchronisation in time and space, most of the current ink painting style reproduction techniques concentrate on static images. This work maintains the consistency and smooth transition of ink painting styles by handling complicated animation sequences in addition to style migration on still images.

3 Design and implementation of multilevel GNN: This work constructs a multilevel GNN model capable of simultaneously handling the spatial aspects of the ink painting technique and the dynamic changes of the time series. Although conventional GNNs are generally applied to handle stationary images, our work improves the accuracy and efficiency of style migration by including computer graphics techniques to optimise the spatial structure and temporal dynamics correspondingly at each level.

2 Computer graphics algorithms

Computer graphics algorithms are applied in the reproduction of ink painting styles using a sequence of sophisticated image processing and generating procedures mostly involving image rendering, texture mapping, light modelling and other elements. Among these methods, the most important one is how to replicate, via computer algorithms, the brush strokes, ink diffusion, and light and shadow effects of ink painting. Usually combining the physical rendering of the image with the artistic style modification, computer graphics algorithms help to produce these effects so that the finished artwork can have a visual impact akin to that of conventional ink painting.

Reproduction of the ink painting technique depends especially on the textural depiction of the image (Zhao et al., 2022). Using an image or substance applied to the surface of a 3D model, texture mapping is a technique for approximating the details and surface characteristics of an object. The traditional texture mapping formula follows:

$$v = M \cdot P \tag{1}$$

where v is the final texture coordinate; M is the transformation matrix; P is the original texture coordinate. Usually, texture processing calls for some blurring and detail compression if one wants to replicate the brush strokes of ink paint (Kumar et al., 2019).

Gradually lowering the texture's contrast and sharpness will help one to obtain the 'gradient' effect in the ink style.

Furthermore quite crucial is the application of lighting models. Expression of hierarchy in conventional ink painting depends on the shift of light and shadow (Wu et al., 2022). Usually using the Phong lighting model, the reflection and interaction of light on the surface of an object is simulated; the Phong model has as its formula:

$$I = I_a + I_d \cdot (L \cdot N) + I_s \cdot (R \cdot V)^n \tag{2}$$

where L is the light source direction; N is the normal vector; R is the reflected light direction; V is the viewpoint direction; n is the highlight coefficient; I_a, I_d and I_s are the intensities of ambient, diffuse and specular reflected light correspondingly. Changing these settings helps one to replicate the light and shadow effects in ink painting, therefore strengthening the picture's hierarchy.

Furthermore, the ink dispersion effect in ink painting frequently has to replicate fluid dynamics (Murugaiah and Shahgaldi, 2024). Diffusion equation based techniques are applied to replicate the ink diffusion process. One often used model is the heat conduction equation:

$$\frac{\partial u}{\partial t} = \alpha \nabla^2 u \tag{3}$$

where ∇^2 is the Laplace operator; u is the ink's concentration distribution; α is the diffusion coefficient. Solving this equation helps one to achieve the ink diffusion on paper, therefore replicating the natural flow effect of ink.

Besides, the ink painting technique depends much on edge detection (Wang et al., 2018). Sobel operator can be applied to identify the image margins so stressing the brush strokes in ink painting. Sobel operator has the equation like this:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{4}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{5}$$

$$G = \sqrt{G_x^2 + G_y^2} \tag{6}$$

The gradient and mixing technique of colours is really crucial in the colour depiction of ink painting (Sochorová and Jamriška, 2021). Through variations in colour depth and intensity, ink painting often shows several emotions and feeling of hierarchy. In computer graphics, the RGB or HSV model often denotes the colour mixing (Kusnandar et al., 2024). The RGB model uses a colour mixing formula like this:

$$C_{\text{out}} = C_1 \cdot (1 - \alpha) + C_2 \cdot \alpha \tag{7}$$

where C_{out} is the colour obtained by mixing; C_1 and C_2 are correspondingly two colours; α is the transparency coefficient. In ink painting, one can obtain the gradient colour effect by adjusting the colour mixing.

Furthermore important for better simulation of the brush strokes in ink painting is their production and control (Huang et al., 2019). One can create random strokes with customisation by means of a tailored random method. The random walk method can help one replicate the strokes' naturalism and randomness. The random walk method has this formula:

$$x_{n+1} = x_n + \Delta x \tag{8}$$

$$y_{n+1} = y_n + \Delta y \tag{9}$$

where Δx and Δy are the random steps; x_n and y_n are the current coordinates of the brushstrokes. Random distribution of strokes can thus be produced to replicate the diversity in ink painting.

Moreover, an essential method in ink painting replication is also multiple mapping and texture overlapping (Yue, 2022). Usually, the multiple texture mapping technique – layering several photos together to replicate the various hues and ink levels-helps one to make the image more artistic.

By altering the texture resolution to fit various display needs, multi-level detail (LOD) techniques may now be applied to maximise the detailed representation of the image.

At last, the reproduction of the ink painting style depends much on the anti-aliasing method of the image. Commonly used anti-aliasing techniques like oversampling and subsampling methods guarantee the smoothness of image edges. Supersampling has the following formula:

$$I_{\text{final}} = \frac{1}{N}\sum_{i=1}^{N} I_{\text{sampled,i}} \tag{10}$$

where I_{final} is the last anti-aliased picture; $I_{\text{sampled,i}}$ is the pixel value of the i^{th} sample point; N is the total number of sample points. Boosting the sample count helps to efficiently lower the jagged phenomenon in the image, so smoothing the ink painting edges and boosting their naturalness.

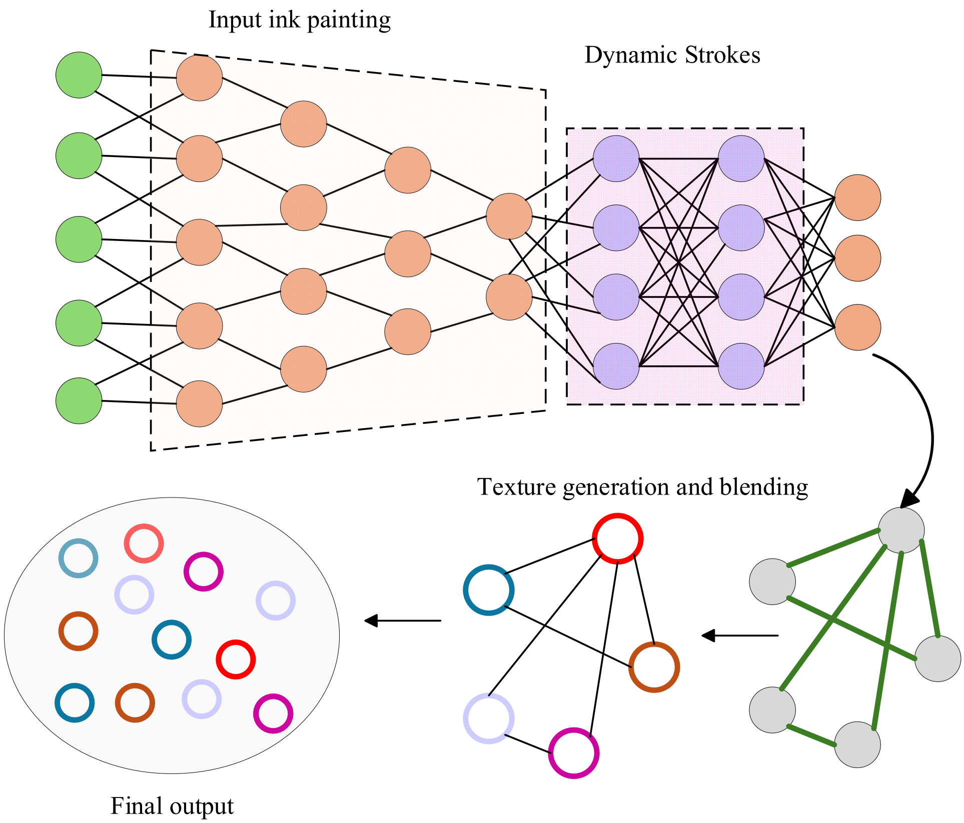
Involving techniques ranging from texture mapping to lighting models, from diffusion equations to edge detection, spanning all facets of image synthesis, processing, and rendering, computer graphics algorithms essentially play a key part in the replication of ink painting styles. By means of rational use of these techniques, computers can replicate creative effects like to those of conventional ink paintings and accomplish an artistic union between the virtual and the real.

3 A framework for reproducing ink painting style in animation

This chapter will walk over how computer graphics techniques allow one to replicate the ink painting style in animation. See Figure 1 for the different modules that make up the overall framework: ink painting style rendering, dynamic stroke and ink simulation, texture production and fusion, and output and optimisation of animation effects.

Particularly, this work presents the GNN, which uses its benefits in spatial relation learning and dynamic effect generation to improve the reproduction of ink painting style in animation.

Figure 1 Ink painting style reproduction framework in animation (see online version for colours)



3.1 Ink-and-wash style rendering

Ink painting has stylistic elements like changes in the thickness of the brush strokes, slow tonal changes, and ink flow (Sarkar, 2022). This work uses techniques based on image rendering algorithms, in particular the use of colour dithering and multi-layer rendering, so as to duplicate the blurring and rendering effects of ink in each frame of the image, so attaining this style in animation. First, a grey scale based filter simulates the ink penetration effect by processing the picture.

By adding some random changes in the grey scale value space of the image, this study can produce the overall rendering similar to the delicate texture in the ink painting assuming that the colour value of each pixel point of the image is $C(x, y)$. The Colour Dithering technique helps in this regard. The formula is:

$$C(x, y)_{\text{new}} = C(x, y) + \Delta C(x, y)$$

$$C(x, y)_{\text{new}} = C(x, y) + \Delta C(x, y) \tag{11}$$

where $\Delta C(x, y)$ is the noise produced by a dithering function modelled by varying paper degrees of ink absorption and permeability. This technique will create an ink halo effect in every animation frame, therefore mimicking the natural ink flow on paper.

3.2 Dynamic stroke and ink simulation

The simulation of brush strokes is one of the main elements allowing animation to replicate the ink painting technique. Often depending on the wetness of the ink, the pressure of the brush tip, and the movement trajectory of the brush, brush strokes in ink paintings sometimes show fluidity and gradient effects. This work uses an algorithm based on particle systems and physical simulation to replicate the flow, penetration, and diffusion events of ink, so efficiently simulating this process.

Ink penetration is modelled by a particle system. This work assigns several particles to each stroke or ink mark in every frame, and each particle replicates the diffusion process of ink on a two-dimensional plane depending on its flow law (Hossain et al., 2020). The particle updating equation is:

$$r_i(t+1) = r_i(t) + v_i(t) \cdot \Delta t + a_i(t) \cdot \Delta t^2 \tag{12}$$

$$v_i(t+1) = v_i(t) + a_i(t) \cdot \Delta t \tag{13}$$

where $a_i(t)$ is the acceleration of the particle; $r_i(t)$ is its position at time t; $v_i(t)$ is its speed; Δt is the time interval. The particle system allows one to faithfully replicate the natural diffusion and penetration process of ink on various surfaces.

Simulating ink penetration combines hydrodynamic model to replicate ink flow and moist diffusion on the paper surface (Yin et al., 2018). One may characterise the dispersion of ink by use of the following equation:

$$\frac{\partial C(x, y, t)}{\partial t} = D \cdot \nabla^2 C(x, y, t) + S(x, y, t) \tag{14}$$

where D is the diffusion coefficient of the ink; $\nabla^2 C$ is the Laplace operator of the concentration; $S(x, y, t)$ is the source term, therefore indicating the injection process of the ink at position (x, y).

This work introduces GNN to improve the ink diffusion model so more faithfully simulating the natural law of ink flow. Every ink particle is considered as a node of the graph, and edges define the link among the nodes (Natsiopoulos et al., 2019). GNN can learn the spatial link between ink particles and their diffusion patterns, so guiding the ink flow towards more natural and delicate direction.

Graph convolution of a neural network is computed as:

$$H^{(k+1)} = \sigma\left(\hat{A} H^{(k)} W^{(k)}\right) \tag{15}$$

where $\hat{A}$ is the normalised adjacency matrix, which shows the link between the particles; $W^{(k)}$ is the weight matrix obtained via learning; $H^{(k)}$ is the node feature matrix of the k^{th} layer, which denotes the state of the ink particles. σ is the activation function. By means of multi-layer graph convolution, the GNN learns and optimises the ink diffusion pattern, so enabling more delicate and consistent with artistic expression of ink painting dynamic strokes and ink simulation.

3.3 Texture generation and fusion

Ink painting expresses not only the flow of ink but also one of its main characteristics – paper texture. The production and integration of texture defines the detail performance and texture of the picture in the animation of ink painting technique. This work uses GNN and Perlin noise combining approach to replicate the textural effect of ink painting paper.

Perlin noise has a generating formula like this:

$$P(x) = \sum_{i=1}^{n} \alpha_i \cdot cos\left(2\pi \cdot f_i \cdot x + \theta_i\right) \tag{16}$$

where α_i is the amplitude of every noise layer; $P(x)$ is the result of the texture pattern; f_i is the frequency; θ_i is the phase. Changing these settings produces a natural and variable paper texture that enhances the realism of the ink drawing impact.

Following texture generation, this work uses GNN to maximise the fusion of several textures. Every texture block is shown as a node in the graph, and graph convolution helps one to learn the interrelationships among several textures. This guarantees a natural change of the textures and helps the animation to have a more detailed ink-and-paper feel.

Texture combines with ink concentration in the following manner:

$$I_{\text{final}}(x, y) = \sum_{i=1}^{n} T_i(x, y) \cdot M_i(x, y) \tag{17}$$

where $T_i(x, y)$ is the i^{th} layer texture value; $M_i(x, y)$ is the matching ink concentration map. To create an image with ink painting influence, the texture and ink images of every layer are progressively layered at several rendering phases.

3.4 Animation output and optimisation

This work integrates crucial frame interpolation and smoothing methods to maximise the animation and guarantee the natural flow of the produced ink drawing effect. And it reduces leaps or unnatural transitions and produces a visually smoother animation by interpolating between keyframes, therefore enabling a seamless transition of the ink strokes.

Further, It presents a bilateral filtering technique to smooth the image and preserve the sharpness of the ink stroke details, so optimising the animation effect (Gao et al., 2019). By concurrently doing weighted averaging in the spatial and colour domains, bilateral filtering reduces noise and efficiently retains edge information. Bilateral filtering has as its formula:

$$I_{\text{output}}(p) = \frac{1}{W_p} \sum_{q \in \Omega} \exp\left(-\frac{\| p - q \|^2}{2\sigma_d^2}\right) \exp\left(-\frac{\| I(p) - I(q) \|^2}{2\sigma_r^2}\right) I(q) \tag{18}$$

This helps to efficiently smooth the ink effect in the dynamic picture to improve the artistic sense and animation's smoothness.

At last, the animation effect gets evaluation and optimisation. This work quantifies the influence of every frame using conventional picture quality assessment measures including structural similarity index (SSIM) and peak signal-to-noise ratio (PSNR), so ensuring that the generated ink painting style animation satisfies the expectation (Pérez-Delgado Celebi, 2024). The SSIM and PSNR calculations follow here:

$$SSIM(x, y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)} \tag{19}$$

$$PSNR(x, y) = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE(x, y)}\right) \tag{20}$$

This work can quantitatively assess the animation effect depending on SSIM and PSNR by means of comparison between the ink painting style animations produced by several techniques. Furthermore, adding the hand subjective evaluation guarantees that the final output animation achieves the intended artistic effect, so optimising the visual smoothness and ink effect of the animation.

4 Experimental results and analyses

4.1 Datasets

Two publicly available real datasets are used in this work to validate the efficiency of the suggested computer graphics technique for animation watercolour painting reproduction. Suitable for image style conversion activities, the first dataset is Watercolour image Dataset, which features many watercolour painting style images. Comprising artworks from artists all around the world encompassing a broad spectrum of art genres, including ink painting, the second collection is the WikiArt collection. Especially in the optimisation of keyframe interpolation and animation transition effects, this dataset not only offers a great number of artworks for the reproduction of ink painting styles but also helps to test the application in the creation of dynamic ink painting effects.

These two datasets are exemplary described in Tables 1 and 2.

These two datasets offer a great variety of image samples and artistic styles, which helps this work to evaluate and maximise the algorithm in depth for replication of ink painting style in animation in the framework of several ink painting styles.

Table 1 Watercolour image dataset information

Index	*Image ID*	*Original Image*	*Style transformed image*	*Label*
1	img001	original1	watercolour1	Landscape
2	img002	original2	watercolour2	Animal
3	img003	original3	watercolour3	Portrait
4	img004	original4	watercolour4	Floral
5	img005	original5	watercolour5	Cityscape

Table 2 WikiArt dataset information

Index	*Artwork ID*	*Category*	*Style*	*Artist*	*Label*
1	art001	Landscape	Ink painting	Zhang Daqian	Landscape
2	art002	Animal	Ink painting	Qi Baishi	Animal
3	art003	Portrait	Modern ink	Xu Beihong	Portrait
4	art004	Floral	Ink painting	Wu Changshuo	Floral
5	art005	Traditional	Ink painting	Tang Bohu	Ink painting

4.2 Evaluation of the effect of reproducing ink painting style in animation

The major objective of this project is to assess how well computer graphics techniques replicate the ink painting style in animation. First picked in the testing method were sample key frames and continuous frames covering landscapes, people, and dynamic scenes. The effect was assessed using two indices, SSIM and PSNR once the algorithm transformed these key frames and sequential images into ink painting style graphics. PSNR is used to evaluate the pixel difference between the generated image and the original image; the higher PSNR value indicates that the reproduction effect of ink painting style is better; PSNR is used to evaluate the structural similarity between the generated image and the original image; hence, the higher the value indicates that the reproduction effect of ink painting style is better in animation than in the original image. The pixel difference between the created image and the source image is assessed using PSNR; a higher PSNR value denotes better quality of the resulting ink painting style image. This work efficiently quantifies the impact of the algorithm in duplicating the ink painting style in dynamic animation by computing the SSIM and PSNR values of several frames.

Figures 2 and 3 respectively demonstrate the experimental outcomes.

The results reveal that the ink painting style replication preserves a great degree of structural similarity since the SSIM values of all the frames in Watercolour Image Dataset are rather near to each other, ranging from 0.71 to 0.95. The PSNR values, however, vary somewhat, ranging from a low of 28.12 to a high of 36.66, so suggesting that the pixel quality of the image changes and signalling that the frame preserves both higher structural integrity and lesser distortion in the ink painting style replication.

The SSIM values of the WikiArt Dataset are usually high, ranging from 0.79 to 0.95, showing that the picture quality of this dataset preserves a certain degree of stability and the ink painting style is replicated more precisely. Conversely, the PSNR values are better balanced, ranging from lowest of 30.21 to maximum of 37.88, thereby indicating that the image quality is good and that the ink painting technique has been best realised.

Collectively, the testing findings reveal that during the conversion of animation frames, the suggested ink painting style reproduction algorithm can sufficiently preserve high picture quality and structural integrity. Though the SSIM and PSNR values vary somewhat depending on the dataset and frame, overall the results demonstrate that the technique can produce acceptable reproduction in some settings, particularly in landscape animation.

Figure 2 Evaluation of ink painting style reproduction on watercolour image dataset (see online version for colours)

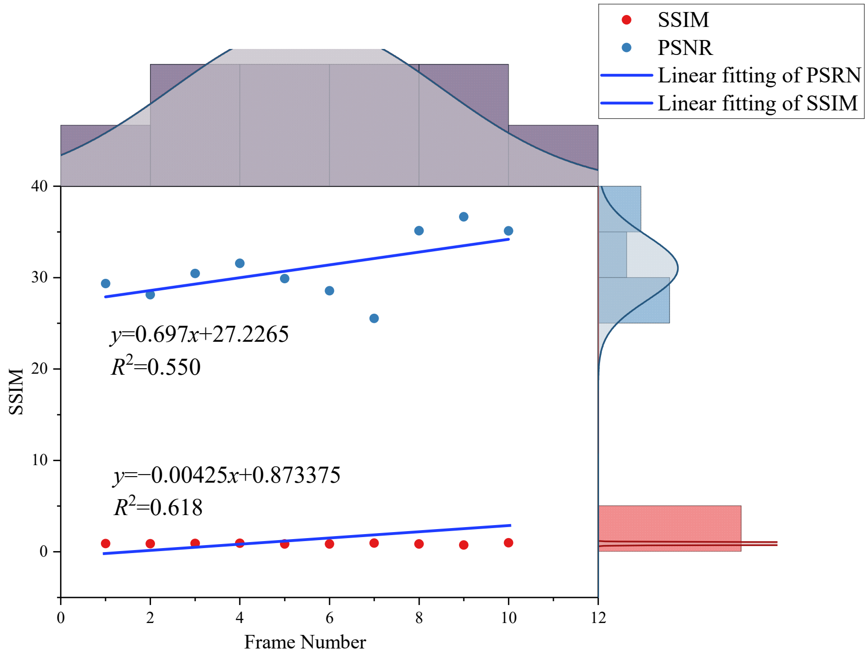
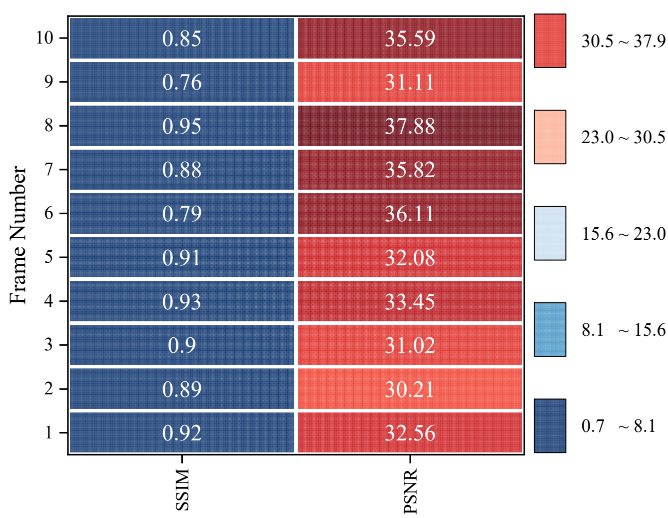


Figure 3 Evaluation of ink painting style reproduction on WikiArt dataset (see online version for colours)



4.3 User perception assessment of ink painting style reproduction

This work evaluates the efficiency of the algorithm in ink painting style replication by means of user perception assessment in experiment 2. A total of 500 participants –

including students and professionals in the domains of computer graphics, art design and animation production – were recruited to guarantee the completeness and dependability of the experimental results. Every participant assessed the effectiveness of the algorithmically produced animation frames in faithfully imitating the ink painting technique. The rating scale was divided into five levels: very good, good, fair, poor, and extremely poor to help to improve the assessment criteria.

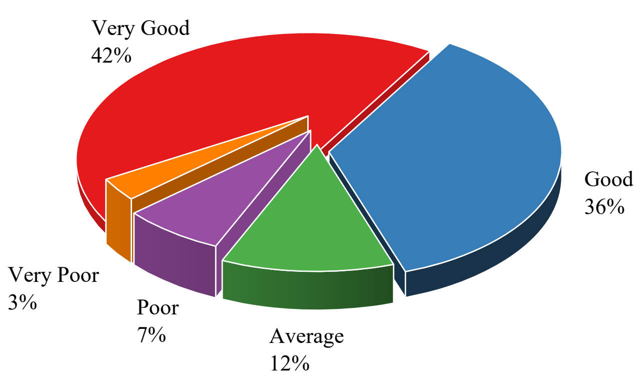
Participants in this experiment had to make a thorough assessment grounded in the following elements: the ink colour hierarchy in the animation frames, line smoothness, image ink painting texture, and general artistic performance. Defining the scoring criterion, respectively:

- Very good: the style is quite rich and lifelike in detail, highly exact and near to traditional ink painting.
- Good: although the details are little rough, the technique reflects the major traits of ink painting, such ink gradation and line texture.
- Fair: Although the parts of the ink painting are clear and the technique is rather good, the general performance is unsatisfactory lacking in delicate brushwork and detail.
- Poor: The image is not properly layered and textured, and the style is not faithfully replicated lacking the basic traits of ink painting.
- Very poor: the image quality is clearly below expectations, the style replication is absolutely lacking the style of ink painting, and lacks the artistic quality that ink painting should have.

For the experiment, several animation frames from Watercolour Image Dataset and WikiArt dataset were chosen covering various style reproduction effects. During the experiment, participants saw these frames and scored each one based on the given standards. Every participant separately scored each frame; the individual scoring data were then compiled to determine the percentage of every scoring category.

Figures 4 and 5 present the experimental outcomes.

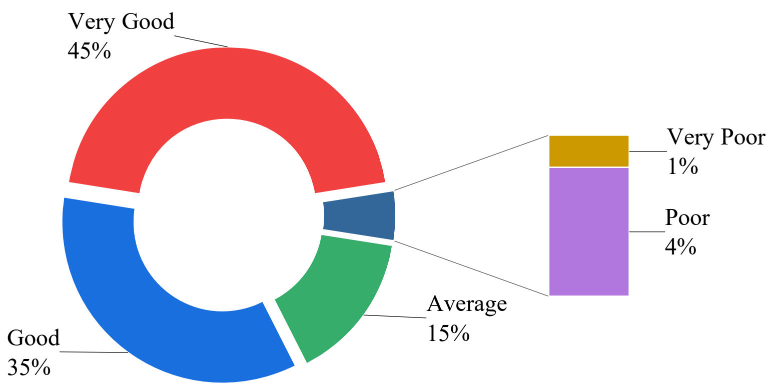
Figure 4 User perception evaluation on watercolour image dataset (see online version for colours)



42% of the animation frames from the Watercolour Image Dataset were judged as ‘very good’, meaning that these frames displayed a great degree of ink painting texture in the style reproduction. By contrast, the WikiArt Dataset frames also exhibit superior results; 45% of the frames are assessed as 'very good'. This indicates that the method can efficiently and reasonably replicate the ink painting technique and manage several kinds of visual data.

Overall, the participants' subjective evaluation of the suggested ink painting style reproduction algorithm on several datasets shows that most of the animation frames were able to effectively depict the artistic style of ink painting with a positive subjective evaluation. This experiment offers insightful user-perception input to help to maximise and support the ink painting style replication approach.

Figure 5 User perception evaluation on WikiArt dataset (see online version for colours)



5 Conclusions

Our computer graphics algorithm-based technology replicates ink painting style in animation. Our framework and GNN included ink painting style feature extraction, style change, and optimisation, and we tested the method on several datasets to prove its efficacy and adaptability. The suggested method has high user ratings and can recreate the ink painting style while maintaining animation smoothness, according to experiments.

Even though this effort has improved ink painting animation, there are still limitations. First, even if GNN maximises style transforming effect, style replication in increasingly complex dynamic animation contexts is less stable and smooth. Long animation sequences can undermine the authenticity of dynamic transitions and the stability of ink painting. Second, except for highly interactive animation and real-time rendering, this paper largely processes stationary animation frames and lacks efficiency and optimisation in dynamic circumstances. Finally, while GNN offers a new technique to style reproduction, more research is needed to improve the network model to better portray ink paintings' abstract creative features.

Future studies can be broad in the following respects:

1 Improving the stability and smoothness of style reproduction in dynamic scenes: Future research can improve the style transition effect in dynamic scenarios to keep the ink painting style consistent and natural over many time periods and conditions

with large frame variations. To achieve real-time rendering and high frame rate requirements, animation ink painting style performance must be optimised.

2 Improving the combination of subjective and objective evaluation systems: This research used objective evaluation indices like SSIM and PSNR for experimental validation, yet the style reproduction effect of ink painting is not merely measured by these quantitative indexes. Future studies should study more objective-subjective assessment methods to better determine the style reproduction effect. Combining users' perceptual evaluation with picture quality indicators creates a more complete assessment method.

3 Research on more diversified art style reproduction methods: Though art style reproduction is a broad issue, this study focuses on ink painting. To expand the library of art styles, future studies can replicate the styles of other traditional art forms (e.g., oil painting, drawing, printmaking) and explore how to incorporate several artistic expressions into animation.

In conclusion, while this study has advanced, many aspects still need thorough analysis and improvement. Future research can promote the development of this field and provide more effective and expressive tools and methods for ink painting style reproduction in art creation, animation production, and virtual reality by developing computer graphics, GNN, and art style reproduction technology.

Declarations

All authors declare that they have no conflicts of interest.

References

Ao, J., Ye, Z., Li, W. and Ji, S. (2024) 'Impressions of Guangzhou city in Qing dynasty export paintings in the context of trade economy: a color analysis of paintings based on k-means clustering algorithm', *Heritage Science*, Vol. 12, No. 1, p.77.

Gao, J., Li, D. and Gao, W. (2019) 'Oil painting style rendering based on kuwahara filter', *IEEE Access*, Vol. 7, pp.104168–104178.

Hossain, S., Fuwad, A., Kim, K-Y., Jeon, T-J. and Kim, S.M. (2020) 'Investigation of mixing performance of two-dimensional micromixer using Tesla structures with different shapes of obstacles', *Industrial & Engineering Chemistry Research*, Vol. 59, No. 9, pp.3636–3643.

Huang, L., Hou, Z-X., Zhao, Y-H. and Zhang, D-J. (2019) 'Research progress on and prospects for virtual brush modeling in digital calligraphy and painting', *Frontiers of Information Technology & Electronic Engineering*, Vol. 20, No. 10, pp.1307–1321.

Kumar, M.P., Poornima, B., Nagendraswamy, H. and Manjunath, C. (2019) 'A comprehensive survey on non-photorealistic rendering and benchmark developments for image abstraction and stylization', *Iran Journal of Computer Science*, Vol. 2, pp.131–165.

Kusnandar, T., Santoso, J. and Surendro, K. (2024) 'Enhancing Color Selection in HSV Color Space', *Ingenierie Des Systemes d'Information*, Vol. 29, No. 4, p.1483.

Li, L. and Li, T. (2022) 'Animation of virtual medical system under the background of virtual reality technology', *Computational Intelligence*, Vol. 38, No. 1, pp.88–105.

Liu, G., Yu, T., Yao, Z., Xu, H., Zhang, Y., Xu, X., Xu, X., Gao, M., Sun, Q. and Zhang, T. (2022) 'ViviPaint: Creating dynamic painting with a Thermochromic Toolkit', *Multimodal Technologies and Interaction*, Vol. 6, No. 8, p.63.

MacDonald, S. and Wiens, B.I. (2019) 'Mobilizing the "multimangle": why new materialist research methods in public participatory art matter', *Leisure Sciences*, Vol. 41, No. 5, pp.366–384.

Mao, W., Yang, S., Shi, H., Liu, J. and Wang, Z. (2022) 'Intelligent typography: artistic text style transfer for complex texture and structure', *IEEE Transactions on Multimedia*, Vol. 25, pp.6485–6498.

Murugaiah, D.K. and Shahgaldi, S. (2024) 'Recent progress in understanding the dispersion stability of catalyst ink for proton exchange membrane fuel cell and water electrolyzer', *International Journal of Hydrogen Energy*, Vol. 66, pp.156–169.

Natsiopoulos, I., Intzes, S., Liappis, T., Zarampoukas, K., Zarampoukas, T., Zacharopoulou, V. and Papazisis, K. (2019) 'Axillary lymph node tattooing and targeted axillary dissection in breast cancer patients who presented as cN+ before neoadjuvant chemotherapy and became cN0 after treatment', *Clinical Breast Cancer*, Vol. 19, No. 3, pp.208–215.

Pérez-Delgado, M-L. and Celebi, M.E. (2024) 'A comparative study of color quantization methods using various image quality assessment indices', *Multimedia Systems*, Vol. 30, No. 1, p.40.

Sarkar, A. (2022) 'Painted spaces: an exploration through embodied and expansive practice', *Journal of Visual Art Practice*, Vol. 21, No. 3, pp.195–216.

Sochorová, Š. and Jamriška, O. (2021) 'Practical pigment mixing for digital painting', *ACM Transactions on Graphics* (*TOG*), Vol. 40, No. 6, pp.1–11.

Wang, L., Gong, X., Zhang, Y., Xu, P., Chen, X., Fang, D., Zheng, X. and Guo, J. (2018) 'Artistic features extraction from Chinese calligraphy works via regional guided filter with reference image', *Multimedia Tools and Applications*, Vol. 77, pp.2973–2990.

Wu, K., Fu, X-M., Chen, R. and Liu, L. (2022) 'Survey on computational 3D visual optical art design', *Visual Computing for Industry, Biomedicine, and Art*, Vol. 5, No. 1, p.31.

Ye, F. (2021) 'Application of photoshop graphics and image processing in the field of animation', *Journal of Sensors*, Vol. 2021, No. 1, p.8677479.

Yin, X., Aslannejad, H., De-Vries, E., Raoof, A. and Hassanizadeh, S. (2018) 'Droplet imbibition into paper coating layer: pore-network modeling simulation', *Transport in Porous Media*, Vol. 125, No. 2, pp.239–258.

Yue, X. (2022) 'Image layout and schema analysis of chinese traditional woodblock prints based on texture and color texture characteristics in the environment of few samples', *Computational Intelligence and Neuroscienc*e, Vol. 2022, No. 1, p.8008796.

Zhang, X-M., Liang, L., Liu, L. and Tang, M-J. (2021) 'Graph neural networks and their current applications in bioinformatics', *Frontiers in Genetics*, Vol. 12, p.690049.

Zhao, Y., Samuel, R.D.J. and Manickam, A. (2022) 'Research on the application of computer image processing technology in painting creation', *Journal of Interconnection Networks*, Vol. 22, No. Supp05, p.2147020.