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AI technology-assisted oil painting traditional techniques modernization innovation path research

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SUMMARY: *Accompanied by the rapid development of today's AI technology, the combination of science and technology and art has led to the emergence of numerous oil paintings with AI technology as the creative carrier and expressive medium. On the basis of elaborating the application value of traditional techniques of oil painting, the article analyzes the performance of traditional techniques of oil painting empowered by AI technology. Then, a deep deterministic gradient algorithm based on Actor-Critic framework is used to establish a simulation model of oil painting strokes, and weighted least squares filtering is used to extract the edges of the strokes and realize the rendering of oil painting strokes. Based on the model training, simulation analysis and subjective research are carried out, and the results show that the oil painting stroke simulation model scores better on the FID and LPIPS indexes, and the model rendering efficiency is faster, and more than 80% of the users are satisfied with the oil painting stroke simulation results. Therefore, combining AI technology with traditional techniques of oil painting can provide new methods for innovative oil painting strokes, and can also present diverse oil painting techniques through new forms, helping painters to generate more innovative inspiration for oil painting.*

KEYWORDS: *AI technology; deep deterministic gradient algorithm; weighted least squares filtering; oil painting brushstroke simulation*

1 Introduction

With the continuous progress of Artificial Intelligence (AI) technology, the application of AI in art creation has become more and more widespread.AI-assisted painting not only simulates the style of human artists, but also generates unique works of art through complex algorithms [1]. This technological innovation has had a profound impact on traditional oil painting art. In this context, it is of great significance to explore the impact of AI on traditional oil painting art and its modernization and innovation path. On the one hand, AI technical assistance has brought new creative tools and methods to traditional oil painting [2]; on the other hand, it has restricted the creative process of artists, aesthetic standards, and changed the pricing of paintings in the art market in a certain sense [3].

AI means binding individual consciousness with standardized and homogenized technological paradigms, shaking the subjectivity of painting. The relationship of technique in painting has always been discussed as a subject, but in a technologically oriented society, technique in painting has developed into a way of doing things or a state of mind [4, 5]. The core advantage of AI in oil painting is its ability to dissolve the technical thresholds of complex painting techniques and revolutionize and optimize the process [6]. Henrickson, L argues that

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AI-assisted painting is a work of art created by a computational system through a degree of autonomy, in which the system is able to perceive environmental inputs and make decisions based on those inputs, thereby influencing the form of the final presentation [7]. Essentially, AI-assisted painting is a process of analyzing the visual characteristics of a large number of artworks, parsing the content composition and stylistic elements, and ultimately generating new image results [8]. In their review, Rani, S et al. noted that Edmond de Belamy, a portrait created by Generative Adversarial Network (GAN) technology, fetched $432,500 at Christie's, a stage when, thanks to breakthroughs in deep learning technology, the system was able to generate more realistic works by analyzing image databases, and marking the formal entry of AI art into the mainstream [9].

When technological empowerment makes material operation more convenient, and visual language breaks through the limitations of creators' experience, it is necessary to be alert to the possibility that the framework produced by technology may produce blindness [10]. AI rewrites individual thinking and cognition, and when creators are confronted with a brand-new technology and can rely on it, silent domestication has already taken place, and the subject is no longer deeply involved in the process of creating paintings, and the role of the subject is only embodied in injecting aesthetic concepts and judgments [11, 12]. An experiment by Hong, J W and Curran, N M on the comparison between human artists and AI artists found that AI art based on algorithmic logic is essentially just a kind of “imitation”, which lacks the creative characteristics of human art [13]. In addition, Tao, W et al. found that when AI paintings show high anthropomorphism and creative autonomy, individuals will increase their perception of the system's functionality, and will be willing to give the generated paintings “high scores” and identify with their “painter” identity [14]. As a “thinker”, oil painting creators can deeply explain the dilemmas of the times and the spiritual world, but when AI intervenes in oil painting, human comprehension and adaptability are lost, and the works are produced in the process of setup and manipulation, which is essentially devoid of the kernel of autonomous expression of the author [15].

Oil paintings directly reflect the ideological dimension and spiritual level of their creators, inherently possessing a measure of reflection on the self. AIthough it can imitate the characteristics of all other art forms, as well as the ability to express the conceptual art form, placing the perceptual relationship between the individual and the object in the laws of digitalized counterparts, it is equally confronted with the realistic dilemma of how to aesthetize the aesthetics of the art form [16]. A research study by Xu, J et al. showed that hedonic motivation, perceived trust, perceived usefulness to the user, and perceived ease of use are the main factors that make creators willing to adopt AI technology to assist in the creation of paintings [17]. Therefore, to a certain extent, the “fourth wall” broken by AI technology still needs to be filled, and the narrowing of the distance between the work and the viewer is due to the mechanical execution of the program instructions, rather than from the need for social observation and emotional expression, and thus the real meaning of the work is lacking and ambiguous, and it does not convey an aesthetic attitude. Shen, Y and Yu, F believe that the assistance of AI technology makes painting art creation become richer and richer, and the expression of content becomes intelligent, interactive and data-driven, and the relationship between technology, art and people becomes increasingly close [18]. On the other hand, AI-assisted oil painting creation can accumulate a large amount of material by virtue of algorithms, but its breakthrough of the traditional aesthetic framework is not based on the establishment of a new aesthetic system, which leads to a vacuum in aesthetic interpretation [19]. Liu, X argues that the mechanical nature of AI painting's own expressive methods limits its diverse choices of painting materials and the setting of brushstroke parameters, so that the artworks it creates cannot achieve the kind of vivid and humanized expressive style of traditional painting [20].

Leiser, A and Schlippe, T argue that AI painting is essentially a process that mimics human painting, which involves aspects such as position, sequence, shape, color, and contour of the drawn area, and that AI can set aesthetic gaps when exploring the boundaries of intervention, removing algorithmic optimization on processes that facilitate the formation of aesthetics [21]. Li, L discusses Disco diffusion, an open-source AI painting creation project whose unconditional openness and greater extensibility have piqued the interest of art enthusiasts, and analyzes the current impact of AI art creation on artists and contemporary art [22].

The article establishes a model-based DDPG algorithm and applies it to the oil painting stroke simulation model, and combines weighted least squares filtering and LICDoG preprocessing algorithms for oil painting stroke style rendering. The effectiveness of the application of the oil painting brushstroke simulation model is analyzed through the dimensions of model training, objective evaluation and subjective user research. This study aims to enhance the expression method of traditional techniques of oil painting, and also provides a new research path for the deep integration of AI technology and traditional techniques of oil painting.

2 AI technology empowers the innovation of traditional techniques of oil painting

Artificial Intelligence (AI) technology immersed in the field of art creation, so that the contemporary art field presents a new ecological landscape, oil painting is also difficult to escape the impact of artificial intelligence, not only from the way of art creation and the way of viewing, but also from the cultural value, the way of dissemination and so on, affecting the creation of oil painting as a “pure art”. Therefore, discussing the modernization and innovation of traditional techniques of oil painting with the assistance of AI technology will help to better promote the depth of AI and oil painting techniques, and further realize the innovation of traditional oil painting.

2.1 Categories of Traditional Techniques in Oil Painting

As people's scientific and cultural knowledge continues to improve and social science and technology continues to progress, the creation of paintings, people have gradually increased a wider and wider range of oil painting techniques, and traditional oil painting techniques as a benchmark, adding a new element, prompting the transformation of oil painting techniques to more personalized and diversified. Traditional oil painting techniques mainly include:

(1) Flat painting method. In the production process of oil painting, flat painting method generally refers to the process of creating oil paintings, first of all, scientifically select the base color, mostly brown, gray, etc., after completing the base color processing, you can carry out deep painting processing.

(2) Transparent painting method and non-transparent painting method. Transparent painting method refers to the use of color mixing oil to dilute the pigment, and then constantly carry out multi-frequency depiction, in this process, there is no need to apply white, prompting the works in the color rendering has excellent transparency. In the non-transparent painting method, first of all, you need to use monochrome to draw the form of the painted scenery, and then choose different colors to complete the layered shaping, the dark part of the paint is generally thinner, and the bright part of the painting will be thickly coated.

(3) Comprehensive painting method. Creators need to regulate and carefully deal with the overall color, and then more reasonable application of color in the whole work, to enhance the artistic expression of the work to the maximum extent.

(4) Scatter Painting Method. Scatter painting refers to a kind of brushwork that separates

the strokes and reveals the strokes, but the overall color layer of the oil painting does not have an obvious difference between thin and thick. Most of this oil painting technique needs to intuitively deal with the light and dark of the work, so that all the bright parts of the oil painting can be more prominent.

2.2 The value of applying oil painting techniques

(1) Expanding the language of expression and aesthetic depth. The updating of oil painting techniques enables the composite expression of images on multiple levels of structure, color and texture, thus significantly expanding the narrative dimension and sensory experience of creation. Effective application of techniques establishes a stable chain from observation to transformation through the synergy of "structure-color-material", so that the works can strike a balance between accurate modeling, unity of light and imagery, and maintain stable quality control and reproducibility in multiple creations of the same theme.

(2) Promote material innovation and technology inheritance. The development history of oil painting is itself a history of material science and technology. Tiny changes in the type of resin, pigment particles, binder ratio, primer absorption and varnish formula will all affect the color reproduction, interlayer adhesion and durability. The prerequisite for effective application is to carry out bounded material experiments on the basis of respecting the process chain.

(3) Connecting art education and creative practice. Effective application does not exclude individuality, but exchanges methodological stability for freedom of expression, enabling learners to form "controlled contingencies" between regularity and contingency. This enables learners to form "controlled contingencies" between the regular and the occasional, so that the transformation from subject to project can be accomplished more quickly in creation and practice, the ability of collaborative communication and cross-media cooperation can be enhanced, and the connection between art and society can be expanded.

2.3 AI-enabled oil painting technique performance

As painting in the traditional sense, we usually focus on the pictoriality of a work. The so-called painterly nature is in fact a myriad of visual experiences constructed by countless brushstrokes dipped in paint, and the diversity and combination of brushstrokes essentially determines the richness of the painterly nature of this piece of work. Empowered by AI technology, a huge number of possibilities of brushstroke combinations can be listed in a few seconds, which can be unfolded on a flat surface in the form of a map, allowing the artist to have a full view of all the visual possibilities.

To a certain extent, for artists in a creative bottleneck, once they get used to a certain combination of brushstrokes, it is also a period of stagnation and repetition of painting techniques and expressions. In order to break through the creative bottleneck and produce new visual effects, it is necessary to break through these habitual techniques so as to find new pictorial visual effects. In this case, then, the introduction of AI technology may shorten the time of this quest to a great extent. Through AI technology, the artist can keep combining and arranging, and from all the databases, list out all kinds of possibilities of combining and arranging, and show them in front of their eyes instantly. However, this does not mean that the artist can give up the concept of the creative subject and directly use the effect shown by AI technology. But more as a reference tool, it plays the role of an individual artist who is trapped in a certain thinking cycle, thinking about the internal consumption of the situation, in the side to pull you a hand. This is very intuitive, and the artist may reduce the time for self-exploration by months or even years.

3 Reinforcement learning-based simulation of oil painting strokes

With the rapid development of AI technology and the advent of the digital era, the in-depth integration of AI technology and traditional painting has gradually become an important branch of today's art research. while enriching artistic expression, AI technology also brings artists brand new creative tools and carriers. In this environment, cross-field integration has become an important development direction, which breaks through the traditional art form and provides more possibilities and innovative space for artistic creation, and the same is true for the innovation of traditional techniques of oil painting.

3.1 Model-based DDPG algorithm

3.1.1 Deep deterministic gradient algorithm

The Deep Deterministic Policy Gradient (DDPG) algorithm is often used to deal with the high-dimensional continuous action space reinforcement learning problem, which employs the deterministic policy gradient theorem and deep neural network techniques in order to improve the performance and applicability of the algorithm. The aim of this algorithm is to achieve effective control of continuous actions in complex environments by combining deep learning and policy optimization.The algorithmic framework of the DDPG algorithm is shown in Fig. 1, and its basic structure is an Actor-Critic framework, where the Actor network outputs the actions that should be taken in a particular state, and the Critic network evaluates the quality of the actions output by the Actor network.

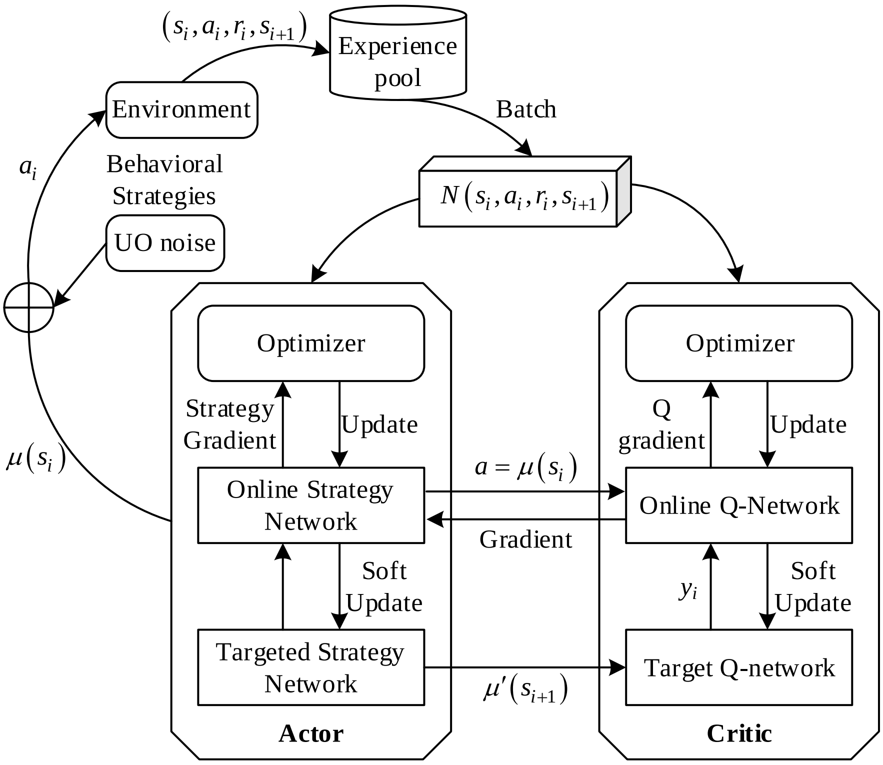


Figure 1: DDPG algorithm framework.

In particular, the deterministic action strategy is the action taken by the intelligent body at each time step a_t, which is computed by a strategy network that approximates the deterministic action strategy function using a convolutional neural network. Relatively, in order to find more potentially better strategies, the random strategies adopted by the intelligent body during the exploration process constitute the behavioral strategies, and in order to realize the behavioral strategies, the DDPG algorithm introduces the Uhlenbeck-Ornstein stochastic process as a noise, and the set of states generated by the intelligent body constitutes the behavioral strategy distribution function.

In addition, the value function represents the expected gain from taking a certain action a_t in a certain state s_t and executing that action according to a deterministic action strategy μ, and is defined using the Bellman equation. Namely:

$$Q^{\mu}\left(s_t, a_t\right) = \mathbb{E}\left[r\left(s_t, a_t\right) + \gamma Q^{\mu}\left(s_{t+1}, \mu\left(s_{t+1}\right)\right)\right] \tag{1}$$

According to the above equation, the value function of the DDPG algorithm is recursive in nature, therefore a convolutional neural network Q network i.e. value network is used to approximate the value function to avoid recursive computation of value $Q^{\mu}\left(s_t, a_t\right)$.

In the DDPG algorithm, the Actor network and the Critic network play different roles. the Actor network is used for the updating of the deterministic policy $a = \mu\left(s \mid \theta^{\mu}\right)$ while the Critic network is used to approximate the value function of the state-action pairs $Q\left(s, a \mid \theta^{Q}\right)$ .The Critic network, by learning the value function of the state-action pairs, provides the gradient information needed to solve Bellman's equation, which guides the direction of the Actor network's updates.

The objective function of the DDPG algorithm is the expected value of the reward accumulated throughout the training rounds, i.e.:

$$J_{\beta}(\mu) = \mathbb{E}_{\mu}\left[r_1 + \gamma r_2 + \gamma^2 r_2 + \cdots + \gamma^n r_n\right] \tag{2}$$

where β is used to denote the behavioral strategy and μ is used to denote the deterministic action strategy. The gradient algorithm is used for updating and the objective function $J(\mu)$ is optimized to update the parameters of the Actor along the direction of boosting the value of the action In order to find the optimal deterministic behavioral strategy μ^*. That is:

$$\mu^* = \arg\max_{\mu} J(\mu) \tag{3}$$

Gradient descent updates the Actor network in a way that can be derived from the chain rule. Specifically, the gradient of the objective function $J(\mu)$ with respect to the strategy function parameter θ^{μ} is equivalent to the gradient of the action-valued function $Q\left(s, a \mid \theta^{Q}\right)$ with respect to the desired gradient of θ^{μ}. That is:

$$\begin{aligned} \nabla_{\theta^{\mu}} J &\approx \mathbb{E}_{s_t \sim \rho^{\beta}}\left[\nabla_{\theta^{\mu}} Q_{\mu}\left(s_t, \mu\left(s_t\right)\right)\right] \\ &= \mathbb{E}_{s_t \sim \rho^{\beta}}\left[\nabla_{\theta^{\mu}} Q\left(s, a; \theta^{Q}\right)\Big|_{s=s_t, a=\mu\left(s_t; \theta^{\mu}\right)}\right] \end{aligned} \tag{4}$$

The action state value that can be generated when the action is chosen according to the deterministic strategy μ in state s is denoted as $Q_\mu\left(s_t, \mu\left(s_t\right)\right)$, and the state s conforms to the distribution ρ^β in case Q -value is expressed in expectation as $\mathbb{E}_{s_t \sim \rho^\beta}$. The deterministic strategy is $a = \mu\left(s \mid \theta^\mu\right)$, and equation (4) can be changed to:

$$\nabla_{\theta^\mu} J = \mathbb{E}_{s_t - \rho^\beta}\left[\nabla_a Q\left(s, a; \theta^Q\right)\Big|_{s=s_t, a=\mu(s_t)} \nabla_{\theta^\mu} \mu\left(s_t; \theta^\mu\right)\Big|_{s=s_t}\right] \tag{5}$$

Optimization of the objective function is done using a gradient ascent algorithm, where the goal of the gradient ascent is to maximize the objective function so that the algorithm updates the parameters of the policy network θ^μ in the direction of boosting the value of the action $Q\left(s, a \mid \theta^Q\right)$. The current policy network is updated using minimizing the loss function approach, i.e.:

$$\nabla_{\theta^Q} = \mathbb{E}_{s,a,r,s' \sim R}\left[\left(\text{Target}\, Q - Q\left(s, a; \theta^Q\right)\right)\nabla_{\theta^Q} Q\left(s, a; \theta^Q\right)\right] \tag{6}$$

where $\text{Target}\, Q$ is the Q-value of the target network, i.e:

$$\text{Target}\, Q = r + \nabla_{\theta^g} \gamma Q'\left(s', \mu\left(s'; \theta^{\mu'}\right)\right) \tag{7}$$

In the DDPG algorithm, the computation of the objective value involves the parameters of the target strategy network $\theta^{\mu'}$ and the target value network $\theta^{Q'}$ and in order to update the parameters of the network, the optimization is carried out using a gradient descent algorithm.

3.1.2 Simulation model of oil painting strokes

In order to realize the innovative expression of the traditional techniques of oil painting, this paper establishes a simulation model of oil painting strokes based on the DDPG algorithm as shown in Fig. 2, and the core of the framework is the painting intelligence. The goal of this intelligent body is to decompose a given target image into a number of brush strokes, and let these brush strokes reconstruct the target image on the drawing board through the renderer, the so-called “model-based” refers to the explicit model utilizing the discriminator. In order to simulate the process of human brushstroke representation in oil painting technique, this paper will use a serialized Markov decision process to model it. In the inference phase, the intelligent body decides the control parameters (i.e., actions) for the next stroke in each step based on the observed target image and the current state of the drawing board, and the renderer receives the control parameters and draws the strokes on the drawing board. In the training phase, the training samples are first randomly sampled from the experience recall cache, then the TD target is computed to update the value network using the reward given by the discriminator, and finally the policy network is trained with the state values estimated by the value network.

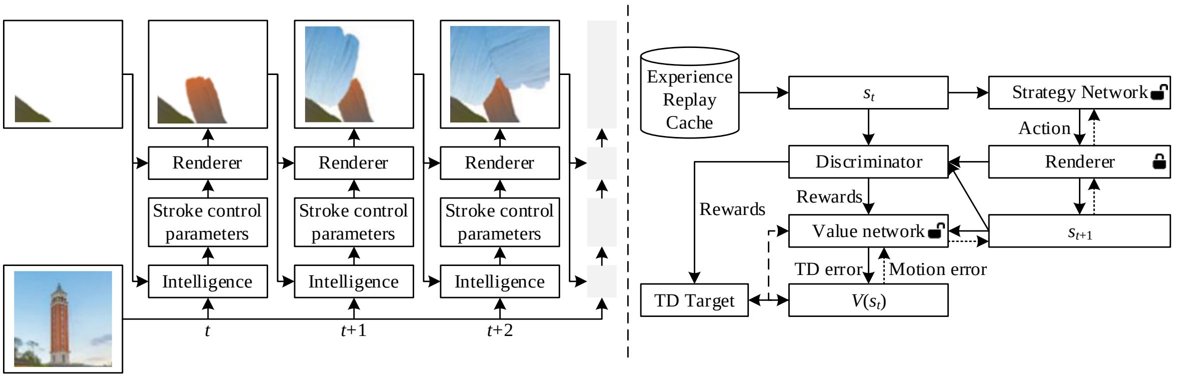


Figure 2: Oil painting brushstroke simulation model

The environment for oil painting stroke simulation mainly consists of a target image I, a drawing board C and a renderer R, and the initial state of the board is C_0. Given a finite number of steps n, at each step, the renderer renders a new state C_{t+1} of the drawing board based on the current state of the drawing board C_t and the received stroke control parameter a_t using weighted least squares filtering, i.e., $C_{t+1} = R(C_t, a_t)$, where t is the current number of steps. The goal of the intelligent body is to find a sequence of stroke control parameters $a_1, a_2, \ldots, a_n$ such that the final rendered drawing board C_n is as close as possible to the target image visually. This process is modeled as a state space of $\mathcal{S}$, an action space of $\mathcal{A}$, a state transfer function of $\text{trans}(s_t, a_t)$, and a reward function of $r(s_t, a_t)$ for a Markov decision process.

(1) State and state transfer function. Here the state is divided into three parts, including the state of the drawing board, the target image, and the current step ratio. That is, $s_t = (C_t, I, t/n)$, where the state C_t of the drawing board and the target image I are represented by a 24-bit RGB image of size $\mathrm{H} \times \mathrm{W} \times 3$ and the step ratio $\mathrm{t/n}$ is a small number that provides information about the number of remaining steps to facilitate planning by the intelligence. The state transfer function $s_{t+1} = \text{trans}(s_t, a_t)$ defines the way in which the drawing board is transferred between states from this step to the next, which is partially known due to the use of the renderer R.

(2) Actions. The action $a_t \in \mathcal{A}$ consists of a set of parameters controlling the position, shape, and color of the stroke, which are decimals between $[0,1]$. In this paper, the intelligent body's strategy function π is defined as a deterministic strategy function, namely $\pi : \delta \to \mathcal{A}$. At moment t, the intelligent body observes the state s_t and then uses the strategy function to predict the stroke control parameter $a_t = \pi(s_t)$ for the next stroke, and the environment receives the action and moves to the next state $s_{t+1} = \text{trans}(s_t, a_t)$.

(3) Reward. Choosing an appropriate reward function and calculating the reward obtained by the intelligent body at each step is the key to training the intelligent body. In this paper, the reward function is defined as:

$$r_t = r(s_t, a_t) = d_t - d_{t+1} \tag{8}$$

where r_t denotes the reward obtained by the intelligent body at the tth step, d_t denotes the distance between C_t and the target image I, and d_{t+1} denotes the distance between C_{t+1}

and the target image I. In this paper, we draw on the idea of generative adversarial networks to compute the distance between two oil painting strokes by constructing a neural network-based discriminator D.

3.2 Rendering algorithm for oil brush style

In the oil painting brushstroke simulation model designed in this paper, the brushstrokes on the drawing board need to be rendered by the neuralizer and then input into the discriminator to realize the simulation of the brushstrokes, as a result, this paper establishes an oil painting brushstroke style rendering algorithm based on weighted least squares filtering. It uniformly spreads the pixel value information of the main shape location of the oil painting brushstroke to its neighboring regions according to the characteristics of the original image, so as to produce the effect of oil painting brushstroke. By setting different model parameters, oil painting style brushstroke images with different brushstroke ranges and abstraction levels can be obtained.

3.2.1 Weighted Least Squares Filtering

Weighted Least Squares Filtering can protect the edges of an image while smoothing it and has excellent performance in multi-scale detail processing.The weighted least squares filtering operation on an input image can be inscribed by the equation, i.e.:

$$\arg\min_{I_P^{WLS}} \sum_{p\in S}\left[\left(I_p^{WLS}-I_p\right)^2+\lambda\left(w_{x,p}(I)\left(\frac{\partial I}{\partial x}\right)_p^2+w_{y,p}(I)\left(\frac{\partial I}{\partial y}\right)_p^2\right)\right] \tag{9}$$

where S denotes the window of the filtering operation and represents the coordinates corresponding to the pixel points in the window. The I and I^{WIS} are the input original image and the image after the weighted least squares filtering operation, respectively. Where $\left(I_p^{WLS}-I_p\right)^2$ is called the data term, taking a very small value can ensure that the difference between the input term and the output term is minimized, which plays a role in fidelity. $\left(w_{x,p}(I)(\partial I/\partial x)_p^2+w_{y,p}(I)(\partial I/\partial y)_p^2\right)$ is called the canonical term, and taking the very smallest value achieves the goal of smoothing the image. λ is a parameter used to balance the data term and the regular term. The $(\partial I/\partial x)_p$ and $(\partial I/\partial y)_p$ denote the gradient in the direction of x and the gradient in the direction of y at the pixel point p, respectively. The specific expressions for the gradient weight coefficients $w_{x,p}(I)$ and $w_{y,p}(I)$ are:

$$w_{x,p}(I)=\left(\left|\left(\frac{\partial I}{\partial x}\right)_p\right|^{\alpha}+\varepsilon\right)^{-1} \tag{10}$$

$$w_{y,p}(I)=\left(\left|\left(\frac{\partial I}{\partial y}\right)_p\right|^{\alpha}+\varepsilon\right)^{-1} \tag{11}$$

The α in Eq. determines the sensitivity of the gradient weight term to the image edges, and ε is introduced to prevent the denominator of the expression from being 0. For ease of computation, the optimization problem described above can be transformed into the following matrix form, viz:

$$\arg\min_{I_p^{WLS}}\left[II^{WLS}-I\right)^T\left(I^{WLS}-I\right)+\lambda\left(I^T D_x^T W_x D_x I+I^T D_y^T W_y D_y I\right)\right] \tag{12}$$

where I^{WLS} and I denote the $M \times N$ -dimensional matrices generated by the weighted least squares filtering action and the input image by columns, respectively, and M and N correspond to the length and width of the image, respectively. The W_x and W_y are $M \times N$ -dimensional diagonal matrices with the gradient weight coefficients $w_x(I)$ and $w_y(I)$ as diagonal elements, respectively. For the convenience of numerical implementation, the forward difference quotient is used instead of the micro-quotient in the experiments, and the difference quotient in the x direction is represented by the $M \times N$ -dimensional matrix D_x , and similarly the difference quotient in the y direction is represented by the $M \times N$ -dimensional matrix D_y . When a pixel is located in a region of the image where the difference in gray values is small, the values on the diagonal of W_x and W_y are large, and the smoothing effect on the image is more obvious; on the other hand, when a pixel is located in a region of the image where the difference in gray values is large, e.g., at the edges, the values on the diagonal of W_x and W_y are small, and the smoothing effect on the region is more obvious. Will be smaller, and then the smoothing effect for this region will be weakened, so as to achieve the purpose of protecting the edge of the image.

From Eq. (12), the optimal solution of I^{WLS} implies that the final image I^{WLS} is not only sufficiently close to the input image I , but also smooth enough. The optimal solution of Eq. (12) satisfies the following linear system, namely:

$$\left[E+\lambda\left(D_x^T W_x D_x+D_y^T W_y D_y\right)\right]\times I^{WLS}=I \tag{13}$$

where E is the matrix whose diagonal elements are all one, and the meanings of the other symbols are consistent with Eq. (12).

3.2.2 Stroke Edge Extraction Methods

In the oil painting stroke rendering diffusion, the line feature extraction of the strokes in any input image is required first, and this is used as the input for the oil painting stroke diffusion. Analogous to the real oil painting, the line position after stroke edge feature extraction represents the location where the painter's brush falls, and the gray value of the pixel represents the gray feature information of the point. In order to be able to realize the stroke rendering by GPU acceleration, this paper adopts the LICDoG preprocessing method to extract the strokes of any input image.

(1) DoG filter preprocessing. The DoG filter obtains the second-order derivative $\nabla^2 G$ by Gaussian convolution, which can be formally defined as:

$$G_\sigma(x)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{\|x\|^2}{2\sigma^2}\right) \tag{14}$$

$$E(x,y)=G_{s_1}(x)-t\times G_{s_2}(x) \tag{15}$$

After obtaining the filtering result $E(x,y)$, the final edge effect can be obtained by binary processing, which can be formally defined as:

$$Edge(x,y)=\begin{cases} 1 & E(x,y)>0 \\ 1+\tanh\left(\varphi_e \times E(x,y)\right) & else \end{cases} \tag{16}$$

(2) Calculate the image structure tensor. Let F denote the input image, and $G_{\sigma,x}$ and $G_{\sigma,y}$ denote the derivatives of the Gaussian distribution in the direction of the x-axis and in the direction of the y-axis, which are formally defined as:

$$G_\sigma(x)=\frac{1}{2\pi\sigma^2}\exp\left(-\frac{\|x\|^2}{2\sigma^2}\right) \tag{17}$$

Convolution of F yields the partial derivatives f_x, f_y on the x- and y-axes, and the structure tensor is denoted:

$$J(\nabla F)=\begin{bmatrix} f_x \bullet f_x & f_x & f_y \\ f_x \bullet f_y & f_y & f_y \end{bmatrix}=\begin{bmatrix} E & F \\ F & G \end{bmatrix} \tag{18}$$

The non-negative eigenvalues of the structure tensor are:

$$\lambda_{1,2}=\frac{E+G\pm\sqrt{(E-G)^2+4F^2}}{2} \tag{19}$$

The direction of the structure tensor eigenvector can be expressed as:

$$t=\begin{bmatrix} \lambda_1 - E \\ -F \end{bmatrix} \tag{20}$$

The local direction is defined as $\theta=\arg(t)$. For the edge image obtained by DoG filtering, the softened edge image can be rendered by LIC filtering using the direction field of the eigenvector as a guide.

(3) LIC Line Integral Convolution: LIC takes the discontinuous edges obtained by DoG filtering as input, computes the streamlines along the direction of the eigenvectors for the pixel points in the vector field, and then convolves the edge values of the pixel points corresponding to the streamlines, and the result is taken as the output edge value. I.e:

$$h(t)=\int_{s_t}^{s+\Delta s_t} k(\tau)d\sigma, s_t=s_{t-1}+\Delta s_{t-1} \tag{21}$$

where Δs_t is the step size at step t, s_t is the length of the streamline after step t, and h_t denotes the weights, from which the LIC convolution pixel grayscale values are obtained, i.e:

$$F_{out}(x,y)=\frac{\sum_{t=0}^{l}F_{in}\left(p_t\right)h_t+\sum_{t=0}^{l'}F_{in}\left(p_t'\right)h_t'}{\sum_{t=0}^{l}h_t+\sum_{t=0}^{l'}h_t'} \tag{22}$$

Always $\mathbb{F}_{out}(x,y)$ is the grayscale value at the output pixel (x,y), $\mathbb{F}_{in}\left(p_t\right)$ is the grayscale value at the edge image pixel p_t, and p_t and p_t' are the pixel coordinate values at step t along the streamline in the forward and reverse directions, respectively. l and l' are the number of integration steps in the forward and reverse directions of the streamline, respectively, h_t are the weights, and h_t' denotes the reverse weights.

4 Analog analysis of brushstrokes in traditional oil painting techniques

Artificial Intelligence has a significant assisting role in oil painting creation, such as in analyzing oil painting composition, color application and brushstroke use, prompting artists to generate more inspiration and providing more innovative suggestions. By exploring the visual characteristics of oil paintings from a multi-dimensional perspective, such as brushstrokes, colors and textures, painters can accurately identify them. Through color matching, composition analysis and brushstroke design, oil paintings are visually balanced and attractive, highlighting the special artistic effect and style of oil paintings.

4.1 Experimental setup and model training

4.1.1 Data set and parameterization

This paper utilizes crawler technology to obtain oil paintings in the Internet to make a data set, through a variety of data preprocessing methods to ensure the effectiveness of the data set, a total of 2700 oil painting images were obtained, in which all kinds of techniques are more obvious performance. In this paper, the training set and test set are divided according to the ratio of 7:3, in order to eliminate the randomness of the experiment and ensure the validity of the experimental results, the dataset is run 500 times, and each experiment only determines the number of training set and test set, randomly selects oil paintings, and takes the optimal result in 500 times as the final result.

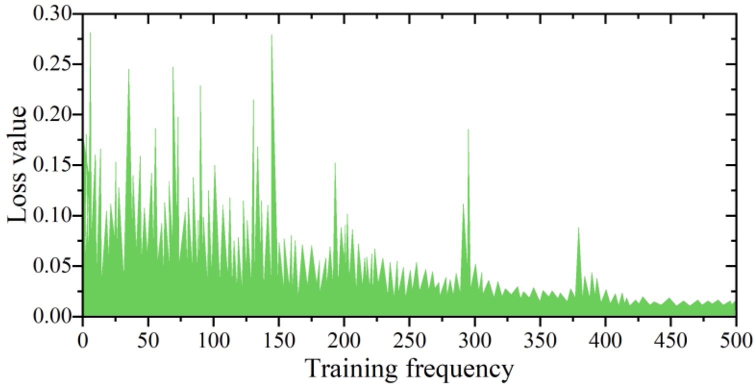
For the oil painting stroke simulation model established in this paper, the grid search algorithm is used to calculate its parameters, and the search interval is set to (0,50]. For the dataset randomly partitioned in the ratio of 7:3, the classification results of all parameters were evaluated using the ten-fold cross-validation method. It was run 500 times with the same dataset and the parameter with the highest average correctness was taken as the final parameter.

4.1.2 Model training loss value changes

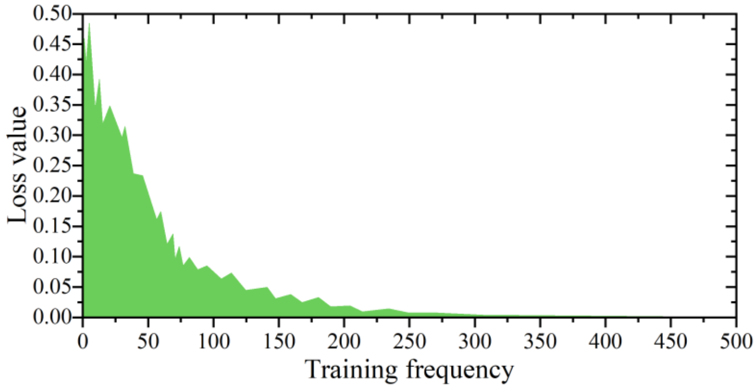
The experimental environment in this paper is NVIDIA GTX4090 graphics card with 8GB video memory, and the experiments are mainly realized using the deep learning framework TensorFlow. Figure 3 shows the loss changes during the training process of the model, where Figure 3(a)~(b) shows the loss changes on the training set and validation set, respectively.

As can be seen from the figure, during the training process of the model, the overall training set loss function changes more drastically, in the training to reach 400 times after the loss value gradually stabilized at about 0.017, the loss value is gradually becoming smaller. In the training process of the validation set, the loss value decreases rapidly from about 0.5 to about 0.017

after about 200 iterations, and the loss value of the model decreases to 0 after about 300 iterations. Therefore, the overall training results of the oil painting brushstroke simulation model established in this paper are good, and more accurate results can be obtained by applying it to oil painting brushstroke simulation, which provides support for the innovative expression of traditional techniques of oil painting empowered by AI technology.



(a) Training data



(b) Verification data

Figure 3: Changes in the loss value of model training

4.2 Objective analysis of oil painting strokes

4.2.1 Comparison of objective evaluation indicators

The experiments use the FID metric to assess the difference between the oil painting stroke simulation image and the content image as input as well as the reference image.The FID metric measures the Fréchet distance between the feature distributions of the two sample sets.The FID metric approximates how the human eye assesses the realism of the generated images, and the samples produced by a model with a lower FID will have a more similar visual perception to the training data. In comparing the ability of the oil painting stroke simulation methods to maintain oil painting strokes, the experiments also used the LPIPS metric to assess the differences in the perceptual level of the features in the aligned images.LPIPS is a metric used to assess the perceptual similarity between images.LPIPS is a metric that is more reasonable to measure the effectiveness of the reinforcement learning task models, which can all learn perceptual similarity to each other, as compared to the statistical features that are compared to the pixel values directly. It is more reasonable in terms of metric effect than comparing the statistical features of pixel values directly.

For the FID metrics, rendering all the generated oil painting stroke simulation images as a whole sample set, the evaluation algorithm computes the FID metrics with the content image set and the style reference image respectively, and obtains $FIDc\ ontent$ indicator with $FIDstyle$ indicator. Figure 4 shows the comparison results of the objective evaluation metrics of different simulation models.

From the figure, it can be seen that the GAN-BiGRU model has the best performance on the $FIDcontent$ indicator (213.68), and this paper is based on the DDPG algorithm to establish the oil painting brushstroke simulation model (226.84) is 6.16% lower, while this paper's model has better FID metrics than the rest of the compared models. Although the GAN-BiGRU model performs optimally, its rendering characteristics that tend to fit the texture only from the hue and brightness of the object also lead to the failure of the oil painting strokes generated by the GAN-BiGRU model to correctly reflect the texture of the stylized reference image, resulting in a $FID\ style$ on poorer performance. In contrast, the oil painting stroke simulation model designed in this paper is able to correctly learn the texture of the stylized reference image and migrate it to the image content on $FIDstyl$ outperforms other comparative models on e, obtaining very competitive results.

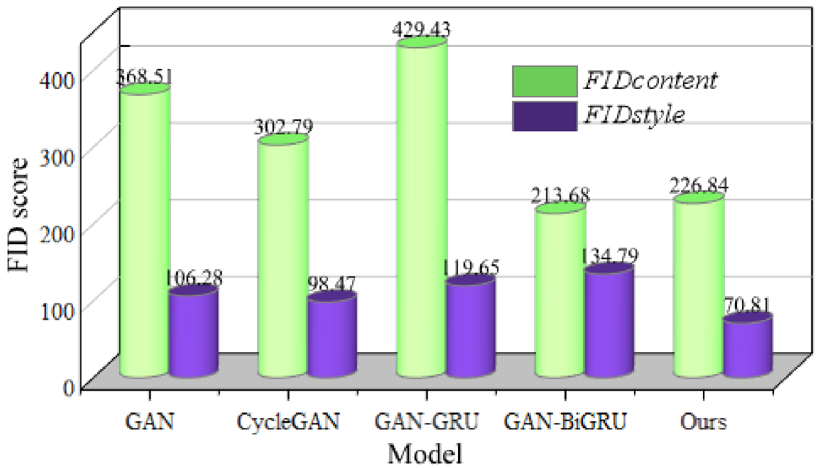


Figure 4: The comparison results of objective evaluation indicators

For the LPIPS metric, the experiments counted the perceptual similarity distances between all the simulated images and the content images, and their average values were used as the final LPIPS metric values. Figure 5 shows the distribution of LPIPS metrics for all test samples. It can be seen that the simulated stroke images obtained by the oil painting stroke simulation model designed in this paper have more concentrated LPIPS metrics, while the results obtained by the other simulation models for rendering images with different contents are more dispersed and random in the distribution of LPIPS metrics. This indicates that the oil painting brushstroke simulation model designed in this paper is able to maintain oil painting brushstrokes more stably, and obtains more stable performance in terms of semantically perceived similarity of images, with fewer cases of simulation failure. Overall, the model in this paper obtains better metrics results in terms of correctly migrating oil painting brushstroke textures and has a more stable and competitive play in terms of semantic retention.

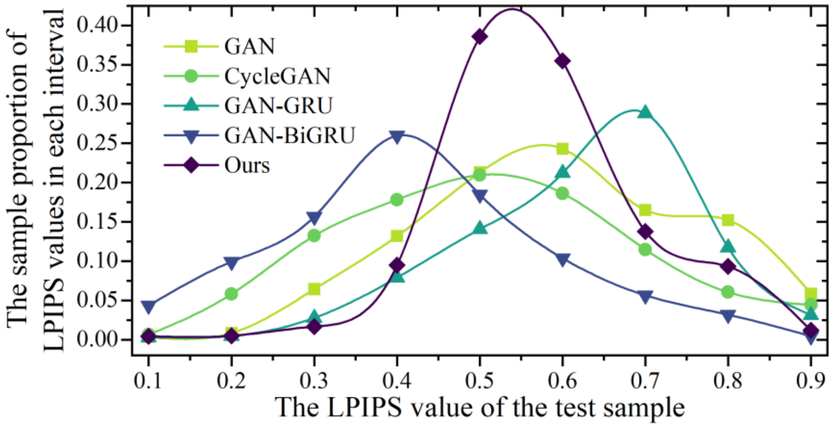


Figure 5: The comparison of the LPIPS performance

4.2.2 Comparison of model experimental times

In order to show the efficiency of the models in this paper, the running time of the models in this paper is compared with that of multiple simulation models. The rendering time and training time of each model are shown in Table 1, and all models use the same content image and style image for rendering.

As can be seen from the table, compared with each comparison model, although the model in this paper spends longer rendering time (3.76s) for oil painting stroke simulation, the method in this paper shortens the running time of the program by taking the points to generate the oil painting curve stroke parameters through the weighted least squares filtering algorithm, which does not require additional dataset training algorithms. In addition, the GAN model is only applicable to the migration of stylized images, while the model in this paper can generate multiple types of oil painting strokes. Compared with the derivative model of GAN, the oil painting stroke simulation model designed in this paper obtains oil painting strokes that can retain more details of oil painting strokes.

Table 1: Comparison of model experiment time

Model	Render/s	Training/h	Dataset
GAN	1.29	3.29	Need
CycleGAN	2.48	4.18	Need
GAN-GRU	1.04	4.65	Need
GAN-BiGRU	1.37	5.07	Need
Ours	3.76	8.24	No Need

4.3 Users' subjective research evaluation

4.3.1 Analysis of individual evaluation results

In order to obtain as objective and comprehensive experimental conclusions as possible, this paper characterizes the quality of the output results of each algorithm through a user-study qualitative analysis method. Based on the results of the brush strokes, layouts, and tonal characteristics of the oil paintings, a single evaluation analysis was carried out. The participants in the evaluation included 10 oil painting professionals and 10 college students not majoring in oil painting. The participants scored the five models in the range of 1~10 and calculated the average value, with higher scores indicating better migration and visual effects. The results of the participants' individual evaluations are shown in Figure 6.

The results show that in terms of the performance of brushstroke features, the GAN-BiGRU model and this paper's model perform better, and both of them can migrate the oil painting brushstroke features of the reference style well. In the performance of layout features, GAN-GRU, GAN-BiGRU and this paper's model can maintain the oil painting layout to different degrees. In terms of the performance of oil painting tones, the GAN-BiGRU model and the model in this paper perform better, and are able to migrate the oil painting tones of the reference style in a better way. Combining the above performances, the DDPG-based oil painting brushstroke simulation model proposed in this paper performs the best among the three individual evaluations.

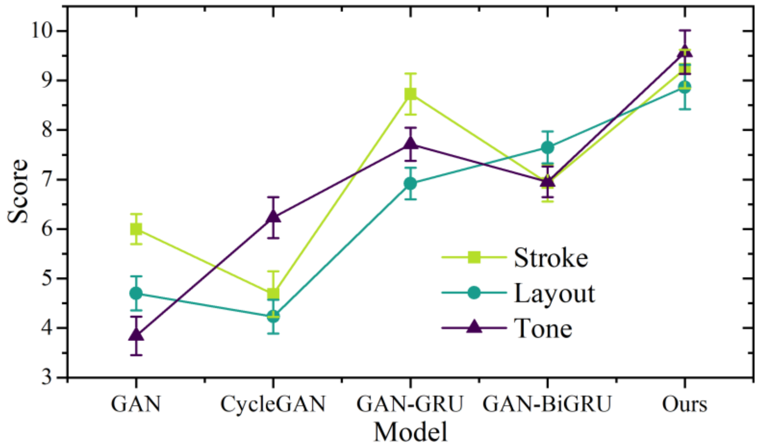


Figure 6: Individual evaluation results of the participants

4.3.2 Oil Brushstrokes Research Results

By designing a user questionnaire, the effectiveness of the model in this paper was evaluated from two aspects: the simulation process and the result perception of oil painting brushstrokes. The content of the questionnaire is shown in Table 2. It mainly consists of 8 questions, and each question provides 5 options ranging from "very" to "not very", "comparatively", "generally", "comparatively not", and "very not". Then the professional and amateur user groups of oil painting were investigated separately to comprehensively evaluate the effectiveness of the oil painting stroke simulation model. Each question provided scoring options on a 5-point scale, corresponding to different degrees of evaluation semantics, where the best evaluated score was 5 and the worst was 1.

Table 2: User study questionnaire

Question	1	2	3	4	5
Q1: It conforms to the logic of oil painting creation					
Q2: It conforms to simulation results of oil painting brushstrokes					
Q3: It has distinct characteristics of oil painting					
Q4: The rendering result is more realistic					
Q5: The model has a relatively high operational efficiency					
Q6: The model is quite convenient to apply					
Q7: Stroke simulation is relatively time-consuming					
Q8: Recommended for amateurs to use					

A total of 20 users were invited to participate in the survey, and the results of the questionnaire survey were counted to obtain the statistical results of the questionnaire survey as shown in Figure 7. The results show that more than 80% of the users recognized the oil painting stroke simulation effect of this paper's model, and in terms of model use, 85% of the users recognized the usability of this paper's model, but at the same time proposed the use of the process is relatively time-consuming and the simulation of a single stroke shortcomings.

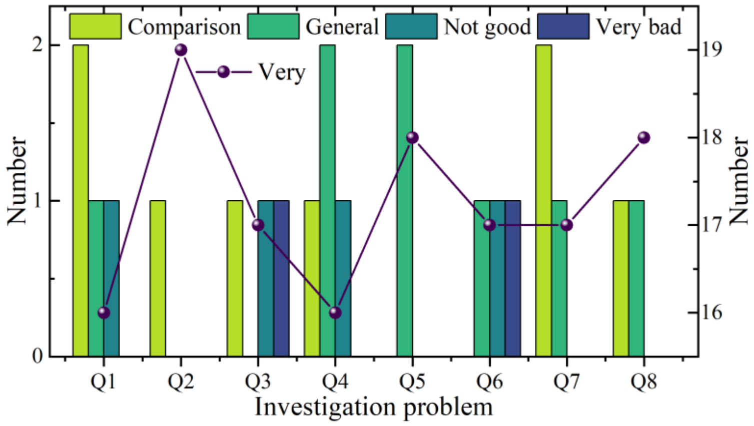


Figure 7: Statistics of the questionnaire feedback

5 Conclusion

The article proposes a model-based DDPG algorithm, which is applied to oil painting stroke simulation, and takes weighted least squares filtering to realize oil painting stroke style rendering. It is found that the oil painting brushstroke simulation model based on the DDPG algorithm obtains a FIDcontent index of 226.84, which is 6.16% higher than the best-performing model, and the results of the LPIPS index are more concentrated. Based on the results obtained by the oil painting brushstroke simulation model, the overall user satisfaction is better. Therefore, relying on AI technology to assist the traditional techniques of oil painting can enhance the expression of traditional techniques of oil painting and provide creative inspiration for painters with more diversified simulation results.

About the Author

My name is Chen Jiang. I was born in Zhengzhou, Henan Province, China in 1991. I earned a Bachelor of Arts degree from Zhongyuan University of Technology in 2014 and a Master of Fine Arts degree from Henan University in 2022. Currently, I am pursuing a doctoral degree at Capital Normal University, specializing in oil painting within the Fine Arts discipline.

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