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REGULAR PAPER

ShadowPainter: Active Learning Enabled Robotic Painting through Visual Measurement and Reproduction of the Artistic Creation Process

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Abstract

In this paper, we present an active learning enabled robotic painting system, called ShadowPainter, which acquires artist-specific painting information from the artwork creating process and achieves robotic reproduction of the artwork. The artist's painting process information, including interactive trajectories of paintbrushes with the environment and states of the canvas, is collected by a novel Visual Measurement System (VMS). A Robotic Painting System (RPS), accompanied by the VSM, is developed to reproduce human paintings by actively imitating the measured painting process. The critical factors that influence the final painting performance of the robot are revealed. At the end of this paper, the reproduced artworks and the painting ability of the RPS are evaluated by local and global criteria and metrics. The experimental results show that our ShadowPainter can reproduce human-level brush strokes, painting techniques, and overall paintings. Compared with the existing work, our system produces natural strokes and painting details that are closer to human artworks.

Keywords Painting reproduction · Robotic painting · Robotic system · Vision-based measurement

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1 Introduction

Technology and art have been intermingling and promoting each other for a long history [1]. The combination of intelligent technology and art has received increasing attention in recent years. Researchers, engineers, and artists are using robotic systems and AI technologies to create art. In particular, robotic painting [2] and its supporting technology, stroke-based rendering (SBR) [3, 4], have been widely studied. The robotic painting explores machine creativity, especially in realistic artworks. It also reveals the mechanism of the human artistic creation process and empowers humans' creation through assisted painting.

Some pioneers began exploring robotic painting as early as the last century, like Jean Tinguely, Harold Cohen, and Holger Bär. They use mechanical devices to perform new forms of artistic painting. Harold Cohen built a plotter, named AARON [5], to create abstract drawings. It is considered the most influential painting machine in contemporary art. Until now, lots of artists utilize robots to expand the way they create art. Among them, Dulcinea [6] produces quite amazing paintings by reinterpreting various data not visible to the naked eyes. In these systems, the robots are used as actuators for painting and are not able to paint autonomously.

With the development of intelligent technology, autonomous robotic painting emerged. Early robotic painting mainly focuses on sketch and calligraphy [7]. A sketching robot named Paul was developed by Tresset et al. to create portraits at live [8]. Similar to Paul, Sylvain Calinon et al. developed a humanoid robot to implement portrait drawings using a quill pen [9]. For these robots, the painting process is simplified and relatively easy to control, which means only simple sketches can be drawn.

At present, robotic systems can complete more complex paintings with diverse contents and painting mediums. A competition called ”RobotArt” [10] was held annually between 2016 and 2018. Many robots that appear in the competition achieve pleasing visual effects. Hod Lipson developed a robot called PIX18 [11] to perform acrylic painting based on brush strokes generated using a genetic algorithm. It generates textures similar to humans but lacks details. RobotArtist, described in [12], succeeds in creating a gradual change in color using the overlay technique. And Busker Robot produces watercolor painting using a well-designed paint rendering algorithm [13, 14]. And ArtCybe, developed by Artur I. Karimov, created monochrome paintings with special tone rendition with the help of a novel color mixing device [15]. E-David, developed by Thomas Lindemeier et al. [16, 17] from the University of Konstanz, achieved a fascinating effect on acrylic paintings based on visual feedback. And the stroke generation is guided by semantic hints [18] and hardware limitations [19, 20]. Machine learning algorithms are applied in the stroke rendering for robotic painting [21] in recent years. For example, Huang et al. [22] uses Reinforcement Learning to solve the stroke arrangements. And [23] uses content-masked loss to generate strokes for robotic portrait painting with time-efficient stroke planning based on [22]. These methods apply pre-defined brush models and painting rules to generate stroke sequences by minimizing the distance between the canvas and the target image. Then the stroke sequences are executed by the robot to complete the painting. However, the robotic painting results can be easily distinguished from the human paintings because of unnatural brush strokes, which have different distributions from human strokes. We argue that this is caused by the following problems.

Monotonous Brush Stroke Model Human painters use varying stroke shapes and painting techniques depending on the painting contents and regions [24]. In contrast, the canvas is filled with regular strokes to approximate the target image for simplicity in existing methods. For digital rendering, if the pixel size of the brush tip is small enough, the rendered results can be close to or even identical to the given image at the pixel level. But for a robot, painting granularity is limited by physical brushes. The stroke sequences generated by these methods lead to monotonous strokes painted by the robot. Zhu et al. use template images of captured human strokes to generate better visual effects of strokes [25, 26]. However, these methods are only limited to image rendering and cannot be applied to robotic painting [27, 28]. Human-like natural brush strokes are required for the robot to improve the painting results.

Lack of Painting State Constraints and Skill Guidance Most methods only take the target image as a reference rather than actively using artist-specific painting techniques collected from the artwork creating process. Instead of approximating a target image using strokes directly, human painting has abstraction and multi-stage objectives. The explicit information from the target image is insufficient, lacking the skill guidance of intermediate painting state and painting techniques. It is difficult for the robot to find a human-like painting sequence reversely through optimizing an objective constrained by a reference image.

To tackle the problems illustrated above and achieve human-level autonomous painting, it is necessary to collect sufficient painting information from the artist's painting process for robotic active learning. Therefore, we focus on a **fine art painting reproduction** task to verify whether the robot has the potential to achieve human-level paintings. In this paper, we explore human-level robotic painting by measuring and imitating the human's painting process, rather than following manually defined painting rules, as the existing work does. As far as we know, we are the first to perform a human-level fine art painting reproduction using robots. Compared with the literature, our ShadowPainter achieves natural strokes, a variety of painting techniques (blending, shading, etc.), and human-level reproduction paintings benefiting from the active imitation of the human painting process, as shown in Fig. 1. The results demonstrate that the collected painting information is sufficient for painting reproduction. Thus, our system is also deployed to collect expert painting data for training an autonomous agent to paint in future work.

Firstly, we formulate the artistic painting process as interactions between the painting tools and the environment. We develop a Visual Measurement System (VMS) to acquire sufficient painting information for fine art reproductions, including interactive trajectories and painting states. The extracted painting information can be used for robotic painting skills learning in future work. This also allows the digitization of artists' artworks and painting knowledge for perpetual reservations.

We further develop a Robotic Painting System (RPS) to reproduce the human paintings based on the collected painting information. At the same time, we reveal the critical factors influencing the final results for robotic painting. The original artwork accompanied by the digital

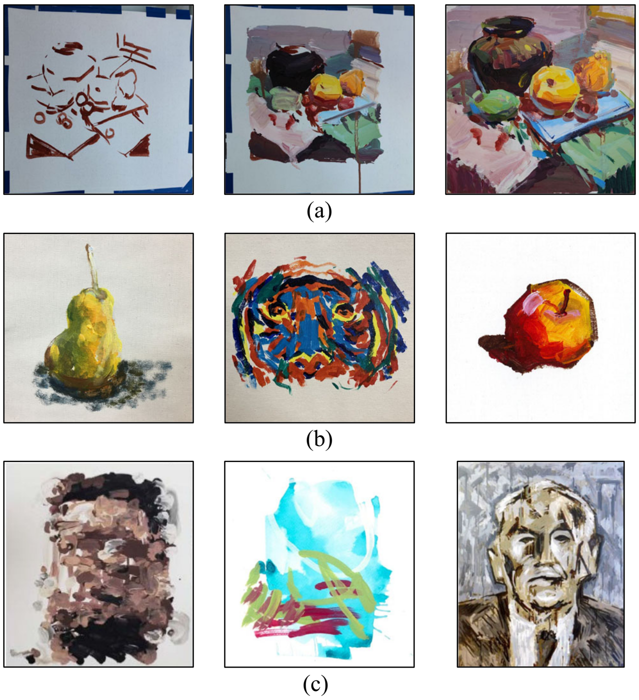

Fig. 1 Reproduction paintings of our ShadowPainter compared with other painting robots. (a) A painting process of the Still Life by our ShadowPainter. (b) Some other painting results of our ShadowPainter. (c) Highest voted paintings of the state of the art [23, 29, 30] in the user study in terms of the frequency mistaken as human painting. Compared with existing work, our ShadowPainter achieves natural strokes, varying painting techniques, and human-level reproduction paintings benefiting from the active imitation of the human painting process

painting data and its reproductions can be licensed through the blockchain, like NFT [31], to avoid impersonation.

Besides, there is no consensus on evaluation criteria and metrics of robotic paintings. We propose to use IoU and color difference in Lab space, which are widely used in image detection tasks and color science separately, to evaluate the reproduction of the strokes and painting techniques. And we implement a Visual Turing Test covering diverse painting types and participants with different knowledge backgrounds to assess the overall paintings. Finally, we conduct three-level reproduction experiments to verify the effectiveness of our ShadowPainter. Experimental results show that our ShadowPainter achieves natural strokes and human-level overall painting effect on simple acrylic and gouache paintings, which distinguishes it from existing other painting robots.

The contributions of this paper are:

- We design a Visual Measurement System and algorithms to acquire creative actions and painting states as the representation of the creative painting process, which is sufficient to reproduce the artworks created by artists.
- We present a Robotic Painting System to reproduce human-level paintings based on the collected painting information and reveal the critical factors influencing the final results for robotic painting.
- We propose local and global evaluation criteria and metrics to assess the robotic painting. Experimental results show that our ShadowPainter achieves natural strokes and human-level overall painting effect on simple acrylic and gouache paintings through active measurement and imitation of the human painting process. As far as we know, we are the first to perform a human-level fine art painting reproduction using robots.

The rest of the paper is organized as follows. Section 2 demonstrates how we formulate the painting process to make it recordable and reproducible. Besides, an implementation overview of the whole system is also described. Then, the VMS and RPS are introduced in Section 3 and Section 4 respectively. In particular, we analyze several critical factors influencing the results of robotic painting reproduction. In Section 5, we present the evaluation criteria and metrics of the stroke reproduction, brush technique reproduction, and overall painting reproduction. We conduct three-level comparative experiments in Section 6 according to the evaluation criteria and present the results. Finally, Section 7 concludes the paper and reports the future work.

2 Task Formulation

In this section, we describe how we formulate the artistic painting process to collect sufficient painting information for further painting reproduction and introduce the overall architecture of our ShadowPainter.

2.1 Formulation of the Artistic Painting Process

Artist's painting knowledge is accumulated in painting processes over a long time. A typical painting process includes several phases: artwork conception, idea development, making the artwork, finishing the artwork, and developing knowledge [32]. The artwork conception and idea development in a painting process are generally implicit and unobservable. While making the artwork, the interactions between the painting tools and painting medium and the changes of the painting state are completely observable and can be collected for a robot to imitate and learn. We refine the original model to formulate the artistic painting process for our task, as shown in Fig. 2. The refined artwork-making process involves several steps: (1) Tools interact with the environment while painting action trajectories are applied to them. (2) Current brush strokes are produced on the canvas through the interactions. (3) Brush strokes accumulate into

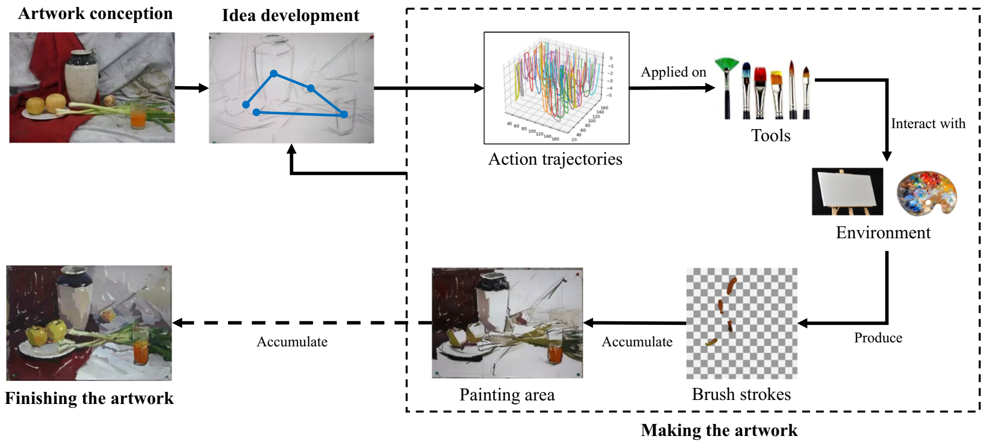

Fig. 2 Formulation of the artistic painting process for our task. We combine the original creation model [32] with the refined artwork-making process to derive our formulation of the painting process. Elements inside the dashed box are measured by our VMS for painting reproduction

painting areas on the canvas. (4) Painting areas accumulate over time to produce the final painting.

According to the formulation of a painting process, the painting reproduction can be formulated as a reproduction of the interactions between the tools and the environment. The interactions between the soft brushes, the viscous pigment medium, and the canvas are uncertain, which makes the interactive results uneasy to control. But if this uncertainty could be limited, the creative interactions can be further simplified as relative pose transformations between the tools and the environment. To this end, we extract the environmental state to control its uncertainty and to provide references for the robotic visual feedback.

Therefore, the information needed to complete human-level painting reproductions includes (1) a series of creative actions $\mathcal{A} = (\mathbf{a}^1, \ldots, \mathbf{a}^{id})$, with $\mathbf{a}$ consisting of the attributes of the tools and their relative pose trajectories with the environment, (2) a series of painting states $\mathcal{S} = (\mathbf{s}^1, \ldots, \mathbf{s}^{id})$ produced by $\mathcal{A}$, with $\mathbf{s}$ consisting of canvas state $\mathbf{s}_{can}$ and environmental state $\mathbf{s}_{env}$ (auxiliary area like palettes, etc.). id denotes the action step, which counts from 1 at the beginning of a painting process. A painting process is then represented by $\mathcal{P} = (\mathcal{A}, \mathcal{S})$.

We design a VMS to measure the painting information $\mathcal{P}$ illustrated above and an RPS to reproduce the painting process $\mathcal{P}$. In future work, we will further simulate the soft interaction characteristics to improve the reproduction accuracy of the whole painting process.

2.2 Overview of the ShadowPainter

The overall architecture of our ShadowPainter is shown in Fig. 3. The system consists of a VMS and an RPS, which communicate through RPyC protocol and share painting data on a database based on MongoDB and WebDAV.

The VMS is designed to extract sufficient painting information for painting reproduction, including the creative actions $\mathbf{a}$, the canvas states $\mathbf{s}_{can}$ and environmental states $\mathbf{s}_{env}$. This vanilla painting data is distilled into painting knowledge including stroke statistical features and painting rules. The painting data is a permanent digital form of the artwork, which is used for robotic reproduction painting. It can also be used as training data to teach machines to create.

The RPS aims to reproduce the human-level paintings by imitating the painting procedure and painting actions with visual feedback on the painting state. The system could also perform autonomous painting using stroke sequences generated by SBR algorithms, which is beyond the scope of this paper.

The VMS and RPS can operate asynchronously offline or synchronously. They could also be deployed in different places, which is convenient for artists and robots to collaborate.

3 Visual Measurement of the Painting Process

As formulated in Section 2.1, the painting process $\mathcal{P}$ is represented by the painting actions $\mathcal{A}$ and painting states $\mathcal{S}$. We design the Visual Measurement System to acquire $\mathcal{A}$ and $\mathcal{S}$ following two steps alternately. **Step T** collects the creative interactive actions as relative pose trajectories of the painting tools with respect to the environment. **Step S** extracts the painting states based on the captured images and action trajectories collected in Step T. The deployment of the VMS is shown in Fig. 4.

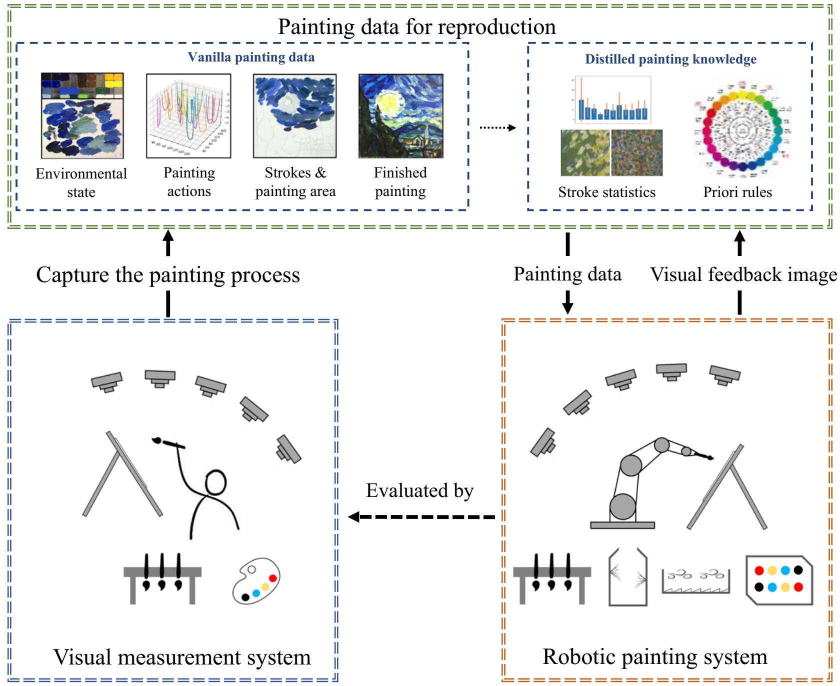

Fig. 3 The overall architecture of our ShadowPainter

3.1 Step T: Extracting the Creative Actions

Definition of the Tools and the Environment As illustrated in Section 2.1, the interactions between the soft brushes, the viscous pigment medium, and the canvas are uncertain and unpredictable. We assume that a flexible brush produces approximately the same interactive characteristics and painting effects when the same relative trajectory is applied to it. We ensure this assumption by keeping the external variables (the material and humidity of the pigments, the material and shape of the brush) consistent manually. Thus, we consider all the tools and environmental entities involved in the painting process as rigid bodies $\mathcal{B}$ and represent their interactions by relative pose motions between them in 3D space.

We set up two rigid bodies $\mathcal{B}_{can}$ and $\mathcal{B}_{aux}$ and the corresponding coordinate systems as environmental entities. $\mathcal{B}_{can}$ denotes the rigid body of the canvas. $\mathcal{B}_{aux}$ denotes

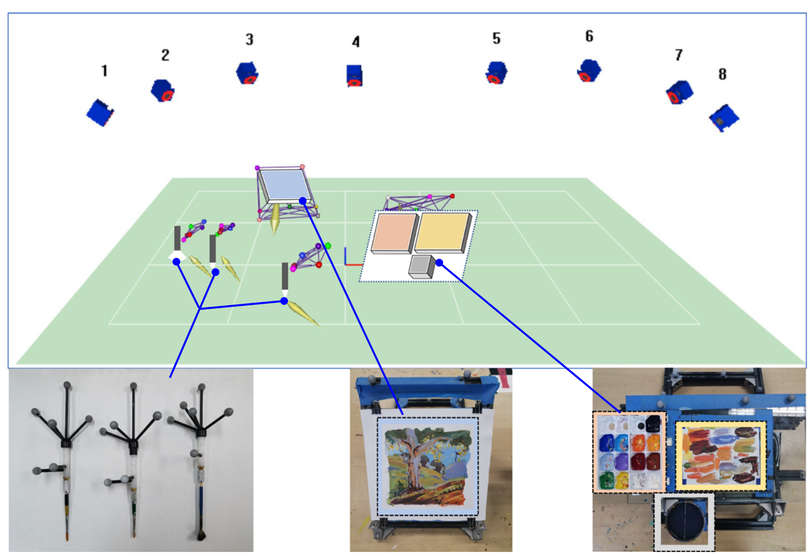

Fig. 4 The deployment of our VMS and the measured entities in it

the rigid body of the auxiliary area, including pigment container, palette, and brush cleaner. For a flexible brush, we define the rigid bar of it as its rigid body $\mathcal{B}^i_{brush}$ and set the tool coordinate system at the endpoint of the brush, as shown in Fig. 5. The tool coordinate system overlaps with the brush when it is stationary, and the origin of the tool coordinate system is a virtual point in space when painting. All the rigid bodies are calibrated before painting.

Calculating the Relative Poses To achieve non-contact measurement of rigid body trajectories, we use a motion capture camera system for good high-speed performance, robustness, and spatial measurement range. An action trajectory of a rigid body $\mathcal{B}$ is captured as a sequence of poses $\Gamma = (\mathbf{p}^1, \ldots, \mathbf{p}^t)$ along the time frame t. $\mathbf{p}$ is represented by a 6-DOF pose of $\mathcal{B}$ with respect to a specific coordinate system:

$$\mathbf{p} = (x, y, z, Rx, Ry, Rz), \tag{1}$$

where (x, y, z) denotes the position of $\mathcal{B}$, (Rx, Ry, Rz) denotes the orientation of $\mathcal{B}$. The Euler angles are defined in the ZYX convention. And the 6-DOF pose of the calibrated entities is acquired in real-time. Then, we calculate the relative pose of the brush $\mathcal{B}^i_{brush}$ with respect to the canvas $\mathcal{B}_{can}$ and the auxiliary area $\mathcal{B}_{aux}$ respectively using the following coordinate transformation:

$$\begin{aligned} T_{i,can} &= T_{can,w}{}^{-1} T_{i,w}, \\ T_{i,aux} &= T_{aux,w}{}^{-1} T_{i,w}, \end{aligned} \tag{2}$$

where $T_{can,w}, T_{aux,w}, T_{i,w}$ denotes the homogeneous representation of the pose of $\mathcal{B}_{can}$, $\mathcal{B}_{aux}$, $\mathcal{B}^i_{brush}$ in the world coordinate system w separately. Matrix T is composed of a rotation matrix R and a translation vector $\mathbf{t}$, which could be calculated from the Euler angles and the position in a 6-DOF pose $\mathbf{p}$. The painting action trajectory is then represented by the sequences of poses $\mathbf{p}^t_{i,can}$ and $\mathbf{p}^t_{i,aux}$.

Action Attribute Assignment There are many types of creative actions that a person can take during painting. To identify the type of captured action $\mathbf{a}^{id}$, we divide the canvas and the auxiliary area into several spatial recognition zones. We assign one of the types $(canvas, palette, cleaner, waiting)$ to an action, denoted as a^{id}_{type}, according to where the action trajectory Γ^{id} is located. The action types will determine the operation modes in the RPS.

Filtering of Painting Data During the human painting process, the large linear velocity of the tool coupled with the occasional occlusion of the motion capture markers leads to outlier noises in the captured trajectories. Thus, the trajectories are then filtered to exclude the outlier points using a statistical outlier removal filter [33].

In conclusion, the Step T gets new action points $\mathbf{p}^t$ to form an action trajectory Γ^{id} and identify its action type a^{id}_{type}. A creative action is finally represented by:

$$\mathbf{a}^{\mathbf{id}} = (id, \mathcal{B}^i_{brush}, \Gamma^{id}, a^{id}_{type}). \tag{3}$$

3.2 Step S: Extracting the Painting States

In addition to the creative actions, the painting state is critical to provide reference during robotic painting. The painting state refers to the set of the canvas states and environmental states of the auxiliary area.

Environmental State The environmental state mainly includes the status of the palette and pigment container. During robotic painting, the state of pigment has a great influence, which will be illustrated in detail in Section 4.3. The environmental state $\mathbf{s}_{env}$ is captured using RGB cameras.

To obtain positive views of the captured images and align frame coordinates, we apply perspective warping with the help of Aruco markers. By measuring the k coordinates of Aruco markers $X = [x_1, \ldots, x_k], Y = [y_1, \ldots, y_k]$ and their k corresponding detected spots in the captured images $U = [u_1, \ldots, u_k], V = [v_1, \ldots, v_k]$, we can obtain the warping matrix $M_{3\times3}$ by solving the linear least-square problem in Eq. 4, which is applied to perspective warping of the captured images during painting.

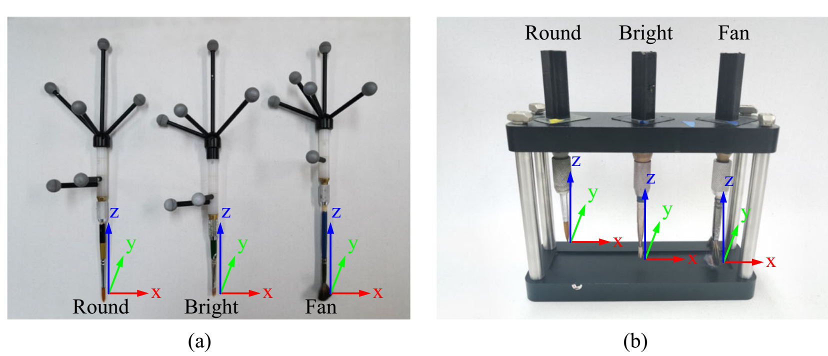

Fig. 5 Configurations of brushes and their tool coordinate system. (a) Brushes designed for artists. (b) Brushes designed for our robot

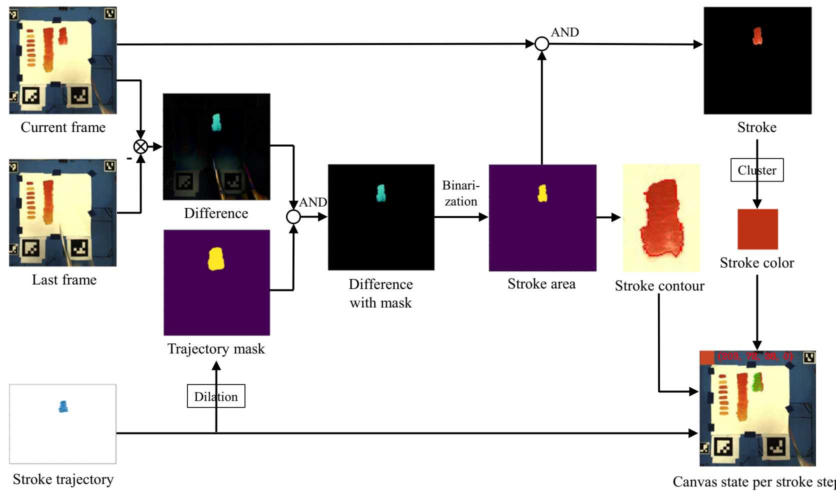

Fig. 6 Extraction of canvas state at each stroke step. The canvas sate is composed of painting canvas, stroke trajectories, stroke contour, and stroke color

$$\begin{bmatrix} X \\ Y \\ \mathbf{1} \end{bmatrix} = M_{3\times3} \begin{bmatrix} U \\ V \\ \mathbf{1} \end{bmatrix}. \tag{4}$$

Color correction is also applied afterward. Firstly, we balance illuminance in Lab color space with a pre-determined illuminance map. Then, a pre-defined color correction matrix (CCM) is applied for color correction in RGB color space. The CCM $A_{3\times3}$ is obtained by filming a standard color checker and solving:

$$P_{m\times3} = O_{m\times3} A_{3\times3}, \tag{5}$$

where O and P are the filmed color array and standard color array respectively. With the color correction, the mean color difference in Lab space between the corrected images and the true value is within 5, which is acceptable in our application [34].

Canvas State The canvas state is extracted from the canvas image I_{can} captured following the same process as above. The canvas state consists of three-level information along the painting timeline: stroke at each action step, painting area, and the overall painting. And the attributes of a stroke include the trajectory of the stroke, the contour of the stroke, the color of the stroke, and the brush technique of the stroke. The algorithm flow for extracting the stroke attributes is shown in Fig. 6.

We get the stroke trajectory $\tau = [(u_1, v_1), \ldots, (u_n, v_n)]$ on the warped image plane according to the $[x, y]$ locations in partial action poses $\mathbf{p}^t_{i,can}$, filtered with a depth constraint $\mathbf{p}^t_{i,can}[z] < 0.5mm$ to improve the accuracy and robustness of the stroke extraction.

The stroke trajectory τ is dilated to form a location constraint to eliminate the effect of environmental changes in the stroke area extraction by applying a trajectory mask to the differences between adjacent image frames. Then, a clear stroke contour $\mathcal{C}$ is extracted from the stroke area. In a painting process, the color of a stroke is usually uneven. Thus extracting the color within the whole brush stroke area

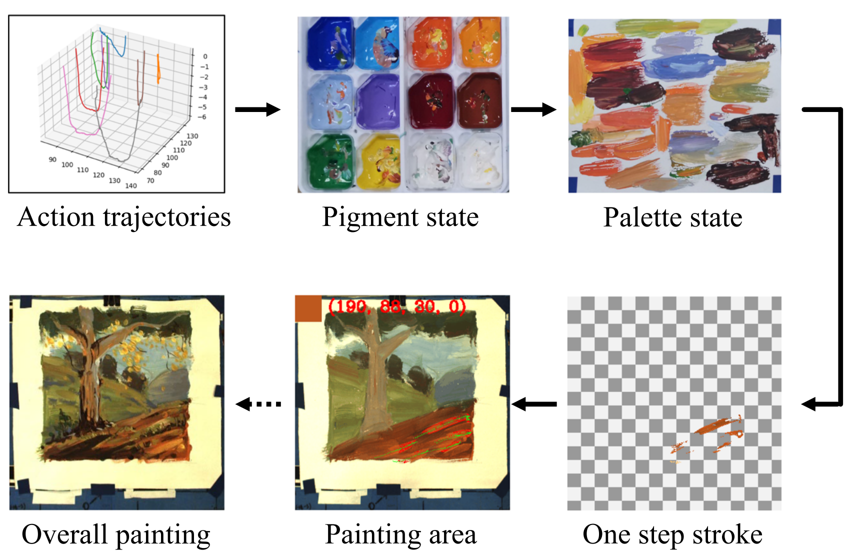

Fig. 7 A demonstration of the painting information extracted by the VMS

is inaccurate. We further perform K-means clustering on the pixels in the extracted stroke area and select the dominant color c. The pixels far from the color in the stroke area are excluded to optimize the stroke contour $\mathcal{C}$ in return. The stroke extraction procedure described above can be expressed as a StrokeExtractor:

$$\mathbf{s}^{id}_{stroke} = StrokeExtractor(I^{id}_{can}, I^{id-1}_{can}, \Gamma^{id}_{i,can}), \tag{6}$$

where $\mathbf{s}^{id}_{stroke} = (\tau, \mathcal{C}, c)$ denotes a stroke represented by its trajectories, contour and colors. The input of the StrokeExtractor are I^{t}_{can}, I^{t-1}_{can} and $\Gamma^{id}_{i,can}$. Finally, a painting state is formulated as:

$$\mathbf{s^{id}} = (id, \mathbf{s}^{id}_{stroke}, \mathbf{s}^{id}_{can}, \mathbf{s}^{id}_{env}). \tag{7}$$

The extracted painting state is distilled further to get the artist-specific painting knowledge. The distribution of the strokes in different painting regions, which reflect an artist's painting style, is calculated using the stroke characteristics (straightness, elongatedness, density, etc.) proposed by [24]. Some basic painting rules, like the layering order, are also acquired by stacking a series of extracted strokes and painting canvas images. Besides, the stroke information and environmental state provide a reference for the feedback in the robotic painting process.

3.3 Overall Procedure of the Visual Measurement

As stated in Section 2.1, a painting process $\mathcal{P}$ is represented by the painting actions $\mathcal{A}$ and painting states $\mathcal{S}$. During the painting process, the actions and states are iteratively obtained following the **step T** and the **step S**. The overall procedure of the visual measurement is illustrated in Algorithm 1, which applies the methods described in Sections 3.1 and 3.2. In short, Step T gets new action points $\mathbf{p}^t$ to form an action trajectory Γ^{id} and identify its action type a^{id}_{type}. Step S extracts the current strokes according to the captured images and the action trajectories collected in Step T after a *canvas* action takes place. If the ShadowPainter is running in online mode, the process is slightly different. In this situation, each action $\mathbf{a^{id}}$ is uploaded to MongoDB in real-time. And the Inverse Kinematics of the robot is performed to check whether the current action can be executed successfully by the robot. The painting information extracted by the VMS following the Algorithm 1 is demonstrated in Fig. 7.

Algorithm 1 Visual measurement of the painting process.

initialize Perspective Warping Matrix M using Eq. 4;
initialize Color Correction Matrix A using Eq. 5;
$id = 1$;
$\mathcal{A} = \emptyset$;
$\mathcal{S} = \emptyset$;
while painting process is not over **do**
Step T. Extracting the creative actions
    get poses $\mathbf{p}^{t}_{can,w}$, $\mathbf{p}^{t}_{aux,w}$ and $\mathbf{p}^{t}_{i,w}$ of $\mathcal{B}_{can}$, $\mathcal{B}_{aux}$, and $\mathcal{B}^{i}_{brush}$;
    calculate relative poses $\mathbf{p}^{t}_{i,can}$ and $\mathbf{p}^{t}_{i,aux}$ using Eq. 2;
    accumulate the poses to an action trajectory Γ^{id};
    if a^{t}_{type} changes **then**
        $\Gamma^{id} = outlier\_removal\_filter(\Gamma^{id})$;
        assign an action type a^{id}_{type} to Γ^{id};
        $\mathbf{a^{id}} = (id, \mathcal{B}^{i}_{brush}, \Gamma^{id}, a^{id}_{type})$;
        accumulate the actions $\mathbf{a^{id}}$ to $\mathcal{A}$;
Step S. Extracting the painting states
        if a^{id}_{type} is *canvas* **then**
            take pictures I^{id}_{can}, I^{id}_{env};
            $I^{id}_{env} = perspective\_warping(M, I^{id}_{env})$;
            $\mathbf{s}^{id}_{env} = color\_correction(I^{id}_{env}, A)$;
            $I^{id}_{can} = perspective\_warping(M, I^{id}_{can})$;
            $I^{id}_{can} = color\_correction(I^{id}_{can}, A)$;
            $\mathbf{s}^{id}_{stroke} = StrokeExtractor(I^{id}_{can}, I^{id-1}_{can}, \Gamma^{id}_{i,can})$;
            $\mathbf{s^{id}} = (id, \mathbf{s}^{id}_{stroke}, \mathbf{s}^{id}_{can}, \mathbf{s}^{id}_{env})$;
            accumulate the actions $\mathbf{s^{id}}$ to $\mathcal{S}$;
        end if
        $id = id + 1$;
    end if
end while
$\mathcal{P} = (\mathcal{A}, \mathcal{S})$;
return $\mathcal{P}$.

4 The Robotic Painting System

In this section, we introduce how we construct the robotic system of ShadowPainter and how we reproduce the painting actions and final painting results by actively imitating the extracted painting information. We not only introduce the architecture and execution logic of the RPS but also analyze the critical factors that affect the painting results, from algorithm and engineering perspectives.

4.1 System Overview

The architecture of our RPS is shown in Fig. 8. The robot is equipped with an electric gripper to hold and change painting brushes. In order to reproduce the human painting process, the RPS uses a similar tool configuration to the VMS, including the brushes, pigments, and canvases, and perform painting movements as close as possible to the captured painter's actions $\mathcal{A}$. Other non-creative movements are flexibly performed using automatic devices. Similar to the VMS, we use cameras to shoot the canvas and

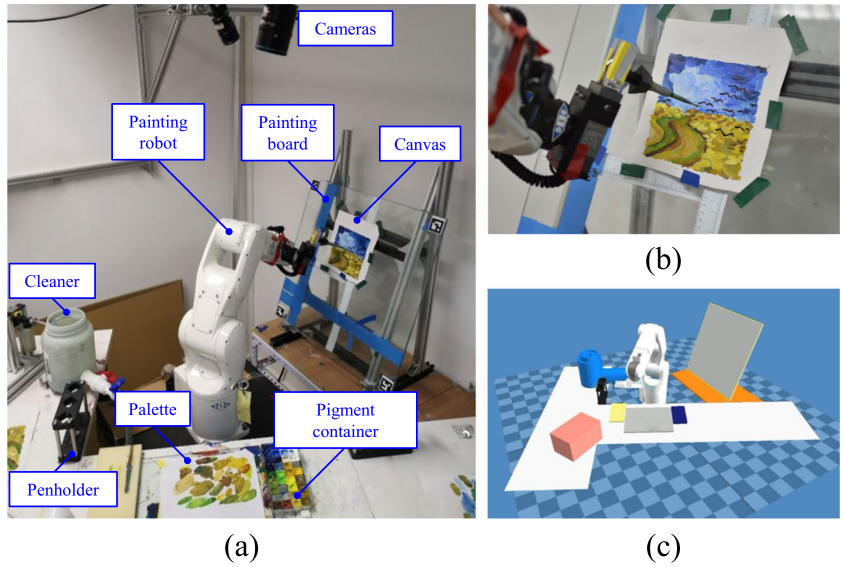

Fig. 8 The architecture of our RPS. (a) The setup of the robot and the auxiliary devices. (b) A close up of robotic painting. (c) A demo of asynchronous simulation

the palette respectively and perform image processing operations during the robotic painting process.

4.2 Reproduction of Creative Actions

Creative actions are applied in the painting reproduction process to obtain desired colors and draw desired shapes. These actions require the robot to move as close to the human movements as possible to preserve stroke effects such as blending and textures. These effects are particularly difficult to achieve for a robot on its own. Therefore, we require the robot to plan and move along the captured action trajectories by the VMS. The challenge lies in ensuring the reproducibility of the trajectories.

Considering continuous long strokes are painted on most occasions, there are several failure situations in the robotic painting, including singular points, possible collision, inconsistent posture, or points out of reach. To tackle these problems, we make efforts in the following aspects.

Painting Space The placement of the pigments and palette are horizontal, as is done in the VMS, to prevent fluid flow. A 6-DOF Denso VS060 robot manipulator is deployed as our robotic platform, whose limit reach is 60/70cm with/without a brush. We place the painting board at a 67° angle to vertical in a 35cm distance and transform the painting trajectories to finish more actions in a sweet spot of $25 \times 25cm^2$ square region. By this deployment, the robot can perform most painting actions completely.

Simulation of Painting Actions Long trajectories are sometimes inexecutable due to inconsistent posture, although every individual point on it is reachable. Therefore, it is required to check if the painting data can be well operated by the robot in advance. Because if there is a failure, there is no going back. We perform painting action simulations in the Denso WincapsIII software. And if the trajectories or points are not executable, we modify the trajectories or points by assigning close poses to them and re-evaluate the completeness until converging.

Real-time Alarm Although we use a 6-DOF robot manipulator to paint, its reach is still more constrained than the human arm in the $SO(3)$ space because of potential physical collisions. Therefore, we provide real-time alarms to restrict human movements during painting if necessary. According to the D-H parameters of the Denso VS060 robot, as listed in Table 1, we calculate the Inverse Kinematics (IK) with the aid of ROS MoveIt motion planning library [35]. When an IK solution fails, we alarm the painter to interrupt the current stroke and make a compensating motion. In this way, we obtain actions with better reproducibility.

4.3 Reproduction of Non-Creative Actions

As detailed in Section 3.1, the extracted painting information only contains key action attributes and the corresponding trajectories rather than every complete movement. We design auxiliary automatic devices to execute the non-creative actions depending on the action type $\mathbf{a^{id}}[a^{id}_{type}]$.

Automatic Brush Changing Artists usually use a variety of painting tools during painting, and we deploy the same brush configurations for the robot, as shown in Fig. 5(b). The robot chooses and changes its brush automatically according to the painting action $\mathbf{a^{id}}[\mathcal{B}^{i}_{brush}]$.

Table 1 D-H parameters of the robot manipulator

Joint i	θ_i	d_i	a_i	α_i	Joint Limits(degrees)
1	q_1	d_1	0	$\pi/2$	$-160, 160$
2	q_2	0	a_2	0	$-120, 120$
3	q_3	0	a_3	$-\pi/2$	20,160
4	q_4	d_4	0	$\pi/2$	$-160, 160$
5	q_5	0	0	$-\pi/2$	$-120, 120$
6	q_6	d_6	0	0	$-360, 360$

where $d_1 = 0.125$m, $a_2 = 0.21$m, $a_3 = -0.075$m, $d_4 = 0.21$m and $d_6 = 0.07$m

Automatic Brush Cleaning and Drying Artists clean their brushes by stirring in water and dry them up by wiping. These movements are inefficient for robots, and we design a cleaner and a dryer for the robot instead. In fact, these devices guarantee both time efficiency and cleaning effect.

4.4 Critical Factors in the Painting Reproduction

Since our goal is to reproduce human painting techniques rather than produce unique painting effects of robotic style, it is much more difficult to implement the painting than other painting robots. The influencing factors in the painting reproduction are also critical for human-level robotic painting.

Brush Calibration Although the robot's brushes are measured in advance, it is difficult to guarantee that their base position is aligned with the brushes used by humans. Therefore, we calibrate the brushes before painting, i.e., determining the origin of the tool coordinate system. To this end, we test the stroke width w with respect to the depth below the canvas $\triangle z = \mathbf{p}_{i,can}[z]$, like other painting robots do [13, 16]. The base depth of used brushes is selected according to the $w \sim \triangle z$ relation map so that the brush paints a consistent width with human actions.

Characteristics of Pigments The condition of the pigments has a huge impact on the painting result since varying moisture of the pigments leads to huge differences in the dipped amount and the adhesion when they are applied to the canvas. Other robotic systems use diluted pigments to simplify the interactions between the pigments, brush, and canvas for controllable stroke textures. To achieve a consistent painting effect as humans, the same pigment configurations are used in our experiments. We ensure a controllable pigment state by controlling the initial pigment state and the overall painting time. The experiment proves

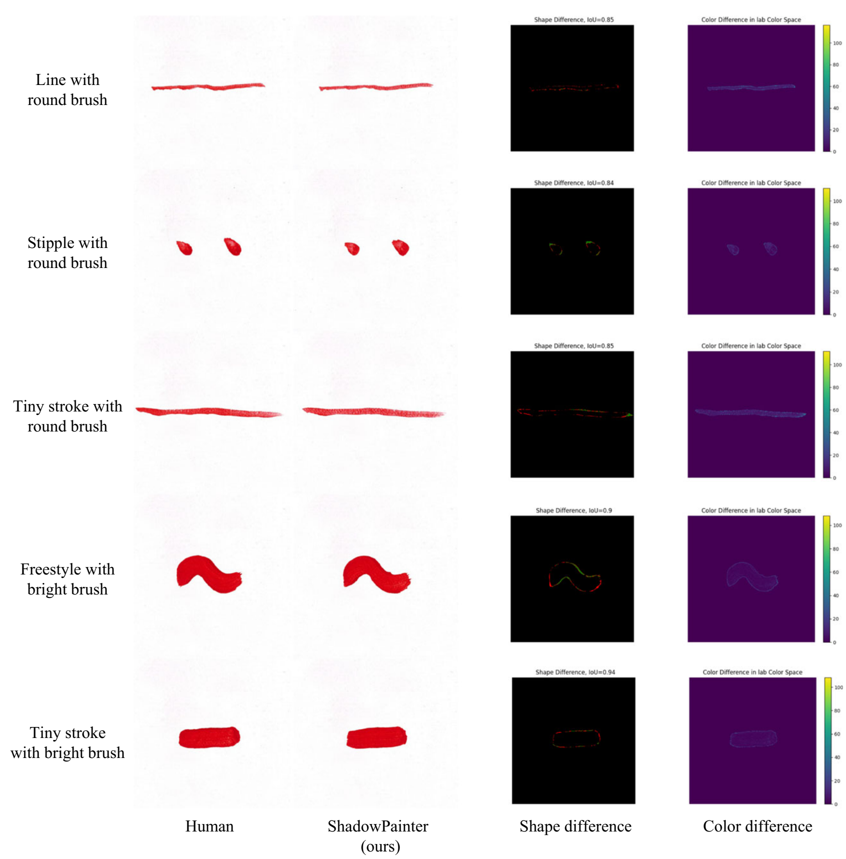

Fig. 9 Reproductions of brush strokes. Our ShadowPainter reproduces similar strokes to humans with a mean IoU of 88%

that this scheme is effective when the painting time is within 3 hours.

Movement Speed The trajectories are collected with timestamps, which can be used to schedule action speeds and accelerates. However, the 6-DOF manipulator has a limited speed when moving along trajectories in high precision odometer mode, and the robot moves dramatically slower than human movements. This scene is common in the back-and-forth movements which are mostly seen in color mixing. The speed difference between robot movements and human movements result in the difference of color intensity for single strokes and also cause the pigment state to be uncontrollable in long-term execution. This problem can be mitigated by changing the robot configuration to increase the moving speed of the end-effector, for example by using a parallel robot.

5 Evaluation of the Robotic Painting

In this section, we describe the evaluation criteria and metrics to evaluate whether our ShadowPainter can perform painting techniques and produce complete paintings with similar visual effects to humans.

Due to the diversity of the paintings and the subjectivity of painting appreciation, there is no consensus on evaluation criteria and metrics of robotic painting. Most of the existing work uses subjective assessment indicators to evaluate the painting results, for example, *visual quality*, *creative*, *aesthetically pleasing*, etc. However, these criteria are too vague resulting in widely varying evaluation results from human evaluators and thus are not suitable for our painting reproduction task.

Considering painting is composed of various brush strokes while varying brush techniques are applied. Only if these strokes and painting techniques could be reproduced by the robot, the human-level painting is promising. Therefore, we propose to evaluate the robotic painting at three levels: single strokes, brush techniques, and finished painting results, covering local and global painting features.

5.1 Evaluation of Single Strokes and Brush Techniques

The visual effect of a painting area can be split into two aspects, shape and texture, which is a common practice in computer graphics [36]. For strokes, the shape determines the final result decisively while the overall texture is more important for brush techniques. We use IoU and color difference in Lab space, which are widely used in image detection tasks and color science respectively, to evaluate the reproduction effect of the single strokes and the brush techniques. IoU shows the shape difference between two painting entities, while the ΔE_{Lab} tells how much difference between painting colors.

We conduct the stroke reproduction experiments covering commonly used strokes and brushes: (1) line stroke, stipple stroke, and tiny stroke with a round brush, and (2) tiny stroke, freestyle stroke with a bright brush. And nine brush techniques covering most painting situations are tested, including wash, scumbling, drybrush, double load, color mixing, wet in wet, overlay, and blending.

5.2 Evaluation of the Overall Paintings

To quantitatively measure our ShadowPainter's ability to reproduce the paintings, we should choose a metric to measure the similarity between the robotic painting result

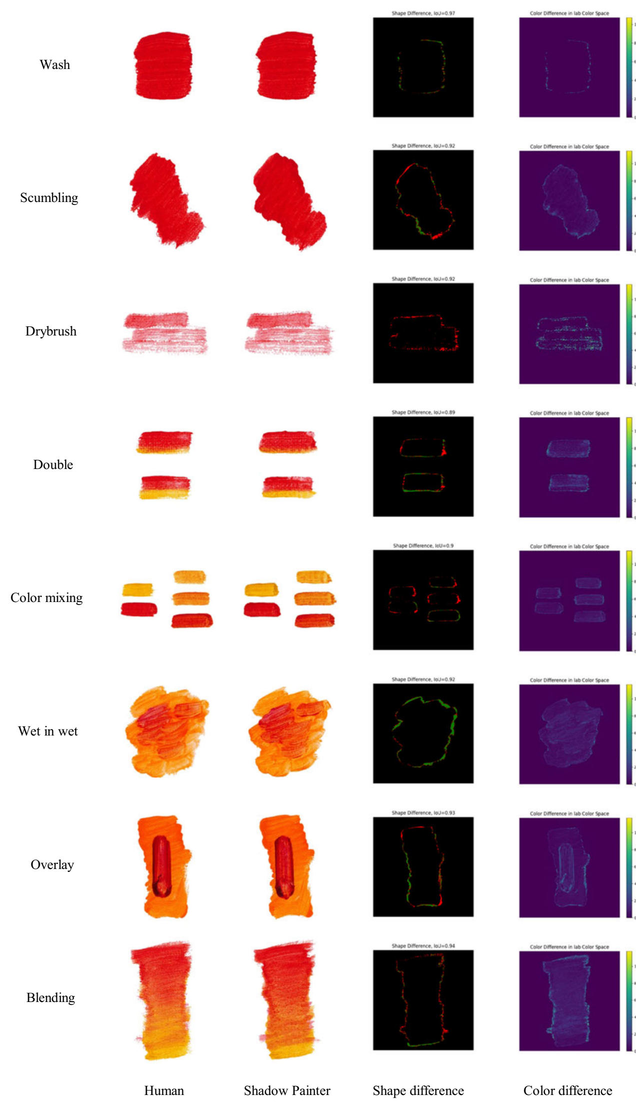

Fig. 10 Reproductions of brush techniques. Our ShadowPainter can reproduce similar effects of brush techniques to humans

I_r and the human result I_h. A painting is an accumulation of strokes using a variety of painting techniques. Even human painters cannot reproduce the same painting. Therefore, the evaluation of the similarity between paintings should consider perceptual features instead of pixel-wise differences and should be insensitive to scale and location. Zhang et al. [37] have shown that activations of deep neural networks trained for high-level tasks correspond to human perceptual judgments better than the commonly used metrics like SSIM [38]. We evaluate the similarity between I_h and I_r using an improved perceptual difference [37, 39]:

$$\mathcal{D}_{pcpt} = \sum_{l} \frac{1}{H_l W_l} \sum_{h,w} \left\| w_l \odot \left(\hat{y}^l_{hw} - \hat{y}^l_{rhw} \right) \right\|_2^2, \quad (8)$$

Fig. 11 Sketch paintings using the demonstrated brush techniques. The benefit of handling diverse painting techniques is that our ShadowPainter can produce naturalistic visual effects in paintings as humans do

where $\hat{y}^l_{hw}, \hat{y}^l_{rhw} \in \mathbb{R}^{H_l \times W_l \times C_l}$ for layer l denote the activations in a pre-trained network by passing image patches of I_h and I_r separately. The activations are scaled channelwise by vector $w^l \in \mathbb{R}^{C_l}$ before calculating ℓ_2 distance. We further compare the reproduction ability of our ShadowPainter with professional human painters using $\mathcal{D}_{pcpt}$ to demonstrate the painting ability of our system.

Besides, we perform a Visual Turing Test covering diverse participants with different knowledge backgrounds. The participants are asked to vote whether a painting is painted by a human or a robot.

6 Experimental Results and Analysis

In this section, we conduct painting reproduction experiments at three levels, according to the evaluation criteria

Fig. 12 Guess which one is painted by humans and which one is painted by our ShadowPainter in each pair? The answer is given in Table 2.

Table 2 The answer of the overall painting results in Fig. 12

Human	ShadowPainter
ShadowPainter	Human
ShadowPainter	Human
Human	ShadowPainter

and metrics introduced in Section 5. We compare our painting results with humans and other painting robots to demonstrate the effectiveness and advantages of our ShadowPainter.

6.1 Experimental Setup

In the experiments, we test diverse painting styles (still life paintings, portrait paintings, and landscape paintings) and commonly used brushes (round liner, bright brush, and fan brush) on acrylic paintings and gouache paintings to verify the effectiveness of our ShadowPainter. Note that the original human paintings in our experiments are not painted by experts and our purpose is to imitate the painting techniques and paintings instead of achieving excellent overall visual effects. If the painting data is collected from experts, the painting results will be better. The operating speed and acceleration of the robot are limited to 65% and 60% of the maximum for safety. And the trajectory execution density of the robot is set to 1 mm.

6.2 Reproduction of Brush Strokes

The reproductions of single strokes are evaluated using IoU and ΔE_{Lab}. As shown in Fig. 9, our ShadowPainter reproduces the strokes with a mean IoU of 88% relative to the artists' strokes. The results demonstrate that our system can reproduce almost the same results in terms of strokes, the lowest unit in a painting. This also proves that the uncertainty of the interactions between the soft brushes and environment is limited using the methods proposed in this paper. It is worth emphasizing that the experiments were done using the same configurations as in daily human painting. If we use diluted pigments, as many other painting robots do, the quantitative indicators will be better due to the reduced randomness of pigment interactions.

6.3 Reproduction of Brush Techniques

In terms of brush techniques, texture is more important than shape. This is because the brush technique is reflected as an area effect. As shown in Fig. 10, our ShadowPainter can reproduce similar effects of brush techniques to humans, while the other painting robots can only implement wash and overlay techniques. And sketch paintings using the described brush techniques are demonstrated in Fig. 11. The benefit of handling diverse painting techniques is that our ShadowPainter can produce more naturalistic visual effects in paintings as humans do.

6.4 Reproduction of Overall Paintings

The reproductions of overall paintings are shown in Fig. 12. Guess which one is painted by humans and which one is painted by our ShadowPainter in each pair (Table 2)?

Qualitative Comparison The reproduction paintings are similar to human paintings in terms of overall visual effect, including the overall tone and portrayal of entities. In close observation, many strokes do not have the same texture as human paintings. For example, the robot produces a brighter sky area in the Wheat Field. The difference does not affect the feel of the scene or the shaping of the content. Even an artist would not paint two identical paintings.

The reproduction paintings parameters are listed in Table 3. Our ShadowPainter uses fewer strokes and less painting time than other painting robots but produces better visual effects. Besides, we achieve more painting techniques, which results in human-level painting effects. These findings indicate the advantage of imitating the human painting process other than using existing robotic tailored SBR methods.

Quantitative Comparison The perceptual difference $\mathcal{D}_{pcpt}$ of reproduction paintings is shown in Table 4. To provide a comparison baseline, we get reproduction painting pairs from [40], which are painted by professional painters to imitate famous paintings. And we also get different painting pairs with the same painting style and similar contents as another baseline. There are samples of these two baselines in Fig. 13. The perceptual difference of our reproduction

Table 3 Reproduction paintings parameters

Artwork	Number of strokes	Brushes	Number of pigments	Painting time	Used brush techniques
Still life	482	Round, Bright, Fan	12	3.5h	Wash, Drybrush, Overlay, Double
Portrait	421	Round, Bright, Fan	12	2.7h	Wash, Drybrush, Overlay, Wet in Wet
Landscape	280	Round, Bright, Fan	12	2h	Wash, Drybrush, Overlay, Scumbling, Blending
Wheat field	532	Round, Bright	11	1.7h	Wash, Drybrush, Overlay, Color mixing

Table 4 Perceptual difference $\mathcal{D}_{pcpt}$ between the original painting and the reproduction. Smaller values mean closer to original paintings

	$\mathcal{D}_{pcpt}$ Mean	$\mathcal{D}_{pcpt}$ Stddev
ShadowPainter - Simple sketch paintings	**0.312**	0.052
ShadowPainter - Overall paintings	**0.504**	0.025
Professional painter - Reproductions	0.434	0.047
Professional painter - Different paintings	0.758	0.075

pairs is close to the professional painters, showing good painting reproductions of our ShadowPainter.

Failure Cases There are failure flaws in some areas that degrade the visual effect. The left side of the plate in Still Life has a large area of underpainting omission. The tree trunk in the Landscape is thicker and less coordinated. The former is caused by the unreachable trajectory points while executed by the robot. The latter occurs due to the difference in the shape of the fan brush, resulting in the oversized underpainting. These problems will be further improved in future work.

6.5 Visual Turing Test

We conduct a visual Turing test on the mixed set of our reproductions, original human paintings, and robotic paintings from the state of the art to make a comparison.

There are 24 paintings in total, including 6 paintings created by humans, 9 paintings created by our ShadowPainter, and 9 paintings created by other painting robots from the state of the art [8, 12, 13, 15, 23, 29, 30]. And we got 202 test

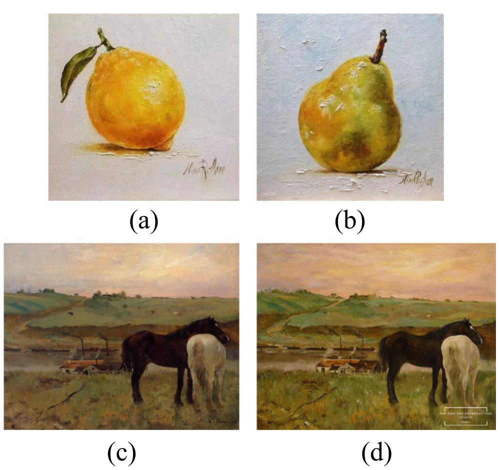

Fig. 13 Samples of baseline painting pairs in the quantitative comparison of $\mathcal{D}_{pcpt}$. $\mathcal{D}_{pcpt}$ of the different painting pair (a) and (b) is 0.7. $\mathcal{D}_{pcpt}$ of the reproduction painting pair from professional painters (c) and (d) is 0.41. Images credits: (a), (b) are from [41]. (c), (d) are from [40]

Table 5 Frequency voted as human paintings by Visual Turing Test participants. H, SP, OR refer to paintings created by humans, our ShadowPainter, and other painting robots respectively

	Average	Stddev
H	0.59	0.14
SP(ours)	0.68	0.08
OR	0.41	0.10

results, among which there are 75 participants with professional painting training, 24 participants with robotic system development experience, and 103 participants with no relative backgrounds. In the test, participants are asked to vote whether a painting is created by a human or robot. And if the participants have relative backgrounds, *Q2* will be asked.

Q1: Is this painting created by a robot or human? (only one choice allowed from ”human” and ”robot”)

Q2: Which is the biggest difference between robot-created paintings and human-created paintings helping you tell them apart? (Whether the strokes are monotonous, Whether the elements are rich, The overall feel, Unusual flaws, Whether there are enough details)

Results The statistical frequency implying a sample is voted as human-created is shown in Table 5. Our ShadowPainter achieves the highest frequency ($> 50\%$) that paintings are voted as human-created. We conduct a two-tailed t-test to check if there are significant differences between the three test groups. The result shows that there is no statistically significant difference between our reproductions and human paintings with $p > 0.2$, while the painting results of other robots are significantly different from both ours and humans with $p < 0.001$ and $p < 0.05$ respectively.

To look into details, we demonstrate the distribution of the three groups in Fig. 14. And we wonder what

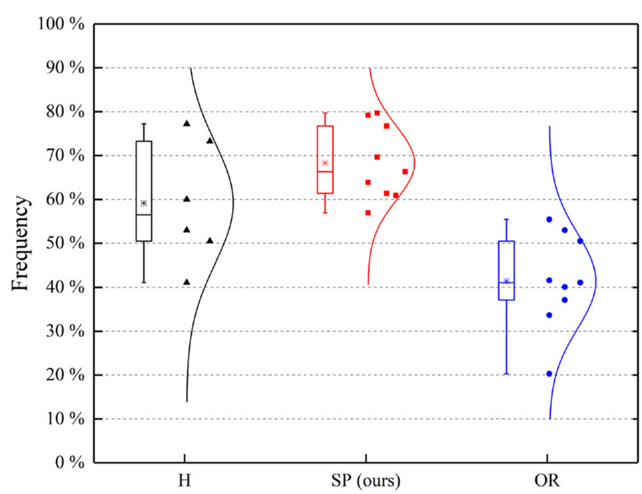

Fig. 14 Distribution of the Visual Turing Test results

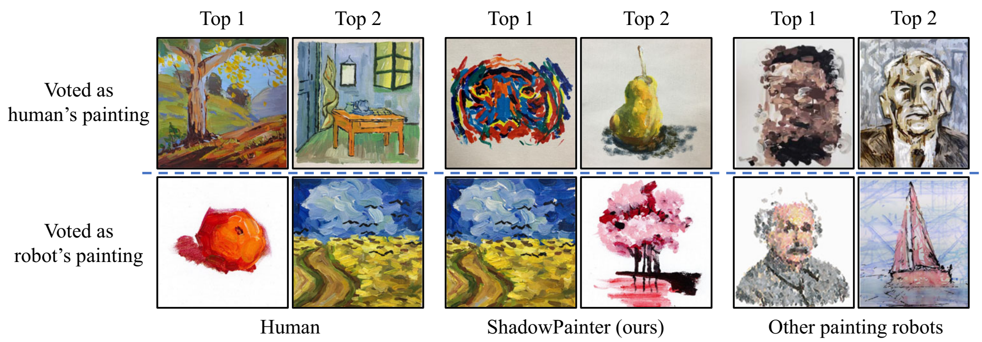

Fig. 15 The top 2 samples that are considered as human paintings and robotic paintings from each painting groups (human, our ShadowPainter, other robots [8, 12, 13, 15, 23, 29, 30])

factors influence whether a painting is considered human-created or robot-created. Thus, we picked the top 2 samples that are considered as human paintings and the top 2 samples that are considered as robotic paintings from each group, as shown in Fig. 15. We found that people tend to separate human artworks from robotic artworks based on the diversity and naturalness of the painting strokes. This is consistent with the results of *Q2* in the user study.

7 Conclusion and Future Work

In this paper, we focus on a new task: fine art painting reproduction. Firstly, we design a VMS to acquire sufficient painting information that can be used for robotic active learning to reproduce the painting results. Then an RPS is developed to achieve human-level reproduction paintings. At the same time, we reveal the critical factors influencing robotic painting. Finally, we propose local and global evaluation criteria and metrics to assess the reproductions of individual brush strokes, brush techniques, and overall paintings.

The experimental results imply that our ShadowPainter can reproduce similar brush strokes, painting techniques, and overall painting results to human artists. Compared with the existing work, we achieve human-level robotic painting with natural strokes, which makes it indistinguishable from human paintings. Professional painting data can be collected by our ShadowPainter for robotic skill learning. In addition, our system can also be deployed to capture and imitate other complex human manual skills, which is helpful to replace manual labor and serve as a teaching template for education.

This paper explores the feasibility of human-level robotic painting reproduction, which will be the starting point for human-level autonomous robotic painting and human-robot collaborative creation, as discussed in [42]. The artists and machines will benefit each other in the painting process [43]. Robot learns painting skills from human demonstrations and provides painting assistance in return. In future work, we will further improve the fidelity of our system and train an agent to paint autonomously using the collected painting data.

Author Contributions All authors contributed to the research.

Fei-Yue Wang formulated research goals;

Fei-Yue Wang and Xiao Wang provided supervision and ideas;

Chao Guo, Tianxiang Bai, and Yue Lu developed methodology and the system;

Chao Guo and Xiangyu Zhang performed the experiments, and prepared the manuscript;

Chao Guo, Tianxiang Bai, Xingyuan Dai, Xiao Wang, and Fei-Yue Wang reviewed and edited the manuscript.

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Declarations

Conflict of Interests The authors declare that they have no conflict of interest.

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