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Technical Section

Humanistic Oriental art created using automated computer processing and non-photorealistic rendering

Adrian David Cheok*, Zheng Shawn Lim, Roger Thomas KC Tan

Mixed Reality Lab, National University of Singapore, Singapore

Abstract

In this paper, we present a new system of non-photorealistic rendering which allows landscape photographs to be automatically converted to look like Oriental paintings. Using various computer vision and image processing techniques, we can generate images with the rules and features commonly found in Oriental paintings. With such a system, anyone can create realistic Oriental paintings easily, without the years of practice that are usually required by Oriental artists.

Keywords: Non-photorealistic rendering; Image segmentation; Image interpolation; Rendering

1. Introduction

For a long period of time, the main goal in computer graphics was to strive for photorealism. While this goal has generally been achieved in recent years, a new form of computer graphics research called non-photorealistic rendering (NPR) emerged. NPR is any process that does not render objects realistically, but rather simulates different artistic styles [1].

In the few years that NPR research has been carried out, various types of artistic styles such as sketching, pen-and-ink [2], watercolors [3] and oil painting have been simulated. However, these styles tend to suit Western art, since Oriental art is rather different. Oriental art is less concerned with the actual physical appearance of the objects, but rather is more focused on painting the perception that the artist has of the scene. Oriental art also has an element of simplicity. Paintings are usually achieved with a minimum of strokes, with the emotion and thought of the artist conveyed through the speed, movement, placement and pressure of the brush strokes.

There has previously been some NPR research carried out on Oriental art. However, the research mainly either focuses on rendering pre-constructed 3D models [1,4,5] or provides an interactive painting system that allows users to control a simulated painting brush [6–8]. The disadvantage of these methods of NPR make it relatively difficult for non-experts to use, since they require knowledge of computer graphics or Oriental art in order to use them.

Thus, we propose in this paper a new system which can automatically generate Oriental paintings from normal landscape photographs which are taken in a stereo pair. The system will create images that follow the painting rules found in Oriental landscape paintings. Using this system, any person will be able to create realistic Oriental landscape paintings from photographs, without requiring knowledge of Oriental landscape paintings.

The paper is organized as follows. Section 2 details the background information as well as the principles and rules of Oriental paintings. Section 3 introduces the work previously done by other researchers in the area of NPR, particularly for Oriental paintings. Section 4 describes the different steps in our proposed system. Section 5 concludes our proposed system.

2. Background

Oriental painting as a traditional art form has evolved continuously over thousands of years. It originated from Chinese calligraphy and shares with it several similar

*Corresponding author.
E-mail addresses: adriancheok@mixedrealitylab.org, elecad@nus.edu.sg (A.D. Cheok).

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characteristics. There are four main elements in Chinese paintings and calligraphy: the brush, ink, inkstone and paper. These are also known as the "four treasures" [9].

There are three popular types of subjects in Chinese paintings. They are landscapes, flowers and plants, birds and animals. Landscape paintings are considered to be the highest level in Chinese paintings, on the same level with Chinese calligraphy, and landscapes were the subject of the earliest paintings by the intellectual class, the scholars and officials. Traditional landscape paintings consist of six different objects: rocks, trees, mountains, water, people and buildings [10].

There are several different features which are commonly found in Chinese paintings, which we try to reproduce in our NPR system.

- Atmospheric depth—Background objects in Chinese paintings are usually painted with more dilute ink to add a feeling of depth to the painting, since distant objects usually appear hazy and blurred due to atmospheric effects.
- Irregularity—Due to the unpredictable nature of the interactions of the ink and the paper surface, brush strokes are never completely uniform in intensity. The edges of a stroke are also not distinct, but appear blurred, due to the effects of ink diffusion.
- Blank space—Long brush strokes will exhibit empty spaces in between. This occurs when the brush runs out of ink due to the limited amount of ink that the brush can store at one time. Omission of the background is also acceptable and commonly found in Chinese paintings.
- Seal—Most Chinese paintings contain one or more red imprints of seals, and perhaps some calligraphy expressing the author's thoughts and feelings. The seals are an important part of the painting, and are usually found near an edge of the painting.
- Composition—Chinese paintings do not require artists to strictly follow reality or a particular angle of view. The artist is free to rearrange the objects in a scene or paint objects from a different point of view. In landscape paintings, Oriental artists try to convey the impression that the scene is viewed from a high vantage point.

We use the above rules in Chinese landscape painting to generate Oriental paintings from a stereo pair landscape image. The detail of our proposed method is described in Section 4.

3. Previous works

One of the earliest works in NPR was the modelling of hairy brushes by Strassmann in 1986 [11]. His model had four classes of objects: brush, stroke, dip and paper. Using a 1D array, he modelled brush strokes using cubic splines and polygons. However, the user interface required users to enter and edit strokes using a mouse which was quite unnatural.

Yeh and Ouhyoung [1] created a set of algorithms to automatically render 3D animal models in the Chinese painting style. Their process used borderline stroke making and interior shading together with special effects like dry brush effect and turning effect to create the Chinese painting effect. This NPR process produces realistic Oriental painting images, but it requires 3D models of the objects prior to the NPR process.

Ink diffusion effects in Chinese paintings have been modelled by Huang et al. [12] using a physical based model. They simulated the effect of ink diffusion by taking into account four factors, the gradient of water, absorbency of paper, paper texture and the inertia of water. This system can create realistic diffusion effects, but has the disadvantage that it is very computationally intensive.

Lee [6] created an interactive painting system that enabled users to paint virtually on the computer. His system used a 3D brush model that used Hooke's law to calculate the deformation of the brush under pressure. Due to the use of a complex brush model, the output looks very similar to real Oriental paintings, but the user needs to be experienced in Oriental paintings to use it effectively (in effect the screen brush replaces the real one, and thus the user must have a similar skill to the true Oriental brush artist). Yeh et al. [7] went a step further and included the use of haptic feedback in their interactive painting system.

There has also been research on how to render individual elements found in Oriental landscape paintings. Way [13] proposed a hemp-fiber stroke to synthesize rock textures in Chinese landscape painting and to synthesize portraits in Chinese figure painting. A system to automatically draw trees in the Chinese ink painting style from 3D polygonal models was presented by Way [14]. By focusing on particular elements, the objects are rendered very realistically, but the NPR process is limited to only those class of objects, and cannot be applied to other kinds of objects.

4. Proposed Oriental painting algorithm

The algorithm used for the NPR in this research comprises five main parts. The overall block diagram of the algorithm is shown in Fig. 1. The input to the system is a pair of stereo photographs of the same scene. The algorithm operates as follows: first, all the objects in the image are segmented. This is because for Oriental landscape paintings, the individual objects are extracted and rearranged in the painting to follow the composition rules. Once the objects are segmented, their relative depths are determined using stereo depth information. This depth information is used later in the composition stage. Next, the objects which are partially occluded and have missing regions are filled in automatically using interpolation techniques. This is necessary as the missing regions should be visible after the rearrangement of the objects.

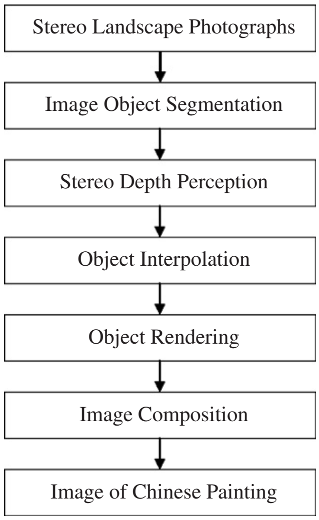

Fig. 1. Overall algorithm.

After the objects are filled in completely, each object will then be rendered in the Oriental painting style. This is so that each object appears to have been painted using Oriental ink and brushes. Finally, the rendered objects are arranged according to Oriental painting composition rules, in order for the final image to appear similar to real Oriental landscape paintings. In the rest of this section, we will explain each part of the algorithm in more detail.

4.1. Image object segmentation

Image segmentation involves splitting the image into meaningful parts, i.e. objects. There are two common techniques for accomplishing this: histogram thresholding and region growing [15].

Thresholding involves finding all the pixels in the image with similar color, and considering them as a single object. However, this method cannot be used in the image segmentation system, since the spatial information of the pixels are not taken into account in this method, but would rather focus on the pixel colors only. If this method was adopted, the segmentation system would have difficulty distinguishing between separate objects which share a particular color range, for example the green pixels belonging to a tree object would be confused with green pixels that belong to a grass background. Also, objects which comprise a wide range of colors that vary slowly over position, such as a sky which fades from dark blue to white, are likely to be segmented into several objects.

Thus a more suitable method, termed "region growing," involves selecting seed pixels in the image, and growing regions from these seed pixels by adding neighboring pixels which are similar to those in the region until no further pixels can be added or another separate region is encountered. The similarity criterion is usually based on the color of the pixels. This method has an advantage over thresholding that the spatial information of each pixel is actively considered, together with the color information.

Unfortunately region growing method faces two difficulties: first, the number and position of the seed pixels have to be determined. The resulting segmentation is heavily dependent on the initial selection of seed pixels: if the number and placement of the seed pixels are chosen incorrectly with respect to the image, the final output of the segmentation process is likely to be either under-segmented or over-segmented [15].

Currently available algorithms to generate seed pixels based on watersheds and gradients in the image are very complex and do not produce very good results. Another main problem with region growing is that the separate regions cannot be considered as a single object since it grows regions from neighboring pixels. This is a problem as many images will have objects (e.g. background objects such as mountains) that are partially occluded by objects in front of them (such as tress in the foreground), causing the object to appear as several disconnected regions in the image.

Since both thresholding and region growing suffer from certain limitations, they cannot be used alone for segmentation. Instead, we propose a new hybrid method, which combines the strengths of the two techniques. An overview of this new segmentation technique is shown in Fig. 2.

The proposed algorithm for segmentation comprises three parts. The first step is to perform region growing using a seedless region growing algorithm. The next step involves finding all the regions that contain fewer pixels than a certain criterion and merging them with the most similar neighboring region, with the similarity criterion of regions being average color. This process is repeated until the areas of all the regions in the image are equal to or greater than the specified minimum region criterion. In the last stage each region is compared to all the other regions regardless of whether they are adjacent or not. If any two regions are similar, they are then merged together and considered as one object.

In each step, for computing similarity of colors, the CIELUV color space is used instead of the normal RGB

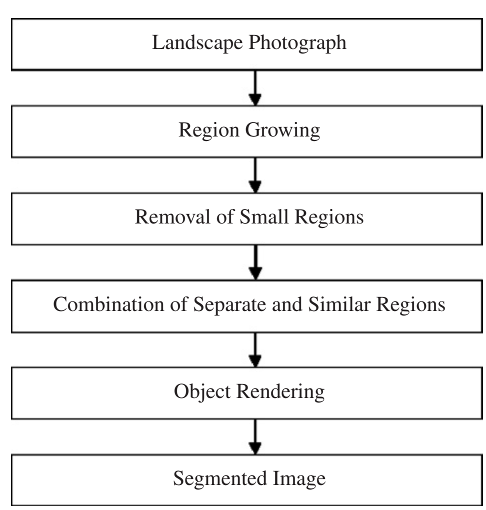

Fig. 2. Segmentation algorithm.

color space. This is because the color distance in the CIELUV color space has been shown to be a much closer approximation of human perception of color differences [16]. Colors are considered similar if the color distance is less than a defined threshold. The method to convert from RGB color space to CIELUV color space via the CIEXYZ color space is as follows:

Conversion from RGB to CIE XYZ:

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.490 & 0.310 & 0.200 \\ 0.177 & 0.813 & 0.011 \\ 0.000 & 0.010 & 0.990 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}. \quad (1)$$

Conversion from CIE XYZ to CIE LUV:

$$u_p = \frac{4X}{X + 15Y + 3Z}, \quad (2)$$

$$v_p = \frac{9Y}{X + 15Y + 3Z},$$

$$L = \begin{cases} 116\left(\dfrac{Y}{Y_n}\right)^3 - 16 & \text{for } \left(\dfrac{Y}{Y_n}\right) > 0.008856, \\ 903.3\left(\dfrac{Y}{Y_n}\right) & \text{otherwise}, \end{cases} \quad (3)$$

$$U = 13L(u_p - u_n),$$

$$V = 13L(v_p - v_n),$$

where reference white light is chosen such that $[X_n \; Y_n \; Z_n] = [1 \; 1 \; 1]$, so $u_n = \frac{4}{19}$ and $v_n = \frac{9}{19}$.

We use the Euclidean distance D_{luv} for perceptual color distance between two colors $L'U'V'$and $L''U''V''$in the CIEUV color space:

$$D_{luv} = \sqrt{(L' - L'')^2 + (U' - U'')^2 + (V' - V'')^2}. \quad (4)$$

In the rest of this section we describe our proposed segmentation steps in more detail.

4.1.1. Region growing

For each pixel $p(i,j)$ we assume that its upper and left pixels, $p(i,j-1)$ and $p(i-1,j)$, belong to regions R_l and R_m, respectively. Then based on the perceptual color distance between these pixels, we classify $p(i,j)$ as follows:

- IF $D_{luv}[p(i,j), p(i,j-1)] \leqslant T$ and $D_{luv}[p(i,j), C_{R_l}] \leqslant T$ THEN $p(i,j) \in R_l$,
- IF $D_{luv}[p(i,j), p(i-1,j)] \leqslant T$ and $D_{luv}[p(i,j), C_{R_m}] \leqslant T$ THEN $p(i,j) \in R_m$,
- IF $p(i,j) \in R_l$ and R_m THEN Merge R_l and R_m,
- IF $p(i,j) \notin R_l$ or R_m THEN $p(i,j) \in New(R)$,

where C_R is the average color value for the pixels belonging to region R. This value is updated in every loop of this step.

4.1.2. Removal of small regions

The result of the previous step contains many small regions and these small regions must be merged to one of their larger regions. In this step for each region R_i if its area is smaller than a minimum threshold, we merge the region to one of its neighbors with closest perceptual distance color C_{R_i}. This process is continued till merging of all small regions in the image.

4.1.3. Thresholding

In this step each region R_i is compared with all the other regions in the image. If the perceptual distance between the region average colors C_R is less than the specified threshold, the regions are merged together.

Fig. 3 shows an example result of our segmentation algorithm. As shown in this figure, the input image (left) has been segmented into five different objects (right).

4.2. Stereo depth perception

Once the objects are extracted in the image object segmentation stage, their relative depth has to be found. This is because the objects need to be classified into three different depth categories, foreground objects, midground objects and background objects, as this information is used later in the rendering and composition stages. Stereoscopic information is used to determine the relative depth of the objects in the image, where the binocular disparity (lateral displacement) in the two images is inversely proportional to the relative distance to the objects.

The pair of stereograms is obtained with a single digital camera taking an image of the same scene twice, at two different positions such that the optical axes of the camera at the two positions are parallel and 2.5 in apart, which is about the average separation between a pair of human eyes [17]. Since there are no dynamic changes in

Fig. 3. From left to right: test photo and segmented output.

the scene (as it is assumed static landscape type scenes are being captured) this method of stereo image capturing is easier than using two different cameras since both images will have exactly the same optical/color mapping and same distortion effect while by using two cameras we have to solve these problems first (see [18] for more details on evaluation of dense two-frame stereo correspondence algorithms).

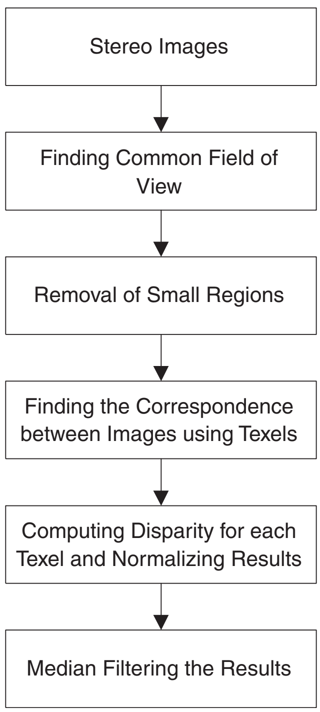

Fig. 4. Stereo depth perception algorithm.

A stereo camera system using two different cameras connected together was experimented with; however, this system produced poor results as a result of the optical and image differences between different cameras (even though they both were the same model, a Sony U-20).

Once the stereo images are obtained, the next step is to find correspondence between the images (which points in left image correspond to points in the right image). An assumption used is that the epipolar lines are horizontal (corresponding points lie on the same image row). The common field of view between the images is found by determining which overlapped regions have the highest correlation. The images are then matched using texels of 4×4 pixels as the base unit, and the disparity of each texel is inversely proportional to the depth at that point. The depth image is then median filtered with a 3×3 filter to remove any errors in the matching process. A flowchart of the depth perception process is shown in Fig. 4. Fig. 5 shows an example result of our stereo depth perception algorithm.

4.3. Object interpolation

After the image segmentation stage, the image will be split into several different objects. Since the real-life objects in the image are located at different depth planes, some objects will be located in front of other objects, partially occluding them. Before the objects are rendered in the Oriental painting style, the missing regions in the partially occluded objects have to be filled in. We perform this process in two stages. In the first stage, the exact boundaries of the full object are extracted. The second stage consists of filling in the unknown pixel values of the parts of the object which are occluded inside the object

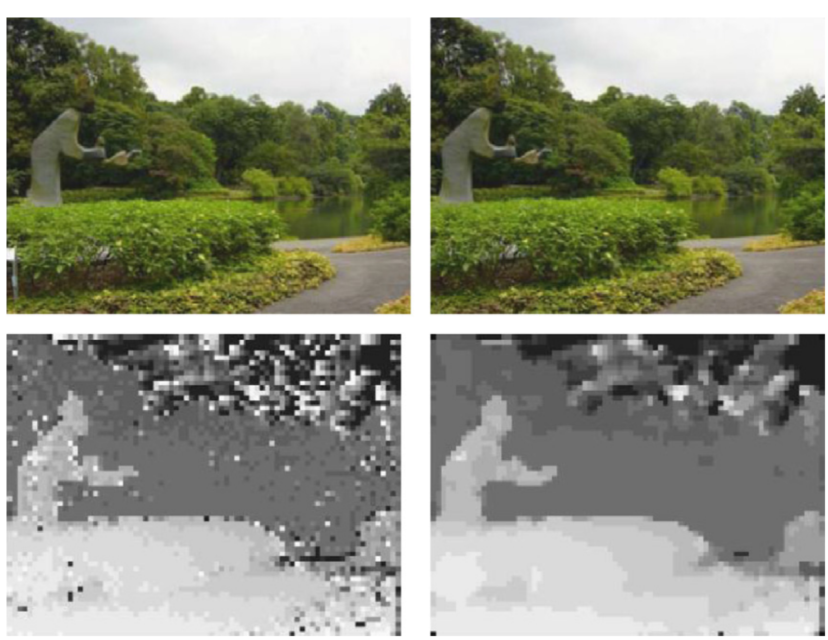

Fig. 5. From top to bottom, left to right: left image, right image, raw depth map and filtered depth map.

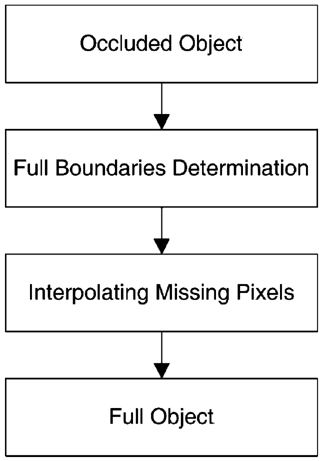

Fig. 6. Object interpolation algorithm.

boundaries which are extracted in the previous stage. A flowchart of the interpolation process is shown in Fig. 6.

For the boundary extraction process, cubic spline interpolation is used to estimate the full boundaries of the object. The pixel values are then determined using a texture synthesis algorithm, similar to the one used by Efros in [19]. Since the missing regions are comparable to the object whole region, normal interpolation methods cannot be applied here.

The proposed method of interpolating the missing part of the objects is as follows:

1. Determining full boundaries of the object: in our proposed method we find the boundary of the object from four sides: top, left, right and bottom. Here we describe the method to find the upper boundary. The algorithm for the other three sides are the same. We use spline interpolation techniques using known parts of the object upper boundary to find the whole object upper part. To perform this task we must find a set of object upper boundary edge pixels first and then apply spline interpolation on them. We show here our proposed algorithm steps to find the object outlines.
   (a) Let set S be the set of pixels belonging to the upper boundary of the object. At first S is null.
   (b) For each image column i, we calculate the upper most edge pixel, P_i:
   $$P_i = \min_j [E(i,j)], \quad (5)$$
   where E is the set of image I edge pixels.
   (c) Calculate the average and standard deviation of P_i:
   $$P_{ave} = \frac{1}{N}\sum_{i=1}^{N} P_i, \quad P_{std} = \frac{1}{N-1}\sum_{i=1}^{N}(P_i - P_{ave})^2. \quad (6)$$
   (d) If $|P_i - P_{ave}| < k \times P_{std}$ where k is a constant, then $P_i \in S$.
   (e) Repeat steps 3 and 4 until values are stable.
   (f) Perform cubic spline interpolation using set S.

2 Interpolating missing pixels: here we fill the inside of the object based on known object pixels. Our proposed algorithm is as follows.
   (a) For an unknown pixel $p(i,j)$, check its neighbors $p(i \pm 1, j \pm 1)$.
   (b) If fewer than three neighboring pixels are known, return to pixel $p(i,j)$ later.
   (c) If at least three neighboring pixels are known, find pixel $p(x,y)$ such that $\sum_{neighbor} |p(i \pm 1, j \pm 1) - p(x \pm 1, y \pm 1)|$ is minimized.
   (d) Assign color of pixel $p(x,y)$ to pixel $p(i,j)$.
   (e) Repeat process for other unknown pixels until there are no more unknown pixels.
   (f) Mask the result image by its foreground object.

As can be seen in the above algorithm, at the last stage we mask the result of the algorithm by the foreground objects standing in front of this object. It is due to this fact that the object can be only occluded by its foreground objects while in the interpolation sometimes other pixels are also filled during the algorithm.

Fig. 7. From top to bottom, left to right: occluded image, initial outline, final outline and filled image. The red circle in top-left image shows the hole in the occluded image caused by the foreground object and the bottom-right image shows our interpolation result.

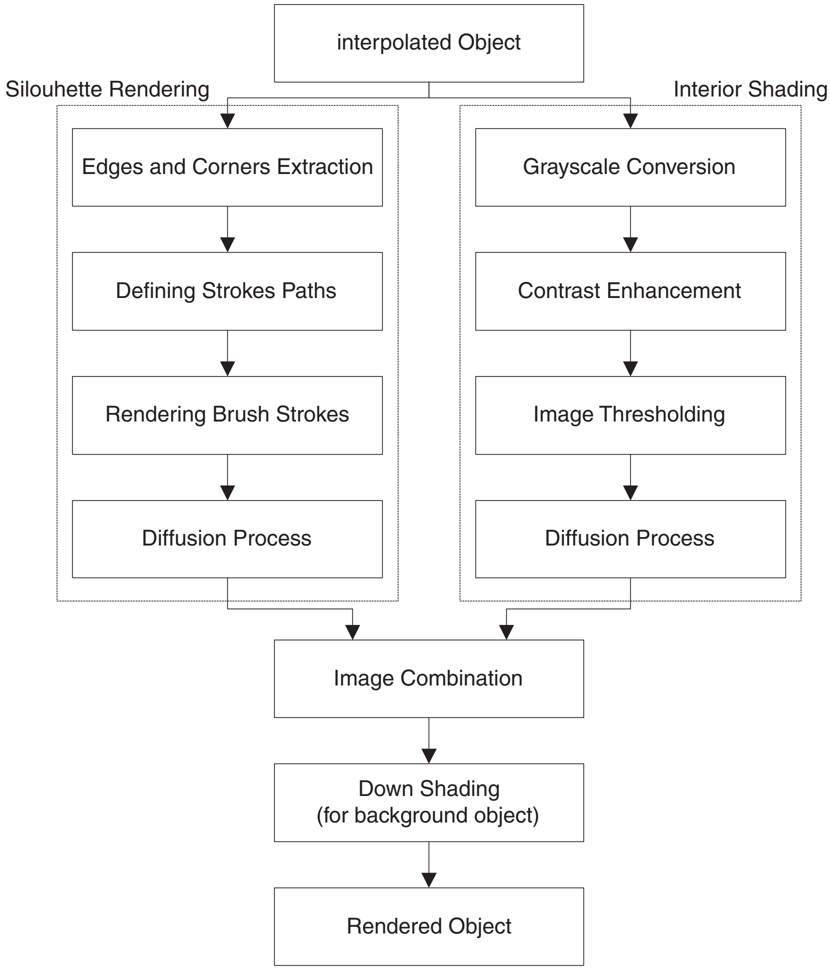

Fig. 8. Rendering algorithm.

$$\begin{bmatrix}1&1&1\\1&0&0\\1&0&0\end{bmatrix}\quad\begin{bmatrix}1&1&1\\0&0&1\\0&0&1\end{bmatrix}\quad\begin{bmatrix}0&0&1\\0&0&1\\1&1&1\end{bmatrix}\quad\begin{bmatrix}1&0&0\\1&0&0\\1&1&1\end{bmatrix}$$

$$\begin{bmatrix}1&0&0\\0&1&0\\1&0&0\end{bmatrix}\quad\begin{bmatrix}1&0&1\\0&1&0\\0&0&0\end{bmatrix}\quad\begin{bmatrix}0&0&1\\0&1&0\\0&0&1\end{bmatrix}\quad\begin{bmatrix}0&0&0\\0&1&0\\1&0&1\end{bmatrix}$$

Fig. 9. Model of corners used in corner detection algorithm.

Fig. 7 shows an example of our interpolation result. As can be seen in this figure there was a big missing area in the object (the red circle in the top-left image) caused by the foreground object. Fig. 7 (bottom-left image) shows the result of our interpolation techniques for the object outline. The result of filling the missing parts is shown in the bottom-right image. As can be seen a natural filling effect of the object is given by the algorithm.

4.4. Object rendering

Rendering the objects in the Oriental painting style is necessary in order for the objects to appear as if they were created normally with Chinese brush and ink, and is done in two parallel stages. In the first stage, the silhouette of the object is rendered by stimulating brush strokes along the edges of the object. In the second stage, the interior of the object is rendered through a series of image processing

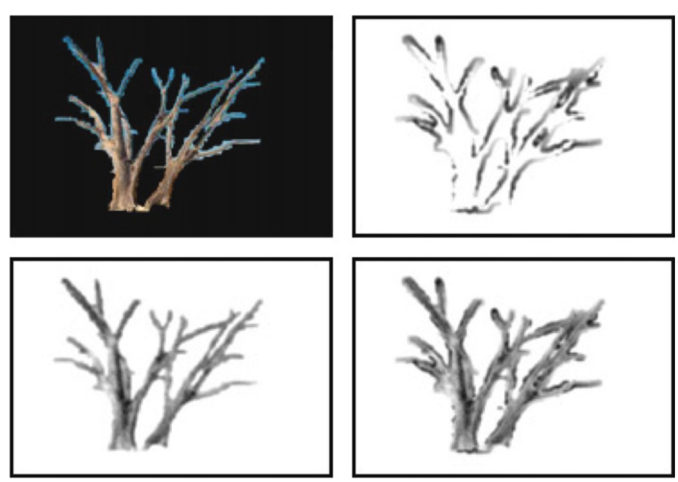

Fig. 10. From top to bottom, left to right: full object, silhouette rendering, interior shading and rendered object.

operations, in which the color image is converted to a grey scale output and after that, the output of the two stages are combined together. Then, if the object is a background object, the final output will then be subjected to a downshading process that will make the object fade into the background at the bottom. The block diagram of the overall rendering process is shown in Fig. 8, with the silhouette rendering on the left branch and interior shading on the right branch.

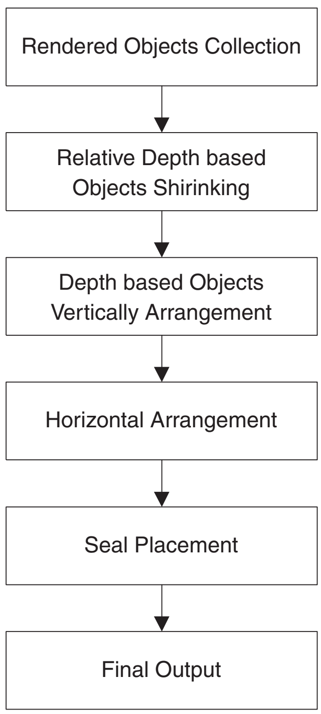

Fig. 11. Composition algorithm.

For silhouette rendering of the object, the first step is to extract the edges. After the edges are extracted, the edge image is split into several stroke paths that an artist would likely use to paint the outline of the object. The assumption used here is that at any point along the edges where the direction of the edge changes sharply (a corner point), the artist is likely to begin a new stroke. We perform corner detection using morphological operators, with the hit-and-miss transform [20], and eight different corner structures.

Fig. 9 shows the models of corners that we use for the corner detection algorithm. If we assume that A is the edge image, we find the corners in A from the following equation which uses the square of the standard deviation.

$$Cornerpixels = (A \otimes B_1) \cap (A \otimes B_2) \cap \cdots \cap (A \otimes B_8) \qquad (7)$$

where $\otimes$ represents the hit-or-miss-transform.

Once the stroke paths are determined, the stroke paths are converted into images of actual brush strokes. This is done using the assumption that the brush stroke width is constant along the center and tapers off at each end. The algorithm for rendering a single stroke path to a brush stroke is as follows: starting from one end of the stroke path, place a small circle on the stroke path. The process is repeated along the stroke path with the radius of the circle slowly increasing until it reaches a maximum with the radius decreasing accordingly as the other end point is reached. At the same time, the intensity of the circle slowly decreases geometrically until it reaches a certain threshold, at which point the intensity is restored to the original value and begins decreasing again. This is to simulate the effect of the amount of ink in the brush decreasing as the painter

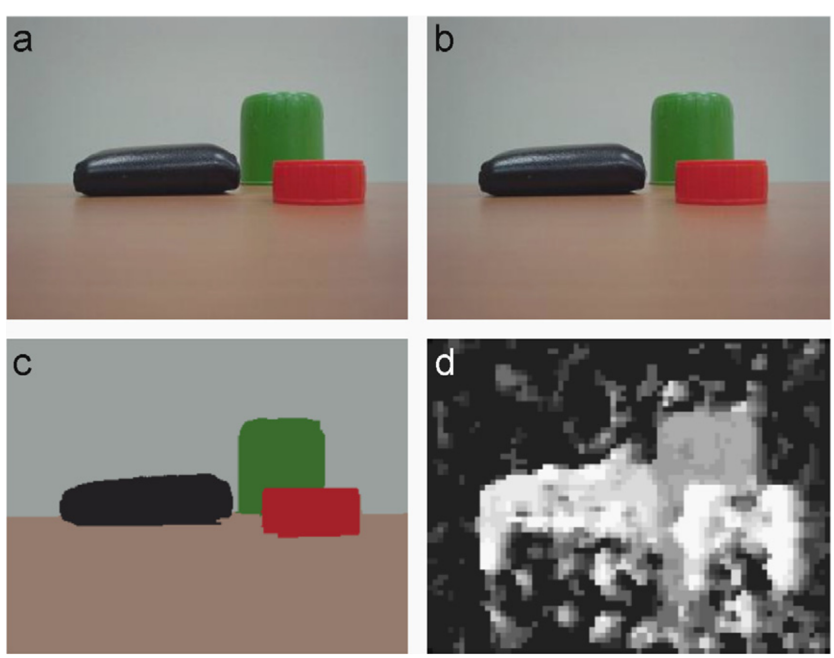

Fig. 12. Results of each step of the proposed algorithm on a stereo test image: (a) left test image taken by camera; (b) right test image taken by camera; (c) result of image segmentation and (d) result of the depth detection.

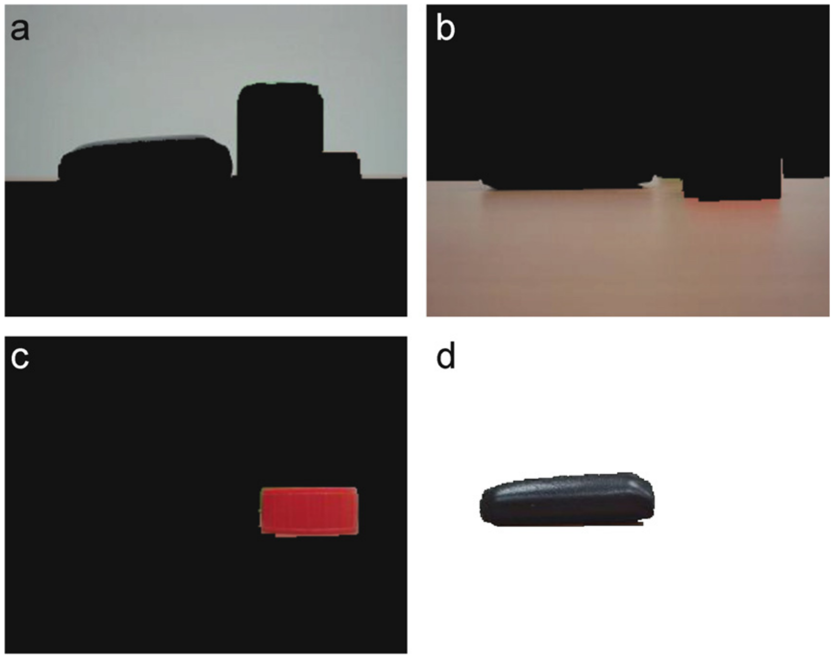

Fig. 13. Results of each step of the proposed algorithm on a stereo test image: (a) separation of image objects: "sky region" (b) separation of image objects: "ground region" (c) separation of image objects: "first object region" and (d) separation of image objects: "second object region".

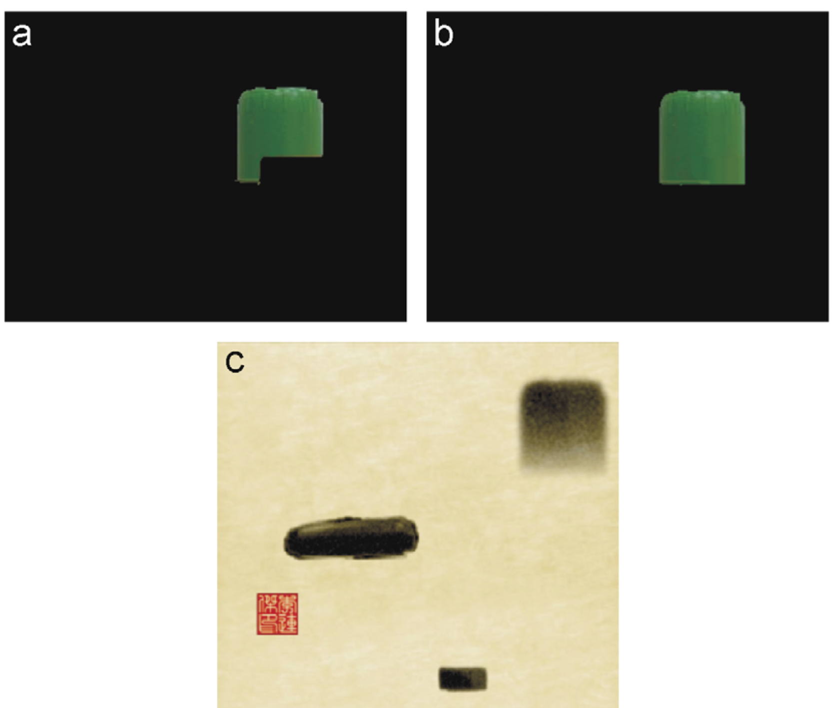

Fig. 14. Results of each step of the proposed algorithm on a stereo test image: (a) separation of image objects:"third object region" (b) result of filling of third object occluded part and (c) final oriental painting result containing rendering output of objects 1,2,3 and composition stage.

moves the brush along the stroke, and the refilling of ink in the brush when the ink level is low.

After the creation of brush strokes, the output image is placed through a diffusion process that simulates the effect of ink diffusion that is a particular characteristic of Oriental paintings. The diffusion process is basically a process that allows ink to flow from the area where the strokes are applied to the neighboring areas, and is based on the method proposed by Huang in [12]. The factors that are used to affect the flow of ink from pixel to pixel are the differences in ink level between the pixels, and the absorbencies of the paper at the pixels. The paper itself is modelled as an array with random absorbencies for each pixel. This allows the simulation of the unpredictable diffusion effects found in Oriental paintings, which is normally painted on natural fiber papers.

The interior of the object is rendered using an interior shading rendering process. Since the input to this process is a 2D image, it is difficult if not impossible to extrapolate and render brush strokes to create the interior shading. Instead, a series of image processing operations are used as the artist is likely to create a painted image which is similar to the original image. To begin, the color image is converted into a grey scale image. This is because most Oriental paintings are painted in shades of grey. The contrast of the grey scale image is then maximized, since the grey scale operation is likely to produce an image with poor contrast. The image is then uniformly thresholded into five different shades of grey, with image intensities of 0.2, 0.4, 0.6, 0.8 and 1.0. This is to simulate the five shades of ink that are commonly used in Oriental paintings [21]. Finally, a diffusion process similar to the one used in silhouette rendering is used to simulate the diffusion effects for the interior shading.

For background objects, the intensity of the output images is decreased and the number of cycles used in the diffusion process is increased. This is to simulate the "washed out" effect that artists use for background objects which is normally achieved by adding more water to the ink. The image is also multiplied with a function that varies from 1.0 to 0.0 from the top to the bottom of the image. This is to achieve the down-shading effect, where the bottom of the object is supposed to be faded smoothly into the background. An example of the rendering process is shown in Fig. 10.

4.5. Image composition

The final stage of the NPR process is the composition stage. The goal of this stage is to arrange the rendered objects on the canvas such that the objects are evenly spaced out, while maintaining the left–right balance of the painting. A main feature of Oriental paintings is the foreshortening effect [10]. This means that instead of normal images where closer objects are overlaid over further objects, the objects are vertically aligned based on the depth. As a result the closer objects are displayed at the bottom and the furthest objects are drawn at the top of the painting. This achieves the effect of a *vantaged* viewpoint found in Oriental paintings which is enhanced by reducing the size of objects which are closer to the viewer. The block diagram of the composition process is shown in Fig. 11.

For the composition stage, the objects are first sorted according to their depth, with each object being assigned to one of three possible depths: foreground, midground and background. The background objects are then placed at the top of the canvas, followed by the midground object, and the foreground objects below them. The exact order of each object for each depth is not necessary, and midground objects are shrunk by 75%, foreground objects are shrunk by 50% to achieve the *vantaged* viewpoint mentioned earlier.

The objects are also displaced in a zigzag manner toward the left and right side. This is to achieve the spacing and left–right balance that is important in the composition of Oriental paintings [10]. In Oriental paintings, the objects are distributed evenly throughout the painting, with approximately the same number of objects on the left and right sides. Once all the objects are placed on the canvas, the red seal commonly found in Oriental paintings is then placed. The horizontal position of the seal depends on the current left–right balance of the painting. Its vertical position is between the midground and foreground objects. If the right side of the painting has a higher intensity of ink, the seal is placed on the left side of the painting and vice versa, with the exact position of the seal dependent on the ratio of the left and right ink intensity. The seal is also set such that it will not be located near the center, since such seals are usually located near the edge of the image, never in the center.

Figs. 12–14 show the result of our algorithm in each stage on a test image containing three objects. In this test

Fig. 15. Results from a landscape photo of a house and mountain: (a) input landscape photo and (b) final output image.

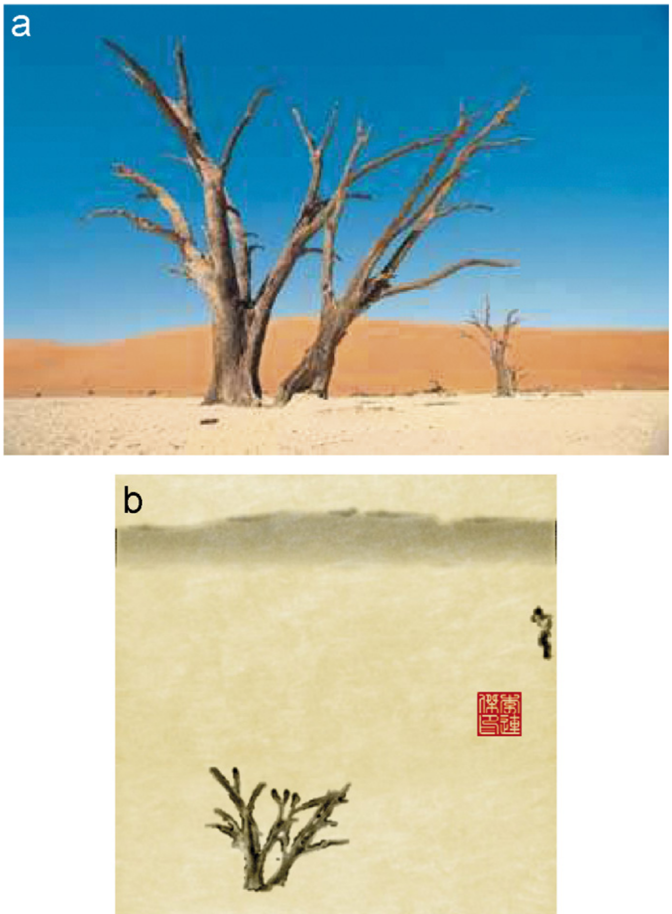

Fig. 16. Results from a landscape photo of a tree and hill: (a) input landscape photo and (b) final output image.

image each output step of the algorithm is shown in detail. Note that even with a simple photograph of artificial modern objects, one can still achieve a likeness to Oriental painters. One can see a visual appeal similar to Oriental rocks produced from this test.

Figs. 15–17 show examples of the composition algorithm on actual landscapes. Here we show the result of our algorithm on a test image and three landscape images. As can be seen in these figures, the final output result of our proposed method provides the visual feeling of an Oriental Chinese painting style.

5. Conclusion and discussion

In this paper, a novel system which allows automatic generation of Oriental paintings from landscape photographs is presented. Using various computer vision and image processing techniques, the system allows anyone to create images which look like Oriental paintings. Some of the algorithms used are image segmentation based on region growing and thresholding, depth perception based on binocular disparity, image interpolation using texture synthesis, object rendering using silhouette and interior shading and composition using various Oriental painting rules.

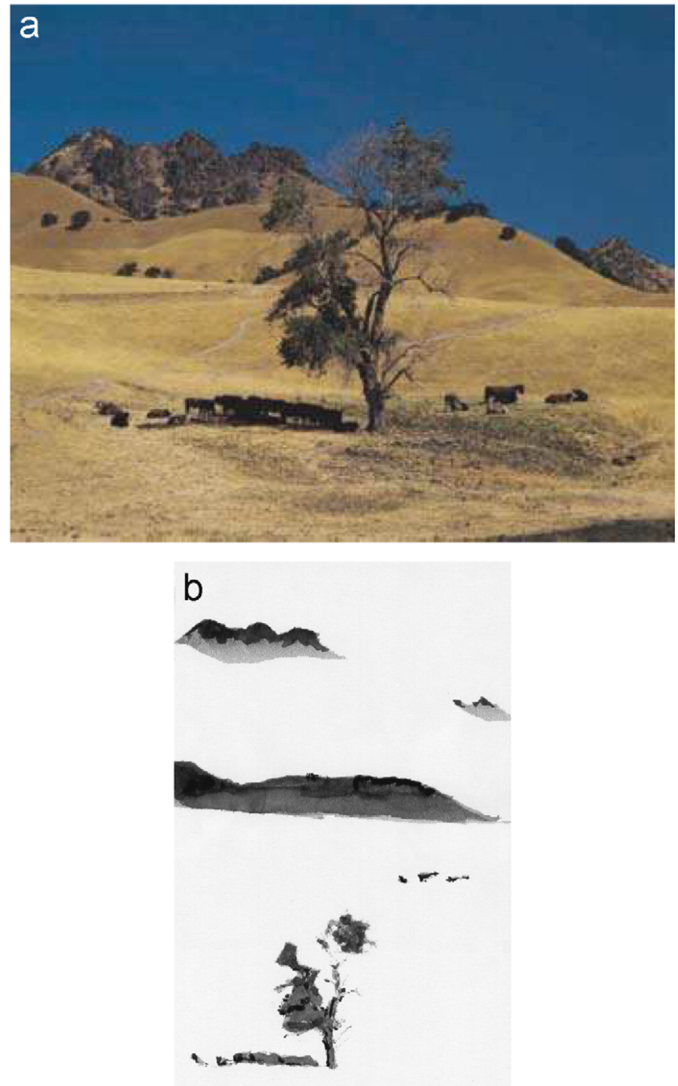

Fig. 17. Results from a landscape photo of tress, hills and animals: (a) input landscape photo and (b) final output image.

The system does have certain limitations and drawbacks. Since the segmentation algorithm uses color to segment objects, it has difficulty differentiating between different objects with similar colors, or recognizing an object composed of multiple regions of different colors. For the interpolation algorithm, it sometimes finds an incorrect outline of the object, or the filled regions may show a pattern that does not exist. This occurs particularly if the object is complex, or if the object is not well segmented at the edges.

Despite above mentioned limitations, our proposed algorithm is able to capture the general features and rules of Oriental paintings for creation of a new and unique non-photorealistic system which can produce Oriental paintings. This is an advantageous system, since it allows anyone, even those without artistic inclinations, to create such Oriental art.

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