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Oil Painting Style Rendering Based on Kuwahara Filter

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ABSTRACT The Kuwahara filter can generate local smoothed color regions similar to hand-painted strokes, and therefore it can be used to image artistic rendering. However, the existing Kuwahara filtering methods often adopt a fixed-sized filter kernel, which leads to a homogeneous size of strokes. In view of this problem, a multi-scale anisotropic Kuwahara filtering method is proposed in this paper. By using image saliency as control information to adjust the size of filter kernel, strokes with abundant varied geometric scales are generated. This paper also presents an automatic rendering framework based on the proposed algorithm that automatically transforms images into an oil painting style. Using the image's orientation field of edge, edge gradient magnitude and image saliency to control the bump mapping, the senses of thickness and layers of oil painting's strokes are generated. By adopting this framework, an artistic oil painting style similar to the "impasto technique" can be simulated well.

INDEX TERMS Anisotropic filtering, image stylization, oil painting.

I. INTRODUCTION

In some painting styles, painters discard some of the inessential details, adopt fewer strokes to show the object's main structure features (e.g., feature lines and object contours), and use simplified color details to fill the object's internal region. In the field of Non-photorealistic Rendering(NPR), image stylization, which simulates a painter's artistic simplified technique, is called "artistic image abstraction" [1], [2]. Artistic image abstraction often adopts filtering methods to keep the edge features and smooth the unimportant image region. Nevertheless, most filtering methods cannot generate obvious stroke shapes. Most of the current studies on artistic abstraction focus on the extraction of the main feature structure and region smoothing algorithms, which roughly generate a visual effect similar to a "cartoon style". There are very few researchers studying how to use a filter to generate the art styles with obvious stroke shapes, such as oil painting and gouache styles. The "stroke-based rendering method" is often adopted for this kind of style rendering with obvious traces of strokes [3], [4].

The Kuwahara filter [5] is a kind of edge-preserving nonlinear filter. Its output value is the mean color of a subregion of the filter kernel, which can generate local small "color blocks". An isotropic Kuwahara filter leads to a mosaic-like style effect. Based on the Kuwahara filter of round kernel, Kyprianidis *et al.* [6] proposed a kind of anisotropic Kuwahara filter, forming short bar-shaped color blocks along image edge tangent. This kind of anisotropic bar-shaped color blocks can express the semantic structure of images well, and moreover, it has hand-painted stroke shapes. This makes it possible to perform image stylization with obvious stroke shapes. However, their filter is based on a unified-scale filter kernel. Even though it can generate strokes with variable shapes, the stroke sizes have few changes. For art styles like oil painting, when depicting objects, painters usually adopt strokes of different scales to express the image semantics according to the object's structure features or the image's saliency.

The pigment used in oil painting is a mixture of vegetable oil and color concentrate. It has high viscosity and covering power. Due to the movement of the brush, a sense of "flowing" roughness is produced obviously on the surface of strokes. Meanwhile, much pigment gathers at the edge of a single stroke, which strengthens the sense of thickness and layers of strokes (as shown in Fig. 1). In oil painting techniques, the method of making full use of stroke's senses of thickness and layers to strengthen the three-dimensionality

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FIGURE 1. Stroke effect of the impasto technique in oil painting. (Note: In the right enlarged picture, much pigment is accumulated in the edge of a single stroke of oil painting, resulting in a stronger sense of layers among strokes.

and texture of the image is called the ''impasto technique''. The bump mapping [7], [8] used in illumination calculation can generate the flowing-shape traces of brush movement. However, all the previous oil painting texture generation methods based on bump mapping did not consider the pigment thickening effect of stroke contours, which causes a lack of the sense of layers among the strokes.

In this paper, a filter-based image stylization method for oil painting style is proposed. This method can generate the senses of thickness and the layers of oil painting strokes. The main contributions in this paper are summarized below:

- Based on a uniform scale anisotropic Kuwahara filter, a multi-scale anisotropic Kuwahara filter is proposed. Saliency is used to control the filter kernel size. Different filter kernel sizes are adopted in different saliency regions to generate different scales of strokes that are closer to the painting techniques of painters.
- Combining the edge tangent flow map, edge gradient magnitude, and saliency of the image to control the bump mapping to generate the stroke texture of an oil painting. It can generate the effect of thickening pigment at the edge of strokes, thus generating a stronger sense of layers. Moreover, it also can generate strokes with different senses of thickness in different image regions.

II. RELATED WORKS

Artistic image stylization is a popular study topic in Non-photorealistic Rendering (NPR). Image stylization methods can be classified into three categories: image artistic abstraction; stroke-based rendering; and neural style transfer (NST) which was proposed in recent years. The first two are based on low-level image features, such as color and gradient, while NST uses high features.

A. STROKE-BASED RENDERING (SBR)

The SBR model [3] studies the image transfer algorithm based on a single stroke. The main research topics of SBR include the stroke's distribution, shape, direction, and stroke texture style rendering. The pixel's color, gradient, and depth are the main features used to control the stroke texture synthesis and distribution of strokes. For stroke distribution, random sampling [1], [2], [9]–[11] can be adopted. Alternatively, it can be modeled as an energy relaxation problem [12], where the optimization goal is to cover the original image with as few strokes as possible and to approximate the original image in terms of the image feature as much as possible. The adopted methods used to construct the direction field of stroke are color gradient [13], [14]. or primal sketch [4], et cetera. To reflect different levels of artistic abstraction and generate richer stroke styles or stroke scales, saliency map or image segmentation [11], [15], [16] can be used to guide the distribution and rendering of strokes. Stroke texture rendering can be classified into two categories. One category is using a program to generate stroke textures directly [7], [8], [17]–[20]. One of the important advantages of the procedure texture is that it can maintain the frame-to-frame consistency of the stroke texture during video stylization. The other category is using hand-drawing texture samples to synthesize the stroke's texture [21], [22], or to map the hand-drawing strokes directly to the rendering areas [4]. In this paper, the proposed method of oil painting texture rendering utilizes the procedure method by bump mapping. Stroke-based rendering simulates a painter's painting process to some extent. For most painting styles, especially for the ones with obvious stroke shapes, it can achieve better rendering results. However, it usually requires a large amount of calculation. In addition, during video stylization, how to keep the frame-to-frame consistency for the strokes' movement, shape, and textures is still a challenging topic in SBR.

B. ARTISTIC IMAGE ABSTRACTION

Artistic simplification is the main problem for artistic image abstraction. Simplification is usually achieved by keeping or enhancing the main features of images, and smoothening color details of rather rough image structures. [1], [2], [23], [24] used feature lines to express the main structural features of the image, and then region segmentation and color quantization were performed to reduce the region details. Farbman *et al.* [25] decomposed images into different levels of structures details and kept the finer image structure, smoothened the rougher image structure, and then mixed the different levels of image structures into one image. Some classic filtering methods can be used for edge detection, such as the Sobel, Canny, and Dog algorithms. Afterward, machine learning is also applied to edge detection [26]. Region segmentation and color simplification often use edge-preserving filters, and the frequently-used filtering methods can be classified into global filtering and local edge-preserving nonlinear filtering. Global filtering adopts a globally-optimized framework to smoothen the whole image while keeping main image features. Common global filtering algorithms include L0 gradient minimum [27], [28], weighted least square method [25], [29], [30], total variation minimum [31], [32], et cetera. Local filtering methods that can be used for image abstraction include: bilateral filtering [24], [33], guided filtering [34], [35], domain transformation filtering(DTF) [36] and anisotropy diffusion [37], [38]. Based on DTF [36], Yang [39] introduced a machine learning method. They used the edge confidence computed by the classifier in Dollá r's work [26] to adjust the pixel distance in the filtering calculation, which smoothes the image regions according to the different scales of semantic structure. Although the filters above have been widely applied to image stylization, they can be only used to produce a ''cartoon'' style, and the main problem to be solved is the key features extraction and the smoothing of region colors.

Kuwahara filters [5] are also a kind of edge-preserving filters, which divides the filtering region into several subregions. The output value is the average color of the sub-region with minimum color deviation, which leads to small color blocks. Anisotropic Kuwahara, proposed by Kyprianidis *et al.* [6], generates the color blocks with directivity, and the color blocks have a hand-painted stroke shape. The filtering method proposed in this paper is a further improvement to an anisotropic Kuwahara filter, and it can generate strokes with different scales.

C. STYLE TRANSFER BASED ON DEPTH FEATURES

NST is a kind of style rendering method that has gained increasing popularity due to the breakthrough of deep learning in recent years. It is similar to earlier image analogies [40]. The difference is that NST synthesizes the image from high-level features. NST, by virtue of a well-trained deep neural network used for classification (e.g.,VGG [41]), obtains the depth features of the constraint images (content images) and the artistic sample image at different layers; trains an image generating network [42]–[44] or optimizes the target image directly [45], [46] and makes the target image have both the semantic structure features of content image and the texture features of the style samples. NST is a universal style rendering model and does not need to design specific algorithm model for a specific style. However, until now, people have not yet understood the exact meaning of the parameters that are learned in deep neural networks, and the concerned key issues in NPR such as stroke's direction and scale cannot be controlled effectively in NST algorithms. How to separate the texture's geometrical information from high-level features is still a challenge for NST.

III. RENDERING FRAMEWORK

An artistic rendering framework of an oil painting style based on the Kuwahara filter is proposed. An image can be automatically transformed into an oil painting style through this framework. Fig. 2 displays the processing flow of the proposed framework. The rendering process includes the following steps:

1) Use structure tensor or color gradient of the original image to calculate the edge tangent vector field. Then detect the saliency of the original image and get a saliency map. The saliency map is a grey-scale image with color values in the range of [0, 1]. The edge tangent vector field is visualized by line integral convolution algorithm and an edge tangent flow map is generated. The edge tangent flow map will be applied to the following bump mapping
2) The color value of the saliency map is taken as the control factor of the filter kernel scale. Different filter kernel diameters are adopted in different saliency region. In stronger saliency regions, a smaller filter kernel is adopted to keep more image details; otherwise, a bigger filter kernel is adopted for better image simplification. After filtering, an image with artistic strokes is generated.
3) Carry out edge detection for the filtered image to generate the edge gradient map. Edge gradient map, edge tangent flow map, and the saliency map are taken as the control factors of bump mapping at the same time. In this paper, they are blended to a height map.
4) Use the height map to perform bump mapping for the filtered image and obtain the final images with oil painting stroke textures.

In Step 2), users can adjust the stroke scale according to the image resolution. In Step 3), users can adjust the mixing ratio of stroke edge gradient map, thereby changing the pigment thickness of stroke edge and generating the sense of different intensity of stroke thicknesses.

IV. STROKE GENERATION BASED ON KUWAHARA FILTERING

Our multi-scale anisotropy filter is based on anisotropic Kuwahara filter [6]. A brief introduction of anisotropic Kuwahara filtering is given below.

A. REVIEW OF ANISOTROPY KUWAHARA FILTERING

Anisotropic Kuwahara filtering adopts an elliptic filter kernel that is divided into several subsections, as shown in Fig. 3. The long axis direction of the ellipse is determined by the

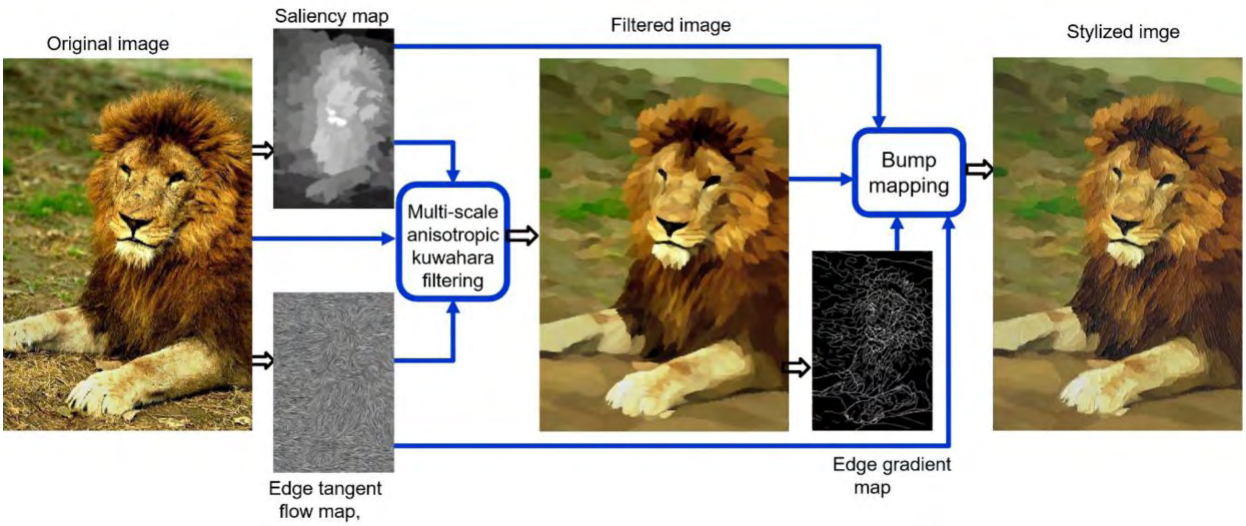


FIGURE 2. **Automatic rendering framework for oil painting style based on Kuwahara filtering.**

FIGURE 4. **Filtering iterations and the effects of standard deviation σs and σr on anisotropic Kuwahara filtering.**

tangential direction of the image's local edge. The ellipse filter kernel is obtained by scaling up and down the standard round filter kernel along the direction of edge tangent and its vertical direction respectively, and the scaling ratio is determined by local anisotropy degree. In [6], the edge tangent vector field and anisotropic measuring factors are calculated by the image's structure tensor. One advantage of the structure tensor is that linear smoothing of the structure

FIGURE 3. Filter kernel with fixed scale adopted by the anisotropy filter [6]. Round filter kernel is transformed to ellipse according to local edge tangent vector and anisotropy degree.

tensor results in non-linear smoothing of the eigenvectors. A bigger feature vector plays a decisive role in the smoothing results. A smooth edge tangential vector field can be obtained by smoothing the structure tensor field with Gaussian filter.

The ellipse filter kernel is obtained from a standard round filter kernel by the rotating and scaling transformations. Assume that R^2 is the input image, and the ellipse filter kernel of a pixel x_0 on the image is defined as:

$$\Omega_{x_0} = \left\{ x \in R^2 : ||S_{aniso} \cdot R_{-\varphi} \cdot (x - x_0)|| \leq h \right\} \quad (1)$$

where h is the radius of round filter, R-φ and $Saniso$ are the rotating and scaling matrices:

$$R\varphi = \begin{pmatrix} \cos\varphi & -\sin\varphi \\ \sin\varphi & \cos\varphi \end{pmatrix} S_{aniso} = \begin{pmatrix} \frac{\alpha}{\alpha + A} & 0 \\ 0 & \frac{\alpha + A}{\alpha} \end{pmatrix}$$

φ is the direction angle of the edge tangent of x_0. α in S_{aniso} is a parameter to adjust the elliptical eccentricity, $\alpha \in (0, \infty)$, and when α is smaller, the anisotropy degree is larger. A is the anisotropy measuring factors at x_0 and calculated by the eigenvalues λ_1 and λ_2 of the structure tensor matrix:

$$A = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}$$

where $\lambda_1 > \lambda_2$, and the corresponding eigenvector of λ_1 is the edge tangential vector. The product of two nonzero elements on the diagonal of S_{aniso} is 1, and therefore, although the filter kernel shape defined by (1) may change, the area of the filtered neighborhood will not change. Hence, such a filter is a scale-invariant filter.

The weights in the sectors of the round filter kernel the two-dimensional Gaussian distribution, which is smoothed by Gaussian filter, can be defined as follows:

$$K_i = (\chi_i * G_{\delta s}) \cdot G_{\delta r} (^* \text{ is the convolution calculation.}) \quad (2)$$

where χ_i is the weight mask of the ith sector, $G_{\sigma r}$ is the weight's Gaussian distribution function in filter kernel, and $G_{\sigma s}$ is the Gaussian smoothing filter to weight mask. Assuming the direction angle of the edge tangential vector at x is arg(x), then the weight mask χ_i is defined as follows:

$$\chi_i = \begin{cases} 1 & \frac{(2i-1)\pi}{N} < arg(x) \leq \frac{(2i+1)\pi}{N} \quad i \in [0, N-1] \\ 0 & else \end{cases}$$

where N is the number of sectors. Due to the function of G_σ, some overlapping of the non-zero weights among different sections may occur. The filter output will not directly use the color with the minimum standard deviation but perform an additional weighted averaging for the color mean of all the subsections. This effectively reduces the Gibbs phenomena [5]. The determinations of subsection output weights can be referred to in [5], [6].

B. MULTI-SCALE ANISOTROPY KUWAHARA FILTERING

As introduced in Section IV-A, the color blocks generated by Kuwahara filtering are geometrically similar to stroke's shapes in oil painting, as shown in Fig. 4. The color blocks come from the Gaussian smoothing effect of $G_{\sigma r}$ in (2). It is obvious that increasing the value of the standard deviation σr of $G_{\sigma r}$ should enhance the smoothing effect and generate larger color blocks. The second row in Fig. 4 shows the different results when using $\sigma r = 3, 5$, and 9. This shows that when σr is small, the generated stroke scale is small, and the image can keep more structural details. When σr increases, a larger stroke can be produced, but more structure details are eliminated (in all the experiments of this paper, the filter radius $h = 2\sigma r$).

In (2), the weighted smoothing function $G_{\sigma s}$ makes the adjacent sectors form a small of overlapping area of the non-zero weights. This kind of overlapping can also restrain the high-frequency region of the image. When increasing σs, there will be larger non-zero weight overlapping regions, which have a stronger smoothing effect. The third row of the image in Fig. 4 is the corresponding filtering results of different σs values when the standard variation $\sigma r = 13$. When the filter kernel is larger (i.e., σr is larger) and the σs is smaller (as shown in the left figure), then the Gibbs phenomenon occurs. The stroke edges display an irregular shape but more image details can be reserved. A rather complete and large stroke can be generated when σs increases (as shown in the right figure) but the images will be too blurred. It is found through experiments that when $\sigma s \approx \sigma r/3$, a compromised ideal result can be achieved (as shown in the middle figure).

Although the proper selection of σr and σs can form strokes of different scale, when σr is large, the formed stroke edge is rather blurred. This problem can be solved after several iterations of filtering. The first row of the image in Fig. 4 is the results after two and three iterations of filtering when $\sigma s = 4$ and $\sigma r = 12$, respectively. This shows that the results of the twice and thrice repeated filtering have little difference. Generally, rather good results can be achieved after only filtering twice.

During the painting process, painters describe important regions more delicately using thinner strokes while ignoring the details for the unimportant regions by using bold strokes. The saliency detection of the image is to detect the attention-getting regions according to a human's visual attention mechanism. The region with a high degree of saliency is usually the part that painters describe more carefully. Hence, in this paper, the image saliency is used to control the

FIGURE 5. Results comparison between the proposed filter and [6]. (a) Saliency image generated by GBMR algorithm [48]; (b) result of the anisotropy filter [6], where $\sigma r = 5$; (c) result of the multi-scale anisotropy filter of this paper, range of σr is 3 to 10.

stroke scales, and the image is stylized from different details degrees. For the region with high saliency, a small filter kernel is adopted; otherwise, a large filter kernel scale is adopted. Based on (1), a scaling transform is added to change the filter kernel scale. The anisotropic filter kernel in (1) is redefined as follows:

$$\Omega_{x_0} = \{x \in R^2 : \|S_{aniso} \cdot R_{-\varphi} \cdot S_{sal} \cdot (x - x_0)\| \leq h\} \quad (3)$$

where S_{sal} is a scaling matrix relevant to the saliency of pixel x_0:

$$S_{sal} = \begin{pmatrix} \frac{g+\mathrm{p}}{1+g} & 0 \\ 0 & \frac{g+p}{1+g} \end{pmatrix}$$

where p is the value of saliency ($p \in [0, 1]$). g is a factor to adjust the range of stroke scales, and its value can be determined according to the image resolution or the detail level to the expression. In all the experiments of this study, $g = 0.4$. (3) is equal to amplifying 1 to $(1+g)/g$ times of standard variation σr. Fig. 5 shows a results comparison of the anisotropy filter [6] and our multi-scale anisotropy filter based on saliency. There are many existing algorithms used for saliency detection. The GBMR algorithm can make a rather complete local saliency region but it is hard to keep inter-frame coherence when processing video sequences. On the contrary, the FT algorithm [47] can keep the inter-frame coherence well. In all the experiments of this study, the GBMR algorithm was adopted for a single image, and the FT algorithm was adopted for video saliency detecting.

C. STROKE TEXTURE

The edge tangent flow map (generated by LIC [49]) was used as a height map to perform bump mapping for the filtered image to generate stroke textures with traces of brush movement. However, the oil painting texture generated by only using the tangent flow cannot reflect the sense of layers among strokes. This is especially the case in the ''impasto technique'' of oil painting; since much pigment concentrates on the edge of stroke, the stroke edge will be higher than the previous layer of stroke. To simulate this phenomenon, the edge map of the stroke image is extracted to serve as an extra height control during bump mapping. There are many edge detection algorithms, such as classic the Canny algorithm and the DOG algorithm. As the edge line obtained by the Canny algorithm has excellent continuity, it was used to extract the edge map in our study. The values of all edge points are set to be the gradient magnitudes of the point. So, the edge map is a grey-scale image, rather than a binary image. This is to avoid the edge thicknesses of all the strokes being the same, which results in monotone look. In addition to this, painters usually adopt a thicker stroke in the region with a stronger saliency while adopting a rather thinner stroke in the region with weaker saliency (e.g., the background). Therefore, the saliency map is also taken as the factor of height control of bump mapping. We blend the edge tangent flow map, edge gradient magnitude map, and saliency map into one as the final height map. The following formula is adopted to blend the three maps:

$$H = \text{normalize}((F + \gamma \cdot E^{\frac{1}{3}}) \cdot \frac{\lambda + S}{1 + \lambda}) \quad (4)$$

F, E, and S are the pixel values of edge tangent flow map, edge map, saliency map, respectively, and H is the final height map. All the maps are expressed by a float value in the range of [0,1]. γ is a weight to adjust the mixing between the edge map and the edge tangent flow map. Increasing γ can improve the sense of the thickness of the stroke edge, but can meanwhile decrease the movement traces on the surface of stroke. After the experiments, it is thought that $\gamma = 1$ to 1.4 is fairly appropriate. The purpose of taking a cube root of E is to improve the value of weak edge in the edge map. λ is used to adjust the effect of saliency on the height map. Fig. 6 shows the height map overlapping results of the lion image in Fig. 2.

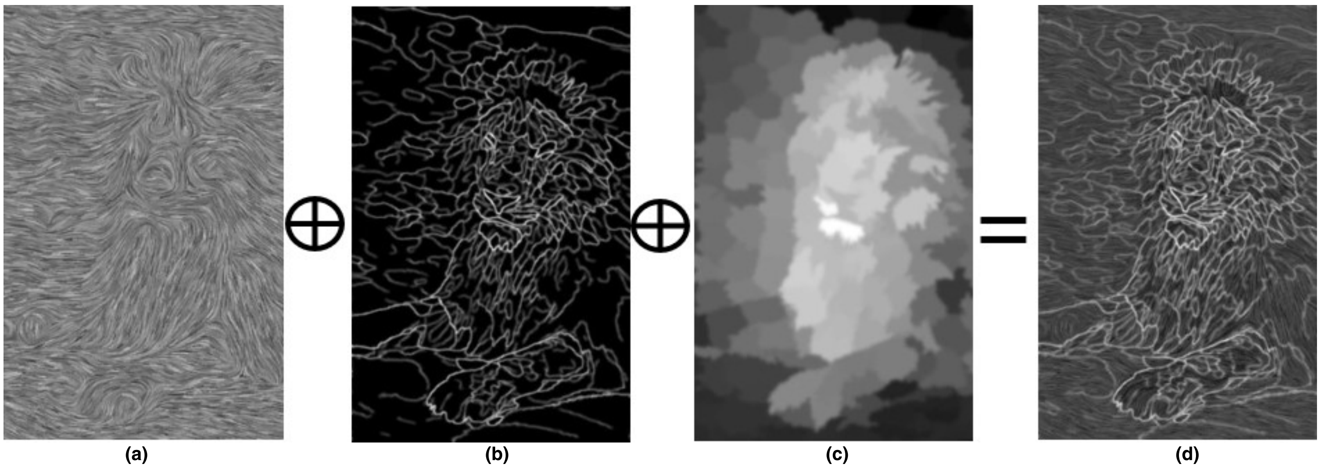


FIGURE 6. Final height map (d) for bump mapping is created by blending the (a) edge tangent flow (b) edge map and (c) saliency map.

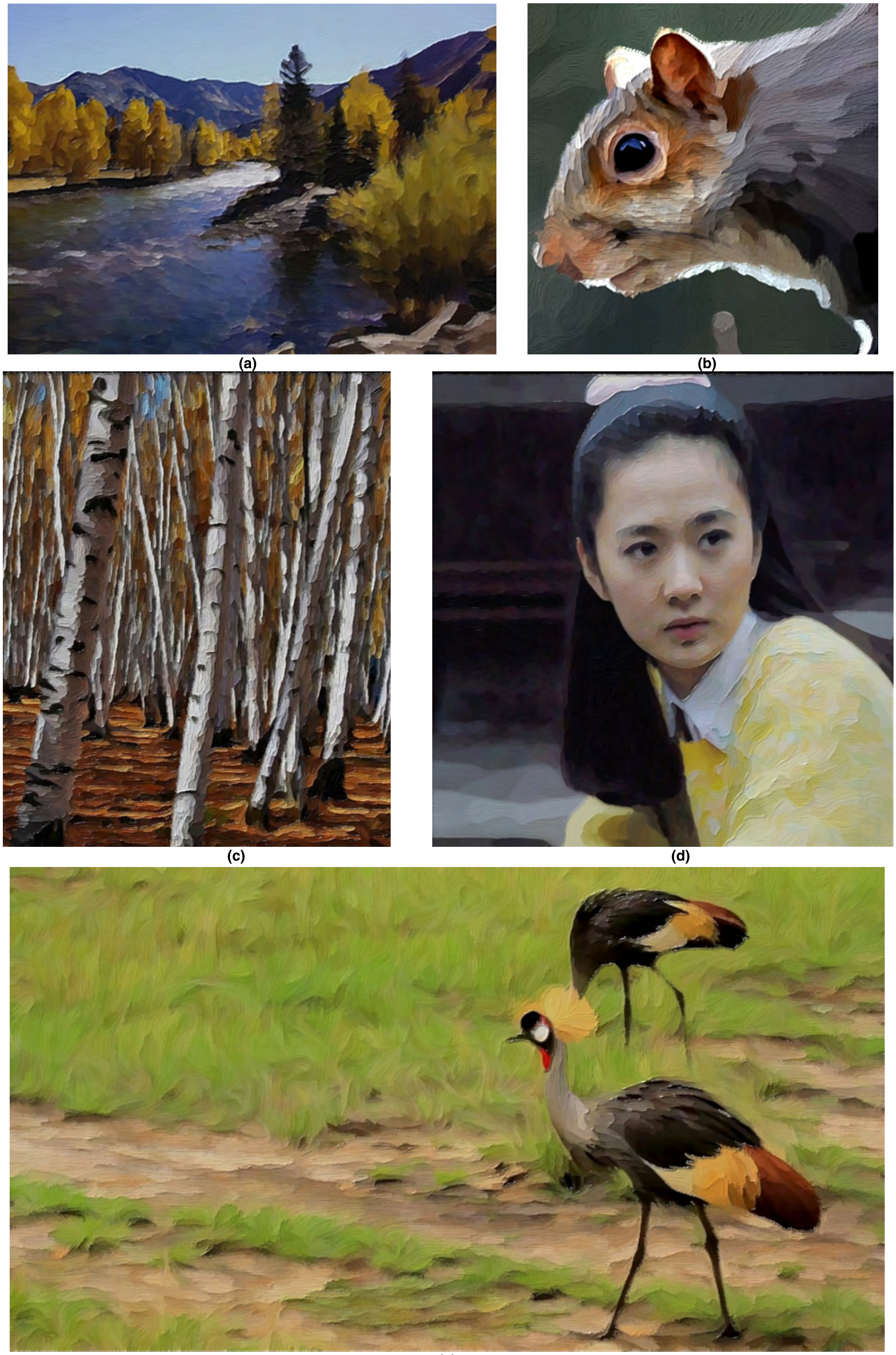
FIGURE 7. Results comparison between the proposed method and Semmo *et al.* [8]. (a) Semmo *et al.* [8] Method; (b) the method of this paper.

The oil painting texture rendering method presented by Semmo *et al.* [8] is similar to the method proposed in this paper. However, they merely used the edge tangent flow map as the height map during bum mapping and did not consider the stroke thickness variance in different regions nor the edge pigment residual effect on the contour of a single stroke, which lacks a sense of layers. Fig. 7 shows a result comparison between our method and the method of Semmo *et al.* [8]. It is obvious that the strokes generated by our method have a stronger sense of layers and three-dimensionality.

V. RESULTS AND DISCUSSION

Fig. 8 shows the stylization results for different types of scenarios using the oil painting rendering model proposed in this paper. It can be see that our multi-scale anisotropic Kuwahara filter can generate variable size of strokes in different regions of image, and the stroke texture generated through the height map constructed in this paper could simulate the brush movement traces well. Moreover, it could create strokes with different senses of thickness in different image regions and the sense of layers among strokes. For example, the tree shown in Fig. 8(a) and the squirrel in Fig. 8(b) both have high saliencies and a stronger sense of stroke thickness while the sky in Fig. 8(a) and the backgrounds in Fig. 8(b) and 8(c) have a weak sense of thickness, which makes the image a have stronger sense of layers.

As stated in Section II, the stroke-based rendering method simulates a painter's painting process from the aspect of a single stroke, which is best for rendering a painting style with obvious stroke shapes. The oil painting style rendering model presented by Zeng *et al.* [4] is a kind of classic stroke-based methods. They established the stroke texture library by collecting painter-drawn stroke textures, and mapping the appropriate strokes selected from the texture library to the stroke regions according to the image's local features. Since the stroke textures come directly from real hand-painted strokes, the stroke texture effect is generally superior to the procedure texture method. Fig. 9 shows a comparison between the filter-based rendering method of this paper and the stroke-based rendering method proposed by



(a) (b) (c) (d) (e)

FIGURE 8. Rendering results using the proposed method for different scenery images.

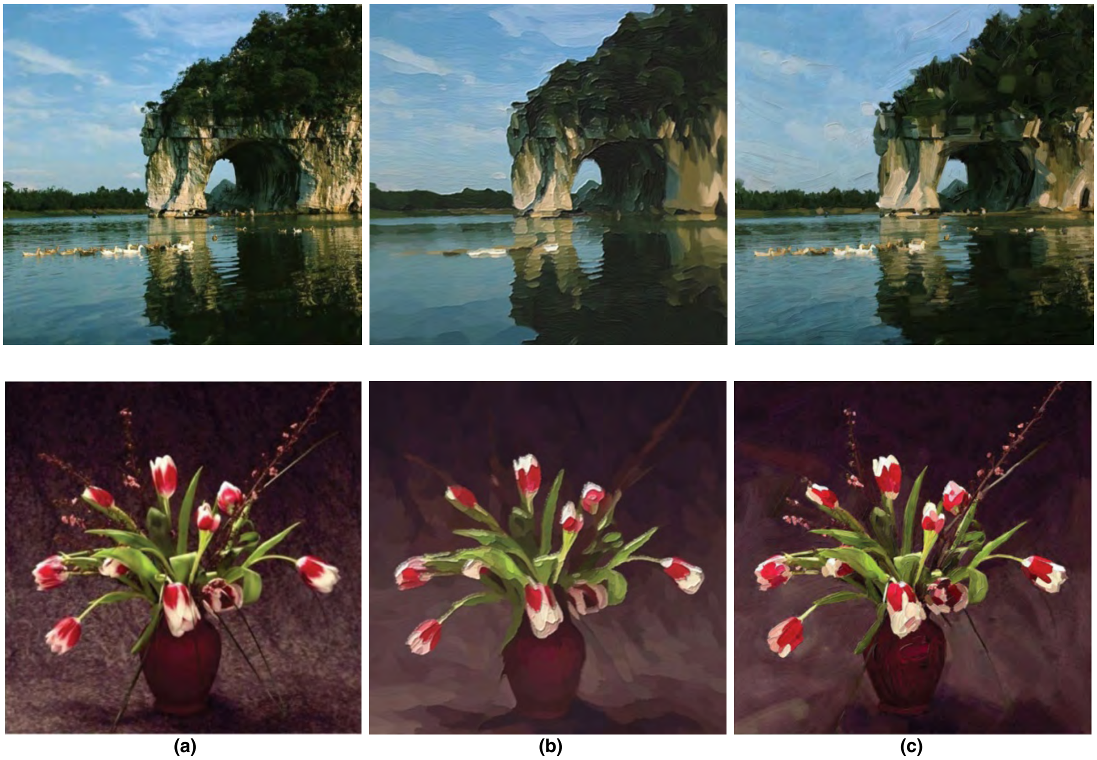


FIGURE 9. Results comparison between the filter-based method in this paper and the stroke-based method of Zeng *et al.* [4]. (a) Original image; (b) the method in this paper; (c) Zeng *et al.* [4] method.

Zeng*et al.* [4] (the comparison pictures in the figure come from the author's article [4]). The figure shows that the rendering result proposed in this paper is already very close to the stroke-based rendering method. In addition, the stroke-based method is hard to keep the inter-frame coherence of the stroke's movement, shape, and texture when processing video frames. However, our filter-based rendering framework and procedure oil painting texture generation method can easily maintain inter-frame coherence. Using the proposed rendering framework and the FT algorithm [47] to detect the saliency, we successfully stylized some videos.

Although we use saliency to control the stroke scale and thickness in this paper, in fact user can control them interactively by assigning the regions of the detail levels when processing a single image.

Compared to the anisotropy filter [6], the multi-scale Kuwahara filter does not increase an extra computational burden except for the transformation of the coordinates of pixels. Through hardware acceleration, real-time rendering can be realized. As Kyprianidis *et al.* [6], we use texture maps to store the weights of the standard round kernel sectors and any point weight can be obtain through looking up the texture maps after transformation by (3). Computation time is related to the kernel size and input image size. We adopt OpenGL's shading language (GLSL) to implement this process and bump mapping to accelerate the rendering. For a resolution of 512×512 input video, using $\sigma r = 5$ and scale range of [0.5,3], the processing rate can reach 17 fps on a laptop with GPU/Nvidia Quadro M1200.

There are two limitations of filter-based artistic stylization method. Firstly, the quality of the strokes generated by the Kuwahara filter is related to the image's frequency and the edge tangent field. In a region where there are many image details and the edge tangent vector changes smoothly, the generated color block shape shows a long bar, exhibiting a good stroke style (such as the cat in Fig. 4 and the body hair of the squirrel in Fig. 5. In a region of flat colors, it is easier to form irregular color blocks, which cannot form the realistic stroke shape well (such as the forehead of the girl in Fig. 8(c). Secondly, our multi-scale anisotropic Kuwahara filter can generate some artistic styles with obvious stroke shapes such as oil painting, gouache and watercolor, but it is not suitable to those styles with more fine lines, such as pen & ink drawing, sketch and Chinese painting.

VI. CONCLUSION

In this paper, an artistic rendering method that automatically transfers images into an oil painting style is proposed. Based on an anisotropic Kuwahara filter, the saliency control is introduced to control stroke sizes. The proposed method can generate rich stroke scales and describe the object from different detail levels, which better approaches the painting techniques of painters. The edge tangent flow field, saliency, and edge gradient magnitude are used to control bump mapping, which makes the stroke textures have a more authentic sense of thickness and layers. The method in this paper is simple for implementation. Experiments showed that this oil painting rendering framework can better simulate the "impasto technique" [50] of oil paintings, and it can maintain inter-frame coherence well during stylizing videos.

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