Image-Based Rendering for Ink Painting

Lingyu Liang School of Electronic and Information Engineering South China University of Technology Guangzhou, China lianglysky@gmail.com

Abstract—Ink painting is one of the traditional forms of expression in oriental art and it is fascinating to generate the distinctive ink painting effect using modern non-photorealistic rendering (NPR) technique. Since most stroke-based rendering (SBR) methods require much user interaction and professional knowledge about painting, it should be more convenient to employ image-based rendering (IBR) methods to directly produce the ink wash effect from photos. According to our knowledge, however, most current IBR methods are based on ad-hoc algorithm, and they fail to perform well in generical scenario.

In this paper, we propose a new IBR framework for ink painting, which could effectively simulate ink diffusion in absorbent paper, and produce various types of black or color ink painting effects. First, significant edges of the original image are detected as the constraint regions. Second, the pixel values of the edges are propagated to the blank regions out of them using an edge-preserving energy minimization model in edit propagation technique. Third, absorbent paper appearance is simulated through texture synthesis and detail manipulation. Finally, we compose the ink diffusion results with the absorbent paper background to generate the whole ink painting. Experiments illustrate that various types of ink diffusion effects and absorbent paper appearance could be effectively produced by our method.

Index Terms—Non-photorealistic rendering (NPR), ink painting, edit propagation, texture synthesis.

I. INTRODUCTION

Recently, non-photorealistic rendering (NPR) has been attracting growing interest in computer graphics community [2]. Although NPR techniques have achieved remarkable success, ink painting rendering is still a challenging problem. The reason is twofold. First, it is a complex process in reality when the ink and water diffuse in absorbent paper. Second, there are various ink painting styles for different subject, like landscape, flower and bird or portrait. To simplify our research, we only focus on ink diffusion problem in this paper and leave the second one in our future research.

Generally speaking, there are two main approaches for ink painting simulation: stroke-based rendering (SBR) and imagebased rendering (IBR).

SBR approach refers to simulate different ink diffusion effect in absorbent paper by placing strokes according to user interaction, and it has been extensively researched [3], [4], [5], [6], [7]. Recently, Chu and Tai presented a real-time ink dispersion system called MoXi [8]. Based on the modified lattice Boltzmann equation, MoXi simulates spontaneous shape evolution and porous media flow, and achieves various ink dis-

Lianwen Jin School of Electronic and Information Engineering South China University of Technology Guangzhou, China lianwen.jin@gmail.com



Fig. 1. Two types of ink painting produced by our method. Left: input image taken from Caltech 101 database [21]. Middle: black ink painting. Right: color ink painting.

persion effects. Xie et al. presented an interactive sketch-based rendering system called iR2s [9], which could automatically estimate the brush trajectory from the outline of the shapes provided by the users. However, most SBR approaches require users to place the strokes properly, which it seems difficult for the common users who lack of professional knowledge.

IBR approach appears to be more convenient, since it directly generates ink painting from photos. Yu et al. proposed a Chinese landscape painting synthesis method, which is composed of brush stroke texture primitives (BSTP) collection, control picture construction, fog synthesis and BSTP mapping [10]. Farbiz et al. described an Asian painting generation system using humanistic fuzzy logic rules [11] and more details of the method were presented in [12]. These rendering methods are based on texture mapping or ad-hoc synthesis algorithm, which results in the limitation of the performance in general scenarios. Yang and Yu proposed a rendering method for ink painting with pine tree using mean curvature flow [13]. However, this method requires much specific priors of pine tree, and it may fail to generalize to other subjects.

To the best of our knowledge, the work of Wang and Wang [14] is most similar to ours. They proposed a rendering algorithm to simulate color ink diffusion in absorbent paper. They simplified the reference image by luminance division and color segmentation, modeled color mixing by Kubelka-Munk theory, simulated the color diffusion by generalizing the model of Kunii et al. [15], and simulated absorbent paper appearance using texture synthesis technique. Although both the methods aim at ink diffusion simulation using the model with a physical base, the distinction is apparent. Our method employ the image-guided energy minimization framework in edit prop-



Fig. 2. The process of our ink painting rendering method. First, edges of input image are obtained by Canny detector [20]. Second, we perform edit propagation [1] to implement ink diffusion according to the gradients of some guided image. Third, texture synthesis and details extraction are implemented for paper texture simulation, and more details of this process are illustrated in Fig 5. Finally, the corresponding ink diffusion results and paper texture are composed to produce black ink and color ink painting respectively.

agation [1], while Wang's is based on other model [15]. In absorbent paper simulation, we not only synthesis the paper appearance, but also manipulate the paper details to promote the performance.

In this paper, we propose a new IBR framework for both black and color ink painting (some results are shown in Fig. 1). The framework includes two phases, as illustrated in Fig. 2. In the first phase, ink diffusion is simulated using an edgepreserving energy minimization model [1]. This model is originally aims at edit propagation for local tonal adjustment, which could smoothly propagate the sparse user edit input to the whole image according the gradient of the guided image [1]. In our method, we take the significant edges of the original image as the user inputs, and propagate the pixel values of the edges to the other regions. In the second phase, absorbent paper appearance is simulated using image quilting [16] and detail manipulations [17].

In summary, our specific contributions include: (i) a new IBR framework for ink painting; (ii) an effective and flexible scheme for black ink and color ink painting generation; (iii) introducing the idea and model from edit propagation to ink painting rendering; (iv) absorbent paper appearance simulation based on texture synthesis and detail manipulation.

II. INK DIFFUSION VIA EDIT PROPAGATION

In our method, both black ink and color ink diffusion are taken into consideration. Since both the process share the same basic model, we only present the details for black ink diffusion based on edit propagation model. According to the distinctive feature of oriental ink painting, we assume that the more important areas of the painting are the significant edges, and the pixel value of other areas should be lighter than these edges. Therefore, the goal of our method is to smoothly propagate the pixel values of the significant edges to their neighbors, which is similar to physical process of ink diffusion in absorbent paper.

To implement ink diffusion process, we borrow the method from edit propagation. Edit propagation is image editing technique that has been widely used in many applications, like tonal adjustment [1], HDR [18] and matting [19]. Generally speaking, it aims at propagating sparse user edits to a whole image according to the pixel affinity [19]. Therefore, edit propagation and ink diffusion share the similar goal. If we regard the significant edges of the painting as the sparse user input and provide a proper affinity measurement of the pixels, we could implement ink diffusion by an edit propagation model.

In this paper, we implement the edge-preserving energy minimization method proposed by Lischinski [1] to simulate ink diffusion. In this model, the gradients between the nearby pixels of a guided image are taken as the affinity measurement. Therefore, the ink diffusion process could be controlled by not only the model parameters but also the gradient property of the guided image.

For clarity of presentations, we denote the original input image as I. Then, Canny operator [20] is performed to extract the edges of I, denoted as E. Assume that the diffusion or propagation image of our goal is P, and the edges image

E is regarded as the input constraint. Then the ink diffusion effect could be achieved by minimizing the following energy functional:

$$P = \underset{P}{\operatorname{argmin}} \left\{ \sum_{\mathbf{x}} w(\mathbf{x}) \left(P(\mathbf{x}) - E(\mathbf{x}) \right)^2 + \sum_{\mathbf{x}} h(\nabla P, \nabla R) \right\}$$
(1)

where,

$$h(\nabla P, \nabla R) = \lambda \left(\frac{|P_x|^2}{|R_x|^{\alpha} + \varepsilon} + \frac{|P_y|^2}{|R_y|^{\alpha} + \varepsilon} \right)$$
(2)

The first term of Eq. (1) is the data term, whose objective is to keep P and E as close as possible in the constrained regions. The weight w (between 0 and 1) indicates the specific constrained pixels. The larger weight of the pixel, the more similar value between P and E would be obtained in the constraint pixel. In our ink diffusion, the edges determined by E are the constrained pixels, while the blank regions are non-constrained pixels.

The second term of the functional is the smooth term. The detail is shown in Eq. (2), where the subscript x and y denote horizontal and vertical differentiation of the P and R. Here R is the diffusion guided image, whose gradient could control the diffusion range. According to the property of our model, in the area where R have small gradient or R is smooth, the range of diffusion would be large; in contrast, in the area where R have large gradient, diffusion would be stopped by the significant gradient. We use the smooth log-luminance channel of I as R to guide the diffusion, for we want to preserve the similarity between the original image and the ink painting. In fact, different diffusion effect could be obtained by adding different texture details to the guided image, and it will be discussed in our experiment section.

There are three parameters in Eq. (2). ε is a small constant ($\varepsilon = 0.0001$) to avoid division by zero. The exponent α controls sensitivity of gradient of P to the guided image (the smoothed log-luminance channel of I), and the guided image would exert more influence to P when α is increased. λ balances the weight between the data term and smooth term, and increasing λ would produce more smooth P. In Fig. 3, different diffusion results are obtained under different combination of α and λ .

Color ink diffusion shares the same process with the black ink. First, luminance channel and two color channel a^* and b^* of the original image are separated in CIELAB space. Then we use the extracted edges as the input constraint, and perform the propagation model guide by the smoothed log-luminance channel. The color ink diffusion in a^* and b^* are shown in Fig. 4.

III. PAPER TEXTURE SIMULATION

To obtain more natural ink painting effect, the absorbent paper appearance of painting background should be taken into consideration. In [14], Wang and Wang synthesis the paper appearance by image quilting [16]. According our experiment



Fig. 3. The comparison of ink diffusion under different parameter combination of α and $\lambda.$



Fig. 4. Color ink diffusion in CIELAB space. The left sides of the two images are the input edges, while the right sides are the output of edit propagation based on the edges.



Fig. 5. The process of the absorbent paper simulation. First, image quilting [16] is implemented to synthesize a whole paper texture, then it is cropped according to the size of the input. Second, we use WLS filter [17] to perform edge-preserving smoothing to obtain the large lighting variant component of the paper texture, and it is removed to obtain the detail component. Then absorbent paper effect could be produced by transferring the detail and color to the ink diffusion results.

and observation, adding detail manipulation [17] after the texture synthesis could achieve better performance. The process of the absorbent paper simulation is shown in Fig. 5.

The whole paper texture is firstly synthesized by a patch texture using image quilting method [16]. The input texture could be captured by digital camera from real paper or generated by some random distribution.

To achieve better paper simulation, only the texture details and color are transferred to the painting background. The luminance and color of the synthesized texture are separated in CIELAB space. Then the large-scale lighting information of the luminance channel is obtained using edge-preserving smoothing filter. Here WLS filter is implemented for its effectiveness in detail manipulation [17]. Then, we could obtain the



Fig. 6. Absorbent paper effects with different detail enhancement. Left: with no detail. Middle: with 0.2 detail. Right: with 1 detail.

detail of the paper texture by removing the large-scale lighting in the luminance channel.

Finally, the detail and color layer of the paper texture and ink diffusion results are composed to produce the ink painting. Note that different paper effect could be generated by different detail enhancement, as shown in Fig. 6.

Although we only simulate the absorbent paper appearance, the extracted texture details could be added to the diffusion guided image to control the ink propagation process. We will discuss it in the experiment section.

IV. EXPERIMENT

To evaluate our method, we performed experiments under different parameter setting on the test photos taken from Caltech101 database [21].

In Fig. 9, different black ink and color ink painting effects are generated from the same input. When λ and α are small, the painting would contain more detail; when λ and α are large, more diffusion is performed and more abstract painting style would be generated. It indicates that our method could effectively produce different ink painting styles with the proper combination of model parameters.

Apart from the model parameters, the gradient feature of the guided image controls ink diffusion as well. When α is large, the diffusion is sensitive to the gradient of the guided image. Then different ink diffusion effect could be obtained by changing the gradient property of the guided image, as illustrated in Fig. 10. When log-luminance channel of the input is used as the guided image, the propagation results would have the similar gradient feature to it. But if we add texture details of some pattern to the guided image, different results are produced. In the smooth regions of the guided image, propagation is performed in a large range. In contrast, in the regions where has significant gradients, the propagation would be stopped.

In Fig. 7, different absorbent paper backgrounds are produced. It can be seen that changing the color and texture pattern of paper background could build a different feeling about the whole painting.

Comparison of our result with Wang's [14] is shown in Fig. 8. Our result seems to better capture the essence of ink painting, whose distinctive idea is to express only the essence of the object or scene but not reappearing it exactly. Wang's result seems to retain too much color and detail in the less significant regions of the painting.



Fig. 7. Ink painting rendering with different absorbent paper effects.



Fig. 8. Comparison with Wang's result [14]. Our result appears to better capture the essence of ink painting, while Wang's result seems to retain too much color and detail in the less significant regions of the painting.

V. CONCLUSION

In this paper, we have proposed an image-based rendering approach for ink painting. Experiments illustrate that our method could effectively produce black and color ink painting from realistic photo. Different types of ink diffusion effect can be simulated by setting the model parameters or choosing the proper diffusion reference. Distinct absorbent paper appearance is synthesized by image quilting and detail manipulation.

Since we implement ink diffusion by propagating the pixel value from the edges, it is essential to extract the significant edges by a proper operator. However, the original Canny operator is not designed specifically for this problem, and the detected edges may fail to satisfy the requirement for ink painting rendering. It could be an interesting research direction to integrate the semantic description of scenes and objects into a rendering algorithm [22].

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(a) Input image

(b) $\alpha = 0.4, \lambda = 0.6$

(c) $\alpha = 0.8, \lambda = 1$

Fig. 9. Ink painting effects produced with different parameter combination of α and λ . When λ and α are small, more details are retained in the painting; when λ and α are large, abstract painting style would be obtained.



Fig. 10. Ink diffusion effects with different detail pattern of guided image. (a) Input image. (b) Diffusion result guided by the log-channel channel of the input image. (c) \sim (e) Diffusion results by adding different texture detail to the guided image of (b).

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