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Paper

A Novel Method of Converting Photograph into Chinese Ink Painting

Fan Guo*, Non-member
Hui Peng[a]*, Non-member
Jin Tang*, Non-member

Chinese ink painting is a traditional art form that is highly regarded throughout the world for its theory, expression, technicality, and artistry. In this paper, we present a method to convert a photograph into a Chinese ink painting. First, the structure description map (SDM) for a photo is estimated to build the object appearance depiction. To make the converted Chinese painting's color be consistent with traditional color requirement of Chinese ink painting, a color transform algorithm is proposed to put color on the SDM. A qualitative evaluation approach is also proposed to carry out a comparative study with other simulation methods. Conversion results demonstrate that, using the proposed method, one can produce very beautiful Chinese ink painting from a photo with less user interaction and much faster conversion speed compared to other approaches. © 2015 Institute of Electrical Engineers of Japan. Published by John Wiley & Sons, Inc.

Keywords: photograph, Chinese ink painting, conversion, structure description map, color transform

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1. Introduction

With fast improvements in computer and network technology, more and more Chinese painting art images can be exhibited on the Internet. However, drawing Chinese painting by hand is very difficult and highly demanding, and is not an easy job for common people and is also not likely to create too many paintings in this way. Nevertheless, taking photographs is very easy. If a technique for converting photos into beautiful Chinese paintings is developed, a lot of simulated Chinese paintings can be easily created. This is very important for propagating Chinese painting and the Chinese culture, and also will have a positive influence on promoting cultural exchange in the world.

Chinese ink painting, also known as "Shui-mo Hua", is famous for its freehand brushwork and natural aesthetic values. Unlike western styles, such as water color and oil painting, where the goal of realism plays an important role, and modern art too, Chinese painting uses only a few strokes to represent an object. Each stroke conveys information about the scene and painter's personality through its shape and texture. Its appearance depends on the shape of the object painted, the brush trajectory, and the distribution of the ink and water in the brush. As a non-photorealistic rendering (NPR), Chinese painting simulation refers to the generation of hand-drawn ink-style graphics using computer technology [1]. Chinese painting often portrays figures and the nature. Objects in such pictures are generally faithful to their real shape and appearances though rendered using sparse brush strokes. This justifies an attempt to use real images as a basis for the rendering of Chinese painting style. To be a good painter of Chinese ink painting requires many years of practice. What if ordinary people who have little or no painting experience but still want to create an acceptable Chinese painting from an input photo by themselves? The most difficult part for them to draw a Chinese painting is to grasp the shape and outline the profile of the objects they want to paint. Li [2] developed a new type of view-dependent feature line, called side lines, and used the side line to convey mountain shape. However, the drawing technique used in the method is only for landscape paintings. In this paper, we propose a method to generate an acceptable Chinese ink-style painting from a given photo. Other potential applications of the proposed method are the generation of backgrounds with the style of Chinese painting in animation, education, and entertainment. Being able to produce part of objects directly from real images could also save much work and cost.

By investigating the drawing process of a Chinese ink-painter through observation, we can find that artists often adopt simple strokes to capture the outline of the scene objects, and then use a relatively large amount of ink to color the interior of the objects. Thus, in this work we present a novel algorithm to simulate this drawing process. Based on the observations, we divide the whole simulation process into three steps. The first and second steps are stroke detection and enhancement. A structure description map (SDM) for the input photograph can be obtained during the process to render the outline of the objects. The last step is the color transformation based on statistical analysis. A color transform algorithm is used on the SDM to match the color of traditional Chinese paintings. The motivation of our method is to simulate the drawing processes of a Chinese ink-painter and make the rendering process of Chinese ink painting easy for a person with little or no painting experience. Compared with other algorithms, the proposed method focuses on the simulation of the rendering effect, rather than the analog to the physical characteristics of the drawing media. Thus, the method can greatly reduce the computational complexity and improve the painting efficiency. Experimental results indicate that the proposed algorithm may generate promising results with good ink and water effects. The main contribution of this paper can be described as follows:

- So far, there have been many attempts to directly synthesize Chinese ink painting without a reference image, but only few researches have focused on converting a photograph into Chinese ink painting, which is more practical for a person with little or no painting experience. The proposed method takes a photo as the input image and presents a framework and

[a] Correspondence to: Hui Peng. E-mail: huipeng@mail.csu.edu.cn

* School of Information Science and Engineering, Central South University, Changsha, Hunan 410083, China

the specific steps for converting the photo into a Chinese ink painting based on the drawing processes of a Chinese painter.
– An overview of the special features of Chinese ink painting art is given in this paper. Based on the analysis, we summarize the drawing experience and statistical regularity of Chinese ink painting to guide the making process of the Chinese ink painting.
– By conducting appropriate qualitative evaluation, the quality of the simulation results of the proposed method can be effectively measured.

The rest of this paper is organized as follows: In Section 2 we review background information and related works on the simulation of Chinese painting. Section 3 presents the proposed simulation method. To show the effectiveness of the proposed method, the experimental results and performance evaluations are given in Section 4, and conclusions are drawn in Section 5.

2. Related Work

This section first introduces the characteristics of Chinese ink painting, and then discusses the related research concerning generating a Chinese-style painting.

2.1. Characteristics of Chinese painting Traditional Chinese painting is highly renowned the world over for its long history, original style, and unique national features. The paintings are classified into three categories: figure, birds and flowers, and landscape. Chinese painting is an outstanding representative of oriental art. From the point of view of the art form, Chinese painting falls into two categories: the "Xie yi" (literally "painting the feeling") school and the "Gong bi" (meticulous brush-work) school. "Xie yi" is freehand brush work characterized by vivid expression and bold outline. All painting in the initial period came from sketch work. Compared to Western painters, Chinese painters pay more attention to the relation between the object and the painter, so the painter must adopt a subjective approach in depicting an object and in expressing the painter's feelings. Thus, Chinese painters often combine Gong-bi style with Xie-yi style on the basis of sketching. Because Chinese painting stresses the painter's feelings, blank spaces are emphasized. For instance, while painting a fish or a mountain, the blank spaces can be regarded as water or clouds.

Chinese painting is done by using Chinese brush pen, ink, ink-stone, Xuan paper, and pigments. Those were invented by the ancient Chinese. Paper, ink, brush-pen and ink-stone are called "four treasures in the study room". Among the four treasures, the brush-pen is the most important tool to artists. Different sizes of brushes are chosen according to the size of the written Chinese characters, and different brushes can produce different strokes.

2.2. Chinese painting simulation Research on simulating Chinese ink painting has achieved some encouraging results. For Chinese painting simulation, previous methods can be mainly divided into two types: software-based methods and image-based methods. Software-based methods generate Chinese ink paintings using image processing software tools [3,4], such as Photoshop, Maya, etc. However, although these software tools can produce a synthesized Chinese painting that is visually close to the hand-made work, the detail, color, and rendering effect may not be very satisfactory owing to the simple filter they used for rendering. A more feasible and effective option is the image-based methods. This kind of method aims to reproduce the real painting process using image processing techniques. For example, Sun *et al*. [5] put forward a Chinese ink-wash painting styled 3D rendering algorithm based on the idea of components and multilayer rendering. Yu *et al*. [6] proposed a framework for synthesizing Chinese landscape painting using brush stroke texture primitives taken from the hand-made work. Xu *et al*. [7] proposed a novel approach to animate Chinese painting through stroke decomposition. Yuan *et al*. [8] implemented a real-time rendering system to generate a Chinese ink-and-wash cartoon. Yin *et al*. [9] developed a novel Chinese painting and calligraphy system that serves as an expressive vehicle for interactively creating Chinese traditional ink-wash painting and calligraphy works. However, these works need some hand-made painting as the reference image of the painting style or require users to have good painting skills. Cao *et al*. [10] presented a method to generate a Chinese painting from an input image. The method renders both outline and interior parts of the image, and adopts a paper model to simulate the effect of Xuan paper. Although the method is relatively fast computationally, it can only produce gray-level simulation results.

Painting medium is an important factor in Chinese painting. For example, ink is the main pigment for Chinese ink painting and various ink shades rendered in the painting are produced by mixing the ink with water. The ink dispersion and diffusion along the boundaries is especially important for Chinese ink painting. Thus, Chu *et al*. [11] proposed a physically based method to simulate ink dispersion in absorbent paper. A fluid flow model based on the lattice Boltzmann equation was devised to simulate percolation in disordered media, such as paper. Zhang *et al*. [12] presented a Chinese ink painting NPR method based on ink diffusion, and Fang *et al*. [13] proposed a water model to simulate the Chinese painting in a good ink-and-water style. For brush modeling, the previously proposed models can also be roughly categorized into two main streams, namely the physically based and the example-based models. The former stream is supposed to simulate the physical processes involved in stroke drawing or painting, including the models of stroke elements, media, etc. Among this stream, representative works for Chinese paintings include the brush footprint model proposed by Yang *et al*. [14] and a parameterized spline model [15] that controls the stroke's details for animating running water in Chinese painting style. Besides, Way *et al*. [16] proposed a method that simulates various tonal expressions on different papers by employing a Kubelka–Munk model to simulate optical effects. At the same time, in order to avoid great computational and manipulative complexity of physically based methods, example-based models are adopted in Chinese painting simulation. Plenty of work has been carried out for this kind of method. One particularly relevant method was proposed by Zhao *et al*. [17,18] for Western oil painting. They built a brush dictionary containing a large set of brush examples with varying shapes and texture appearances, and the selection of the brushes is guided by the semantics included in a parse tree. However, these algorithms have two major problems while applying the methods to simulate Chinese-style painting. The first problem is that the painting process of Chinese ink painting should be constrained by its shape, and producing a Chinese painting using the algorithm has to use different painting styles for different parts of the image. Zhao's oil painting method is not suitable to our issue. The other problem is that it is very hard to control or design a parse tree by pure intuition to achieve a certain style, making it an obstacle for Chinese-style painting simulation.

To our knowledge, there has been little or no work on helping the users who have little painting experience create an acceptable Chinese-style painting from a given photograph. Thus, in this work we present a method to generate Chinese ink paintings by converting a photograph into an artistic style image.

3. Proposed Simulation Method

3.1. Algorithm procedure Before we simulate a painting, we first estimate the SDM of the input photograph, and then

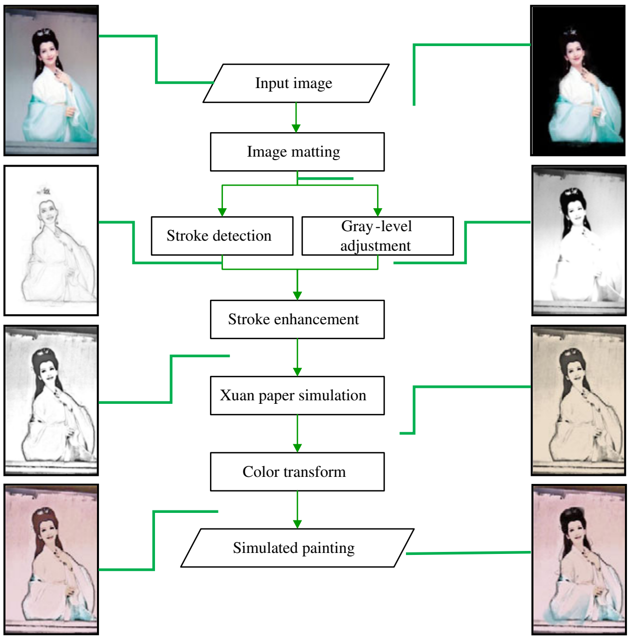


Fig. 1. Steps used in the proposed painting simulation method

use the proposed color transform algorithm to make the color of the SDM close to the traditional Chinese painting color as much as possible. A graphical overview of our simulation method is depicted in Fig. 1, which also shows an example image, the intermediate results, and the final output. The basic steps are as follows: estimate the SDM, use a color transform algorithm to color the SDM, and finally obtain the simulated ink **painting**.

3.2. Chinese painting simulation Given a real captured photograph, the SDM can be estimated for the input photo. This estimation process consists in the following steps: image matting, stroke detection, gray-level adjustment, and stroke enhancement.

3.2.1. Image matting In practice, the foreground objects (e.g., figures, birds, flowers, etc.) are the main parts that painter wants to highlight in Chinese ink painting, so image matting is used here to extract these scene objects from the image background. For image matting, the close-form matting algorithm proposed by Levin *et al*. [19] has proven to be very effective in extracting the image foreground due to the small amount of user input and high-quality matting results of the algorithm.

The key assumption of this matting method [19] is the color line model: the foreground (or background) colors in a local window lie on a single line in the RGB color space [20]. It can be proved that is a linear transformation of **I** in the local window:

$$\alpha_i = \mathrm{a}^T \mathrm{I}_i + b,\ \forall i \in \omega, \tag{1}$$

Here, i is a pixel index, I_i and **a** are 3×1 vectors, and **a** and b are assumed to be constants in the local window ω.

Accordingly, a cost function $J(\alpha, \mathrm{a}, b)$ can be defined to encourage the alpha obeying this model:

$$J(\alpha, \mathrm{a}, b) = \sum_{k \in \mathrm{I}} \left(\sum_{i \in \omega_k} (\alpha_i - \mathrm{a}_k^T \mathrm{I}_i - b_k)^2 + \varepsilon \mathrm{a}_k^T \mathrm{a}_k \right), \tag{2}$$

where ω_k is the window centered at pixel k, and ε is a regularization parameter. By minimizing the cost function, a quadratic function of α can be obtained:

$$J(\alpha) = \alpha^T \mathbf{L} \alpha, \tag{3}$$

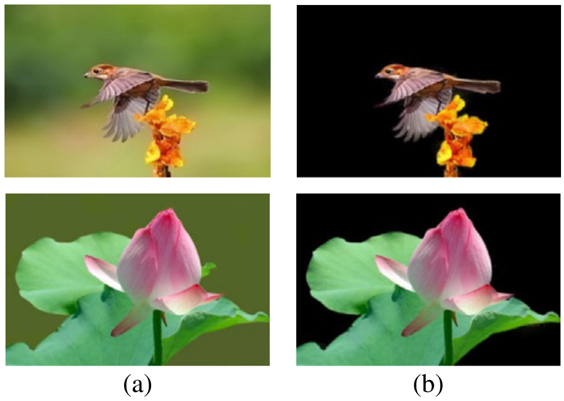


Fig. 2. Image matting results. (a) Original input photos. (b) Their corresponding matting results

Here, α is denoted as an $N \times 1$ vector, where N is the number of unknowns. And L is called matting Laplacian. It is an $N \times N$ symmetric matrix whose (i, j) element is

$$\sum_{k|(i,j) \in \omega_k} \left(\delta_{i,j} - \frac{1}{|\omega_k|} \left(1 + (\mathrm{I}_i - \mu_k)^T \left(\sum_k + \frac{\varepsilon}{|\omega_k|} \mathbf{U} \right)^{-1} (\mathrm{I}_i - \mu_k) \right) \right), \tag{4}$$

where δ_{ij} is the Kronecker delta, μ_k and $\sum_k$ are the mean and covariance matrix of the colors in window ω_k. $|\omega_k|$ is the number of pixels in ω_k, and U is a 3×3 identity matrix.

Combining this cost function with the user-specified constraints (trimap), the whole cost function is defined as

$$E(\alpha) = \alpha^T \mathrm{L} \alpha + \lambda (\alpha - \beta)^T \mathrm{D} (\alpha - \beta), \tag{5}$$

where β is the trimap, D is a diagonal matrix whose elements are 1's for constraint pixels and 0 otherwise, and λ is a large number. The cost function (5) can be optimized by solving a sparse linear system:

$$(L + \lambda D)\alpha = \lambda \mathrm{D} \beta. \tag{6}$$

In Ref. [19], a coarse-to-fine scheme is proposed to speed up the linear system solver, and an accurate matting result can be produced by the white and black scribbles drawn on the input photo. Some matting results obtained using Levin's method are shown in Fig. 2.

3.2.2. Stroke detection and gray-level adjustment From the drawing processes of a Chinese ink-painter, we know that artist first adopts simple strokes to capture the outline of the scene objects, and then uses a relatively large amount of ink to color the interior of the objects. Based on the observations, the proposed method first extracts sketches from the input photo to describe the outline of the objects from both detail and contour aspects. Since the strokes in traditional Chinese ink painting have certain shapes (width, length, shades, etc.) and the gray-level image of the input photo contains all these information, we thus adjust the intensity of the gray-level image and combine it with the sketch fusion result to obtain our initial SDM.

For stroke detection, we first convert the input photo to two types of sketches: detail sketch and contour sketch. Detail sketch captures detail information in the foreground areas obtained by image matting. To obtain the detail sketch, the input color image I is initially converted to a gray-level image I_{gray}. The inversion operation is thus performed as $I_{\mathrm{inv}} = 255 - I_{\mathrm{gray}}$. Subsequently, the Gaussian blur as a low-pass filter is introduced to obtain the blurred image I_{blur}: $I_{\mathrm{blur}} = G(I_{\mathrm{inv}})$. Finally, the detail sketch I_{ds} is inferred as

$$I_{\mathrm{ds}} = \min\left(I_{\mathrm{gray}} + \frac{I_{\mathrm{gray}} \times I_{\mathrm{blur}}}{(255 - I_{\mathrm{blur}})}, 255\right), \tag{7}$$

Contour sketch describes the sharp edge discontinuities and the profile of the objects. The basic idea of contour sketch is performing gradient computation to generate neon effect, and then using inversion operation and gray-level conversion to obtain the contour sketch. Formally, for an input image I, we define

$$I^{c}_{\mathrm{gradt}} = 2 \times \sqrt{(c_1 - c_2)^2 + (c_1 - c_3)^2}\, c \in \{r, g, b\}, \tag{8}$$

In (8), c_1 is a color channel of $I(x, y)$, (x, y) is the 2D spatial location of each pixel, and c_2 and c_3 are the color channel of $I(x + 1, y)$ and $I(x, y + 1)$, respectively. The inversion operation is thus computed as $I^{c}_{\mathrm{inv}} = 255 - I^{c}_{\mathrm{gradt}}$. Then to convert I^{c}_{inv} to a gray-level image, the contour sketch I_{cs} can be obtained. Since the detected stroke should contain both details information and object contour, we combine the detail sketch with the contour sketch. The image fusion process can be written as

$$I_{\mathrm{tmp}} = 255 - ((255 - I_{\mathrm{ds}}) + (255 - I_{\mathrm{cs}})), \tag{9}$$

$$I_{\mathrm{fusion}} = \frac{(I_{\mathrm{tmp}} - I_{\mathrm{tmp\_min}}) \times 255}{(I_{\mathrm{tmp\_max}} - I_{\mathrm{tmp\_min}})}, \tag{10}$$

where I_{ds} and I_{cs} denote the detail sketch and the contour sketch, respectively. I_{tmp} is the intermediate image, and $I_{\mathrm{tmp\_max}}$ and $I_{\mathrm{tmp\_min}}$ are its maximum and minimum value, respectively. Thus, the image fusion result I_{fusion} can be obtained.

On the other hand, the image gray-level adjustment is also very important for estimating SDM. The adjustment process can be summarized as

$$I_{\mathrm{tmp2}} = I_{\mathrm{gray}} + I_{\mathrm{inv}}, \tag{11}$$

$$I_{\mathrm{gray\_adjust}} = \min_{(x',y')\in\Omega(x,y)} (I_{\mathrm{tmp2}}(x', y')). \tag{12}$$

where I_{gray} and I_{inv} are the converted gray-level image and the inversion result of the input image, respectively. $\Omega(x, y)$ is a local patch centered at (x, y). Therefore, the gray-level adjustment result for input image $I_{\mathrm{gray\_adjust}}$ can be computed as the minimum value of each pixel in the intermediate image I_{tmp2}.

3.2.3. Stroke enhancement The scene objects generally have clear outline in traditional Chinese ink painting. However, the initial SDM obtained by combing the sketch fusion result with the gray-level adjustment result is not obvious. To overcome the deficiency, we thus use a guided filter [21] to enhance the initial SDM. The detailed process of the stroke enhancement is described in the following steps.

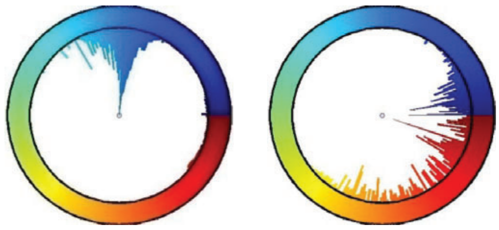
Step 1. Using (9) and (10) to fuse the sketch fusion result I_{fusion} and the gray-level adjustment result I_{gray_adjust} obtained by the algorithm presented above, the initial SDM, i.e., SDM$_{init}$ is obtained.

Step 2. For the initial SDM, we first compute the linear coefficients a_k andb_k for the guided filter:

$$a_k = \frac{\frac{1}{|\omega|}\sum_{(x,y)\in\omega_k} I_{guid}(x, y)\tilde{s}(x, y) - u_k \bar{s}_k}{\sigma_k^2 + \varepsilon}, \tag{13}$$

$$b_k = \bar{s}_k - a_k u_k$$

where I_{guid} is the guidance image and $\tilde{s}$ is the input image of the guided filter since the filter is a general linear translation-variant filtering process, which involves a guidance image and an input image. Here, both I_{guid} and $\tilde{s}$ are given to be SDM$_{init}$. In (13), ε is a regularization parameter that keeps a_k from being too large. u_k and σ_k^2 are, respectively, the mean and variance of I_{guid} in a window ω_k that is centered at the pixel k. $|\omega|$ is the number of pixels in ω_k, and $\bar{s}_k = (1/|\omega|)\sum_{i\in\omega_k} \tilde{s}_i$ is the mean of $\tilde{s}$ in ω_k.



(a) (b)

Fig. 3. Comparison of distribution of hue and color temperature between natural images and ink painting images. (a) Hue distribution of selected typical natural image samples. (b) Hue distribution of selected typical ink painting image samples

Step 3. Once the linear coefficients (a_k,b_k) are obtained, we can compute the filter output by

$$s_f(x, y) = \bar{a}_k \tilde{s}(x, y) + \bar{b}_k. \tag{14}$$

where $\bar{a}_k = (1/|\omega|)\sum_{i\in\omega_k} a_i$ and $\bar{b}_k = (1/|\omega|)\sum_{i\in\omega_k} b_i$. $\tilde{s}$ is the initial SDM, and the filter output s_f is the enhanced final SDM.

3.2.4. Color transform based on statistical analysis The traditional color view of the Chinese painting is "colors should be presented in accordance with the requirements of different categories of objects". Chinese painting does not depict the complexities of light and color, but, all the same, it achieves true effects with high artistic appeal. The method of coloring in Chinese painting, stressing mainly the intrinsic colors, does not aim at naturalistic imitation. It proceeds from content and is subordinate to the requirements of the theme. It can exaggerate to the fullest extent and boldly change the intrinsic colors of the object, bringing out the theme prominently and expressing the artist's ideas and feelings to achieve ideal artistic effect and producing direct, pure, and bright aesthetic appeal.

Here, we provide an algorithm to transform the color of whole image to match the color statistics of Chinese paintings to achieve more rendering effects. Inspired by Zeng's work [18], we compare the colors of natural images and find obvious statistical difference between some of their marginal distributions. For example, by defining a color temperature on saturation S and hue H as

$$\text{Color temperature}\,(S, H) = \frac{S \cdot \sin H}{(S \cdot \cos H)^2 + 1}, \tag{15}$$

with orange as the warm pole ($H = \pi/2$) and blue as the cool pole ($H = -\pi/2$) according to human perception, it is observed that Chinese paintings by artists tend to appear warmer than natural images. Also, a study on color statistics by Cohen-Or *et al*. [22] has shown that the color scheme of an image is in harmony when its hue follows a V-shape distribution. In our experiments, we find both the natural image and its corresponding ink painting follow the V-shape harmony distribution. In addition, compared with natural images, Chinese ink paintings mostly use light colors, and the background color can be light pink, which makes the color temperature of ink paintings consequently usually warmer than the former, as shown in Fig. 3.

A color transform algorithm is proposed here to transform the color of final SDM into the color manifolds of Chinese ink paintings. The first step of color transformation consists in altering background color for the enhanced SDM. By applying (9) and (10), we fuse the enhanced SDM with the simulated Xuan paper color, which is set to be [234, 220, 200]$^{\mathrm{T}}$. Besides, the color of the original natural image for the main objects, such as birds and flowers, is an important reference for the final ink painting image.

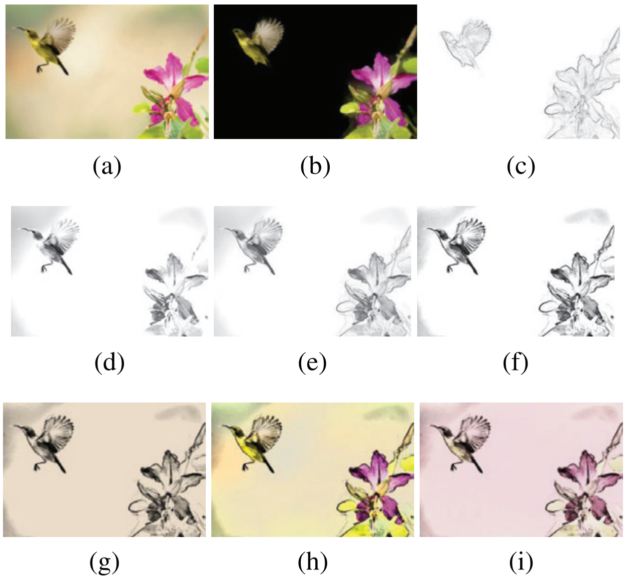


Fig. 4. Process of SDM estimation for figure or bird-and-flower painting. (a) Original image. (b) Image matting result. (c) Fusion result of detail sketch and contour sketch. (d) Gray-level adjustment result. (e) Initial SDM. (f) Enhanced final SDM. (g) Background altered result. (h) Color synthetic result. (i) Color transfer result

We therefore generate a synthetic image by combining the hue and saturation components of the natural image with the intensity component of the background-altered image. In the experiment, we find that the color of the synthetic result is just naturalistic imitation and is too bright for ink painting image. Thus, we transform the color using Gaussian matching method according to the statistical distribution of the ink painting image in $L\alpha\beta$ color space. Formally, for an obtained synthetic image I_{syn}, we define

$$\alpha' = \frac{\alpha - \bar{\alpha}}{\sigma_1}\sigma_1' + \bar{\alpha}'. \tag{16}$$

where α and α' are the alpha component value before and after the color transfer operation. $\bar{\alpha}$ and σ_1 are the mean and variance value of the synthetic image I_{syn}, and that of the ink painting image are $\bar{\alpha}'$ and σ_1', respectively. Similarly, the transform on beta component follows the same steps. Our colored SDM can thus be obtained by converting the new $L\alpha\beta$ color space to the RGB color space. Figure 4 illustrates an example of the SDM estimation process for a typical bird-and-flower painting. Note that the light color in the transform result effectively reflects the intrinsic colors of the image objects.

4. Experimental Results

In order to verify the effectiveness and validity of the proposed Chinese painting simulation method, three criteria have been considered: (i) parameter adjustment, (ii) qualitative evaluation, and (iii) performance comparison. In the experiments, all the results are obtained by executing MATLAB R2008a on a PC with a 3.10-GHz Intel® CoreTM i5-2400 CPU.

4.1. Parameter adjustment for color transfer

Four parameters $\bar{\alpha}'$, σ_1', $\bar{\beta}'$, σ_2' are used to control the aspect of the ink painting color [see (16)]. The values of $\bar{\alpha}'$ and σ_1' control the strength of color transform in alpha component, and the values of $\bar{\beta}'$ and σ_2' control the color transform in beta component.

Figure 5 shows different rendering effects resulting from the proposed method by adjusting these parameters. In Fig. 5, the value of the four parameters are gradually increased, and the degree of color enhancement increases correspondingly. Since the main features of Chinese painting color are "Dan Cai Bo Mo" (literally "light color and light ink") and the middle image where $\bar{\alpha}' = 15$, $\sigma_1' = 60$, $\bar{\beta}' = 4$, $\sigma_2' = 60$ meets the requirement of Chinese painting color. Thus, we fix the four parameters to these values for all the results reported in this paper. The over-coloring cases are also shown in Fig. 5.

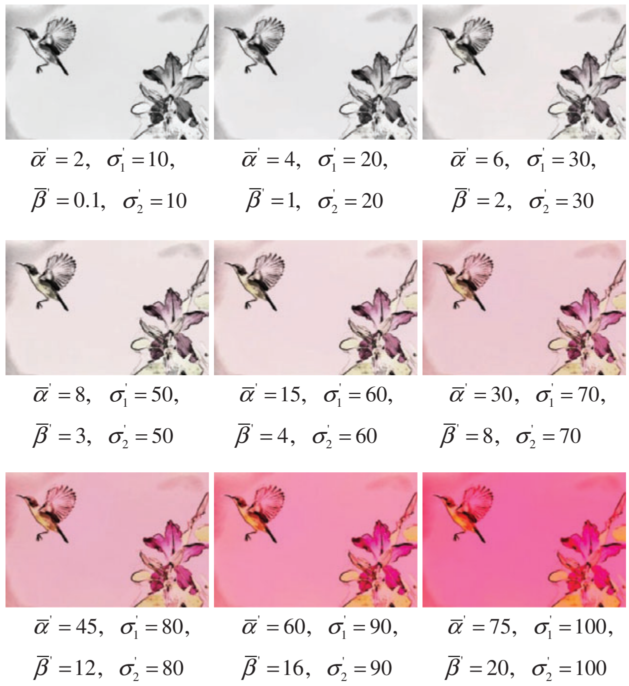


Fig. 5. Different color effects with different parameters

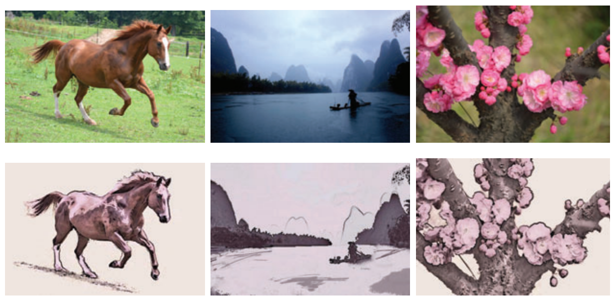
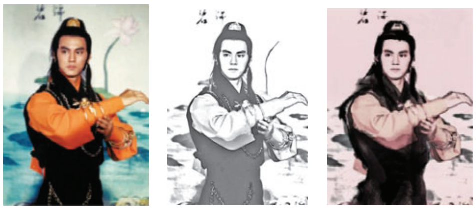


Fig. 6. Color transfer results obtained using the same parameter values ($\bar{\alpha}' = 15, \sigma_1' = 60$, $\bar{\beta}' = 4$, $\sigma_2' = 60$). First row: original images. Second row: color transfer results

Since the color transfer step is a very important point in our proposed method, choosing proper parameter values for most input photographs become the focused issue. In our experiment we find that, although the values of the four parameters are application-based, the proposed method can produce impressive results when we fix the four parameters to $\bar{\alpha}' = 15, \sigma_1' = 60, \bar{\beta}' = 4, \sigma_2' = 60$ for all the input photographs. Figure 6 shows the color transfer results obtained using the fixed parameter values. From the figure, we can see that these parameters are suitable for these photographs. Therefore, we can deduce that the fixed value of the four parameters may not the best ones, but they seem reasonable for each input photograph and can produce promising color transfer results that are consistent with Chinese-ink style.

The values of the four parameters $\bar{\alpha}'$, σ_1', $\bar{\beta}'$, and σ_2' are selected based on the statistical observations on a large number of Chinese ink painting images: for most of ink-style images, the



(a) (b) (c)

Fig. 7. Example of ink painting simulation result. (a) Photo of a young swordsman. (b) Its corresponding SDM. (c) Its corresponding ink painting image

(a) (b) (c)

Fig. 8. Example of ink painting simulation result. (a) Photo of a bird and flower. (b) Its corresponding SDM. (c) Its corresponding ink painting image

(a) (b) (c)

Fig. 9. Example of ink painting simulation result. (a) Photo of a lotus pond. (b) Its corresponding SDM. (c) Its corresponding ink painting image

mean value of the alpha component of the Chinese ink painting image $\bar{\alpha}'$ is usually between 10 and 20, and the mean value of the beta component of the ink painting image $\bar{\beta}'$ is usually between 1 and 10. The variance values of alpha and beta components, σ_1' and σ_2' are both between 1 and 100. In our experiments, we find that the visual pleasing results that are consistent with Chinese ink style can be obtained for most input photographs when $\bar{\alpha}' = 15, \sigma_1' = 60, \bar{\beta}' = 4$, and $\sigma_2' = 60$. Besides, the difference of the color transfer results is subtle when the four parameter values are set in the above corresponding ranges. Therefore, it can be deduced that the color of the simulated images is gradually and slowly changed when the parameter values are set in the statistical ranges. However, the difference will be significant when the values are set outside the ranges. Since it is impossible for us to list all the possible combinations, some combinations are chosen to show the obvious changes in image color (from too dark to too strong) and also to compare with the results obtained by our determined parameter values, as shown in Fig. 5.

4.2. Qualitative comparison We have done experiments on hundreds of images of various types of scenes or figures. Some results are shown in Figs 7–9.

Figure 7 shows an example of a young swordsman, and Fig. 8 displays the simulation result for a typical bird-and-flower scene. One can clearly see that a promising ink-and-wash effect can be generated with little user interaction using the estimated SDM. Figure 9 is an image of a common Chinese ink painting scene, including a lotus flower and a lotus leaf. With our simulation solution, different brushes, strokes, and blending effects are created for different objects. Therefore, even a person with little painting experience can generate an acceptable Chinese ink painting using the proposed method.

(a) (b) (c)

Fig. 10. Set of rendered results for the lotus pond by adding goldfishes as foreground objects

(a) (b) (c)

Fig. 11. Comparison results for a photo of a young lady. (a) Original image. (b) Simulated result obtained using Photoshop. (c) Simulated result obtained by the proposed method

(a) (b) (c)

Fig. 12. Comparison results for a photo of a horse. (a) Original image. (b) Simulated result obtained using Cao's method [10]. (c) Simulated result obtained by the proposed method

Besides, we can also use the e-brushes in some software (e.g., Photoshop, Firework, etc.) as a possible "final touch" to make the simulation results more vivid, interesting, and lifelike. An illustrative example is shown in Fig. 10. Here, the simulated ink painting result [see Fig. 9(c)] is regarded as a background image, and some moving goldfish are added as the foreground objects through Photoshop. One can clearly see that the whole images look more harmonious and natural to human visual perception.

To the best of our knowledge, many works that have been done on simulating an ink-style painting that is similar to other Chinese paintings or rendering a photo in the style of Chinese ink painting completely rely on image processing software, such as Photoshop or Maya. However, it is rare in the literature to directly convert a photo to a Chinese painting image using image-based algorithm. In this section, the rendering methods that are used for comparison are all methods for converting a photograph into a Chinese ink painting. The methods for directly simulating an ink-style painting that is like other ink-style paintings are not considered here.

For the software-based method, the whole procedure has many steps and each step need user involvement, which is very hard to control and require good painting skills. Figure 11 shows the comparison of our result with that obtained using Photoshop. One can clearly see that the proposed method can generate comparable result with much less user interaction.

For the image-based method, the method focuses on the simulation of rendering effect or develops a brush model based on physical mechanism. For example, Cao *et al*. [10] used different image processing algorithms for rendering the outline and interior parts of the input image to generate a Chinese painting. However, the method can only produce gray-level simulation results. The method proposed by Way *et al*. [16] simulates the physical behavior of color ink diffusion, and can thus generate various strokes.

(a) (b) (c)

Fig. 13. Comparison results for a photo of a typical bird-and-flower scene. (a) Original image. (b) Simulated result obtained using Way's method [16]. (c) Simulated result obtained by the proposed method

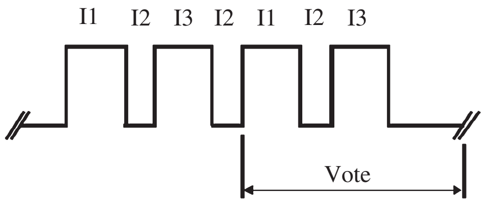


Fig. 14. Example of the test material presentation. I1: original photograph. I2: rendered result obtained by the proposed method. I3: rendered result obtained by other method used for comparison

However, the main problem for this kind of method is that the simulation of physical property and behaviors of Chinese ink painting is a nontrivial process, requiring a number of advanced computational steps and a long time to compute, making it an obstacle for real-time painting. Figure 12 shows the comparisons of our simulation result with the result obtained using Cao's method. One can clearly see that our result is more colorful than Cao's result, which makes the visual effect of our result closer to traditional Chinese ink painting, as shown in Fig. 12(c). Figure 13 shows an example of the simulated result obtained by Way's method, using the photo in Fig. 13(a) as an original. The painting time for the image in Fig. 13(b) was about 1 h since each virtual stroke is manually drawn using the tablet pen device in the Way's system, whereas the proposed method needs only 3 s to obtain an acceptable ink painting effect for a image with a size of 640×480. The simulated result obtained by the proposed method is shown in Fig. 13(c).

4.3. Quantitative evaluation Unlike photorealistic rendering that can be measured by the close degree between the obtained image and the real photo, non-photorealistic rendering technique is inspired by artistic styles and pays more attention to subjective feelings. For artworks, different people may have different opinions depending on their artistic quality. So far, there is no effective objective index or public testing database for measuring the rendering effect of the NPR technique. Therefore, subjective evaluation is the main method to assess the non-photorealistic rendering effect. The same is true for the assessment of Chinese ink painting simulation results.

In our experiments, ten testing photos with different themes and their corresponding rendered results obtained using Photoshop, Cao's method [10], Way's method [16], and the proposed method were used to perform subjective evaluation.

The evaluation was performed by 20 subjects. The subjects were chosen from among voluntary undergraduate art major students and professional artists. Most of them have knowledge and drawing experience on Chinese ink painting. Prior to the study, each subject candidate was tested for proper aesthetic perception ability using the Meier Art Test [23] and those who failed the test did not participate in the evaluation.

Subjects were given written instructions describing the task that need to be performed and the attributes that need to be rated. For the experiment design, we have followed the double stimulus continuous quality scale (DSCQS) method [24]. According to this procedure, subjects are shown a content, either test or reference; after a brief break, they are shown the other content. Then, both contents are shown for the second time to obtain the subjective evaluation. This process is illustrated in Fig. 14.

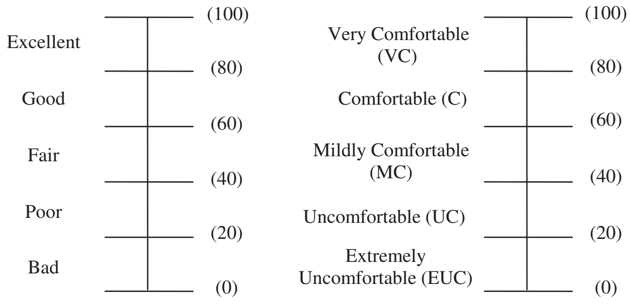


Fig. 15. Rating scales used for evaluation of (a) image naturalness or colorfulness and (b) visual comfort

To evaluate our method and the three other methods, we performed the tests in pairs of slides for each subject. For each pair of slides, our method is used in the test content slide, while the compared method, either Photoshop method or Cao's and Way's method, is used in the reference content slide. The order of the reference and test slides in a pair and the order of the compared methods in consecutive pairs were both determined randomly. The subjects were not informed about either order. This set of tests was executed for each of our photographs. Overall, ten group of test slides were evaluated by each subject.

The participants watched the rendered images obtained using various rendering methods of all cases separately, and they were asked to rate each image on the basis of three criteria. The motivation behind selecting these grading criteria is as follows:

- *Image naturalness*: Image naturalness index (INI) is the degree of correspondence between human perception and reality world [25]. A rendered image of good quality should have natural image color.
- *Image colorfulness*: Image colorfulness index (ICI) presents the color vividness degree [25]. A rendered image of good quality should have vivid image color.
- *Visual comfort*: Visual comfort index (VCI) refers to the subjective sensation of comfort that accompanies the physiological change [26]. A good-quality rendered image should provide a comfortable viewing experience.

For assessment of the content, we first asked the subjects to rate the color naturalness, colorfulness, and visual comfort of both the reference and test slides separately, by filling out a five-segment scale for each slide. Thus, there were no comparisons among various rendering methods here; the evaluation result only depended on each method itself. The color naturalness and colorfulness were assessed using the discrete scale shown in Fig. 15(a), and visual comfort was assessed using that shown in Fig. 15(b).

In order to analyze the tester assessment, we computed the average percentage of tester grades for each method, as well as the average scores for tester ratings. Table I shows the voting results for the four rendering methods. From Table I, one can clearly see that the results obtained by the proposed method have better image naturalness compared with the results obtained using other rendering methods, and fewer subjects have evaluated the naturalness impression of our method as "bad" or "poor". This was due to the fact that our method is based on the drawing experience and statistical regularity of the Chinese ink painting. The comfort

Table I. Subjects' ratings and average scores for each method

Method	Percentage of grades for image naturalness					Average score
	Bad	Poor	Fair	Good	Excellent	
Photoshop	0	8.5%	19.7%	69.5%	2.3%	70.4
Cao	4.1%	19.6%	10.8%	63.9%	1.6%	66.3
Way	0	5.1%	9.5%	82.9%	2.5%	74.6
Proposed	0	3.5%	7.9%	85.6%	3.0%	78.3

Method	Percentage of grades for image colorfulness					Average score
	Bad	Poor	Fair	Good	Excellent	
Photoshop	0	8.5%	35.5%	50.3%	5.7%	71.8
Cao	3.6%	10.4%	37.9%	45.7%	2.4%	63.5
Way	0	1.2%	23.6%	64.9%	10.3%	82.9
Proposed	0	4.3%	27.5%	59.3%	8.9%	79.3

Method	Percentage of grades for visual comfort					Average score
	EUC	UC	MC	C	VC	
Photoshop	0	5.4%	38.7%	52.7%	3.2%	79.6
Cao	0	6.0%	42.7%	49.5%	1.8%	68.2
Way	0	0	22.1%	57.4%	20.5%	82.1
Proposed	0	0	8.6%	64.5%	26.9%	86.7

Table II. One way ANOVA results

Index	Source	DF	Sum of squares	Mean square	F	P
INI	Model	5	24875.05	4975.01	134.96	1.28×10^{-13}
	Error	18	663.54	36.86		
	Total	23	25538.59			
ICI	Model	5	18190.94	3638.19	96.28	2.41×10^{-12}
	Error	18	680.15	37.79		
	Total	23	18871.09			
VCI	Model	5	20078.14	4015.63	46.38	1.16×10^{-9}
	Error	18	1558.48	86.58		
	Total	23	21636.62			

ratings also revealed that our method was generally rated better than other methods. However, in terms of image colorfulness, the score of the proposed method is higher than those obtained using Photoshop and Cao's method, but slightly lower than that of Way's method. The high performance of the Way's method is due to the fact that Way's system is an interactive system and it is the user who determines the color of each stroke. Thus, we can deduce that our method yields better average than Photoshop software and Cao's method in all measures and has fewer user interaction compared with Way's method.

We also carried out a statistical analysis using the analysis of variance (ANOVA). ANOVA is a collection of statistical models used to analyze the differences between group means and their associated procedures. Here, we use the statistical method to determine whether the five-segment scales of the three indicators have significant influence on the results of various rendering methods. If so, these algorithms can be effectively measured. The indicator value of each rendering algorithm for the ten testing photos and their corresponding simulated images were compared by applying one-way ANOVA with a 0.05 significance level. Table II shows the one-way ANOVA results of the indicator data obtained by the software called "OriginPro". When the P-value in Table II is less than 0.05, there is a significant difference between the groups with a confidence level of 95%. According to this rule, the three indicator values of different algorithms were significantly different from each other. Therefore, they

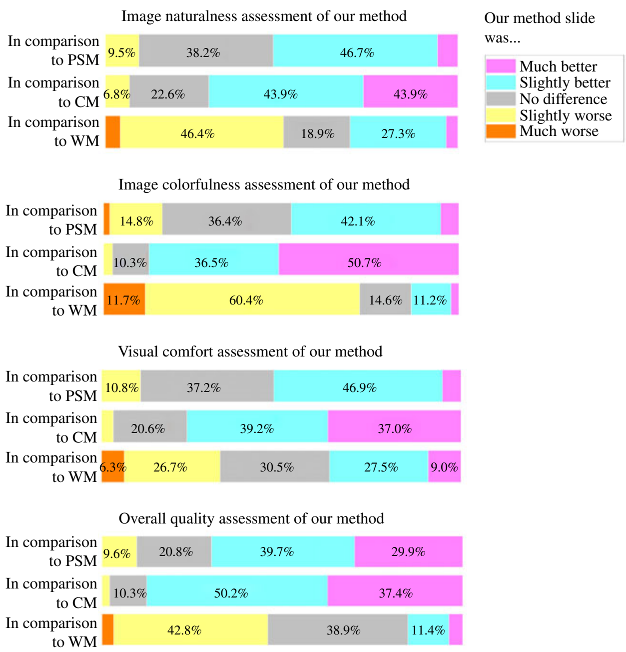


Fig. 16. Aggregated results from our slide comparison questionnaires demonstrating relative tester preferences of our proposed method in percentages. Scores are relative to Photoshop method (PSM) in the first row, Cao's method (CM) in the second, and Way's method (WM) in the third

can effectively assess various rendering methods from different aspects.

This conclusion illustrates that for the three indicators INI, ICI, and VCI, different rendering algorithms have significant difference on these indicators. Thus, they can effectively measure the ink simulation effect for each algorithm. From Table I, we can see that, compared with other rendering algorithms, the proposed algorithm, as the whole, can get a better trade-off between image naturalness and colorfulness and provide a more comfortable viewing experience as well. Thus, we can deduce that the best overall quality can be obtained by using the proposed algorithm. This confirms our observations on Figs 11–13.

Besides, at the end of each slide pair, we also used the psychometric assessment method by asking the subjects to compare between the two slides. For this purpose, we asked the following questions in the evaluation forms:

– Which slide provided better color naturalness?
– Which slide provided better color colorfulness?
– Which slide was more comfortable to watch?
– Which slide provided better overall quality?

Figure 16 shows results of the preferences collected from the questions comparing our method with other methods. Different from the rating analysis of the methods, this chart shows the preferences in percentages for our method directly in comparison with other three methods. These preferences are determined by the subjects by taking into account color naturalness, colorfulness, visual comfort, and overall quality. The study showed that the proposed method was preferred in overall quality over the three other methods, with 69.6, 87.6, and 15.1% preference, respectively; whereas in 10.8% of the cases the Photoshop method (PSM) was preferred over ours, 2.1% showed preference of Cao's method (CM), and 46% showed preferences of Way's method (WM). The high performance of Way's method (WM) is due to the fact that the color of each virtual stroke is manually determined in an interactive way. Thus, its speed is much less than that of our method.

5. Conclusions

A novel and effective method was proposed to simulate Chinese ink paintings from photos in this paper. What is particularly useful is that the proposed method makes a person with little painting experience produce a Chinese ink painting image easily from a photo.

In order to convert a photo into a Chinese ink painting image, we proposed a method that uses the SDM to characterize object appearance. The developed color transform algorithm plays a critical role in allowing the painting's color to be consistent with traditional Chinese ink painting color requirement. Experimental results showed that the proposed method could produce very beautiful Chinese ink painting from a photo with less user interaction and much higher conversion speed compared to other approaches. The most important contribution of this work is that it provides a framework and specific steps to convert a photograph into a Chinese ink painting. Nevertheless, the proposed method may fail for some types of photos with some complex landscape scenes, in which the image foreground and background are hard to differentiate by the SDM technique. We will try to investigate the simulating techniques that can handle complicated landscape scenes in the future.

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Fan Guo (Non-member) received the B.S. degree in Computer Science and Technology in 2005 and the M.S. and Ph.D. degrees in Computer Application Technology in 2008 and 2012, respectively, all from the Central South University (CSU), Changsha, China. Currently, she is a Postdoctoral Fellow and Lecturer with the School of Information Science and Engineering, CSU. Her main research interests include image processing, pattern recognition, and virtual reality.

Hui Peng (Non-member) received the B.Eng. and M.Eng. degrees in Control Engineering from Central South University (CSU), Changsha, China, in 1983 and 1986, respectively, and the Ph.D. degree in Statistical Science from the Graduate University for Advanced Studies, Hayama, Japan, in 2003. He is currently a Professor with the School of Information Science and Engineering, CSU. His research interests include nonlinear system modeling, statistical modeling, system identification, parameter optimization, signal processing, predictive control, robust control, and process control.

Jin Tang (Non-member) received the B.S. and M.S. degrees from Peking University, Beijing, China, in 1987 and 1990, respectively, and the Ph.D. degree in pattern recognition and intelligence system from Central South University (CSU), Hunan, China, in 2002. He is currently a Professor with the School of Information Science and Engineering, CSU, Changsha, China. His current research interests include image processing, pattern recognition, and computer vision.