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# Image Recovery for Ancient Chinese Paintings

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***Abstract***

*This work presents a new method to virtually recover ancient Chinese paintings in electronic form. Two factors result in the degradation of ancient Chinese paintings: pigment fading and paper aging. Thus, the proposed method first uses guided filter to enhance the original painting image. Then, the semi-transparent stroke as the image foreground can be extracted from the background of painting image by adopting a novel bi-extracting method. Two independent maps that respectively produced by the saliency detection and the pseudo-alpha matting are fused to represent the foreground stroke. Finally, the ancient painting image is recovered by altering the color of the background. Experiments on a variety of ancient Chinese paintings show the robustness and accuracy of the proposed method.*

***Keywords:*** *Image recovery, Chinese painting, Saliency map, pseudo-alpha map, fusion*

## 1. Introduction

Painting is a mode of expression. As an important part of the Chinese traditional cultural heritage, ancient Chinese painting is highly-regarded as a precious treasure throughout the world for its theory, expression and techniques. With the steady growth of computer technology, more and more traditional Chinese painting art images are digitalized and exhibited on the Internet. As a significant feature of Chinese paintings, classical Chinese artists often leave extensive empty background spaces in their paintings to give the reviewers more room for imagination. However, since ancient Chinese paintings were painted on hand-made paper, those unpainted regions generally turn yellowish owing to long-term exposure to light. Consequently, the contrast between unpainted and painted parts of an ancient painting may decrease. Furthermore, traditional pigments used in Chinese painting were extracted from minerals or vegetables. They could easily fade as times goes by. Color degradation, thus, is inevitable [1]. Therefore, recovering ancient Chinese painting is very important for propagating the Chinese traditional culture and promoting the cultural exchange in the world.

However, recovering ancient Chinese paintings in electronic form is a non-trivial work. This mainly because most ancient Chinese paintings that have preserved till today were produced on xuan-paper or silk, the pigment used for paintings are extracted from minerals or vegetables. Thus, the physical characteristic of painting materials make the pigments diffuse and penetrate seriously and the paper gets yellowish after hundreds of years of exposure to light. Almost every pixel from painting strokes is affected by both pigments and paper. The diffusion and penetration of ink and pigments make it difficult to extract the foreground from the paintings only based on three-band image that widely used in image matting [2]. Therefore, it is a daunting work and only a few studies in literature.

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In this paper, a new foreground extraction technique is proposed to recover the appearance of ancient Chinese paintings. In general, the main contribution of this work can be summarized as follows:

- A novel bi-extracting method (BEM) is proposed for extracting foreground strokes. Two independent maps that respectively produced by the saliency detection and the pseudo-alpha matting are used to represent the image foreground. Based on the final confidence map created by fusion of the two maps, the image foreground is extracted without using any prior knowledge or user interaction.
- The bi-extracting method is applied to ancient Chinese paintings and calligraphies, which extracts the foreground strokes from the overlay of background strokes. Thus, a better recovering result can be obtained.
- The bi-extracting method is compared with other image foreground extraction method for recovering paintings. The comparative and quantitative evaluation on a variety of ancient Chinese paintings shows that better quality results can be obtained by using the proposed method.

The reminder of this paper is organized as follows. First, Section 2 introduces some related works. Section 3 describes the proposed Chinese painting recovery method. Next, the experimental results are presented in Section 4. Finally, conclusions are given in Section 5.

## 2. Related Works

Many works have been done to recover the ancient Chinese painting. For example, a color enhancement scheme [1] which comprises two subsequent methods: background adjustment and saturation enhancement, was presented to virtually restore ancient Chinese paintings. The method mainly aims to restore the color of background and foreground of the paintings. Zhang [2] *et al*., adopted a multispectral matting method to extract semi-transparent foreground stroke from the overlay of background strokes of Chinese paintings. A spectral reconstruction system consists of color digital camera, interference filter, color card and spectrophotometer is used to estimate the algorithm parameter. pei [3] *et al.*, presented a novel algorithm using color contrast enhancement and lacuna texture synthesis for the virtual restoration of ancient Chinese paintings. Ding [4] *et al* developed a color recovery prototype system for Chinese painting by using the chromatics theory and image processing technology. Shih [5] *et al*., proposed a restoration algorithm which decomposed a Chinese painting into several layers and recovered each layer separately. The final recovering result is obtained by using a layer fusion strategy. Yen [6] *et al.*, studied the way to extract inscriptions from a traditional Chinese painting, so the inscription and the paintings can be enjoyed or studied separately. Li [7] *et al*., presented a new method for restore the color fading of Chinese Dunhuang fresco. The method first acquire a fresco's color structure by color clustering and separate the fresco image into several layers, and then restore every color layer of the mural image according to the color fade and change rules over time of pigments. Finally, the restored color levels are combined into one image so as to obtain the color-restored mural image.

On the other hand, matting in Chinese paintings is significant because the semi-transparent stroke as the image foreground need to be extracted from the background during the recovering process of painting images. Early matting methods try to simplify the problem by photographing objects against a constant-color background, which is called blue screen matting [8]. However the method is requiring the object against two distinctive backing colors, which limits its application in Chinese painting since it is impossible to obtain the foreground strokes of our Chinese paintings against two different backgrounds. Recent methods attempt to extract the foreground matte directly from one natural image. The most representative algorithms includes a close form solution to image matting [9], the algorithm proposed by Ruzon [10] *et al*, Bayesian matting [11] and Poisson matting [12]. All these methods start by letting the user segment the image into three regions: foreground, background and unknown region, which are often referred to as a trimap. The problem is thus reduced to estimating F, B and $\alpha$ in the unknown region. Previous natural image matting methods heavily rely on the user specified trimap. Ideally, the unknown region in the trimap should be as thin as possible to achieve the best matting result. Partial opacity values are then computed only for pixels inside the unknown region. These pre-segmentation algorithms fail if the images have large portions of semi-transparent foreground that it is difficult to create a trimap even manually [2]. Wang [13] *et al*., proposed a more efficient method to extract high quality mattes for foreground with significant semi-transparent regions. The iterative matting system solves for a matte directly from a few scribbles specified by the user instead of a carefully specified trimap and each marked pixel is given a $\alpha$ value 0 (background) or 1 (foreground). However, Chinese paintings are painted on xuan-paper or silk, the strokes of semi-transparent caused by the diffusion and penetration of ink and pigments take up most of a painting. In most cases, it is difficult to identify foreground pixels with $\alpha$ value of 1. Therefore, how to effectively extract the semi-transparent stroke from the image background is very important for Chinese painting recovery.

## 3. Proposed Algorithm

Given a Chinese painting image, the image is first enhanced by using the guided filter [14]. Then, the image foreground is extracted by fusing the two independent maps (Saliency map and Matting map) that respectively produced by the saliency detection and the pseudo-alpha matting. Finally, the ancient painting can be recovered by altering the color of the background. This process is also depicted in Figure 1.

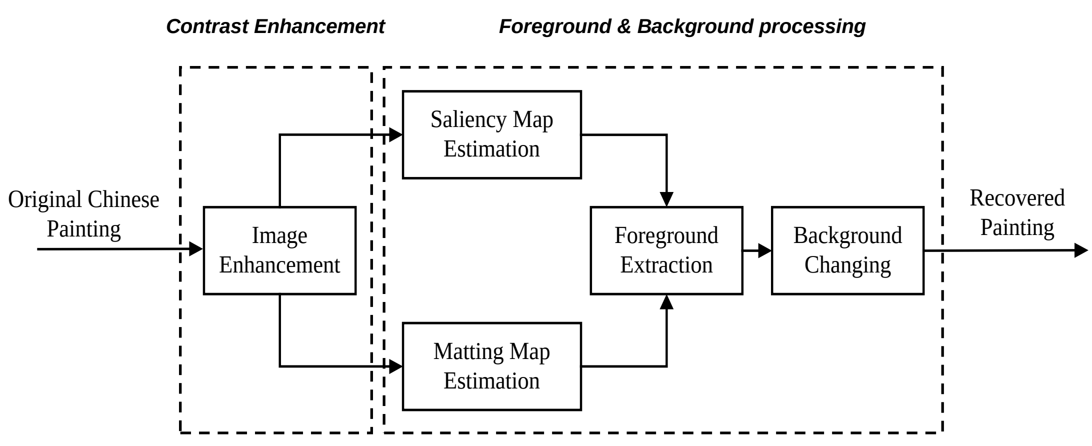



**Figure 1. Procedure of Ancient Chinese Painting Recovery**

### 3.1. Contrast Enhancement

The most intuitive method of enhancing the original contrast of Chinese painting is to make the color of painted regions more vivid and the sharp of the edge be well maintained. As the guided filter has been proved to be quite efficient for detail enhancement [14], so the filter is used to improve the image contrast and image color.

Specifically, for the original painting image, it assumes the output of the guided filter is a linear transform of the original (guidance) image $I(x,y)$ in a window $\omega_x$ centered at pixel $(x,y)$,

$$\hat{t}(x,y) = a_x^T I(x',y') + b_x, \ \ \forall (x',y') \in \omega_x, \tag{1}$$

where $a_x$ and $b_x$ are linear coefficients assumed to be constant in $\omega_x$. To make the difference between the output $\hat{t}(x,y)$ and the input $\tilde{t}(x,y)$ as small as possible, the following cost function is minimized in the local window $\omega_x$ centered at pixel $(x,y)$,

$$E(a_x, b_x) = \sum_{(x',y')\in\omega_x} ((a_x^T I(x',y') + b_x - \tilde{t}(x,y))^2 + \varepsilon a_k^2) \tag{2}$$

The small variable $\varepsilon$ is a regulation parameter preserving $a_x$ from being too large. The solution to Equation (2) is given by:

$$\begin{aligned} a_x &= (\Sigma_x + \varepsilon U)^{-1}\Big(\frac{1}{|\omega|}\sum_{y\in\omega_x} I(x,y)\tilde{t}(x,y) - u_x \bar{t}(x,y)\Big), \\ b_x &= \bar{t}(x,y) - a_x^T u_k \end{aligned} \tag{3}$$

where $\Sigma_x$ is the $3\times3$ covariance matrix of $I(x,y)$ in $\omega_x$, $U$ is a $3\times3$ identity matrix, $\bar{t}(x,y)$ is the mean value of the input $\tilde{t}(x,y)$ in window $\omega_x$ and $u_k$ is the mean vector of $I(x,y)$ in window $\omega_x$. By substituting Eq. (3) into Eq. (1), the filter output $\hat{t}(x,y)$ can be computed for the image. Once the output image $\hat{t}(x,y)$ is obtained, the enhancement of the original image can be performed by:

$$I_{enh}(x,y) = 5\times(I(x,y) - \hat{t}(x,y)) + \hat{t}(x,y) \tag{4}$$

In (4), $I_{enh}(x,y)$ represents the enhanced image, $I(x,y)$ is the original painting image, $\hat{t}(x,y)$ is the output image of guided filter. Two illustrative examples for painting image enhancement are shown in Figure 2.

(a) Original Image (b) Enhanced Image

**Figure 2. The Enhancement Results of Ancient Chinese Painting by using the Guided Filter**

### 3.2 Foreground and Background Processing

To recover an ancient Chinese painting, the semi-transparent stroke as image foreground, needs to be extracted from the background of painting images. The best way to do this is to decompose the foreground from the painting and alter the color of the background. Thus, foreground extraction is the most important step for recovering the paintings. Here, a novel Bi-extracting method (BEM) is proposed to extract the foreground of the enhanced image obtained by the algorithm presented above. For the ancient Chinese painting, there are generally two distinctive features are considered here: (i) extensive empty background space and (ii) background color is rather achromatic.

Recently, many foreground extraction algorithms have been treated as image segmentation algorithms. Park's segmentation method [15] extracts foreground regions from still images by background elimination and graph technique. The saliency inspired video object extraction (VOE) method [16] detects visual and motion salient regions and integrates such saliency information with the associated color model via condition random field to achieve VOE. However, they need prior knowledge on the background regions or the temporal characteristic of the input video. In this paper, a novel Bi-extracting method (BEM) is proposed for the enhanced image, in which the image foreground is described with two relatively independent maps − the saliency map (SM) and the pseudo-alpha map (PAM). Each map is used to keep certain features of the image foreground. Given a Chinese painting image, two confidence maps are produced by the saliency detection and the pseudo-alpha matting, respectively. Finally, the image foreground is extracted by the final confidence map, which is obtained by a fusion strategy. The BEM does not need any prior knowledge or any interaction from the users. Extensive experiments demonstrate that the proposed BEM is robust and accurate in extracting image foreground. Following we will introduce the proposed BEM in details.

#### 3.2.1. Saliency Map Estimation

Generally, the foreground stroke is the salient region for an ancient Chinese painting, because its background color is rather achromatic. Since the salient region detection method proposed by Achanta [17] *et al.*, can output a full resolution saliency map with well-defined boundaries of salient objects, so this method is adopted in the proposed method for detecting the salient region in the ancient Chinese painting.

Specifically, define $F(x, y)$ to be Gaussian with standard derivation $\sigma$, which is a typical low-pass smoothing function. Firstly, the enhanced image is convoluted with smoothing function. The process can be expressed as follows:

$$I_{blur}(x, y) = I_{enh}(x, y) * F(x, y) \tag{5}$$

$$F(x, y) = Ke^{-(x^2+y^2)/\sigma^2} \tag{6}$$

where $K$ is normalized factor, $\sigma$ is standard deviation and controls the degree of blurring. Assuming that the function uses $w \times w$ window and K satisfying the constraint that make the sum of F(x, $y$) equals one. Thus, the blurred image $I_{blur}$ can be computed by using Eq. (5).

Then, the Gaussian blurred image $I_{blur}$ is transformed from *RGB* color space to *Lab* color space, and the mean vector of the three components in *Lab* space can also be computed. The saliency map SM can thus be formulated as:

$$SM(x,y) = \left\| I_{Lab}^{blur}(x,y) - \bar{I}_{Lab}^{blur} \right\| \tag{7}$$

where $I_{Lab}^{blur}(x,y)$ is the image pixel vector value in Gaussian blurred version of the enhanced image, and $\bar{I}_{Lab}^{blur}$ is the corresponding mean value vector of the image pixel vector in three components. $\|\cdot\|$ represents the Euclidean distance. Using the *Lab* color space, each pixel location is an $[L,a,b]^T$ vector. Thus, the two vectors can be written as:

$$I_{Lab}^{blur}(x,y) = \begin{bmatrix} L(x,y) \\ a(x,y) \\ b(x,y) \end{bmatrix}, \qquad \bar{I}_{Lab}^{blur} = \begin{bmatrix} L_m \\ a_m \\ b_m \end{bmatrix}. \tag{8}$$

Figure 3 shows the results of salient region detection for the ancient Chinese paintings. It can be seen that the saliency regions is basically in the image foreground regions, and the estimated saliency map highlight the saliency regions with well-defined borders.

(a) Original image (b) Saliency map

**Figure 3. Saliency Detection Results**

### 3.2.2. Pseudo-alpha Map Estimation

The key step for BEM is pseudo-alpha map (PAM) estimation. Unlike many existing methods [18, 19], the PAM is estimated by not using the trimap. Instead, the map is computed based on a key observation that the image degradation model Equation $I = Jt + (1-t)A$ [20] has a similar form with the image matting equation $I = \alpha F + (1-\alpha)B$ [21]. Thus, the transmission map $t$ in the image degradation model is exactly an alpha map $\alpha$ . Therefore, we applied the image degradation model and dark channel prior [22] that widely used to estimate transmission map $t$ to obtain the initial pseudo-alpha map PAM.

According to the dark channel prior (Eq. 9), the image degradation model can be rewritten as (10):

$$J^{dark}(x,y) = \min_{c \in \{r,g,b\}} \Big( \min_{(x',y') \in \Omega(x,y)} J^c(x',y') \Big) \tag{9}$$

$$\min_c\left(\min_{(x',y')\in\Omega(x,y)}\left(\frac{I^c_{enh}(x',y')}{A}\right)\right)=1-t(x,y) \tag{10}$$

Introducing a constant parameter $\omega_1\,(0<\omega_1\le 1)$ to adjust the amount of light for distant objects, the transmission map, also the initial pseudo-alpha map PAM$_{init}$ can be estimated as:

$$\mathrm{PAM}_{init}(x,y)=1-\omega_1 * \left(\frac{J^{dark}(x,y)}{A}\right) \tag{11}$$

where $\Omega(x,y)$ is a local block centered at $(x,y)$. $J^{dark}(x,y)$ is the dark channel image obtained by (9). $A$ is the global atmospheric light in the image degradation model Equation. To compute $A$, the top 0.1% brightest pixels are first picked in the dark channel, and then the pixel with highest intensity is selected in the input enhanced image as the atmospheric light. Note that the initial map PAM$_{init}$ may produce some block effects, thus the guided filter [14] is also used here to obtain the final pseudo-alpha map. This filtering process involves two images: a guidance image and an input image. Here, the guidance image $I$ in Eq. (1) is the enhanced image $I_{enh}(x,y)$, the input image $\tilde{t}(x,y)$ in Eq. (2) is the initial map PAM$_{init}$. Once the parameter $a_x$ and $b_x$ in Eq. (3) are computed, the final PAM can be obtained by taking $a_x$ and $b_x$ into Eq. (1). Thus, the final PAM is the output image of the guided filter with well-preserved details and boundaries. The framework for PAM estimation is shown in Figure 4.

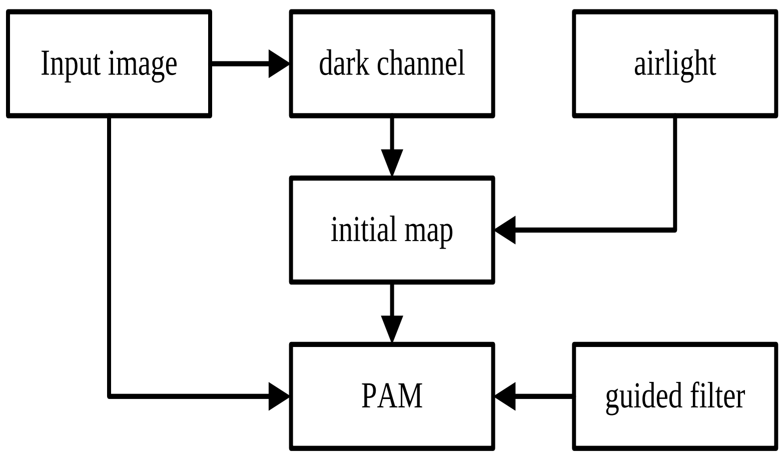



**Figure 4. Flowchart of PAM**

Figure 5 shows the results of estimated initial PAM and the final PAM. It can be seen that the final PAM preserves the detail and boundary of the candidate foreground objects. However, the map also covers some regions that not belong to the foreground.

(a) Input image (b) Initial PAM (c) Final PAM

**Figure 5. The Results of Estimated Initial PAM and the Final PAM**

### 3.2.3. Two Map Fusion

Once the SM and PAM are derived from the enhanced image, both map can be combined to calculate the associated final confidence map for later foreground extraction purposes, as depicted in Figure 6. Noting that when combing both maps, it is preferable to make the foreground strokes stand out relative to its neighbors, and preserve the detail and boundary information of the image foreground since the ultimate goal of proposed method is to segment the foreground. Therefore, the two maps are fused with linear weight method, and an edge-preserving parameter $\omega_2$ is also introduced into the determination of the final confidence map:

$$\mathrm{Fusion}(x,y) = \mathrm{SM}(x,y) + \omega_2 * \mathrm{PAM}(x,y) \tag{12}$$

where SM and PAM indicate the saliency map (Figure 6*b*) and the pseudo-alpha map (Figure 6*c*) for the enhanced image (Figure 6*a*) obtained by using guided filter, respectively. Fusion(*x*, *y*) is the final confidence map (Figure 6*d*). Based on the final confidence map, the binarization operation (Figure 6*e*) is adopted to find the foreground strokes (Figure 6*f*). Note that, although the PAM preserves the detail and boundary of the candidate foreground strokes, the map also covers some regions that not belong to the foreground. While the SM can achieve high precision on the detection of foreground object, but some detail information is lost in the map. Thus, Eq. (12) is used to leverage both maps while the weight for the PAM is proportional to the values of the associated pixels. This alleviates the problem of resulting in a biased final confidence map if the matting information is more dominant.

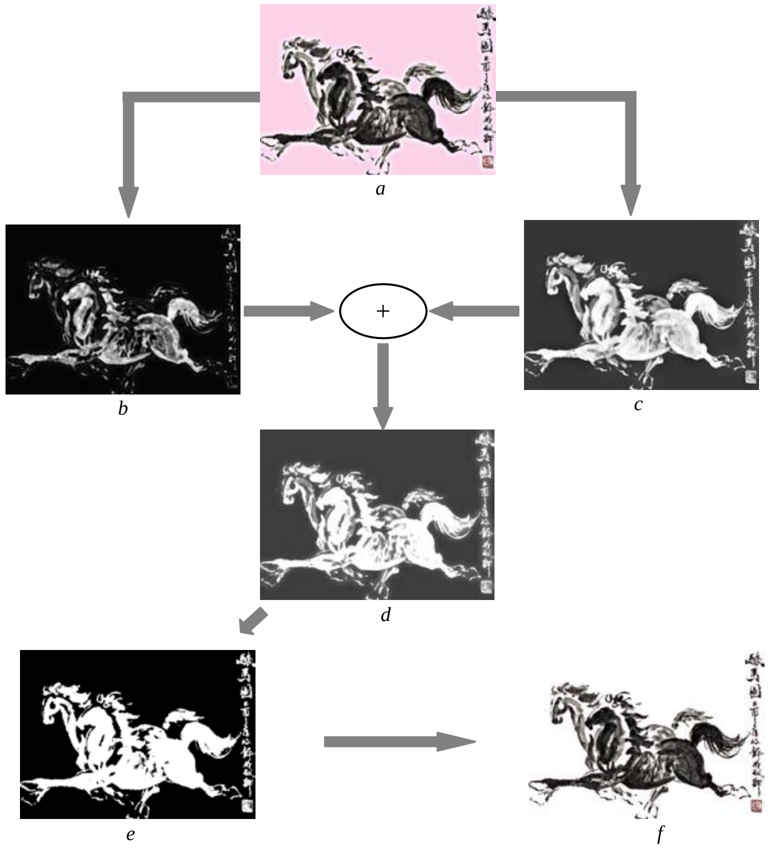
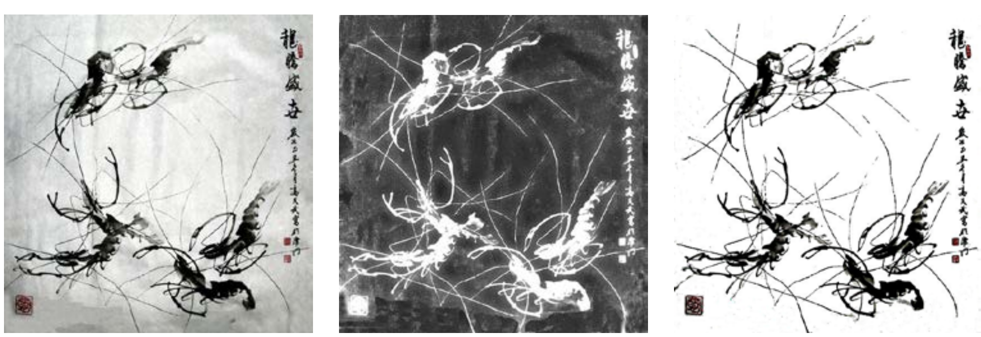



**Figure 6. Processing of Creating Confidence Maps and Foreground Extraction Results. (a) Enhanced Image. (b) Confidence Map of SM. (c) Confidence Map of PAM. (d) Binarization Result of Final Confidence Map. (e) Binarization Result. (f) Foreground Extraction Result**

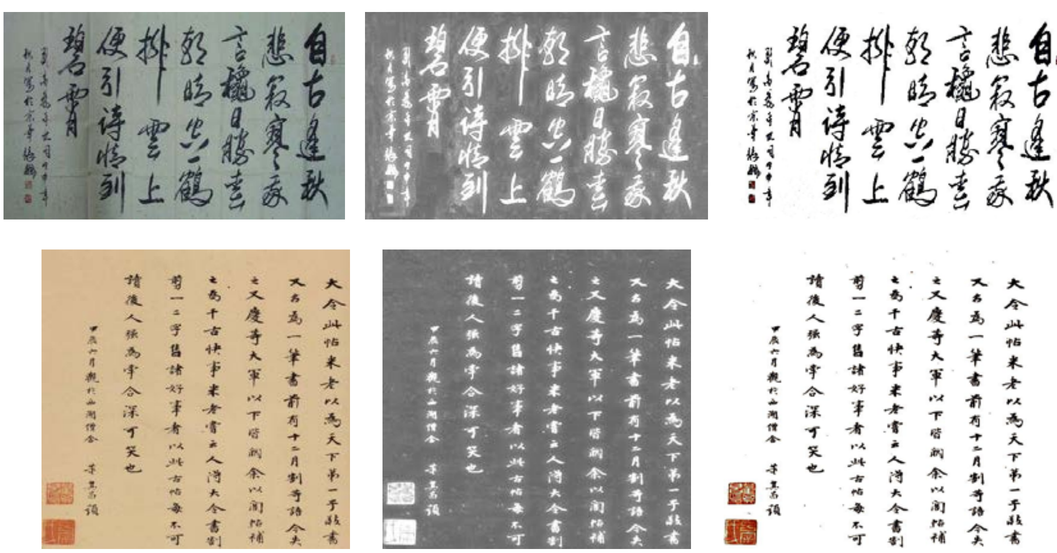
The proposed method has been tested using a large quantity of test painting images with different background colors formed by different paper materials. Figure 7 shows some experimental results. As shown in Figure 7, even though the image background is not very smooth due to the crinkly paper, or the background color is close to that of the foreground objects, the foreground objects can still be sharply separated from the image background using the proposed BEM.



(a) (b) (c)

**Figure 7. Foreground Extraction Results and their Final Confidence Maps for Chinese Painting Images. (a) Input Images. (b) Final Confidence Maps. (c) Extraction Results with BEM**

Besides, the proposed BEM is also applied in recovering the Chinese calligraphy since the calligraphy works also face the same problem as the Chinese painting. Figure 8 presents some results. It can be seen that the Chinese characters as the image foreground are extracted from different image background. Then, the Chinese calligraphy images can be also recovered by altering the background color.



(a) (b) (c)

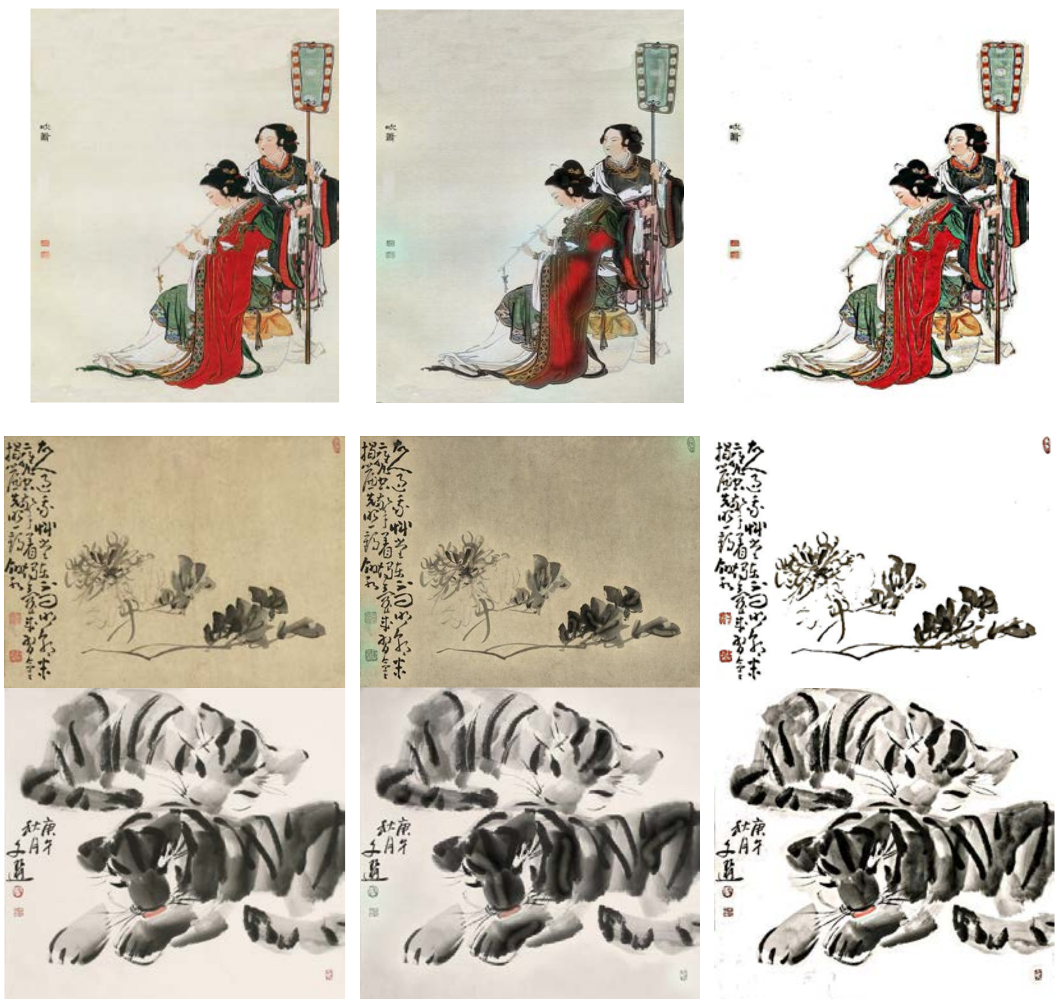
**Figure 8. Foreground Extraction Results and their Final Confidence Maps for Chinese Calligraphy Images. (a) Input Images. (b) Final Confidence Maps. (c) Extraction Results with BEM**

## 4. Experimental Results

The proposed foreground extraction results are also compared with those obtained by Levin [9] *et al* since Levin's method is one of the most representative image matting methods.

It can be observed that Levin's results (see Figure 9b) can hardly captured the foreground pixels. The reason for the failure is that Chinese paintings are painted on Xuan-paper or silk, the strokes of semi-transparent caused by the diffusion and penetration of ink and pigments take up most of the painting. In most cases, it is difficult to identify foreground pixels only based on the three-band image that used in Levin's method and other typical image matting methods. While the proposed method can achieve good foreground extraction results (see Figure 9c), it can be seen that the background color is successfully altered along the foreground object boundary and the image contrast is also improved. This verifies that the proposed method has better background separation and contrast enhancement capability especially for ancient Chinese paintings.



(a) (b) (c)

**Figure 9. Comparison with Levin's Work. (a) Original Chinese Painting Images. (b) Levin's Foreground Extraction Results. (c) The Foreground Extraction Results Obtained by the Proposed Method**

## 5. Conclusions

In this paper, a new method is presented to virtually recover ancient Chinese paintings in electronic form. The guided filter is first used to enhance the original paintings, and then a novel bi-extracting method is adopted to extract the foreground stroke from the painting background. Finally, the ancient painting can be recovered by altering the background color.

The proposed method is applied to a large quantity of ancient Chinese paintings and experimental results show that the method is acceptable and promising. However, the proposed method still needs further improvement since the method is based on the conditions that the painting has extensive empty background space and its background color is rather achromatic. Thus, the method will be extended to the complicated painting images with more varied background in the future.

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