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Abstract

Digital matting, the process of extracting a foreground object from an image, is an important task in image and video editing. Applying matting techniques to Chinese painting image processing can create novel composites or facilitate other editing tasks. However, Chinese paintings are painted on xuan-paper or silk, the semi-transparent strokes resulted from the diffusion and penetration of ink and pigments make it difficult to extract the foreground from the paintings only based on three-band image. In this paper, we demonstrate a new multispectral image matting technique for Chinese painting image editing. We derive a similarity function from Kubelka-Munk turbid media theory, and this allows us to find the optimal alpha matte. By adopting multispectral matting method, semi-transparent foreground stroke can be extracted from the overlay of background strokes. Experimental results show the approach acceptable and promising.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Computer Graphics]: Picture/Image Generation—Display algorithms; I.3.4 [Computer Graphics]: Graphics Utilities—Graphics editors

1. Introduction

Painting is a mode of expression. As an important part of the Chinese traditional cultural heritage, ancient Chinese painting is highly regarded throughout the world for its theory, expression and techniques. With the steady growth of computer power, more and more traditional Chinese painting art images are digitalized and exhibited on the Internet.

Nowadays, image processing of Chinese paintings attracts more and more attention. A novel algorithm using color contrast enhancement and lacuna texture synthesis was presented for the virtual restoration of ancient Chinese paintings [PC04]. Soo-Chang Pei [PC06] presented a color enhancement scheme to virtually restore ancient Chinese paintings in electronic form. Shuqiang Jiang [JS03] et al proposed a scheme to classify traditional Chinese paintings using three low-level features to achieve a high-level classification and Shwu-Huey Yen [YSH06] et al studied how to extract inscriptions from a traditional Chinese painting so that the inscriptions and the paintings can be enjoyed or studied separately. Their work focused on different processings of Chinese paintings and had little to do with matting. We put emphasis on image matting which is applied to Chinese paintings.

Digital matting [PD84], the process of extracting a foreground object from an image, is an important task in image and video editing. Matting in Chinese paintings is significant because applying matting techniques to ancient Chinese paintings can create novel composites or facilitate other editing tasks. However, most ancient Chinese paintings that have preserved till today were produced on xuan-paper or silk. The pigments used for paintings are extracted from minerals or vegetables. The physical characteristic of painting materials makes 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 based on three-band image.

Furthermore, conventional color acquisition devices capture spectral signals by acquiring only three samples, critically suffering from metamerism. Metamerism is specially problematic in painting digital applications as two physical samples sometimes appear to be the same color under a certain light but "turn different" under different lights. Although metamerism is the basis of many imaging techniques

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used for color imaging reproduction, metameric imaging has many limitations. For example, in metameric imaging, the color of objects can not be distinguished from the color of the illumination, and it is impossible to render the captured scene under a different illumination [Nys06]. To avoid metamerism ambiguity and achieve high image acquisition quality, multispectral imaging techniques have been applied to digitally archiving of art works to improve color reproduction [MY02]. Superior to three-band image acquisition device, spectral devices increase the number of samples and can reconstruct spectral information for each scene pixel.

Here we introduce a new multispectral image matting technique for Chinese painting image editing. The main contributions of this paper are as follows. First, we derive a similarity function for the observed image model from Kubelka-Munk turbid media theory, which allows us to find the optimal alpha matte. Second, we apply the multispectral matting method to ancient Chinese paintings, extracting the foreground strokes from the overlay of background strokes and leading to a better recovery of paintings.

The rest of this paper is organized as follows. We illustrate our researches on previous work in section 2. In section 3 and section 4, we describe our multispectral imaging system and multispectral matting method, respectively. Results of some experiments and applications are presented in Section 5, and then we conclude this paper in Section 6.

2. Previous work

One important character of ancient Chinese paintings is that the pigments used in ancient Chinese paintings are extracted from minerals or vegetables. With time going by, they could easily fade and the paper gets yellowish. A novel algorithm using color contrast enhancement and lacuna texture synthesis was proposed for the virtual restoration of ancient Chinese paintings to eliminate undesirable aged painting patterns(e.g. stains, crevices and artifacts) and then fill the lacuna regions with the appropriate textures [PC04]. Soochang Pei [PC06] recovered the color of Chinese paintings by adjusting the background color and enhancing the saturation contrast of a given image. These two methods are both performed in color space, which can easily suffer from metamerism.

Early matting approaches try to simplify the problem by photographing objects against a constant-colored background, which is called blue screen matting [SB96]. However, the approach is based on the theory that the foreground object is known against two distinct backing colors. Although our Chinese paintings have a constant-colored background, it is still impossible to obtain the foreground strokes against two different backgrounds.

Recent approaches attempt to extract the foreground matte directly from one natural image. The most successful systems include Knockout 2 [COR02], the approach proposed by Ruzon and Tomasi [RT00], Bayesian matting [YCS01] and Poisson matting [JSS04]. All these systems start by having the user segment the image into three regions: definitely foreground, definitely background and unknown regions, which is often referred to as a trimap. The problem is thus reduced to estimating F, B and α in the unknown region. As we mentioned before, previous natural image matting approaches heavily rely on the user specified trimap. Ideally, the unknown region in the trimap should only cover pixels whose alpha values are neither 0 nor 1 actually. In other words, 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-segmention approaches fail if the images have large portions of semi-transparent foreground that it is difficult to create a trimap even manually. Wang Jue [Wan05] 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 α 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 α value of 1.

In this paper, we propose a multispectral image matting method for Chinese paintings. It is worth mentioning that spectral matting algorithm [AL07] can automatically extract a matte from an input image which consists of a modest number of visually distinct components. However, as the authors agreed, the automatic approach has a number of limitations. It is difficult to extract components for highly cluttered images. Another challenge in spectral matting is determining the appropriate number of matting components for a given image. The author presented the spectral matting method to natural image matting while we apply multispectral matting to Chinese paintings by using a new similarity function.

3. Basic work

Dividing the pigments of Chinese paintings from the background is not a hard segmentation problem, because the colors of some pixels are composed of the color of background material and color of pigments. In digital image processing, images can be decomposed into layers and foreground can be extracted by using image matting. Porter and Duff [PD84] gave a mathematic definition of this issue in 1984.

The observed image $I(z)$ $(z = (x,y))$ is modeled as a linear combination of foreground image $F(z)$ and background image $B(z)$ by an alpha map:

$$I(z) = \alpha_z F(z) + (1-\alpha_z)B(z) \tag{1}$$

where α_z can be any value between 0 and 1.

If we constrain the alpha value to be either 0 or 1, then the

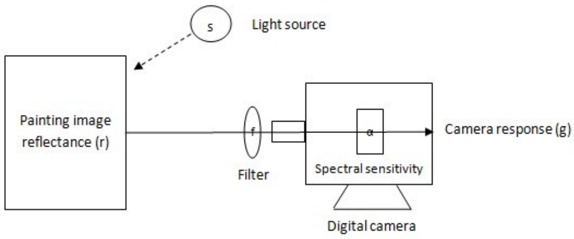


Figure 1: *Multispectral image acquisition model.*

matting problem degrades to be the segmentation problem, in which each pixel is assigned to be either fully foreground or fully background. For natural images, seven values need to be estimated for every pixel, which are three dimensional color vector $F(z)$ and $B(z)$, and one dimension alpha value α_z, thus it is inherently an under-constrained problem. Moreover, previous image matting methods based on three-band image always led to metamerism. As a consequence, we introduce multispectral imaging techniques into image matting of Chinese paintings to avoid metamerism and a new function is obtained to reduce the calculations.

Our multispectral image matting method consists of two steps. The first step is getting multispectral images of the painting. Second, we pull a matte by solving the derived function.

3.1. Multispectral images acquisition

Multispectral imaging system are developing rapidly because of their strong potential in many domains of application. Francis Schmitt et al presented a multispectral system with a single chip camera and a liquid crystal tunable filter [FSH99]. The CRISATEL multispectral acquisition system was built in 2005, which consisted of a monochrome digital camera and 13 interference filters [RAC05]. Here we use a multispectral image acquisition model [RA08], which is shown in Figure 1.

In this model, the spectral reflectance of object is illuminated by a light source and the reflected light is filtered by a spectral bandpass filter which is arranged in front of the camera and then passes through the digital camera. Generally, the camera signals are integrating results of the spectral sensitivity α of the camera system, the spectral distribution s of light source, the spectral reflectance r of an object and the spectral transmittance f_m of filter, discarding noises (i.e. camera shake and camera noise). Then, the camera response g of the channel j for an image is then equal to

$$g_j = \int_{\lambda_{\min}}^{\lambda_{\max}} s(\lambda) r(\lambda) f_m(\lambda) \alpha(\lambda) d\lambda. \tag{2}$$

$\lambda_{\min}$ and $\lambda_{\max}$ are the minimal and maximal wavelengths, respectively.

By modeling and inverting this optical digital model, we can obtain the spectral reflectance of every pixel by the method called spectral reconstruction. Only one optical filter is represented in Figure 1, but in a multispectral capture system, several filters are acquired to get a series of multispectral images so that we can calculate the spectral reflectance more precisely.

3.2. Spectral reconstruction

We usually divide the wavelength $[\lambda_{\min}, \lambda_{\max}]$ evenly into N wavelength intervals for ease of calculation, and the center of each wavelength interval is indicated by the subscript n. Thus, the Eq. (2) is rewritten as follows:

$$g_j = \sum_{n=1}^{N} s(\lambda) r_n(\lambda) f_m(\lambda) \alpha(\lambda). \tag{3}$$

We can obtain the 81-dimensional spectral reflectance vector $\mathbf{r}$ by sampling all the spectra at the interval of 5 nm in the visible range. Therefore, the Eq. (3) can be rewritten as a scalar product in matrix notation as follows:

$$\mathbf{g} = \mathbf{Qr} \tag{4}$$

where the vector $\mathbf{g} = [g_1 \ g_2 \ \cdots \ g_m]^T$ represents the camera signals for the set of m filters. Transition matrix $\mathbf{Q}$ is a n-by-m matrix where n accounts for the number of wavelengths, and m is the number of filters. $\mathbf{Q}$ stands for the spectral characteristics of the whole camera system including filters. The row vector in $\mathbf{Q}$ is defined as:

$$[s(\lambda_i) f_1(\lambda_i) \alpha(\lambda_i) \ \ s(\lambda_i) f_2(\lambda_i) \alpha(\lambda_i) \ \ \cdots \ \ s(\lambda_i) f_m(\lambda_i) \alpha(\lambda_i)].$$

And for each wavelength, the spectral reflectance can also be written in a vector notation as:

$$\mathbf{r} = [r(\lambda_1) \ \ r(\lambda_2) \ \ \cdots \ \ r(\lambda_n)]^T.$$

For multispectral imaging, it is necessary to calculate the reflectance information from the camera response. The problem of calculating $\mathbf{r}$ from $\mathbf{g}$ can be solved by finding an inverse linear operator $\mathbf{Q}$ that minimizes a distance between measured $\mathbf{r}$ and retrieved reflectance factors $\hat{\mathbf{r}}$ for Eq. (5):

$$\mathbf{r} = \mathbf{Q}^{+} \mathbf{g}. \tag{5}$$

$\mathbf{Q}^{+}$ is the pseudoinverse of $\mathbf{Q}$. In practice, it is difficult to get $\mathbf{Q}$ by measuring $s(\lambda)$, $f(\lambda)$ and $\alpha(\lambda)$ directly, so we estimate $\mathbf{Q}^{+}$ using training samples of standard color cards. The reflectance factors of standard color cards are measured in advance by a spectrophotometer and the corresponding camera output signals $\mathbf{g}$ are obtained from our multispectral image acquisition model. Having $\mathbf{Q}$, $\mathbf{Q}^{+}$ is calculated using least square method according to Eq. (4) and retrieve reflectance factors $\hat{\mathbf{r}}$ by solving the Eq. (5).

4. Multispectral image matting

4.1. Multispectral matting model

We derive the multispectral matting model Eq. (6) from the observed image model of Eq. (1). Since Chinese paintings always have lots of vacancy in the background and the background color is rather achromatic [PC06], we take all the pigments except the background as a whole, and derive a similarity function for the observed image model as follows:

$$\left(\frac{K}{S}\right) = c_b\left(\frac{K}{S}\right)_b + c_f\left(\frac{K}{S}\right)_f. \tag{6}$$

Here K is the absorption coefficient and S is the scattering coefficient. $(K/S)_b$ stands for the ratio of absorption to scattering of the background and $(K/S)_f$ for a mixture of foreground pigments. c_b, c_f are coefficients of background and foreground respectively and $c_b + c_f = 1$.

We get the optimal matte by using Eq. (6), which is derived from Kubelka-Munk(K-M) turbid media theory [Zha08]. The K-M theory can be used to predict the relationship between pigment concentrations and spectral reflectance for transparent, translucent or opaque paint film in contact with an opaque ground from the absorption and scattering properties of the film.

We take the pixels whose K/S are similar to $(K/S)_b$ as background and those whose K/S are similar to $(K/S)_f$ as foreground. Unknown parameters to be estimated are reduced from seven (three dimensional color vector $F(z)$ and $B(z)$, and one dimension alpha value α_z) to three by introducing this function. Those three parameters are $(K/S)_b$, $(K/S)_f$ and c_b.

4.2. Parameter calculation

4.2.1. The calculation of K/S

By introducing hyperbolic cotangent function $\coth x$, the spectral reflectance factor r of a film can be expressed as a function of four parameters: the absorption coefficient K, the scattering coefficient S, the film thickness X, and the spectral reflectance of the background r_g, as shown in Eq. (7) [Zha08], where two auxiliary variables $a = \frac{K}{S} + 1$ and $b = \sqrt{a^2 - 1}$.

$$r = \frac{1 - r_g(a - b\coth bSX)}{a - r_g + b\coth bSX} \tag{7}$$

The general model could be greatly simplified for opaque specimens over an opaque background, indicating that the film thickness approaches infinity ($X \to \infty$). The spectral reflectance for this case is indicated by r, and can be simply calculated from absorption and scattering coefficient, as shown in Eq. (8):

$$r = 1 + \frac{K}{S} - \sqrt{\left(\frac{K}{S}\right)^2 + 2\left(\frac{K}{S}\right)}. \tag{8}$$

Derived from Eq. (8), the ratio K/S can be calculated using Eq. (9)

$$\frac{K}{S} = \frac{(1-r)^2}{2r}. \tag{9}$$

Now the problem is turned to calculate the spectral reflectance r, which has been gotten by spectral reconstruction.

4.2.2. The estimation of c_b

In order to solve this model, we define measurement angle as Eq.(10) to measure the similarity of the image spectrum t and the reference spectrum r:

$$angle = \cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{\left(\sum_{i=1}^{nb} t_i^2\right)^{1/2} \left(\sum_{i=1}^{nb} r_i^2\right)^{1/2}}\right) \tag{10}$$

where *angle* denotes the similarity between the image spectra and the reference spectra and *nb* is the number of bands.

Generally speaking, background color takes up most of a Chinese painting and the background color is rather achromatic [PC06]. The painting paper turns yellowish after hundreds of years of exposure to light. A three-dimensional histogram in the Lab color space is used to determine the distribution of the background pixels of a deteriorated Chinese painting. And then we calculate the average spectral reflectance of all the pixels in the background region by the following equation:

$$\bar{r}(z) = \frac{1}{S}\sum_{S} r(z) \tag{11}$$

where S is the number of pixels and $r(z)$ represents spectral reflectance of each pixel in the region. Pixels whose spectral reflectances are somewhat similar to $\bar{r}(z)$ are classified as background and others as foreground. The spectral similarity between the image spectra t and the reference spectra r is determined by calculating the "*angle*" between the two spectra, using the Spectral Angle Mapper (SAM) algorithm [KF93], as shown in Eq. (10).

As can be seen from Eq. (10), the more similar t and r are, the smaller the value of *angle* is. From Eq. (6) we can conclude that the value of c_b is smaller if the pixel is more similar to the background. Thus, we assume that c_b is in direct proportion to *angle* and can be obtained by multiplying *angle* by a constant coefficient. After testing, we take c_b = 1.7**angle* in the experiment to get a good matte.

4.3. The evaluation of multispectral image matting

The calculation of main parameters (K/S and *angle*) have a lot to do with the obtention of the spectral reflectance r, which is attained by spectral reconstruction. That is to say, if we want to know whether the multispectral image matting

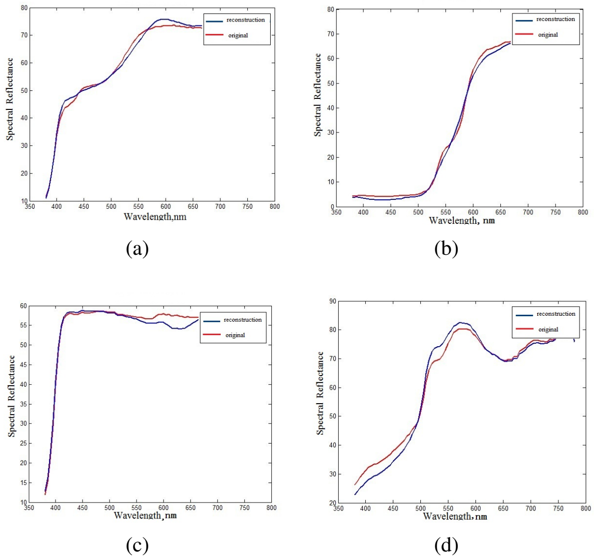


Figure 2: *Spectral estimation of four samples.*

Table 1: *Quality of reconstruction of spectral reflectances.*

No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
GFC	99.98	99.84	99.88	99.87	99.76	99.90	99.96	99.91	99.78	99.63	99.52	99.87	99.68	99.96	99.98
ΔE^*_{ab}	2.23	1.41	3.35	2.23	3.05	4.12	6.16	3.16	5.47	7.22	8.12	3.57	7.48	2.23	1.414

is efficient, we have to estimate the spectral reconstruction model to verify that the accuracy of Q, Q^+ and r is acceptable.

Two measures are applied to evaluate whether the result of the spectral reconstruction is acceptable. The first measure is goodness-of-fit coefficient (GFC), which is a commonly used for measuring spectral similarity [EM07]. Values range from 0 to 100%, with GFC $\geq$ 99.5% corresponding to acceptable recovery and GFC $\geq$ 99.95% to an almost-exact fit. The second one is the CIELAB color difference , which takes the eye's sensitivity to color difference into account [EM07]. Average color differences that are less than 3.0 are classified as hardly perceptible, between 3.0 and 6.0 are perceptible and acceptable and more than 6.0 are not acceptable [JC04].

5. Experiments and Applications

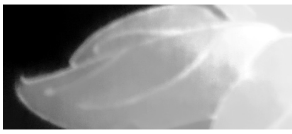
5.1. Experiments

Our spectral reconstruction system consists of a color digital camera (Canon 5D MARK-II) and 8 interference filters that their maximum senitivity wavelength are 405nm, 409nm, 447nm, 470nm, 506nm, 532nm, 650nm and 740nm, respectively. 210 RALK7 color cards are used to estimate $\mathbf{Q}$. The spectral reflectances of these cards are measured by UV-VIS Spectrophotometer. Among 210 cards, 195 of them are taken as training samples and the other 15 cards are test samples. Some spectral reconstruction curves are shown in Figure 2 and evaluations using GFC and ΔE^*_{ab} are showed in Table 1.

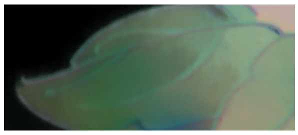
As can be seen from Table 1, the results of GFC are all greater than 99.5%, and the average of ΔE^*_{ab} is 4.081. According to evaluation criterion suggested in [JC04], our spectral reconstruction result is acceptable.

We implement multispectral image matting of Chinese paintings based on the system and make a comparison with the closed form solution method, extracting foreground images in RGB color space, proposed by Anat Levin [AL06], and the results are shown in Figure 3.

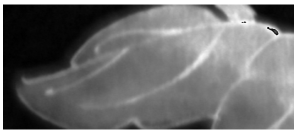
Multispectral imaging enables to obtain the spectral radiance or reflectance, to greatly improve the colorimetric accuracy, and to reproduce colors under different illuminations. Applying this system to Chinese paintings which are photoed under standard illumination D65, we can get a result of spectral reconstruction under the same light, as shown in Figure 4. We can see that the result of spectral reconstruction is closed to the orignal one and the saturation is enhanced.



(a) Alpha matte obtained by the method in [AL06].



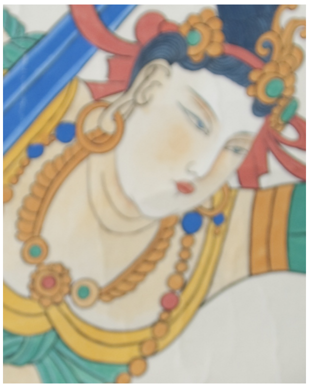
(b) The foreground image corresponding to (a).



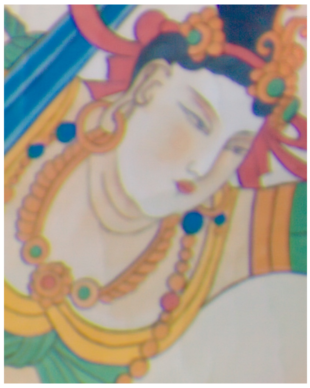
(c) Alpha matte obtained by our method.

(d) The foreground image corresponding to (c).

Figure 3: *A comparison of alpha mattes extracted by different algorithms.*



(a) The input image photoed by a digital camera.



(b) The result of spectral reconstruction.

Figure 4: *A comparison of the original image and the result of spectral reconstruction.*

5.2. Applications

As an important character of Chinese paintings, extensive empty background spaces are usually left to give the viewers more room for imagination. However, paintings change colors, especially the paper or silk becomes yellowish as time goes by, which decreases the contrast between unpainted and painted parts of an ancient painting. The multispectral image matting can be used to decompose the foreground from an painting due to different spectral reflectances. We can recover an ancient painting by altering the color of background using multispectral mapping method [RA08]. As shown in Figure 5, the result is obtained by only recovering the background color.

There is an urgent need to build digital image databases with adequate colorimetric accuracy for museums, achieves and libraries. Using spectral information can prevent images from suffering from metamerism, which has a great importance to image recovery.

6. Conclusion and Future work

In this paper, we have presented a new digital matting method—multispectral image matting. We derive a similarity function from Kubelka-Munk turbid media theory, which allows us to find the optimal alpha matte. We have applied our new multispectral image matting algorithm to Chinese paintings and experimental results show that our approach is acceptable and promising. However, our color representation needs further improvement. So we will enhance our system by a more promising multispectral image reconstruction method [RSBZ08] in future.

So far, we have applied our method to Chinese paintings to recover the background of paintings. The pigments used in ancient Chinese paintings are extracted from min-

(a) The input image photoed by a digital camera.

(b) The output image with background recovered.

Figure 5: *A comparison of the original image and the recovered image.*

erals or vegetables. Consequently, they could easily fade as time goes by. The spectral reflectance of a pigment is different from other pigments, so we expect to decompose Chinese paintings into layers due to different spectral reflectances, and then recover the color of the pigments in the future. Furthermore, we hope to extend our method to natural images against constant background, so that we can pull the matte without the user's operation.

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