ALPHA ESTIMATION IN PERCEPTUAL COLOR SPACE

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ABSTRACT

This paper presents an efficient algorithm for alpha estimation based on perceptual color space in natural image matting. A user specifies a trimap which partitions an image into definitely foreground, definitely background and unknown. For each pixel in the unknown region, the algorithm separates intensity and chroma information from RGB color after its foreground and background color components are estimated. Consequently, alpha component is decomposed into intensity part and chroma part. The weighted mean of these two parts yields the final alpha value. Experimental results demonstrate the efficiency and advantage of the proposed algorithm over other approaches.

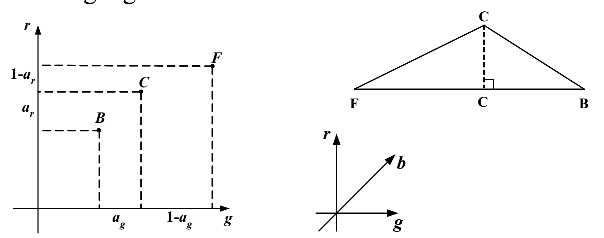
1. INTRODUCTION

Image matting aims to extract objects from one image and to synthesize them into another one. It is used widely in film and video industry and can be classified as blue screen matting [1] and natural image matting [2,3,4,5,6] according to background images. In former approach, the alpha value can be easily and uniquely determined due to constant color background and additional constraints on foreground elements. Natural image matting, in which the background is arbitrary, typically involves three steps: region segmentation, color estimation and alpha estimation. Color estimation is difficult because there are infinite possible solutions for the foreground and background color pair. In addition, alpha estimation still remains a hard work even after the foreground and background color components are determined. In this paper, we focus on the alpha estimation problem.

The remainder of this paper is organized as follows. First, we give a review of previous alpha estimation approaches in Section 2. Our algorithm is introduced in Section 3. Next, we present experimental results in Section 4. Conclusions and future work are given in Section 5.

2. RELATED WORK

Natural image matting is a more general problem than blue screen matting. Typical natural image matting techniques include Knockout [2], Ruzon [3], Hillman [4], Chuang [5] and Poisson matting [6]. Among them, Ruzon, Hillman and Chuang use the same projecting algorithm in character to estimate alpha value. Knockout adopts a decomposing algorithm. In contrast, Poisson matting estimates the alpha value by solving a Poisson equation on the gradient field. Here we briefly describe their alpha estimating algorithms.



(a) (b)

Figure 1 Illustration of previous alpha estimating algorithms proposed by (a) Knockout and (b) Ruzon, Hillman and Chuang.

For an observed color C, when its foreground color component F and background color component B are computed, Knockout approach decomposes the final α into three alpha components α_r , α_g , α_b along three axes in RGB space using the following formula:

$$\alpha = \frac{f(C) - f(B)}{f(F) - f(B)} \tag{1}$$

where $f(\cdot)$ projects a RGB color onto one of the r-, g-, b- axes. Figure 1(a) illustrates alphas on r- and g- axes. These three alpha components are computed separately by projection onto the three axes, and the final α is taken as a weighted mean over all the projections, where the weights are proportional to the denominator in equation (1) for each axis. This approach decomposes α into three components along the axes in RGB space.

Some other matting techniques project color C onto the line segment FB in RGB space (see Figure 1(b)). Their alpha calculation formula is given as follows:

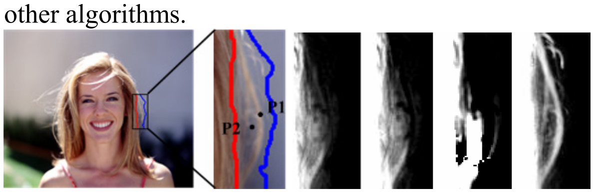
$$\alpha = \frac{(C - B) \cdot (F - B)}{\| F - B \|^2} \tag{2}$$

Clearly, this projecting depends only on the shape of ΔCFB in RGB color space. In these algorithms [3,4,5], this projecting alpha estimating scheme can achieve the maximal occurring probability of color C because the projected point on FB is the nearest point to color C. In practice, the computed value is not always the best perceptual value in human eyes. Poisson matting estimates alpha by solving a Poisson equation iteratively with Dirichlet boundary condition. However, the global Poisson matting technique can not achieve satisfactory results in some cases. Local Poisson matting, on the other hand, can achieve much better result, but involves too many user interactions.

In our implementation, we use a simple but efficient way to estimate alpha without user interaction. The key idea is to decompose α in perceptual color space instead of in RGB space, producing more perceptually optimized results.

3. PERCEPTION BASED ALPHA ESTIMATION

After the segmentation of input image, we only use the pixels on nearby contour to compute the color components of a given unknown pixel. These pixels' colors are assigned different weights and we take the weighted mean of these colors as the final color components. Then, we separate the chroma and intensity information from RGB color and handle them differently. Figure 2 gives a comparison between our algorithm and other algorithms.

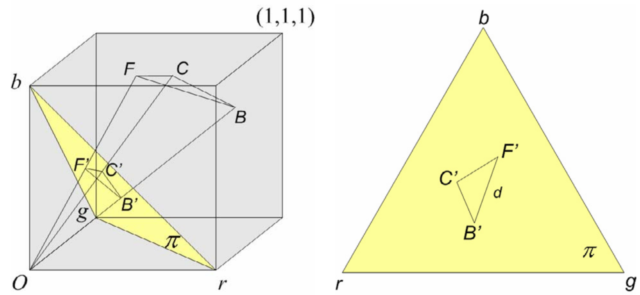


(a) (b)

Figure 2 Examples of Syringe image in which previous alpha estimating methods may not produce correct results. (a) The small black rectangle is enlarged to the right, where P1 and P2 indicate two pixels of incorrect results by previous algorithms. (b) The results of this black rectangle using Knockout, Chuang, global Poisson matting and ours (from left to right).

In Figure 2(a), C(160,147,144) is the color of P1 on hair strands, F(121,90,77) is the weighted mean of colors on the strands, and B(116,120,145) is the weighted mean of background. Viewed from human eyes, C is supposed to approximate foreground F. As a result, we sort P1 into strands rather than background according to the dominant chroma information, although P1's luminance tends to be closer to the background.

According to Knockout's method, large weight should be assigned to the alpha component whose respective denominator in equation (1) is larger, e.g., large weight is put on α_b for P1. However, the red component of P1(160,147,144) is dominant as that of foreground color is. Knockout approach leads to error result shown in Figure 2(b). In Chuang's algorithm, the projecting algorithm may change the dominant color of a pixel. Take pixel P1 for example, the original color is C(160,147,144), and the dominant color component is red. After we project P1 onto FB, the projected pixel is C1(116,123,151), and the dominant component color is changed to blue. This change results in a final false result. Note that global Poisson matting is an iterative algorithm and the error at one complex pixel may be magnified after multiple iterations and eventually lead to several error areas. In addition, this algorithm requires transferring the original image to gray scale image as a preprocess, yielding a loss of color information.



(a) (b)

Figure 3 Illustration of our alpha estimating algorithm (a) in RGB color space and (b) on unit plane.

Rather than in RGB color space, we propose to estimate the alpha value in perceptual color space, which consists of two chroma dimensions and one intensity dimension. Significant information, either chroma or intensity, is emphasized, and insignificant information is ignored. We decompose RGB color as perceptual color space does, so as to avoid the tight intertwinement of chroma and intensity. Alpha depends not only on ΔCFB 's shape but also on its position in RGB color space.

For the convenience of computing and description, we adopt a simple perceptual color space modified from RGB space directly. Assume the color coordinates are normalized to on the interval [0,1]. Given color $c=[R_c,G_c,B_c]$, let $c'=[r_c,g_c,b_c]$ be the chroma of color c, and its intensity L_c equals $(0.114R_c+0.588G_c+0.298B_c)$. In RGB color space, chroma c' also represents a color whose RGB components are given as: $r_c=R_c/(R_c+G_c+B_c)$, $g_c=G_c/(R_c+G_c+B_c)$, $b_c=B_c/(R_c+G_c+B_c)$. Obviously, chroma color c' lies on unit plane (Δrgb in Figure 3(a)).

This converted color space consists of L_c and (r_c, g_c, b_c). The latter has two free dimensions, because chroma color c' lies on unit plane. Hence the resultant color space is actually (Lc, r_c, g_c). The first dimension represents intensity, i.e. the length of RGB color vector; the other two indicate chroma, i.e. the direction of RGB color vector. We call it LRG color space, a modified perceptual color space.

To analyze the individual effect of chroma and intensity on alpha computing, we decompose alpha into the chroma alpha:

$$\alpha_{CH} = \frac{(C'-B')\cdot(F'-B')}{\|F'-B'\|^2} \tag{3}$$

which is a vector and intensity alpha:

$$\alpha_{IN} = \frac{L_C - L_B}{L_F - L_B} \tag{4}$$

Here, α α_{CH} and α_{IN} are normalized in [0, 1].

Let $\rho = \min(L_F, L_B)/\max(L_F, L_B)$ ($\rho \in (0,1]$). When ρ approaches zero, the intensity difference between F and B is large enough that the intensity dominates, requiring larger weight for α_{IN} . When ρ approximates one, the chroma prevails over the intensity, so as for α_{CH} . Besides ρ , the distance $d = |F'B''|$ ($d \in [0, \sqrt{2}]$) (Figure 3(b)) to unit plane takes effect in the weight computing. The ranging of d has the similar effect to that of ρ . By practically choosing ρ^3 and d^3 to stress these changes and emphasize the dominant information, we derive the weight of α_{CH} and α_{IN} as

$$W_{IN} = \frac{u}{d^3} + \frac{v}{\rho^3} \tag{5}$$

and

$$W_{CH} = sd^3 + t\rho^3 \tag{6}$$

where u, v, s, t are adjustable constants. Practically, s is much larger than u,v and t. The final alpha is computed as weighted mean of α_{CH} and α_{IN} :

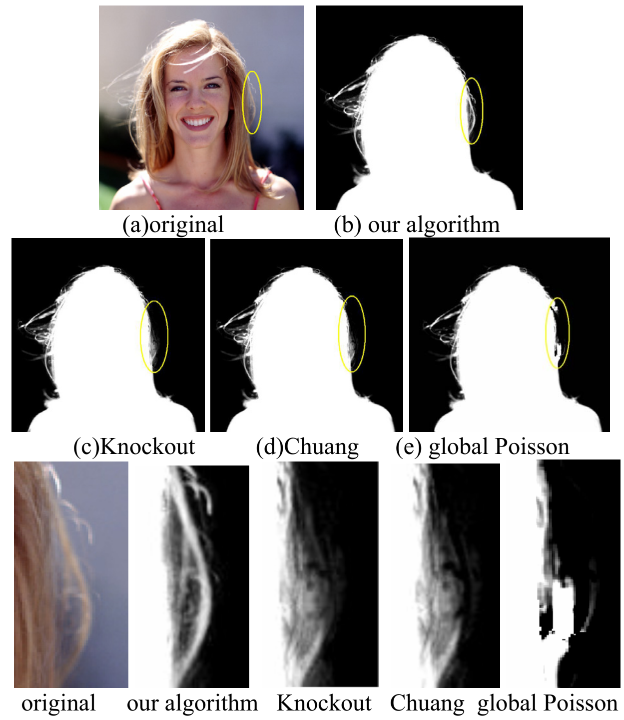
$$\alpha = \frac{W_{IN}\alpha_{IN} + W_{CH}\alpha_{CH}}{W_{IN} + W_{CH}} \tag{7}$$

When C is on FB, the result of Chuang's projection approach is accurate. Though our method will cause deviation in this case, the chance that C is exactly on FB is quite small. Moreover, this deviation is too subtle to be detected by human eyes. On the other hand, our algorithm achieves fair results in other color spaces including HSV,YUV and Lab. The perceptual color space we adopted is convenient for the intuitional description and understanding of weight computing.

4. RESULTS

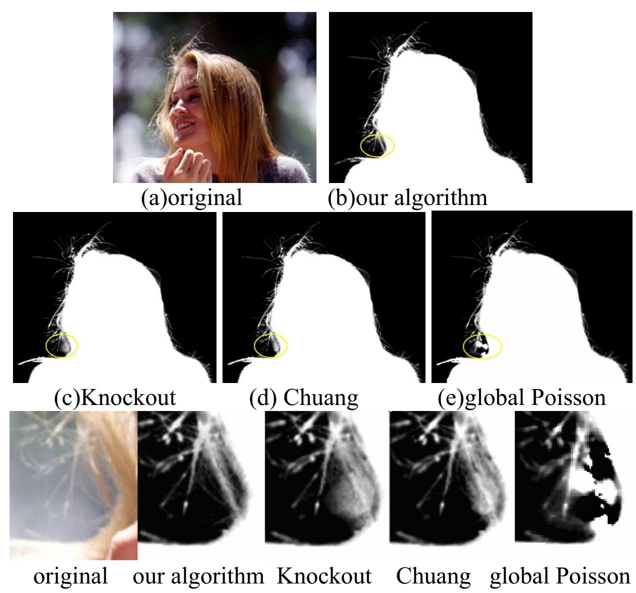
We compare the results of Knockout, Chuang's, Poisson matting and our alpha estimating algorithm by using the same C, F, B, where C denotes the observed color, and F, B represent C's foreground and background color component respectively.

In Figure 4, Knockout, Chuang and global Poisson matting obtain quite good result except in the drawn ellipse area, where they all lose some strands and generate obvious distortion. Figure 4(f) zooms in the regions bounded by the yellow ellipse. This zooming in shows the advantage of our algorithm over other algorithms: none of the above artifacts are found in our result.



(f) Zooming in of the regions bounded by the yellow ellipse

Figure 4 Comparison of Syringe image.



(f) Zooming in of the regions bounded by the yellow ellipse.

Figure 5 Comparison of Feather_edge image.

From the zooming in illustrations in Figure 5, it is obvious that Knockout Chuang and Poission matting algorithms yield observable distortion, but our method exhibits none of these artifacts.

(a)original (b) matte

Figure 6 Other results of our own. Top: Gandalf image, bottom: Tiger image.

Figure 6 shows other two results by means of our algorithm. Almost all hair strands are recovered correctly in Gandalf image. In the background region where color changes sharply in Tiger image, our method still performs correct.

From the aforementioned experiment results, we conclude that our algorithm produces better matte than the other three algorithms.

5. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented an efficient alpha estimation algorithm in natural image matting based on a modified perceptual color space. Our algorithm follows the same decomposing scheme as Knockout approach but differs in that we decompose RGB color into chroma and intensity, rather than into R, G and B components of RGB color space. We estimate alpha value as a weighted mean of chroma alpha and intensity alpha components. This way, important component is emphasized and insignificant component is ignored. In other words, we choose the optimized alpha value in "perception", not in "probability" as Ruzon[3], Hillman[4] and Chuang[5] do. Under the conditions of the same colors C, F and B, the comparison of results clearly shows the advantage of our algorithm over Knockout, Chuang's and global Poisson matting. For local Poisson matting, it can achieve better results while doing with complex images, but involves many human interactions.

As future work is concerned, we want to build an effective model to estimate the foreground and background color in high color-variation images to make full advantage of our algorithm. By analysing W_{IN} and W_{CH}, we would like to explore other factors besides ρ and d to estimate alpha value more accurately.

6. ACKNOWLEDGEMENTS

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