IMAGE MATTING USING SVM AND NEIGHBORING INFORMATION

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Abstract: Image matting is a technique for extracting a foreground object in a static image by estimating the opacity at each pixel in the foreground image layer. This problem has recently been studied in the framework of optimizing a cost function. The common drawback of previous approaches is the decrease in performance when the foreground and background contain similar colors. To solve this problem, we propose a cost function considering not only a single pixel but also its neighboring pixels, and utilizing the SVM classifier to enhance the discrimination between the foreground and background. Optimization of the cost function can be achieved by belief propagation. Experimental results show favorable matting performance for many images.

1 INTRODUCTION

1.1 Image Matting

Image matting is one of the primary processing techniques in image and video editing. In this problem, an image is assumed to be a composite of foreground and background image layers. Let a given image, the foreground image, and the background image be denoted by $\tilde{c} = (c_1, c_2, \ldots, c_N)$, $\tilde{f} = (f_1, f_2, \ldots, f_N)$, and $\tilde{b} = (b_1, b_2, \ldots, b_N)$, respectively. Each element, c_i, f_i, and b_i $(i = 1, 2, \ldots, N)$, is the RGB value (3-dimensional vector; each pixel value ranges from 0 to 255) of pixel i, and N is the number of pixels. Then, the observed image $\tilde{c}$ is modeled by the linear combination of a foreground image $\tilde{f}$ and a background image $\tilde{b}$ at each pixel as

$$c_i = \alpha_i f_i + (1 - \alpha_i) b_i, \tag{1}$$

where $\alpha_i \in [0, 1]$ is the mixing rate called *alpha value* or *opacity*. The task of image matting is to estimate the opacity $\tilde{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_N)$, foreground colors $\tilde{f}$, and background colors $\tilde{b}$ for each pixel in a given image $\tilde{c}$.

This task is inherently an under-constrained problem, since the number of constraints in Eq.(1) is much less than the number of variables to be estimated ($\tilde{\alpha}$, $\tilde{f}$, and $\tilde{b}$). Moreover, as the foreground object a user intends to extract is unknown, the user is usually required to impose constraints, by indicating parts of the foreground and background, which provide clues for classifying the remaining pixels (Figure 1). In this paper, we utilize this user-input information, as well as previous approaches.

1.2 Previous Work

Blue screen matting (Smith and Blinn, 1996) was developed as a technique for motion picture photography, which is well known as chroma-key compositing. Recent approaches attempted to extract foreground mattes directly from natural images without assuming a constant background. Several methods required a user to prepare a *trimap*, which is a roughly segmented map consisting of three regions: definitely foreground, definitely background, and unknown regions (Figure 1 (b)). *Knockout 2* (Berman et al., 2000) extrapolates the known foreground and background colors into the unknown region. Ruzon and Tomasi first introduced a probabilistic view to image matting, and estimated alpha mattes using foreground and background distributions around unknown pixels (Ruzon and Tomasi, 2000). Chuang et al. solved the matting problem based on the Bayesian framework

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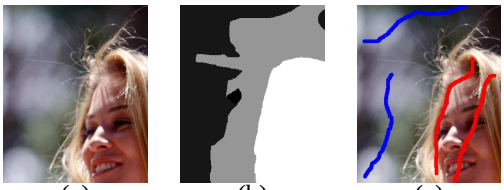
and maximum *a posteriori* estimation (Chuang et al., 2001). Sun et al. obtained the alpha matte by solving the Poisson equation between the gradients of alpha value and color intensities (Sun et al., 2004). Grady et al. formulated image matting from the viewpoint of transition probabilities in random walks (Grady et al., 2005).

For high-quality matting, users need to carefully generate the trimap, which is a troublesome and time-consuming task. This problem was partially solved by (Wang and Cohen, 2005). In their approach, a user draws few strokes in the foreground object and the background, as illustrated in Figure 1 (c), where pixels on the red strokes are in the foreground, and those on the blue strokes are in the background. They defined a cost function for alpha estimation on the Markov random field (MRF), and minimized it using the belief propagation (BP) (Pearl, 1988). Recently, under the assumption that the foreground and background colors lie on a straight line in RGB color spaces, a closed form solution to image matting has been derived, and the alpha value was analytically obtained (Levin et al., 2006).



(a) (b) (c)

Figure 1: Methods of indicating the target object. (a) Original image. (b) Trimap. A user roughly segments the image into definitely foreground (painted white), definitely background (painted black), and unknown regions (painted gray). (c) Input strokes. A user marks the foreground (red strokes) and background (blue strokes).

1.3 Objective of this Paper

The common drawback of the aforementioned algorithms is that the performance tends to deteriorate when the foreground and background regions contain similar colors. One solution is to provide an interactive user interface to modify imperfections, which has been adopted by Poisson matting (Sun et al., 2004).

In this paper, we aim at improving the performance itself using neighboring information around the referred pixel, while traditional algorithms use only the information of a single pixel. This extension, to a certain extent, incorporates texture-like information into the image matting. Furthermore, we enhance the discrimination between foreground and background with support vector machine (SVM).

2 COST FUNCTION

2.1 Formulation

The formulation of our cost function is partially similar to (Wang and Cohen, 2005). They considered two terms in their cost function: the local smoothing term, and the likelihood term which expresses the sufficiency level of the matting equation (1) when the alpha value is estimated. However, their formulation seems so complicated that the essence is slightly ambiguous.

In this paper, we incorporate three factors into a cost function for high-quality matting: fidelity to the matting equation (1), local smoothness, and discrimination based on user inputs. Thus, our cost function is expressed as

$$U(\tilde{\alpha},\tilde{f},\tilde{b};\tilde{c}) = \lambda_M \sum_{i\in\mathcal{P}} U_M(\alpha_i, f_i, b_i; c_i) + \sum_{(ij)\in\mathcal{N}} U_S(\alpha_i,\alpha_j; c_i, c_j) + \lambda_D \sum_{i\in\mathcal{P}} U_D(\alpha_i; g_i), \quad (2)$$

where U_M, U_S, and U_D express the matting, smoothing, and discrimination terms, respectively. The introduction of the discrimination term is novel to image matting, and g_i is the 15-dimensional color vector defined below. The symbols $\mathcal{P}$ and $\mathcal{N}$ represent the set of pixels and adjacent pixel pairs, respectively. The positive parameters λ_M and λ_D control the balance between these three terms. We specify these terms below.

2.2 Matting Term

Since the basic assumption of image matting is described by Eq.(1), the desirable alpha matte should satisfy this equation. Here, we explicitly introduce the fitness of this model using the square error as

$$U_M(\alpha_i, f_i, b_i; c_i) = ||c_i - \alpha_i f_i - (1-\alpha_i) b_i||^2. \quad (3)$$

2.3 Smoothing Term

The smoothing term is defined as

$$U_S(\alpha_i,\alpha_j; c_i, c_j) = \frac{1}{||c_i - c_j|| + 1} \cdot (\alpha_i - \alpha_j)^2. \quad (4)$$

This expression means that the smoothness in a given image $\tilde{c}$ also enforces that in alpha mattes.

2.4 Discrimination Term

2.4.1 Extension of Image Vector

Traditional approaches focused only on the RGB vector of each pixel. However, including a similar color

in a foreground object and the background makes it difficult to classify the two regions based on pixel-wise RGB colors. One solution is to incorporate neighboring information with pixel-wise colors, and extract effective features from the local image for natural image matting.

Based on this perspective, we use the information of each pixel and its four nearest neighbors as one of the straightforward extensions. Although there are several alternatives for color information, such as HSV colors and SIFT (Lowe, 2004), we adopt standard RGB colors to facilitate comparison of our method with previous work. Therefore, we construct a 15-dimensional vector consisting of the RGB intensities of each pixel and its four nearest neighbors for the discrimination term. The array of these vectors is denoted by $\tilde{g} = (g_1, g_2, \ldots, g_N)$, where g_i is a 15-dimensional vector at pixel i.

We expect this configuration to extract some texture information. It is natural that the RGB color combinations among five pixels have more divergences than in the case of a single pixel, and therefore, extending 3-dimensional RGB colors to 15-dimensional vectors provides additional information for more accurate classification.

2.4.2 Classification by Svm

We enhance discrimination between foreground and background by using the 15-dimensional vectors to extract effective information for image matting. The support vector machine (SVM) with the *kernel trick* provides a scheme for carrying out this task. Input vector $\vec{x}$ is classified by $y = \Theta[f_{\mathrm{SVM}}(\vec{x})]$, where $y \in \{0,1\}$ is a class label, $f_{\mathrm{SVM}}(\cdot)$ is the SVM output function, and $\Theta[z]$ is 1 for $z \geq 0$ or 0 otherwise.

We construct the discrimination term based on the outputs of the SVM classifier. Note that the training data consists of the proposed 15-dimensional vectors at user-marked pixels, and class labels express the foreground ($y = 1$) and background ($y = 0$). For pixels that a user does not mark, the discrimination term is defined as

$$U_D(\alpha_i; g_i) = \alpha_i d_i^0 + (1 - \alpha_i) d_i^1. \tag{5}$$

In this expression, d_i^1 and d_i^0 represent the affinity of pixel i to the foreground and the background, respectively. They are defined by the SVM output function $f_{\mathrm{SVM}}(g_i)$ as

$$d_i^{k_i} = \frac{1}{1 + \exp\{-a_{k_i} | f_{\mathrm{SVM}}(g_i)|\}}, \; d_i^{1-k_i} = 1 - d_i^{k_i}, \tag{6}$$

where $k_i \equiv \Theta[f_{\mathrm{SVM}}(g_i)]$ is the classification result. The coefficients a_1 and a_0 should be determined appropriately; here, we empirically set these parameters as $a_{k_i} = 4/J_{k_i}$, where J_1 and J_0 denote the average values of the SVM output function for the foreground and background training data, respectively. In this study, we adopt the Gaussian kernel (Muller et al., 2001)

$$K(\vec{x}, \vec{x}') = \exp\left(-\frac{||\vec{x} - \vec{x}'||^2}{2\sigma^2}\right), \tag{7}$$

where σ is a parameter fixed as $\sigma^2 = 1000$ throughout the paper.

Figure 2 shows the effectiveness of the 15-dimensional vectors and classification by the SVM. This figure shows the value of d_i^1 in 256 gray-levels, when using the standard 3-dimensional RGB vectors ((b), (e), and (h)) and the 15-dimensional extended vectors (our method, (c), (f), and (i)). Red and blue strokes indicate user inputs of foreground and background, respectively. Figure 2(a) is an artificial graphic produced to help understand the effectiveness of the proposed 15-dimensional vectors, in which a foreground object (the yellow ball) exists in a background texture of a striped pattern of width one pixel. Since a similar color exists in both the foreground and background, the performance of pixel-wise methods degrades (b), while our method (the 15-dimensional vector and classification by SVM) provides favorable discrimination result (c) as well as (f) and (i).

3 ALGORITHM

It is difficult to minimize the cost function (2) with respect to $\tilde{\alpha}$, $\tilde{f}$, and $\tilde{b}$ simultaneously. This difficulty was also faced by (Wang and Cohen, 2005). As they did, we minimize the cost function for alpha values using belief propagation (BP) keeping $\tilde{f}$ and $\tilde{b}$ fixed, and minimize the cost function for foreground and background colors by sampling method keeping $\tilde{\alpha}$ fixed.

3.1 Estimation of Alpha Values By Bp

Finding optimal alpha mattes with minimum cost corresponds to the MAP estimation problem, which is generally computationally difficult. Thus, we have to employ practically tractable algorithms that generate (sub)optimal solutions.

For discrete combinatorial optimization, the belief propagation (Pearl, 1988) is a promising approach for such tasks. BP has been recently exploited for various computer vision problems (e.g., stereo matching (Sun et al., 2003)) as well as image matting (Wang and Cohen, 2005). Therefore, we quantize the alpha value to 11 levels (at 0.1 intervals between 0 and 1), in

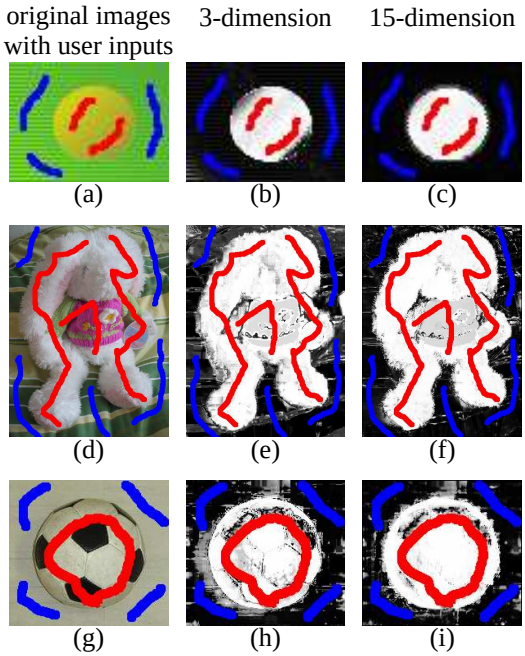


Figure 2: Comparison among the discrimination terms. The pixel in white indicates an affinity for the foreground and the pixel in black indicates that for the background. Traditional 3-dimensional RGB (b) are insufficient to separate the foreground object from the background texture in the toy example shown in (a), whereas the proposed 15-dimensional vectors (c) provide excellent classification. In the example of the stuffed rabbit, although the difference is not necessarily clear, we can see some places in the background where the 15-dimensional case (f) is superior to the 3-dimensional case (e). In the soccer ball image, the 3-dimensional vectors misclassify pixels to the left of the ball (h).

order to transform the current problem into a discrete combinatorial optimization.

On the current MRF, BP is represented as a message passing algorithm between neighboring pixels:

$$m_{ij}^t(\alpha_i) = \min_{\alpha_j} \lambda_M U_M(\alpha_j, f_j, b_j; c_j)/Z_j + \lambda_D U_D(\alpha_j; g_j) + U_S(\alpha_i, \alpha_j; c_i, c_j) + \sum_{k \in \mathcal{N}(j) \backslash i} m_{jk}^{t-1}(\alpha_j), \quad (8)$$

where $\mathcal{N}(j)\backslash i$ denotes the set of nearest neighbors of pixel j other than i, and $t = 1, 2, \ldots$ is an index for iteration steps. The matting term U_M is normalized by a factor $Z_j \equiv \sum_{\alpha'} ||c_j - \alpha' f_j - (1-\alpha')b_j||^2$ to restrict this term to a range $[0,1]$ as well as the other two terms (U_D and U_S) and facilitate the adjustment of parameters λ_M and λ_D.

Note that the messages m_{ij}^t and m_{ji}^t are different variables. After the convergence of the iterations, a *belief* vector is computed for each pixel as

$$b_i(\alpha_i) = \lambda_M U_M(\alpha_i, f_i, b_i; c_i)/Z_i + \lambda_D U_D(\alpha_i, g_i) + \sum_{j \in \mathcal{N}(i)} m_{ij}^*(\alpha_i), \quad (9)$$

where the superscript * represents the value at convergence, and the optimal label at pixel i, denoted as α_i^*, is estimated as

$$\alpha_i^* = \operatorname*{argmin}_{\alpha_i} b_i(\alpha_i). \quad (10)$$

As used in (Wang and Cohen, 2005), we employ the techniques proposed by (Felzenszwalb and Huttenlocher, 2004) to facilitate the calculation of Eq.(8)

3.2 Sampling for Foreground and Background Colors

We must estimate the foreground and background colors, $\tilde{f}$ and $\tilde{b}$ as well as alpha values. Foreground and background colors appear only in the matting term. We determine these values by a sampling approach.

Let the current value of the matting term at pixel i be denoted as $v_i \equiv ||c_i - \alpha_i f_i - (1-\alpha_i)b_i||^2$. For each pixel i, we sequentially search the optimal foreground and background colors in its neighboring pixel j from the nearest neighbors within a radius of 20 pixels. We focus f_j if $\alpha_j > \alpha_i$ (or b_j if $\alpha_j < \alpha_i$), and replace the foreground (background) colors $f_i(b_i)$ with $f_j(b_j)$ if the matting term is reduced, i. e.,

$$\begin{aligned} ||c_i - \alpha_i f_j - (1-\alpha_i)b_i||^2 &< v_i \\ (||c_i - \alpha_i f_i - (1-\alpha_i)b_j||^2 &< v_i). \end{aligned}$$

3.3 Algorithm Flow

We use the multiscale technique proposed by (Felzenszwalb and Huttenlocher, 2004) to facilitate the computation and obtain better results. We begin with an estimation for the coarsest image, and use the results as initial values for the finer image. The final alpha matte is obtained as a result of the original scale. Our entire algorithm is described below.

1) Generation of multiscale images Multiscale images for an original image and the user strokes are generated by the standard quad-tree method.

2) Classification by SVM The elements of the discrimination term d_i^1 and d_i^0 are calculated.

3) Initialization We set $f_i = c_i$ for user-marked foreground pixels, and $b_i = c_i$ for user-marked background pixels. Unmarked pixels take over the values of corresponding pixels at the previous coarser scale.

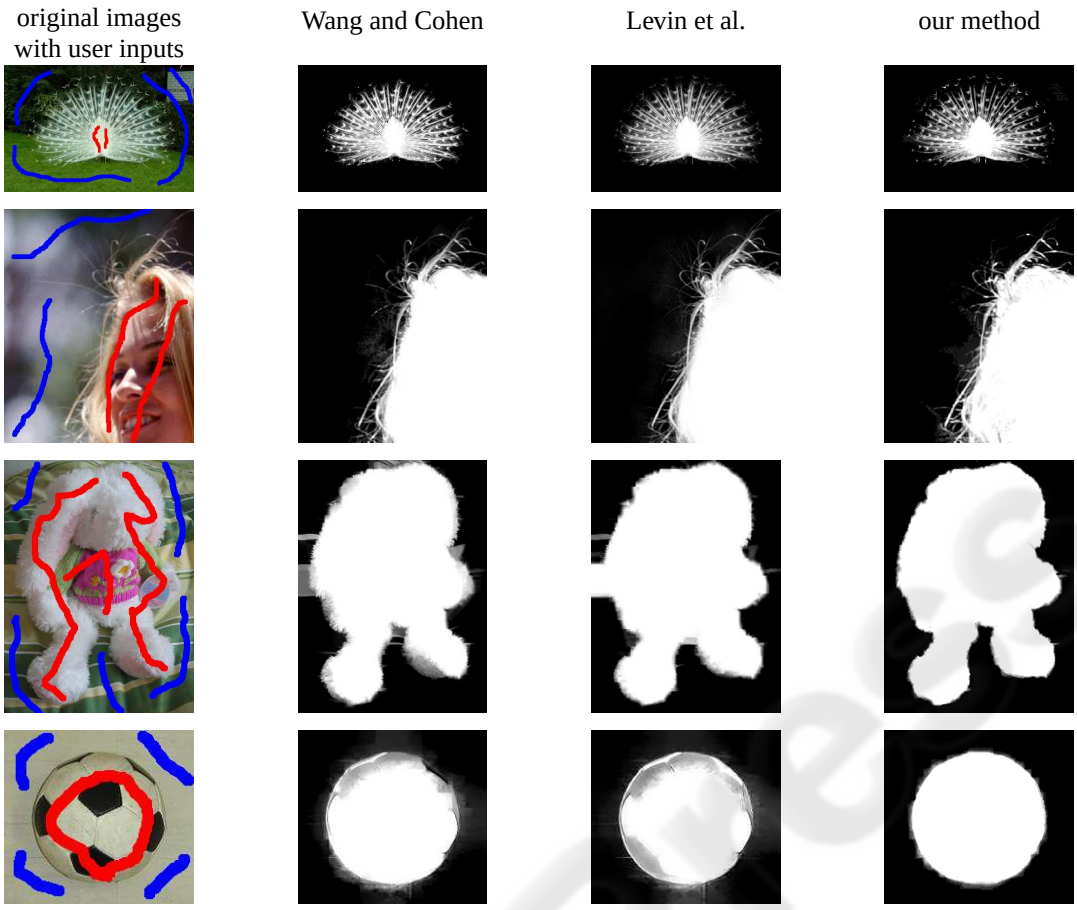


Figure 3: Examples of experimental results. The first column shows original images with user-specified strokes. The other columns show the results of (Wang and Cohen, 2005), (Levin et al., 2006), and our method. The parameters λ_M and λ_D as well as those included in the two previous approaches are adjusted so that the performance is optimal by appearance.

4) Estimation of alpha values The alpha values are estimated by the BP with foreground and background colors fixed.

5) Estimation of foreground and background colors The foreground and background colors are estimated by sampling from neighboring pixels with the alpha values fixed.

6) Repeat the steps 4 and 5 until the values of $\tilde{\alpha}$, $\tilde{f}$, and $\tilde{b}$ remain constant.

7) Return to the step 3 and start the estimation for the next finer scale.

4 EXPERIMENTAL RESULTS

The proposed approach has been tested for various images. Figure 3 shows several results obtained by our method, compared to other methods, (Wang and Cohen, 2005) and (Levin et al., 2006). The results of these previous works were obtained using the programs provided on their websites. There are four multiscales for every image. The upper three examples were also used in the previous works, and we set user-marked inputs in places similar to those studies. The parameters λ_M and λ_D in Eq.(2) were determined manually for each image so that the performance is optimal by appearance, and the parameters in the other methods were also optimized by hand.

It is basically difficult to obtain ground truth and quantitatively evaluate matting performance. Therefore, we resort to subjective evaluation. Previous approaches work well on the images of a peacock and a face, and our approach also compares favorably on those images. In the latter two images which contain similar colors in the foreground and background, our method extracts the foreground object better than the other algorithms on the whole, which indicates that the proposed 15-dimensional color vectors and classification by SVM are effective for image matting. However, in some instances, our method does not necessarily capture the details as well as the other methods. Figure 4 shows an example of a composite image, the stuffed rabbit extracted by our method

with a blue background. The enlarged details in the red square are relatively reasonable, while those in the green square are missing in the composite image.

The performance of these matting algorithms depends on the positions and the quantity of the user inputs. In particular, when a user draws only a few strokes, the performance can deteriorate drastically.

An example of the calculation time is as follows. Using a 2.66 GHz CPU with 3 GB RAM, an image size of 341×455 pixels (the stuffed rabbit in Figure 3) requires about 23 sec for the classification by SVM and about 17 sec for the subsequent estimation by BP and sampling without specific programming optimization.

5 CONCLUSION

This paper has proposed the improvement of the cost function for image matting. A key contribution is the use of neighboring information in terms of higher dimensional vectors, instead of considering the information in a single pixel. In addition, we enhanced the discrimination between foreground and background with SVM. We obtained high-quality matting results even when a foreground object and background had similar colors.

Our future work includes further improvements to the cost function and estimation process for foreground and background colors, in order to obtain more desirable results. Setting the parameter values also influences matting results. In this study, we manually set optimal values for λ_M and λ_D, which may not be implemented in practice. Statistical inference methods, such as the maximum of marginal likelihood (Tanaka, 2002) could be used for this parameter estimation. Another problem is the optimal setting of the parameters σ and a_{k_i} in the SVM formulation. Cross validation method is one promising solution for this problem.

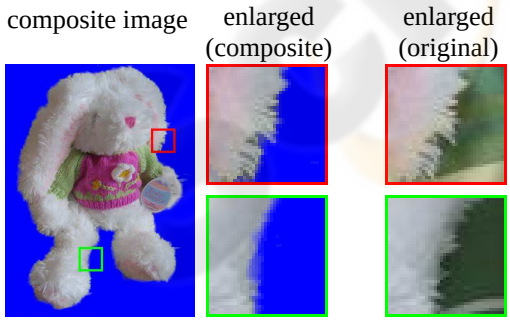


Figure 4: An example of composite images with blue background. It can be seen that some details in the original image are missing in the composite image.

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