NOVATEUR PUBLICATIONS
INTERNATIONAL JOURNAL OF INNOVATIONS IN ENGINEERING RESEARCH AND TECHNOLOGY [IJIERT]
ISSN: 2394-3696
VOLUME 2, ISSUE 12, DEC.-2015

AN IMPLEMENTATION OF ADAPTIVE PROPAGATION-BASED COLOR SAMPLING FOR IMAGE MATTING

Nilesh N. Chawande
Department of Computer Science & Engineering,
SGBAU University, GHRCEM, Amravati, India

Prof. Amit M. Sahu
Department of Computer Science & Engineering,
CHRCEM, Amravati, India

ABSTRACT

Natural image matting refers to the problem of an extracting the region of interest such as foreground object from an image based on the user inputs like scribbles or trimap. The proposed algorithm combines propagation and color sampling methods. Unlike previous propagation-based approaches that used either local or non local propagation method, the proposed framework adaptively uses both local and non local processes according to the detection result of the different region in the image. The proposed color sampling strategy, which is based on the characteristic of super pixel uses a simple sample selection criterion and requires significantly less computational cost. Proposed method used another method to convert original image to trimap image, which is based on selection process. That use roipoly tool to select a polygonal region of interest within the image, it can use as a mask for masked filtering. In which used the Chan-Vese algorithm for image segmentation

INTRODUCTION

Natural image matting refers to the problem of accurate foreground extraction in an images. Figure 1 shows the general process of image matting, which shows the process of extracting foreground object from the background of original image with determining both full and partial pixel opacity.
In general, an observed image ‘I’ can be modelled as a convex combination of a foreground object or foreground image ‘F’ and a background object or background image ‘B’ using ‘α’, an alpha matte, which is the foreground opacity.

$$I = \alpha F + (1 - \alpha) B \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

From the matting equation (1), we can see that there are three unknown values ‘α’ , ‘F’, and ‘B’ and one known value ‘I’, which makes matting an under-constrained problem. Therefore, a user specified trimap image where the user manually partitions an image into foreground, background, and unknown, is often required.

Figure 1: The general process of image matting.

Existing matting methods used dataset trimap images to find the value of alpha matt, proposed method convert original image to trimap image, which is based on selection process. That preserves the advantages of use roipoly tool to select a polygonal region of interest within the image, and it returns a binary image that we can use as a mask for masked filtering. In which it used the Chan-Vese algorithm for image segmentation and shown that it is effective on a wide variety of images. It is especially useful in cases where an edge-based segmentation algorithm will not suffice, since it relies on global properties. Figure 2 shows the general process of trimap conversion.

Proposed method work on both methods, namely converted trimap images and dataset trimap images.

Figure 2: The general process of trimap conversion.

Existing matting approaches can be divided into two categories, propagation-based approaches and color sampling-based approaches [4]. Propagation-based approaches interpolate the unknown alpha values from the known regions.Propagation-based matting algorithms can be divided into two categories, local propagation-based approaches [1] and nonlocal propagation-based approaches [8].

Color-sampling methods can be divided into two categories, parametric color-sampling methods and nonparametric color-sampling methods.
Parametric color-sampling methods usually fit parametric models to the color distributions of the nearby foreground and background samples. Given an unknown pixel, these models are then used to measure the unknown pixels similarity with the foreground and background distributions, leading directly to its alpha estimation. They are less valid, however, when the image does not satisfy the model. Previous matting approaches that use either local or nonlocal propagation methods, or use both methods with color sampling method, but limitation of previous matting approaches is that, they can find the alpha matting, here adaptively uses both of them, this method depends on the detection results from different regions of the image; hence, it can leverage both local and nonlocal propagation principles [5].

In this paper, propose a new propagation framework for image matting and set extracted foreground on different background.

LITERATURE SURVEY

Closed-Form Matting

CF matting [1] i.e. close form matting is a typical local propagation method based on the local smoothness assumption of the foreground and background colors. The underlying assumption is originally from Omer and Werman's work, which demonstrated that in many natural images, the distribution of colors is locally linear in the RGB space. Inspired by this paper, CF matting assumes that in a small window, each foreground F and background B is a linear combination of two colors. That is, the values of F_i in a small window lie on a single line in the RGB color space,
$F_i = \beta_i F_1 + (1 - \beta_i)\ F_2$. It is the same for the background values of β_i. This is also called the color line model. Based on this assumption a quadratic cost function can be derived and globally optimal alpha mattes can be obtained by solving a sparse linear system of equations [1].

KNN Matting

KNN matting [8], is the K nearest neighbours (KNN), It capitalizes on the nonlocal principle by using K nearest neighbours in matching nonlocal neighbourhoods, and contributes a simple and fast algorithm that produce competitive results with sparse mark-ups. KNN matting constructs clustering Laplacian based on feature vector, the choice of elements in feature vector is instrumental.
KNN matting shows that the same Laplacian formulation can be used for layer extraction once the alpha values are known. KNN performed qualitative and quantitative evaluation for extracting overlapping layers in natural image matting [8].

KNN smoothness Matting

KNN smoothness matting [6] is a nonlocal propagation method based on the nonlocal smoothness assumption of the foreground and background colors F and B. It assumes that the K nearest neighbours searched in the feature space satisfies the color line model. Specifically, each feature is composed of both color and spatial information. For each pixel i, the feature vector is defined as

$$X(i) = (I^R, I^G, I^B, x, y)_I \text{ .... } (2)$$

Where, all color and spatial variables are normalized. The K nearest neighbour search uses the Euclidean difference measure

$$\|X(i) - X(i)\| \text{ ....(3)}$$

and is implemented with [24], which is very efficient. Based on this assumption, a quadratic cost function can be derived and a closed form solution can be obtained by solving the linear system. KNN smoothness matting can achieve fine matting results in non-uniform color distribution regions [6].

Adaptive Matting

Adaptive matting [5] approach used adaptive propagation based color sampling method, in which adaptively uses both local and nonlocal propagation with color sampling method. This method used three components for getting alpha value, which is based on detection of different regions, model selection and color sampling strategy.

For color sampling strategy, used nonparametric color sampling method, this kind of sampling method assumes that for each unknown pixel p, its true foreground and background colors can be found in the sample sets. Based on this assumption, alpha values can be estimated through a matting equation as

$$\alpha_p = \frac{(I_p - B^j)(F^i - B^j)}{\|F^i - B^j\|^2} \quad \ldots\ldots\ldots \quad (4)$$

Where, F^i and B^j are sample candidates with indices *i* and *j.* As for each unknown pixel, more than one sample pair is collected, the number of estimated alpha values will correspond to the number of sample pairs. A selection criterion, therefore, is required to determine the final estimated alpha value. This color-sampling method alone will result in matte discontinuities since all alpha values are estimated independently based on their sampling candidates. Usually, therefore, this color-sampling method is used in conjunction with a propagation method that can assure the matte continuity. From the above illustration, we see that adaptive matting used three matting approaches to extract the alpha matt image, but to set extracted foreground on different background is needed [5].

PROPLEM STATEMENT AND DISCUSSION

Existing matting approaches can be divided into two categories, propagation-based approaches and color sampling-based approaches. Propagation-based matting algorithms can be divided into two categories, local propagation-based approaches and nonlocal propagation-based approaches. Using local propagation-based approaches get fine result on smooth regions and using nonlocal propagation-based approaches get fine result on non-smooth region i.e. non uniform color distribution regions.

Color-sampling methods use nonparametric methods. These collect color samples from the foreground and background sample sets to estimate the unknown alpha values. The methods perform well when the true foreground and background colors are in the sample sets, using nonparametric color-sampling method get fine result on isolated regions. Problem is that no one single method performs fine result on smooth regions and non-smooth regions.

Proposed matting algorithm can extract high-quality mattes from different regions of an image and set extracted foreground on different background.

- Proposed algorithm combines propagation and color-sampling methods. Unlike previous propagation-based approaches that use either local or nonlocal propagation methods.
- Proposed method adaptively uses both local and nonlocal processes according to the detection results of the different regions in the image.
- Color-sampling strategy, which is based on the characteristics of the super-pixel, uses a simple sample selection criterion and requires significantly less computational cost than previous color-sampling methods.

ISSN: 2394-3696
VOLUME 2, ISSUE 12, DEC.-2015

- Proposed propagation framework, alone, outperforms the state of the art propagation based approaches. Combined with color-sampling method, it can effectively handle different regions in the image and produce both visually and quantitatively high-quality matting results, and set extracted foreground on different background.
- Proposed method used another method to convert original image to trimap image, it used roipoly tool to select a polygonal region of interest within the image, and it returns a binary image that we can use as a mask for masked filtering.
- Proposed method used the Chan-Vese algorithm for image segmentation and shown that it is effective on a wide variety of images.

PROPOSED METHOD

Proposed algorithm contains three parts, detection of the different regions, model selection and color-sampling strategy. Each component is described in the following sections [5].

Detection of the Different Regions

Detection of the different regions is necessary to efficiently leverage these approaches. We know that local propagation methods are good for smooth regions, while nonlocal propagation methods are good for non-uniform color distribution regions. We adaptively use these two propagation methods by splitting an image into two parts, smooth regions and non-smooth regions. Non-smooth regions include both non-uniform color distribution regions and isolated color regions. From the propagation perspective, smooth regions are good for local propagation, while non-smooth regions will block the local propagation of alpha. The detection of smooth regions, therefore, is the same process as the detection of locally well-propagated regions. Since propagation is from known pixels to unknown pixels, we can find that locally well-propagated regions are where there is no large intensity difference from the trimap foreground and background boundary.

Model Selection

After post-processing, we can split the image into two parts, smooth regions and non-smooth regions. For the smooth regions we use a local color line model [1]. For the other regions, we use a nonlocal color line model [6]. We then have, therefore, a hybrid 4-D linear model

$$\alpha_p = a_i^R I_p^R + a_i^G I_p^G + a_i^B I_p^B + b_i \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where,

$$\begin{cases} p \in L_i, \text{ if } & i \in R_s \\ p \in N_i, \text{ otherwise.} \end{cases}$$

Here, *Li* and *Ni* are the local neighbours in a 3x3 small window and K nearest neighbor of pixel *i,* respectively. *ai* and *bi* are linear coefficients that are invariant in a window. It denotes the smooth regions. Using the hybrid 4D linear model in (5), we can estimate the linear coefficients by minimizing the cost function

$$J = \sum_{i \in I} \sum_{p \in W_i} (\alpha_p - \sum_c a_i^c I_p^c - b_i)^2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

ISSN: 2394-3696
VOLUME 2, ISSUE 12, DEC.-2015

Where,

$$W_i = \begin{cases} L_i, \text{ if } & i \in R_s \\ N_i, \text{ otherwise} \end{cases}$$

Which yields an alpha dependent cost function

$$J = \alpha^{\mathrm{T}} L_h \alpha. \qquad \text{.......................... (7)}$$

Here, α is an *N x 1* vector, and *Lh*, is an N x N matrix, whose (j, k)th element is

$$L_h(j,k) = \sum_{i|(j,k)\in W_i} \left(\delta_{jk} - \frac{1}{|W_i|} \left(1 + (I_j - \mu_i)^{\mathrm{T}} (\Sigma_i + \frac{\epsilon}{|W_i|} I_3)^{-1} (I_k - \mu_i) \right) \right) \qquad \text{....(8)}$$

Where,

$$W_i = \begin{cases} L_i, \text{ if } & i \in R_s \\ N_i, \text{ otherwise.} \end{cases}$$

Here, δ_{jk} is the Kronecker delta, *N* is the number of pixels, Σi is a 3 x 3 covariance matrix, μ_i is the 3 x 1 mean vector of the intensifies of the pixels in neighbour vector W*i*, | W*i*,| is the number of pixels in this vector, I3 is the 3 x 3 identity matrix, and ε is a small constant.

Color-Sampling Strategy

We add prior information through a color-sampling method to non-smooth regions that contain both non-uniform color distribution and isolated color regions, aiming to improve the matting performance. For isolated regions, prior information is necessary as mentioned before. For non-uniform regions, prior information can help improve the matting quality, but does not require significantly more computational cost. This is because, typically, the non-smooth regions occupy only a very small part of the whole image. We apply color-sampling strategy, therefore, to all the non-smooth regions. Usually, sample candidates are from the foreground and background boundary pixels in the trimap. These boundaries cover sufficient color variations. Since there are numerous foreground and background boundary pixels, how to collect samples becomes a challenging issue. If all the boundary pixels are collected as sample candidates, the computational cost will be high. Furthermore, the final matting results will be degraded in the case that some boundary pixels, remote from the unknown pixel happen to explain the unknown pixel's color well due to noise. Remote boundary pixels, therefore, are unnecessary. Collecting all the nearby boundary pixels as sample candidates is not necessary since pixels share similar colors locally. Formally, given a pair of samples $(F^i\ ,\ B^j)$ with the sample indices *i* and *j*. We first estimate the alpha value $\hat{\alpha}$ of an unknown pixel *I* by

$$\hat{\alpha} = \frac{(I - B^j)(F^i - B^j)}{\| F^i - B^j \|^2}. \qquad \text{................................ (9)}$$

Then, we apply a color fitness model to describe how well a sample pair fits the matting equation

$$\varepsilon(F^i, B^j) = \| I - (\hat{\alpha} F^i + (1 - \hat{\alpha}) B^j) \|. \qquad \text{.............................. (10)}$$

Intuitively, the smaller $\varepsilon(F^i , B^j)$ means two samples F^i and B^j are more similar to the true foreground and background of the unknown sample.

Optimization

After estimating the alpha value of each pixel independently using (9), we can obtain the final alpha values by solving a global optimization problem, as in. The $\hat{\alpha}$ in (9) is used as a data term that contains prior alpha values, and the smoothness term is a Laplacian matrix L_h as in (8). Specifically, the final alpha is computed by

$$\alpha = \operatorname{argmin} \alpha^T L_h \alpha + \lambda(\alpha - \hat{\alpha})^T D(\alpha - \hat{\alpha}) \quad \text{.................} (11)$$

Where λ is a small constant weighting parameter and D is a diagonal matrix whose element is a large constant for the known pixel, a confidence f for the non-smooth pixel, and 0 for the smooth pixel. The solution to (11) can be obtained by solving a linear system.

In the proposed method, we can also convert original input image to trimap image for which required freehand selection ROI tool and required chan-vese algorithm to image segmentation, detail of this tool and algorithm given below.

Polygonal ROI

Polygonal ROI is based on selection process, Roipoly creates an interactive polygon tool, associated with the image displayed in the current figure, called the target image. With the polygon tool active, the pointer changes to cross hairs + when we move the pointer over the image in the figure. Using the mouse, we specify the region by selecting vertices of the polygon. We can move or resize the polygon using the mouse [11].

Chan-Vese Algorithm

The Chan-Vese algorithm for image segmentation and it is effective on a wide variety of images. It is especially useful in cases where an edge-based segmentation algorithm will not suffice, since it relies on global properties. The Chan-Vese algorithm is prohibitively slow for some applications. Depending on the type and size of the image and the number of iterations needed, the segmentation can take several seconds, which is too slow to keep up with typical video frame rates [7].

Experimental result

The experimental matting result with its graphical representation of proposed method compare with the result of CF matting, KNN matting, KNN smoothness matting and Adaptive method.

Matting Result of Trimap Image

Table 1 shows the matting result for trimap image, result of proposed method compare with previous matting methods such as CF matting, KNN matting, KNN smoothness matting, Adaptive matting.

Table 1. Matting result for trimap image.

	CF Matting	KNN Matting	KNN Smoothness	Adaptive Matting	Propose Method
MSE	$2.18*10^2$	$2.44*10^2$	$1.97*10^2$	$1.17*10^2$	$1.09*10^2$
SAD	$5.32*10^7$	$6.11*10^7$	$5.00*10^7$	$4.78*10^7$	$4.50*10^7$

The performance parameter of MSE and SAD compare with CF matting, KNN matting, KNN smoothness matting, Adaptive matting, and proposed method is shown below.

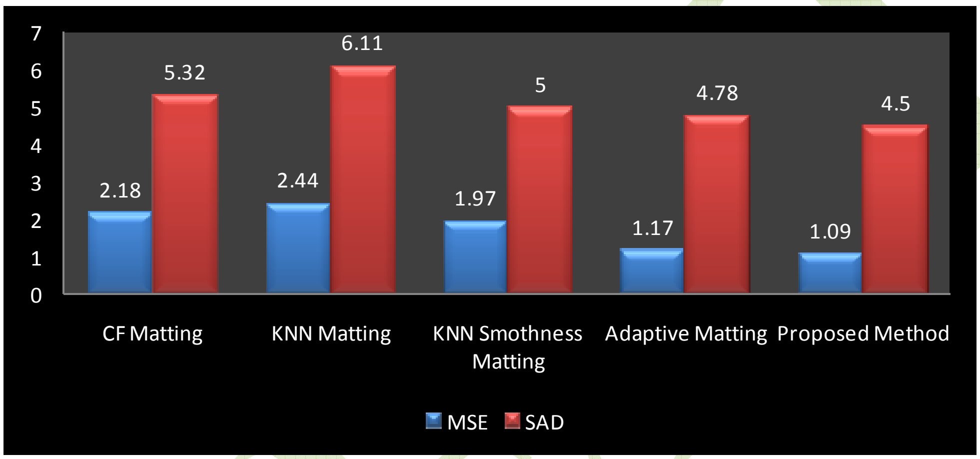

Figure 3: Performance of MSE and SAD of trimap image.

Figure 3 shows the performance of MSE and SAD of trimap, in above figure, proposed method compare with CF matting, KNN matting, KNN smoothness matting and Adaptive matting. Proposed method performed slightly better than previous matting methods.

(a) **(b)** **(c)** **(d)** **(e)**

Figure 4: Matting result of trimap image.

In figure 4 (a) shows the dataset original image, figure (b) shows the three standard trimap images, figure (c) shows the mask images, figure (d) shows the matt images and figure (e) shows the extracted foreground on different background.

ISSN: 2394-3696
VOLUME 2, ISSUE 12, DEC.-2015

Matting Result for Converted Trimap Image

Table 2 shows the matting result for converted trimap image, result of proposed method compare with previous matting methods such as CF matting, KNN matting, KNN smoothness matting, Adaptive matting.

Table 2. Matting result for converted trimap image.

	CF Matting	KNN Matting	KNN Smoothness	Adaptive Matting	Proposed Method
MSE	$2.18*10^2$	$2.44*10^2$	$1.97*10^2$	$1.17*10^2$	$1.24*10^2$
SAD	$5.32*10^7$	$6.11*10^7$	$5.00*10^7$	$4.78*10^7$	$1.86*10^7$

The performance parameter of MSE and SAD compare with CF matting, KNN matting, KNN smoothness matting, Adaptive matting, and proposed method is shown below.

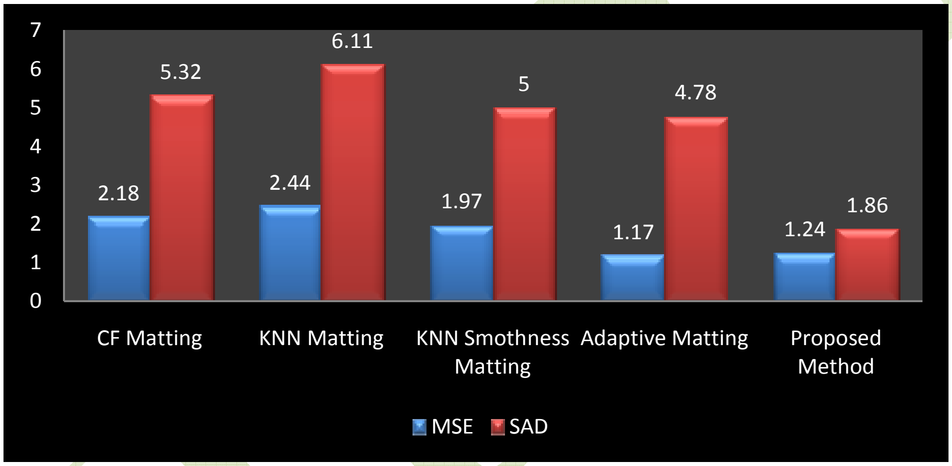

Figure 5: Performance of MSE and SAD of converted trimap image.

Figure 5 shows the performance of MSE and SAD of converted trimap image, proposed method take a value of the calculated MSE and SAD of converted trimap image. In above figure, proposed method compare with CF matting, KNN matting, KNN smoothness matting and Adaptive matting. Proposed method performed slightly better than previous matting methods, such as CF matting, KNN matting, KNN Smoothness matting.

(a) (b) (c) (d) (e) (f)

Figure 6: Matting Result for Converted Trimap Image.

In figure 6 (a) shows the original input image, figure (b) shows the selected ROI of input image, figure (c) shows the converted trimap images, figure (d) shows the mask images, figure (e) shows matt images and figure (f) shows the extracted foreground on different background.

CONCLUSION

In this paper, proposed method preserves the advantages of three approaches, local and nonlocal propagation-based approach and color sampling-based approach, and can obtain fine matting results in different regions, such as on smooth regions, non uniform color distribution regions, and isolated color regions.
Proposed method convert original image to trimap image, which is based on selection process. That use roipoly tool to select a polygonal region of interest within the image, it can use as a mask for masked filtering. In which used the Chan-Vese algorithm for image segmentation.
Proposed method, find out the value of known alpha and unknown alpha for extraction of foreground from background, and set the extracted foreground on any different background image, white background image, black background image respectively.

REFERENCES

[1] A. Levin, D. Lischinski, and Y. Weiss. *A closed-form solution to natural image Matting. IEEE Trans. Pattern Anal. Mach. Intell. , vol. 30, no. 2, pp. 228-242, Feb. 2008.*

[2] Christoph Rhemann, Carsten Rother, Jue Wang, Margrit Gelautz, Pushmeet Kohli, Pamela Rott. *A Perceptually Motivated Online Benchmark for Image Matting. in proc. IEEE, Int. CVPR. Jun. 2009, pp. 1826-1833.*

[3] J. Wang and M. F. Cohen. *Optimized color sampling for robust matting. in Proc. IEEE Int. CVPR. Jun. 2007, pp. 1-8.*

[4] J. Wang and M. F. Cohen. *Image and video matting a survey. Found. Trends Campus Graph. Vision, vol. 3, no. 2, pp. 97-175, 2007.*

[5] M. Jin, Byoung-Kwang Kim, and Woo-Jin Song. *Adaptive Propagation-Based Color-Sampling for Alpha Matting. IEEE Trans. on circuits system for video technology, Vol.24, No. 7, July 2014.*

[6] M. Jin, B. K. Kim, and W. J. Song. *KNN-based color line model for image Matting. In Proc. IEEE Int Image Process., Sep. 2013, pp. 2480-2483.*

[7] Nassir Salman. *Image Segmentation and Edge Detection Based on Chan-Vese Algorithm. The International Arab Journal of Information technology, vol.3, No.1, January 2006.*

[8] Q. Chen, D. Li, and C. K. Tang. *KNN matting. in Proc. IEEE Int. CVPR, Jun.2012, pp. 869476.*

[9] R. Achanta, A. Shaji, K. Smith, A. Lucchi2274-2282, Nov.2012, P. Fua, and S. Susstrunk. SLIC superpixels *compared to state-of-the-art super-pixel methods. IEEE Trans. PatternAnal.Mach.Intell,vol.34,no.11,pp.2274-2282,Nov.2012.*

[10] Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, Clifford Stein. *Introduction to Algorithms. Cambridge, MA, USA,: MIT press, 2001.*

[11] William J. Palm III. Introduction to MATLAB for Engineers. *Mc Graw Hill* Education, ISBN 0073534870 / 9780073534879, February 8, 2010, Mixed media product, 576 pages.