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A REVIEW ON "ADAPTIVE PROPAGATION-BASED COLOR-SAMPLING FOR IMAGE MATTING"

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Abstract: Image matting refers to the problem of accurate foreground extraction or estimation in an image and transparency determination of each pixel in an image whether it is foreground, background, or mixing parameter. Although different matting algorithms are proposed, most are not sufficiently strong to get satisfactory matting results in different regions of an image. Analyze the previous propagation-based approaches that use either local or non-local propagation methods, our propagation framework adaptively uses both local and nonlocal processes according to the detection results of the different regions in an image. Propose color-sampling method, which is based on the characteristics of the super-pixel, combined with propose color-sampling method, it can effectively handle different regions in an image and produced visually and quantitatively high-quality matting results.

Keywords: Propagation, Detection, Model Selection, Color-Sampling, Super-Pixel

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INTRODUCTION

Image matting refers to the problem of accurate foreground extraction or estimation in an image. it is an important technique in several image editing applications. Fig.1 shows the general process of matting. Accurately separating a foreground object from the background involves determinative full and partial pixel opacity. In general, an observed that I can be modelled as a convex combination of a foreground image F and a background image B

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

Using α, an alpha matte, which is the foreground opacity. from the matting equation (1), we can easily see that there are three unknown values α, F, and B and one known value I, which makes matting an under-constrained problem. Hence, a user-specified tri-map where the user manually partitions an image into foreground, background, and unknown, is often required.

Existing matting approaches are divided into two categories, namely propagation-based approaches and color sampling-based approaches [1]. Propagation-based approaches interpolate the unknown alpha values from the known regions. In particular, they define the affinities between neighboring pixels according to assumptions on the image statistics. Propagation-based matting algorithms can be divided into two categories, local propagation-based approaches [2]-[9] and nonlocal propagation-based approaches [10]-[12].

Since affinities are defined between a small number of neighboring pixels, correlations among them are usually strong, resulting in smooth matting effects. The performance of propagation-based approaches can also be improved by combining them with color-sampling methods [13]-[16].

As propagation-based approaches interpolate unknown alpha values from the known regions, small errors can be propagated and accumulated to produce larger errors. Color sampling-based approaches sample known foreground and background colors for each unknown pixel. According to how these sampled pixels will be used, color-sampling methods can be divided into two categories, parametric color-sampling methods [17]-[19] and nonparametric color-sampling methods[13]-[16],[20][21].

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. recent 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. In this paper, we propose a new propagation framework for alpha matting. Unlike previous matting approaches that use either local or nonlocal propagation methods, ours adaptively uses both of them. Our method depends on the detection results from different regions of the image, hence it can leverage both local and nonlocal propagation principles.

Fig.1. Example of image compositing. Left: image is the observed image. Center: ground truth alpha matte. Right: new composite image with another background image.

Experimental results show that our framework outperforms previous propagation-based approaches. Propose new framework can also be combined with previous color-sampling methods and improve their matting quality. In addition, a novel color-sampling method is used in conjunction with the adaptive propagation method. Our color-sampling method is based on the characteristics of the super-pixel and incurs significantly lower computational costs than previous color-sampling methods.

LITERATURE SURVEY

In this section analyze that, recent matting methods are mainly based on the assumption of either local or non-local principle, Specifically, we will analyze two representative propagation-based approaches, a local propagation-based method, closed-form (CF) matting[6], and a nonlocal propagation-based method, KNN smoothness matting. The extracted mattes of CF matting and KNN smoothness matting [12] for three diverse regions: smooth, non-uniform color distribution, and isolated color regions. Furthermore, we will show why propagation-based method alone is not adequate to obtain fine matting results. We will demonstrate why the color-sampling method is also necessary to extract high-quality mattes. These insights will motivate the new algorithm presented in the subsequent sections. Which are closely related to our work.

CF matting

CF matting [6] 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 [22], Inspired by this paper, CF matting assumes that in a small window, each of foreground F and background B is a linear combination of two colors. CF matting can extract high-quality matting results in the smooth regions where the local smoothness assumption is well satisfied. It cannot, however, achieve fine matting results in non-uniform color distribution regions. This is because CF matting is based on the local color line model, and in non-uniform color distribution regions, this model is not effective.

KNN smoothness matting

KNN smoothness matting [12] is a nonlocal propagation method based on the nonlocal smoothness assumption of the foreground and background colors F and B respectively. It assumes that the K nearest neighbors searched in the feature space satisfies the color line model. KNN smoothness matting can achieve fine matting results in non-uniform color distribution regions. for non-uniform color distribution regions, although the local color line model is violated, the nonlocal color line model can still be satisfied. This is because the nonlocal propagation principle can always find pixels of similar appearance and these pixels satisfy the color line model. KNN smoothness matting, however, cannot extract as high-quality matting results as CF matting in locally smooth regions.

In these regions, the local color line model is more effective. In addition, this matting algorithm does not perform well in isolated color regions KNN smoothness matting, although it uses the non-local principle, it is spatially constrained and connections cannot be made between the far away similar foreground or background and unknown in this region.

From the above illustration, we see that neither local nor nonlocal propagation approaches can extract fine matting results in isolated color regions. Hence, to obtain fine matting results in these regions, some prior information is needed.

Non-parametric color-sampling

The most common approach to adding prior information is the use of a non-parametric 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

$$\alpha p = \frac{(Ip - B^j)(F^i - B^j)}{|| F^i - B^j ||^2} \quad \text{................(4)}$$

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.

A representative matting method, robust matting, which combines non-parametric color-sampling and a local propagation method, can extract high-quality matting results in isolated color regions because prior information has been added.

This type of matting algorithms, however, also has limitations. for non-uniform color distribution regions, even though prior information can improve the matting performance, the reduced effectiveness of the local color line model will negatively influence the final matting result.

PROBLEM STATEMENT AND DISCUSSION

As mentioned previously, CF matting [6] can extract high-quality matting results for smooth regions. It does not, however, perform well in non-uniform color distribution regions due to the violation of the local color line model.

KNN smoothness matting [12], on the other hand, can achieve high-quality matting results in non-uniform color distribution regions, but is weak for smooth regions because of the inappropriate nonlocal assumption in these regions.

Only a nonparametric color-sampling method combined with a propagation method can achieve fine matting results in isolated color regions. we can easily state, then, that different regions require different matting approaches to obtain high-quality matting results. for smooth regions, CF matting is required. For non-uniform color distribution regions, KNN smoothness matting is effective. Finally, for isolated color regions, a non-parametric color-sampling method matched with a propagation method is necessary. No matting algorithm alone is able to deliver high performance in all these diverse regions. Only an approach that simultaneously preserves the local and nonlocal principles together with prior information can extract high quality matting results in diverse regions.

PROPOSED WORK

Adaptive Propagation-Based Color-Sampling Approach

Proposed Algorithm

To include local and nonlocal propagation principles together with a non-parametric color-sampling property, an intuitive way is a fixed combination of these three matting approaches. This combination has two obvious problems. one is the computational cost. Since the computational cost of a fixed combination is the sum of the three matting algorithms, it will be much higher than previous matting algorithms. The second problem is that a fixed combination cannot leverage each method's advantage efficiently. For instance, in the case of the non-local propagation method whose non-local color line model is not appropriate in smooth regions, the local propagation method alone, which has a well satisfied local color line model in these regions, will certainly outperform a fixed combination of these two methods. Rather than a fixed combination, therefore, we proposed an adaptive approach based on the detection results of the different regions. Propose algorithm can leverage the three matting methods and extract high-quality matting results in diverse regions with a low computational cost. Proposed algorithm contains three parts, detection of the different regions, model selection and color-sampling strategy. Each component of this algorithm is described in the following sections.

Detection of Different Regions

Since different matting approaches are effective for 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.

The threshold is a free parameter which balances between the smooth regions and the non-smooth regions. In general, the lower the threshold value is set to be, the more non-smooth regions are detected, and vice versa. Extreme values for the threshold cannot fully leverage the advantages of the local and the nonlocal propagation methods efficiently, due to noise in the image, however, large intensity differences also exist in smooth regions, In particular, we check the detection result in a super-pixel. If more than half the pixels in a super-pixel are detected as a smooth region, we consider the whole super-pixel as a smooth region since pixels are similar in a super-pixel.

Model Selection

In which 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. For the other regions, we use a non-local color line model.

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.

Apply our color-sampling strategy, to all the non-smooth regions. Usually, sample candidates are from the foreground and background boundary pixels in the tri-map. 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. Based on the above considerations, propose an efficient color-sampling method based on the super-pixel property that has a very simple sample selection criterion and a low computational cost, but still delivers high performance.

Tri-map foreground and background boundary pixels and select one sample from each group to represent it. In particular, our grouping method is based on the SLIC super-pixel method [23]. With this method all foreground and background boundary pixels can be grouped into different super-pixels. The selected sample is the median pixel in each group and has the minimum sum of intensity difference with the other pixels in the same group. We collect ten spatially closest median pixels as sample candidates from the foreground and background boundaries, respectively.

CONCLUSION

In this paper, we propose a propagation-based color-sampling approach for image matting. The approach that distinguishes this paper from previous image matting work is that propose an adaptive local and nonlocal propagation-based approach. Specifically, used a detection method and split an image into two regions, smooth and non-smooth.

Based on the detection results, local and nonlocal propagation methods were adaptively used to leverage their advantages. propose adaptive propagation method can be used as a general framework for other color sampling-based approaches. In addition, a super-pixel-based color-sampling method was applied in the non-smooth regions to improve the matting performance. This color-sampling method, which used a simple sample selection criterion and required significantly less computation than previous color-sampling methods, still delivered high performance. Propose method preserves the advantages of three matting algorithms, local and nonlocal propagation-based matting algorithms and color sampling-based matting algorithm, and can obtain fine matting results in different regions.

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