IMPROVING DEEP IMAGE MATTING VIA LOCAL SMOOTHNESS ASSUMPTION

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ABSTRACT

Natural image matting is a fundamental and challenging computer vision task. Conventionally, the problem is formulated as an underconstrained problem. Since the problem is ill-posed, further assumptions on the data distribution are required to make the problem well-posed. For classical matting methods, a commonly adopted assumption is the local smoothness assumption on foreground and background colors. However, the use of such assumptions was not systematically considered for deep learning based matting methods. In this work, we consider two local smoothness assumptions which can help improving deep image matting models. Based on the local smoothness assumptions, we propose three techniques, i.e., training set refinement, color augmentation and backpropagating refinement, which can improve the performance of the deep image matting model significantly. We conduct experiments to examine the effectiveness of the proposed algorithm. The experimental results show that the proposed method has favorable performance compared with existing matting methods.

Index Terms— Image matting, backpropagating refinement, data augmentation

1. INTRODUCTION

Natural image matting is an important task in image editing. In this task, the natural image $I$ is assumed to be a convex combination of the foreground $F \in \mathbb{R}^{h\times w \times 3}$ and the background $B \in \mathbb{R}^{h\times w \times 3}$ weighted by $\alpha \in [0,1]^{h\times w}$, the opacity of the foreground. Formally, the color at $i \in \{1,\ldots,h\} \times \{1,\ldots,w\}$ satisfies the compositing equation

$$T_i = \alpha_i F_i + (1 - \alpha_i)B_i, \quad c = 1, 2, 3.$$  \hspace{1cm} (1)

Given an input image $I$, the goal is to estimate $\alpha$. Note that there are 3 equations with 7 unknowns at each pixel. This results in the nonidentifiability of $F$, $B$ and $\alpha$. Specifically, suppose that the triplet $(F,B,\alpha)$ satisfies (1). Then for any $Q \in \mathbb{R}^{h\times w}$ satisfying $0 \leq Q \cdot \alpha \leq \frac{1}{\alpha}$, the triplet $((B_i + (F_i - B_i)/Q)_i, B, (Q,\alpha))$ also satisfies (1). Thus, without further assumption, the natural image matting problem is ill-posed.

To regulate the problem, natural image matting is often aided by human. In a typical human-aided process, the user provides a trimap $T \in \{0, 0.5, 1\}^{h\times w}$ indicating the purely foreground region $\{i : T_i = 1\}$, the purely background region $\{i : T_i = 0\}$, and the unknown region $\{i : T_i = 0.5\}$. It is guaranteed that if $T_i = 1$ then $\alpha_i = 1$ and if $T_i = 0$ then $\alpha_i = 0$. With a trimap $T$, one only needs to estimate $\alpha$ in the unknown region. However, the compositing equation (1) is still ill-posed in the unknown region. In principle, further assumptions are still required to make the problem well-posed.

For traditional image matting methods, local smoothness assumptions on $F$, $B$ or $\alpha$ are commonly used. In a seminal work, Levin et al. [1] proposed the color line model based on the assumption that $F$ and $B$ are approximately constant locally. There are also methods which utilize smoothness assumptions on $\alpha$; see [2] and the references therein. For traditional methods, a main goal of imposing local smoothness assumptions is to formulate tractable models. Consequently, their assumptions may be overly strong.

Thanks to the large training data released by Xu et al. [3] and the advent of convolutional neural networks, deep learning based matting methods have achieved significantly better performances than traditional methods [3–8]. For deep learning methods, one does not need to formulate an explicit model of colors. Rather, the deep neural networks may learn the implicit local smoothness assumptions during training. Intuitively, deep learning methods may be improved if they are explicitly guided by local smoothness assumptions. Unfortunately, to our best knowledge, no existing deep learning method utilizes the local smoothness assumptions explicitly.

In this paper, we explore the use of local smoothness assumption in deep image matting. We consider two seemingly trivial assumptions that should be satisfied by natural images. Surprisingly, these simple assumptions can be violated by
modern deep image matting methods. We propose three techniques to guide deep image matting methods based on the local smoothness assumptions. The proposed three techniques work in the different stages of deep learning methods. We observe that the foreground images in the Adobe Image Matting (AIM) dataset [3] violate our first assumption. Hence our first technique is a training set refinement method which improves the AIM training set. The second technique is a color augmentation method which functions in the training phase. This technique can further improve the local smoothness property of the training data. The third technique is a backpropagating refinement method which functions in the inference phase. It enforces the output of the deep network to satisfy our second assumption. We conduct experiments to evaluate the effectiveness of the proposed techniques. In summary, the contributions of the present paper are as follows:

- This work is the first one to systematically explore the local smoothness assumptions in deep image matting.
- We propose three novel techniques to improve the performance of deep image matting models. In particular, we present the first deep image matting method which uses backpropagating refinement during inference.
- Based on the proposed techniques, we present a simple deep image matting model which achieves the state-of-the-art performance on the testing set of [3] among all methods trained solely on AIM dataset.

2. A BASELINE DEEP IMAGE MATTING MODEL

In this section, we introduce a simple deep neural network for natural image matting which serves as the baseline model.

Network architecture. Our network, as illustrated in Fig. 1, has a standard encoder-decoder architecture. The encoder is ResNet-50-D [9], a variant of ResNet-50 [10]. The input of the encoder is the concatenation of \( I \) and \( T \), which has 4 channels. The input is 32× downsampled in the encoder.

In the baseline model, the backpropagating refinement module is simply the identity operator. In the decoder, to fuse the global information of the feature map, we adopt the blocks in VoVNet [11] which are similar to the SE block [12]. Compared with the SE block, our module has only one convolution and uses the hard sigmoid which is faster than sigmoid.

\[
L(\hat{\alpha}, \alpha) = \frac{1}{C_{\text{Card}}(\{i : T_i = 0.5\})} \sum_{i : T_i = 0.5} \sqrt{(\hat{\alpha}_i - \alpha_i)^2 + \epsilon^2}.
\]

To measure the difference of \( \hat{\alpha} \) and \( \alpha \) at different scales, we apply the above loss function at various scales of \( (\hat{\alpha}, \alpha) \) and use their weighted sum as the final loss function. Specifically, our loss function is \( \sum_{\ell=0}^{4} 2^{-\ell} L(\mathcal{P}(\hat{\alpha}), \mathcal{P}(\alpha)) \), where \( \mathcal{P} \) denotes the average pooling operator with kernel size \( 2^\ell \times 2^\ell \) and stride \( 2^\ell \).

3. UTILIZING LOCAL SMOOTHNESS ASSUMPTIONS

For a position \( i \), let \( \partial \{i\} \) denote the set of 4 surrounding positions of \( i \). For a region \( R \), let \( \partial R \) denote the boundary of \( R \). Formally, \( i \in \partial R \) if and only if \( \{i\} \cup \partial \{i\} \not\subseteq R \) and \( \{i\} \cup \partial \{i\} \not\subseteq R^C \). We consider the following two modest local smoothness assumptions.

Assumption 1. \( F \) is locally constant at the positions 
\[ \{i : \alpha_i = 0\} \cup \partial \{i : \alpha_i = 0\}. \]
Assumption 2. \( \alpha \) is locally constant at the positions \( \partial \{ i : T_i = 1 \} \cup \partial \{ i : T_i = 0 \} \).

Assumptions 1 and 2 impose conditions on \( F \) and \( \alpha \), respectively. These assumptions are fairly weak. We can expect them to hold for general natural images. We do not impose any condition on \( B \). In fact, the background \( B \) is often an unconstrained natural image in practice. Below we propose three techniques based on Assumptions 1 and 2 to improve deep image matting.

3.1. Refining Training Set

Some commonly used data augmentation techniques in deep image matting rely on interpolation techniques. As observed by Forte and Pitié [6], when applying interpolation techniques to \( F \), the nonsmooth colors in the region \( \{ i : \alpha_i = 0 \} \cup \partial \{ i : \alpha_i = 0 \} \) may contaminate the foreground colors in the region \( \{ i : \alpha_i > 0 \} \). That is, the violation of Assumption 1 results in color contamination. To ease this problem, Forte and Pitié [6] used the closed-form foreground estimation method in [1] to re-estimate the foregrounds in AIM dataset. However, the method of [1] was not designed to meet Assumption 1. We shall see that their method has suboptimal performance compared with the proposed re-estimation method.

In the training set of AIM, \( F \) does not meet Assumption 1. Now we present a new method to re-estimate \( F \). Formally, the re-estimation problem is as follows: given an initial foreground \( \hat{F} \) and \( \alpha \), the goal is to output a re-estimated \( \hat{\hat{F}} \) such that \( \hat{\hat{F}} \) has a similar behavior as \( F \) when used to compose an image and that \( \hat{\hat{F}} \) satisfies Assumption 1. To meet these two requirements, we consider the following cost function:

\[
C(\hat{\hat{F}}, F) = \frac{1}{2} \sum_{i \in \{1, \ldots, H\} \times \{1, \ldots, W\}} \sum_{c=1}^{3} \left( \alpha_i^2 (\hat{\hat{F}}_{ci} - F_{ci})^2 + \kappa (1 - \alpha_i^2) \sum_{j \in \partial(i)} (\hat{\hat{F}}_{cj} - F_{cj})^2 \right),
\]

where \( \kappa > 0 \) is a hyperparameter. The cost \( \alpha_i^2 (\hat{\hat{F}}_{ci} - F_{ci})^2 \) ensures \( \hat{\hat{F}}_{ci} \) is close to \( F_{ci} \) when \( \alpha_i \) is large. On the other hand, the cost \( (1 - \alpha_i)^2 \sum_{j \in \partial(i)} (\hat{\hat{F}}_{cj} - F_{cj})^2 \) ensures that \( \hat{\hat{F}}_{ci} \) is locally smooth when \( \alpha_i \) is small, which conforms Assumption 1. Following [13], we use a fast multi-level algorithm to minimize the cost function \( C(\hat{\hat{F}}, F) \).

3.2. Color Augmentation

In this section, we propose a simple color augmentation method to augment the training data. Given a foreground \( F \), we randomly generate an image \( \bar{I} \) with a constant color \( u \), i.e., \( \bar{I}_i = u \) for all \( i \), and a random number \( w \in [0, 1] \). The augmented foreground is defined as \( \tilde{F} = wF + (1 - w)\bar{I} \).

To see why this simple color augmentation method can work, we note that the gradient of \( \tilde{F} \) is \( \nabla \tilde{F} = w \nabla F \). Since \( w < 1 \), the augmented image \( \tilde{F} \) is smoother than \( F \). Consequently, the augmented image is more consistent with Assumption 1.

3.3. Backpropagating Refinement

Now we consider the use of Assumption 2 which basically assumes that the predicted opacity \( \hat{\alpha} \) should take value 1 on \( \partial \{ i : T_i = 1 \} \) and take value 0 on \( \partial \{ i : T_i = 0 \} \). Intuitively, this assumption should be satisfied by any reasonable matting methods. Surprisingly, as illustrated in the first row of Fig. 2, even for deep image matting models with goo performance, the output of the network can violate Assumption 2. It shows that deep learning methods may not automatically guarantee that the known pixels annotated by the trimap has the correct gradient. In fact, similar phenomenon was previously observed in the field of interactive image segmentation [14, 15].

There are two possible causes of this phenomenon. First, in the training phase of most existing methods, the trimaps are obtained by dilating the regions \( \{ i : \alpha_i > 0 \} \) and \( \{ i : \alpha_i < 1 \} \). However, such trimaps cannot fully mimic the input trimap generated by users. Second, the information of sparse regions may not be fully extracted by convolutional neural networks. Specifically, suppose \( R \) is a connected component of the region \( \{ i : T_i = 1 \} \) with a very small area. Then the important information provided by \( R \) may be very likely to be ignored by convolutional neural networks.

Given a testing image \( I \) and its trimap \( T \), if the output of the deep image matting model does not satisfy Assumption 2, we would like to regulate the output to meet Assumption 2. To achieve this, the idea is to use a backpropagating procedure to refine the result during the inference phase. The use of backpropagating refinement in the inference phase has achieved great success in the interactive segmentation task [14, 15]. To the best of our knowledge, the use of backpropagating refinement in deep image matting has never been explored before.

Our backpropagating refinement method works as follows. For \( 2 \leq \ell \leq 5 \), the output of Decoder \( \ell \) is processed by a Backpropagating Refinement Module (BRM) whose architecture is illustrated in Fig. 1. For BRM \( \ell \), there are two trainable parameters \( A \) and \( B \) which are both tensors with dimension \( (2^{8-\ell}, 2^{8-\ell}, C) \) where \( C \) is the channel number of the input of BRM. The output of BRM is \( \exp(\mathcal{F}(A) \cdot \text{Input} + \mathcal{F}(B)) \), where \( \mathcal{F} \) is the interpolation operator such that \( \mathcal{F}(A) \) and \( \mathcal{F}(B) \) have the same dimension as the input. In the training phase, the elements of \( A \) and \( B \) are fixed to \( 0 \), and hence BRM is simply the identity operator. In the inference phase, we freeze all parameters other than the parameters in BRM. Given a testing image, we initialize the elements of \( A \) and \( B \) as \( 0 \) and compute the output of the network \( \hat{\alpha}_{\text{init}} \). After that, \( A \) and \( B \) are iteratively updated via gradient descent to minimize the cost function

\[
C_1(\hat{\alpha}, T) + 0.1C_2(\hat{\alpha}, T),
\]
where $\hat{\alpha}$ is the output of the network and

$$
C_1(\hat{\alpha}, T) = \sum_{i \in \partial(i; T_c=0)} \hat{\alpha}_i^2 + \sum_{i \in \partial(i; T_c=1)} (1 - \hat{\alpha}_i)^2 \frac{\text{Card}(\partial(i; T_c=0)) + \text{Card}(\partial(i; T_c=1))}{\text{Card}(\{i: T_c = 0.5\})},
$$

$$
C_2(\hat{\alpha}, T) = \left\{ \sum_{i \in \partial(i; T_c=0)} |\hat{\alpha}_i - \hat{\alpha}_\text{init}| \right\}^2 .
$$

The cost function $C_1$ regulates the output to meet Assumption 2. There may be only a small number of pixels which severely violate Assumption 2. It is known that the $L_2$ loss is sensible to outliers. Hence in $C_1$, we use the $L_2$ loss which makes sure the output does not largely deviate from the original output of the network. It is known that the $L_1$ loss is robust against a sparse set of outliers. Hence in $C_2$, the squared $L_1$ loss ensures that the majority of pixels are not far away from the original output.

Note that the BRMs are all in the decoder. Hence we only need to forward the full network once and then the backward and forward computation can be restricted to the decoder. This reduces the computational cost. In practice, we set the iteration number to be 100 with learning rate 20.

## 4. EXPERIMENTS

In this section, we report experimental results of the proposed method. The source code is publicly available at https://github.com/kfeng123/LSA-Matting.

**Training data.** For all experiments, the encoder of the network is pretrained on ImageNet [21], and we train the network on the AIM training set [3] which consists of 431 distinct foreground images accompanied with their alpha matte and 43, 100 background images from MS-COCO dataset [22]. No additional data is used. Instead of composing each foreground image with a prespecified background image, we composite each foreground image with a randomly selected background in each iteration of training phase.

**Data augmentation.** Our data augmentation procedure for the baseline model is as follows. First, with probability 0.5, we randomly rotate the pair $(F, \alpha)$ and $B$. Then we randomly crop $(F, \alpha)$ and $B$, centered at a random pixel in the region $\{i: \alpha > 0\}$ with size $k \times k$ where $k$ is randomly chosen in $[\frac{1}{3}h, \frac{2}{3}h]$, and then resize it to $h \times h$ where $h$ is the height of the input image patches in training phase. After that, with probability 0.5, we flip $(F, \alpha)$ and $B$. With probability 0.3, we transform $\alpha$ to $\alpha' = 1 - (1 - \alpha)^{\gamma}$ with equal probability where $\gamma$ is randomly chosen in $[0, 1]$. With probability 0.3, we transform $F$ to $1 - F$. With probability 0.3, we randomly permute the 3 channels of $F$. Finally, we generate the trimap by dilating the regions $\{i: \alpha > 0\}$ and $\{i: \alpha < 1\}$ by random numbers from 1 to 24.

**Implementation details.** We use Adam optimizer [23] with initial learning rate $5 \cdot 10^{-5}$. We halve the learning rate every 20 epochs. The model is trained for 100 epochs with batch size 16 and weight decay $10^{-4}$.

**Evaluation Metrics.** Following [3, 17], we use the following metrics to evaluate matting methods: the sum of ab-

### Table 1. Ablation studies on Composition-1k testing dataset.

| IH | RF | CA | TTA | SAD | MSE | Grad | Conn |
|----|----|----|-----|-----|-----|------|------|
| 320|    |    |     | 32.4| 0.0074| 11.6 | 29.6 |
| 480|    |    |     | 30.0| 0.0067| 10.3 | 26.6 |
| 640|    |    |     | 29.0| 0.0062| 10.3 | 25.4 |
| 640 | ✓ |    |     | 28.9| 0.0058| 10.2 | 25.4 |
| 640 | ✓ |    |     | ✓ | 27.6| 0.0057| 10.1 | 23.6 |
| 640 | ✓ | ✓  |     | 27.9| 0.0056| 9.94 | 23.8 |
| 640 | ✓ | ✓  | ✓   | 25.9| 0.0054| 9.25 | 21.5 |
| 640 | ✓ | ✓  | ✓   | ✓ | 24.6| 0.0045| 8.13 | 19.9 |

### Table 2. Quantitative results on Composition-1k.

| Methods                     | SAD  | MSE  | Grad | Conn |
|-----------------------------|------|------|------|------|
| Closed-form [1]             | 168.1| 0.091| 126.9| 167.9|
| DIM [3]                     | 50.4 | 0.014| 31.0 | 50.8 |
| IndexNet [16]               | 45.8 | 0.013| 25.9 | 43.7 |
| SampleNet [5]               | 40.4 | 0.0099| -   | -   |
| Context-aware [17]          | 35.8 | 0.0082| 17.3 | 33.2 |
| GCA [4]                     | 35.3 | 0.0091| 16.9 | 32.5 |
| HDMatt [7]                  | 33.5 | 0.0073| 14.5 | 29.9 |
| A²U [18]                    | 32.2 | 0.0082| 16.4 | 29.3 |
| TIMI-Net [19]               | 29.1 | 0.0060| 11.5 | 25.4 |
| SIM [8]                     | 28.0 | 0.0058| 10.8 | 24.8 |
| FBA [6]                     | 26.4 | 0.0054| 10.6 | 21.5 |
| FBA + TTA [6]               | 25.8 | 0.0052| 10.6 | 20.8 |
| LFPNet [20]                 | 23.6 | 0.0041| 8.4  | 18.5 |
| LFPNet + TTA [20]           | ✓ | 0.0036| 7.6  | 17.1 |
| RF + CA (Ours)              | 25.9 | 0.0054| 9.25 | 21.5 |
| RF + CA + TTA (Ours)        | 24.6 | 0.0045| 8.13 | 19.9 |

**Fig. 2.** Illustration of the effect of BR. Figures in the first row are tested without BR. Figures in the second row are tested with BR.
Fig. 3. Performance of the proposed method with BR on the AlphaMatting testing set.

Fig. 4. Performance of the proposed method without BR on the AlphaMatting testing set.

solute differences (SAD), the mean square errors (MSE), the gradient errors (Grad) and the connectivity errors (Conn).

4.1. Results on Composition-1k Testing Dataset

In this section, we report evaluation results on the Composition-1k testing dataset [3] to illustrate the effectiveness of two of the proposed techniques: re-estimated foregrounds (RF) and color augmentation (CA). We will evaluate the third technique in the next subsection since this technique is time-consuming in this dataset. In addition, we also test our models with Test Time Augmentation (TTA). TTA was previously used by [5, 6] to improve the performance of the network. When TTA is used, the image is tested at three scales 0.8, 1, 1.25. For each scale, the image is rotated by $k\pi/2$, $k = 0, 1, 2, 3$, and is flipped to generate 8 images. We run the model on these $3 \times 8 = 24$ images and use the averaged output as the final result.

Ablation results. Table 1 lists the ablation results of the proposed techniques. The results indicate the following phenomena. First, while using the closed-form foreground estimation method in [1] can improve the performance, the proposed RF can lead to even better results. Second, the proposed CA can also lead to great improvement. Also, our results give quantitative characterization of the known facts that large input size in the training phase and TTA in the inference phase can lead to significant improvement of the performance.

Comparisons with the state-of-the-art methods. In Table 2, we list the performances of some recent methods on Composition-1k. It can be seen that the methods of [20] are the only ones whose overall performance is better than ours. However, [20] used additional data to pretrain their network. In comparison, no extra data is used in our model. Thus, our model achieves new state-of-the-art performance for all 4 metrics among all methods that are solely trained on the AIM training set.

4.2. Results on AlphaMatting Dataset

While our model is trained on the AIM training set, we also test our model on AlphaMatting dataset [24]. The data distribution of AlphaMatting dataset is different from AIM dataset. To increase the generalization ability of our model, we add an additional data augmentation technique in the training phase, that is, with probability $0.3$, the foreground and background are blurred. Also, we train the model for 200 epochs. For all results, techniques RF, CA and TTA are used by default.

Ablation results. We evaluate the proposed backpropa-

Table 3. Ablation studies on AlphaMatting training set.

| Methods              | SAD   | MSE    | Grad   | Conn   |
|----------------------|-------|--------|--------|--------|
| Without BR           | 2.90  | 0.00540| 2.47   | 2.45   |
| With BR              | 2.87  | 0.00532| 2.43   | 2.42   |
gating refinement (BR) technique on AlphaMatting training set. The results, listed in Table 3, show that BR can improve all 4 metrics. This verifies the effectiveness of BR.

Comparisons with the state-of-the-art methods. We evaluate the proposed method on AlphaMatting testing set. The performances of the proposed method (denoted as LSANet) and some competing methods are illustrated in Fig. 3 and Fig. 4. It can be seen that BR leads to an improvement of the ranking. While the proposed method does not rank among the top methods, it outperforms some recent methods, including [4, 5, 7, 18]. Also, the proposed method uses a simple architecture and is trained solely on AIM dataset. Overall, the performance of the proposed method is promising.

5. CONCLUSION

In this paper, we investigated the use of local smoothness assumptions in deep image matting and proposed three techniques which can improve the performance of the deep image matting model significantly. We adopted a simple network and trained the model on AIM training data. Extensive experiments verified the effectiveness of our method.

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