Abstract

We propose Mask Guided (MG) Matting, a robust matting framework that takes a general coarse mask as guidance. MG Matting leverages a network (PRN) design which encourages the matting model to provide self-guidance to progressively refine the uncertain regions through the decoding process. A series of guidance mask perturbation operations are also introduced in the training to further enhance its robustness to external guidance. We show that PRN can generalize to unseen types of guidance masks such as trimap and low-quality alpha matte, making it suitable for various application pipelines. In addition, we revisit the foreground color prediction problem for matting and propose a surprisingly simple improvement to address the dataset issue. Evaluation on real and synthetic benchmarks shows that MG Matting achieves state-of-the-art performance using various types of guidance inputs. Code and models will be available at https://github.com/yucornetto/MGMatting.

1. Introduction

Image matting is a fundamental computer vision problem which aims to predict an alpha matte to precisely cut out an image region. It has many applications in image and video editing [31, 33, 16].

Most previous matting methods require a well-annotated trimap as an auxiliary guidance input [31], which needs to explicitly define the regions of foreground and background as well as the unknown part for the matting methods to solve. Although such annotation makes the problem more tractable, it can be quite burdensome for users and limits the usefulness of these methods in many non-interactive applications.

Recently, researchers start to study the matting problem in a trimap-free setting. One direction is to get rid of any external guidance, and hope that the matting model can capture both semantics and details by end-to-end training on large-scale datasets [36, 24]. Nevertheless, these methods are faced with the generalization challenge due to the lack of semantic guidance when tested on complex real-world images. Another line of works investigate alternatives to the trimap guidance, easing the requirement for human input [20, 25, 14, 10]. For example, [14, 10] proposed techniques for automatic trimap generation, while [25] takes...
background images instead as extra inputs. However, these methods often require a very specific type of guidance they are trained with and thus become less appealing when the guidance inputs may have varied characteristics or forms.

In this work, we introduce a Mask Guided (MG) Matting method which takes a general coarse mask as guidance. MG Matting is very robust to the guidance input and can obtain high-quality matting results using various types of mask guidance such as a trimap, a rough binary segmentation mask or a low-quality soft alpha matte. To achieve such robustness to guidance input, we propose a Progressive Refinement Network (PRN) module, which learns to provide self-guidance to progressively refine the uncertain matting regions through the decoding process. To further enhance the robustness of our method to external guidance, we also develop a series of guidance mask perturbation operations including random binarization, random morphological operations, and also a stronger perturbation CutMask to simulate diverse guidance inputs during training.

In addition to alpha matting prediction, we also revisit the foreground color prediction problem for matting. Without accurately recovering the foreground color in the transparent region, the composited image will suffer from the fringing issue. We note that the foreground color labels in the widely-used dataset [33] are suboptimal for model training due to the labeling noise and limited diversity. As a simple yet effective solution, we propose Random Alpha Blending (RAB) to generate synthetic training data from random alpha mattes and images. We show that such simple method can improve the foreground color prediction accuracy without requiring additional manual annotations. As a result, combining with the proposed PRN, MG Matting is able to generate more visual plausible composition results.

Our contributions can be summarized as follows:

- We propose Mask Guided Matting, a general matting framework working with guidance masks in various qualities and even forms, and achieve a new state-of-the-art performance evaluated on both synthetic and real-world datasets.
- We introduce Progressive Refinement Network (PRN) along with a guidance perturbation training pipeline as a solution to learning a robust matting model.
- We study the problem of foreground color prediction for matting and propose a simple improvement using random alpha blending.

In addition, we collect a high-quality matting benchmark dataset of real images to evaluate the real-world performance of matting models. We will release this dataset to advance the research in this area.

2. Related Work

Trimap-based Image Matting. A majority of matting methods requires a trimap as additional input, which divides an image into foreground, background, and unknown regions. Traditional methods are often sampling-based or propagation-based. Sampling-based ones [8, 5, 11, 26, 30] estimate foreground/background color statistics through sampling pixels in the definite foreground/background regions to solve the alpha matte in the unknown region. The propagation-based methods [4, 15, 16, 17, 28, 12], also known as affinity-based methods, estimate alpha mattes by propagating the alpha value from foreground and background pixels to the unknown area.

Recently, deep learning based approaches have achieved great success in natural image matting. [33] created a matting dataset with annotated mattes composited to various background images, and trained a deep network on it. Later, [23] introduced a generative adversarial framework to improve the results. [29] proposed to combine the sampling-based method and deep learning. [22] introduced a new index-guided upsampling and unpooling operations to better keep details in the predictions. [13] proposed a two-encoder two-decoder architectures to simultaneous estimate foreground and alpha. [18] further boost the performance with a contextual attention module.

Trimap-free Image Matting. It is noticeable that there are also some trials [1, 27] to get rid of the trimap to predict alpha matte. [36] proposed a framework consisting of a segmentation network and a fusion network, where the input is only a single RGB image. Later, [20] introduced a trimap-free framework consisting of mask prediction network, quality unification network, and matting refinement network for human portrait matting. The trimap-free matting performance is further boosted with attention module [24]. However, these trimap-free methods still have some gap to trimap-based ones in terms of performance. Another direction is to use an alternative guidance to trimap. [25] introduced a framework taking background images along with other potential priors (e.g., segmentation mask, motion cue) as additional inputs. It shows great potential and can obtain a comparable performance to state-of-the-art trimap-based methods.

Foreground Color Decontamination. Many conventional matting methods [8, 16] proposed to predict both alpha matte and foreground color for extracting foreground objects. However, it is only very recently [13] incorporated the foreground prediction into the deep learning framework. Later, [25] also predicts foreground color to reduces artifacts for a better composition result. Nevertheless, these methods mainly add a foreground decoder and directly learn from color label in [33], which only provides limited training samples and, more seriously, the color labels can be in-
accurate and noisy (see Fig. 3).

Our method differs from algorithms mentioned above in the following folds: 1) Our model works in a more general setting where only an easy-to-obtain coarse mask, no matter user-defined or model-predicted, is needed as guidance. It could handle different qualities and even various types of guidance as input. Thus it could be used as either trimap-based or trimap-free model depends on what guidance is available. Our model could also leverage a stronger guidance to achieve even finer details. 2) Our methods could also predict the foreground color. Unlike [13], where the foreground prediction is directly learned from the color label, we note that the limited training data and inaccurate human label result in undesired results especially in the boundary regions. Instead, we propose to use Random Alpha Blending to avoid the bias in label, which not only introduces more diverse training samples but also avoid the inaccurate color label locating in boundary regions.

3. MG Matting

The problem of image matting can be formulated as:

$$I = \alpha F + (1 - \alpha)B, \alpha \in [0, 1],$$

where $I$, $F$, $B$, and $\alpha$ refer to the image color, foreground color, background color and alpha matte respectively. As only $I$ is observed, this is a very ill-posed problem. To solve the matting problem, most methods require a trimap input, which labels the foreground region (i.e., $\alpha = 1$), the background region (i.e., $\alpha = 0$) and the unknown part. In practice, the trimap input can contain various levels of noise and errors, making the matting results inconsistent.

We relax the strong assumption of the trimap by proposing a Mask Guided Matting method. The mask guidance, such as a predicted segmentation mask or a rough manual selection, only provides a coarse spatial prior of the foreground region. Therefore, our MG Matting method needs more high-level semantic understanding of the input mask, so that it can detect the foreground/background region and the soft transparent part robustly. Meanwhile, our model has to capture image low-level patterns such as edge and texture to produce fine details of the target matte. Coordinating the high-level and the low-level feature learning is the key to the design of our MG Matting method.

To this end, we introduce Progressive Refinement Network (PRN), which provides a coarse-to-fine self-guidance to progressively refine the uncertain regions during the decoding process. In the following, we present the details of PRN, the training formulation and some data augmentation techniques to enhance the robustness of our model.

3.1. Progressive Refinement Network

An overview of the PRN is shown in Fig. 2. The structure of our PRN follows the popular encoder-decoder network with skip connections. Our network takes an image and a coarse mask as input and outputs a matte. During the decoding process, PRN has a side matting output at each feature level. The side outputs with deep supervision have been shown to improve the feature learning at different scales [32]. However, unlike [32], we find that linearly fusing the side outputs is not ideal for the matting problem (see Table 4 for details). This is because image region closer to the object boundary requires lower-level features to delineate the foreground, while identifying internal object regions needs higher-level guidance.

To address this problem, we introduce a Progressive Refinement Module (PRM) at each feature level to selectively fuse the matting outputs from the previous level and the cur-
rent level. Specifically, for the current level $l$ we generate a self-guidance mask $g_l$ from the matting output $\alpha_{l-1}$ of the previous level using the following function:

$$f_{\alpha_{l-1} \rightarrow g_l}(x, y) = \begin{cases} 1 & \text{if } 0 < \alpha_{l-1}(x, y) < 1, \\ 0 & \text{otherwise}. \end{cases}$$ (2)

The $\alpha_{l-1}$ is firstly upscaled to match the size of the raw matting output $\alpha'_l$ of the current level and then produces resultant self-guidance mask $g_l$. The self-guidance mask basically defines the transparent region ($i.e., 0 < \alpha < 1$) as unknown and replaces the unknown region of $\alpha_{l-1}$ with the current raw output $\alpha'_l$ to obtain an updated output $\alpha_l$ of current level:

$$\alpha_l = \alpha'_l g_l + \alpha_{l-1}(1 - g_l).$$ (3)

In this way, confident regions predicted from the previous higher-level features are preserved and the current level only needs to focus on refining the uncertain region.

In practise, we obtain alpha matte side outputs at three feature levels of stride 8, 4, and 1 respectively (see Fig. 2) and slightly dilate the self-guidance masks for a more robust self-guidance. The initial base matte of $1/8$ image size will be progressively upscaled and refined, and the uncertain regions will also shrink gradually through the decoding process using the proposed PRM. The full network is trained end-to-end to auto-balance the refinement focus at multiple feature levels. Such self-guided refinement also makes model less reliant on the external mask guidance, leading to more robust matting performance.

**Training scheme.** For loss functions, we adopt the $l_1$ regression loss, composition loss [33], Laplacian loss [13] and denote them as $L_{l_1}$, $L_{comp}$, $L_{lap}$ respectively. We represent the ground truth alpha with $\hat{\alpha}$ and prediction alpha with $\alpha$. The overall loss functions is the summation of them:

$$L(\hat{\alpha}, \alpha) = L_{l_1}(\hat{\alpha}, \alpha) + L_{comp}(\hat{\alpha}, \alpha) + L_{lap}(\hat{\alpha}, \alpha).$$ (4)

The loss is applied to each output head of the network. To make the training more focused on the unknown region, we further modulate the loss with $g_l$. The final loss function can be formulated as:

$$L_{final} = \sum_{l} w_l L(\hat{\alpha}_l \cdot g_l, \alpha_l \cdot g_l),$$ (5)

where $w_l$ is the loss weight assigning to the outputs of different levels. We use $w_0 : w_1 : w_2 = 1 : 2 : 3$ in our experiments. $g_l$ is generated from $\alpha_{l-1}$ by Eqn. 2, and $g_0$ is a mask filled with one so that the base level output can be supervised over the whole image to provide more holistic semantic guidance for the next level output.

For data augmentation, we follow the training protocol proposed in [18], including random composite two foreground object images, random resize images with random interpolation methods, random affine transformation, color jitters. We random crop $512 \times 512$ patches centered on an unknown region for training. Each patch is composited to a random background image from MS COCO dataset [19].

**Guidance Perturbation.** To ensure that our model can adapt to guidance masks from different sources and with different qualities, we propose a series of guidance perturbation to generate masks from ground-truth alpha matte during training. Given a ground-truth alpha matte, we first binarize it with a random threshold uniformly sampled from 0 to 1. Then, the mask is dilated and/or eroded in random order with random kernel sizes from 1 to 30.

Moreover, we provide a stronger guidance perturbation named CutMask to further improve the model robustness. Inspired by the successful natural image augmentation CutMix [34], we randomly select a patch size ranging from 1/4 to 1/2 image size. Then, two random patches of the guidance are selected and the content of one patch will overwrite another. This stronger perturbation provides additional localized guidance mask corruption, making the model more robust to semantic noises in external guidance masks.

Besides perturbing external guidance masks, we note that perturbing internal self-guidance mask is also very important to improve the robustness. Therefore, we randomly dilate the self-guidance masks to incorporate more variance. Particularly, during training, the self-guidance mask from output stride 8 is dilated by $K_1$ random sampled from [1, 30] and the one from output stride 4 is dilated by $K_2$ from [1, 15]. For testing, we fix $K_1 = 15$ and $K_2 = 7$.

### 3.2. Foreground Color Estimation

As indicated in Eqn. 1, both alpha matte and foreground color need to be solved for foreground object extraction. Nevertheless, only a few matting methods learn to predict the foreground color [15, 25] and all of them used the popular Composition-1k dataset [33] for training.

However, there are a couple of issues in the Composition-1k dataset. First of all, this dataset only contains 431 foreground images with matting and foreground

Figure 3: The color labels in the commonly used training data from [33] are noisy and inaccurate especially near the boundary part. Note that the hair near the ear falsely gets pinker. Best viewed in color and zoomed in.
Denote the corresponding guidance inputs, i.e., TrimapFG, Trimap. The other evaluated methods all require a trimap as input.

color ground truth, which is quite limited to train a foreground color model. Moreover, the foreground color labels, which were estimated using the color decontamination feature in Photoshop [33], are sometimes noisy and inaccurate near the boundary regions (see Fig. 3). This can introduce color spills and other artifacts into the images during data augmentation process, making the learning less stable. Besides, labels are only provided where the alpha value is greater than zero, so existing methods can only apply supervision to the foreground region [13], leading to unstable behaviors in the undefined part.

To address these issues, we propose a simple yet effective method, named Random Alpha Blending (RAB), to generate synthetic training data by blending a foreground image and a background image using a randomly selected alpha matte. Although the composited images may not be semantically meaningful, they can provide accurate and unbiased foreground color labels in the transparent region. The random alpha blending can also significantly make training data more diverse and improve the generalization of the foreground color prediction. Besides, we also note that RAB makes it possible to apply loss supervision over all image, leading to a much smoother prediction which is desired for robust compositing. (See Fig. 4)

For the foreground color prediction, we train a separate model using a basic encoder-decoder network, with takes an image and an alpha matte as input. The loss function is the summation of $l_1$ regression loss, compositing loss, and Laplacian loss. We note that although training a single model for both matte and foreground color prediction is possible, empirically this will degrade the matting performance [13], and the random alpha blending will destroy the semantic cue for the matting model. In addition, decoupling foreground color prediction from matting can make the color model transferable to the use cases where the matte is already given.

### 4. Experiments on Synthetic Datasets

In this section, we report the evaluation results of our method under the traditional synthetic data setting, where the test images are generated using foreground images with ground truth mattes and random background images.

**Evaluation Metrics.** We follow previous methods to evaluate the results by Sum of Absolute Differences (SAD), Mean Squared Error (MSE), Gradient (Grad) and Connectivity (Conn) errors using the official evaluation code [33].

**Network Architectures.** We adopt ResNet34-UNet proposed in [18] with an Atrous Spatial Pyramid Pooling (ASPP) [3] as the backbone for both PRN and color prediction. The first convolution layer is adjusted to take a 4-channel input consisting of a RGB image along with an external guidance input. Moreover, an alpha prediction head (Conv-BN-ReLU-Conv) is attached to the features at output stride 4 and 8 respectively to obtain side outputs.

**Training stage.** To fairly compare with previous deep image matting methods, we train our MG Matting model using the Composition-1k dataset [33] which contains 431 foreground objects and the corresponding ground-truth alpha mattes for training. The network is initialized with ImageNet [6] pre-trained weight. We use crop size 512, batch size of 40 in total on 4 GPUs, Adam optimizer with $\beta_1 = 0.5$ and $\beta_2 = 0.999$. The learning rate is initialized to $1 \times 10^{-3}$. The training lasts for 100,000 iterations with warm-up at the first 5,000 iterations and cosine learning rate decay [21, 9]. We also apply a curriculum learning manner to help the PRN training. Particularly, for the first 5,000 iterations, the predictions of output stride 4 and 1 will be guided by guidance mask generated from ground-truth alpha, and for the next 10,000 iterations, the guidance will be evenly and randomly generated from self-prediction and ground-truth alpha. Afterwards, each alpha prediction

Table 1: Results on Composition-1k test set. The subscripts denote the corresponding guidance inputs, i.e. TrimapFG, Trimap. The other evaluated methods all require a trimap as input.

| Methods                        | SAD (Mean) | MSE (10^-3) | Grad | Conn |
|-------------------------------|-----------|-------------|------|------|
| Learning Based Matting        | 113.9     | 48          | 91.6 | 122.2|
| Closed-Form Matting [16]      | 168.1     | 91          | 126.9| 167.9|
| KNN Matting [4]               | 175.4     | 103         | 124.1| 176.4|
| Deep Image Matting [33]       | 50.4      | 14          | 31.0 | 50.8 |
| IndexNet Matting [22]         | 45.8      | 13          | 25.9 | 43.7 |
| AdaMatting [2]                | 41.7      | 10.2        | 16.9 | -    |
| Context-Aware Matting [13]    | 35.8      | 8.2         | 17.3 | 33.2 |
| GCA Matting [18]              | 35.3      | 9.1         | 16.9 | 32.5 |
| Ours TrimapFG                  | 31.5      | 6.8         | 13.5 | 27.3 |
| Ours Trimap                   | 32.1      | 7.0         | 14.0 | 27.9 |

Table 2: Matting refinement results on Distinction-646 test set. Results with * are from methods trained on Distinction-646 train set as reported in [24] for reference. Other results are only trained on composition-1k.

| Methods                        | SAD (Mean) | MSE (10^-3) | Grad | Conn |
|-------------------------------|-----------|-------------|------|------|
| Learning Based Matting* [37]  | 105.04    | 21          | 94.16| 110.41|
| Closed-Form Matting* [16]     | 105.73    | 23          | 91.76| 114.55|
| KNN Matting* [4]              | 116.68    | 25          | 103.15| 121.45|
| Deep Image Matting* [33]      | 47.56     | 9           | 43.29| 55.90 |
| HAAttMatting* [24]            | 48.98     | 9           | 41.57| 49.93 |
| IndexNet Matting [22]         | 48.73     | 11.2        | 42.60| 49.55 |
| + Ours                        | 36.58     | 7.2         | 27.37| 35.08 |
| Context-Aware Matting [13]    | 35.82     | 5.8         | 25.75| 34.23 |
| + Ours                        | 36.32     | 7.1         | 29.49| 35.43 |
| GCA Matting [18]              | 35.04     | 5.4         | 24.55| 33.35 |
| + Ours                        | 39.64     | 8.2         | 32.16| 36.77 |
| Ours Trimap                   | 35.93     | 5.7         | 25.94| 34.35 |

We follow previous methods to evaluate the results by Sum of Absolute Differences (SAD), Mean Squared Error (MSE), Gradient (Grad) and Connectivity (Conn) errors using the official evaluation code [33].
Table 3: The foreground result ($\alpha \cdot F$) on the Composition-1k dataset.

| Methods              | SAD      | MSE      |
|----------------------|----------|----------|
|                      |          | ($10^{-3}$) |
| Global Matting [11]  | 220.39   | 36.29    |
| Closed-Form Matting [16] | 254.15   | 40.89    |
| KNN Matting [4]      | 281.92   | 36.29    |
| Context-Aware Matting [13] | 61.72    | 3.24     |
| Ours                 | 49.80    | 2.48     |

Testing on Composition-1k. The test set consists of 50 unique objects which are composited with 20 background images chosen from Pascal VOC [7], thus providing 1000 test samples in total. We note that since these synthetic datasets use PASCAL VOC images as background which may contain other salient objects, saliency/segmentation models may not be applicable to obtain a reasonable coarse mask. To best fairly compare MG Matting with other trimap-based methods, we test our model under two settings: 1) TrimapFG: We adopt the confident foreground regions in a trimap as a coarse guidance mask for our network; 2) Trimap: We normalize trimap to $[0, 1]$ with the unknown pixels being 0.5 and use this soft mask as guidance. We follow the the evaluation setting in Composition-1k which only computes the evaluation on the unknown region.

We summarize the alpha results and foreground color results in Table 1 and Table 3 respectively. We note that although our model is not trained with trimap, it still shows great robustness and transferability on these unseen types of guidance. Our model surpasses previous state-of-the-art models by a large margin. It also performs consistently considering the gap between trimap and trimapFG. We also note that our foreground color prediction not only reduces the errors significantly, but also produces much smoother results (see Fig. 4), which is desired in complex real-world scenarios where alpha matte can be noisy.

Testing on Distinction-646. Distinction-646 [24] is a recent synthetic matting benchmark dataset, which improves the diversity of Composition-1k. It contains 1000 test samples obtained in a similar manner as Composition-1k. However, this dataset is released without official trimaps or other types of guidance, making it difficult to compare with previously reported results. Therefore, we use this benchmark mainly as a testbed to show how our method can refine a matte produced by another method.

We test a few state-of-the-art trimap-based baselines trained on Composition-1k. We firstly generate trimaps from ground-truth alpha mattes by thresholding and unknown region is dilated by kernel size 20. Then, we use these trimap-based methods to generate the matting results. Finally, we use these predicted alpha mattes as the guidance to our MG Matting method, and produce refined mattes.

As shown in Table 2, using the MG Matting as a refinement method consistently improves the results of other state-of-the-art methods. We also show the results reported by [24] in Table 2 for reference.
Ablation Studies. To validate the design of PRN and the introduced guidance perturbation, we conduct ablations studies as summarized in Table 4. Trimap is used as guidance masks in these experiments. However, we do not assume that the guidance type is known, so we purposefully do not use it to post-process the prediction by replacing the known foreground and background region. Instead, we report the two scores calculated over the whole image and the unknown region respectively for a more comprehensive evaluation of the robustness of our method.

We report performance of different variants in Table 4. Baseline refers to a pure backbone without any add-ons. Adding side outputs and deep supervision to baseline can already improve the performance on both whole image or unknown area. We also try to use two convolution layers to fuse different outputs. However, linearly fusing the side outputs may not lead to better results. In contrast, the proposed PRN can better coordinate the semantic refinement and low-level detail refinement at different levels, thus obtaining a consistent improvement. We also show that the CutMask perturbation can further improve both the performance and robustness.

We also validate the effectiveness of RAB. We calculate the MSE and SAD of foreground color ($F$) over foreground regions (i.e. $\alpha > 0$). The baseline achieves $\text{MSE} = 0.00623$ and $\text{SAD} = 82.30$, while with RAB, the performance is boosted to $\text{MSE} = 0.00321$ and $\text{SAD} = 62.01$.

5. Experiments on Real-world Portrait Dataset

We note that although the synthetic datasets are well-established benchmarks and provide sufficient data to train a good model, it remains an open question whether models trained on them are robust enough and can produce comparable results in real images. For example, [13] found that some easy data augmentations such as re-JPEGing and gaussian blur can avoid some shortcomings of the synthetic dataset and significantly improve the model’s performance on real-world images, though at a cost of higher errors on the synthetic benchmark. This begs the question: can the
**Implementation Details.** We use the Composition-1k training set to train the model. Considering the semantic gap between the two datasets, we remove the transparent objects from the training data using the data list of [25]. Following [13], we also apply re-JEPGing, gaussian blur, and gaussian noises to the input image to make the model better adapt to real-world noises which are rarely seen in the synthetic dataset. Since these augmentations can change the color of the composited training image, thus the original color label may not be applicable. Therefore, we remove the composition loss from the supervision. Other training settings remain the same as in Sec. 4.

For trimap-based baselines, we follow [25] to generate trimaps from segmentation [35] automatically by labeling each pixel with foreground class probability $> 0.95$ as foreground, $< 0.05$ as background, and the rest as unknown. The unknown region is further dilated by $k = 20$ to ensure it will not miss the long hairs. For our model, we threshold the segmentation at $\text{prob} = 0.5$ to a binary mask.

**Results.** We compare the results with state-of-the-art trimap-based methods DIM [33], GCA [18], IndexNet [22], Context-Aware Matting [13], and trimap-free method Late Fusion Matting [36] which is trained on Composition-1k training set and an additional portrait dataset. The results of baselines are obtained through either the open-source inference demos or the provided pre-trained weights.

We summarize the results in Table 5 under two settings: Whole Image, where the errors are calculated across the whole image, which can measure the overall quality; Details, where the errors are calculated only in manual-labeled regions containing hair details or other soft areas.

Compared to other methods, our model can achieve a superior performance, especially regarding to the detail part, which illustrates the ability of our model to capture the boundary details. We also note that the trimap-free method LFM performs badly, which could be caused by the fact that their portrait training data is not diverse enough and thus limits the the generalizability of their model (see Fig. 5 for examples).

We also compare our results with another trimap-free method BSHM [20]. We contacted the authors and obtained the test results on a 100 images subset of our portrait dataset. Since [20] can only deal with low-resolution images, we downsample images to longer-side 720, and the metrics are also computed on this scale. [20] achieves MSE $0.0155$ and $\text{SAD}$ $10.66$ for whole image and MSE $0.0910$ and SAD $7.60$ for detail regions, while our MG Matting obtains a superior performance with MSE $0.0095$ and SAD $8.01$ for whole image and MSE $0.0637$ and SAD $5.94$ for details.

**Robustness to Guidance.** To verify how robust our model is to the external guidance mask, we conduct an experiment to feed the network with perturbed external guidance mask. Particularly, we erode/dilate the mask with kernel size $10, 20, 30$ respectively. We note that the model predict consistently given differently perturbed external guidance. The SAD error increases from $26.8$ to $27.1, 27.2, 27.4$ with mask eroded by $10, 20, 30$ respectively. For dilation, the SAD error goes to $27.0, 27.4, 28.1$ with kernel $10, 20, 30$ respectively. A visual example is provided in Fig. 6.

**6. Conclusion**

In this paper, we present Mask Guided (MG) Matting, a general framework to resolve the natural image matting problems.
problem. Unlike previous methods, our method is not tailored to some specific guidance mask. Instead, it can handle versatile guidance masks such as a trimap, a rough segmentation mask, or a low-quality alpha matte. The key of the robustness of our model lies in the Progressive Refinement Network, which provides self-guidance and progressively refine the uncertain regions during the decoding process. Further, we also propose a simple yet effective method called Random Rendering to resolve the limitation of existing dataset and learn a better foreground color estimation model, which is important yet rarely studied before. Moreover, we release a new real-world matting dataset with high-quality label to better quantitatively evaluate matting models in a real-world scenario, which we hope could shed some light on the direction towards a real-life matting.

References

[1] Yağiz Aksoy, Tae-Hyun Oh, Sylvain Paris, Marc Pollefeys, and Wojciech Matusik. Semantic soft segmentation. *ACM Transactions on Graphics (TOG)*, 37(4):1–13, 2018. 2

[2] Shaofan Cai, Xiaoshuai Zhang, Haoqiang Fan, Haibin Huang, Jiangyu Liu, Jiaming Liu, Jiaying Liu, Jue Wang, and Jian Sun. Disentangled image matting. In *ICCV*, pages 8819–8828, 2019. 5

[3] Liang-Chieh Chen, George Papandreou, Iasonas Kokkinos, Kevin Murphy, and Alan L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *TPAMI*, 40(4):834–848, 2017. 5

[4] Qifeng Chen, Dingzeyu Li, and Chi-Keung Tang. Knn matting. *TPAMI*, 35(9):2175–2188, 2013. 2, 5, 6

[5] Yung-Yu Chuang, Brian Curless, David H Salesin, and Richard Szeliski. A bayesian approach to digital matting. In *CVPR*, volume 2, pages II–II. IEEE, 2001. 2

[6] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. ImageNet: A large-scale hierarchical image database. In *CVPR*, pages 248–255. Ieee, 2009. 5

[7] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. In *IJCV*, 88(2):303–338, 2010. 6

[8] Eduardo SL Gastal and Manuel M Oliveira. Shared sampling for real-time alpha matting. In *Computer Graphics Forum*, volume 29, pages 575–584. Wiley Online Library, 2010. 2

[9] Priya Goyal, Piotr Dollár, Ross Girshick, Pieter Noordhuis, Lukasz Wesolowski, Aapo Kyrola, Andrew Tulloch, Yangqing Jia, and Kaiming He. Accurate, large mini-batch sgd: Training imagenet in 1 hour. arXiv preprint arXiv:1706.02677, 2017. 5

[10] Vikas Gupta and Shanmuganathan Raman. Automatic trimap generation for image matting. In *2016 International Conference on Signal and Information Processing (IC-SPIP)*, pages 1–5. IEEE, 2016. 1

[11] Kaiming He, Christoph Rhemann, Carsten Rother, Xiaou Tang, and Jian Sun. A global sampling method for alpha matting. In *CVPR*, pages 2049–2056. IEEE, 2011. 2, 6

[12] Kaiming He, Jian Sun, and Xiaou Tang. Fast matting using large kernel matting laplacian matrices. In *CVPR*, pages 2165–2172. IEEE, 2010. 2

[13] Qiqi Hou and Feng Liu. Context-aware image matting for simultaneous foreground and alpha estimation. In *ICCV*, pages 4130–4139, 2019. 1, 2, 3, 4, 5, 6, 7, 8, 11, 13, 14, 15

[14] Chang-Lin Hsieh and Ming-Sui Lee. Automatic trimap generation for digital image matting. In *2013 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference*, pages 1–5. IEEE, 2013. 1

[15] Philip Lee and Ying Wu. Nonlocal matting. In *CVPR*, pages 2193–2200. IEEE, 2011. 2

[16] Anat Levin, Dani Lischinski, and Yair Weiss. A closed-form solution to natural image matting. *TPAMI*, 30(2):228–242, 2007. 1, 2, 5, 6, 11

[17] Anat Levin, Alex Rav-Acha, and Dani Lischinski. Spectral matting. *TPAMI*, 30(10):1699–1712, 2008. 2

[18] Yaoyi Li and Hongtao Lu. Natural image matting via guided contextual attention. In *AAAI*, volume 34, pages 11450–11457, 2020. 1, 2, 4, 5, 7, 8, 13, 14, 15

[19] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *ECCV*, pages 740–755. Springer, 2014. 4

[20] Jinlin Liu, Yuan Yao, Wendi Hou, Miaomiao Cui, Xuan Song Xie, Changshui Zhang, and Xian-sheng Hua. Boosting semantic human matting with coarse annotations. In *CVPR*, pages 8563–8572, 2020. 1, 2, 8

[21] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *ICLR*, 2017. 5

[22] Hao Lu, Yutong Dai, Chunhua Shen, and Songcen Xu. Indices matter: Learning to index for deep image matting. In *ICCV*, pages 3266–3275, 2019. 2, 5, 7, 8, 13, 14, 15

[23] Sebastian Lutz, Konstantinos Amplianitis, and Aljosa Smolic. Alphagan: Generative adversarial networks for natural image matting. *BMVC*, 2018. 2

[24] Yu Qiao, Yuhao Liu, Xin Yang, Dongsheng Zhou, Mingliang Xu, Qiang Zhang, and Xiaopeng Wei. Attention-guided hierarchical structure aggregation for image matting. In *CVPR*, pages 13676–13685, 2020. 1, 2, 5, 6

[25] Soumyadip Sengupta, Vivek Jayaram, Brian Curless, Steven M Seitz, and Ira Kemelmacher-Shlizerman. Background matting: The world is your green screen. In *CVPR*, pages 2291–2300, 2020. 1, 2, 5, 8

[26] Ehsan Shahriari, Deepu Rajan, Brian Price, and Scott Cohen. Improving image matting using comprehensive sampling sets. In *CVPR*, pages 636–643, 2013. 2

[27] Xiaoyong Shen, Xin Tao, Hongyun Gao, Chao Zhou, and Jiaying Liu. Semantic soft segmentation. In *CVPR*, pages 248–255, 2009. 5

[28] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *ECCV*, pages 740–755. Springer, 2014. 4

[29] Jinlin Liu, Yuan Yao, Wendi Hou, Miaomiao Cui, Xuan Song Xie, Changshui Zhang, and Xian-sheng Hua. Boosting semantic human matting with coarse annotations. In *CVPR*, pages 8563–8572, 2020. 1, 2, 8

[30] Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. *ICLR*, 2017. 5

[31] Hao Lu, Yutong Dai, Chunhua Shen, and Songcen Xu. Indices matter: Learning to index for deep image matting. In *ICCV*, pages 3266–3275, 2019. 2, 5, 7, 8, 13, 14, 15

[32] Sebastian Lutz, Konstantinos Amplianitis, and Aljosa Smolic. Alphagan: Generative adversarial networks for natural image matting. *BMVC*, 2018. 2

[33] Yu Qiao, Yuhao Liu, Xin Yang, Dongsheng Zhou, Mingliang Xu, Qiang Zhang, and Xiaopeng Wei. Attention-guided hierarchical structure aggregation for image matting. In *CVPR*, pages 13676–13685, 2020. 1, 2, 5, 6

[34] Soumyadip Sengupta, Vivek Jayaram, Brian Curless, Steven M Seitz, and Ira Kemelmacher-Shlizerman. Background matting: The world is your green screen. In *CVPR*, pages 2291–2300, 2020. 1, 2, 5, 8

[35] Ehsan Shahriari, Deepu Rajan, Brian Price, and Scott Cohen. Improving image matting using comprehensive sampling sets. In *CVPR*, pages 636–643, 2013. 2

[36] Xiaoyong Shen, Xin Tao, Hongyun Gao, Chao Zhou, and Jiaying Liu. Deep automatic portrait matting. In *ECCV*, pages 92–107. Springer, 2016. 2

[37] Jian Sun, Jiaya Jia, Chi-Keung Tang, and Heung-Yeung Shum. Poisson matting. In *Siggraph*, pages 315–321, 2004. 2

[38] Jingwei Tang, Yagiz Aksoy, Cengiz Oztireli, Markus Gross, and Tunc Ozan Aydin. Learning-based sampling for natural image matting. In *CVPR*, pages 3055–3063, 2019. 2
[30] Jue Wang and Michael F Cohen. Optimized color sampling for robust matting. In CVPR, pages 1–8. IEEE, 2007.

[31] Jue Wang and Michael F Cohen. Image and video matting: a survey. Now Publishers Inc, 2008.

[32] Saining Xie and Zhuowen Tu. Holistically-nested edge detection. In ICCV, pages 1395–1403, 2015.

[33] Ning Xu, Brian Price, Scott Cohen, and Thomas Huang. Deep image matting. In CVPR, pages 2970–2979, 2017.

[34] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Youngjoon Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. In ICCV, pages 6023–6032, 2019.

[35] He Zhang, Jianming Zhang, Federico Perazzi, Zhe Lin, and Vishal M Patel. Deep image compositing. WACV, 2021.

[36] Yunke Zhang, Lixue Gong, Lubin Fan, Peiran Ren, Qixing Huang, Hujun Bao, and Weiwei Xu. A late fusion cnn for digital matting. In CVPR, pages 7469–7478, 2019.

[37] Yuanjie Zheng and Chandra Kambhamettu. Learning based digital matting. In ICCV, pages 889–896. IEEE, 2009.
7. Supplementary

In this supplementary material, we provide more details of our portrait dataset with some examples, and more details of our foreground prediction network along with a more comprehensive and fair comparison between different methods.

Besides, we include more visualizations and some video demos, which illustrate the our model can potentially work with an image/video segmentation network to realize high-quality video matting.

7.1. Our Portrait Dataset Details

Compared to previous publicly available datasets, our dataset is much more various and challenging in terms of resolution, image quality, and object poses or angles. E.g., around 1/5 of the images are in 2k resolution, and half of the images are larger than 1k. In comparison, previous real-world matting images are often smaller than 1k resolution. Besides, we not only include images with great variance in image quality and poses, but also provide a detail map to better evaluate the model’s ability to capture details (See Fig. 7 for examples).

7.2. Foreground Color Prediction

Foreground color prediction, though rarely studied in deep learning methods before, is necessary for a more plausible matting result (see Fig. 8). Here we provide more details of our foreground color prediction network. The network takes an RGB image along with an alpha matte as input. During training time, we generate the alpha matte from ground truth by perturbing it with linear contrast from 0.6 to 1.4, JPEG compression with degree from 0 to 60, gaussian blur with sigma from 0 to 3.0, and additive gaussian noises with scale from 0 to 0.1 * 255. We note that by training with perturbed ground truth alpha, the foreground prediction network can be model-agnostic and more robust to the input alpha matte.

Besides, we note that comparison of foreground estimation following [13] may be unfair. Since it computes SAD and MSE of $\alpha \cdot F$ in unknown regions, the improvement can be from a more accurate alpha matte estimation instead of a better foreground color prediction. Therefore, we provide an additional comparison in Table 6, where the errors are calculated of $F$ directly on regions ground-truth $\alpha > 0$. We note that this setting provides a more comprehensive comparison and illustrates the advantages of our method. We use the same alpha matte predictions of our model as inputs for both Closed-Form Matting [16] and Ours to control the variables.

7.3. More Visualizations

We provide more visual comparison with other state-of-the-art matting methods on internet images. The guidance mask and trimap are generated as described in Sec. 5 based on segmentation prediction of [35]. It is shown that MG Matting achieves superior performance to baselines especially on details.

We also include some video demos to show our model’s potential to work on video matting.

| Methods                     | SAD  | MSE ($10^{-4}$) |
|-----------------------------|------|-----------------|
| Closed-Form Matting [16]    | 126.33 | 21.50           |
| Context-Aware Matting [13]  | 122.43 | 10.98           |
| Ours - baseline             | 82.30  | 6.23            |
| Ours - RAB                  | **62.01** | **3.21**       |

Table 6: The foreground result ($F$) on the Composition-1k dataset. The evaluation is done on regions where ground-truth $\alpha > 0$. 
Figure 7: Examples of our portrait dataset. (4 groups, for each group from left to right: Image, ground-truth, detail map.)

Figure 8: Even for solid objects like human portraits, color decontamination is necessary since directly using the original image as foreground may not be optimal (Note in the middle image golden color is mixed into the hair and also the boundary is not natural).
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |
|-------|----------|----------|------------|----------|---------|-----------|
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |
| Image | LFM [36] | DIM [33] | Index [22] | GCA [18] | CA [13] | MG (Ours) |

Figure 9: Visual Comparison on Internet Images.
Figure 10: Visual Comparison on Internet Images.
Figure 11: Visual Comparison on Internet Images.