Privileged Prior Information Distillation for Image Matting

Cheng Lyu1*, Jiake Xie2*, Bo Xu3*,†, Cheng Lu3, Han Huang4, Xin Huang5, Ming Wu1, Chuang Zhang1, Yong Tang2
1Beijing University of Posts and Telecommunications
2PicUp.Ai
3Xpeng
4AI2 Robotics
5Towson University
{lvccheng, wuming, zhangchuang}@bupt.edu.cn, {jxie,ty}@road.win, Xhuang@towson.edu

Abstract
Performance of trimap-free image matting methods is limited when trying to decouple the deterministic and undetermined regions, especially in the scenes where foregrounds are semantically ambiguous, chromaless, or high transmittance. In this paper, we propose a novel framework named Privileged Prior Information Distillation for Image Matting (PPID-IM) that can effectively transfer privileged prior environment-aware information to improve the performance of trimap-free students in solving hard foregrounds. The prior information of trimap regulates only the teacher model during the training stage, while not being fed into the student network during actual inference. To achieve effective privileged cross-modality (i.e. trimap and RGB) information distillation, we introduce a Cross-Level Semantic Distillation (CLSD) module that reinforces the students with more knowledgeable semantic representations and environment-aware information. We also propose an Attention-Guided Local Distillation module that efficiently transfers privileged local attributes from the trimap-based teacher to trimap-free students for the guidance of local-region optimization. Extensive experiments demonstrate the effectiveness and superiority of our PPID on image matting. The code will be released soon.

1 Introduction
Image matting is one of the most fundamental computer vision tasks, which aims to separate the foreground objects from a single image or video stream. It has tremendous practical value for background replacement task in multimedia applications such as image/video entertainment creation, special-effect film-making and live video. To accurately estimate the opacity of each pixel inside foreground regions, the matting is generally formulated as an image/video frame composite problem, which solves the 7 unknown variables per pixel from only 3 known values:

\[ I_i = \alpha_i F_i + (1 - \alpha_i) B_i, \quad \alpha_i \in [0, 1] \]  \hspace{1cm} (1)

where \( I_i \) refers to known 3-dimensional RGB color at pixel \( i \), while foreground RGB color \( F_i \), background RGB color \( B_i \), and alpha matte estimation \( \alpha_i \) are unknown. According to the above equation, \( \alpha_i = 1, \alpha_i = 0 \), and \( \alpha_i \in (0, 1) \) represent the deterministic foreground, background, and undetermined regions, respectively.

To solve this highly challenging problem, the typical methods (Xu et al. 2017; Hou and Liu 2019; Lu et al. 2019; Li and Lu 2020; Liu et al. 2021) utilize trimap as a piece of environment-aware priori that marks the foreground, background and transition regions to locate the targets and reduce the solution spaces. Unfortunately, a high-quality trimap can not be obtained without tedious manual annotation effort and significant time costs, which limits its practical application in low-cost consumer products. Some trimap-free methods (Zhang et al. 2019; Qiao et al. 2020) are proposed to utilize the typical encoder-to-decoder structures that stem from segmentation and detection, etc., for alpha prediction without auxiliary cues. Although environmental saliency can be roughly predicted by borrowing such transitional network structure and its pre-trained feature, there still remain two tricky challenges in the trimap-free matting setting. First, previous trimap-free matting methods may fail to identify certain attributes when the foreground is semantically ambiguous, chromaless, or with high transmittance. For example in Row 2 of Fig. 1, due to the lack of strong opaqueness and color hue difference, the previous trimap-free net-

Figure 1: Given challenging images of chromaless objects and semantically ambiguous scenes, one SOTA trimap-free matting approach - LFM (Zhang et al. 2019), fails to decouple the deterministic and undetermined regions. However, our PPID-guided model can perform more accurate and fine-grained region decoupling for these hard foregrounds.
work (Zhang et al. 2019) fails to decouple the deterministic and undetermined regions of this highly transmissive ‘glass ball’. That is especially obvious in those upper pixels where the networks are confused by the background (sky) with similar colors.

Second, for most of the existing trimap-free models, the learning of semantic mining often stems from upstream tasks such as segmentation. However, they may fail to identify the complete and meaningful foregrounds when such foregrounds are semantically ambiguous, rare, or spatially sparse, i.e., the cobweb in Row 1 of Fig. 1. Although several current methods try to construct pseudo-trimap or implicitly learn the transition region distribution as a decoupling effort by imposing local supervision on RGB features, they may fail to balance global and local matting quality (i.e., texture similarity, location correlation, etc.) which leads to incomplete information mining.

To address the above challenges, we propose a novel Privileged Prior Information Distillation framework for Image Matting (PPID-IM). Our PPID-IM framework can effectively transfer privileged environment-aware prior information to improve the trimap-free models, leading to 1) more accurate region decoupling for hard foregrounds which are chromaless or with high transmittance 2) better balance between global and local matting quality. We rethink trimap-free matting via privileged information distillation, with the following motivations: a) Trimap provides critical environment-aware information which the trimap-free models may lack and focuses on the undetermined regions with semantic ambiguity and poor color hue. Consequently, it can be formulated as a privileged modality in the knowledge distillation framework. b) Due to the successes of privileged information (i.e., features, extra modalities, etc.) distillation in multiple tasks, i.e., image classification (Lopez-Paz et al. 2015), object detection (Yang et al. 2022), and image super-resolution (Lee et al. 2020), action detection (Zhao et al. 2020), etc., we can borrow a similar idea to introduce trimap as privileged information for knowledge distillation that can improve the performance of alpha matte prediction in a trimap-free setting.

To showcase this new matting framework, we employ multiple models from both original trimap-based methods and the trimap-based variants of state-of-the-art (SOTA) trimap-free methods as teachers to guide the training of their corresponding trimap-free students, which aims to demonstrate the generalization of our PPID for image matting. Each paired teacher and student share the same structure except for the inputs, where both RGB images and trimaps are given to the teacher and only RGB images for the student. To leverage effective privileged features for environment-aware information distillation, we introduce a Cross-Level Semantic Distillation (CLSD) module that guides each student layer to learn from more knowledgeable privileged features of the teacher model in addition to the corresponding layer distillation, for mining more effective environment-aware information. In addition, we propose an Attention-Guided Local Distillation module that efficiently transfers privileged local attributes from the trimap-based teacher to guide local region optimization for the trimap-free student.

Overall, the contributions of this paper are as follows:

- We propose a novel Privileged Prior Information Distillation framework for Image Matting that can effectively transfer privileged prior information to improve the trimap-free models, especially in scenes with chromaless, semantic ambiguity, or irregular objects.
- We introduce a Cross-Level Semantic Distillation (CLSD) module that complements the student networks with more sufficient environmental awareness and higher-level semantic feature representations.
- We also propose an Attention-Guided Local Distillation module to guide local region optimization of the trimap-free student by borrowing privileged local attributes from the trimap-based teacher.
- Extensive experiments on public datasets demonstrate the effectiveness and superiority of our proposed framework, outperforming the SOTA approaches on both synthetic and real-world images by a large margin.

## 2 Related Works

### 2.1 Classic Methods

Classic foreground matting methods can be generally categorized into two approaches: sampling-based and propagation-based. Sampling-based methods (Chen et al. 2013; Jue and Michael F 2007; Kaiming et al. 2011; Yung-Yu et al. 2001) sample the known foreground and background color pixels, and then extend these samples to achieve matting in other parts. Various sampling-based algorithms are proposed, e.g., Bayesian matting (Yung-Yu et al. 2001), optimized color sampling (Jue and Michael F 2007), global sampling method (Kaiming et al. 2011), and comprehensive sampling (Ehsan et al. 2013). Propagation-based methods (Chen, Li, and Tang 2013; He, Sun, and Tang 2010; Levin, Lischinski, and Weiss 2007) reformulate the composite Eq. 1 to propagate the alpha values from the known foreground and background into the unknown region, achieving more reliable matting results. Classic matting methods heavily rely on chromatic cues, which leads to bad quality when the color of the foreground and background show small or no noticeable difference.

### 2.2 Deep Learning-Based Methods

**Trimap-Based Methods.** Initially, some attempts are made to combine deep learning networks with classic matting techniques, e.g., closed-form matting (Levin, Lischinski, and Weiss 2007) and KNN matting (Chen, Li, and Tang 2013). Cho et al. (Cho, Táí, and Kweon 2016) employ a deep neural network to improve the results of the closed-form matting and KNN matting. For facilitating the end-to-end training, Xu et al. (Xu et al. 2017) propose a two-stage deep neural network (Deep Image Matting) based on SegNet (Badrinarayanan, Kendall, and Cipolla 2017) for alpha matte estimation and contribute a large-scale composition image matting dataset (Adobe dataset) with ground truth foreground (alpha) matte. Lutz et al. (Lutz, Amprini, and Šmolic 2018) introduce a generative adversarial network (GAN) for
natural image matting and improve the results of Deep Image Matting (Xu et al. 2017). Subsequently, a range of methods (Hou and Liu 2019; Lu et al. 2019; Li and Lu 2020; Cai et al. 2019) have introduced different theoretical developments for matting performance improvements.

Trimap-Free Methods. Fully automatic matting without any auxiliary additional constraints (e.g., user-annotated trimap) has also been studied. (Chen et al. 2018) tries to predict the trimap first, followed by an alpha matting network. Zhang et al. (Zhang et al. 2019) propose a dual-decoder network for foreground and background classification, followed by a fusion branch to integrate the dual results. Ke et al. (Ke et al. 2022) present a lightweight matting objective decomposition network (MODNet) and introduce an e-ASPP module for efficient multi-scale feature fusion. Lin et al. (Lin et al. 2022) propose a robust real-time matting method (RVM) training strategy that optimizes the network on both matting and segmentation tasks.

2.3 Privileged Information Distillation Methods

Lopez-Paz et al. (Lopez-Paz et al. 2015) first combine Distillation (Hinton et al. 2015) and privileged information (Vapnik, Izmailov et al. 2015) into generalized distillation, and extended it to unsupervised, semi-supervised and multi-task learning scenarios. Li et al. (Li et al. 2022a) propose a cross-modality knowledge distillation model that leverages the additionally privileged depth to guide the training of the monocular visual odometry network. Wang et al. (Wang and Chen 2020) propose a Privileged Modality Distillation Network that improves the RGB-based hand pose estimation by excavating the privileged information from depth prior during training. Zhao et al. (Zhao et al. 2020) consider future frames from the off-line teacher as privileged information to guide the online student for action detection, by knowledge distillation.

3 Methodology

Our Privileged Prior Information Distillation for image matting (PPID-IM) is designed to effectively transfer the privileged prior information that can guide trimap-free students in capturing sufficient environmental awareness information and performing more accurate domain decoupling. The overall architecture of the PPID-IM is shown in Fig. 2. PPID consists of dual key components: cross-level semantic distillation and attention-guided local distillation modules.

3.1 Cross-layer Semantic Distillation

To effectively leverage privileged prior features for environment-aware information distillation, we propose a Cross-Level Semantic Distillation (CLSD) module that guides each student layer to learn higher-level privileged feature representations from the teacher in addition to the corresponding layer distillation. Inspired by multiple tasks (Hu et al. 2018; Hu, Shen, and Sun 2018; Wang et al. 2018; Zhang et al. 2018; Cao et al. 2019) that need a global understanding of a visual scene, we believe that extracting the associations between pixels both within a region (i.e., known, transition, or background regions) and across regions can lead to capturing more sufficient environment-aware information. And then, we employ the Global Context block (GCblock) (Cao et al. 2019) to model the global association context of the teacher’s feature representations. Due to the motivation that learning higher-level semantic information can enhance the students’
perception of more comprehensive information, we further transfer the teacher’s representations to both the corresponding layer and neighbor layer of the student network for effective privileged information distillation. The GCblock ($Gc(F)$) (Cao et al. 2019) is formulated as follows:

$$Gc(F) = F + W_{c2}(ReLU(LN(W_{c1} \left( \sum_{j=1}^{N_p} e^{W_k F_j} \right)))$$

where $W_k$, $W_{c1}$ and $W_{c2}$ denote linear transformation matrices, $LN$ denotes the layer normalization, $N_p$ denotes the number of positions in the feature map ($i.e. N_p = H \cdot W$). The global feature transfer of CLSD can be formulated as:

$$L_{CLSD} = \lambda_1 \cdot \sum_{n=1}^{N_p} \left( Gc(F^T_n) - Gc(F^S_n) \right)^2$$

$$+ \lambda_2 \cdot \sum_{n=1}^{N_p} \left( Gc(F^T_n) - Gc(F^{3 \times 3}_n) \right)^2$$

where $Gc(F)$ represents the GCblock (Cao et al. 2019). $F^T_n$ and $F^S_n$ denote the feature maps of the teacher and student at the $n$-th layer, respectively. $F^{3 \times 3}_n$ is a $3 \times 3$ convolutional operation (stride=2). $\lambda_1$ and $\lambda_2$ are hyper-parameters for balancing the loss. We further update $F^S_n$ to $F^S_{n-1}$ by merging it with the cross-layer distilled feature $F^S_{n-1}$ at $(n-1)$-th layer.

### 3.2 Attention-Guided Local Distillation

Most previous trimap-free methods are limited in terms of domain decoupling on local regions, due to the lack of prior constraints on the solution space. To address this situation, we propose an Attention-Guided Local Distillation (ALD) module that efficiently transfers privileged local attributes from the trimap-based teacher to guide the local region optimization for the trimap-free student. For efficient locally privileged information distillation, we generate a region mask to guide the transfer of effective pixel-level representations to the student, by the following formula:

$$R^{t}_{i,j} = \begin{cases} 1, & \text{if } (i,j) \in t \\ 0, & \text{otherwise} \end{cases}$$

where $t$ denotes the transition region, and $i,j$ refers to the pixel position in the feature map.

Specifically, we also introduce a spatial attention mask to further emphasize crucial information and suppress disturbing information about the target local regions. We follow CBAM (Woo et al. 2018) to respectively apply average-pooling ($AP$) and max-pooling ($MP$) along the channel and then feed the concatenated feature into a $7 \times 7$ convolution layer to generate the teacher’s attention mask, as follows:

$$M^a(F) = \sigma(f^{7 \times 7}(\left[AP(F) ; MP(F)\right]))$$

where $\sigma$ denotes the Softmax function and $[; ; ]$ is a concatenation operation along the channel axis. $T$ is the temperature for the attention distillation function $L_{ALD}$ that can guide the student to learn crucial information distribution of the transition regions from the teacher:

$$L^{a}_{ALD} = l_s(R^{t}_M F^T_n, R^t M^a_{n-1})$$

where $M^n_t$ and $M^n_s$ denotes the attention maps of the teacher and student, respectively. $l_s$ is a L1 loss. Overall, the loss function of the ALD module ($L_{ALD}$) can be formulated by the combination of $L^{f}_{ALD}$ and $L^{a}_{ALD}$:

$$L_{ALD} = \alpha L^{f}_{ALD} + \beta L^{a}_{ALD}$$

where $\alpha$ and $\beta$ are the hyper-parameters to balance the feature loss and attention loss. And then, the final loss function of the privileged prior information distillation is computed as:

$$L_{disf} = L_{CLSD} + L_{ALD}$$

### 3.3 Loss Function of Alpha Prediction

According to Eq. 1, one image can be divided into three solution regions, i.e. known foreground, background, and transition, where the scale of each region is commonly different. The large-scale regions tend to receive more attention in terms of loss, while the supervision in small-scale ones may be weakened due to their low pixel proportion, which will lead to an unbalance in alpha predictions of multiple regions. To address this, we introduce a regional scaling mask to balance the supervision of each region, as follows:

$$S_{ij} = \begin{cases} \frac{1}{N_f}, & \text{if } (i,j) \in f \\ \frac{1}{N_b}, & \text{if } (i,j) \in b \\ \frac{1}{N_t}, & \text{if } (i,j) \in t \end{cases}$$

where $i,j$ denotes the pixel position in the feature map, $N_f$, $N_b$ and $N_t$ represent the total number of pixels in the foreground, background, and transition region, respectively. For the supervision of alpha prediction, we employ L1 loss ($L_1$),
where \( \nabla \) follows:

\[
L_{\text{alpha}} = \sum_{i=1}^{H_a} \sum_{j=1}^{W_a} w_{ij}^{L1} S_{ij} L_i^1 + \sum_{i=1}^{H_a} \sum_{j=1}^{W_a} w_{ij}^{ce} S_{ij} L_i^{ce} + \sum_{i=1}^{H_a} w_{i}^{L} L_{i}^{grad}
\]

(12)

where \( H_a \) and \( W_a \) are the height and width of the final alpha prediction. \( w_{ij}^{L1} \) and \( w_{ij}^{ce} \) denote the weight of \( L_1 \) and \( L_{ce} \) respectively and are set as follows:

\[
w_{ij}^{L1} = \begin{cases} 
1, & f(i, j) \in f \cup b \\
2, & f(i, j) \in t 
\end{cases}
\]

(13)

\[
w_{ij}^{ce} = \begin{cases} 
1, & f(i, j) \in f \cup b \\
0.5, & f(i, j) \in t 
\end{cases}
\]

(14)

where \( f, b, \) and \( t \) denote the foreground, background and transition region, respectively. The \( L_1 \) loss is the absolute difference between the predicted and the ground truth alpha matte, and can recover both the global and local detail alpha values:

\[
L_i^1 = ||\alpha_i - \alpha_i^*||_1
\]

(15)

where \( \alpha_i \) and \( \alpha_i^* \) denote the student output and the ground truth alpha values at pixel \( i \), respectively.

We follow (Zhang et al. 2019) to introduce the \( L_{ce} \) loss to accelerate the convergence of the pixels in foreground and background regions towards their targets, as follows:

\[
L_i^{ce} = -|\alpha_i^* \cdot \log(\alpha_i) + (1 - \alpha_i^*) \cdot \log(1 - \alpha_i)|
\]

(16)

Similar to (Zhang et al. 2019), we set a small weight for \( L_{ce} \) and combine it with \( L_1 \) to supervise alpha prediction in the transition region. In addition, we utilize the gradient loss \( L_{grad} \) to reduce the over-blurred alpha results, as follows:

\[
L_i^{grad} = ||\nabla \alpha_i - \nabla \alpha_i^*||
\]

(17)

where \( \nabla \) denotes the calculation of the gradient magnitude.

### 3.4 Overall Training Loss

Overall, we train the student network with the total loss as follows:

\[
L = L_{\text{alpha}} + \gamma L_{\text{distrn}}
\]

(18)

where \( \gamma \) is the hyper-parameter to balance the alpha-prediction loss \( L_{\text{alpha}} \) and the privileged prior information distillation loss \( L_{\text{distrn}} \).

### 4 Experiments

#### 4.1 Benchmark: Real-1K

We propose the first large-scale UHD (Ultra High Definition) natural image matting test set Real-World Image Matting-1K (Real-1K), which contains 1000 ultra high-resolution (from 4K to 8K) real-world natural samples of transparent and non-transparent attributes. Table 1 shows comparisons between some existing image matting datasets (DAPM (Shen et al. 2016), Adobe (Xu et al. 2017), Distinction-646 (Qiao et al. 2020), AM-2k (Li et al. 2022b), AIM (Li, Zhang, and Tao 2021), and RWP-636 (Yu et al. 2021)) with ours. Real-1K has large-scale image data and multiple object classes including portrait, liquid, glass, animal, plant, fruit, and so on. There are also mixed categories in the same images from Real-1K. Our Real-1K could serve as a new challenging benchmark in the image matting area. We propose the first large-scale UHD (Ultra High Definition) natural image matting test set Real-World Image Matting-1K (Real-1K), which contains 1000 ultra high-resolution (from 4K to 8K) real-world natural samples of transparent and non-transparent attributes. Table 1 shows comparisons between some existing image matting datasets (DAPM (Shen et al. 2016), Adobe (Xu et al. 2017), Distinction-646 (Qiao et al. 2020), AM-2k (Li et al. 2022b), AIM (Li, Zhang, and Tao 2021), and RWP-636 (Yu et al. 2021)) with ours. Real-1K has large-scale image data and multiple object classes including portrait, liquid, glass, animal, plant, fruit, and so on. There are also mixed categories in the same images from Real-1K. Our Real-1K could serve as a new challenging benchmark in the image matting area.

#### 4.2 Composition Datasets

Adobe Matting Dataset (Xu et al. 2017). The training set consists of 431 foreground objects and each of them is composited over 100 random COCO (Lin et al. 2014) images to produce 43.1k composited training images. For the test set, we first composite each foreground from the test set with 20 random VOC (Everingham et al. 2010) images to produce 1k composited testing images (Composition-1K). Then we split Composition-1K into two groups (240 and 760 images, respectively) based on the critical attributes of transparent and non-transparent.

Distinction-646 (Qiao et al. 2020). It includes 596 and 50 foreground objects in training and test sets, respectively. We enforce the same rule, composited ratio, and grouping style with the AIM datasets that split the test set into two groups consisting of 200 and 800 images, respectively.

For testing on Real-1K, we train all models on the combined training set of Adobe (Xu et al. 2017) and Distinction-646 (Qiao et al. 2020).

#### 4.3 Implementation Details

We implement the privileged prior information distillation on different matting models, including both trimap-based and trimap-free ones to evaluate the general applicability of our PPID framework. The teacher and the student use the same models but differ only in the inputs. All the experiments are conducted with Pytorch(Paszke et al. 2019).

#### 4.4 Comparative Study

We conduct a comparative study on Real-1K and two composition benchmarks: Adobe Image Matting (Xu et al. 2017) and Distinction-646 (Qiao et al. 2020). We report mean square error (MSE), sum of the absolute difference (SAD), spatial-gradient (Grad), and connectivity (Conn) between predicted and ground truth alpha mattes. Lower values of these metrics indicate better-estimated alpha matte. To fairly compare, the metrics are computed on the entire image.
Table 2: The quantitative results on our Real-1K.

| Attribute     | Transparent | Non-transparent | Whole Test set |
|---------------|-------------|-----------------|----------------|
| **Methods**   | SAD (MSE)   | Grad (Conn)     | SAD (MSE)       | Grad (Conn)     |
| DIM           | 146.29      | 68.91           |               |               |
| Inet          | 112.80      | 57.90           |               |               |
| GCA           | 103.29      | 51.25           |               |               |
| M-F           | 95.32       | 40.62           |               |               |
| LFM           | 104.71      | 55.68           |               |               |
| Hatt          | 107.58      | 58.21           |               |               |
| AIM           | 102.37      | 55.27           |               |               |

Table 3: Ablation study of the cross-layer semantic distillation (CLSD) module on Adobe dataset (Xu et al. 2017).

| Baselines     | SD CLSD | SAD (MSE) | Grad (Conn) | 96.92 0.019 | 58.87 75.24 |
|---------------|---------|-----------|-------------|-------------|-------------|
| DIM           | ✓       | 92.61     | 57.69       | 70.42       |             |
| IndexNet      | ✓       | 93.80     | 53.46       | 69.70       |             |
| GCA           | ✓       | 67.12     | 38.28       | 60.31       |             |
|               |         | 59.37     | 34.56       | 56.69       |             |
|               |         | 48.35     | 27.39       | 41.70       |             |
|               |         | 72.02     | 43.25       | 54.49       |             |
|               |         | 62.64     | 41.04       | 54.31       |             |
|               |         | 57.27     | 36.90       | 53.83       |             |

Table 4: Ablation study of the attention-guided local distillation (ALD) module on Adobe dataset (Xu et al. 2017).

We summarize the performance comparison in the above two attribute groups among our trimap-free models (with or w/o the privileged prior information distillation) and their trimap-based teachers (i.e., DIM, Inet (Lu et al. 2019), GCA (Li and Lu 2020), MatteFormer Baseline (M-F), Park et al. 2022), LFM (Zhang et al. 2019), Hatt (Qiao et al. 2020), and AIM (Li, Zhang, and Tao 2021)). The trimap-based variants of LFM, Hatt, and AIM share the same network structures with their original models and only replace the input with image plus trimap. We follow the common setting of trimap-based methods to train these variants. For methods without publicly available codes, we follow their papers to reproduce the results with due diligence.

Table 2 shows the quantitative results of trimap-based teachers, trimap-free baselines, and our PPID-guided models on our Real-1K. We notice that our PPID framework significantly improves the performance of trimap-free baseline models in region decoupling, especially on the transparent attribute of both natural real-world and composited images. Although training on a limited amount of composited data, our PPID-guided models can further maintain a slight margin with the trimap-based teachers on real-world images, while the original trimap-free methods may not. It demonstrates that the PPID framework can help students mine more environment-aware information similar to that obtained from environmental priors. PPID can also reduce the weak generalization of trimap-free methods across data domains caused by the gap in data distribution between composited and natural images.

Compared to the existing SOTA methods, we observe that lighter-weighted trimap-free baseline models can achieve more significant performance improvement based on effective environment-aware information complements and guided local attribute optimization from our PPID. Particularly, our IndexNet-PPID gets the most significant performance boost among all competing baseline models, both on transparent (e.g., MSE 61.8% ↓ in Table 2) and non-transparent (e.g., MSE 64.0% ↓ in Table 2) attributes.
4.5 Ablation Study

To validate the effectiveness of our key components in privileged information distillation, we conduct ablation study under the following settings: (a) \textit{CLSD}: cross-layer semantic distillation (CLSD); (b) \textit{SD}: semantic distillation is only performed between the same layers; (c) \textit{ALD}: attention-guided local distillation; (d) \textit{LD}: local distillation w/o attention guidance.

\textbf{CLSD vs. SD.} We report quantitative comparison results of our privileged information distillation on both transparent and non-transparent groups of the Composition-1K (Xu et al. 2017) dataset, with and without the privileged semantic distillation components (CLSD or SD). As summarized in Table 3, either CLSD or SD can significantly contribute to environmental awareness enhancement of the trimap-free baselines, and the alpha prediction performance is further improved on both transparent and non-transparent groups by introducing the CLSD module. That is because the CLSD mechanism can complement more sufficient environment-aware information by guiding each student layer to additionally mine higher-level semantic context.

\textbf{ALD vs. LD.} We perform quantitative comparisons on our PPID-guided models with or without the ALD module under three settings, \textit{i.e.} w/o \textit{ALD}, with \textit{LD}, and with \textit{ALD}. To evaluate the effectiveness of the ALD module on local attribute optimization, we compute the metrics on the transition region of each image in AIM (Xu et al. 2017). As shown in Table 4, the proposed local distillation modules (\textit{ALD} and \textit{LD}) improve the performance in local detail predictions, it offers further gain after introducing the spatial attention guidance that forces the students to focus on the crucial pixels. Additionally, we demonstrate the significant performance gain after combining CLSD and ALD. Some representative visualizations are provided in Fig. 3, which also illustrate the effectiveness of our PPID-IM for trimap-free baselines, especially in the scenarios with foregrounds that are semantically ambiguous (Row 6), chromaless (Row 1 to 4), or irregular (Row 5).

5 Conclusion

In this paper, we propose a privileged prior information distillation framework (PPID), that aims to effectively transfer privileged prior information from the trimap-based teachers to their poor environment-aware trimap-free student models. We also introduce a Cross-Level Semantic Distillation (CLSD) module that complements the student networks with both environmental awareness and higher-level semantic feature representations, for facilitating the cross-modality information distillation. Further, an Attention-Guided Local Distillation (ALD) is proposed to guide local region optimization for the students by efficiently transferring privileged local attributes and crucial information distribution from the teachers. Extensive experiments demonstrate the effectiveness and superiority of our PPID on image matting.
References

Badrinarayanan, V.; Kendall, A.; and Cipolla, R. 2017. SegNet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 39(12): 2481–2495.

Cai, S.; Zhang, X.; Fan, H.; Huang, H.; Liu, J.; Liu, J.; Liu, J.; Wang, J.; and Sun, J. 2019. Disentangled image matting. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 8819–8828.

Cao, Y.; Xu, J.; Lin, S.; Wei, F.; and Hu, H. 2019. Genet: Non-local networks meet squeeze-excitation networks and beyond. In *Proceedings of the IEEE/CVF international conference on computer vision workshops*, 0–0.

Chen, Q.; Ge, T.; Xu, Y.; Zhang, Z.; Yang, X.; and Gai, K. 2018. Semantic human matting. In *Proceedings of the 26th ACM international conference on Multimedia*, 618–626.

Chen, Q.; Li, D.; and Tang, C.-K. 2013. KNN matting. *Proceedings of the IEEE transactions on pattern analysis and machine intelligence*, 35(9): 2175–2188.

Chen, X.; Zou, D.; Zhiying Zhou, S.; Zhao, Q.; and Tan, P. 2013. Image matting with local and nonlocal smooth priors. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1902–1907.

Cho, D.; Tai, Y.-W.; and Kweon, I. 2016. Natural image matting using deep convolutional neural networks. In *Proceedings of the European conference on computer vision (ECCV)*, 626–643. Springer.

Ehsan, S.; Deepu, R.; Brian, P.; and Scott, C. 2013. Improving image matting using comprehensive sampling sets. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 636–643.

Everingham, M.; Van Gool, L.; Williams, C. K.; Winn, J.; and Zisserman, A. 2010. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88(2): 303–338.

He, K.; Sun, J.; and Tang, X. 2010. Fast matting using large kernel matting laplacian matrices. In *Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, 2165–2172. IEEE.

Hinton, G.; Vinyals, O.; Dean, J.; et al. 2015. Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*, 2(7).

Hou, Q.; and Liu, F. 2019. Context-aware image matting for simultaneous foreground and alpha estimation. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 4130–4139.

Hu, H.; Gu, J.; Zhang, Z.; Dai, J.; and Wei, Y. 2018. Relation networks for object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 3588–3597.

Hu, J.; Shen, L.; and Sun, G. 2018. Squeeze-and-excitation networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 7132–7141.

Jue, W.; and Michael F. C. 2007. Optimized color sampling for robust matting. In *2007 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 1–8. IEEE.

Kaiming, H.; Christoph, R.; Carsten, R.; Xiaou, T.; and Jian, S. 2011. A global sampling method for alpha matting. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2049–2056. IEEE.

Ke, Z.; Sun, J.; Li, K.; Yan, Q.; and Lau, R. W. 2022. MODNet: Real-Time Trimap-Free Portrait Matting via Objective Decomposition. In *AAAI*.

Lee, W.; Lee, J.; Kim, D.; and Ham, B. 2020. Learning with privileged information for efficient image super-resolution. In *European Conference on Computer Vision*, 465–482. Springer.

Levin, A.; Lischinski, D.; and Weiss, Y. 2007. A closed-form solution to natural image matting. *IEEE transactions on pattern analysis and machine intelligence*, 30(2): 228–242.

Li, B.; Wang, S.; Ye, H.; Gong, X.; and Xiang, Z. 2022a. Cross-Modal Knowledge Distillation for Depth Privileged Monocular Visual Odometry. *IEEE Robotics and Automation Letters*, 7(3): 6171–6178.

Li, J.; Zhang, J.; Maybank, S. J.; and Tao, D. 2022b. Bridging composite and real: towards end-to-end deep image matting. *International Journal of Computer Vision*, 1–21.

Li, J.; Zhang, J.; and Tao, D. 2021. Deep Automatic Natural Image Matting. In Zhou, Z.-H., ed., *Proceedings of the Thirtieth International Joint Conference on Artificial Intelligence, IJCAI-21*, 800–806. International Joint Conferences on Artificial Intelligence Organization. Main Track.

Li, Y.; and Lu, H. 2020. Natural image matting via guided contextual attention. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, 11450–11457.

Lin, S.; Yang, L.; Saleemi, I.; and Sengupta, S. 2022. Robust High-Resolution Video Matting with Temporal Guidance. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 238–247.

Lin, T.-Y.; Maire, M.; Belongie, S.; Hays, J.; Perona, P.; Ramanan, D.; Dollár, P.; and Zitnick, C. L. 2014. Microsoft coco: Common objects in context. In *Proceedings of the European conference on computer vision (ECCV)*, 740–755. Springer.

Liu, Y.; Xie, J.; Shi, X.; Qiao, Y.; Huang, Y.; Tang, Y.; and Yang, X. 2021. Tripartite information mining and integration for image matting. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, 7555–7564. Springer.

Lopez-Paz, D.; Bottou, L.; Schölkopf, B.; and Vapnik, V. 2015. Unifying distillation and privileged information. *arXiv preprint arXiv:1511.03643*.

Lu, H.; Dai, Y.; Shen, C.; and Xu, S. 2019. Indices matter: Learning to index for deep image matting. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 3266–3275.

Lutz, S.; Amplianitis, K.; and Smolic, A. 2018. AlphaGAN: Generative adversarial networks for natural image matting. In *British Machine Vision Conference (BMVC)*, 259. BMVA Press.
Park, G.; Son, S.; Yoo, J.; Kim, S.; and Kwak, N. 2022. Matteformer: Transformer-based image matting via prior-tokens. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 11696–11706.

Paszke, A.; Gross, S.; Massa, F.; Lerer, A.; Bradbury, J.; Chanan, G.; Killeen, T.; Lin, Z.; Gimelshein, N.; Antiga, L.; et al. 2019. Pytorch: An imperative style, high-performance deep learning library. Advances in neural information processing systems, 32.

Qiao, Y.; Liu, Y.; Yang, X.; Zhou, D.; Xu, M.; Zhang, Q.; and Wei, X. 2020. Attention-Guided Hierarchical Structure Aggregation for Image Matting. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Shen, X.; Tao, X.; Gao, H.; Zhou, C.; and Jia, J. 2016. Deep automatic portrait matting. In Proceedings of the European conference on computer vision (ECCV), 92–107. Springer.

Vapnik, V.; Izmailov, R.; et al. 2015. Learning using privileged information: similarity control and knowledge transfer. J. Mach. Learn. Res., 16(1): 2023–2049.

Wang, K.; and Chen, X. 2020. PMD-Net: Privileged Modality Distillation Network for 3D Hand Pose Estimation from a Single RGB Image. In BMVC.

Wang, X.; Girshick, R.; Gupta, A.; and He, K. 2018. Non-local neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, 7794–7803.

Woo, S.; Park, J.; Lee, J.-Y.; and Kweon, I. S. 2018. Cbam: Convolutional block attention module. In Proceedings of the European conference on computer vision (ECCV), 3–19.

Xu, N.; Price, B.; Cohen, S.; and Huang, T. 2017. Deep image matting. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2970–2979.

Yang, Z.; Li, Z.; Jiang, X.; Gong, Y.; Yuan, Z.; Zhao, D.; and Yuan, C. 2022. Focal and global knowledge distillation for detectors. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 4643–4652.

Yu, Q.; Zhang, J.; Zhang, H.; Wang, Y.; Lin, Z.; Xu, N.; Bai, Y.; and Yuille, A. 2021. Mask guided matting via progressive refinement network. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 1154–1163.

Yung-Yu, C.; Brian, C.; David H, S.; and Richard, S. 2001. A bayesian approach to digital matting. In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), volume 2, 264–271. IEEE.

Zhang, H.; Dana, K.; Shi, J.; Zhang, Z.; Wang, X.; Tyagi, A.; and Agrawal, A. 2018. Context encoding for semantic segmentation. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, 7151–7160.

Zhang, Y.; Gong, L.; Fan, L.; Ren, P.; Huang, Q.; Bao, H.; and Xu, W. 2019. A late fusion CNN for digital matting. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 7469–7478.

Zhao, P.; Xie, L.; Zhang, Y.; Wang, Y.; and Tian, Q. 2020. Privileged knowledge distillation for online action detection. arXiv preprint arXiv:2011.09158.