Layered Depth Refinement with Mask Guidance

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Abstract

Depth maps are used in a wide range of applications from 3D rendering to 2D image effects such as Bokeh. However, those predicted by single image depth estimation (SIDE) models often fail to capture isolated holes in objects and/or have inaccurate boundary regions. Meanwhile, high-quality masks are much easier to obtain, using commercial auto-masking tools or off-the-shelf methods of segmentation and matting or even by manual editing. Hence, in this paper, we formulate a novel problem of mask-guided depth refinement that utilizes a generic mask to refine the depth prediction of SIDE models. Our framework performs layered refinement and inpainting/outpainting, decomposing the depth map into two separate layers signified by the mask and the inverse mask. As datasets with both depth and mask annotations are scarce, we propose a self-supervised learning scheme that uses arbitrary masks and RGB-D datasets. We empirically show that our method is robust to different types of masks and initial depth predictions, accurately refining depth values in inner and outer mask boundary regions. We further analyze our model with an ablation study and demonstrate results on real applications. More information can be found on our project page.\textsuperscript{1}

1. Introduction

Recent progress in deep learning has enabled the prediction of fairly reliable depth maps from single RGB images [20, 31, 32, 47]. However, despite the specialized network architectures [11, 29, 31] and training strategies [32, 46] in single image depth estimation (SIDE) models, the estimated depth maps are still inadequate in the following aspects: (i) depth boundaries tend to be blurry and inaccurate; (ii) thin structures such as poles and wires are often missing; and (iii) depth values in narrow or isolated background regions (e.g., between body parts in humans) are often imprecise, as shown in the initial depth estimation in Figure 1. Addressing these issues within a single SIDE model can be very challenging due to limited model capacity and the lack of high-quality RGB-D datasets.

Therefore, we take a novel approach of utilizing an additional cue of a high-quality mask to refine depth maps predicted by SIDE methods. The provided mask can be hard (binary) or soft (e.g., from matting) and can be of objects or other parts of the image such as the sky. As high-quality auto-masking tools are very accessible nowadays, such masks can be easily obtained with commercial tools (e.g., removebg [33] or Photoshop) or off-the-shelf segmentation models [14, 30, 52, 57]. Segmentation masks can also be annotated by humans [7, 41, 49], and accurate datasets are easier to obtain than RGB-D data, which facilitates the training of auto-masking models.

\textsuperscript{1}https://sooyekim.github.io/MaskDepth/
However, even with such accurate masks, how to effectively train the depth refinement model remains an open issue. As shown in Figure 2(c), directly adding the mask as an input channel to the refinement model still results in blurrier boundaries than the given mask. Therefore, we propose a layered refinement strategy: The mask ($M$) and inverse mask ($1 - M$) regions are processed separately to interpolate or extrapolate the depth values beyond the mask boundary, leading to two layers of depth maps. As shown in Figure 2(e), the refined output is the composite of the two layers using the mask $M$, which fully preserves the boundary details of the mask, as well as filling in the correct depth values for the isolated background regions.

A naive baseline for layered depth refinement would be using an off-the-shelf inpainting method to generate the depth map layers for $M$ and $1 - M$. Unfortunately, as shown in Figure 2(d), generic inpainting may not work well for filling in large holes in a depth map. Moreover, deriving an appropriate region for hole-filling on an imperfect initial depth prediction based on the mask is a non-trivial problem. The hole-filling region often needs to be expanded to cover uncertain regions along the mask boundary, as otherwise, the erroneous depth values may propagate in the hole. However, too much expansion will make the hole-filling task much more challenging as it may overwrite the original depth structure in the scene (see the $1 - M$ layer in Figure 2(d)).

To address the challenge, we propose a framework for degradation-aware layered depth completion and refinement, which learns to identify and correct inaccurate regions based on the context of the mask and the image. Our framework does not require additional input or heuristics to expand the hole-filling region. Furthermore, we devise a self-supervised learning scheme that uses RGB-D training data without paired mask annotations. We demonstrate that our method is robust under various conditions by empirically validating it on synthetic datasets and real images in the wild. We further provide results on real-world downstream applications.

Our contributions are three-fold:

- We propose a novel mask-guided depth refinement framework that refines the depth estimations of SIDE models guided by a generic high-quality mask.
- We propose a novel layered refinement approach, generating sharp and accurate results in challenging areas without additional input or heuristics.
- We devise a self-supervised learning scheme that uses RGB-D training data without paired mask annotations.

2. Related Work

Single Image Depth Estimation Single image depth estimation (SIDE), also commonly termed monocular depth estimation, aims to predict a depth map from an RGB image. A common approach is to train a deep neural network on RGB-D datasets to learn the non-linear mapping from RGB to depth [20, 31, 32, 47]. As for the model architecture, convolutional neural networks (CNNs) are a popular choice [32, 47], with a transformer-based model [31] being recently proposed to overcome the limited receptive field size of CNNs. Transformer models [10, 37] leverage self-attention [39], expanding the receptive field to the entire image at every level. We also base our model architecture on transformers to benefit from the enlarged receptive field.

For training SIDE models, datasets are often augmented with synthetic datasets [4, 27, 43, 44, 50] and relative depths computed from stereo images [20, 40, 46]. Numerous supervision schemes [1, 5, 12, 13, 24, 26, 45, 53, 55, 56] and loss functions [17, 19, 20, 47] have been proposed to optimize the model training for SIDE. Several methods [26, 42, 56] attempt to exploit the relation between image segmentation and SIDE, with Zhu et al. [56] proposing regularizing depth boundaries with segmentation map boundaries in the loss function to enforce sharper edges in the resulting depth maps.
turing highly accurate depth boundaries remains a challenge due to the ill-posed nature of the problem and the lack of pixel-perfect ground truth depth data.

**Depth Inpainting** Inpainting depth maps is often necessary in novel view synthesis for 3D photography to naturally fill in disoccluded regions [16, 27, 35]. Such methods apply joint RGB and depth inpainting in the background region near object edges. Another line of research is depth completion, which aims to fill in unknown depth values from sparsely known annotations. Imran et al. [15] proposed a layered approach, extrapolating foreground and background regions separately from LiDAR data. In our depth refinement method, both the mask and inverse mask regions are inpainted/outpainted while correcting inaccurate depth values and merged afterward to obtain accurate boundaries.

**Depth Refinement** In an inspirational work [25], Miangoleh et al. proposed boosting high-frequency details in SIDE results by merging multiple depth predictions at various resolutions, exploiting the limited receptive field size of CNNs. However, their merging algorithm tends to generate inconsistent depth values in foreground objects, and its refinement degrades with recent transformer architectures as it is based on a fundamental assumption related to CNNs. Furthermore, capturing very thin boundaries and generating accurate depth values in hole regions are still challenging.

In this paper, we explore a novel direction of using generic masks as guidance for depth refinement. Unlike previous methods that upscale or enhance details in the entire depth map, we focus on delicately refining along the boundary and hole regions of the mask. Handling such regions is often important in downstream applications such as Bokeh effect synthesis. Our method is generic and can refine depth maps generated by any SIDE model regardless of the model architecture, as long as the provided mask contains better boundaries than the initial depth map. Note that our method operates in the inverse depth space as many prior works [25, 31, 32], although we continue using the term depth.

### 3. Proposed Method

We propose a layered depth refinement framework for enhancing the initial depth prediction of SIDE models using the guidance of a quasi-accurate mask and an RGB image.

#### 3.1. Data Generation

**Random composition** With an RGB-D dataset consisting of an RGB image \( I \) and its depth map \( D \), a general depth refinement model can be optimized in a self-supervised way by applying random perturbations \( \mathcal{P} \) on \( D \), which inversely simulate initial depth predictions. A neural network \( \mathcal{R} \) can then be trained to predict the refined depth map \( \hat{D} = \mathcal{R}(\mathcal{P}(D), I) \) with an appropriate loss function \( \mathcal{L}(\hat{D}, D) \).

However, collecting a dataset for training a mask-guided depth refinement model is challenging as datasets containing masks along with the RGB-D information are scarce. Hence, we devise a data generation scheme that does not require paired depth and mask annotations. Specifically, a composite depth map \( D' \) is randomly synthesized from two arbitrary depth maps \( D_1 \) and \( D_2 \) using an arbitrary binary mask \( M \) with \( m_{ij} \in \{0, 1\} \), by \( D' = M \cdot D_1 + (1 - M) \cdot D_2 \). Likewise, the corresponding composite RGB image \( I' \) is computed by \( I' = M \cdot I_1 + (1 - M) \cdot I_2 \), where \( I_1 \) and \( I_2 \) are the RGB images corresponding to \( D_1 \) and \( D_2 \), respectively. Examples of \( D' \) and \( I' \) are shown in Figure 3(a). Applying perturbations to \( D' \) leads to \( \mathcal{P}(D') \), and the mask-guided refinement model \( \mathcal{R}_m \) can then be trained with \( \mathcal{L}(\hat{D}', D') \), where \( \hat{D'} = \mathcal{R}_m(\mathcal{P}(D'), I', M) \).

In this way, we can obtain a synthesized depth map \( D' \) and an RGB image \( I' \) that are aligned to \( M \) from any RGB-D dataset and arbitrary masks. Diverse types of masks can be mixed and used, including object and stuff masks from segmentation datasets [21, 54]. Furthermore, we can effortlessly acquire the ground truths for inpainting/outpainting (\( D_1 \) and \( D_2 \)), which are essential for our layered refinement approach, explained in more detail in the next section.

**Perturbations** As shown in Figure 3(b), we apply three
Two-stage training for layered refinement

Although this way, the model can focus on correcting the depth values and merges two individual results based on the approach that refines regions specified by \( M \) from the accurate mask, we propose a combination from concatenated RGB-D and mask inputs leads to sub-optimal results. As shown in Figure 2, to explicitly benefit from the accurate mask, we propose a layered refinement approach that refines regions specified by \( M \) and \( 1 - M \) separately and merges two individual results based on \( M \). In this way, the model can focus on correcting the depth values in each region, and mask boundaries can be fully preserved after the merging stage.

We train our model in two stages shown in Figure 4. In the first stage, the model \( R_m \) is trained for image completion by randomly providing \( M \) or \( 1 - M \) and optimizing either \( \mathcal{L}(\mathcal{R}_m(D', I', M), D_1) \) or \( \mathcal{L}(\mathcal{R}_m(D', I', 1 - M), D_2) \). Note that a single model is trained for both inpainting and outpainting the depth input to always complete regions with \( 0 \) based on regions with \( 1 \) signified by the given mask \( M \) or \( 1 - M \). Then in the second stage, we add perturbations \( \mathcal{P} \) and run the network twice with \( M \) and \( 1 - M \) to obtain two outputs \( \hat{D}_1 \) and \( \hat{D}_2 \), given by

\[
\hat{D}_1 = \mathcal{R}_m(\mathcal{P}(D'), I', M) \quad \text{and} \quad \hat{D}_2 = \mathcal{R}_m(\mathcal{P}(D'), I', 1 - M).
\]

Reasonable \( \hat{D}_1 \) and \( \hat{D}_2 \) are generated from the beginning of the second stage as the model has been pretrained for inpainting/outpainting in the first stage. Finally, \( \hat{D}_1 \) and \( \hat{D}_2 \) are merged to yield the refined output \( \hat{D}' \) as follows:

\[
\hat{D}' = M \cdot \hat{D}_1 + (1 - M) \cdot \hat{D}_2.
\]

Our model is optimized with three losses at this stage: \( \mathcal{L}(\hat{D}_1, D_1) \), \( \mathcal{L}(\hat{D}_2, D_2) \), and \( \mathcal{L}(\hat{D}', D') \). As a result, the network learns to remove perturbations while generating completed depth maps under a unified framework. Although we only utilize composite depth maps as input during training, the randomness in composition (random) depth maps

![Diagram](image-url)
and another 500K iterations for the second stage following

4.1. Implementation Details

4. Experiments

network does not forget the initial depth values.

tionally, a lightweight low-level encoder is introduced to

LayerNorm [3] and MLP layers. The spatial resolution is

eyed to dimensions $d_i \in \{64, 128, 320, 512\}$ and fed into $t_i \in \{3, 4, 18, 3\}$ transformer layers each with self-attention,

As shown in Figure 5, we insert an additional encoder

on each encoder level, overlapping patches are extracted and em-

mean and standard deviation. Furthermore, to benefit from

to the proposed self-supervised learning scheme that supports
diversifying the types of masks, we sample 50% of masks
from diverse object masks, 20% from sky masks and 30%
from human masks, where humans with holes are selected
50% of the time (15% of all masks) during training.

4.2. Evaluation Datasets

Loss function The loss $\mathcal{L}$ is comprised of three different
loss terms summed with unit scale: L1 loss, L2 loss, and
a multi-scale gradient loss with four scale levels [20]. The
gradient loss is adopted to enforce sharp depth boundaries.

3.3. Model Architecture

We base our model architecture on the dense prediction
transformer (DPT) [31] with four transformer encoder lev-

each fusion level, (ii) run the model

as in [51] and RGB images normalized using ImageNet [9]

natural RGB-D images, with depth maps scaled to $[0, 10]$ and
RGB images are further augmented with random contrast,
saturation, brightness, JPEG compression, and grayscale
conversions to make our model more robust to various types
of inputs. Our model is trained on diverse indoor and outdoor
natural RGB-D images, with depth maps scaled to $[0, 10]$ and
RGB images normalized using ImageNet [9].

For data augmentation, we apply random horizontal flip-

inference using segmentation maps To use segmentation
maps in a mask-guided framework, we take the following
steps: (i) compute a binary mask $M_i$ for each instance $i$ with
more than 1% of the total number of pixels in the instance
segmentation map, (ii) run the model $N$ times with $M_i$, and
(iii) merge the refined outputs $D_i$ per each pixel by
$\hat{D} = \arg\max_{D_i} (|D' - D_i|)$, where $D'$ is initial depth.

Figure 5. Our network architecture with DPT [31] as the backbone
model. We add a low-level encoder and a branch for the RGB input.

composited with a random mask) and random perturbations
lead to a robust model that generalizes well to real depth
estimations and diverse masks.

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4.3. Evaluation Metrics

We evaluate the overall error of the output depth maps with the RMSE and the Weighted Human Disagreement Rate (WHDR) [6] measured on 10K randomly sampled point pairs. To evaluate the boundary quality, we report the depth boundary error [18] on accuracy (ε\textsubscript{acc}) and completeness (ε\textsubscript{comp}). In addition, we propose two metrics, mask boundary error (MBE) and relative refinement ratio (R\textsuperscript{↓}). All metrics are measured in the inverse depth space.

MBE computes the average RMSE on mask boundary pixels over the N instances. Mask boundary M\textsubscript{b} is obtained by subtracting the eroded M\textsubscript{t} from M\textsubscript{f} and dilating it with a 5×5 kernel. The MBE is then given by

\[
\text{MBE} = \frac{1}{N} \sum_{i=1}^{N} \sqrt{\frac{1}{N_i} \sum_{b=1}^{N_i} (M_{bi} - M_{fi} \cdot \hat{D})^2},
\]

where \(N_i\) is the number of boundary pixels for each instance \(i\). With ε\textsubscript{acc}, ε\textsubscript{comp} and MBE, we can comprehensively measure the boundary accuracy of the refined depth map: ε\textsubscript{acc} and ε\textsubscript{comp} focusing on depth boundaries and MBE on the mask boundaries of depth maps. Furthermore, we define R\textsuperscript{↓} (relative refinement ratio) as the ratio of the number of pixels improved by more than a threshold \(t\) to the number of pixels worsened by more than \(t\), in terms of absolute error. We set \(t = 0.05\) and compute R\textsuperscript{↓} of refined results over initial results by base models [31, 32]. R\textsuperscript{↓} is a meaningful indicator for assessing the refinement performance.

4.4. Compared Methods

To evaluate the refinement performance, we apply our method to the initial depth predictions of two SIDE models: CNN-based MiDaS v2.1 [32] and SOTA transformer-based DPT-Large [31]. Since there are no existing methods that perform mask-guided depth refinement, we set up the following baselines using masks for comparison:

- Direct-composite produces the refined output without layering and is trained on the same dataset as ours (with composite images and the mask).
- Direct-paired also refines without layering but is trained on paired RGB-D and masks in Hypersim [34]. Hence, we only evaluate on TartanAir [44] for this method.
- Layered models (Layered-propagation and Layered-ours) either apply a propagation-based image completion algorithm [36] or use our model from stage I training, once with the dilated mask for inpainting and the second time with the eroded mask for outpainting. The inpainted/outpainted results are then merged with the mask, similar to our proposed approach.

The network architecture used for Direct-composite and Direct-paired is the same as our encoder-decoder-style transformer model in Figure 5. For the layered models, we set the dilation and erosion kernel to 5×5 for evaluation with segmentation maps. For images in the wild, we manually tweak the kernel sizes for each image to obtain the best results.

Additionally, we compare to bilateral median filtering (BMF) with parameters from [35] (previously used for refining depth maps in [23, 35]) and Miangoleh et al.’s recent depth refinement method [25]. These approaches do not use masks as guidance. For all compared methods, we use the officially released code and weights.

## Table 1. Quantitative results on Hypersim [34] and TartanAir [44] comparing mask-guided depth refinement models. Best values in bold.

| Method                | Hypersim [34]          | TartanAir [44]         |
|-----------------------|------------------------|------------------------|
|                       | \(R^\uparrow\) | MBE\downarrow | \(\varepsilon_{\text{acc}}\) | \(\varepsilon_{\text{comp}}\) | WHDR\downarrow | RMSE\downarrow | \(R^\downarrow\) | MBE\downarrow | \(\varepsilon_{\text{acc}}\) | \(\varepsilon_{\text{comp}}\) | WHDR\downarrow | RMSE\downarrow |
| MiDaS v2.1 [32]       | -                     | 0.0973                 | 2.521                     | 7.074                     | 0.1496        | 0.0966               | -                     | 0.0596                 | 3.483                     | 6.913                | 0.1207               | 0.0533               |
| + Direct-composite    | 3.771                 | 0.0941                 | 1.915                     | 6.233                     | 0.1490        | 0.0961               | 5.897                 | 0.0594                 | 3.183                     | 6.363                | 0.1209               | 0.0534               |
| + Direct-paired       | -                     | -                      | -                         | -                         | -             | -                    | 3.507                 | 0.0575                 | 3.153                     | 6.304                | 0.1196               | 0.0525               |
| + Layered-propagation | 1.097                 | 0.1044                 | 1.942                     | 6.284                     | 0.1629        | 0.1028               | 3.642                 | 0.0608                 | 3.128                     | 6.358                | 0.1255               | 0.0550               |
| + Layered-ours        | 2.332                 | 0.1000                 | 1.871                     | 6.396                     | 0.1560        | 0.0999               | 6.939                 | 0.0580                 | 3.243                     | 6.437                | 0.1230               | 0.0539               |
| + Ours (proposed)     | 5.209                 | 0.0906                 | 1.888                     | 5.931                     | 0.1481        | 0.0958               | 16.569                | 0.0579                 | 2.851                     | 6.272                | 0.1207               | 0.0538               |
| DPT-Large [31]        | -                     | 0.0936                 | 2.071                     | 6.190                     | 0.1347        | 0.0911               | -                     | 0.0496                 | 2.574                     | 5.677                | 0.1091               | 0.0414               |
| + Direct-composite    | 2.574                 | 0.0891                 | 1.599                     | 5.411                     | 0.1339        | 0.0903               | 4.773                 | 0.0486                 | 2.462                     | 5.480                | 0.1086               | 0.0411               |
| + Direct-paired       | -                     | -                      | -                         | -                         | -             | -                    | 2.413                 | 0.0485                 | 2.519                     | 5.394                | 0.1105               | 0.0412               |
| + Layered-propagation | 1.188                 | 0.1007                 | 1.792                     | 5.636                     | 0.1502        | 0.0986               | 2.347                 | 0.0524                 | 2.579                     | 5.527                | 0.1162               | 0.0442               |
| + Layered-ours        | 1.996                 | 0.0954                 | 1.606                     | 5.605                     | 0.1433        | 0.0953               | 5.626                 | 0.0484                 | 2.447                     | 5.342                | 0.1116               | 0.0423               |
| + Ours (proposed)     | 4.455                 | 0.0840                 | 1.491                     | 5.087                     | 0.1333        | 0.0896               | 8.767                 | 0.0474                 | 2.282                     | 5.245                | 0.1078               | 0.0408               |
Figure 6. Qualitative results on Hypersim [34]. The relative improvement maps visualize where the refinement method improved and worsened the initial depth estimation by [32] or [31]. Our method focuses on the edges and hole regions, accurately refining fine structures.

as they measure the average error over all pixels, whereas mask-guided refinement methods aim at refining along mask boundaries and leave most internal regions as is. Our method outperforms all baselines in $R^3$ and MBE, demonstrating the power of our layered refinement approach.

In Table 2, we compare to automatic depth refinement methods without mask-guidance. Conventional image filtering fails to enhance the edge-related metrics. Miangoleh et al.’s method [25] is at times better on the global edge metrics ($\varepsilon_{acc}$ and $\varepsilon_{comp}$) as it enhances all edges in the depth map. However, as it also carries the risk of distorting the original values, $R^3$ values tend to be lower compared to ours, which mostly refines along mask boundaries and leaves other regions intact. Furthermore, as [25] heavily relies on the base model’s behavior, its generalization capability is limited for other architecture types such as a transformer [31]. Our method works well regardless of the base model architecture and generalizes well to both datasets, leading to the best metric values when coupled with [31].

In Figure 6, we show the qualitative results on Hypersim [34]. We also visualize the relative improvement maps showing where the absolute error decreased compared to the base model MiDaS v2.1 [32] or DPT [31]. Our method focuses on refining edges and hole regions and leaves most other regions untouched, whereas Miangoleh et al.’s method [25] often worsens homogeneous regions. Compared to other baselines, our layered refinement approach within a unified framework helps to correct low-level details effectively.

Images in the wild We further evaluate our model on real images in the wild to assess its generalization ability and robustness. Comparisons to baselines are shown in Figure 2 and more results are shown in Figures 1, 7, and 8. Our method is able to generate sharp depth maps consistent with
Ablation study

Table 3. Ablation study on Hypersim [34]. Best values in bold.

| Stage I | Stage II | HP | $R^3$ | MBE$^+$ | $\epsilon_{src}$ | $\epsilon_{compe}$ |
|---------|----------|----|-------|---------|-----------------|------------------|
| DPT-Large [31] | - | 0.0936 | 2.071 | 6.190 |
| ✓ | ✓ | 1.996 | 0.0954 | 1.606 | 5.605 |
| ✓ | ✓ | 2.016 | 0.0890 | 1.915 | 5.320 |
| ✓ | ✓ | 2.613 | 0.0861 | 1.670 | 5.161 |
| ✓ | ✓ | 5.384 | 0.0846 | 1.438 | 5.100 |
| ✓ | ✓ | 4.455 | 0.0840 | 1.491 | 5.087 |

HP: Hole Perturbation

5. Conclusion

Although depth maps are widely used in many practical applications, obtaining sharp and accurate depths from a single RGB image is highly challenging. In this paper, we presented the novel problem of mask-guided depth refinement and proposed a layered refinement approach that can be trained in a self-supervised fashion. Our method can significantly enhance initial depth maps quantitatively and qualitatively. We extensively validated our method by comparing it to mask-guided depth refinement baselines and existing automatic refinement methods. Furthermore, we verified that our method works well on real images with various masks and improves the results of downstream applications. We believe that our method can be potentially extended to other types of dense predictions such as normals and optical flow. More results are provided in the supplementary material.

Limitations

Since our method relies on a high-quality mask for refinement, its refinement performance is bounded by the mask quality. Although many auto-masking tools are available, capturing extremely fine-grained details may require manual work. Furthermore, as our method refines along mask boundaries, initially wrong depth values inside objects are likely to be left unaltered.
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