Depth Super-resolution with Deep Edge-inference Network and Edge-guided Depth Filling

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Introduction

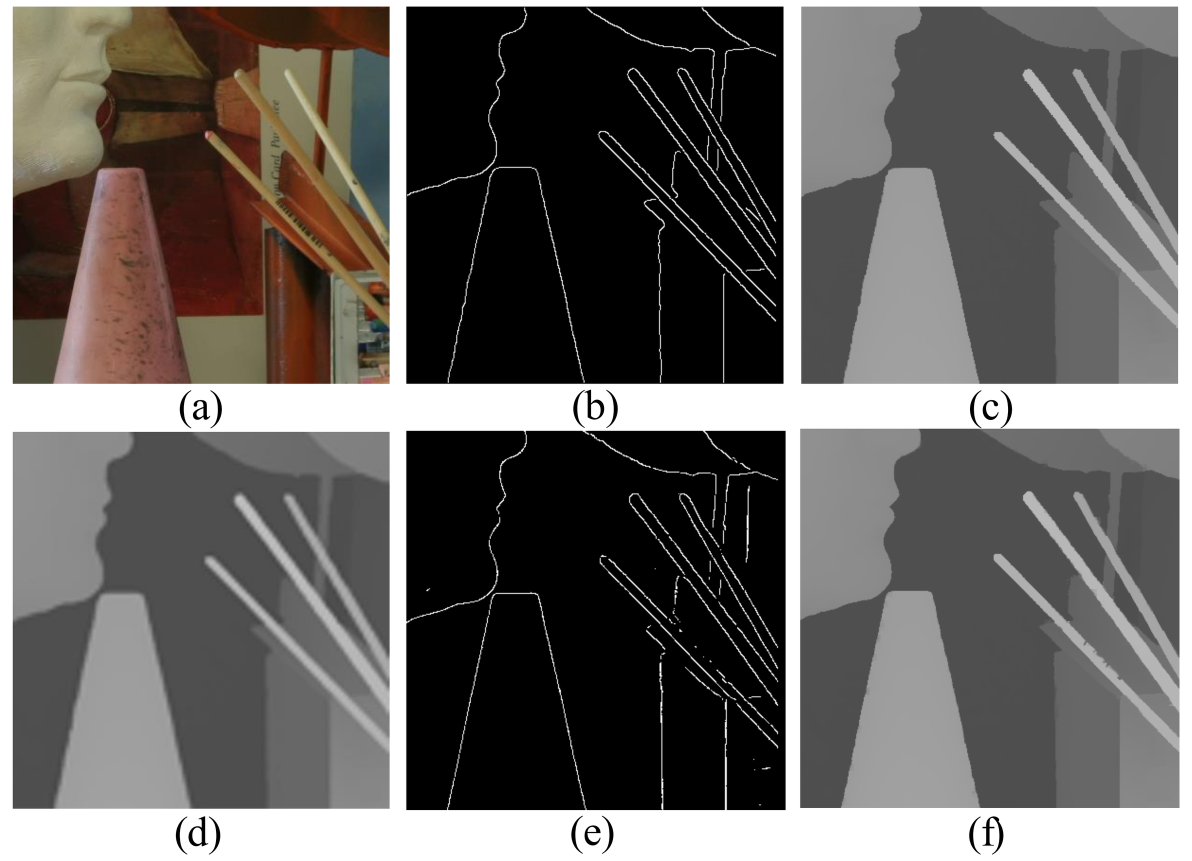


Fig. 1. Depth super-resolution example. (a) Color image; (b) ground truth (GT) edge map; (c) GT depth map; (d) LR depth map upsampling by bicubic interpolation; (e) Our inferred edge map; (f) Our upsampled HR depth map.

the accuracy of depth acquisition are affected due to the complexity of real scenes and the imaging limitation of depth sensors.(Fig. 1(d))

Usually, the basic idea to recover a HR depth map is to use the corresponding color image captured from the same scene .(Fig. 1(a))

1. We first learn a binary edge map from low resolution depth map and corresponding color image. (Fig. 1(e))
2. Then, a fast edge-guided depth filling strategy is proposed to interpolate the missing depth constrained by the acquired edges to prevent predicting across the depth boundaries.(Fig. 1(f))

Proposed Method

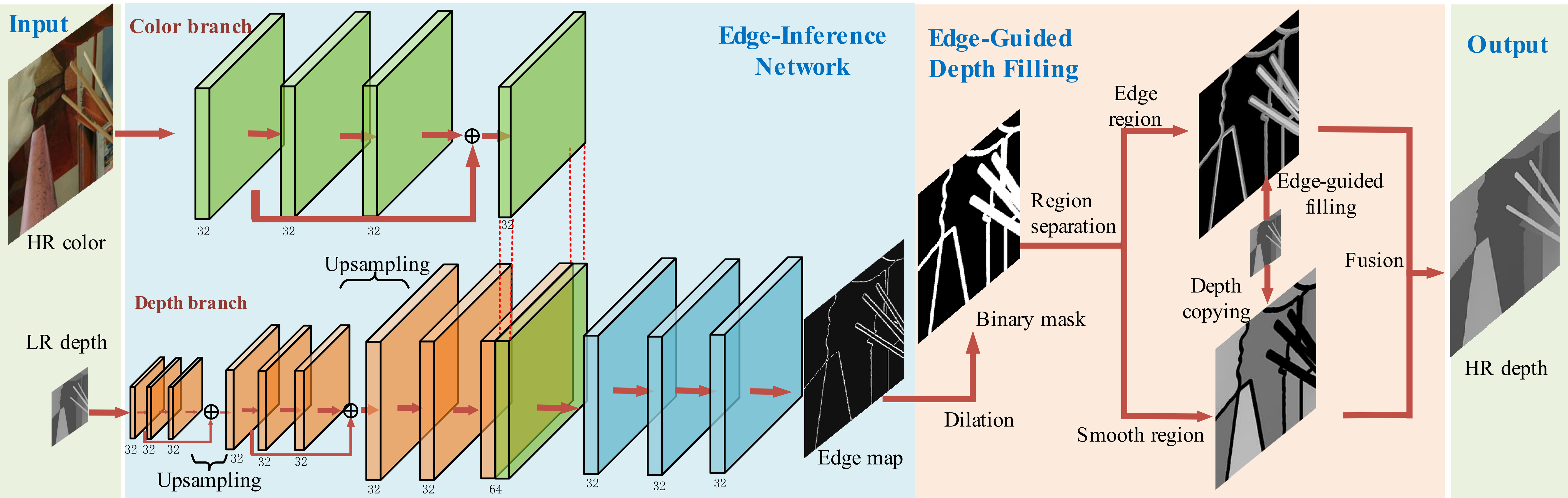


Fig. 2. Depth super-resolution framework. (4X upsamping CNN architecture)

- The color branch acts as a feature extractor to determine informative edge features from color image.
- Then, the upsampled feature maps from depth branch are concatenated with the feature maps extracted from color branch in the same resolution
- convolutional layers are added to extract the final HR edge map.

- Depth values are directly copied from the LR depth map interpolated by bicubic in ***Smooth region***
- Depth D_x is estimated via an joint bilateral filter (Eq.1) in ***Edge Region***.

Edge region

$$D_x = \frac{1}{K} \sum_{y \in \mathcal{N}(x)} G_\sigma(I_x - I_x) \cdot 1(x; y, E) D_y , \quad (1)$$

We upsample the LR depth map D^l to the resolution of HR color image I, and interpolate missing depth values on the HR image grids. For each pixel x in the target HR depth map D, its depth D_x is estimated via an **joint bilateral filter** (Eq.1).
For edge indicator, we consider four cases in fig. 3.

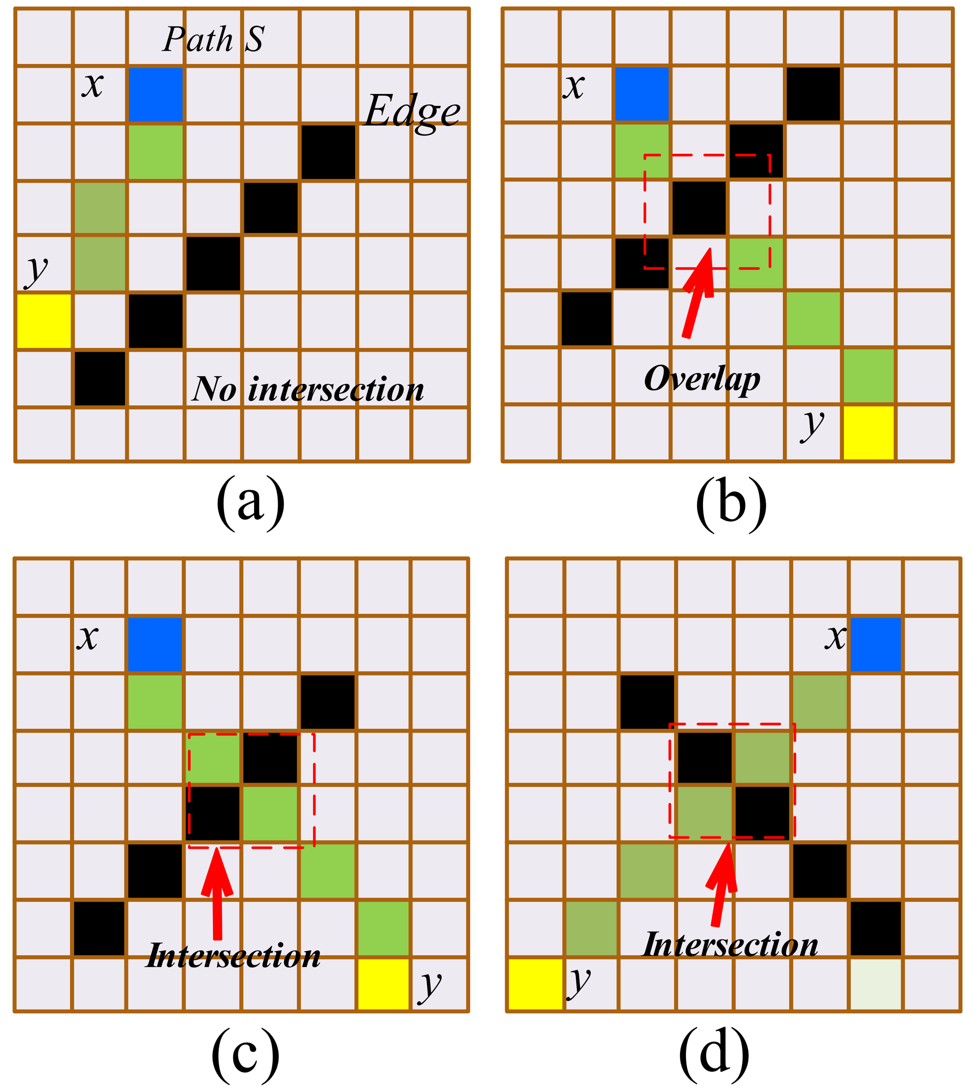
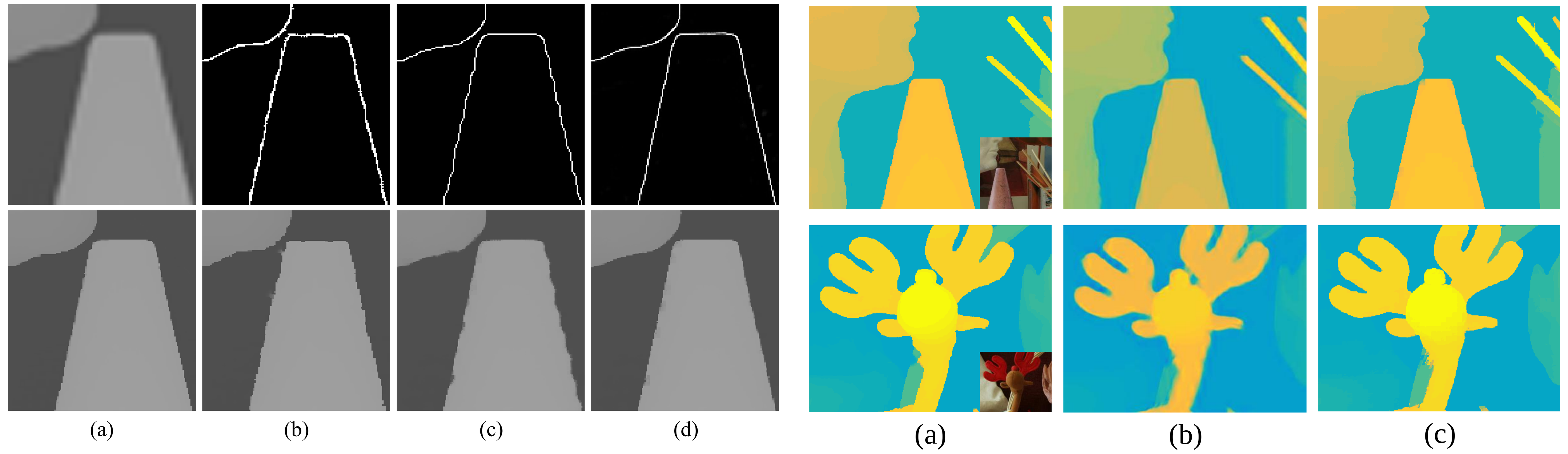
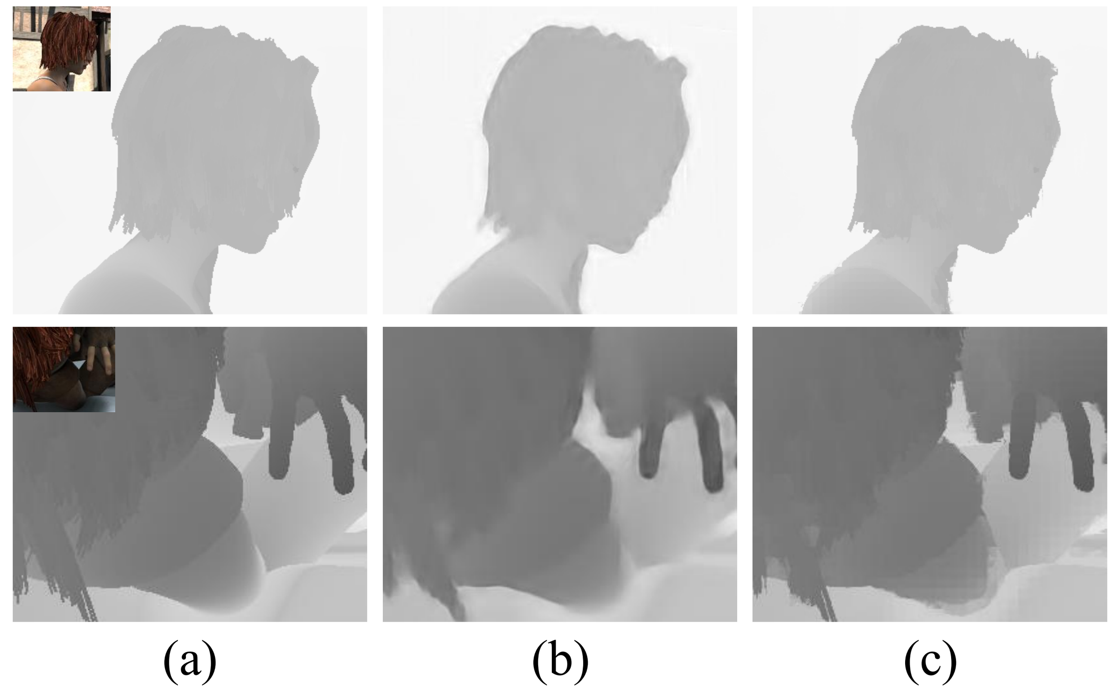


Fig. 3. Illustration of different cases of intersection between the path S (Green) and the depth edge (Black).

Experimental Results



Edge | Depth SR | Generalization



Conclusion

This paper proposes a novel depth super-resolution framework with
(1) deep edge-inference network
(2) and edge-guided depth filling.
Experimental results show that our method outperforms the state-of-art methods in both the edges inference and depth super-resolution, and generalizes well for handling diverse depth datasets.