

DEPTH ENHANCEMENT BASED ON HYBRID GEOMETRIC HOLE FILLING STRATEGY

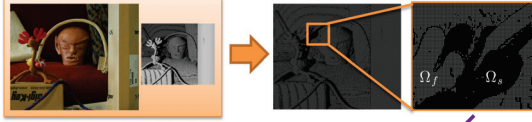
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Abstract

Depth map is a crucial component in various 3D applications. However, current available depth maps usually suffer from low resolution, high noise, random and structural depth missing problems due to theoretical, systematic or hardware limitations. In this paper, we propose a novel method to enhance depth map with the guidance of aligned color image, tackling these problems in a whole framework, where a hybrid strategy of filling hole geometrically by the combination of joint bilateral filtering and segment-based surface structure propagation is introduced. Our experimental results prove the proposed method outperforms existing methods.

Proposed Method

Alignment and Hole Partitioning



Alignment between depth map and RGB image

Partition the holes

Partition holes into two parts:

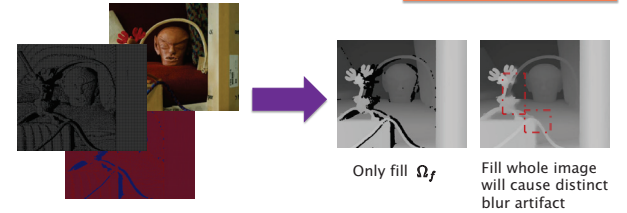
- Enough depth samples in its neighborhood: Ω_f
- Large holes with not enough depth samples: Ω_o

Filter-based Depth Interpolation

- Joint Bilateral Filtering is sufficient

Regions with no depth
 $\Omega = \Omega_f \cup \Omega_o$

Regions with depth Ψ



Only fill Ω_f

Fill whole image will cause distinct blur artifact

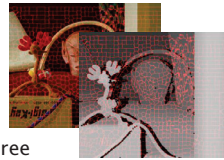
Depth Inference under Segment Constraint

Segment Constraint

- Smooth depth variation in an over-segmented patch
- One surface model in one patch
- ✓ *Linear or Quadratic model*

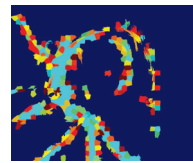
Generate Segments:

- Superpixel -- *simple linear iterative clustering (SLIC)*



Classify patches into three categories

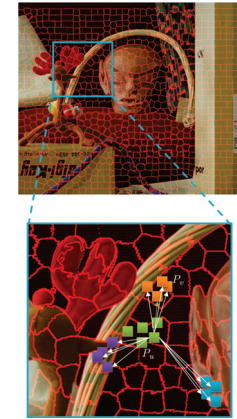
- S_u -- *Cyan patches*: Patches w/o surface Model
- S_v -- *Dark blue patches*: Patches with no holes
- S_w -- *Other patches*: Patches have enough depth samples to estimate its surface model



- Fill in patches S_o by surface fitting -- *RANSAC Model Estimation*
- Surface models of all patches around invisible patches in S_u should be estimated

- Surface propagation for patches in S_u -- *Greedy Algorithm*

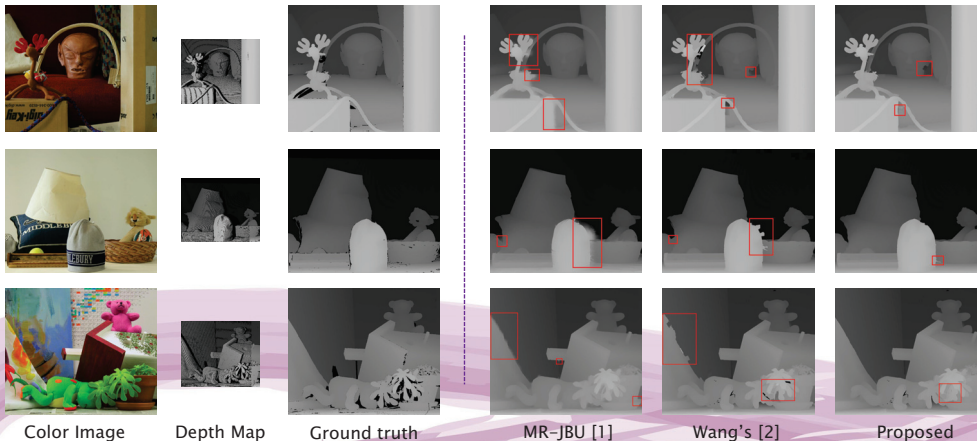
- Assign surface model to a patch in S_u by finding its most similar patch (corresponding to maximum value of *similarity function*) nearby with known surface model



Construct the similarity function

- Randomly select k sub-patches in patches $u \in S_u$ and $v \in (S - S_u) \cap \mathcal{N}(S_u)$
- Dissimilarity cost between two sub-patches $\mathcal{E}_{B_k}^u(B_k^v) = \frac{1}{N_u} \|K_u^u \circ (B_k^u - B_k^v)\|_2^2 + \frac{1}{N_v} \|K_v^v \circ (B_k^v - B_k^u)\|_2^2$
- Calculate the cost of j -th sub-patch of u against the patch v , and find the patch with the minimum cost $v^* = \arg \min_v \mathcal{E}_{B_k}^u(P_v) = \arg \min_v \frac{1}{k} \sum_{i=1}^k \mathcal{E}_{B_k^i}^u(B_k^v)$
- Form a histogram $H_R(P_v)$ indicating the number of sub-patches in u that match with patch v , then normalize it.
- Add spatial constraint, the similarity function is $T_{P_v}(P_u) = H_R(P_v) \cdot \exp(-d(P_u, P_v)^2 / (2 \times \sigma_d^2))$

Experiment Results



	MR-JBU [1]	Wang's [2]	Ours
Reindeer	8.35	3.65	3.33
Midd2	14.10	3.10	2.51
Teddy	7.23	4.09	3.66

Table 1: Comparison of bad pixel rate (BPR) (%)

	MR-JBU [1]	Wang's [2]	Ours
Reindeer	1.13	0.98	0.47
Midd2	1.67	0.62	0.31
Teddy	0.68	0.64	0.40

Table 2: Comparison of mean absolute value (MAD)

- [1] C. Richardt, C. Stoll, N. A. Doddson, H. Seidel, and C. Theobalt, "Coherent spatiotemporal filtering, upsampling and rendering of RGBZ videos," May 2012, vol. 31
- [2] L. Wang, H. Jin, R. Yang, and M. Gong, "Stereoscopic inpainting: Joint color and depth completion from stereo images," in CVPR 2008, pp. 1-8.