Depth Super Resolution by Rigid Body Self-Similarity in 3D (CVPR 2013)

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Objective

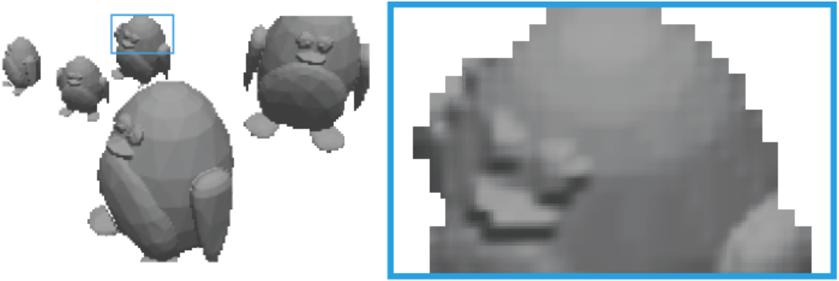
Input:

Single low-resolution, noisy, and perhaps heavily quantized depth map

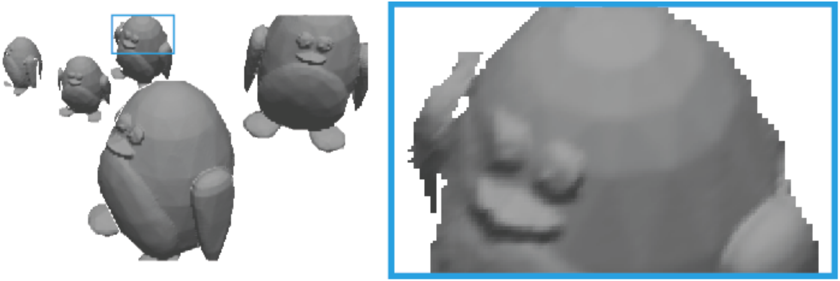
Objective:

Jointly increase spatial resolution and apparent measurement accuracy of input

Motivating Example: 3x Nearest Neighbor Upscaling



Motivating Example: 3x SR Output of Our Algorithm



Related Work: Guiding Image at Target Resolution

Figure : Yang *et al.* [21] iteratively refine low resolution input using aligned guiding color image at target resolution.

Related Work: Multiple Depth Maps

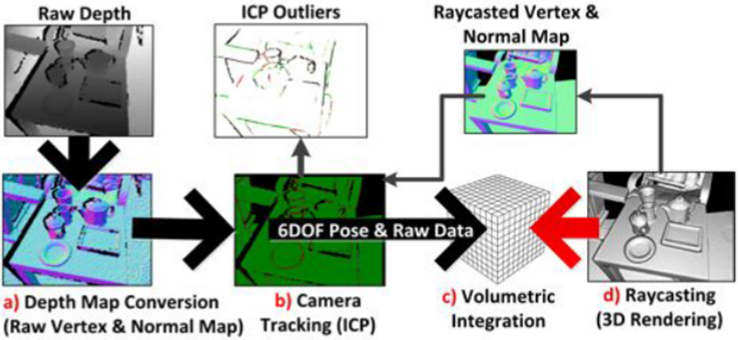


Figure : Izadi *et al.* [10] produce outstanding results by fusing a sequence of depth maps generated by a tracked Kinect camera into a single 3D representation.

Challenges: Ancillary Data or Multiple Depth Maps

Guiding image at target resolution or multiple depth maps often unavailable or difficult to obtain.

Related Work: 'Single Image' SR of Glasner *et al.*

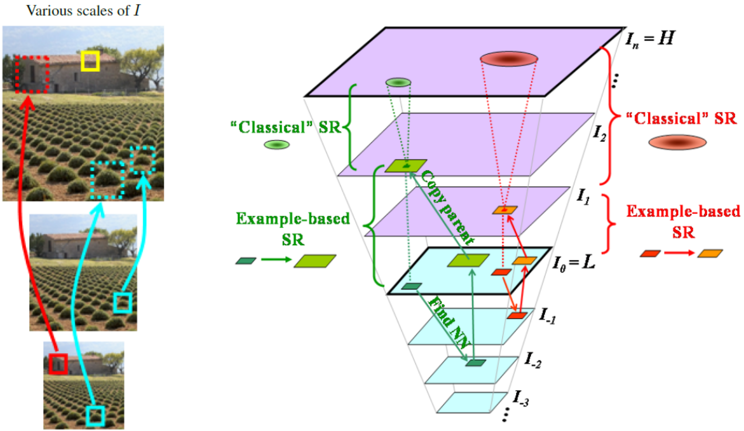


Figure : Assemble SR output using corresponding 5 × 5 pixel patches found across a discrete cascade of downscaled copies of input image.

Related Work: External Patch Database

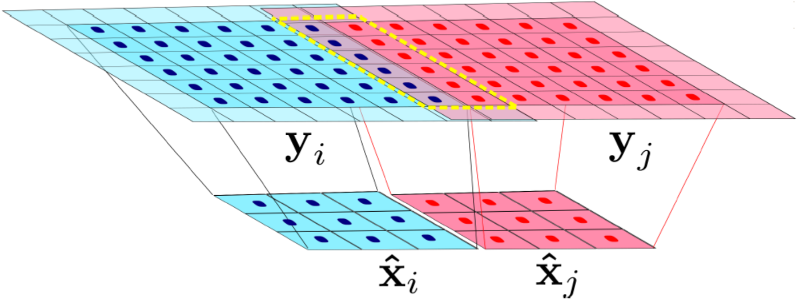


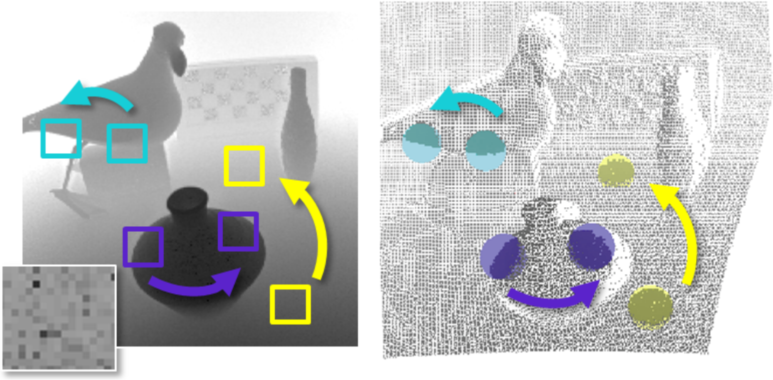
Figure : Mac Aodha *et al.* [12] assemble SR output using external database of 5.2 million high- resolution synthetic, noise-free 2D pixel patches.

Challenges: 2D Pixel Patches

Proceeding 'by example'—by assembling SR output from matched 2D pixel patches—poses its own challenges:

- Different patch depths (depth normalization?)
- Projective distortions (calls for a small patch size)
- Object boundaries (discontinuity handling?)

Challenges: 2D Pixel Patches



Our Contributions

'Single image' depth SR—using information only from input depth map—by:

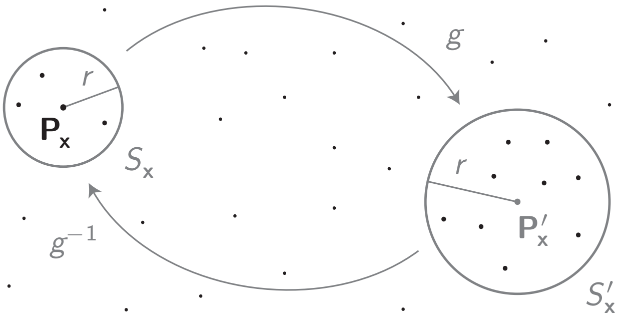
- Reasoning in terms of 3D point patches
- New 3D variant of PatchMatch (cf. Barnes *et al.* [1])
- Simple, yet effective patch upscaling and merging technique

Algorithm Overview

Our depth SR algorithm reduces to two steps:

1. Dense correspondence search via new 3D PatchMatch variant
2. Patch upscaling and merging to generate SR output

3D Point Patches



3D Point Patches

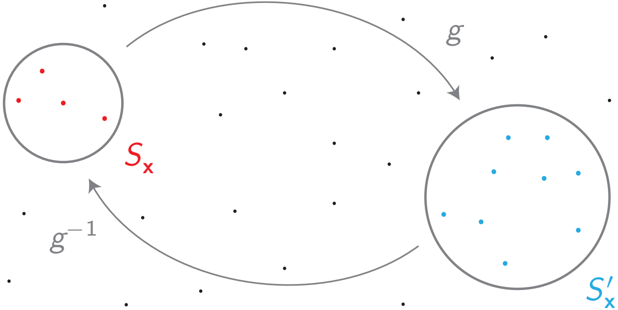
'Further' Patch $S_{\mathbf{x}} \subset \mathbb{R}^3$

Set of 3D points of input depth map within a fixed radius r of pre-image $\mathbf{P}_{\mathbf{x}} = Z_{\mathbf{x}} \cdot \mathtt{K}^{-1}(\mathbf{x}^\top, 1)^\top \in \mathbb{R}^3$ of $\mathbf{x}$, where $Z_{\mathbf{x}}$ is depth encoded at $\mathbf{x}$ in input depth map and $\mathtt{K}$ is 3×3 camera calibration matrix.

'Closer' Patch $S'_{\mathbf{x}} \subset \mathbb{R}^3$

Set of 3D points of input depth map within the same r of point $\mathbf{P}'_{\mathbf{x}} = g(\mathbf{P}_{\mathbf{x}}) \in \mathbb{R}^3$, where $g = (\mathtt{R}, \mathbf{t}) \in SE(3)$ is a 6 DoF rigid body motion in 3D such that depth of $\mathbf{P}'_{\mathbf{x}}$ be less than or equal to that of $\mathbf{P}_{\mathbf{x}}$.

Patch Similarity: ‘Backward’ Cost $c^b(\mathbf{x}; g)$



$$c^b(\mathbf{x}; g) = \sum_{\mathbf{P} \in S_{\mathbf{x}}} \left\| \mathbf{P} - \mathrm{NN}_{g^{-1}(S'_{\mathbf{x}})}(\mathbf{P}) \right\|_2^2 / |S_{\mathbf{x}}|$$

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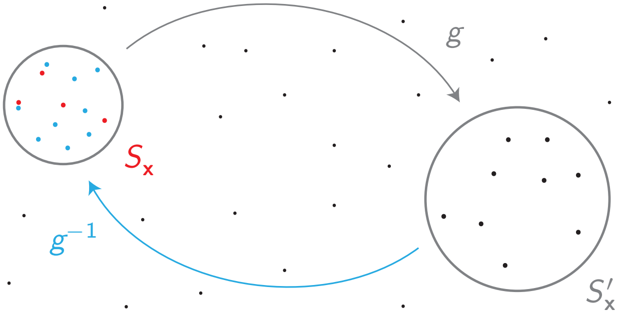

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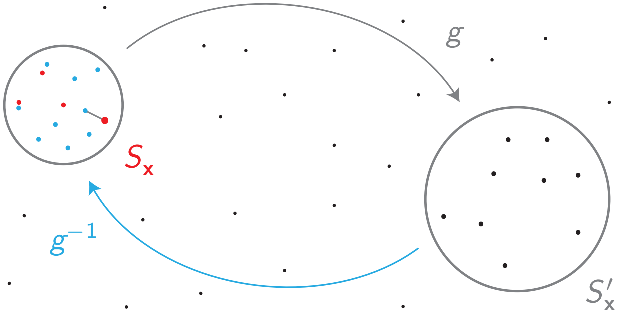

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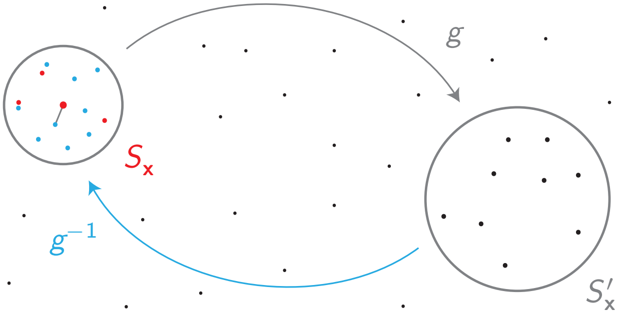

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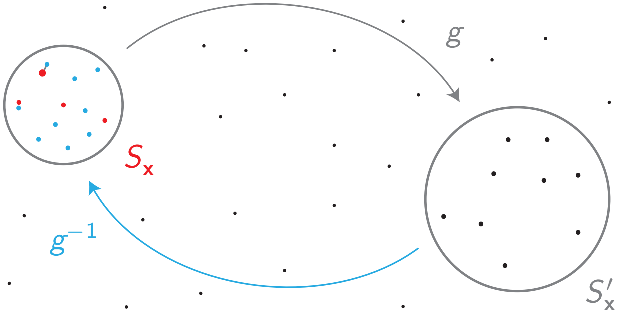

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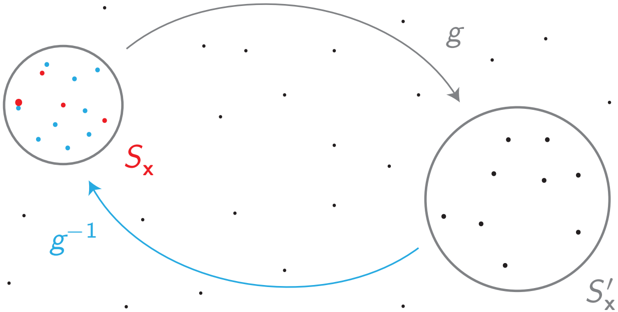

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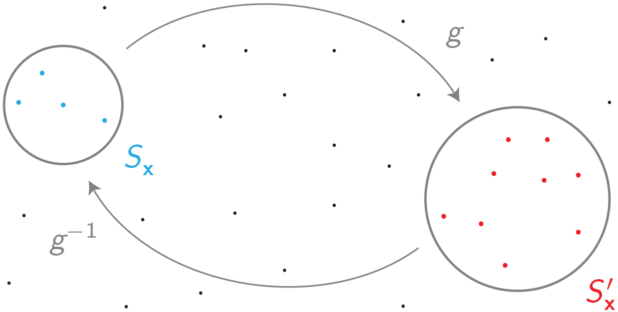
Patch Similarity: ‘Forward’ Cost $c^f(\mathbf{x}; g)$

‘Backward’ cost $c^b(\mathbf{x}; g)$ computes patch similarity without penalizing addition of new detail. To be more confident that such new detail is reasonable, we also compute analogous ‘forward’ cost $c^f(\mathbf{x}; g)$.

Patch Similarity: 'Forward' Cost $c^f(\mathbf{x}; g)$



$$c^f(\mathbf{x}; g) = \sum_{\mathbf{P}' \in S'_{\mathbf{x}}} \left\| \mathbf{P}' - \mathrm{NN}_{g(S_{\mathbf{x}})}(\mathbf{P}') \right\|_2^2 / |S'_{\mathbf{x}}|$$

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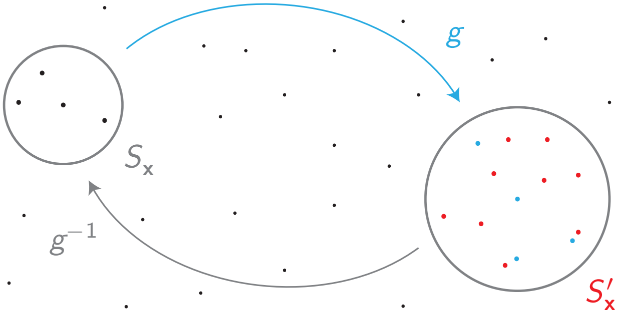

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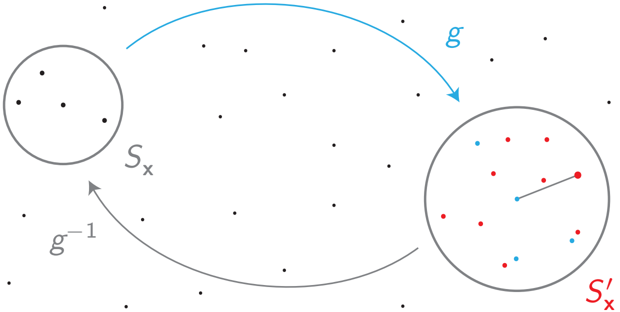

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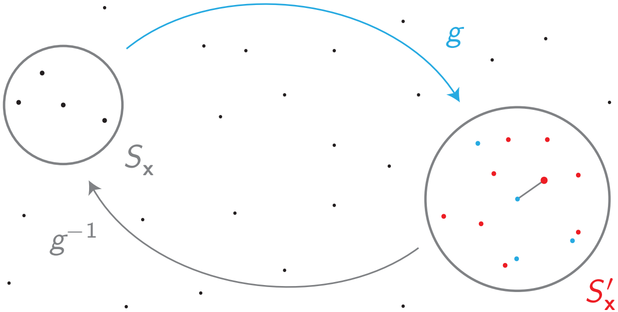

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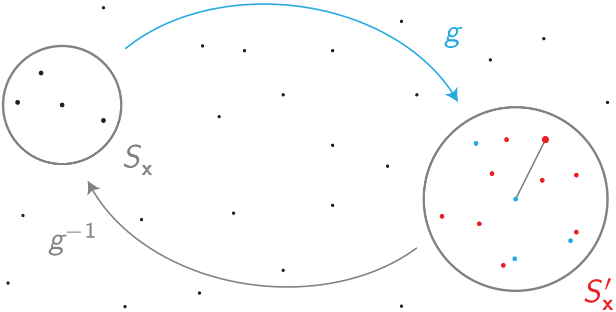

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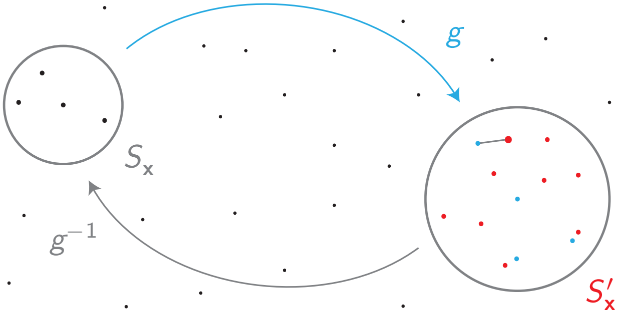

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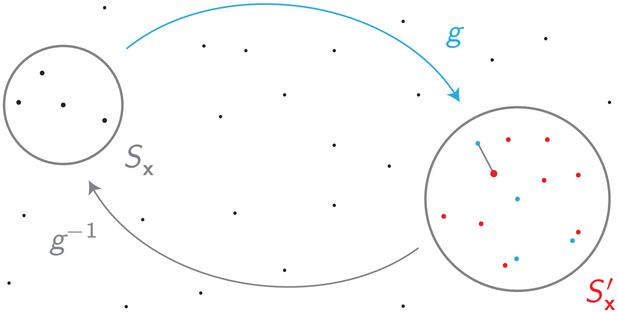

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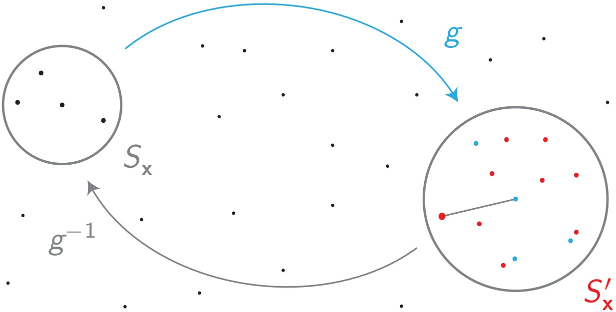

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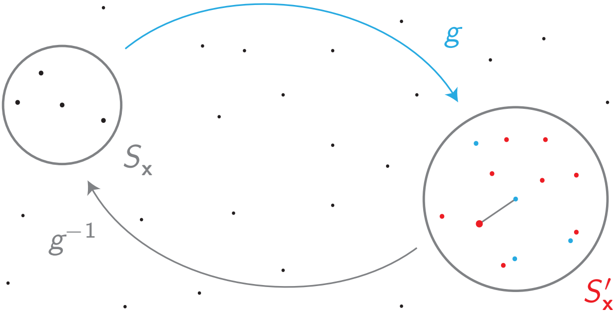

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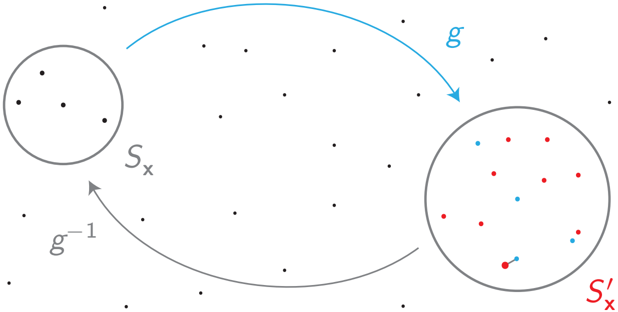

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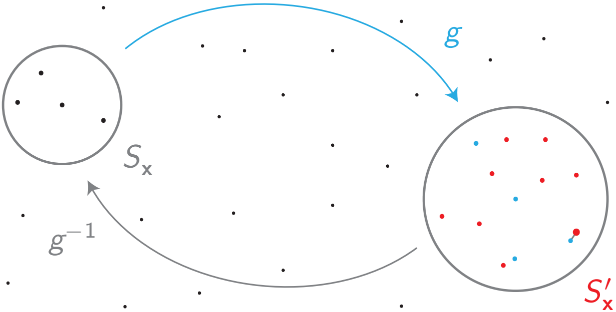


$$c^f(\mathbf{x}; g) = \sum_{\mathbf{P}' \in S'_{\mathbf{x}}} \left\| \mathbf{P}' - \mathrm{NN}_{g(S_{\mathbf{x}})}(\mathbf{P}') \right\|_2^2 / |S'_{\mathbf{x}}|$$

Patch Similarity: Matching Cost $c(\mathbf{x}; g)$

We compute matching cost $c(\mathbf{x}; g)$ according to

$$c(\mathbf{x}; g) = \begin{cases} \alpha \cdot c^b(\mathbf{x}; g) + \alpha' \cdot c^f(\mathbf{x}; g) & \text{if valid} \\ \infty & \text{otherwise} \end{cases},$$

where $\alpha \in [0, 1]$ and $\alpha' = 1 - \alpha$.

Patch Similarity: Validity of g at $\mathbf{x}$

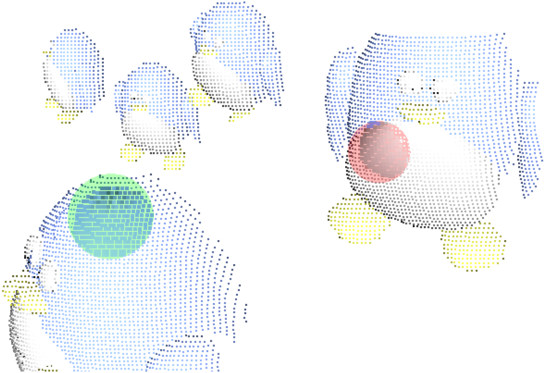
We deem a rigid body motion g valid at $\mathbf{x}$ if

- $\|\mathbf{P}_\mathbf{x} - \mathbf{P}'_\mathbf{x}\|_2 \geq r$ to prevent trivial minimization
- $|S'_\mathbf{x}| \geq |S_\mathbf{x}| \geq 3$ to match to at least as many points

3D PatchMatch for Dense Correspondence Search

Assign to each input pixel $\mathbf{x}$ a valid 6 DoF 3D rigid body motion $g_{\mathbf{x}}$ by (semi-)random initialization followed by i iterations propagation and refinement.

3D PatchMatch: Semi-Random Initialization



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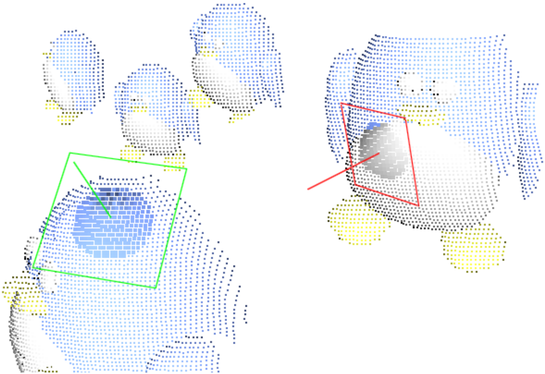
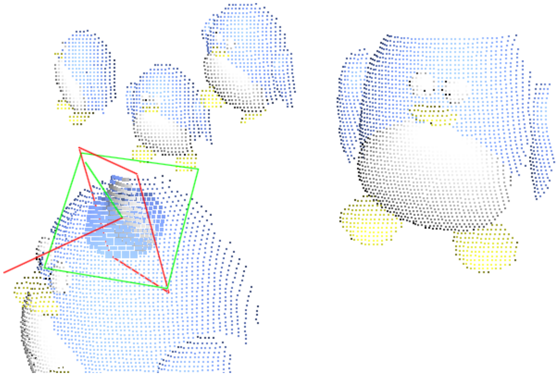
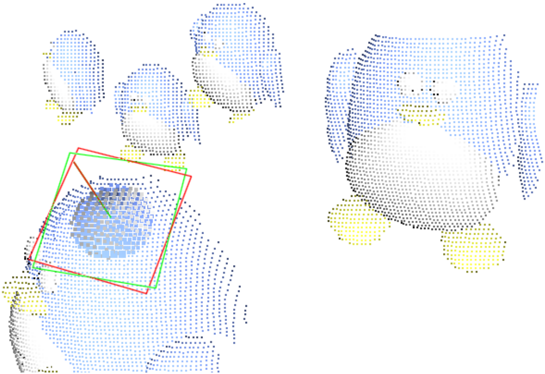


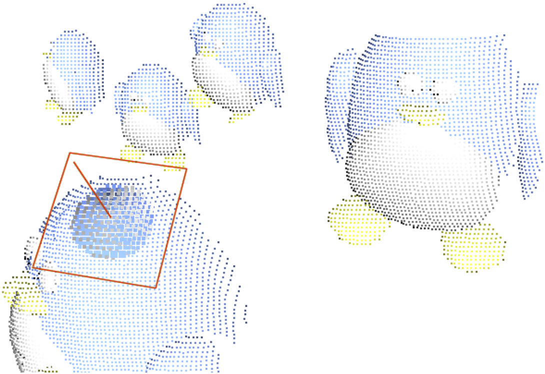
3D PatchMatch: Semi-Random Initialization (1/3)



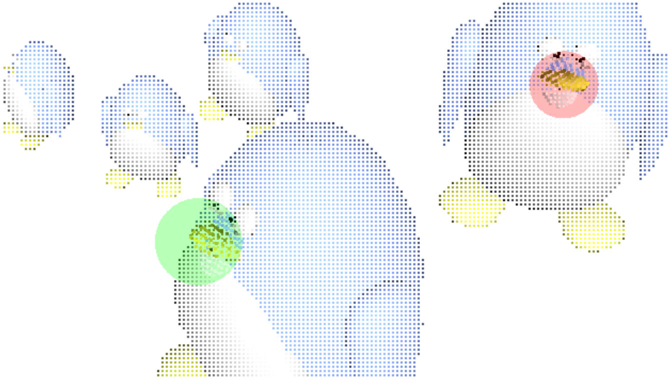
3D PatchMatch: Semi-Random Initialization (2/3)



3D PatchMatch: Semi-Random Initialization (3/3)



3D PatchMatch: Propagation



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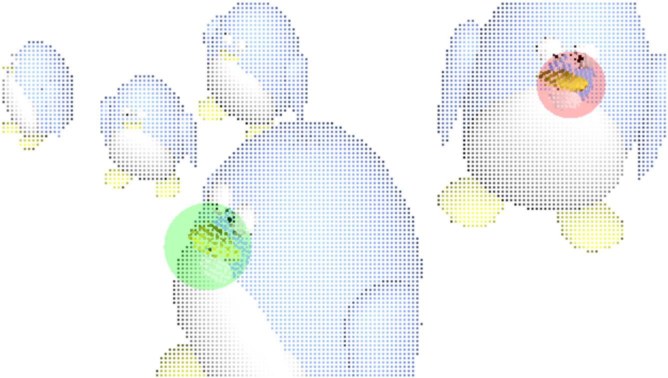

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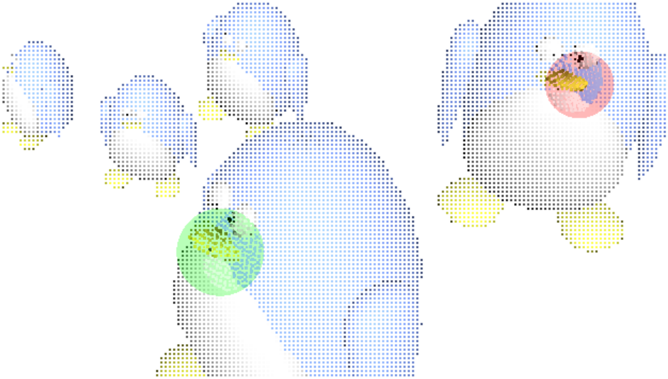

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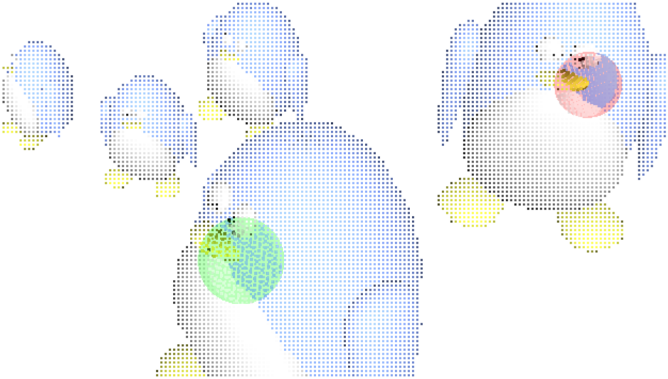

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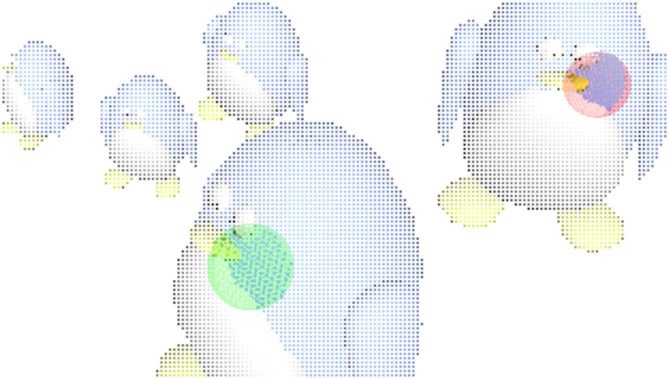

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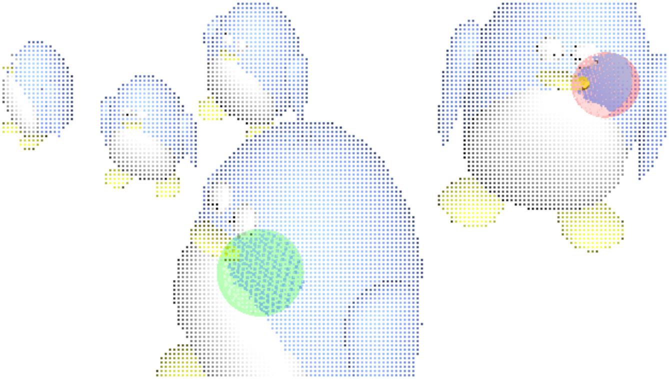
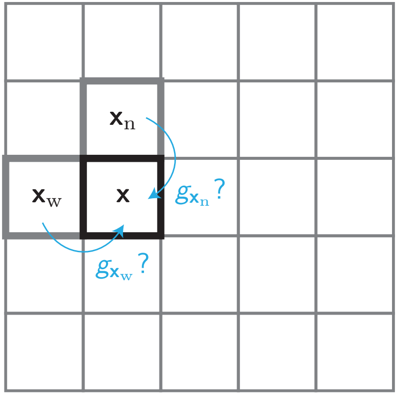


3D PatchMatch: Propagation (Odd Iterations *i*)



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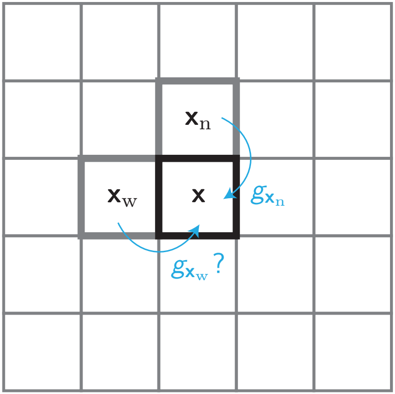

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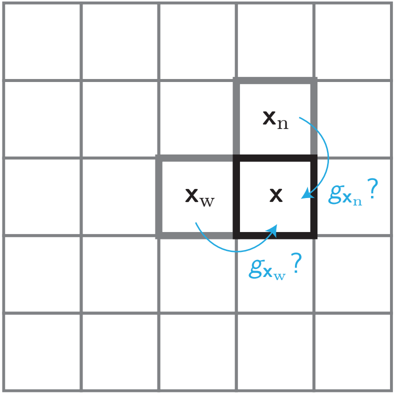

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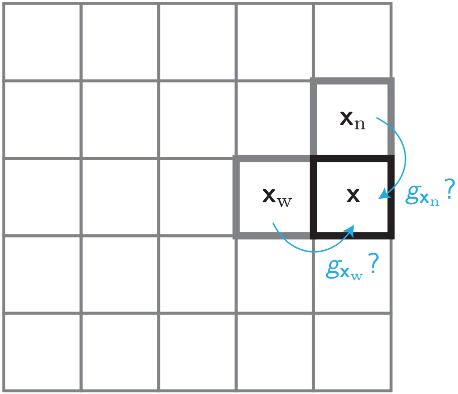
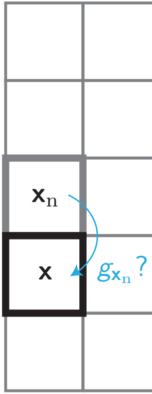


3D PatchMatch: Propagation (Odd Iterations i)



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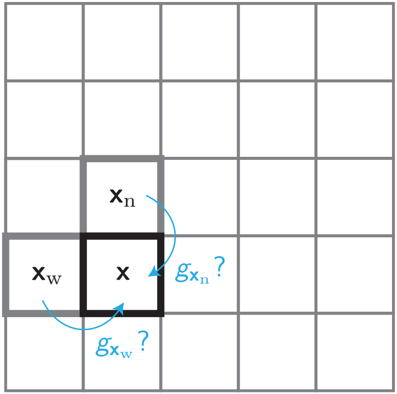
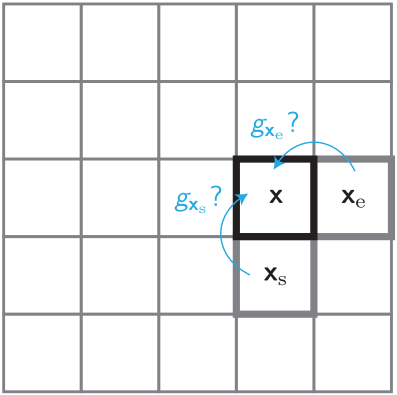


3D PatchMatch: Propagation (Even Iterations i)



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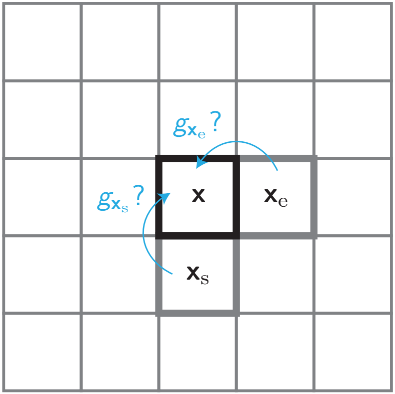

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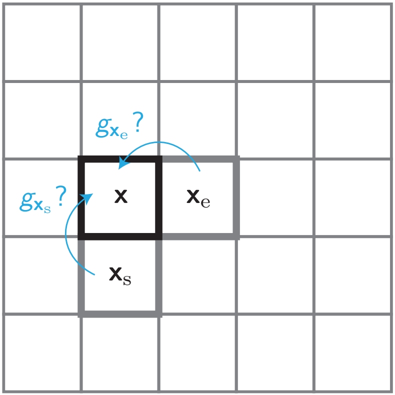

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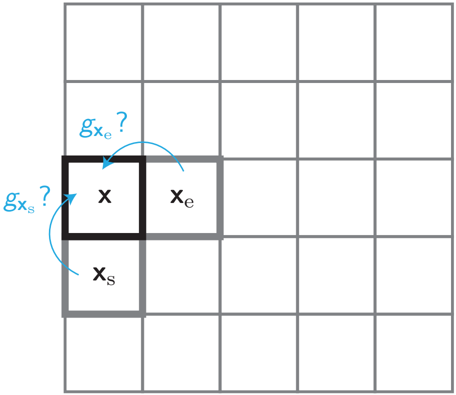

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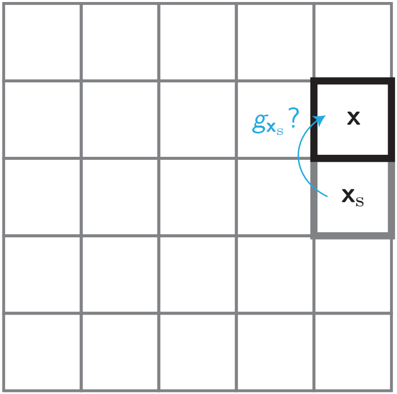

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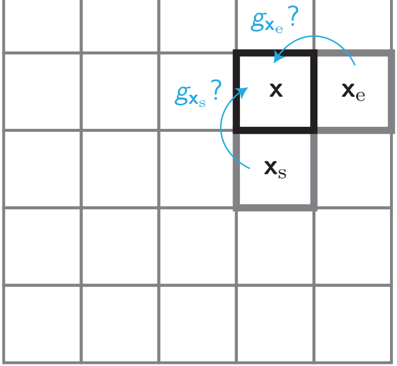
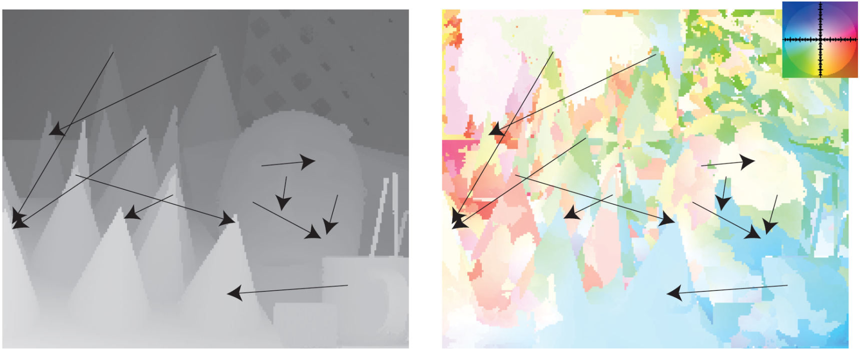


3D PatchMatch: Refinement

We independently carry out k iterations of additional initialization and of perturbation of the translational and rotational components of $g_{\mathbf{x}}$.

3D PatchMatch: Visualization



Putting It All Together?

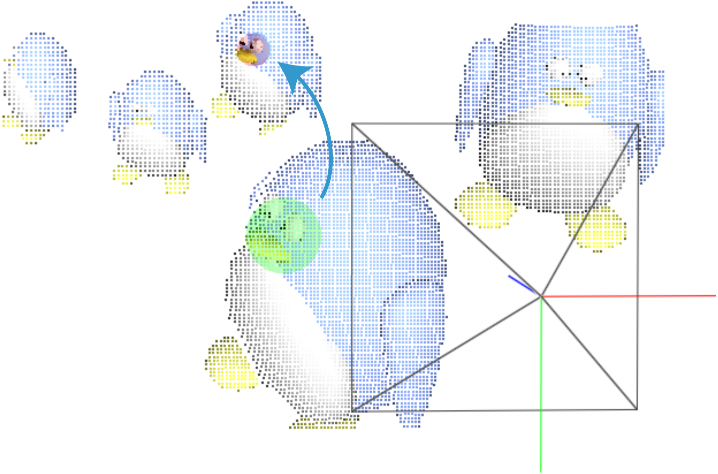
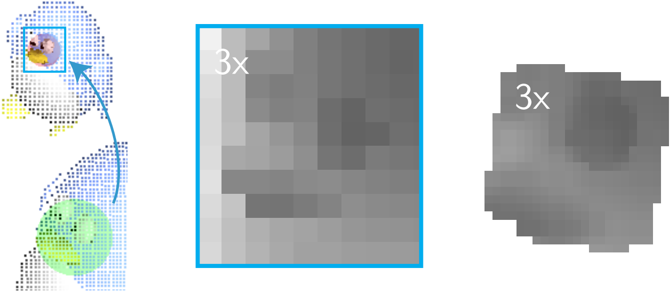


Figure : Overlapping matches? Object boundaries?

Patch Upscaling and Merging: Overlay Masks (1/2)

Patch Upscaling and Merging: Overlay Masks (2/2)

Patch Upscaling and Merging: Overlay Patches



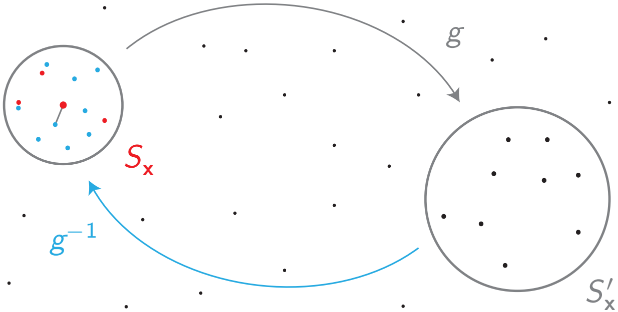
Patch Upscaling and Merging: Merging

SR output generated by weighted sum over overlapping overlay patches. Patch weight $\omega_{\mathbf{x}}$ computed as function of $c^b(\mathbf{x}; g_{\mathbf{x}})$ in order to promote addition of new detail:

$$\omega_{\mathbf{x}} = \exp\left(-\gamma \cdot c^b(\mathbf{x}; g_{\mathbf{x}})\right).$$

If $c^b(\mathbf{x}; g_{\mathbf{x}}) > \beta$, we instead use overlay patch at $\mathbf{x}$ corresponding to identity motion.

Reminder: 'Backward' Cost $c^b(\mathbf{x}; g)$



$$c^b(\mathbf{x}; g) = \sum_{\mathbf{P} \in S_\mathbf{x}} \left\| \mathbf{P} - \mathrm{NN}_{g^{-1}(S'_\mathbf{x})}(\mathbf{P}) \right\|_2^2 / |S_\mathbf{x}|$$

Qualitative Evaluation: Egg Cartons (Stereo)

Figure : Color image.

Qualitative Evaluation: Egg Cartons (Stereo)

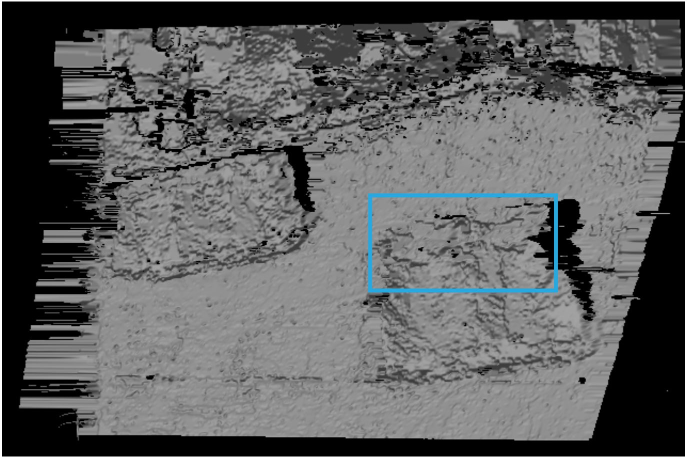


Figure : 2x nearest neighbor (32 bit).

Qualitative Evaluation: Egg Cartons (Stereo)

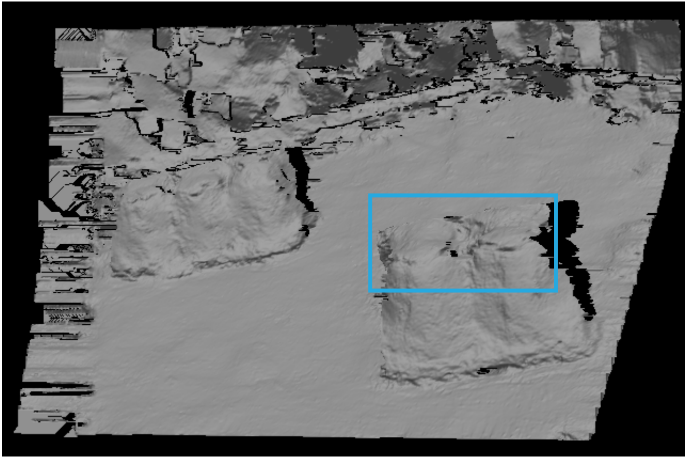


Figure : 2x SR result of our method (32 bit).

Qualitative Evaluation: Egg Cartons (Stereo)

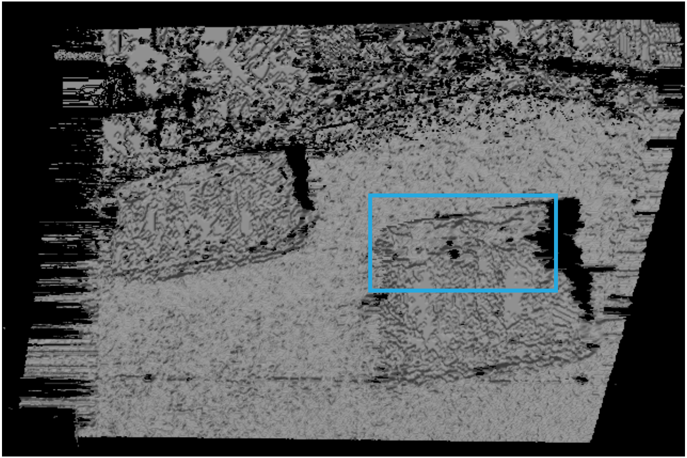


Figure : 2x SR result of Glasner *et al.* [8] (8 bit).

Qualitative Evaluation: Egg Cartons (Stereo)

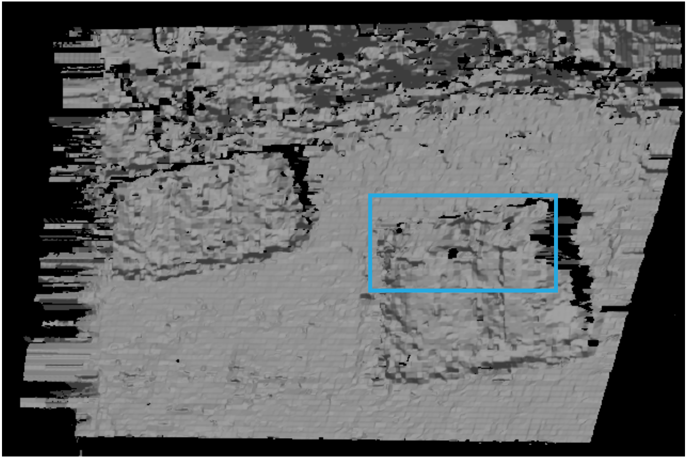


Figure : 2x SR result of Mac Aodha *et al.* [12] (preprocessed, 32 bit).

Qualitative Evaluation: Egg Cartons (Stereo)

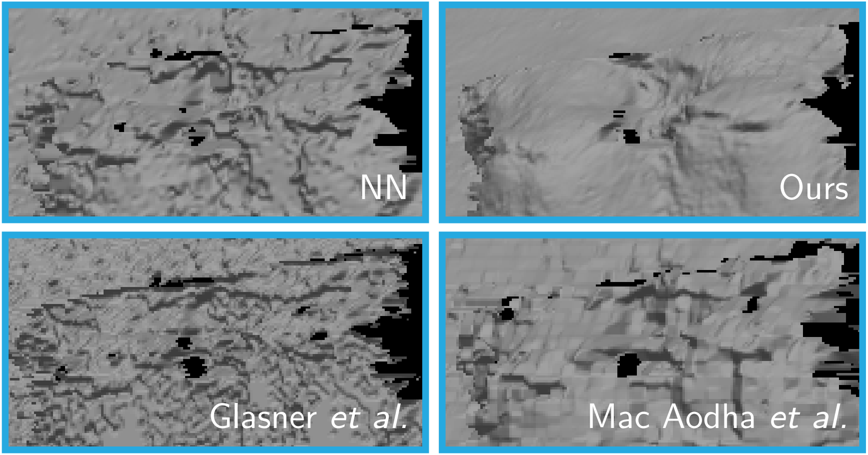


Figure : Zooms.

Qualitative Evaluation: Gull (ToF)

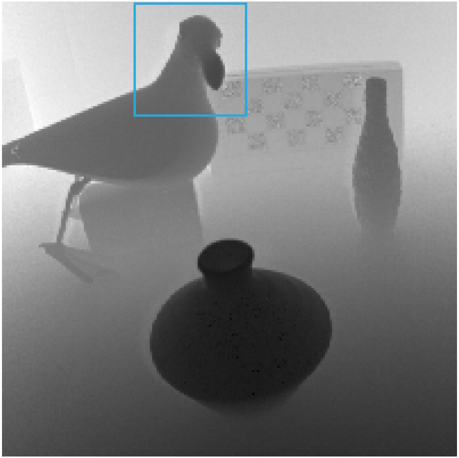


Figure : 4x nearest neighbor.

Qualitative Evaluation: Gull (ToF)

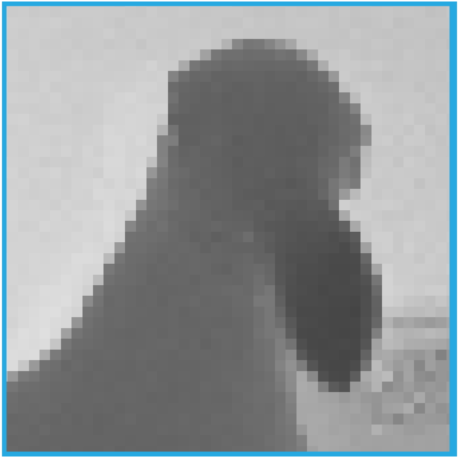


Figure : 4x nearest neighbor (zoom).

Qualitative Evaluation: Gull (ToF)

Figure : 4x SR result of our method (zoom).

Qualitative Evaluation: Gull (ToF)

Figure : 4x SR result of Mac Aodha *et al.* [12] (preprocessed, zoom).

Qualitative Evaluation: Gull (ToF)

Figure : 4x SR result of Glasner *et al.* [8] (zoom).

Qualitative Evaluation: Gull (ToF)

Figure : 4x SR result of Yang *et al.* [20] (zoom).

Qualitative Evaluation: Gull (ToF)

Figure : 4x SR result of Freeman and Liu [7] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

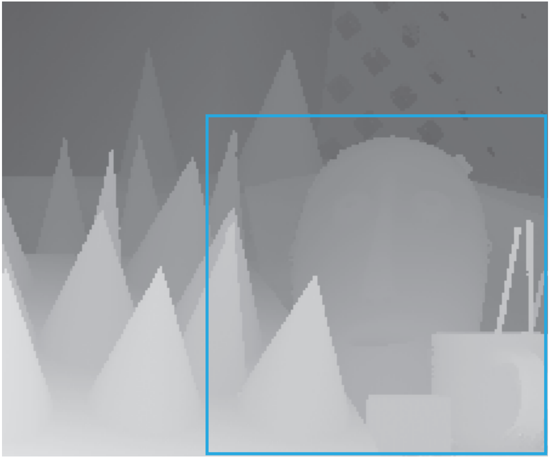


Figure : 2x nearest neighbor.

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x nearest neighbor (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR result of our method (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR of Glasner *et al.* [8] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

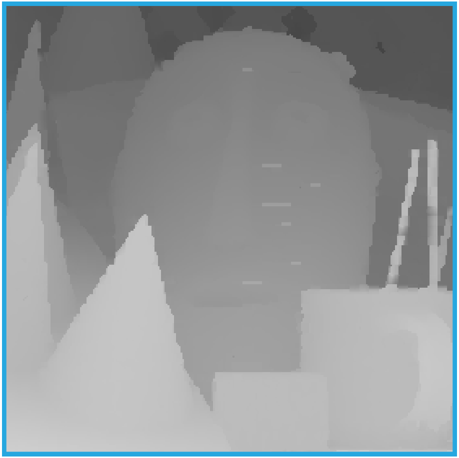


Figure : 2x SR of Mac Aodha *et al.* [12] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR of Yang *et al.* [20] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR of Freeman and Liu [7] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR of Diebel and Thrun [5] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR of Yang *et al.* [21] (zoom).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

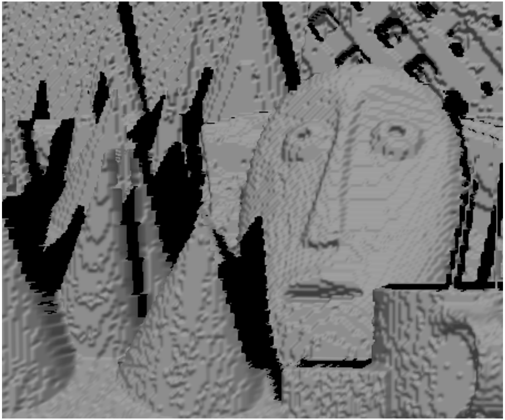


Figure : 2x nearest neighbor (zoom, 32 bit).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

Figure : 2x SR result of our method (zoom, 32 bit).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

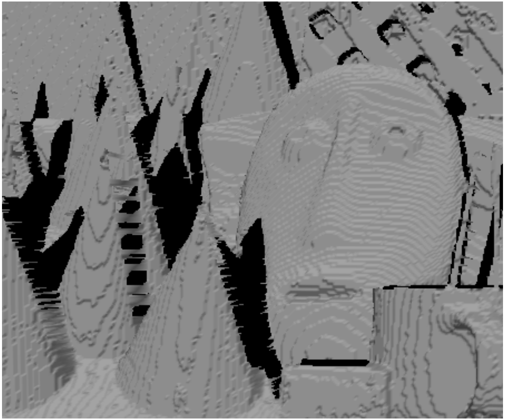


Figure : 2x SR result of our method (zoom, 8 bit).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

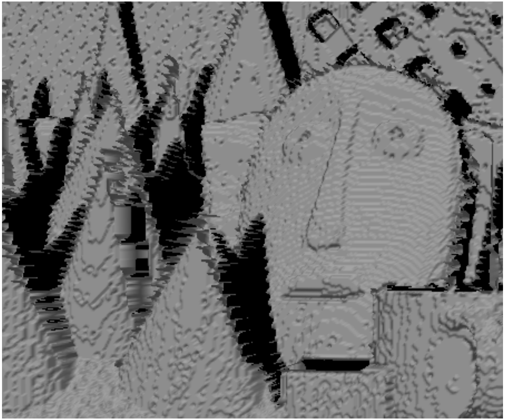


Figure : 2x SR result of Glasner *et al.* [8] (zoom, 8 bit).

Qualitative Evaluation: Middlebury Cones (Struct. Light)

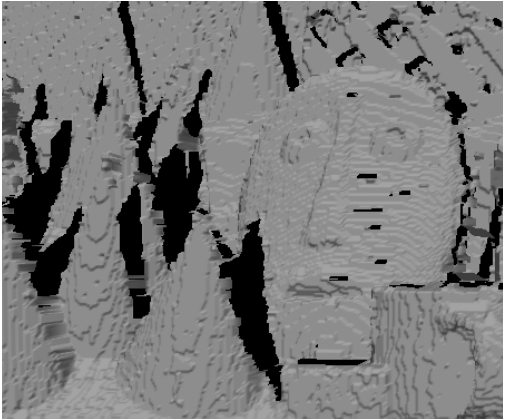


Figure : 2x SR result of Mac Aodha *et al.* [12] (zoom, 8 bit).

Root Mean Square Error (RMSE): Middlebury

	2x				4x			
	Cones	Teddy	Tsukuba	Venus	Cones	Teddy	Tsukuba	Venus
Nearest Neighbor	1.094	0.815	0.612	0.268	1.531	1.129	0.833	0.368
Diebel and Thrun [5]	0.740	0.527	0.401	0.170	1.141	0.801	0.549	0.243
Yang *et al.* [21]	0.756	0.510	0.393	0.167	0.993	0.690	0.514	0.216
Yang *et al.* [20]	2.027	1.420	0.705	0.992	2.214	1.572	0.840	1.012
Freeman and Liu [7]	1.447	0.969	0.617	0.332	1.536	1.110	0.869	0.367
Glasner *et al.* [8]	**0.867**	**0.596**	**0.482**	**0.209**	1.483	1.065	0.832	0.394
Mac Aodha *et al.* [12]	1.127	0.825	0.601	0.276	1.504	**1.026**	0.833	**0.337**
Our Method	0.994	0.791	0.580	0.257	**1.399**	1.196	**0.727**	0.450

Percent Error: Middlebury

	2x				4x			
	Cones	Teddy	Tsukuba	Venus	Cones	Teddy	Tsukuba	Venus
Nearest Neighbor	1.713	1.548	1.240	0.328	3.121	3.358	2.197	0.609
Diebel and Thrun [5]	3.800	2.786	2.745	0.574	7.452	6.865	5.118	1.236
Yang *et al.* [21]	2.346	1.918	1.161	0.250	4.582	4.079	2.565	0.421
Yang *et al.* [20]	61.617	54.194	5.566	46.985	63.742	55.080	7.649	47.053
Freeman and Liu [7]	6.266	4.660	3.240	0.790	15.077	12.122	10.030	3.348
Glasner *et al.* [8]	4.697	3.137	3.234	0.940	8.790	6.806	6.454	1.770
Mac Aodha *et al.* [12]	2.935	2.311	2.235	0.536	6.541	5.309	4.780	**0.856**
Our Method	**2.018**	**1.862**	**1.644**	**0.377**	**3.271**	**4.234**	**2.932**	3.245

Summary

We presented a 'single image' depth SR algorithm, making use of only the information contained in the input depth map. We introduced a new 3D variant of PatchMatch for recovering a dense matching between pairs of closer-further corresponding 3D point patches related by 6 DoF rigid body motions in 3D, and a technique for upscaling and merging matches that predicts sharp object boundaries at the target resolution. We showed our results to be highly competitive with methods leveraging ancillary data.

Acknowledgement

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References

Provided in: Michael Hornáček, Christoph Rhemann, Margrit Gelautz, Carsten Rother. Depth Super Resolution by Rigid Body Self-Similarity in 3D. In *CVPR*, 2013.

Questions?