Extended Patch Prioritization for Depth Filling within Constrained Exemplar-based RGB-D Completion

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3D Image Representations

Many current robotic and systems applications heavily depend on 3D scene imagery. 3D information can be represented in various ways:

- **Graphical Models**
- **Volumetric Images**
- **Meshes**
- **Point Clouds**
- **Depth Images**

Most can be converted into each other!

3D Image Representations

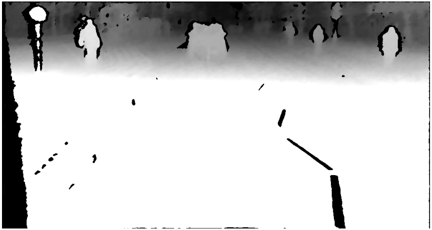
Depth sensing methods are not perfect.

Depth images are efficiently processed and readily available.

Several techinques can be used to acquire depth images:

3D Image Representations

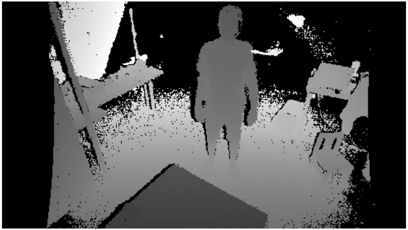
Depth sensing methods are not perfect.



Stereo Camera Correspondence

3D Image Representations

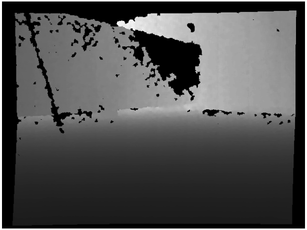
Depth sensing methods are not perfect.



Time-of-Flight Camera

3D Image Representations

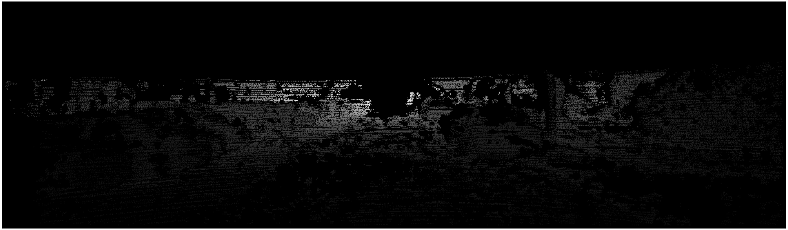
Depth sensing methods are not perfect.



Structured Light Device

3D Image Representations

Depth sensing methods are not perfect.



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Object Removal and Image Completion

Strong literature already exists on color image completion.

Various solutions have been proposed for the problems of object removal and inpainting within the past two decades:

- **Energy Minimization**
- **Anisotropic Diffusion**
- **PDEs**
- **Exemplar-based Completion**
- **Others**

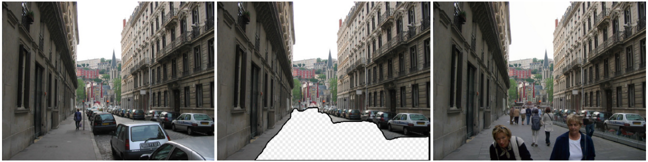
Analogous solutions can be used for depth completion.

Object Removal and Image Completion

A Few Examples

[Bertalmio et al. 2000]

[Criminisi et al. 2004]



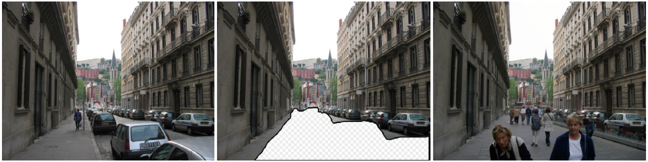
[Hays and Efros, 2007]

Object Removal and Image Completion

A Few Examples

[Bertalmio et al. 2000]

[Criminisi et al. 2004]



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Object Removal and Image Completion

A Few Examples

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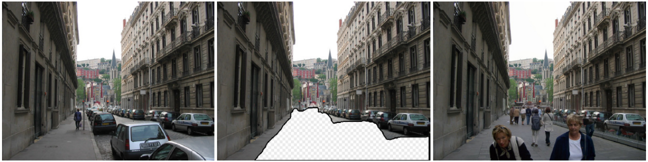

[Hays and Efros, 2007]

Object Removal and Image Completion

A Few Examples

[Bertalmio et al. 2000]

[Criminisi et al. 2004]

[Hays and Efros, 2007]

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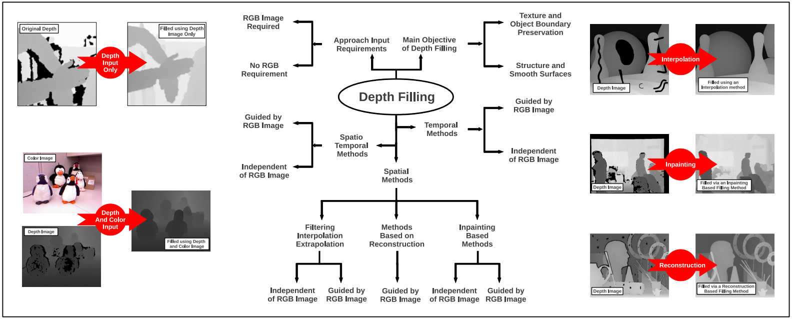
Depth Image Completion Literature

- *Atapour-Abarghouei and Breckon, "A comparative review of plausible hole filling strategies in the context of scene depth image completion." in Computers & Graphics, 2018.*



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Removing Objects from RGB-D Images and Filling Depth Holes

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Texture and Relief in Depth Images

- Depth images are generally smoother and less textured than RGB images. Surface relief is hard to capture in depth maps.

- However, ignoring surface relief and texture detail is a mistake.

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Texture and Relief in Depth Images

- Exemplar-based methods preserve texture in RGB images.

Texture and Relief in Depth Images

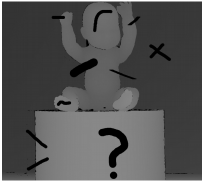
- Criminisi et al. “Region Filling and Object Removal by Exemplar-based Image Inpainting.” In: IEEE Trans. Image Processing, 2004.

Texture and Relief in Depth Images

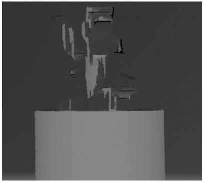
- Exemplar-based methods do not perform well with depth images.

Color Image

Inpainted Color



Depth Image

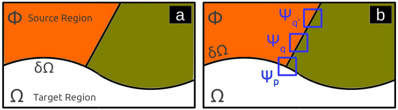


Inpainted Depth

Exemplar based Image Completion

Criminisi et al., 2004.

- Identify target region and boundary.
- Select a patch for filling.
- Query the source region and find the best-matching patch via an appropriate error metric (e.g. sum of squared differences).
- After a candidate is found, update information and start over.



An important factor in generating desirable results is the order in which patches are selected for filling!

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Proposed Approach

Extended Patch Prioritization for Filling within Exemplar-based RGB-D Completion

- The "confidence" term prioritizes patches constrained by more valid values (fewer missing neighbours) in the **depth image**.

  Before the filling process, this term is initialized as:

  $$C(p) = \begin{cases} 0, & \forall p \in \Omega \\ 1, & \forall p \in \Omega - \mathcal{I} \end{cases}$$

- **Confidence Term** (*Depth*): $C(p) = \frac{\sum_{q \in \Psi_p \cap (\mathcal{I} - \Omega)} C(q)}{|\Psi_p|}$

Proposed Approach

Extended Patch Prioritization for Filling within Exemplar-based RGB-D Completion

- The "data" term encourages the filling of patches into which isophotes (lines of equal intensity) flow in the **RGB image**.

  Using this term will preserve the semantics of geometric structures within the image.

- **Data Term** (RGB): $D(p) = \frac{|\nabla \mathcal{I}_p^{\perp} \cdot n_p|}{\alpha}$.

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Proposed Approach

Extended Patch Prioritization for Filling within Exemplar-based RGB-D Completion

- To ensure a better flow of dominant linear structures into the target region, a "boundary" term is added based on the **RGB image**.

  $G_{x \geq \tau}$ and $G_{y \geq \tau}$ are strong intensity gradients in the **RGB image** in the x and y directions respectively, with τ being the gradient threshold (e.g. $\tau = 0.7$)

- **Boundary Term** (RGB): $B(p) = \frac{\sum_{q \in \Psi_p \cap (\mathcal{I} - \Omega)} (|G_{x \geq \tau}(q)| + |G_{y \geq \tau}(q)|)}{|\Psi_p|}$

Proposed Approach

Extended Patch Prioritization for Filling within Exemplar-based RGB-D Completion

- A "texture" term is used in the **depth image** to guarantee a better propagation of texture and relief into the target region.

  $G_{x<\tau}$ and $G_{y<\tau}$ are slight intensity gradients in the depth image in the x and y directions respectively, with τ being the gradient threshold (e.g. $\tau = 0.3$)

- **Texture Term** (*Depth*): $T(p) = \frac{\sum_{q \in \Psi_p \cap (\mathcal{I} - \Omega)} |G_{x<\tau}(q)| + |G_{y<\tau}(q)|}{|\Psi_p|}$

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Proposed Approach

Extended Patch Prioritization for Filling within Exemplar-based RGB-D Completion

- The priority of a patch for filling is thus calculated using the aforementioned terms.
  The priority is calculated for all patches on the "fill front" after every patch is filled.

- **Patch Priority**: $P(p) = C(p)D(p)B(p)T(P)$

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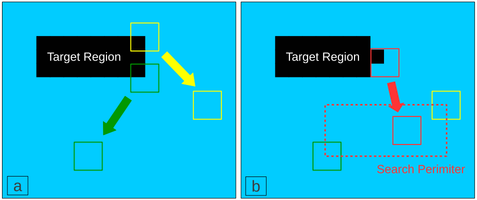
Proposed Approach

Exemplar-based approaches are not known for the efficiency!!

- Our analyses show that **most suitable candidates** are located **close** to **best-matching candidates** in **previous iterations**.
- Therefore, query space can be constrained to improve efficiency.



- In 91.2% of queries, the best matching patch was found inside the perimeter leading to 31% improvement in efficiency.

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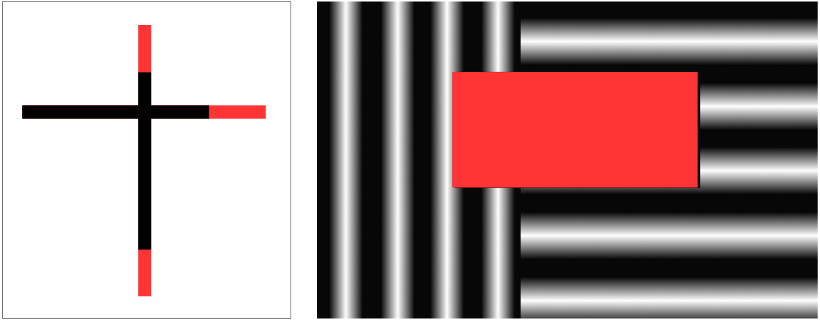
Experimental Results

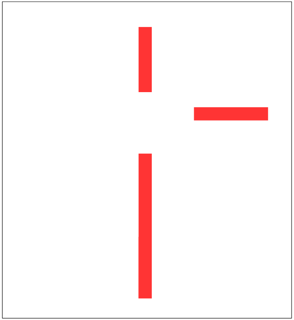
Synthetic images are used to test the capabilities of the approach.

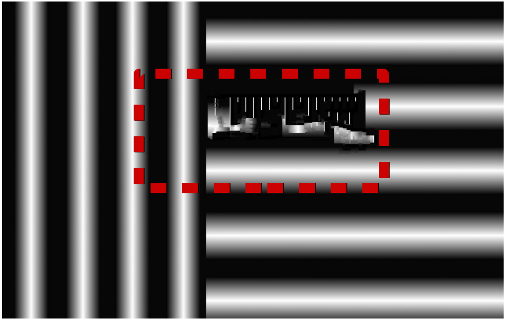


Original Image

Experimental Results

Synthetic images are used to test the capabilities of the approach.





Conventional Exemplar-based Approach *[Criminisi et al. 2004]*

Experimental Results

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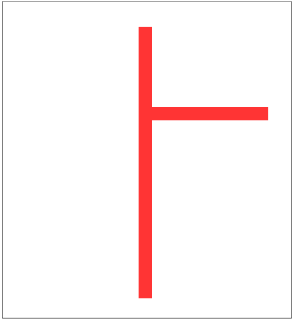
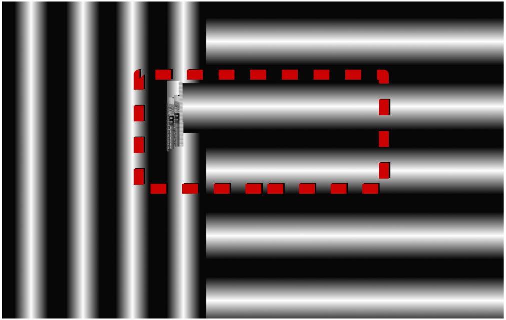




Proposed Approach

Experimental Results

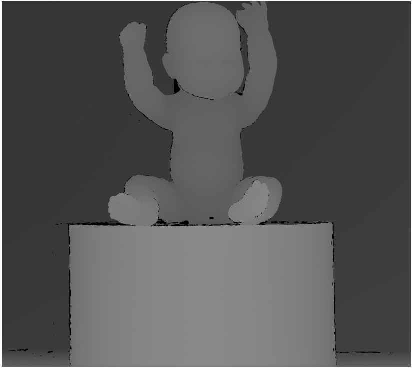
The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Original Input (RGB Image)

Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

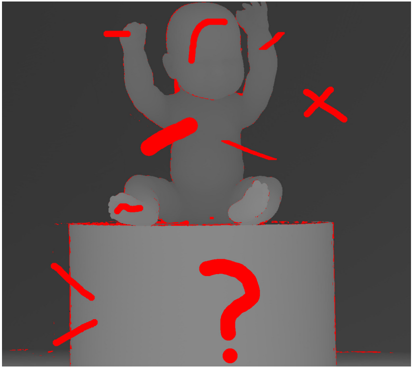
Ground Truth Depth



Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Holes Synthetically Added

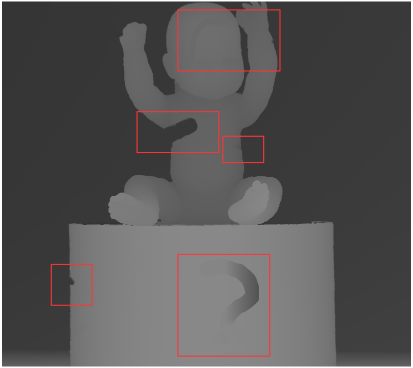


Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Result of [Herrera et al., 2013]

RMSE: 2.9638 **PBMP:** 0.0180 **Run-time:** 71.1200 (s)

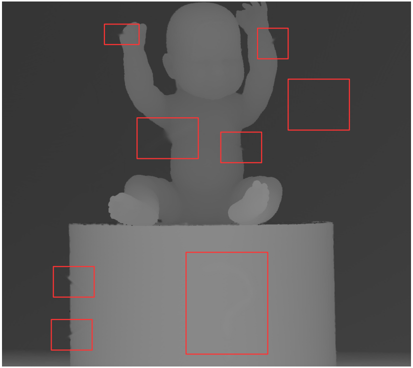


Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Result of [Telea, 2004]

RMSE: 0.8349 **PBMP:** 0.0120 **Run-time:** 0.79400 (s)

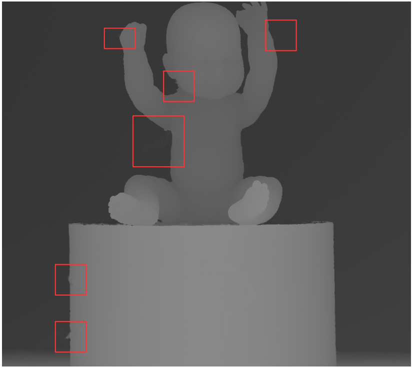


Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Result of [Liu et al., 2012]

RMSE: 0.6008 **PBMP:** 0.0095 **Run-time:** 2.58000 (s)

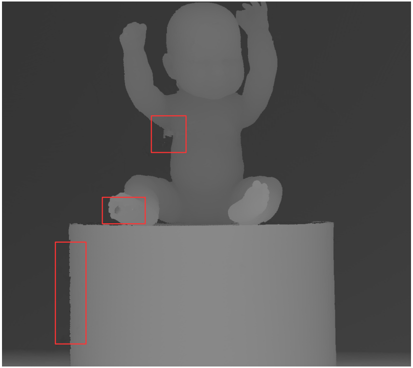


Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Result of [Criminisi et al., 2004]

RMSE: 0.9053 **PBMP:** 0.0025 **Run-time:** 1196.49 (s)

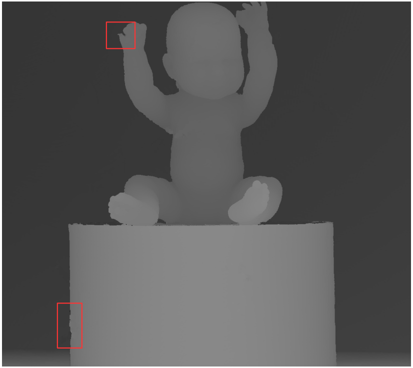


Experimental Results

The approach is tested using the Middlebury dataset [Hirschmuller et al., 2007]

Result of our Approach **RMSE:** 0.6688 **PBMP:** 0.0021

Run-time: 879.730 (s)



Experimental Results

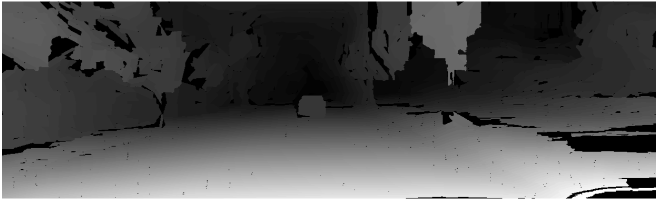
The approach was also evaluated using the KITTI dataset [Geiger et al., 2013]

Original Input (RGB Image)

Experimental Results

The approach was also evaluated using the KITTI dataset [Geiger et al., 2013]

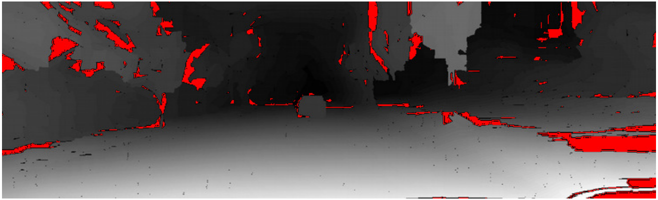
Disparity calculated using [Yamaguchi et al., 2014]



Experimental Results

The approach was also evaluated using the KITTI dataset [Geiger et al., 2013]

Disparity calculated using [Yamaguchi et al., 2014]



Experimental Results

The approach was also evaluated using the KITTI dataset [Geiger et al., 2013]

Result of [Herrera et al., 2013]

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Experimental Results

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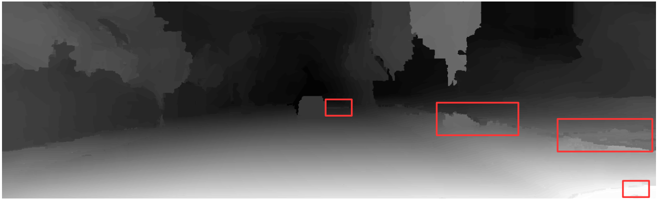
Result of our Approach



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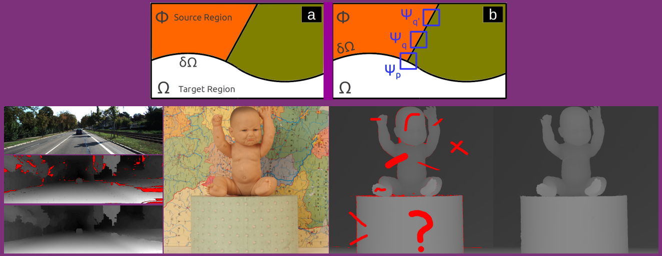

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