High-Quality 3D Reconstruction from RGB-D Sensors

Computer Vision I: Variational Methods

Current Research

Robert Maier

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January 25, 2018

Overview

- RGB-D Sensors & 3D Reconstruction
- Signed Distance Functions
- Real-Time Camera Tracking and 3D Reconstruction Using Signed Distance Functions (Bylow et al, RSS 2013)
- De-noising, Stabilizing and Completing 3D Reconstructions On-the-go using Plane Priors (Dzitsiuk et al, ICRA 2017)
- Intrinsic3D: High-Quality 3D Reconstruction by Joint Appearance and Geometry Optimization with Spatially-Varying Lighting (Maier et al, ICCV 2017)

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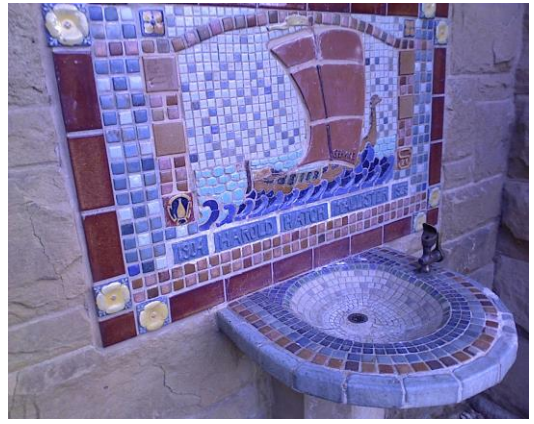
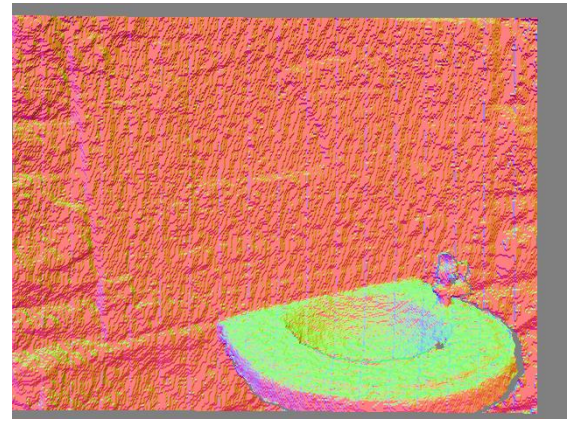
RGB-D Sensors

- RGB-D: color (RGB) + depth (metric!) @ 30 fps





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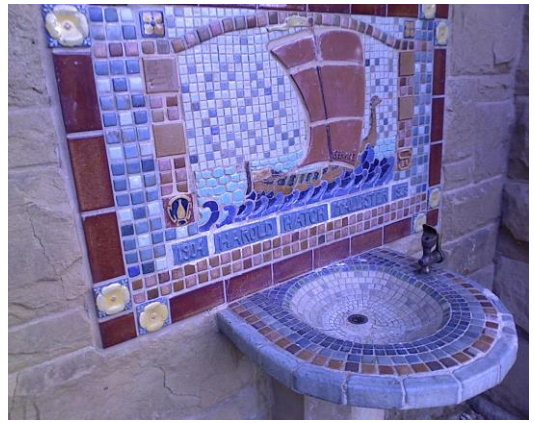
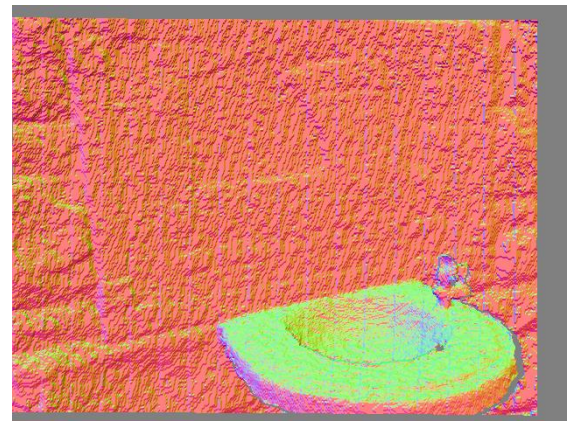
- Low-cost!





Microsoft Kinect v1

Asus Xtion

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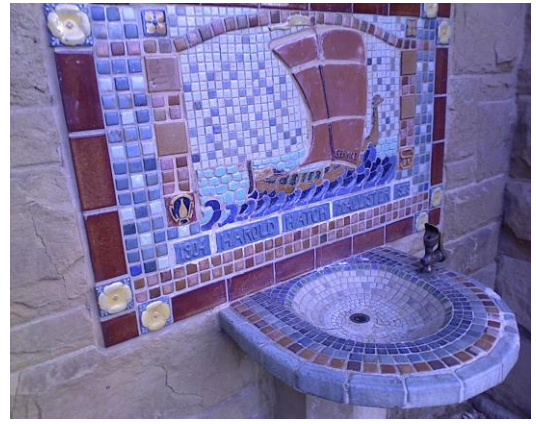

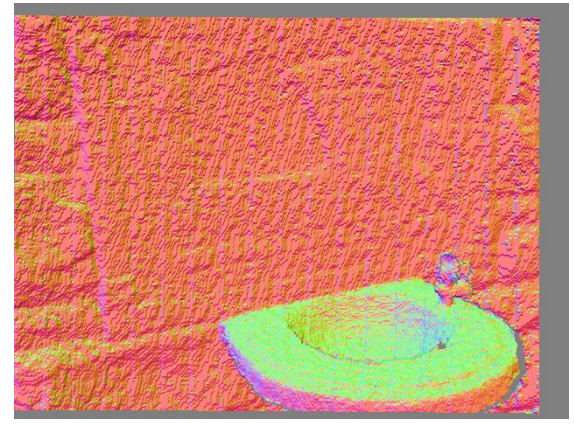

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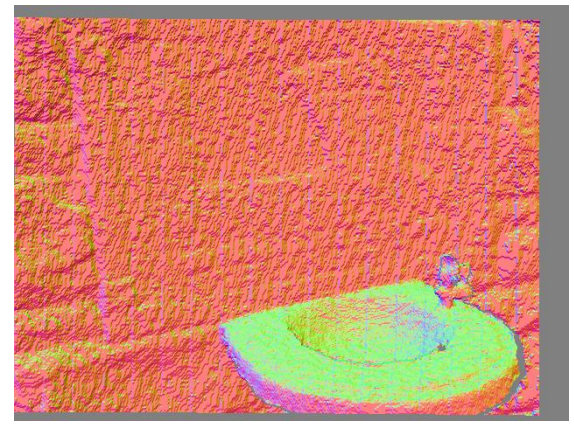

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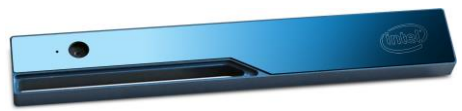

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Google Tango

Lenovo Phab 2 Pro

Asus ZenFone AR

RGB-D based 3D Reconstruction

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RGB-D based 3D Reconstruction

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- **SLAM**: Simultaneous Localization and Mapping (RGB-D-SLAM)
- **Fusion** of RGB-D frames in **dense volumetric 3D representation** (focus in this talk: Signed Distance Fields)

KinectFusion [Newcombe et al., ISMAR 2011]

3D Reconstruction Applications

- **Robotics**: real-time 3D reconstruction of large-scale environments (e.g. autonomous drones)

Parrot AR drone

3D Reconstruction Applications

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    - Wide availability of **commodity RGB-D sensors**: efficient methods for 3D reconstruction of real-word scenes
- Challenge: **how to reconstruct high-quality 3D models from low-cost depth sensors?**

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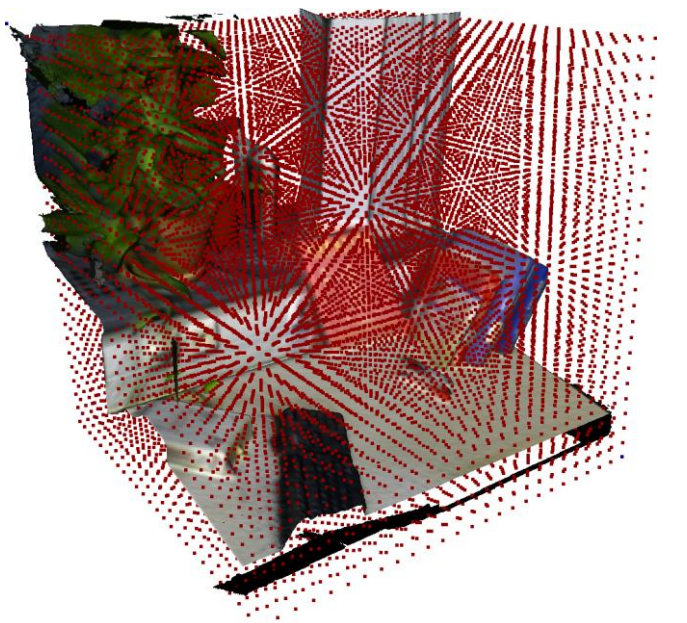
Signed Distance Functions[1]

Volumetric 3D model representation

- **Voxel grid: dense** (e.g. KinectFusion) or **sparse** (e.g. Voxel Hashing)



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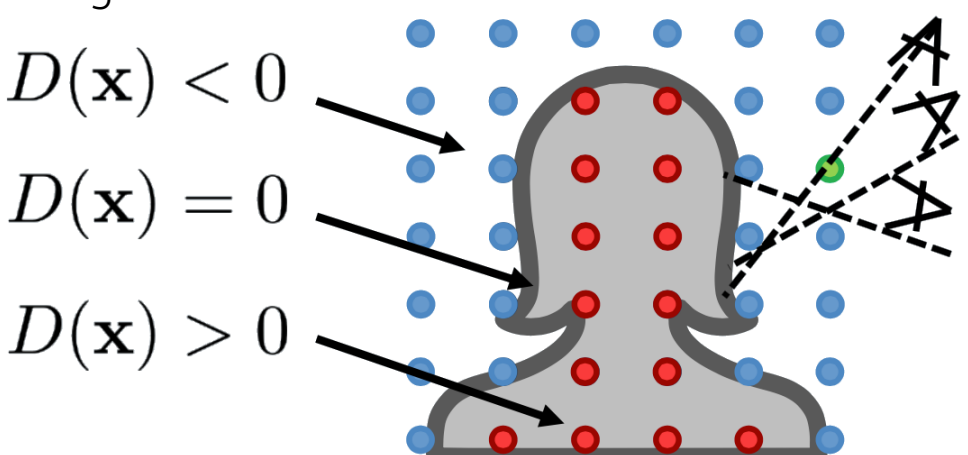
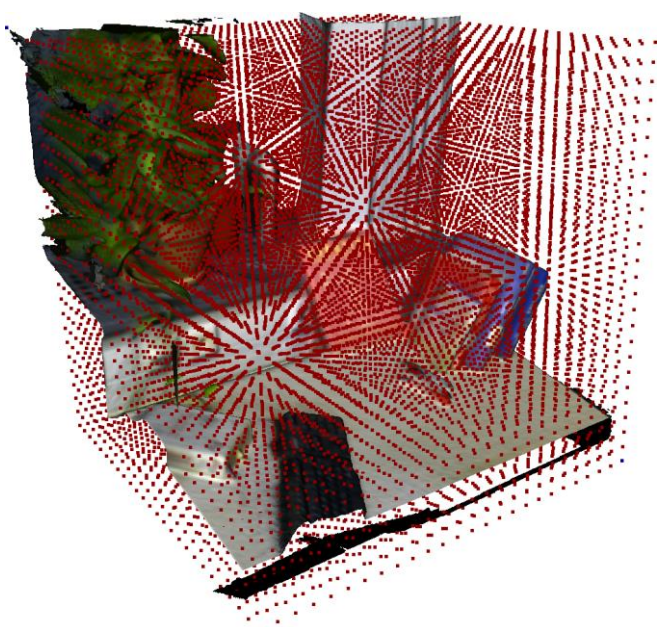
Signed Distance Functions[1]

Volumetric 3D model representation

- **Voxel grid: dense** (e.g. KinectFusion) or **sparse** (e.g. Voxel Hashing)
- Each voxel stores:
  - Signed Distance Function (SDF): signed distance to closest surface
  - Color values
  - Weights





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Signed Distance Fields

Fusion of depth maps

- Integrate depth maps into SDF with their estimated camera poses

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- Voxel updates using weighted average

$$D \leftarrow \frac{WD+wd}{W+w}$$
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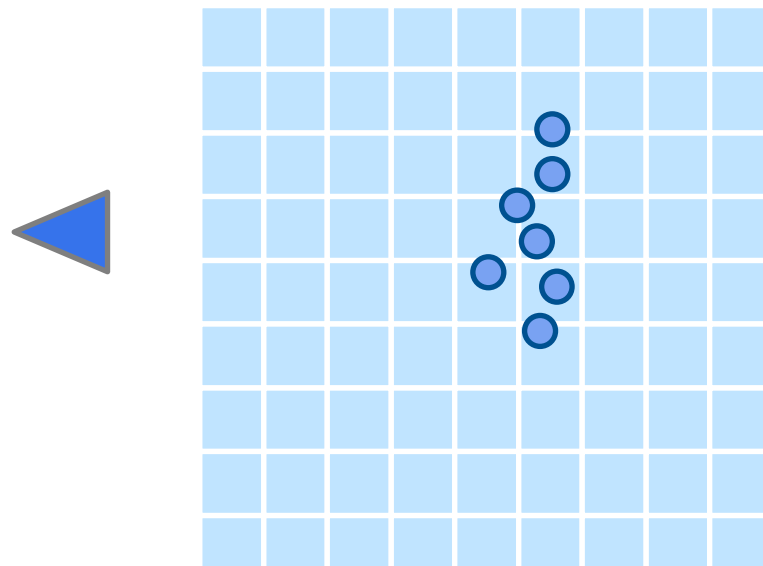

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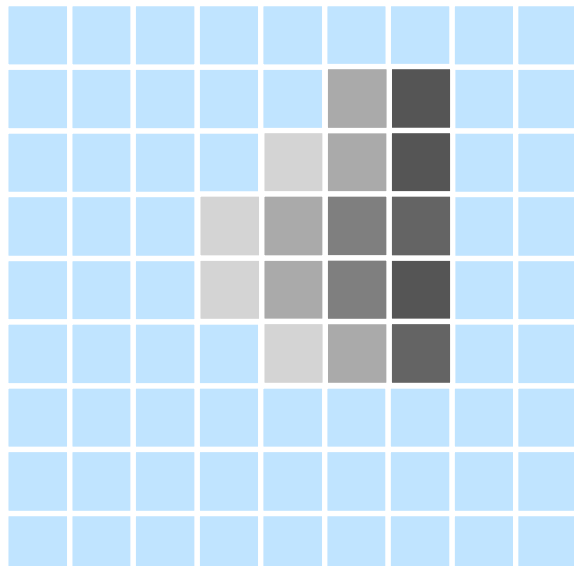

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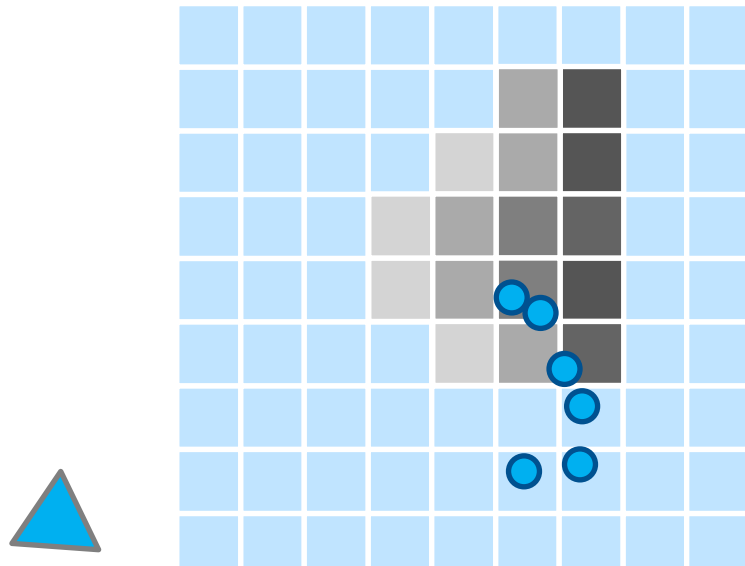

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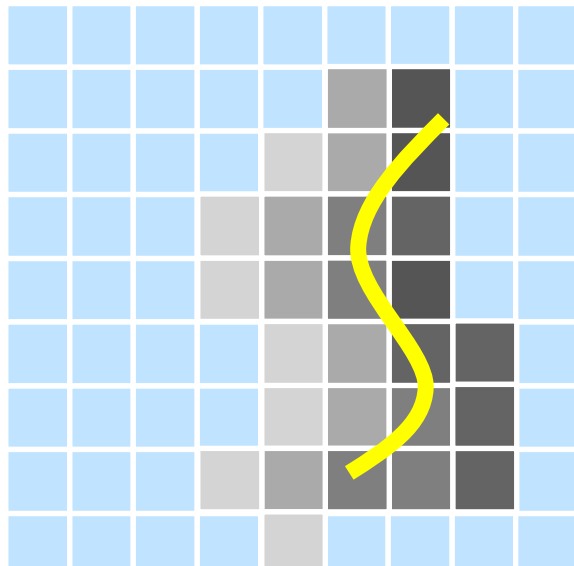

- Extract ISO-surface with Marching Cubes[2] (triangle mesh)

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Real-Time Camera Tracking and 3D Reconstruction Using Signed Distance Functions

E. Bylow[1], J. Sturm[2], C. Kerl[2], F. Kahl[1], D. Cremers[2]

[1] Lund University

[2] Technical University of Munich

Robotics: Science and Systems (RSS)
2013, Berlin, Germany

System Pipeline

- Based on KinectFusion (Newcombe et al, ISMAR 2011)

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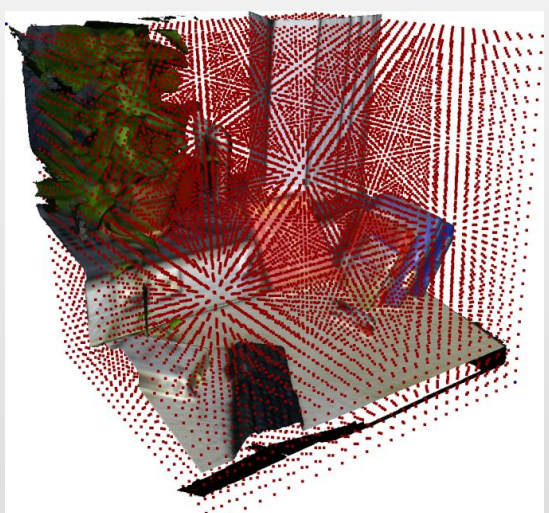
3D model: Signed Distance Field (SDF volume)



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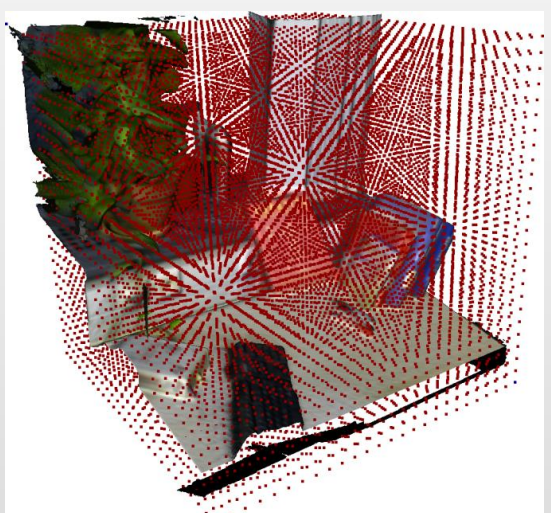

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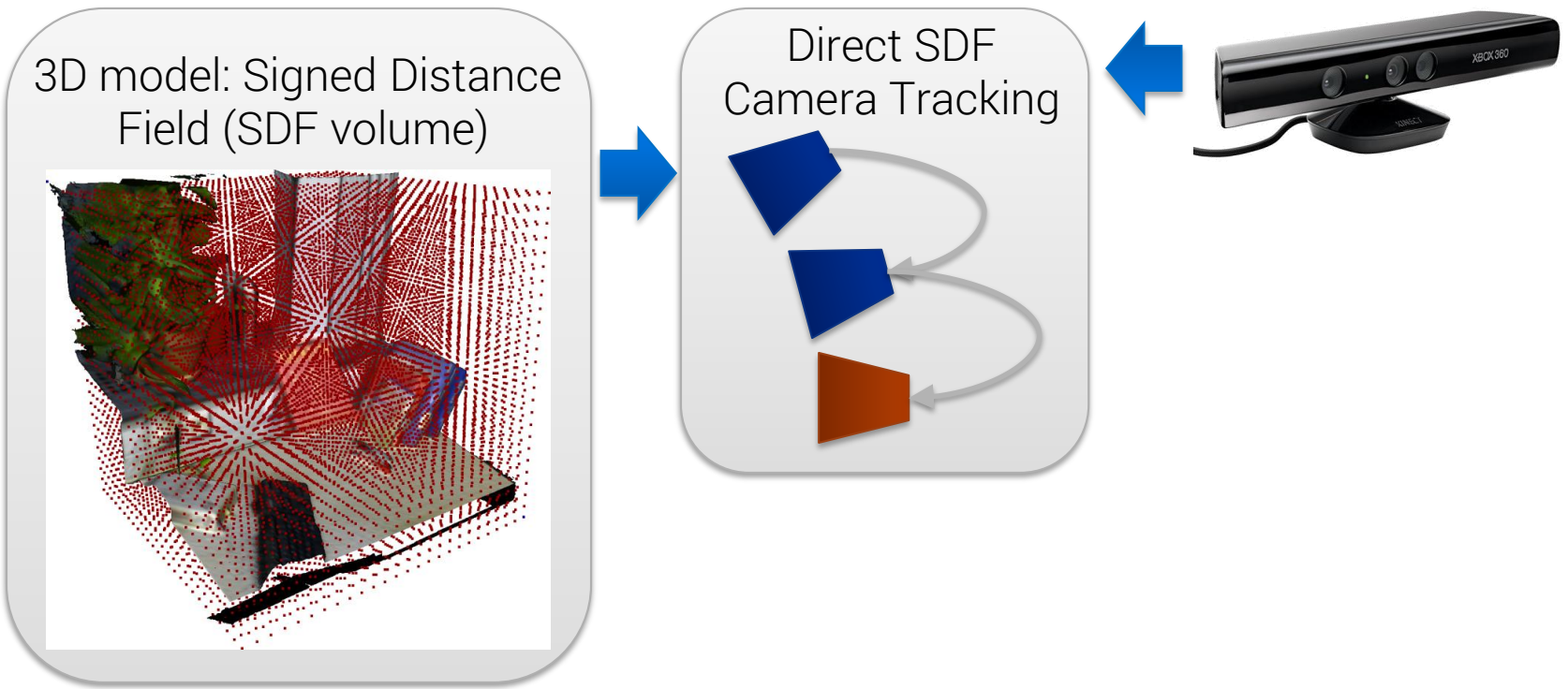

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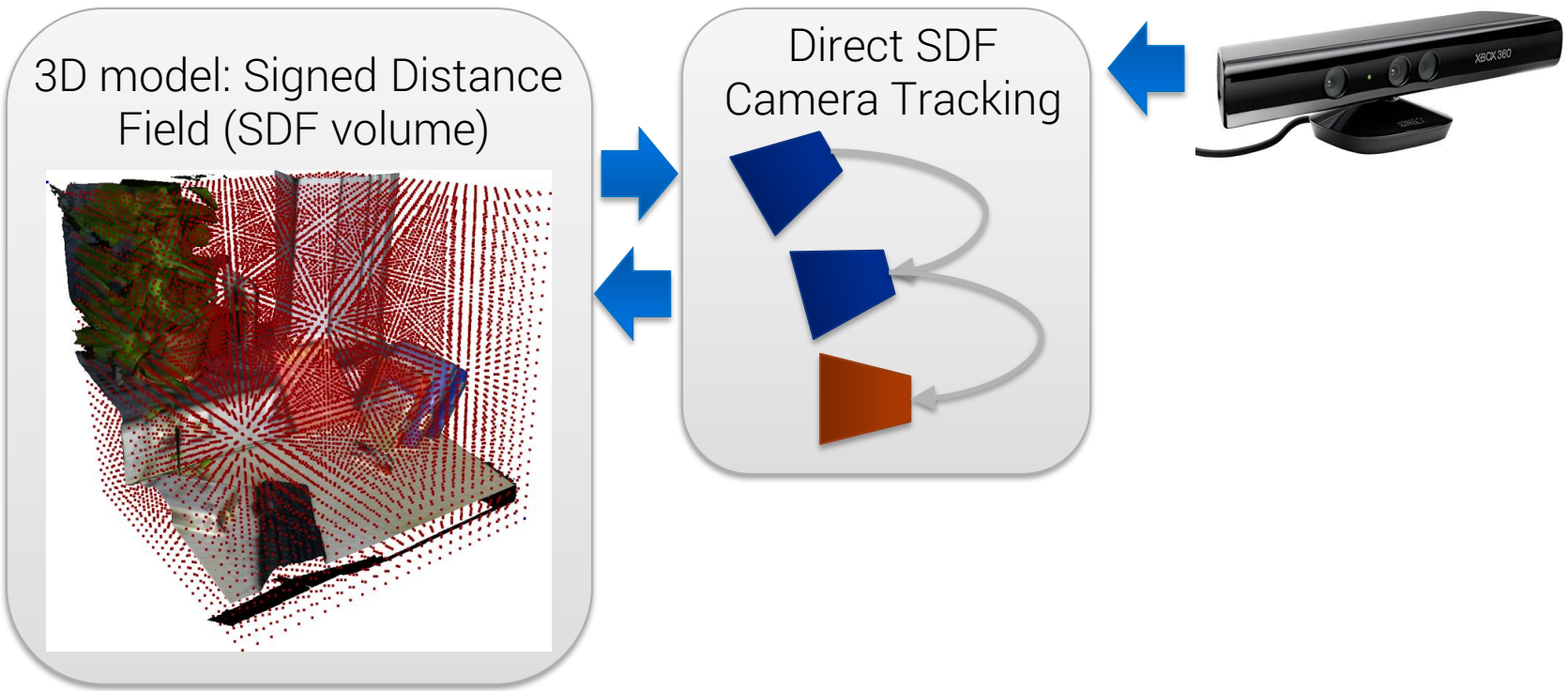

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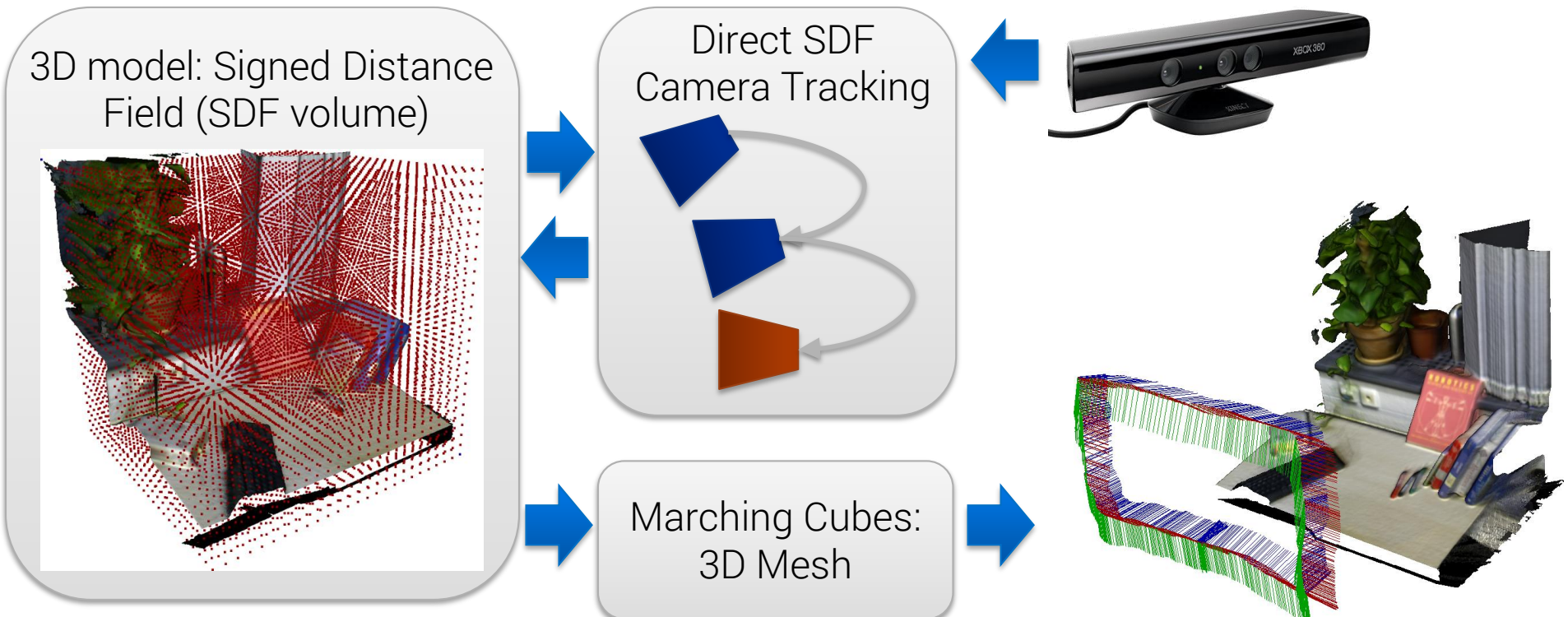

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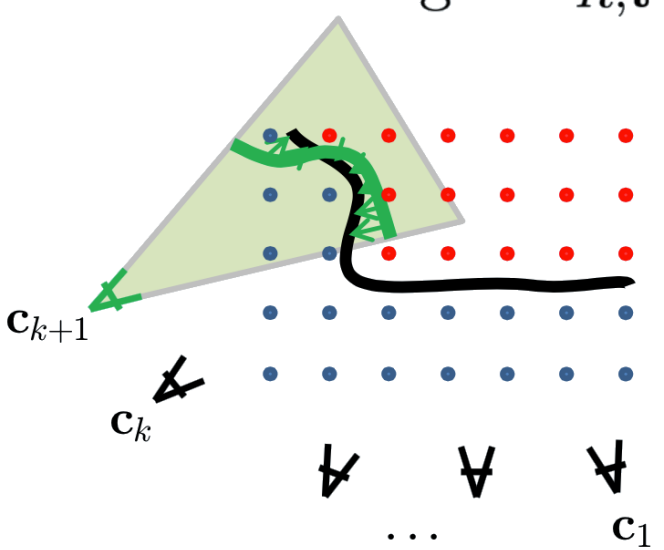

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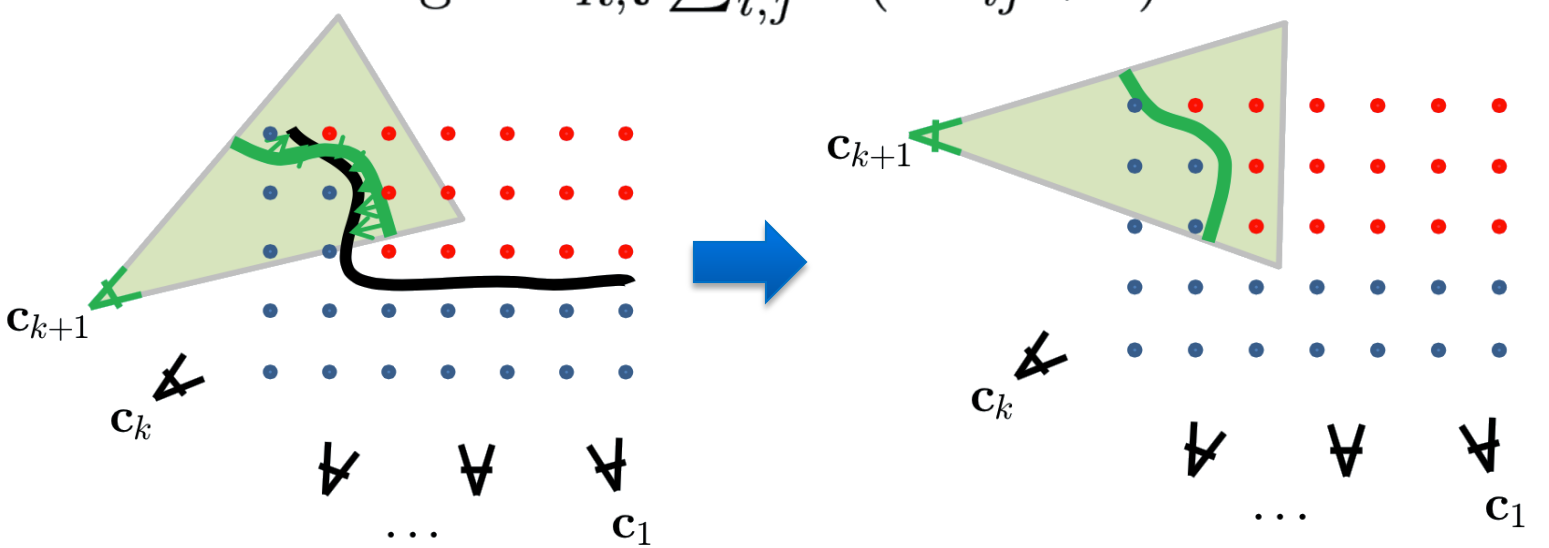


Extension: CopyMe3D

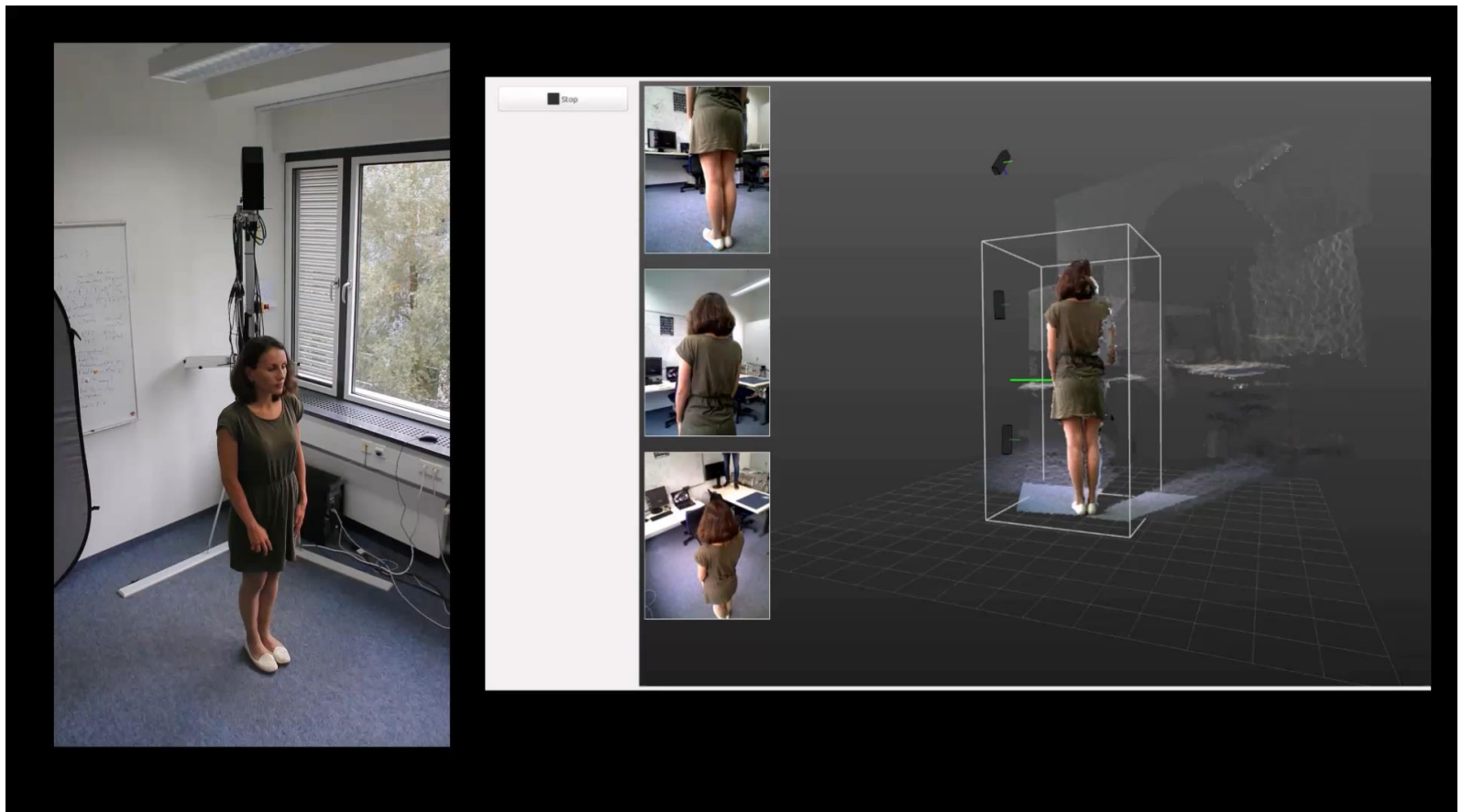
CopyMe3D: Scanning and Printing Persons in 3D (Sturm et al, GCPR 2013)

CopyMe3D

Printed 3D figures

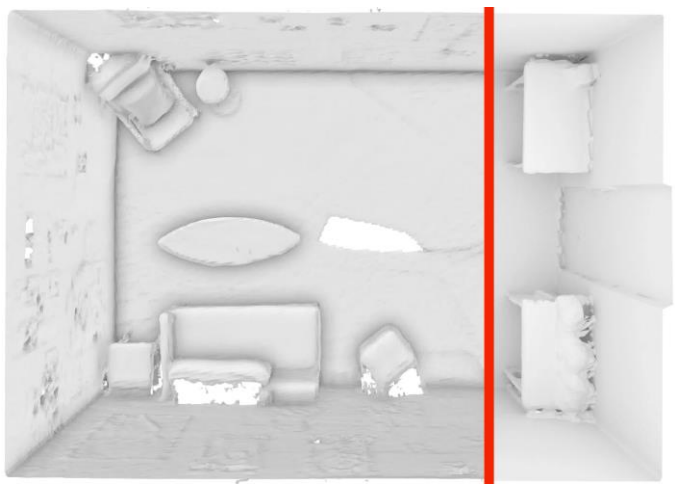
CopyMe3D2

Full-body scanning



De-noising, Stabilizing and Completing 3D Reconstructions On-the-go using Plane Priors

M. Dzitsiuk[1,2], J. Sturm[2], R. Maier[1], L. Ma[1], D. Cremers[1]



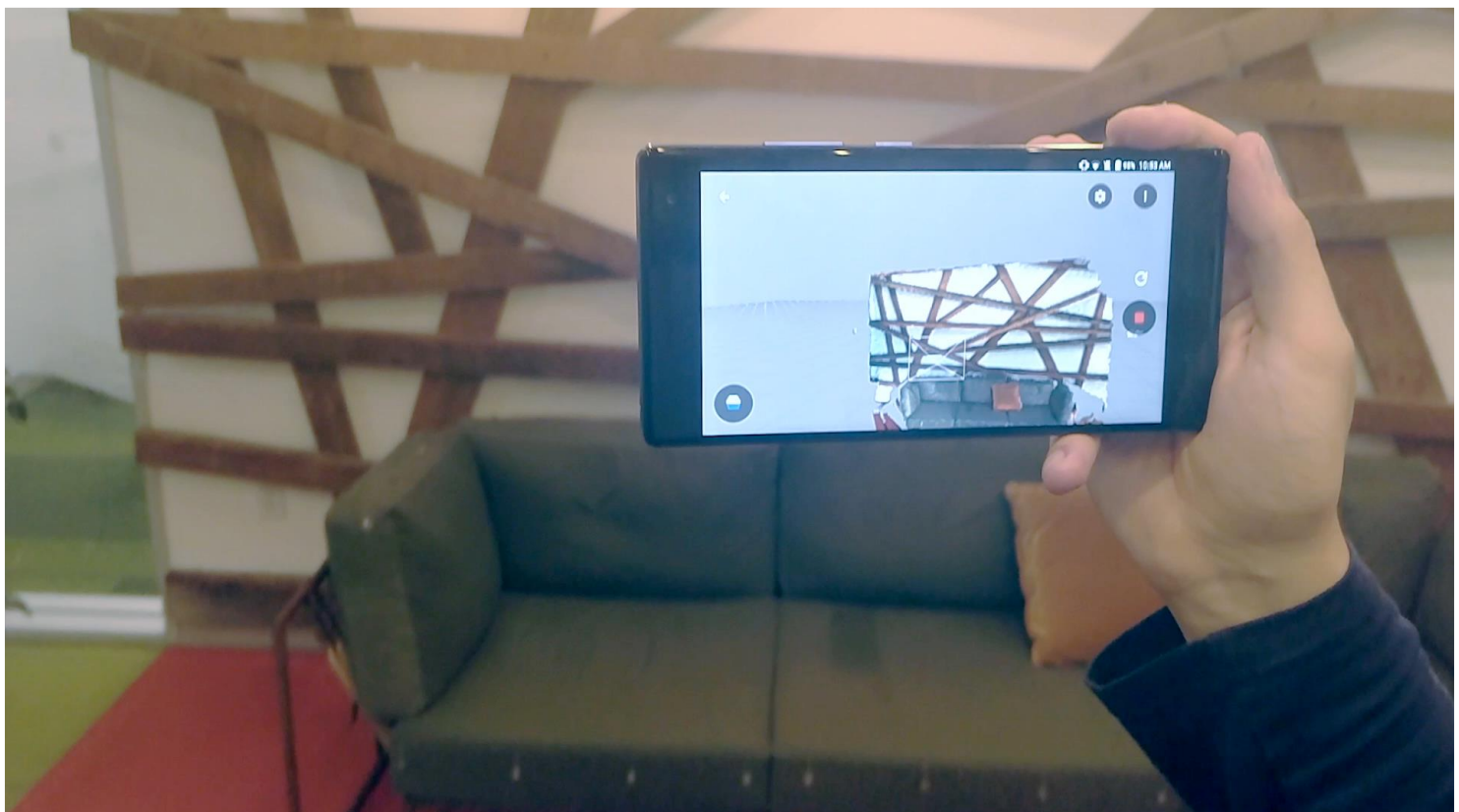
[1] Google

[2] Technical University of Munich

International Conference on Robotics and Automation (ICRA), May 2017, Singapore

3D Reconstruction with Plane Priors

Real-time 3D reconstruction on a mobile device

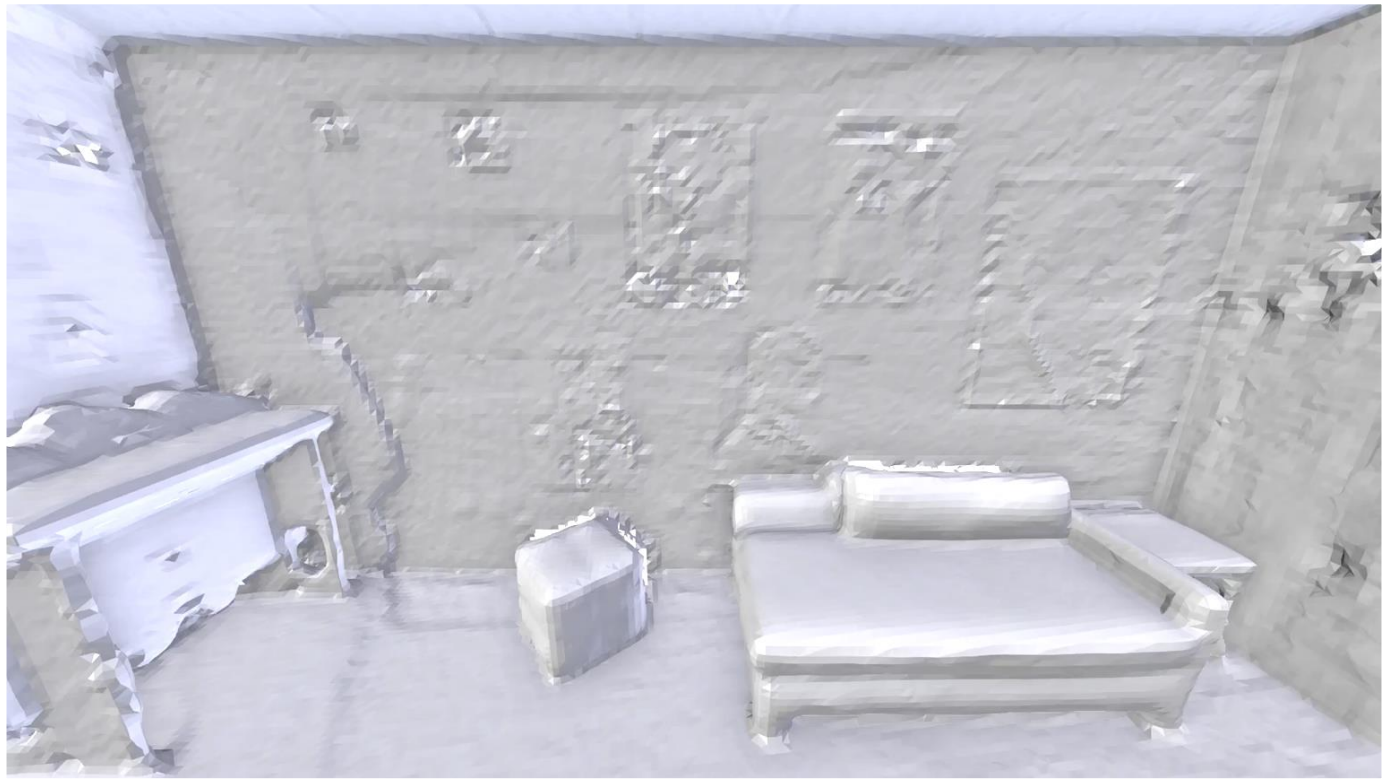


Chisel: Real Time Large Scale 3D Reconstruction Onboard a Mobile Device using Spatially Hashed Signed Distance Fields [Klingensmith et al., 2015]

Tango

3D Reconstruction with Plane Priors

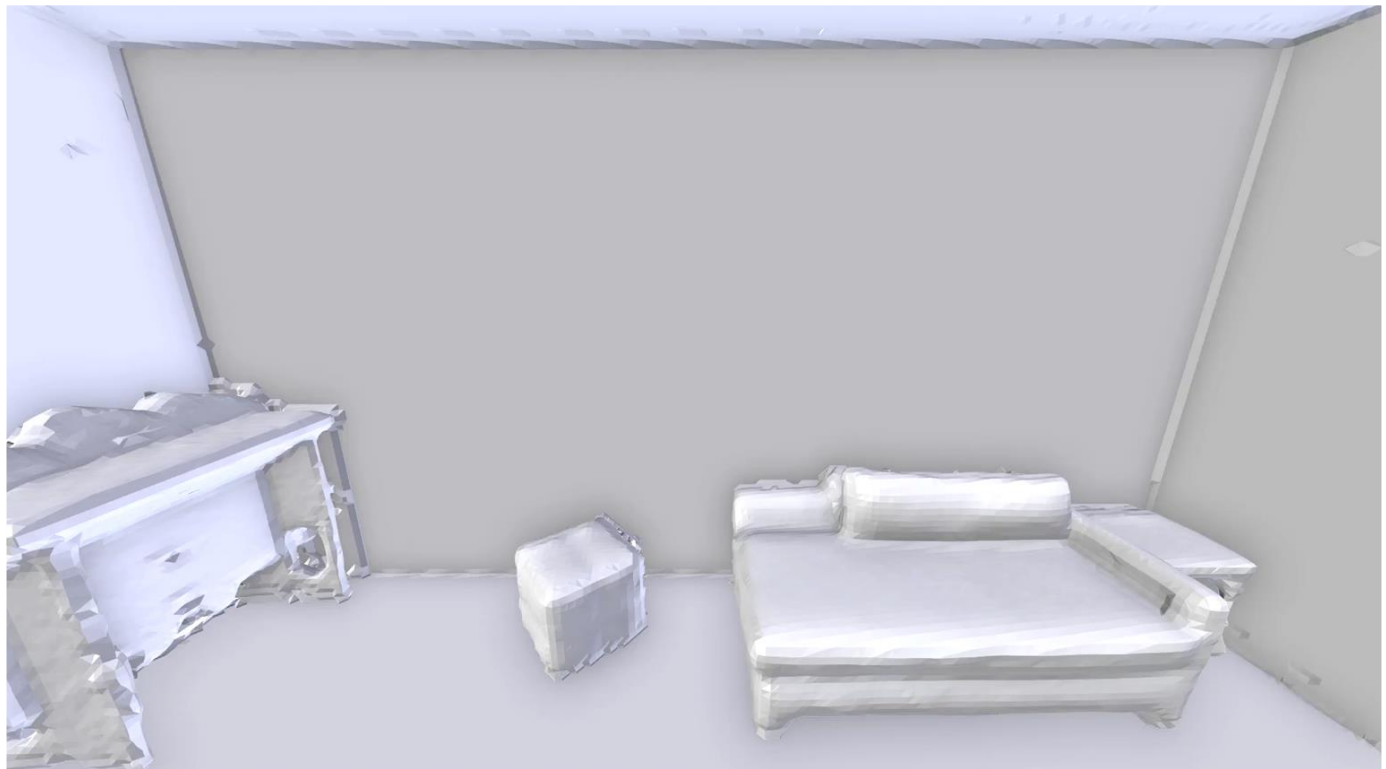
Motivation



Problems with real-time 3D reconstruction: noisy, incomplete, no segmentation

3D Reconstruction with Plane Priors

Motivation

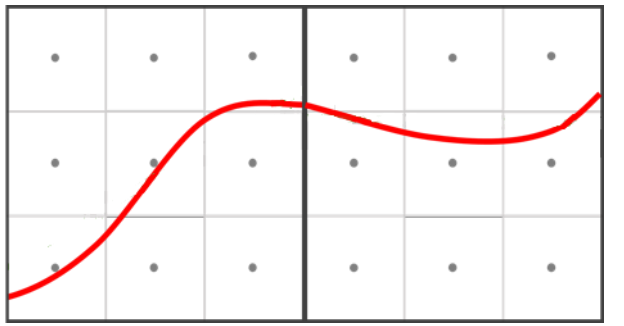


Solution idea: detect and use planes

3D Reconstruction with Plane Priors

Approach

- **Input:** Signed Distance Field divided into voxel blocks



3D Reconstruction with Plane Priors

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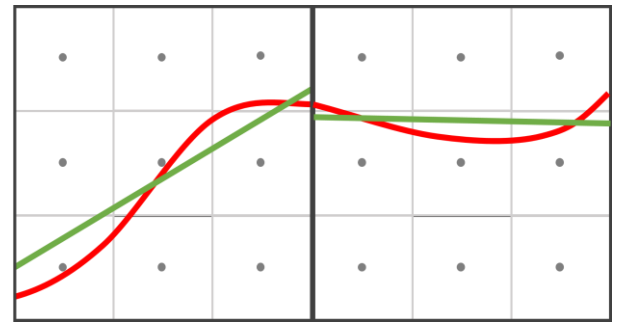

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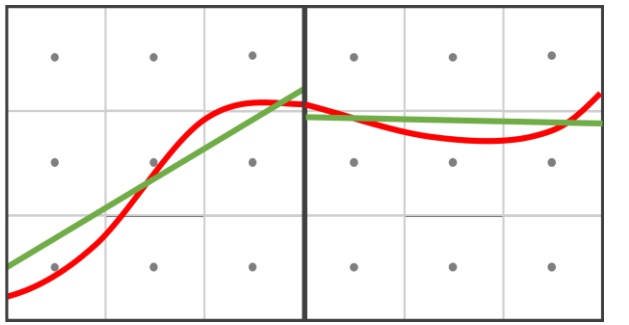
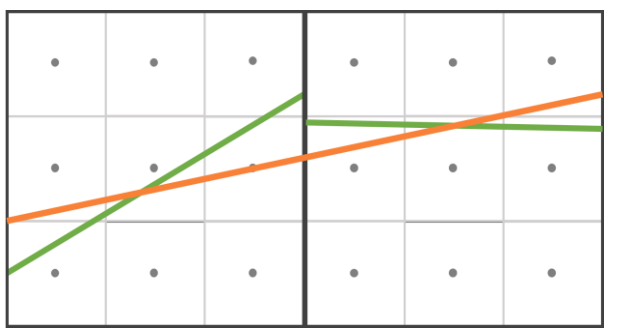


- 2. **Merge planes**



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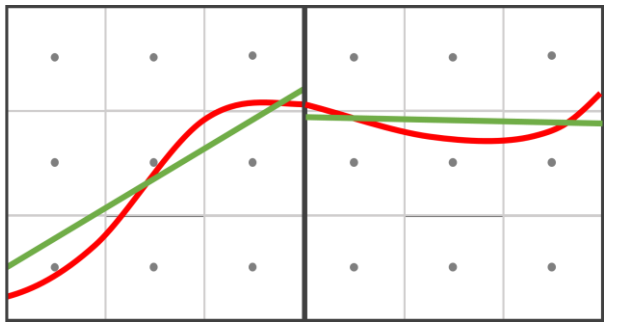

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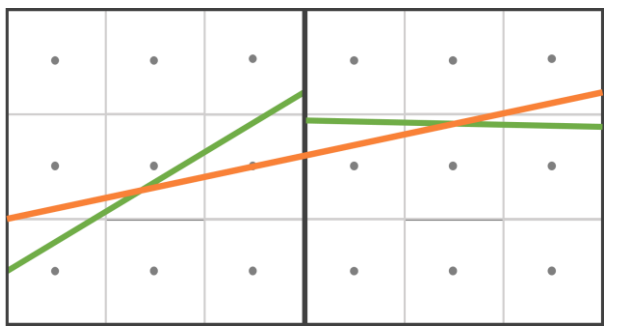
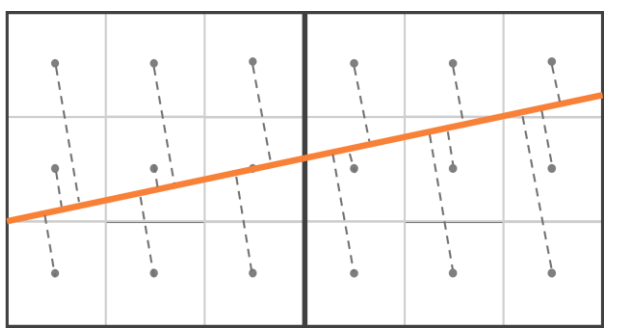


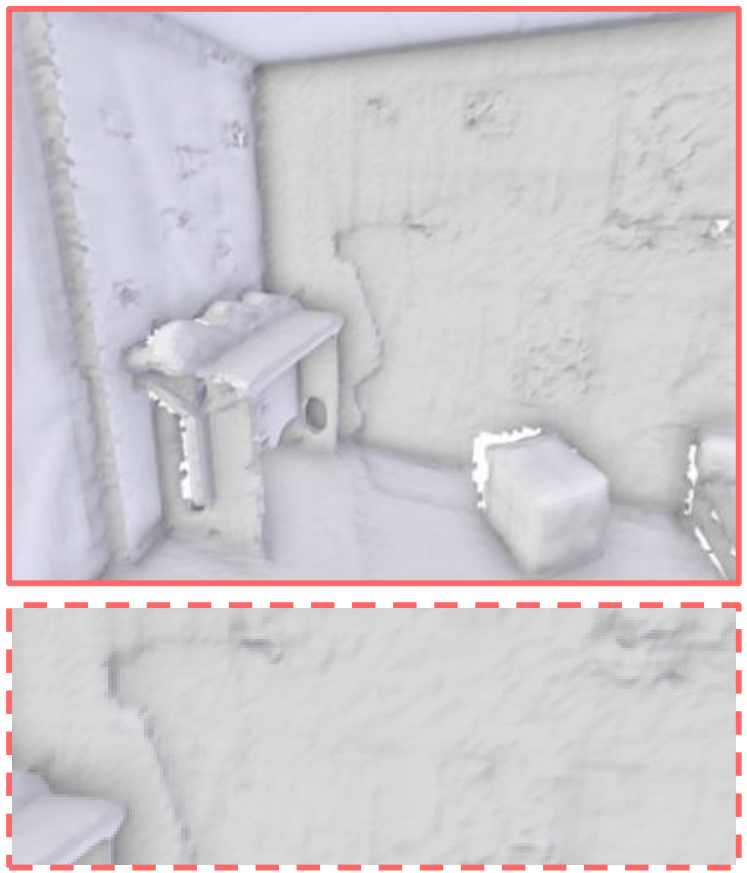
- 3. **De-noising**



3D Reconstruction with Plane Priors

Results: de-noising

Before



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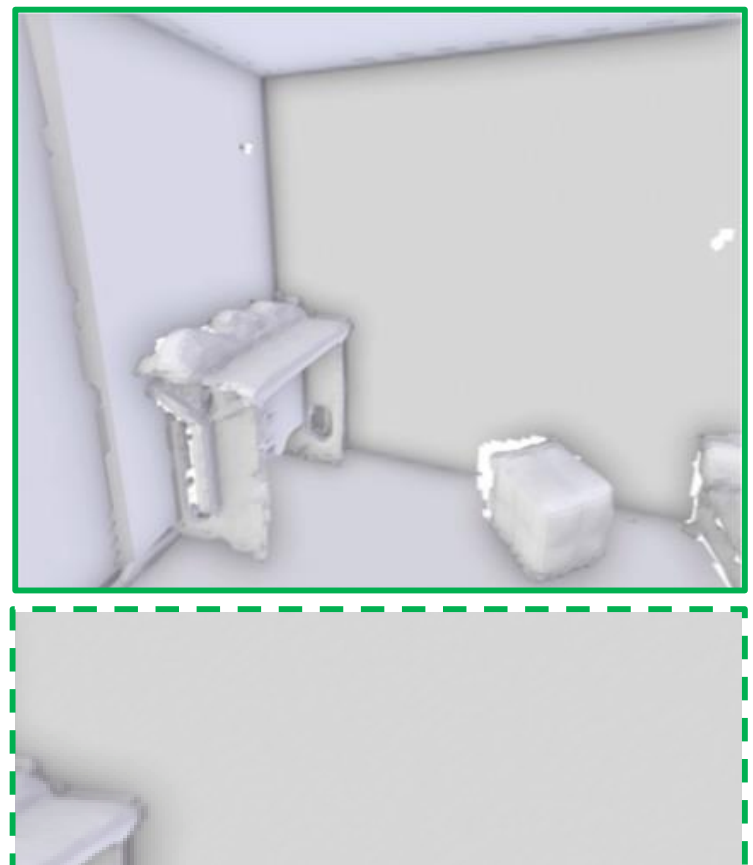
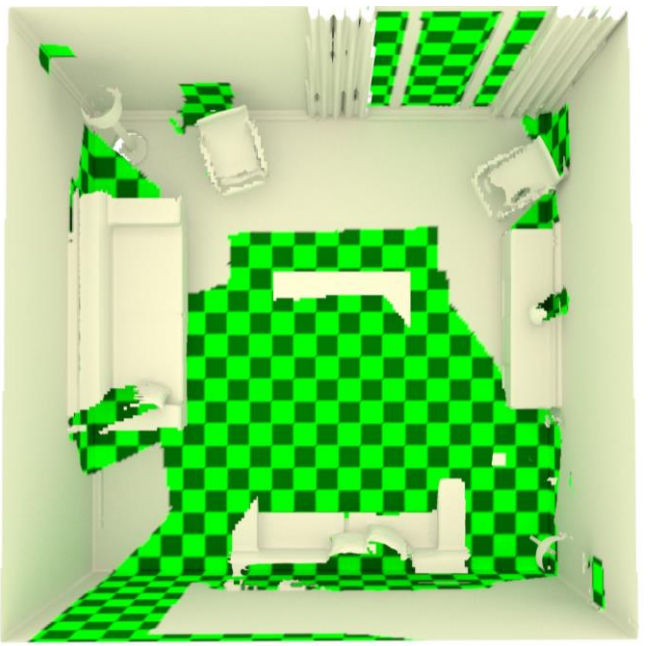


3D Reconstruction with Plane Priors

Results

Hole filling



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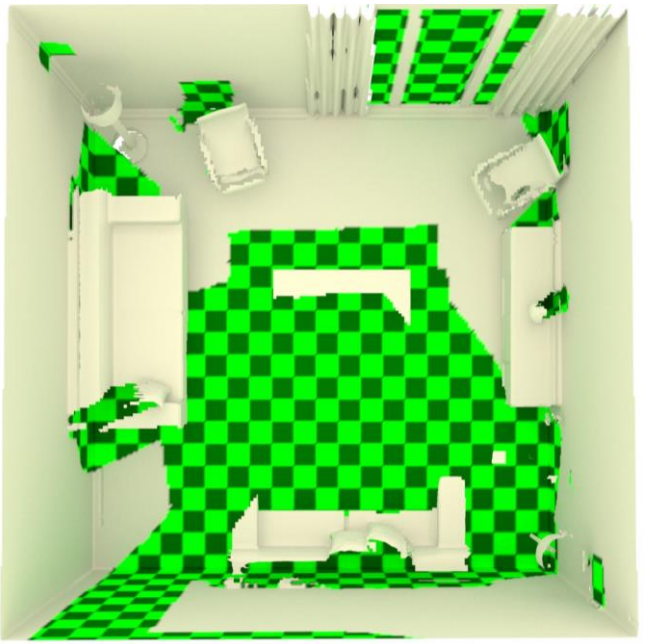
Results

Hole filling



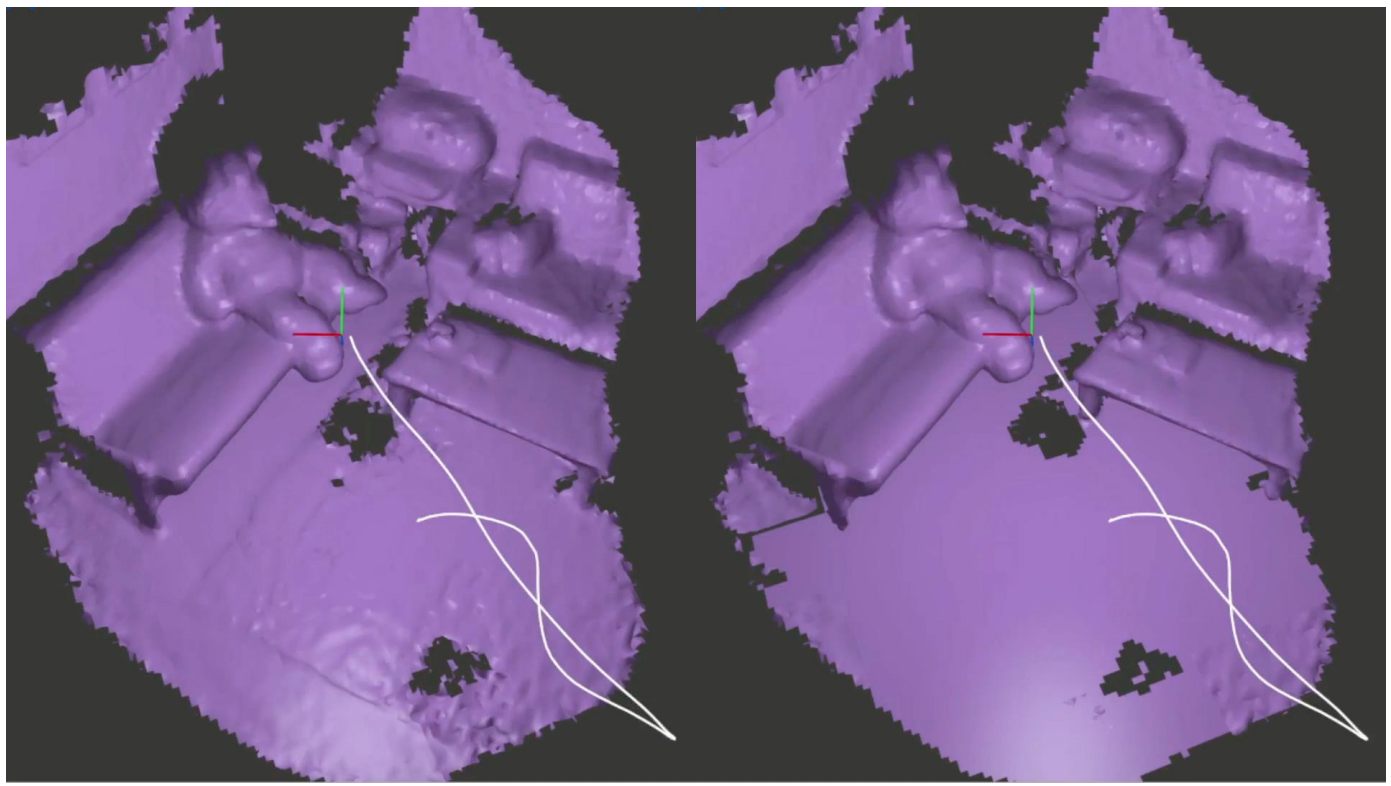
Segmentation

Classify reconstruction geometry:

- **Floor** or **wall** (area, angle with gravity)
- **Object** (mesh connected components)

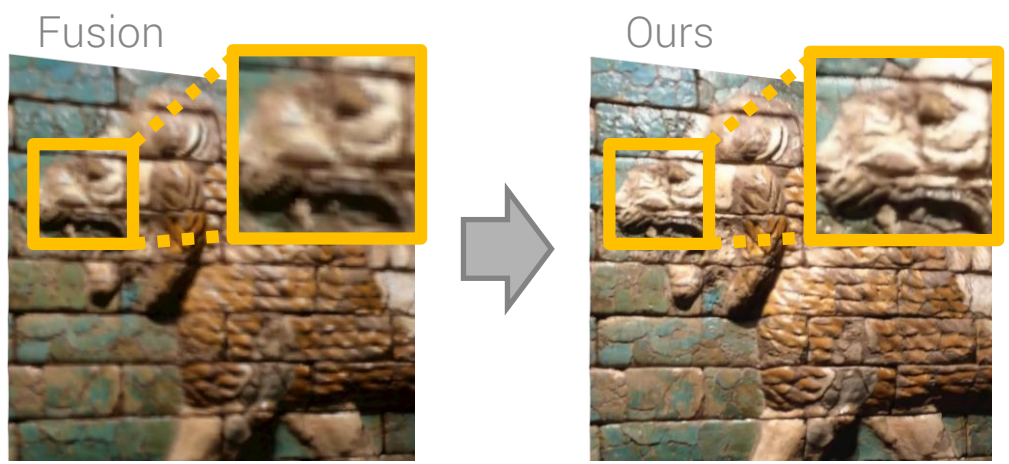
3D Reconstruction with Plane Priors

Results: real-time 3D reconstruction on mobile device



Intrinsic3D: High-Quality 3D Reconstruction by Joint Appearance and Geometry Optimization with Spatially-Varying Lighting

R. Maier[1,2], K. Kim[1], D. Cremers[2], J. Kautz[1], M. Nießner[2,3]



International Conference on Computer Vision (ICCV)
October 2017, Venice, Italy

[1] NVIDIA
[2] TU Munich
[3] Stanford University

State-of-the-art

RGB-D based 3D Reconstruction

- Challenge: how to **reconstruct high-quality 3D models** with **best-possible geometry and color** from **low-cost depth sensors?**

State-of-the-art

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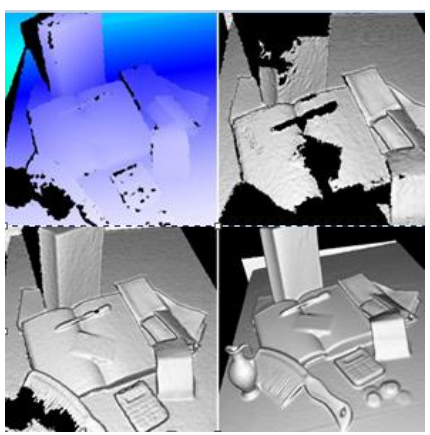
- Challenge: how to **reconstruct high-quality 3D models** with **best-possible geometry and color** from **low-cost depth sensors?**
- Real-time, robust, fairly accurate geometric reconstructions



KinectFusion, 2011

"KinectFusion: Real-time Dense Surface Mapping and Tracking", Newcombe et al., ISMAR 2011.

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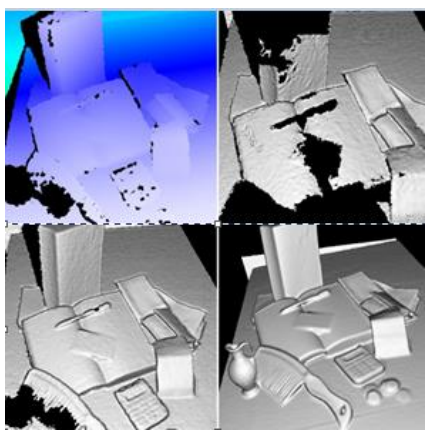

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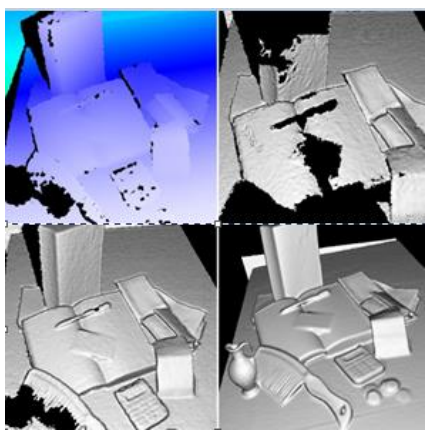

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BundleFusion, 2017

"BundleFusion: Real-time Globally Consistent 3D Reconstruction using On-the-fly Surface Re-integration", Dai et al., ToG 2017.

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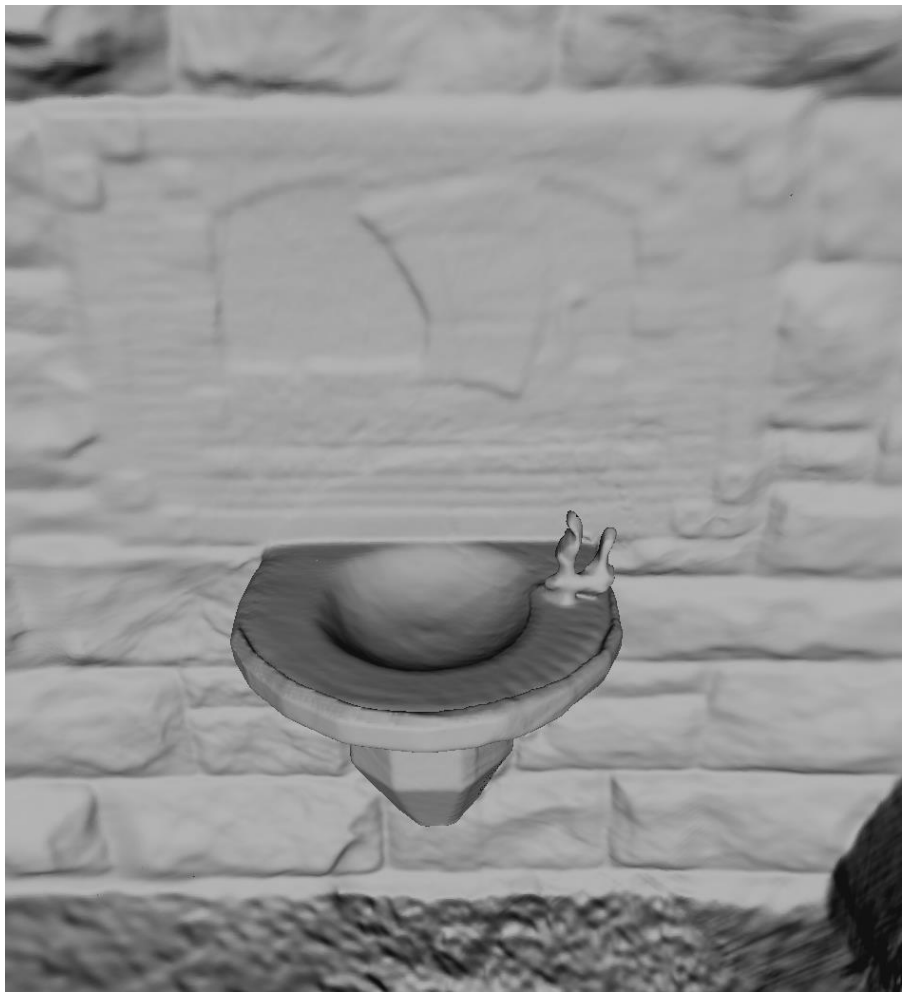
Voxel Hashing

- **Baseline** RGB-D based **3D reconstruction framework**
  - initial camera poses
  - sparse SDF reconstruction



"Real-time 3D Reconstruction at Scale using Voxel Hashing", Nießner et al., ToG 2013.

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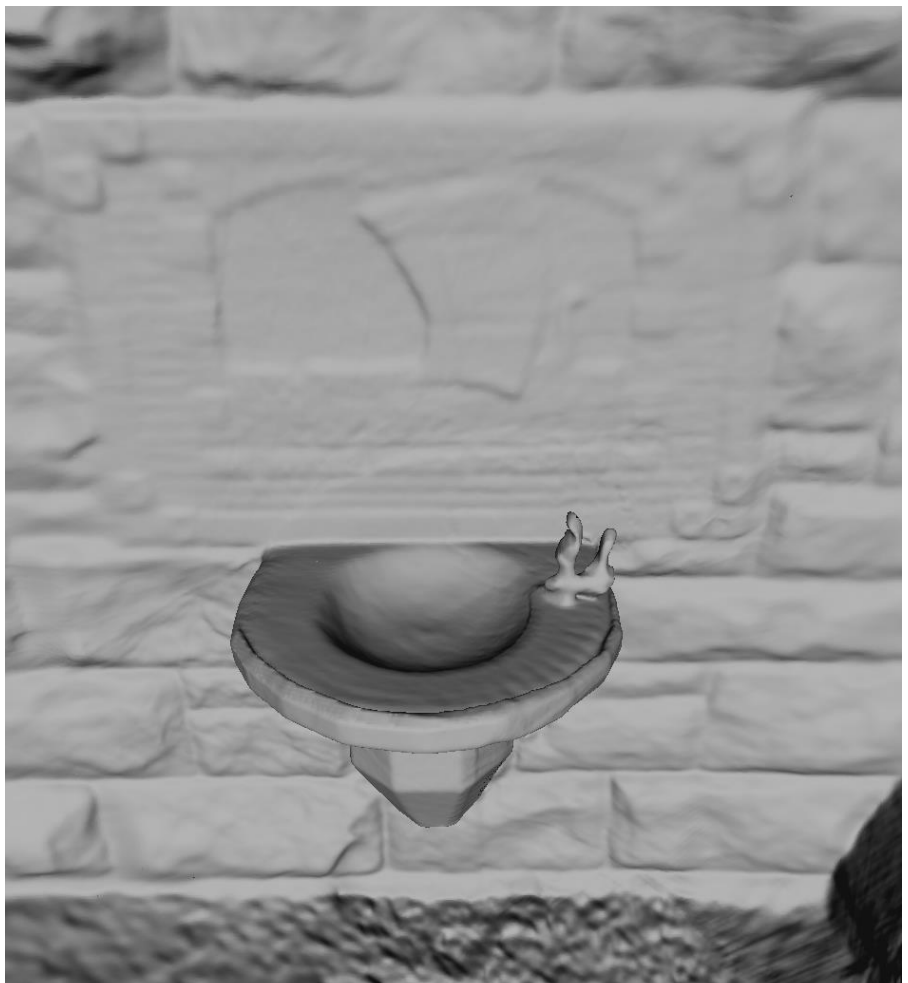

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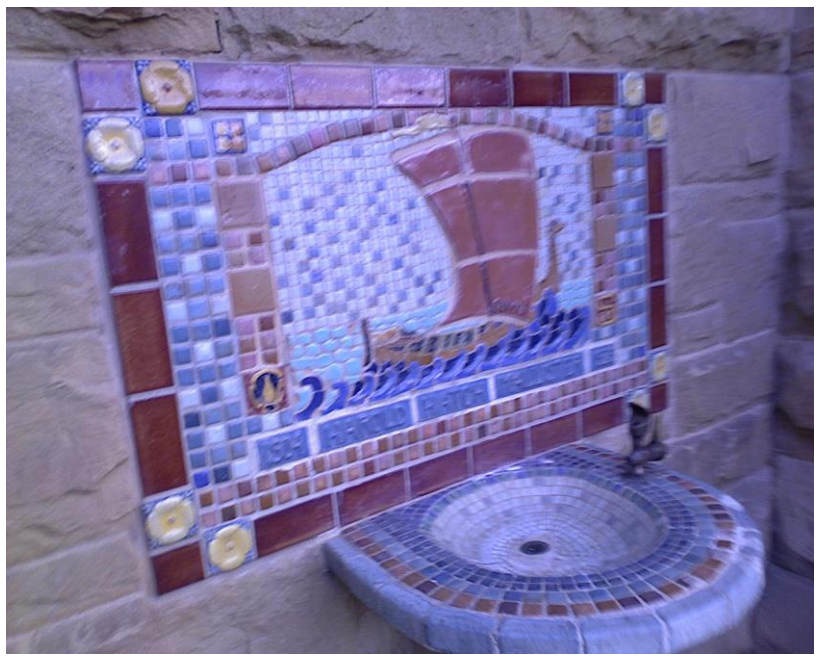

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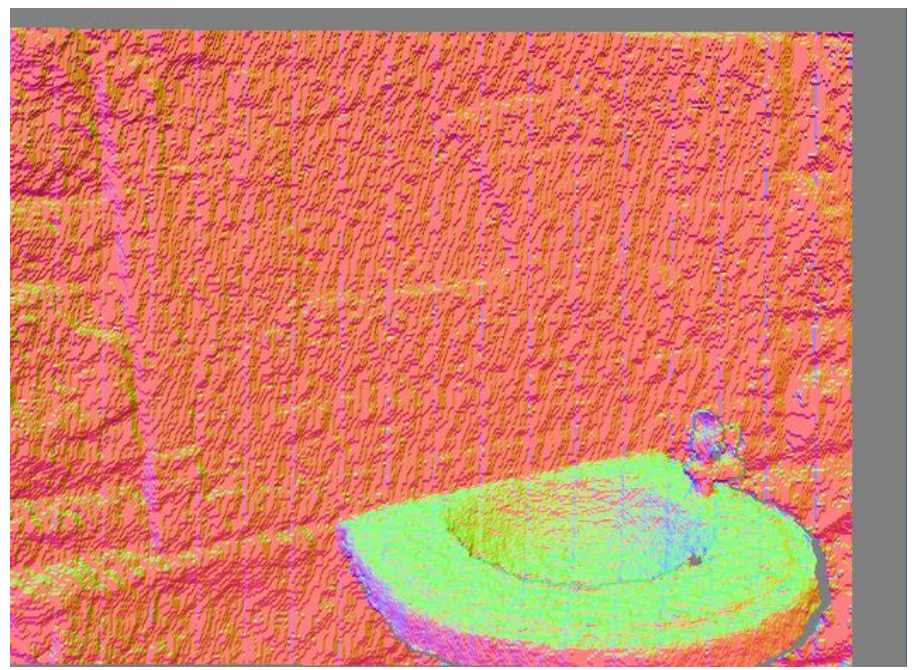

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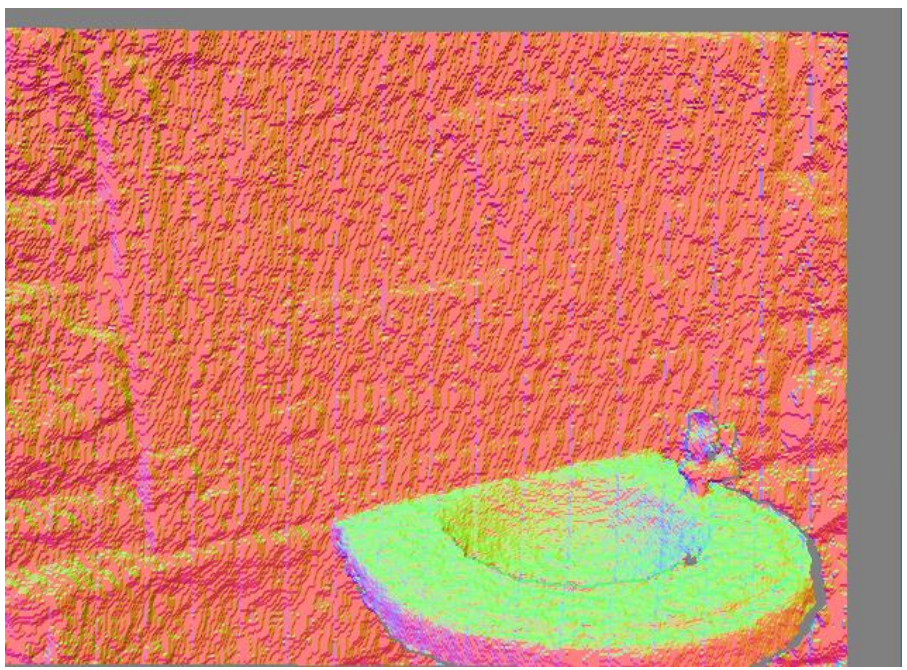
- Goal: **High-Quality Reconstruction of Geometry and Color**



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State-of-the-art

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High-Quality Colors [Zhou2014]

Optimize camera poses and image deformations to optimally fit initial (maybe wrong) reconstruction

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State-of-the-art

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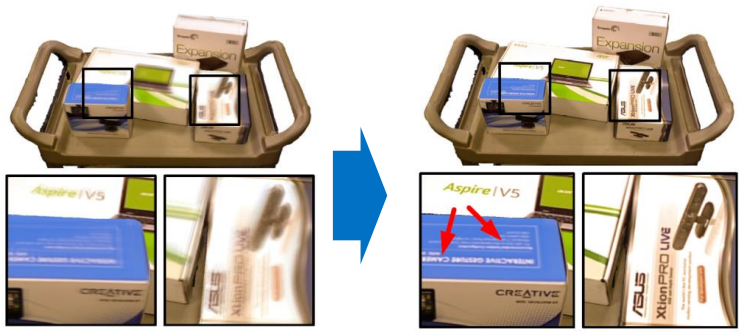

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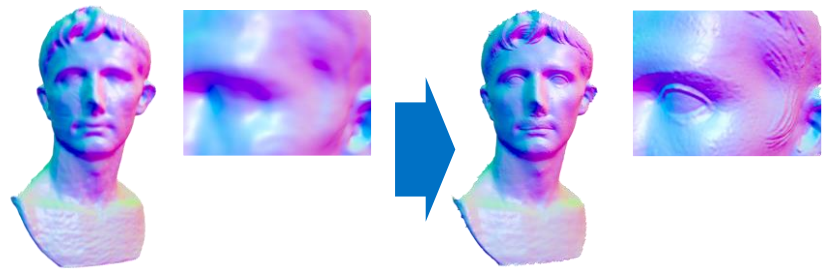

Adjust camera poses in advance (bundle adjustment) to improve color

Use shading cues (RGB) to refine geometry (shading based refinement of surface & albedo)

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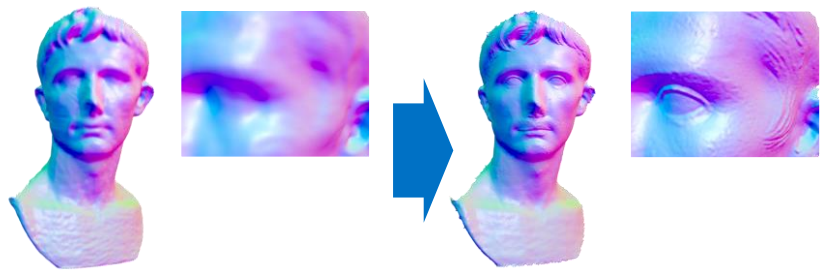

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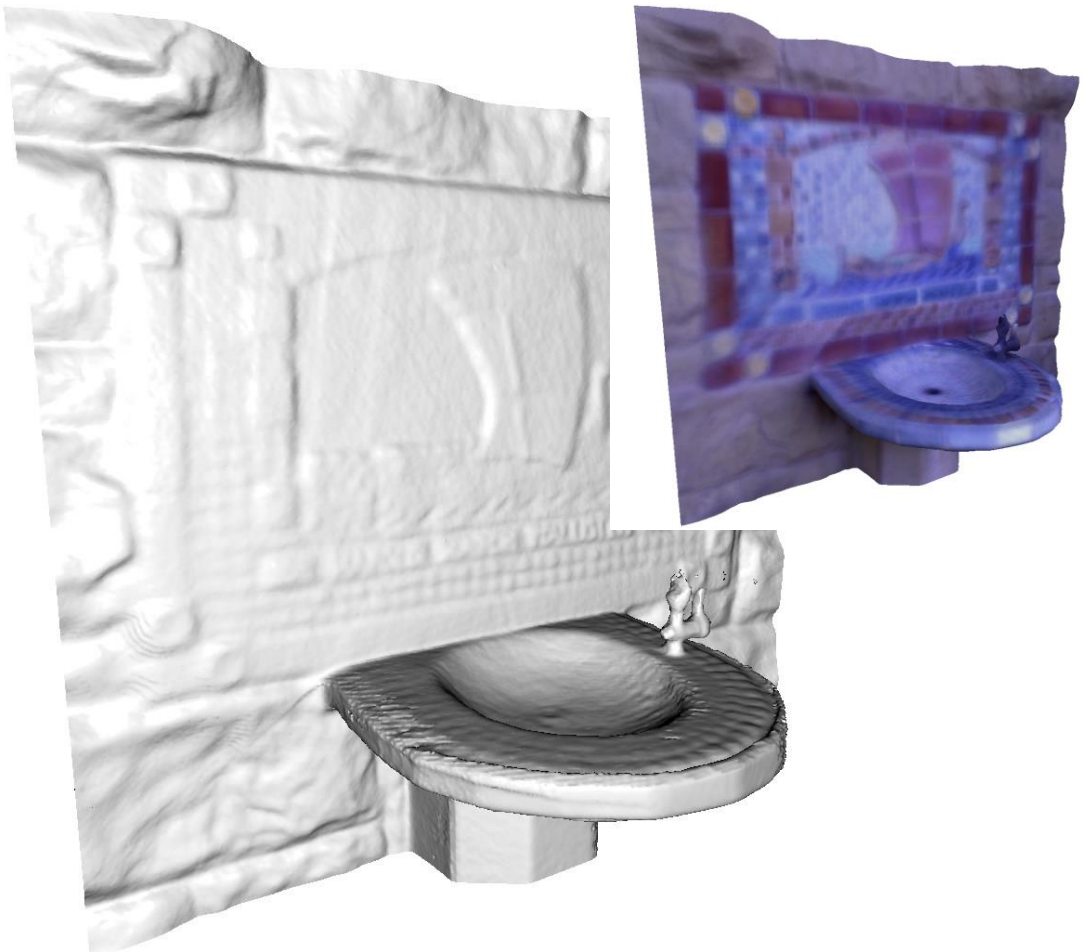
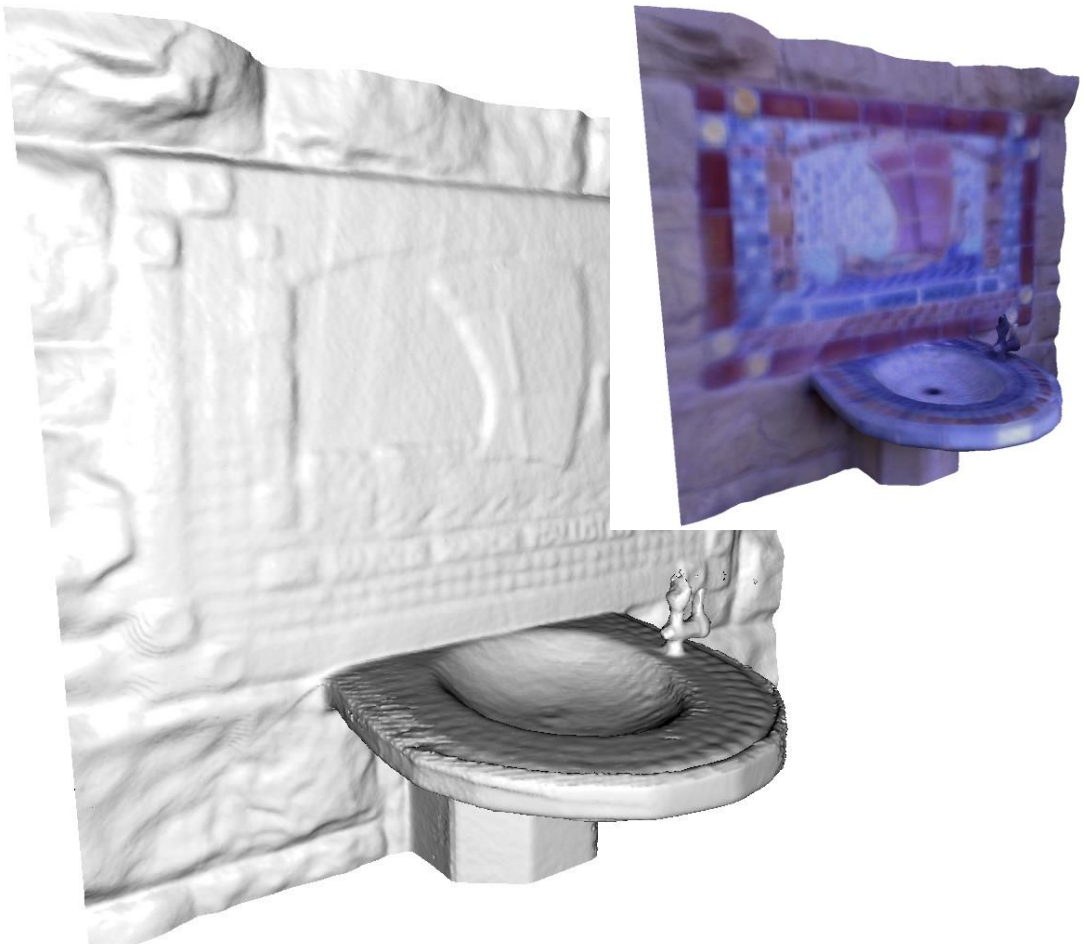
Idea: **jointly optimize for geometry, albedo and image formation model** to simultaneously obtain high-quality geometry and appearance!

Our Method



Our Method

- Temporal view **sampling & filtering** techniques (input frames)



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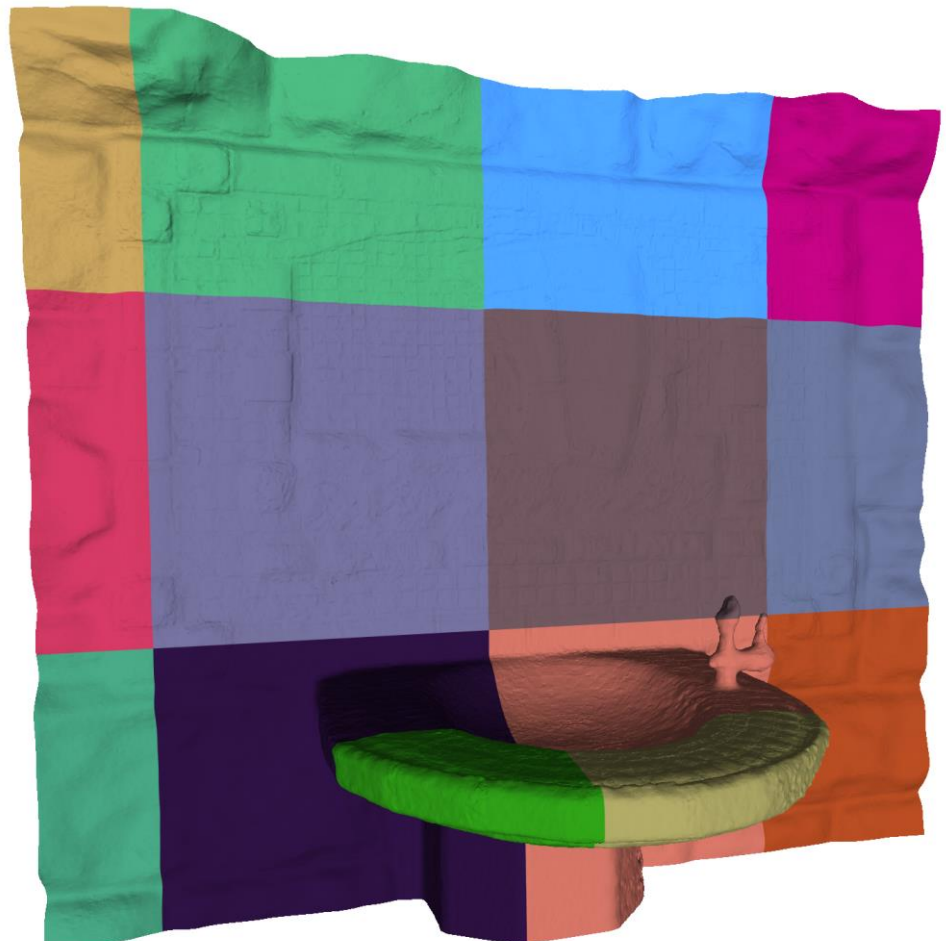

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- **Optimized colors** (by-product)

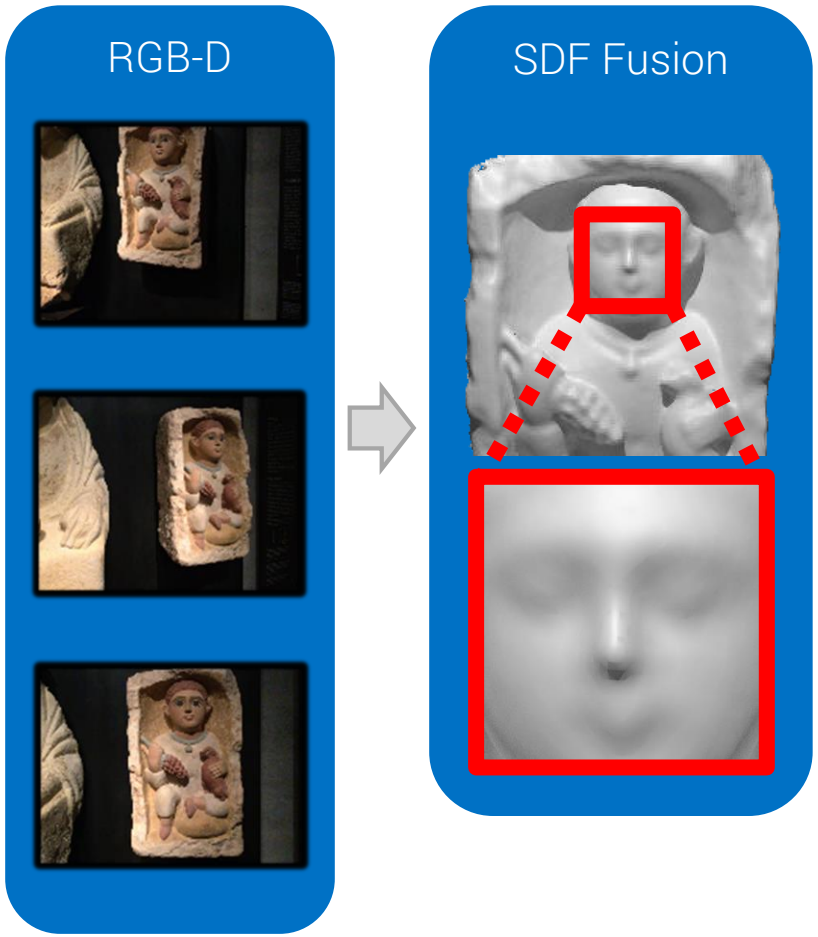
Approach

Overview

RGB-D

Approach

Overview



Approach

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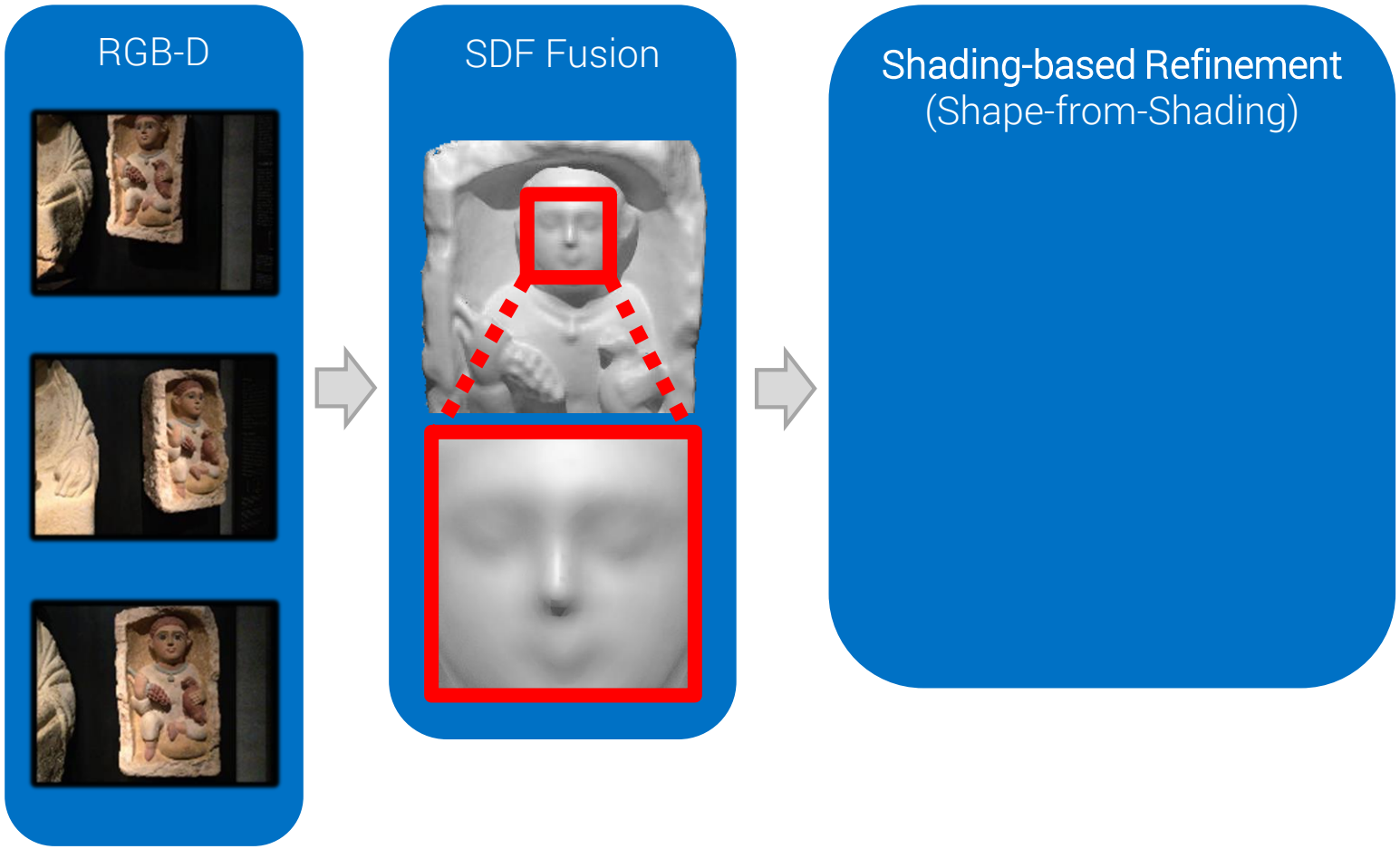

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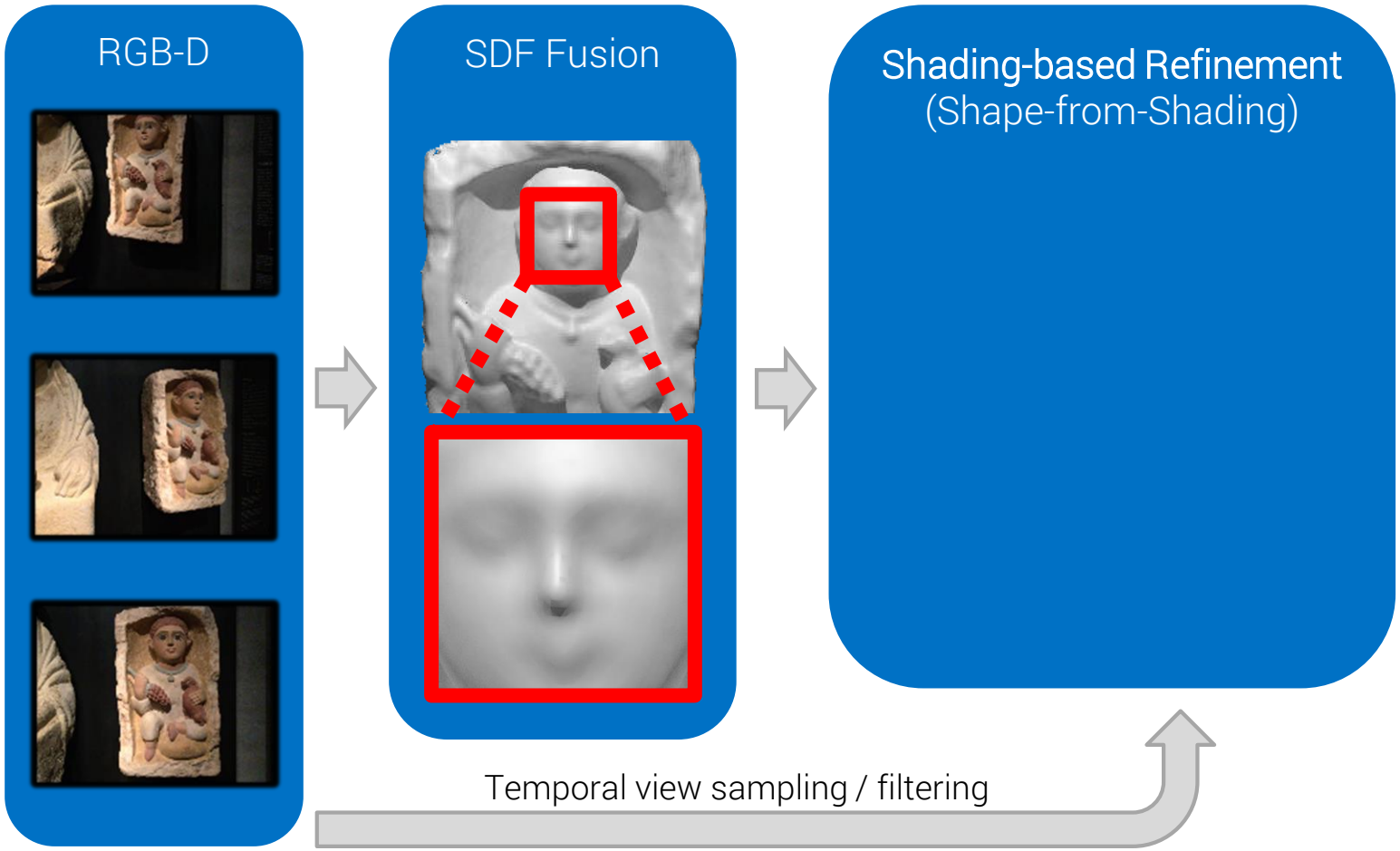

Approach

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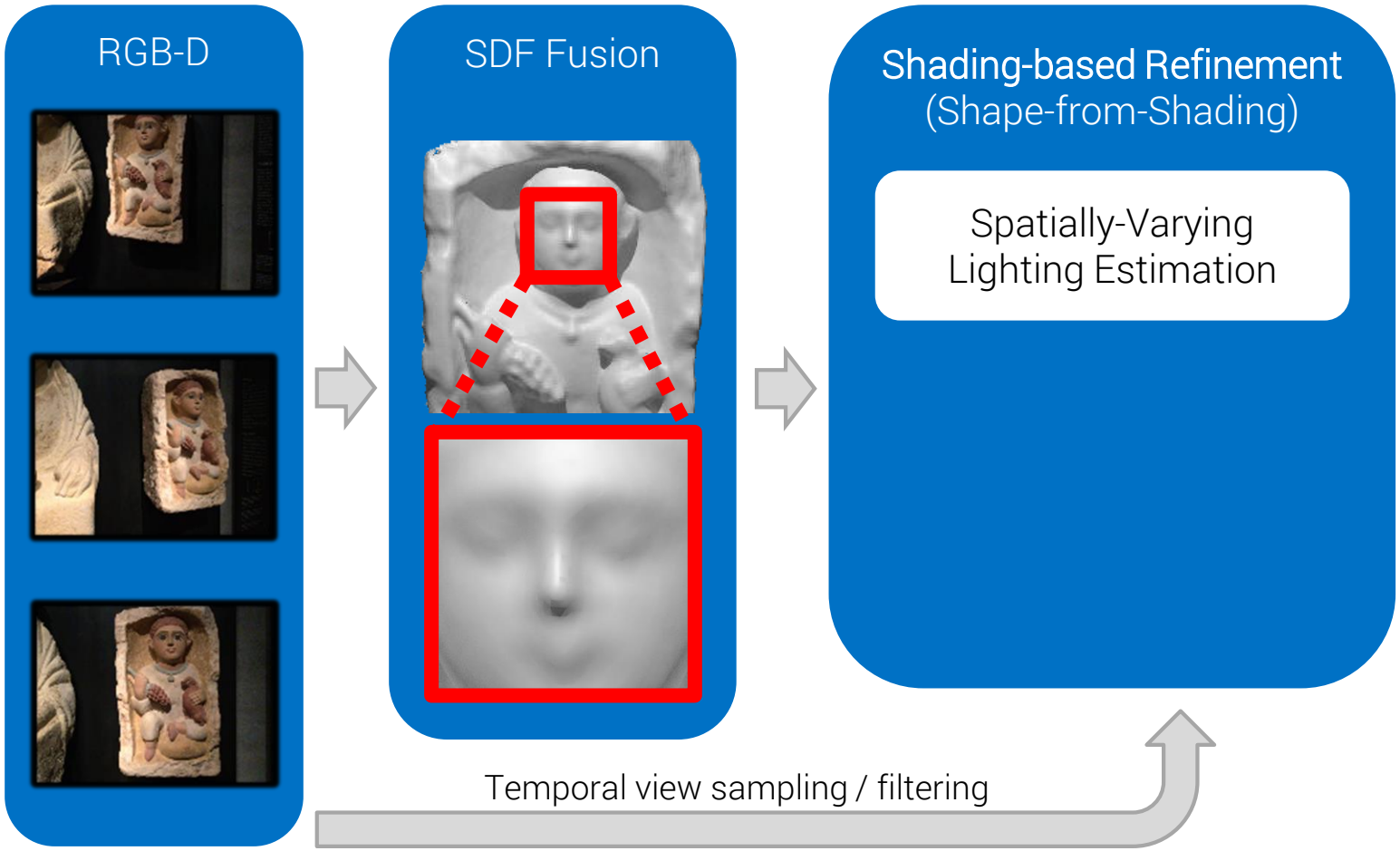

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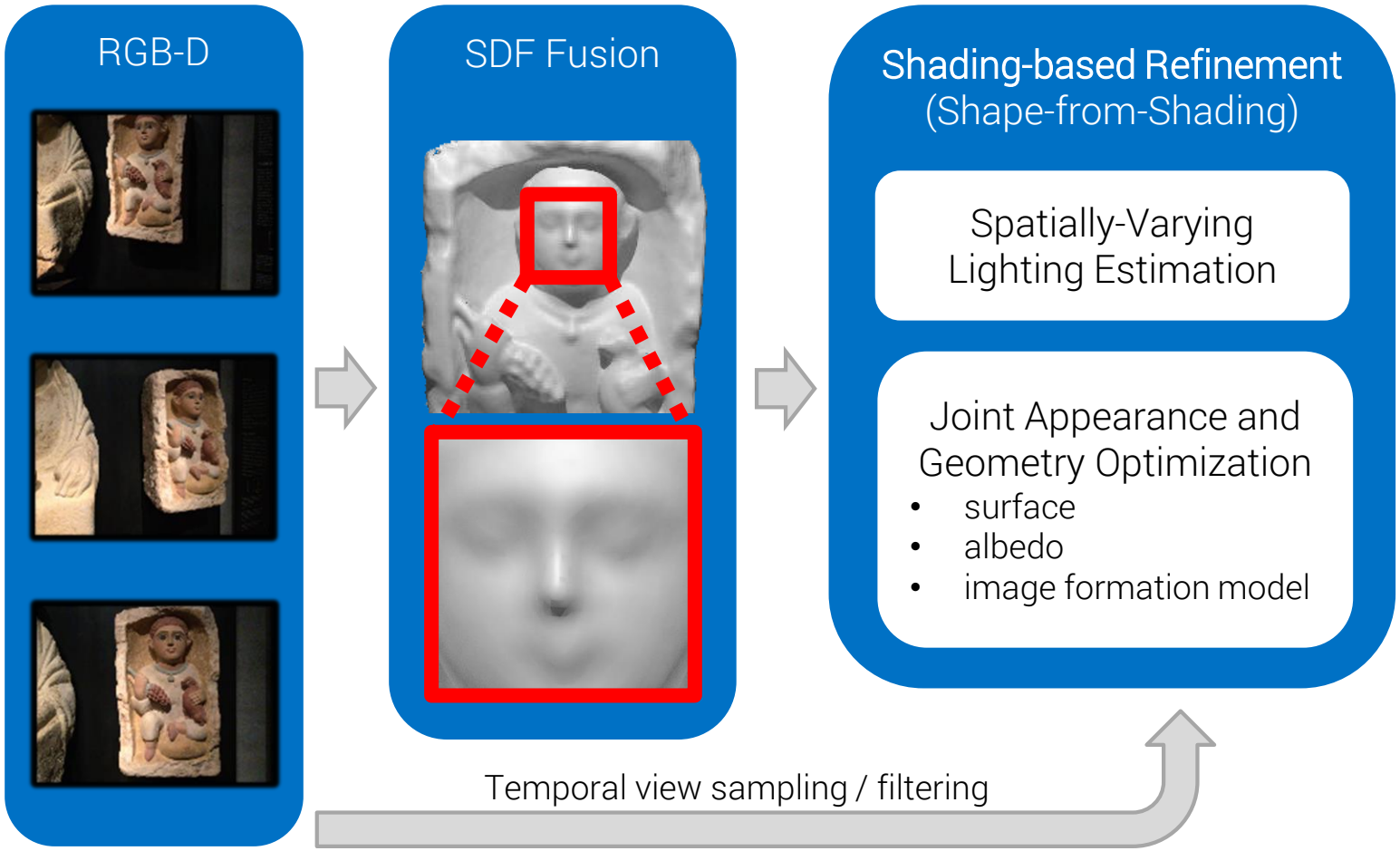

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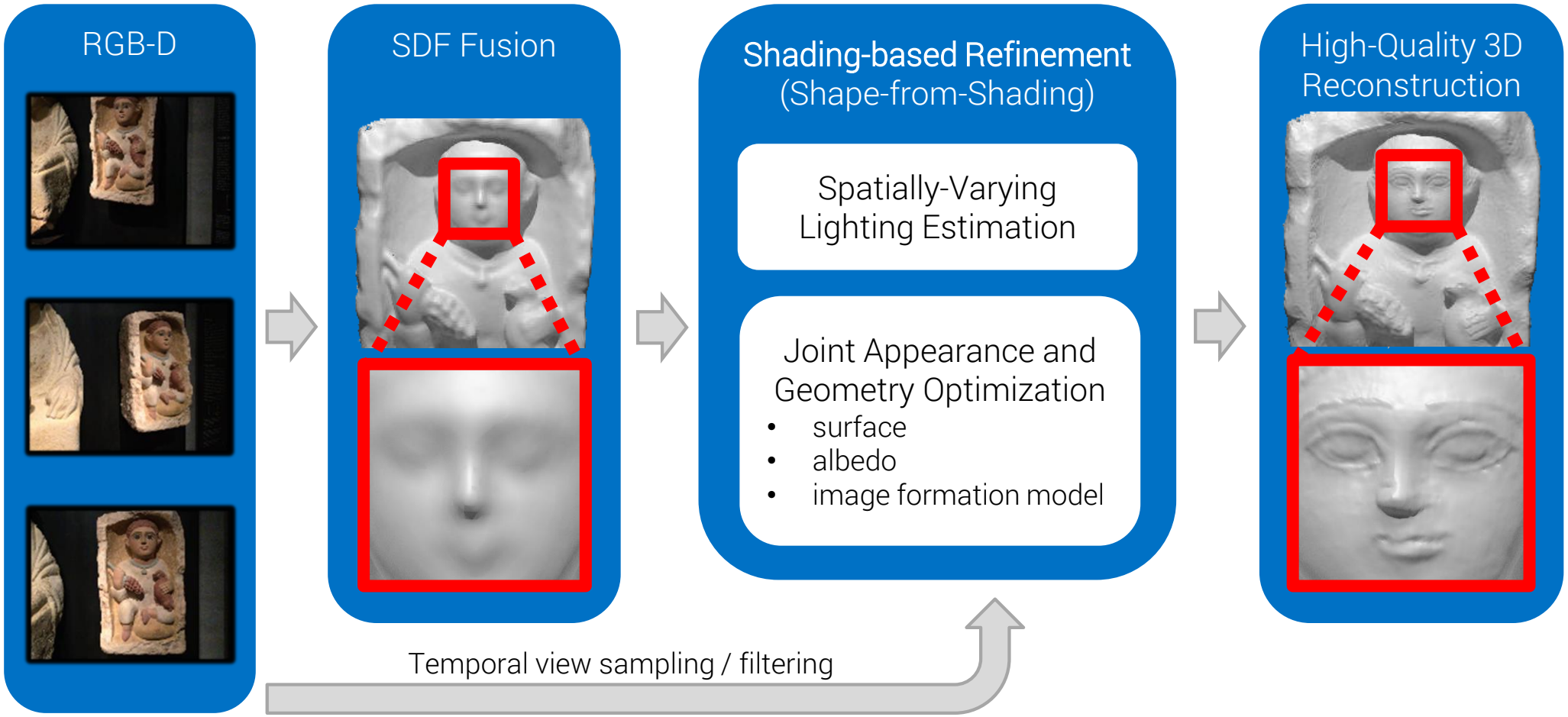

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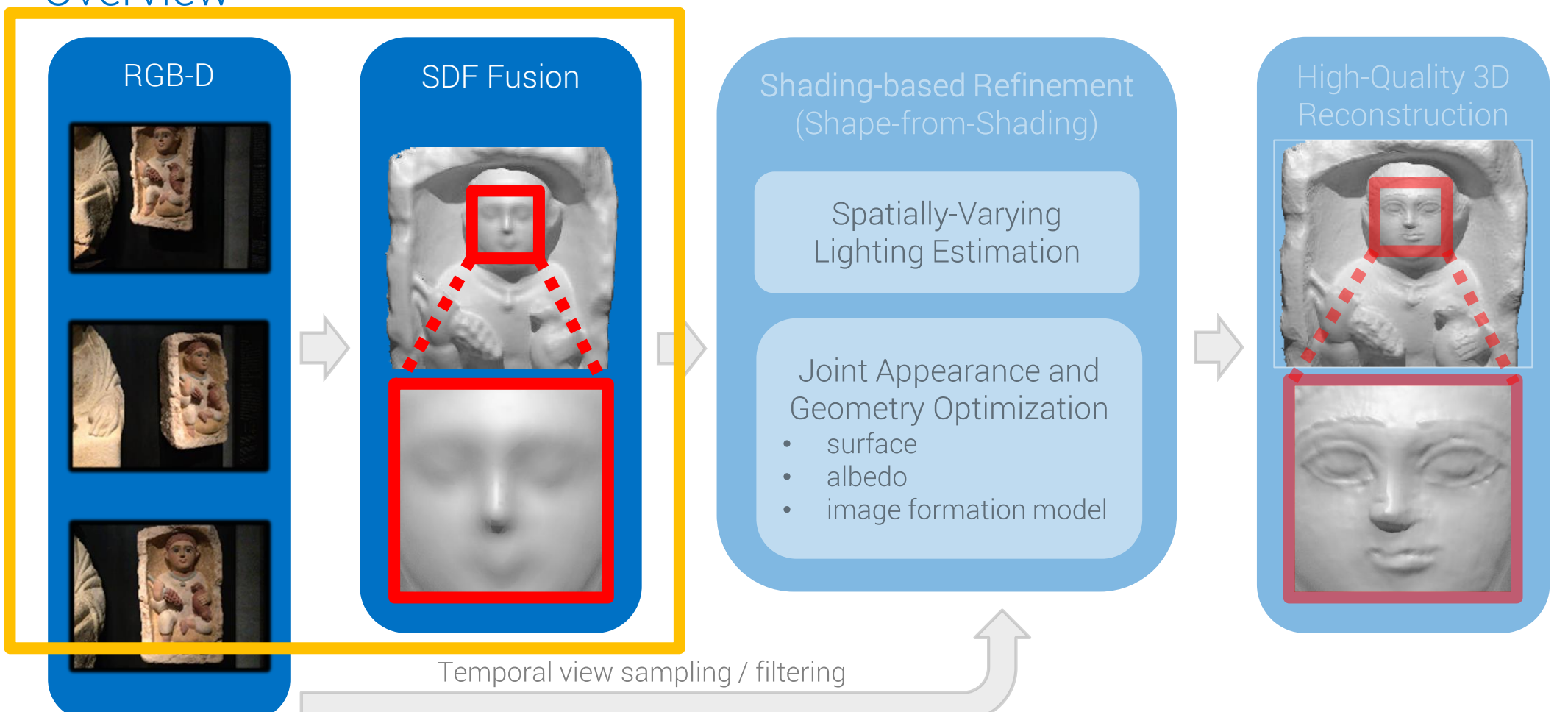

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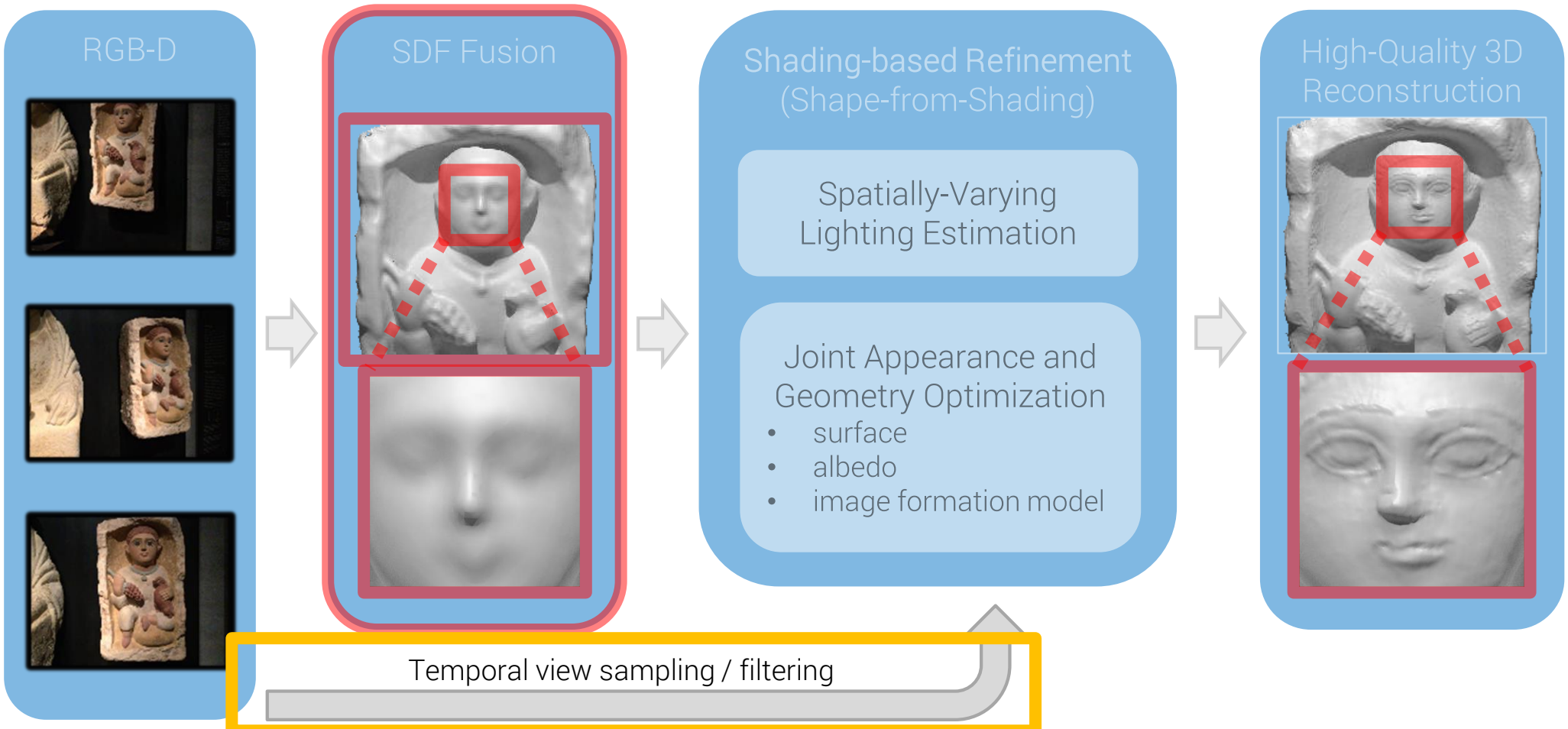


Keyframe Selection

- Compute per-frame blur score (for color image)[3]

Frame 81

Frame 84

- Select frame with best score within a fixed size window as keyframe

[3] "The blur effect: perception and estimation with a new no-reference perceptual blur metric", Crete et al., SPIE 2007.

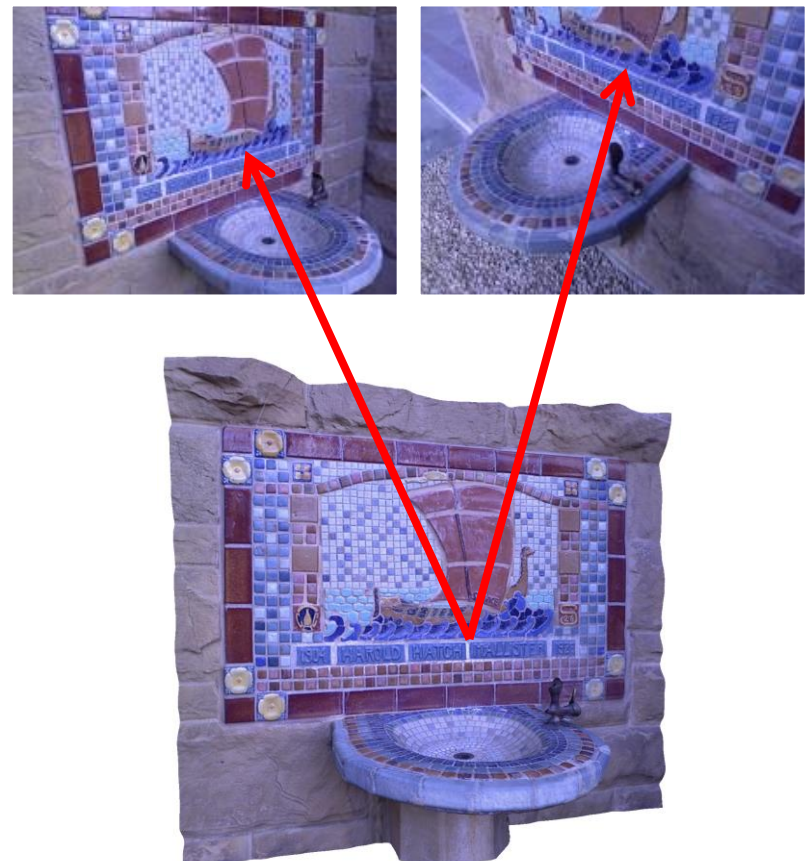
Sampling / Filtering

Sampling of voxel observations

- Sample from selected **keyframes only**
- **Collect observations** for voxel in input views:

$$c_i^v = \mathcal{C}_i(\pi(\mathcal{T}_i^{-1} \boldsymbol{v}_{\text{iso}})).$$

Input keyframes



Reconstruction

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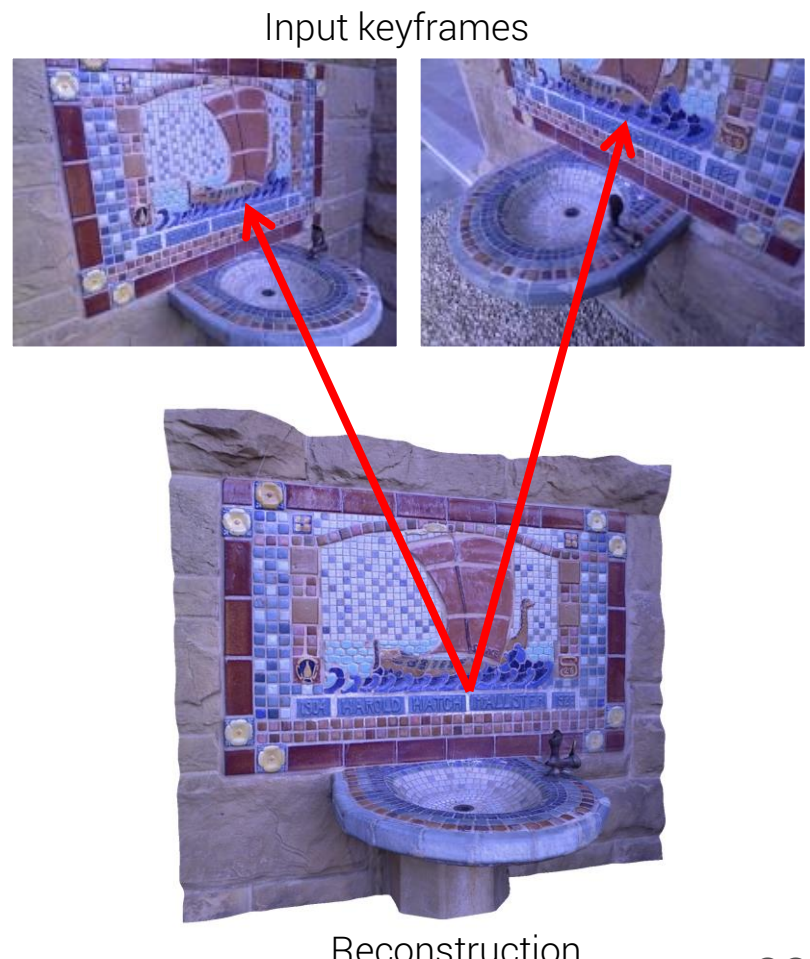
Voxel center transformed and projected into input view



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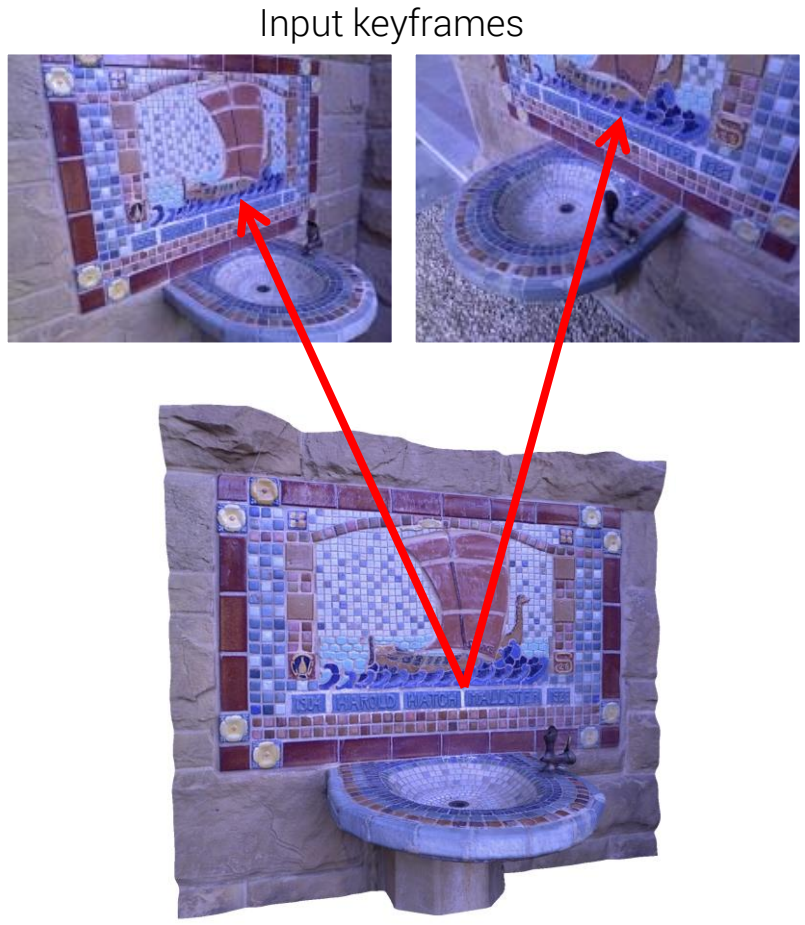
- Observation weights: **view-dependent** on normal and depth

$$w_i^{\boldsymbol{v}} = \frac{\cos(\theta)}{d^2}$$

- Filter observations: keep only **best 5 observations** by weight



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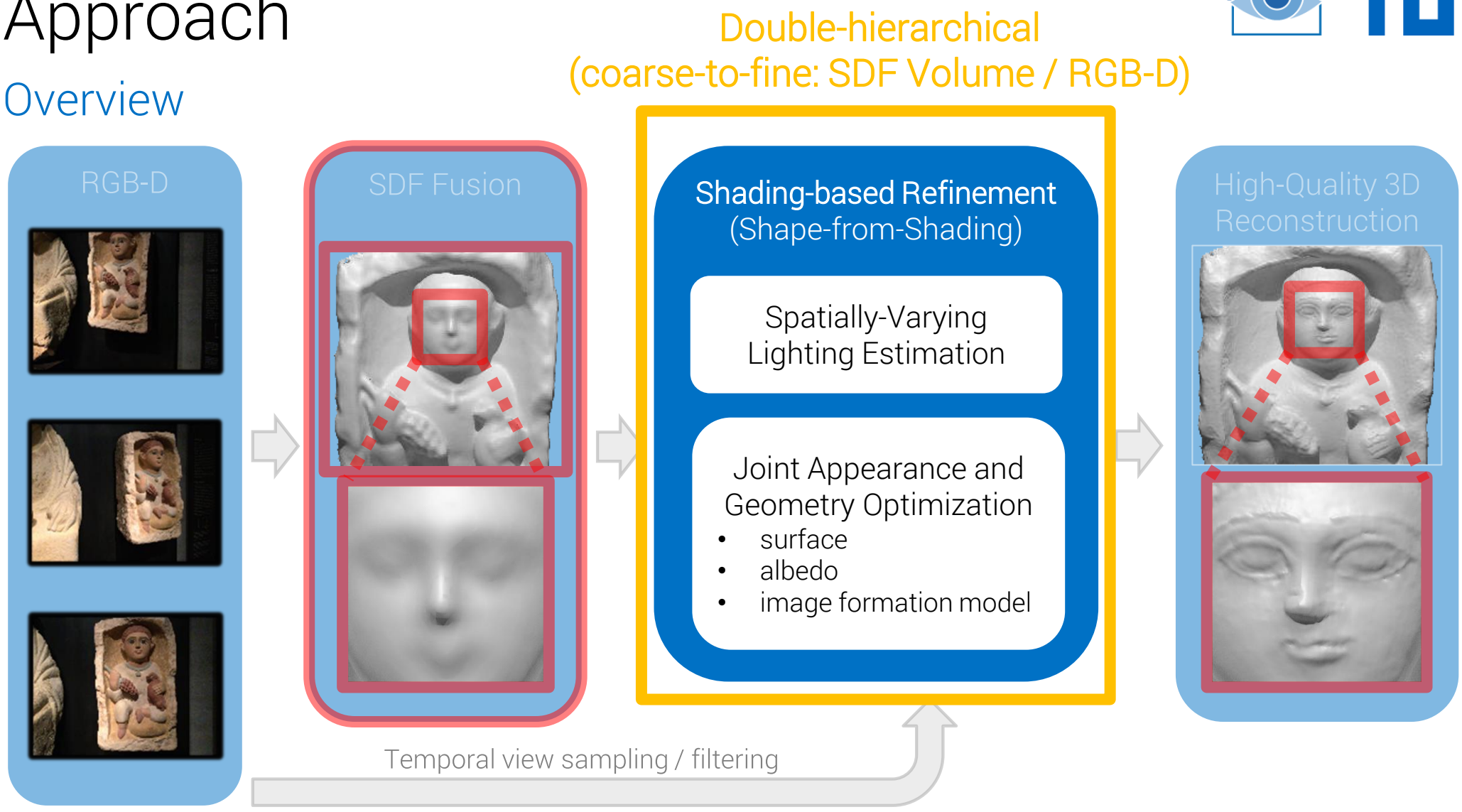

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- Shading equation: $$\mathbf{B}(\boldsymbol{v}) = \mathbf{a}(\boldsymbol{v}) \sum_{m=1}^{b^2} l_m H_m(\mathbf{n}(\boldsymbol{v})),$$

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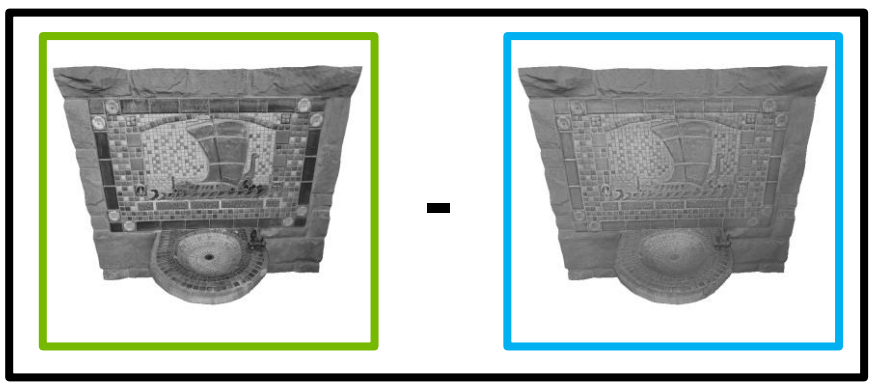
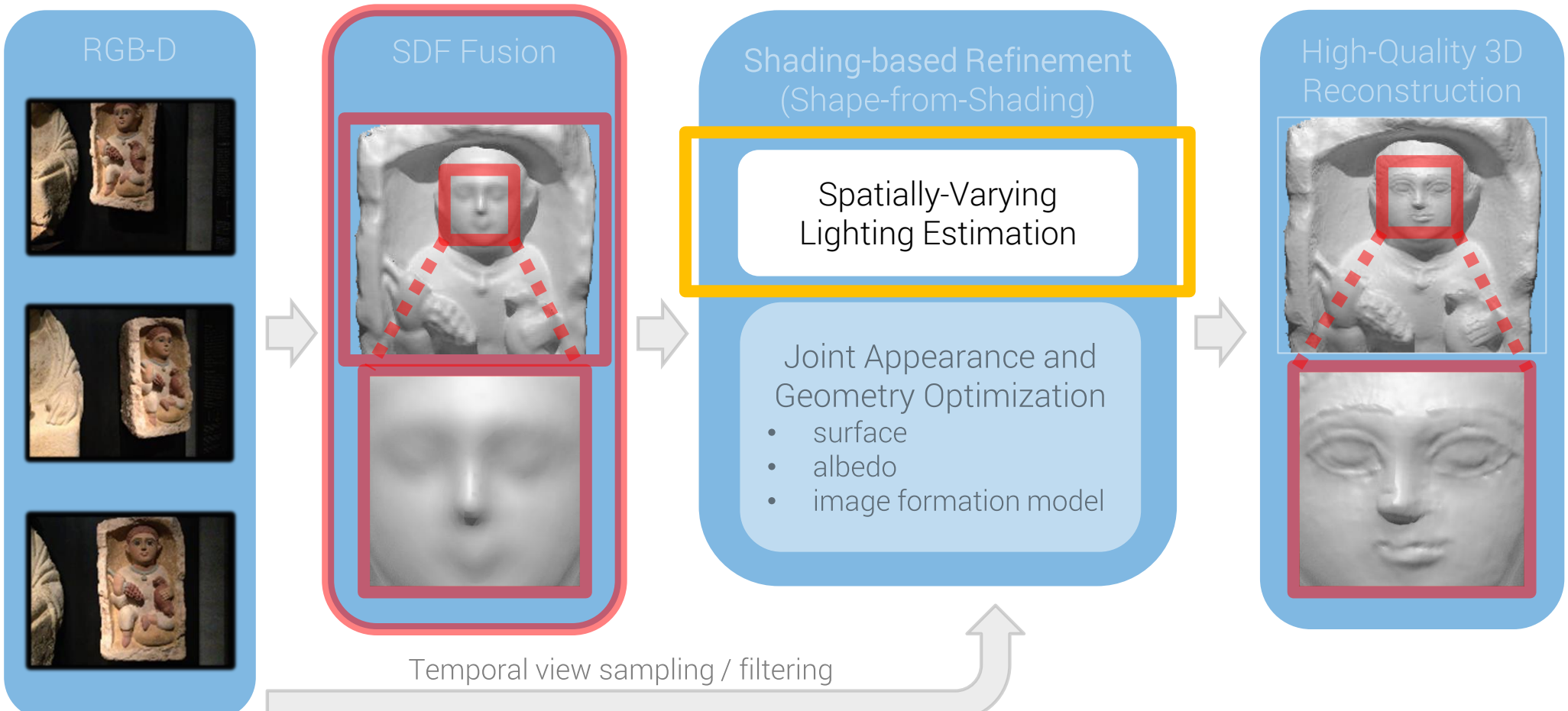


- Shading-based refinement:
  - Intuition: high-frequency changes in surface geometry → shading cues in input images
  - Estimate lighting given surface and albedo (intrinsic material properties)
  - Estimate surface and albedo given the lighting: minimize difference between estimated shading and input luminance

Approach

Overview



Lighting Estimation

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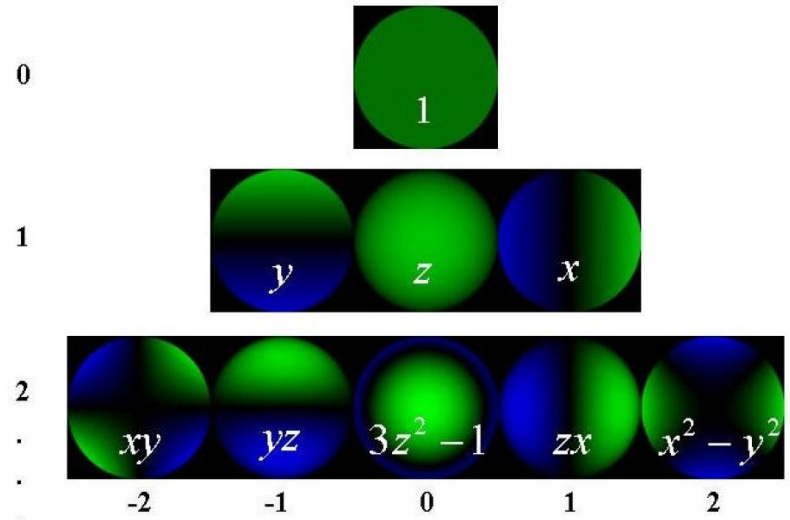

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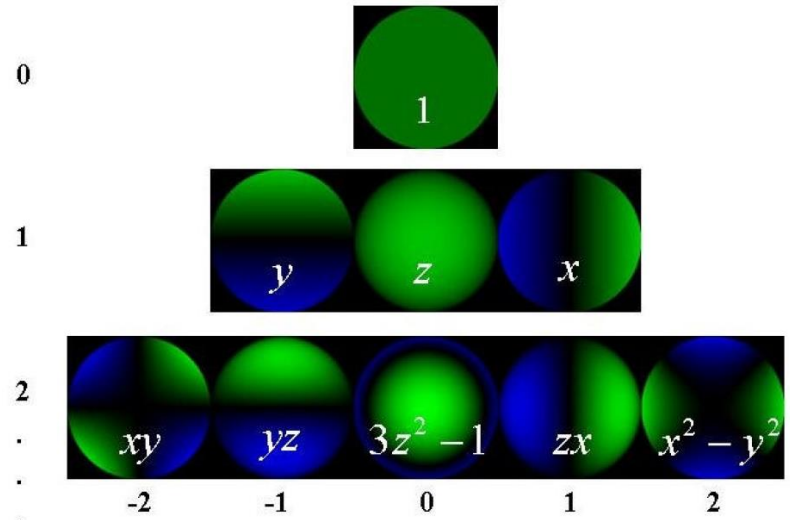

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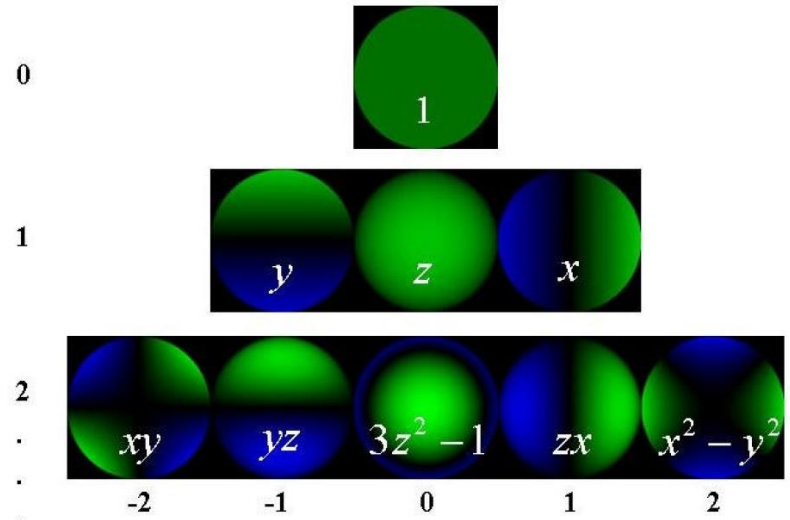
- Estimate SH coefficients: $E_{\text{light}}(\mathbf{l}) = \sum_{\mathbf{v} \in \mathbf{D}_0} (B(\mathbf{v}) - \mathbf{I}(\mathbf{v}))^2$

Lighting Estimation

Spherical Harmonics (SH)



- **Encode incident lighting** for a given surface point
- **Smooth** for Lambertian surfaces
- SH Basis functions H_m parametrized by **unit normal** n

$$\mathbf{B}(\boldsymbol{v}) = \mathbf{a}(\boldsymbol{v}) \sum_{m=1}^{b^2} l_m H_m(\mathbf{n}(\boldsymbol{v}))$$

- **Good approx.** using **only 9 SH basis functions** (2nd order)
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- **Shortcoming**: purely directional → cannot represent scene lighting for all surface points simultaneously

Spatially-Varying Lighting

Subvolume Partitioning

Spatially-Varying Lighting

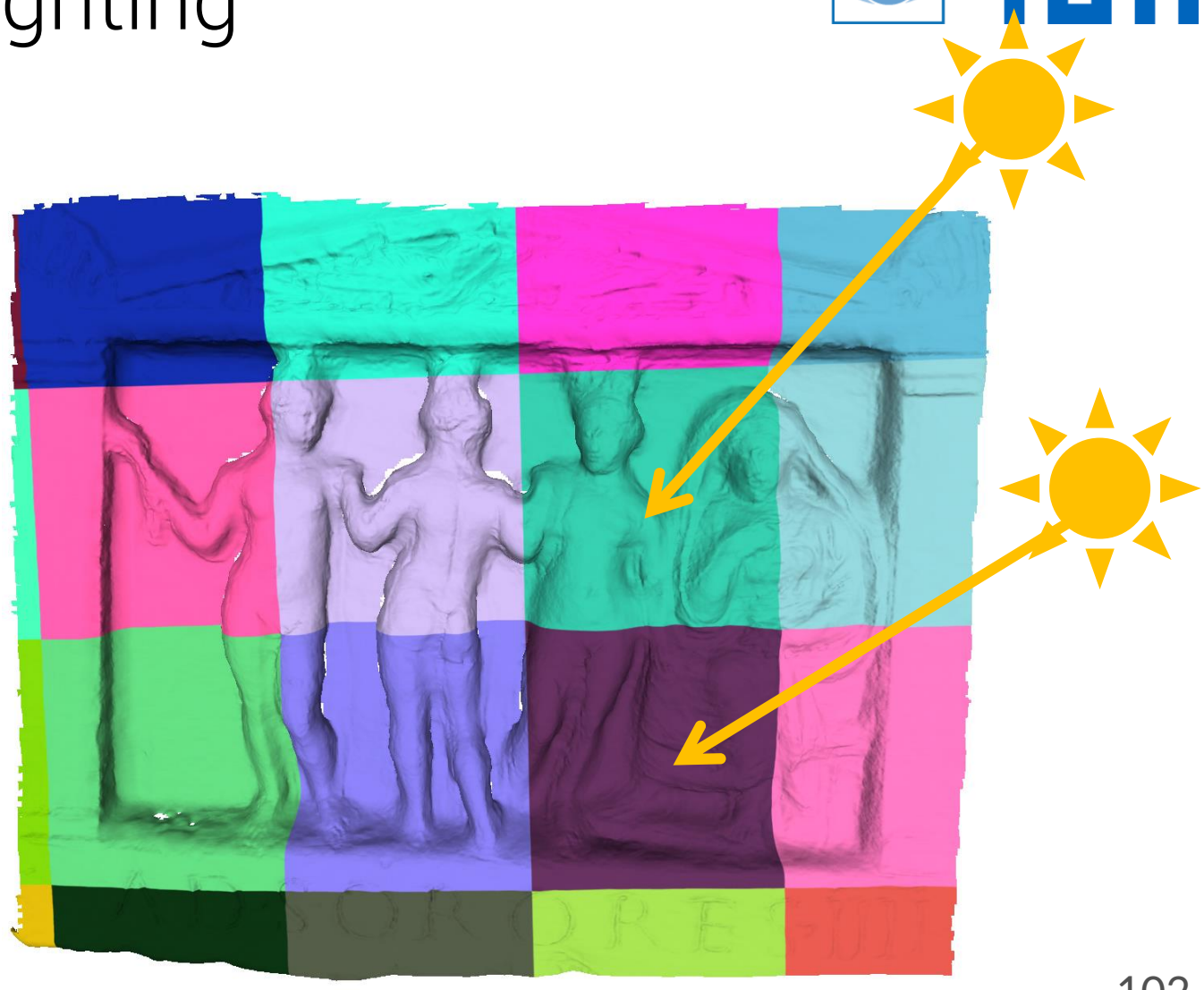
Subvolume Partitioning

- **Partition SDF** volume into subvolumes

Spatially-Varying Lighting

Subvolume Partitioning

- **Partition SDF** volume into subvolumes
- Estimate **independent SH coefficients** for each **subvolume**



Spatially-Varying Lighting

Subvolume Partitioning

- **Partition SDF** volume into subvolumes
- Estimate **independent SH coefficients** for each **subvolume**
- Obtain **per-voxel SH coefficients** through tri-linear interpolation

Spatially-Varying Lighting

Joint Optimization

Spatially-Varying Lighting

Joint Optimization

- Estimate SVSH coefficients for all subvolumes jointly:

$$E_{\text{lighting}}(\boldsymbol{l}_1, \ldots, \boldsymbol{l}_K) = E_{\text{appearance}} + \lambda_{\text{diffuse}} E_{\text{diffuse}}.$$

Spatially-Varying Lighting

Joint Optimization

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$$E_{\text{lighting}}(\boldsymbol{l}_1, \ldots, \boldsymbol{l}_K) = \boxed{E_{\text{appearance}}} + \lambda_{\text{diffuse}} E_{\text{diffuse}}.$$

Data term:

$$E_{\text{appearance}} = \sum_{\boldsymbol{v} \in \mathbf{D}_0} (\mathbf{B}(\boldsymbol{v}) - \mathbf{I}(\boldsymbol{v}))^2.$$

Similarity between estimated shading and input luminance

Spatially-Varying Lighting

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Similarity between estimated shading and input luminance

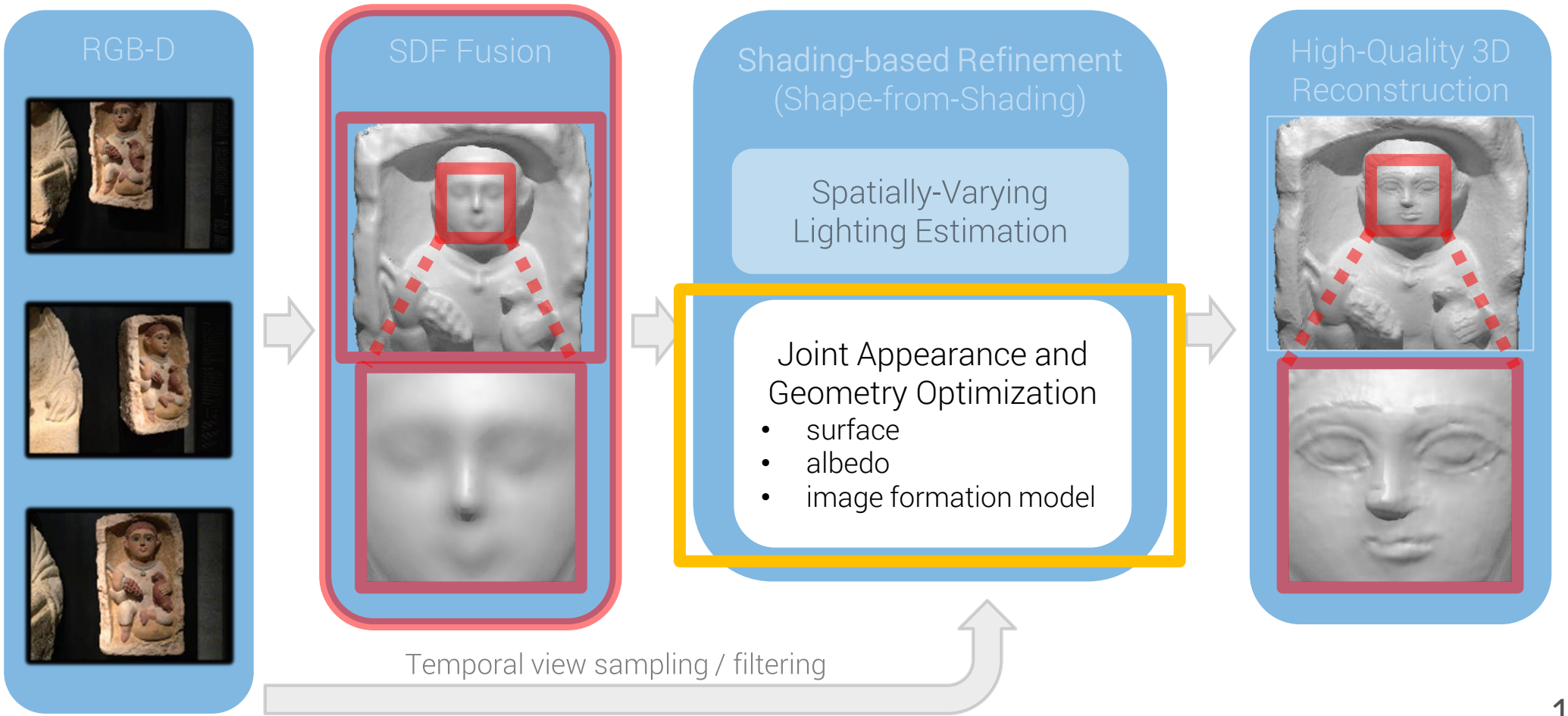
Laplacian regularizer:

$$E_{\text{diffuse}} = \sum_{s \in \mathcal{S}} \sum_{r \in \mathcal{N}_s} (\boldsymbol{l}_s - \boldsymbol{l}_r)^2.$$

Smooth illumination changes

Approach

Overview



Joint Optimization

Shading-based SDF optimization

- **Joint optimization** of geometry, albedo and image formation model (camera poses and camera intrinsics):

$$E_{\text{scene}}(\mathcal{X}) = \sum_{\boldsymbol{v} \in \tilde{\mathbf{D}}_0} \lambda_g E_g + \lambda_v E_v + \lambda_s E_s + \lambda_a E_a$$

with $\mathcal{X} = (\mathcal{T}, \tilde{\mathbf{D}}, \mathbf{a}, f_x, f_y, c_x, c_y, \kappa_1, \kappa_2, \rho_1)$

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Gradient-based shading constraint (data term)

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Gradient-based shading constraint (data term)

Volumetric regularizer: smoothness in distance values (Laplacian)

$$E_v(\boldsymbol{v}) = (\Delta \tilde{\mathbf{D}}(\boldsymbol{v}))^2$$

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Volumetric regularizer: smoothness in distance values (Laplacian)

Surface Stabilization constraint: stay close to initial distance values

$$E_s(\boldsymbol{v}) = (\tilde{\mathbf{D}}(\boldsymbol{v}) - \mathbf{D}(\boldsymbol{v}))^2$$

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with $\mathcal{X} = (\mathcal{T}, \tilde{\mathbf{D}}, \mathbf{a}, f_x, f_y, c_x, c_y, \kappa_1, \kappa_2, \rho_1)$

Gradient-based shading constraint (data term)

Volumetric regularizer: smoothness in distance values (Laplacian)

Surface Stabilization constraint: stay close to initial distance values

Albedo regularizer: constrain albedo changes based on chromaticity (Laplacian)

$$E_a(\boldsymbol{v}) = \sum_{\boldsymbol{u} \in \mathcal{N}_{\boldsymbol{v}}} \phi(\mathbf{\Gamma}(\boldsymbol{v}) - \mathbf{\Gamma}(\boldsymbol{u})) \cdot (\mathbf{a}(\boldsymbol{v}) - \mathbf{a}(\boldsymbol{u}))^2$$

Joint Optimization

Shading Constraint (data term)

- Idea: **maximize consistency** between **estimated voxel shading** and **sampled intensities** in input luminance images (gradient for robustness)

$$E_g(\boldsymbol{v}) = \sum_{\mathcal{I}_i \in \mathcal{V}_{\text{best}}} w_i^{\boldsymbol{v}} \|\nabla \mathbf{B}(\boldsymbol{v}) - \nabla \mathcal{I}_i(\pi(v_i))\|_2^2$$

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Best views for voxel and respective view-dependent weights

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Voxel center transformed and projected into input view

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Best views for voxel and respective view-dependent weights

Shading: allows for optimization of surface (through normal) and albedo

Voxel center transformed and projected into input view

Sampling: allows for optimization of camera poses and camera intrinsics

Recolorization

Optimal colors

- **Recompute voxel colors** after optimization at each level

Recolorization

Optimal colors

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- Sampling
  - Sample from **keyframes only**
  - **Collect, weight and filter** observations

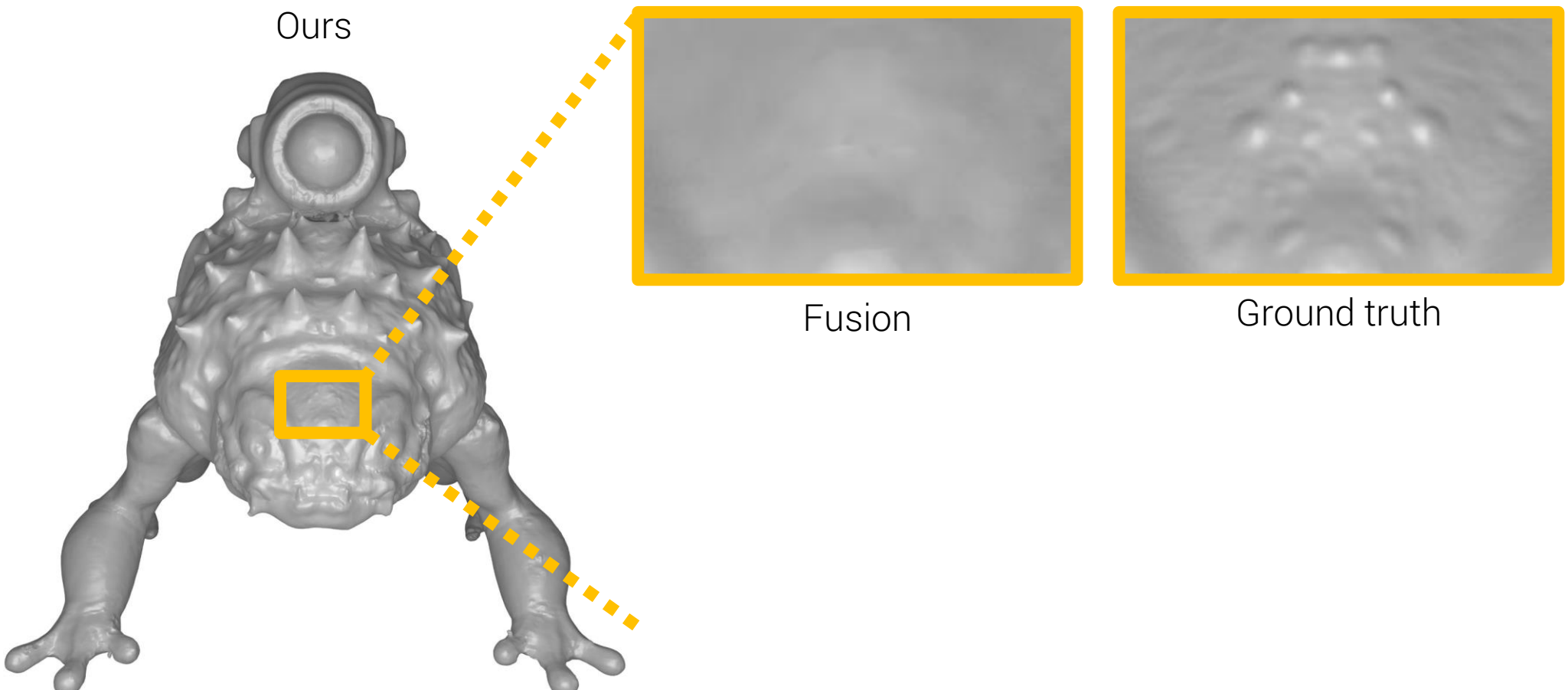
Recolorization

Optimal colors

- **Recompute voxel colors** after optimization at each level
- Sampling
  - Sample from **keyframes only**
  - **Collect, weight and filter** observations
- **Weighted average** $c_{\boldsymbol{v}}^* = \arg\min_{c_{\boldsymbol{v}}} \sum_{(c_i^{\boldsymbol{v}}, w_i^{\boldsymbol{v}}) \in \mathcal{O}_v} w_i^{\boldsymbol{v}} (c_{\boldsymbol{v}} - c_i^{\boldsymbol{v}})^2.$

Results: Ground Truth Geometry

Frog (synthetic)



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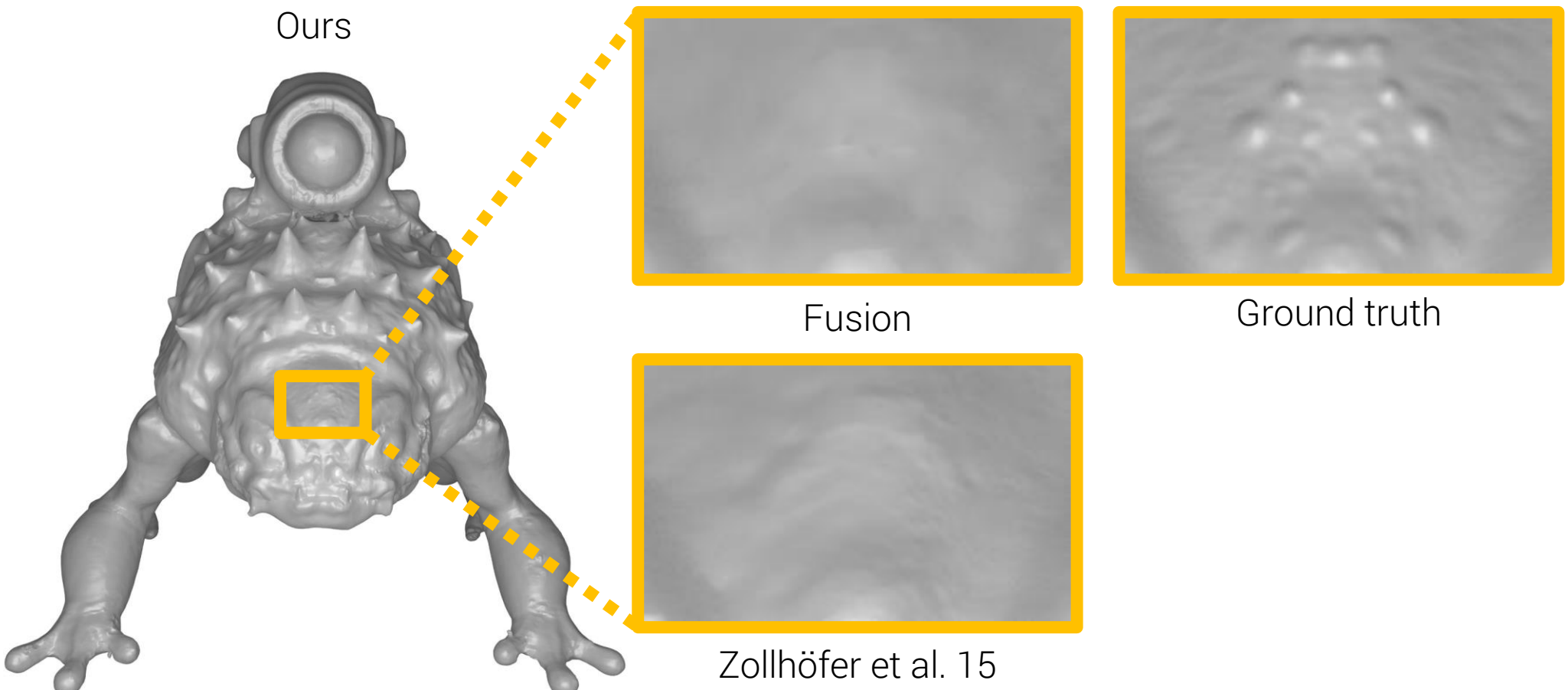

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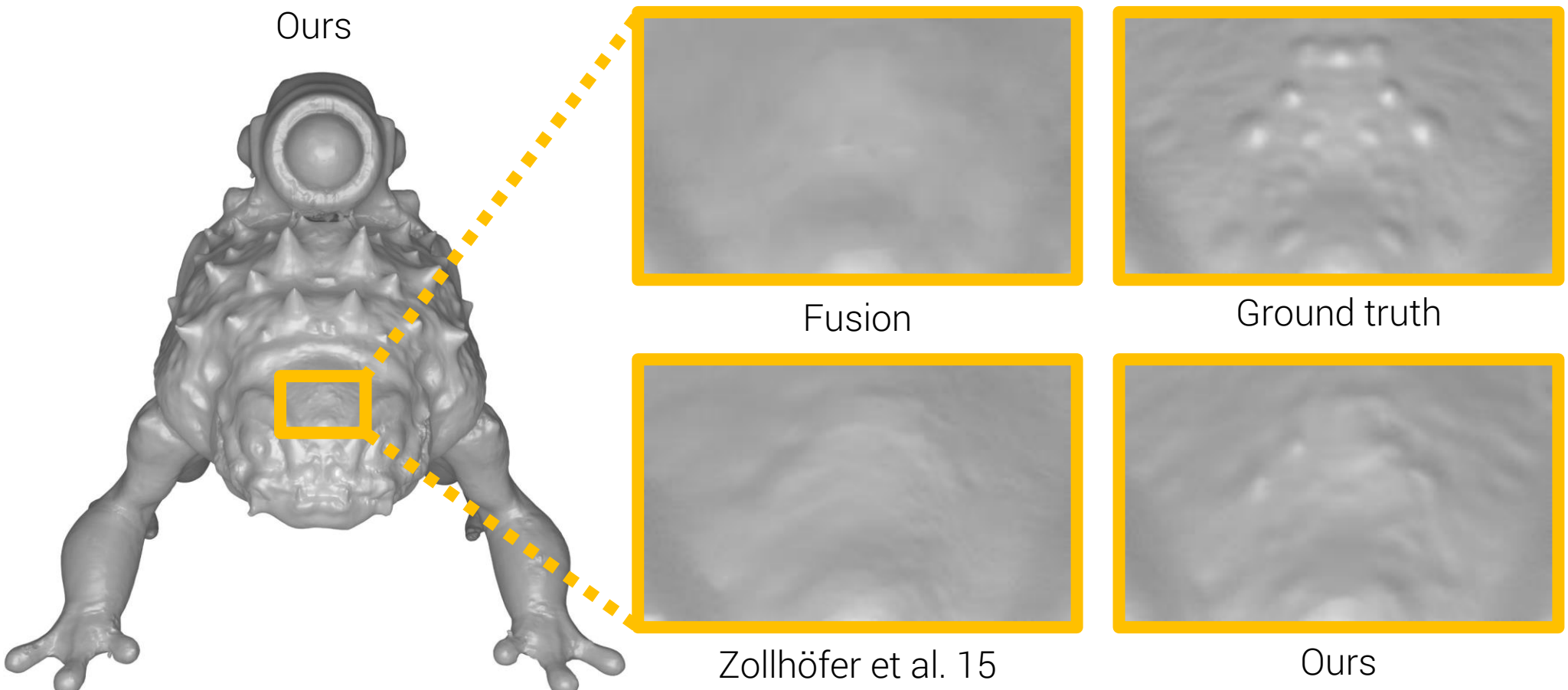
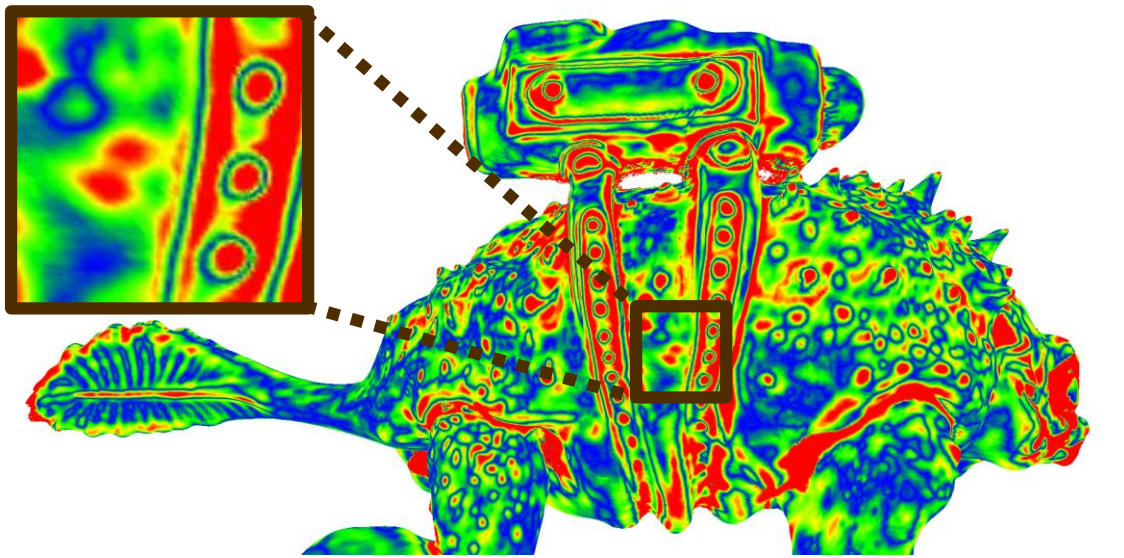


Results: Ground Truth Geometry

Frog (synthetic)

- Quantitative surface accuracy evaluation
- Color coding: absolute distances (ground truth)

Zollhöfer et al. 15



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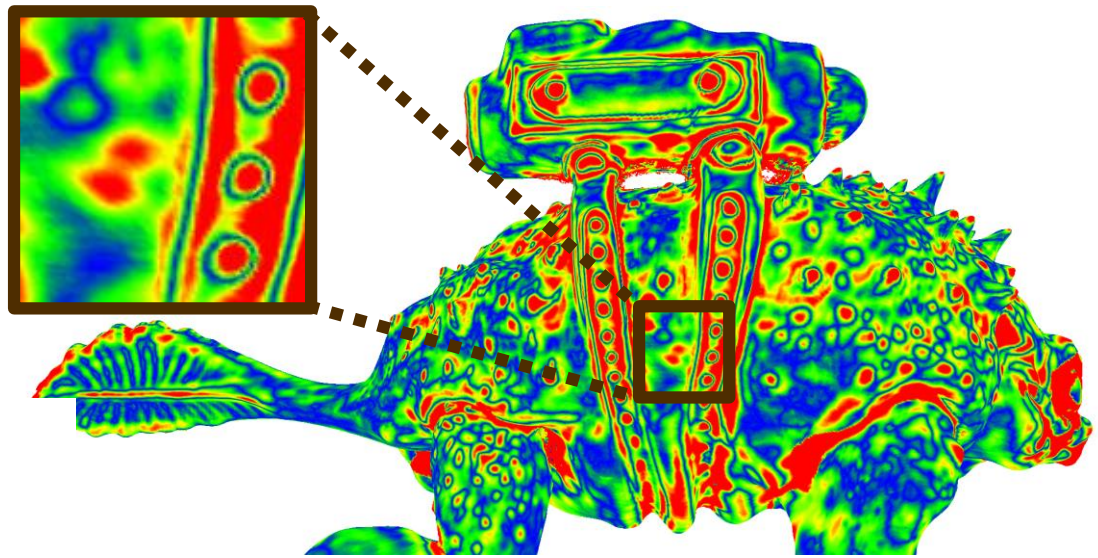
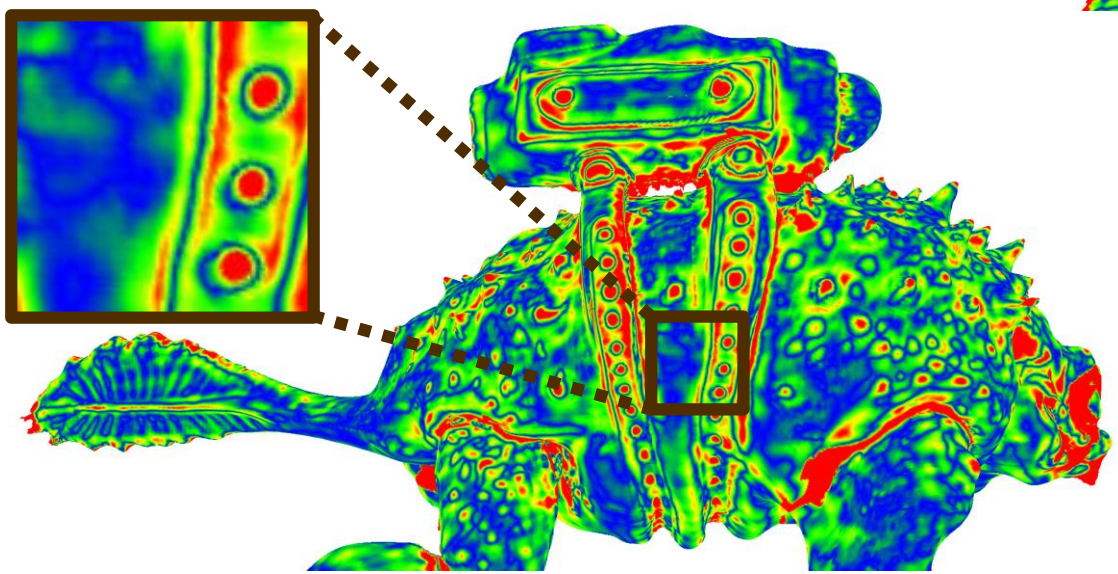


Ours



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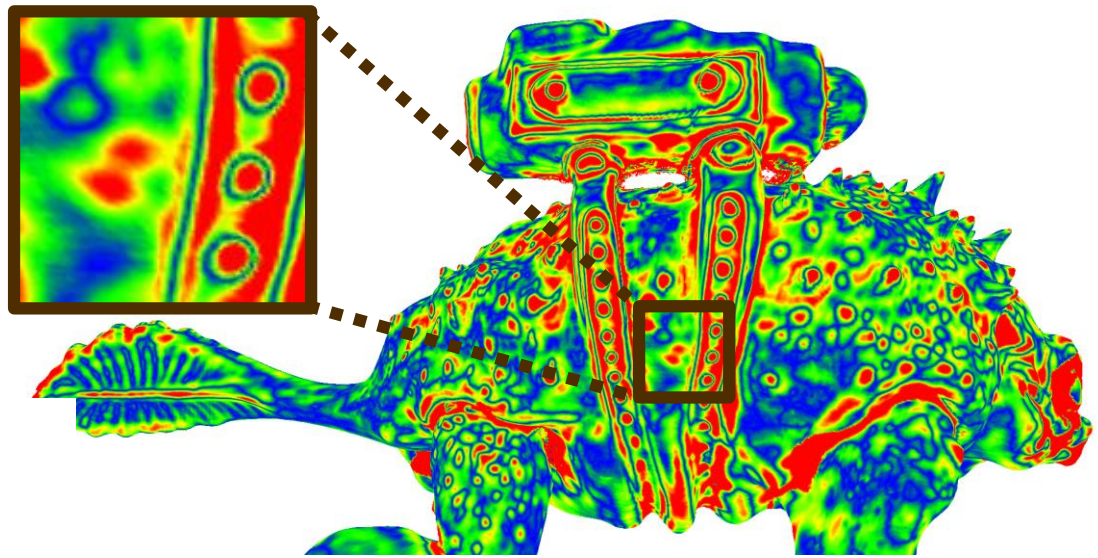

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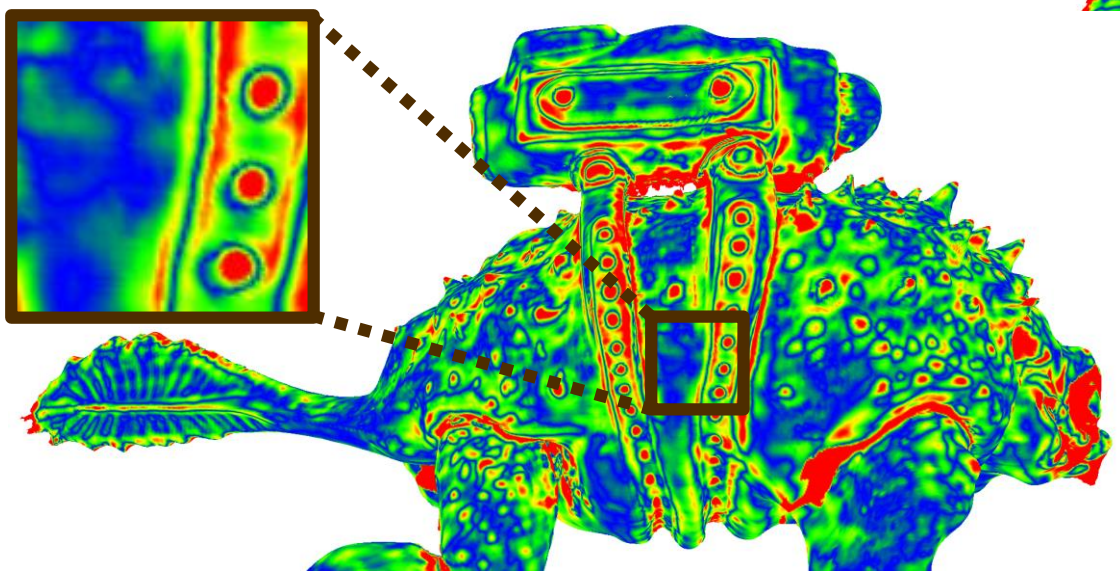


Mean absolute deviation:

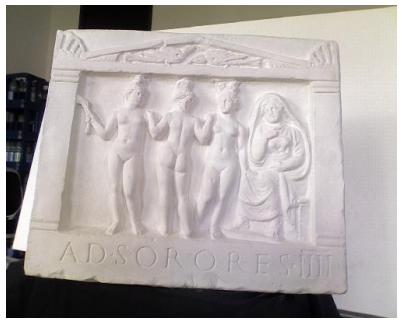
- Ours: 0.222mm (std.dev. 0.269mm)
- Zollhöfer et al: 0.278mm (std.dev. 0.299mm)

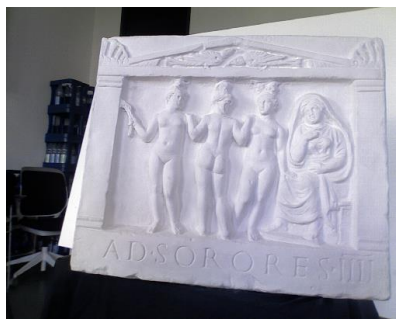
  → 20.14% more accurate

Qualitative Results

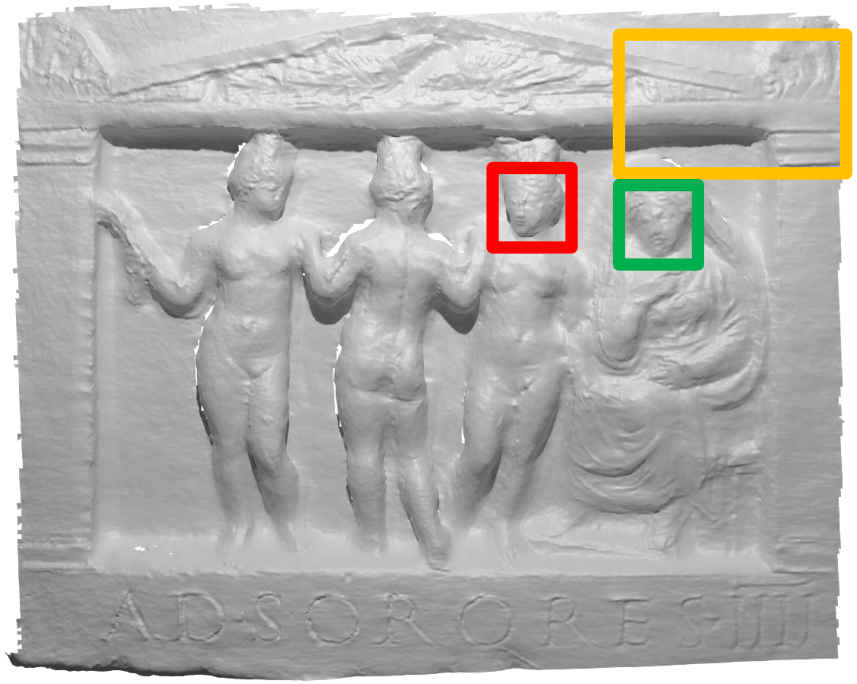
Relief (geometry)

Input Color

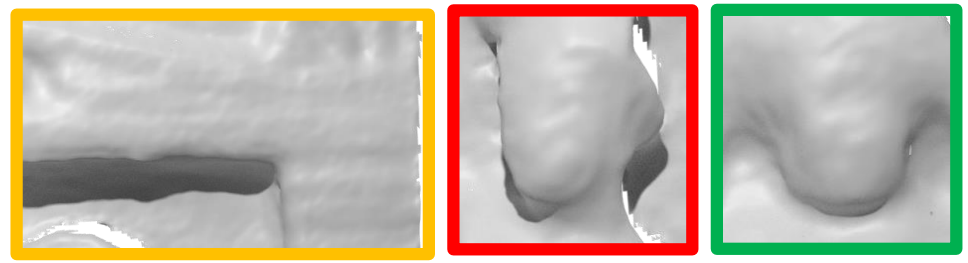




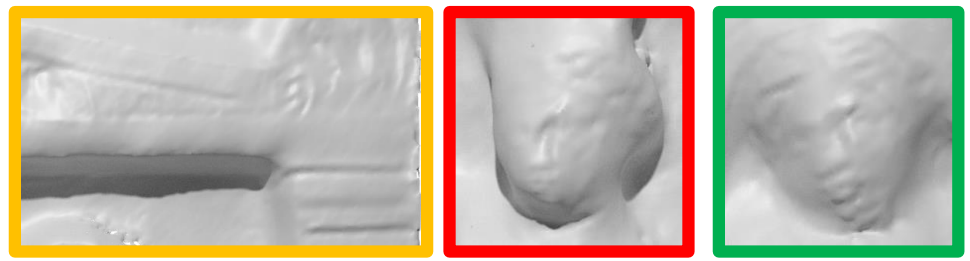
Ours



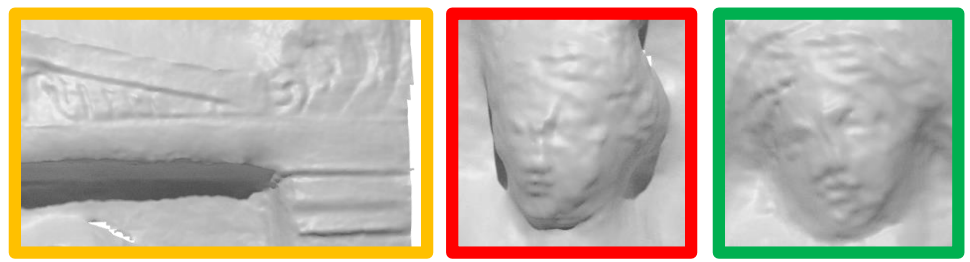
Fusion



Zollhöfer et al. 15



Ours



Qualitative Results

Fountain (appearance)

Input Color

Ours

Fusion

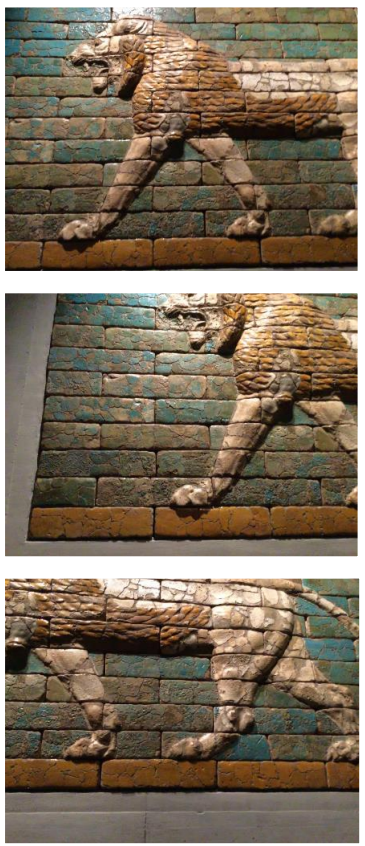
Zollhöfer et al. 15

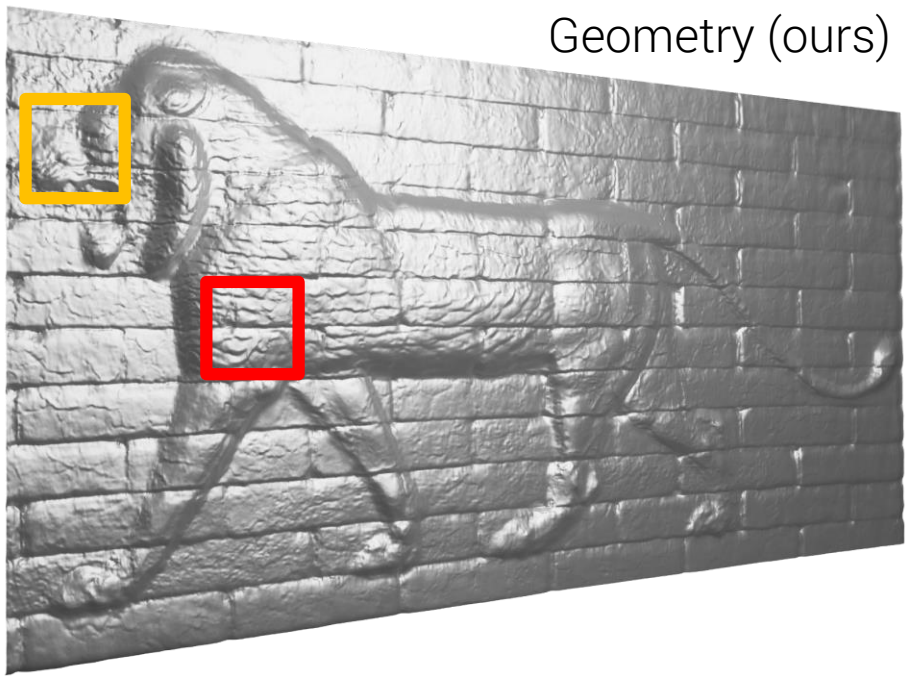
Ours

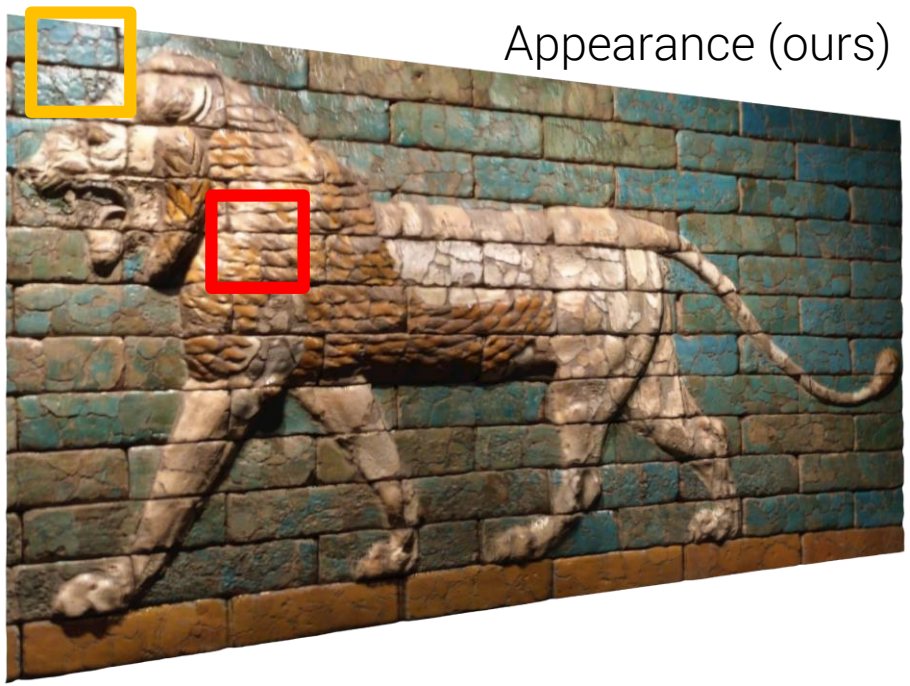
Qualitative Results

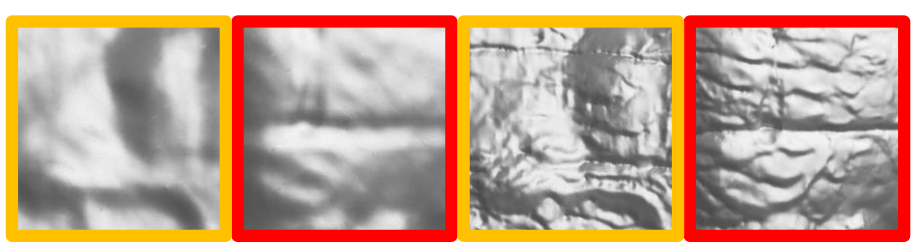
Lion

Input Color

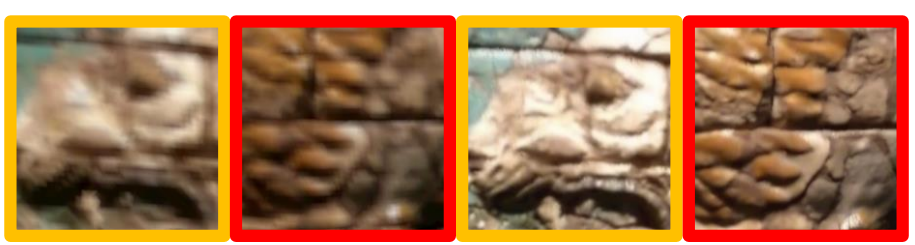








Fusion Ours

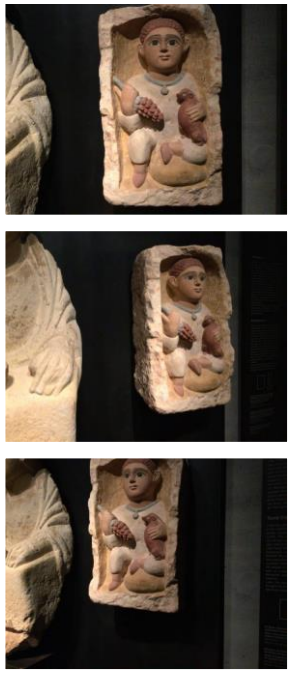


Fusion Ours

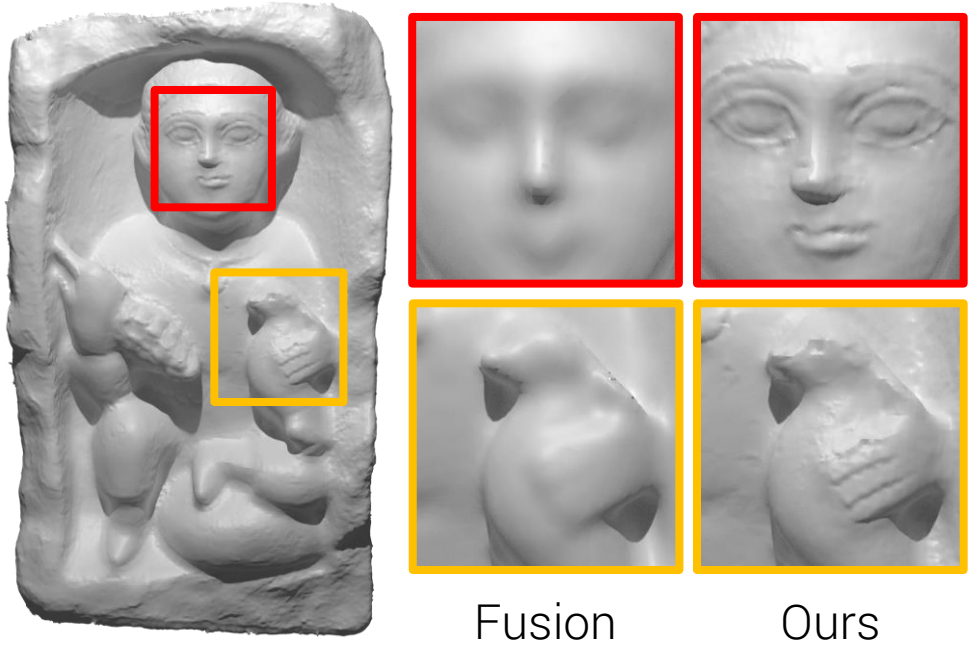
Qualitative Results

Tomb Statuary

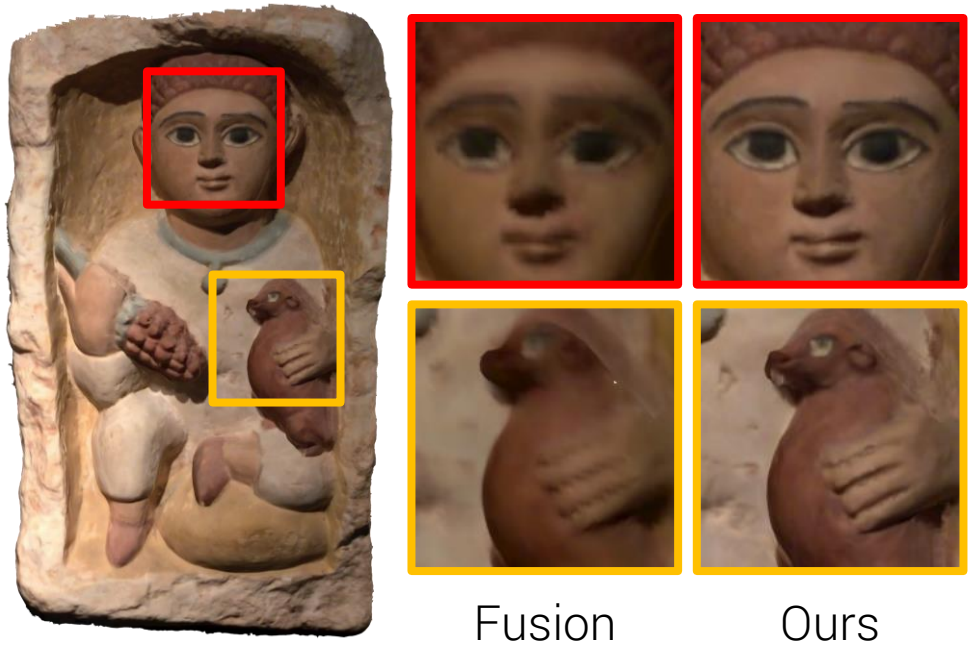
Input Color



Geometry (ours)



Appearance (ours)



Shading: Global SH vs. SVSH

Fountain

Luminance

Shading: Global SH vs. SVSH

Fountain

Luminance

Albedo

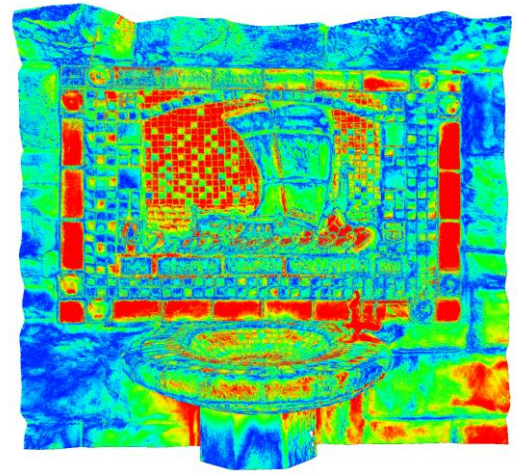
Shading: Global SH vs. SVSH

Fountain

$$\mathbf{B}_{\text{diff}} = |\mathbf{B}(\boldsymbol{v}) - \mathbf{I}(\boldsymbol{v})|$$

Luminance

Shading



Difference

Global SH

Albedo

Shading: Global SH vs. SVSH

Fountain

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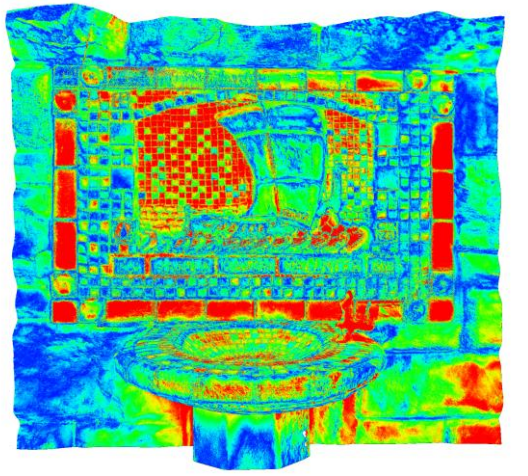
Luminance

Shading

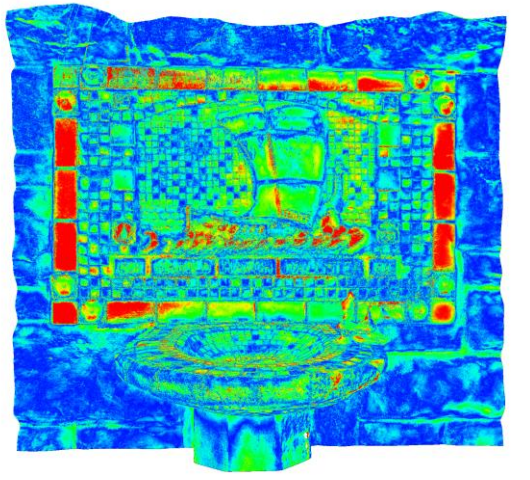


Difference

Global SH

Albedo

Shading



Difference

SVSH

Conclusion

High-Quality 3D Reconstruction of Geometry and Appearance

- Temporal view **sampling & filtering** techniques
- **Spatially-Varying Lighting** estimation
- **Joint optimization** of **surface & albedo** (SDF) and **image formation model**
- **Optimized texture** as by-product

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Thank you!

Questions?

Robert Maier

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Computer Vision Group

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https://vision.in.tum.de/members/maierr