Technical University of Munich

On Joint Estimation of Pose, Geometry and svBRDF from a Handheld Scanner

Matthias Stübinger

Department of Informatics, Technical University of Munich (TUM)

Computer Vision Seminar

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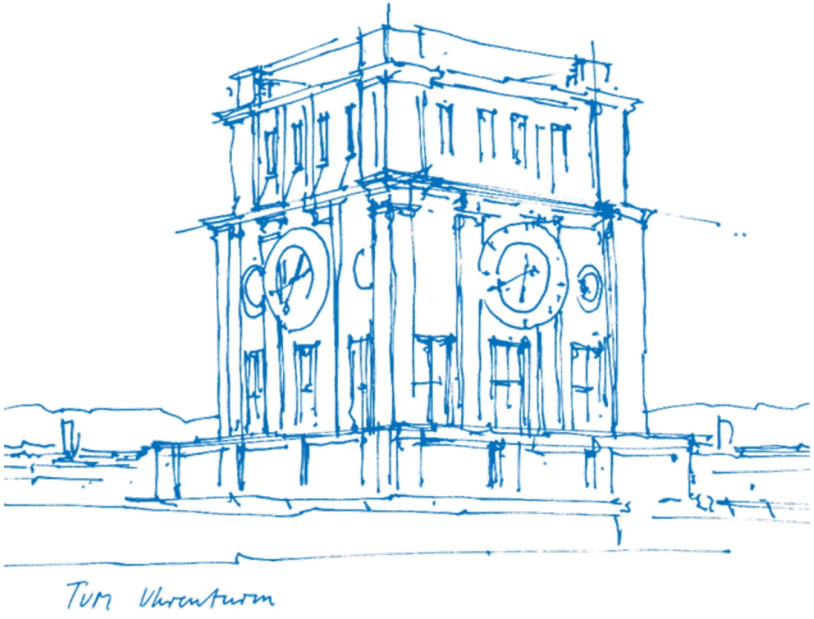

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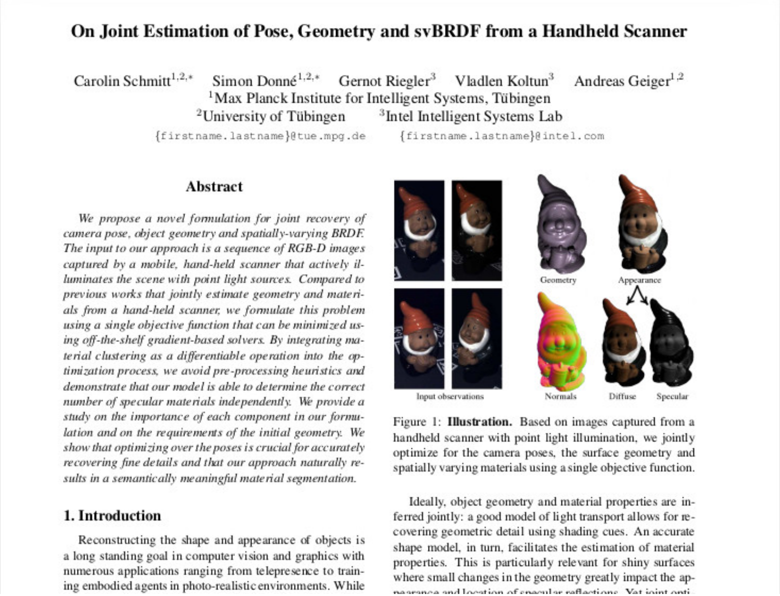
- by Carolin Schmitt, Simon Donne, Gernot Riegler, Vladlen Koltun, Andreas Geiger
- Presented at CVPR 2020, published in the proceedings
- `https://openaccess.thecvf.com/content_CVPR_2020/html/Schmitt_On_Joint_Estimation_of_Pose_Geometry_and_svBRDF_From_a_CVPR_2020_paper.html`
- Video demonstration: `http://www.youtube.com/watch?v=_xxSQPD9qU0`



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Carolin Schmitt[1,2,*] Simon Donné[1,2,*] Gernot Riegler[3] Vladlen Koltun[3] Andreas Geiger[1,2]
[1]Max Planck Institute for Intelligent Systems, Tübingen
[2]University of Tübingen [3]Intel Intelligent Systems Lab
{firstname.lastname}@tue.mpg.de {firstname.lastname}@intel.com

Abstract

We propose a novel formulation for joint recovery of camera pose, object geometry and spatially-varying BRDF. The input to our approach is a sequence of RGB-D images captured by a mobile, hand-held scanner that actively illuminates the scene with point light sources. Compared to previous works that jointly estimate geometry and materials from a hand-held scanner, we formulate this problem using a single objective function that can be minimized using off-the-shelf gradient-based solvers. By integrating material clustering as a differentiable operation into the optimization process, we avoid pre-processing heuristics and demonstrate that our model is able to determine the correct number of specular materials independently. We provide a study on the importance of each component in our formulation and on the requirements of the initial geometry. We show that optimizing over the poses is crucial for accurately recovering fine details and that our approach naturally results in a semantically meaningful material segmentation.

1. Introduction

Reconstructing the shape and appearance of objects is a long standing goal in computer vision and graphics with numerous applications ranging from telepresence to training embodied agents in photo-realistic environments. While

Figure 1: **Illustration.** Based on images captured from a handheld scanner with point light illumination, we jointly optimize for the camera poses, the surface geometry and spatially varying materials using a single objective function.

Ideally, object geometry and material properties are inferred jointly: a good model of light transport allows for recovering geometric detail using shading cues. An accurate shape model, in turn, facilitates the estimation of material properties. This is particularly relevant for shiny surfaces where small changes in the geometry greatly impact the appearance and location of specular reflections. Yet joint opti-

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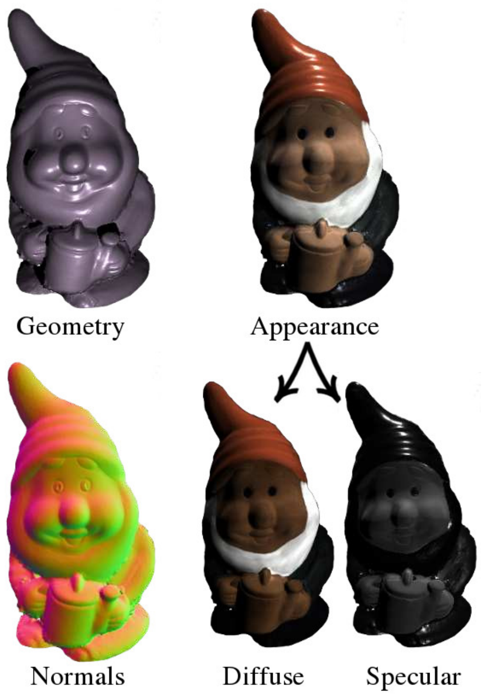

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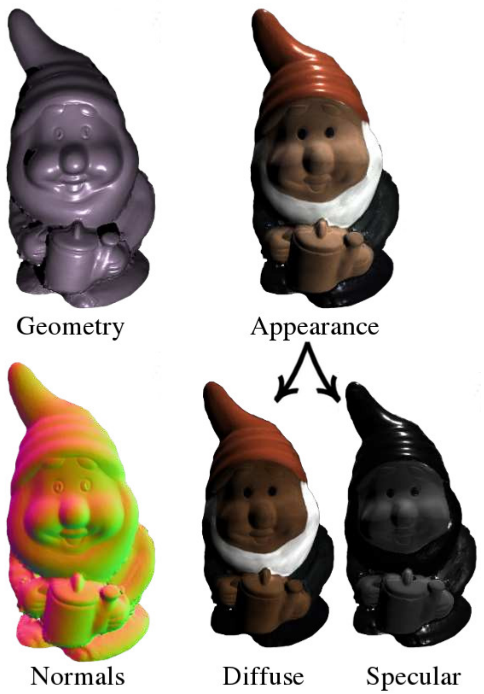

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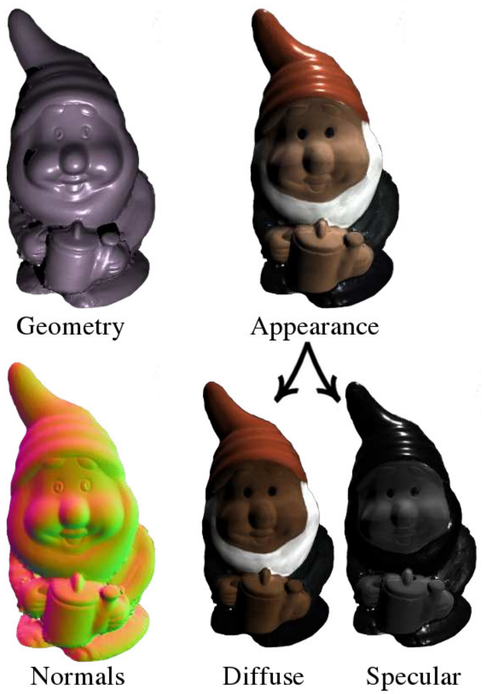

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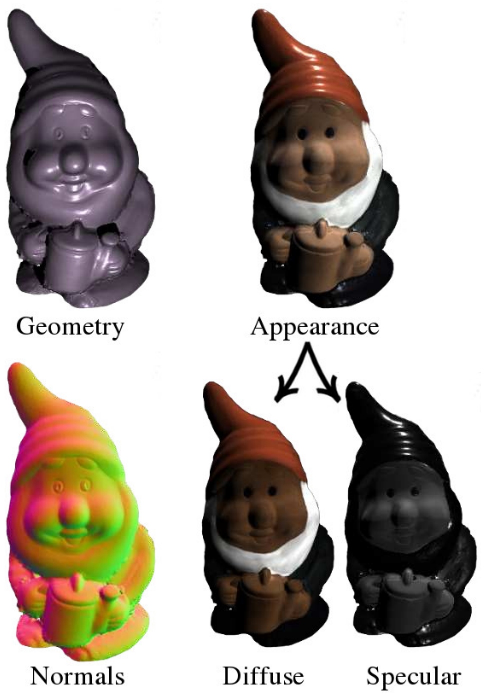

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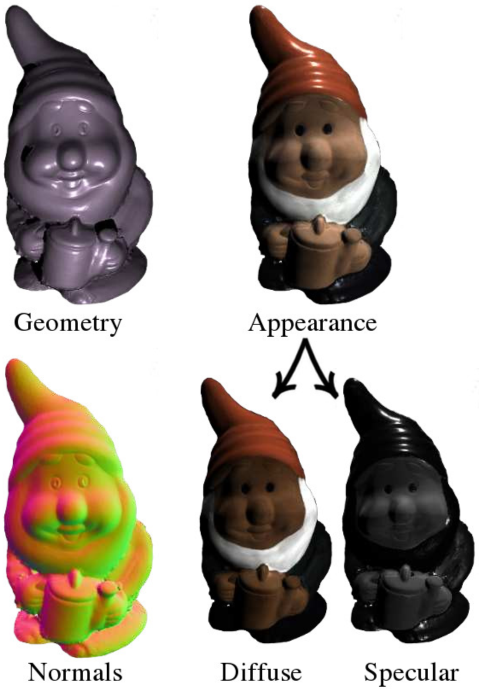

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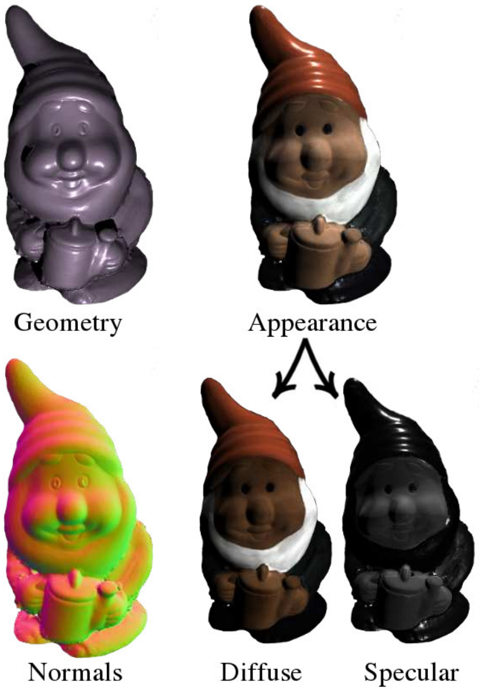

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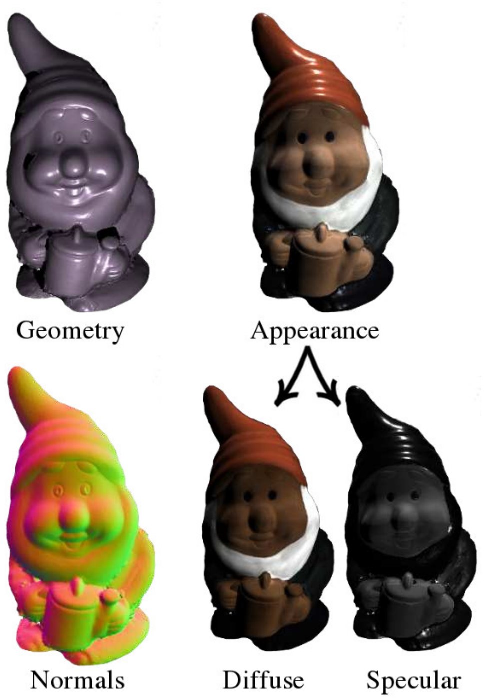

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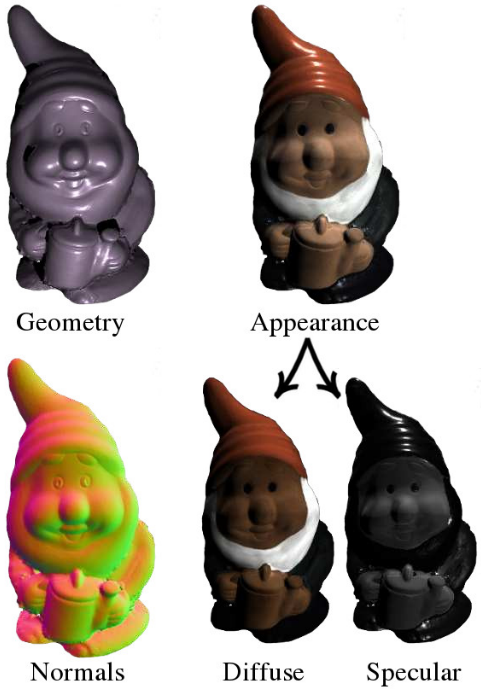
Additional Assumptions

- RGBD camera
- Exactly one point light source in each input image



Model

$$\mathcal{X} = \{\{(z_p, n_p, f_p)\}_{p=1}^{P}, \{\pi_i\}_{i=2}^{N}\}$$

- N undistorted images from a pinhole camera with vignetting removed; the first is called *reference view*
- π_i: projective mapping from view i back to the reference view
- z_p: depth for every pixel
- n_p: normals for every pixel
- f_p: material for every pixel

Representation of Geometry and Depth

Surface points are defined as depth $Z_1 = \{z_p\}$ of pixels p

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- Integrate into depth

svBRDF

Models the fraction of light reflected from direction ω^{in} into direction ω^{out} at a pixel p:

$$f_p(n_p, \omega^{\text{in}}, \omega^{\text{out}}) = d_p + s_p \frac{D(r_p) G(n_p, \omega^{\text{in}}, \omega^{\text{out}}, r_p)}{\pi (n_p \cdot \omega^{\text{in}})(n_p \cdot \omega^{\text{out}})}$$

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- 3 parameters:
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$\rightarrow$ These are optimised as part of the method

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- (s_p, r_p) can vary only between a few specular base materials, with weights $\alpha_p^t \in [0, 1]$:

$$\begin{pmatrix} s_p \\ r_p \end{pmatrix} = \sum_{t=1}^{T} \alpha_p^t \begin{pmatrix} s_t \\ r_t \end{pmatrix}$$

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- only these are optimised

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- Geometric Consistency
- Depth Compatibility
- Normal Smoothness
- Material Smoothness

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$$\psi_P(\mathcal{X}) = \frac{1}{N} \sum_i \sum_p \left\| \varphi_p^i \left[\mathcal{I}_i\left(\pi_i(x_p)\right) - f_p\left(n_p, \omega_i^{\text{in}}(x_p), w_i^{\text{out}}(x_p)\right) \cdot \frac{a_i(x_p) n_p^T \omega_i^{\text{in}}(x_p)}{d_i(x_p)^2} L \right] \right\|_1$$

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- $\frac{a_i(x_p) n_p^T \omega_i^{\text{in}}(x_p)}{d_i(x_p)^2} L$ gives the intesity of that point light

Constraints: Geometric Consistency

$$\psi_{\mathcal{G}}(\mathcal{X}) = -\sum_{p} \vec{n}_p^T \left(\frac{\frac{\partial z_p}{\partial x} \times \frac{\partial z_p}{\partial y}}{\|\frac{\partial z_p}{\partial x} \times \frac{\partial z_p}{\partial y}\|_2} \right) \qquad \frac{\partial z_p}{\partial x} \propto \left[1, 0, \vec{\nabla} \mathcal{Z}_1(\pi_1(\vec{x}_p))^T [f/z_p, 0]^T\right]^T$$

- Geometry and Normals must be consistent

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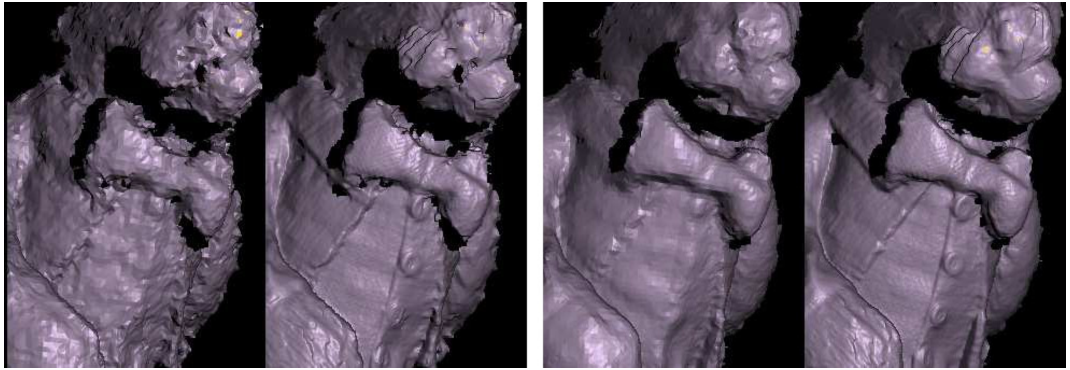
- Align n_p and the cross product of surface tangents by minimising the scalar product
- “Soft coupling” between normals and depth
- Could also enforce equality, but makes the method less robust

Constraints: Depth Compatibility

$$\psi_{\mathcal{D}}(\mathcal{X}) = \sum_{p} \| z_p - \mathcal{Z}_1(u_p, v_p) \|_2^2$$



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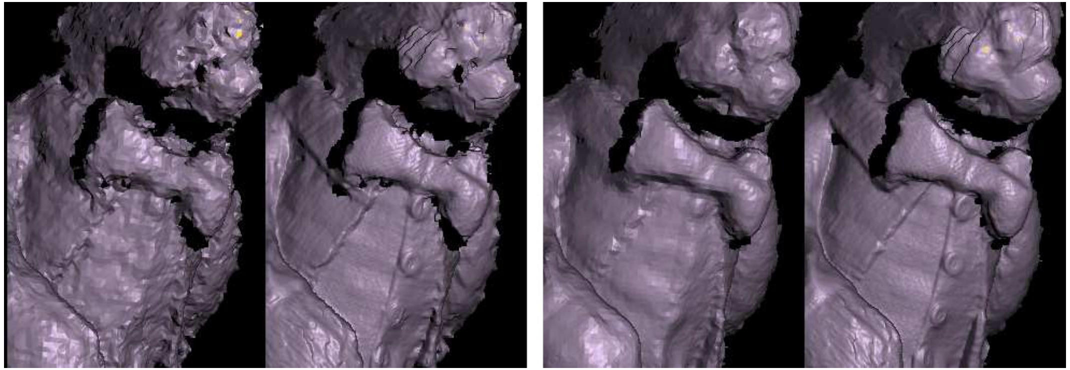
- Regularise against depth measurements in the reference view



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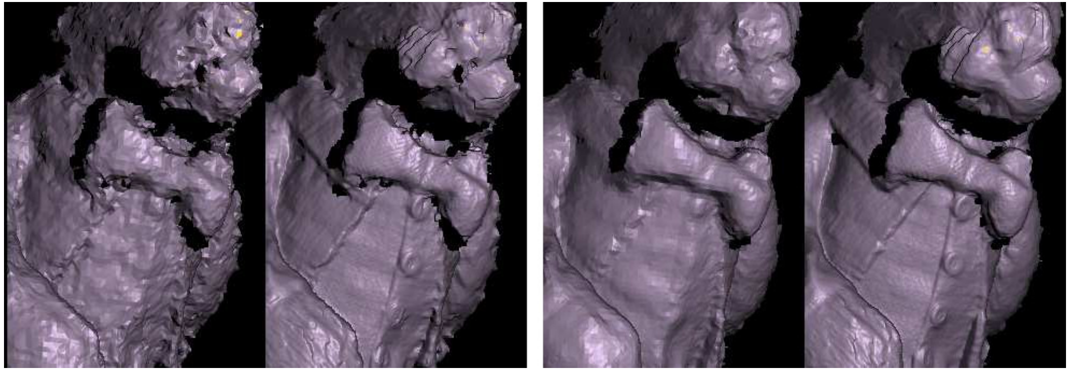
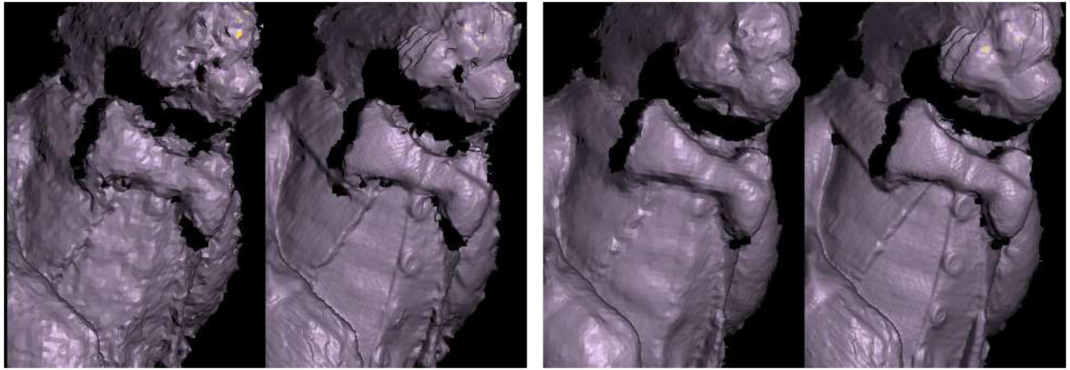
- Regularise against depth measurements in the reference view
- Before optimisation, several measured depth maps can be integrated into the reference view



Constraints: Depth Compatibility

$$\psi_{\mathcal{D}}(\mathcal{X}) = \sum_{p} \| z_p - \mathcal{Z}_1(u_p, v_p) \|_2^2$$

- Regularise against depth measurements in the reference view
- Before optimisation, several measured depth maps can be integrated into the reference view
- Final result will improve on the bare measurements through shading cues



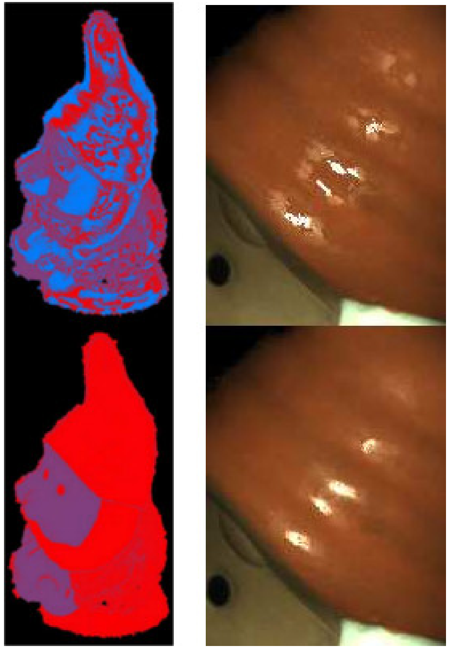
Constraints: Normal Smoothness

$$\psi_{\mathcal{N}}(\mathcal{X}) = \sum_{p \sim q} \|n_p - n_q\|_2^2$$

- Standard smoothness term to encourage smooth surfaces
- Minimise the difference of normals of adjacent pixels $p \sim q$

Constraints: Material Smoothness

$$\psi_{\mathcal{M}}(\mathcal{X}) = \sum_p \left\| \alpha_p - \frac{\sum_q \alpha_q w_q k_{q,p}}{\sum_q q_q k_{p,q}} \right\|_1 - \sum_p \left\| \alpha_p - \frac{1}{P} \sum_q \alpha_q \right\|_1$$



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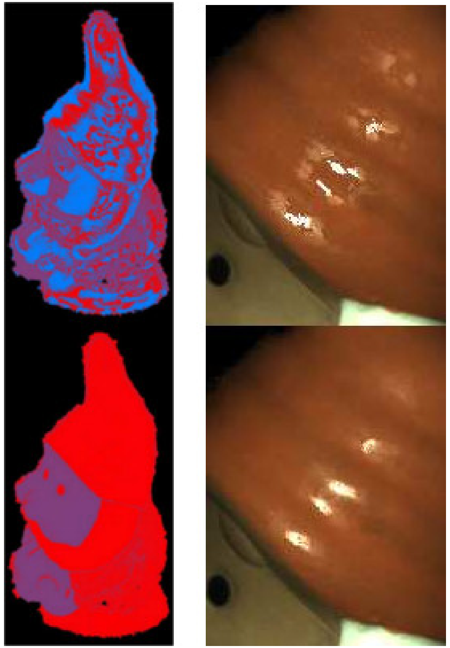
- Only a few pixel will actually contain specular information to reconstruct



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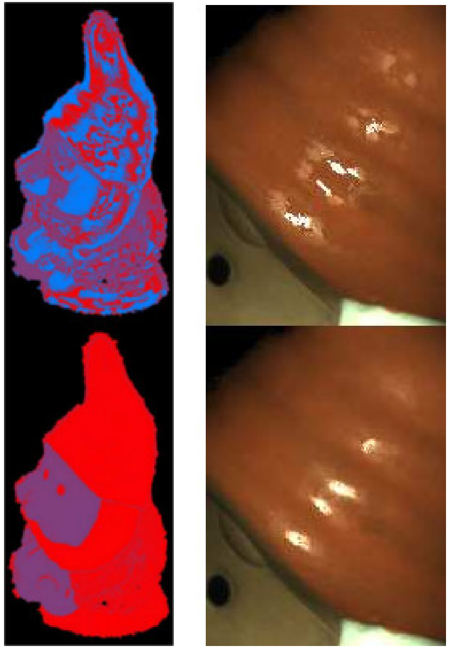

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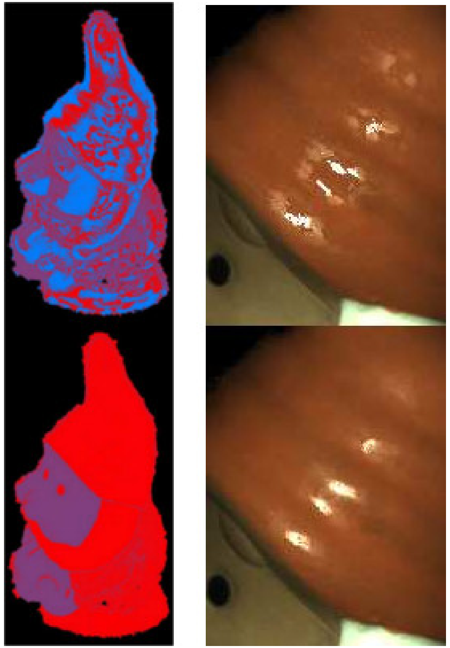
- Therefore regularise across regions with similar appearance



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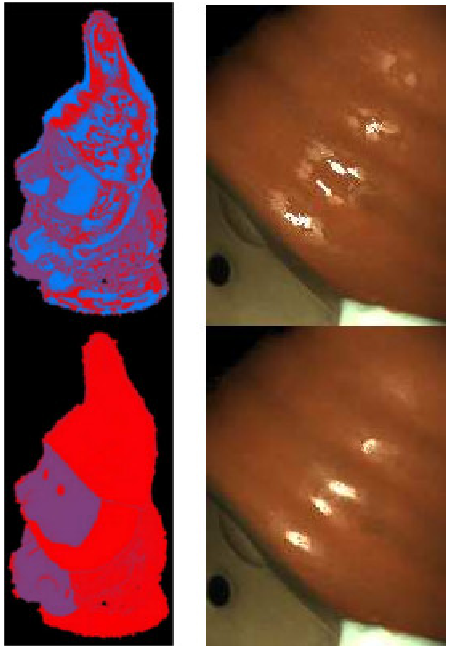

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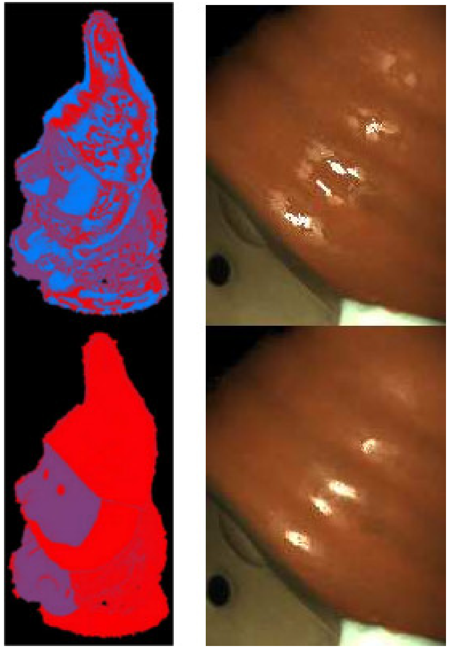

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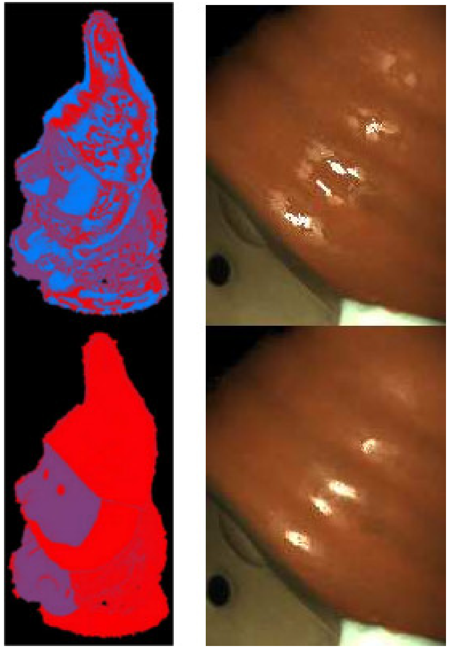
- Also encourage material sparsity: maximise distance from the average weights (second term)



Optimisation: Putting it all together

$$\mathcal{X}^\star = \operatorname*{argmin}_{\mathcal{X}} \psi_\mathcal{P} + \psi_\mathcal{D} + \psi_\mathcal{N} + \psi_\mathcal{M}$$

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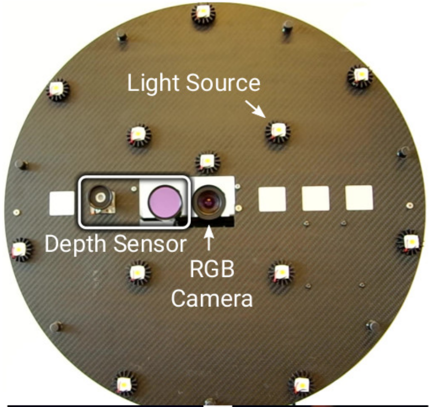
```
Traceback (most recent call last):
  File "main.py", line 358, in <module>
    run_experiment(settings_dict)
  File "main.py", line 218, in run_experiment
    for observation in tqdm(data_adapter.images, desc="Preloading training images")
  File "main.py", line 218, in <listcomp>
    for observation in tqdm(data_adapter.images, desc="Preloading training images")
  File "/home/matthias/Dokumente/TUM/Seminar Computer Vision/handheld_svbrdf_geometry/code/data.py", line 153, i
n get_image
    image = torch.tensor(np.transpose(image_data, (2,0,1)), dtype=torch.float32, device=self.device)
RuntimeError: CUDA out of memory. Tried to allocate 142.00 MiB (GPU 0; 1.95 GiB total capacity; 826.80 MiB alrea
dy allocated; 120.25 MiB free; 29.20 MiB cached)
Preloading training images:  93%|██████████████████████████████████████████    | 42/45 [00:09<00:00,  4.59it/s]
```

Initialisation

$$\mathcal{X} = \{\{(z_p, n_p, f_p)\}_{p=1}^{P}, \{\pi_i\}_{i=2}^{N}\}$$



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- 45 images per object, in a 30° cone around the reference view
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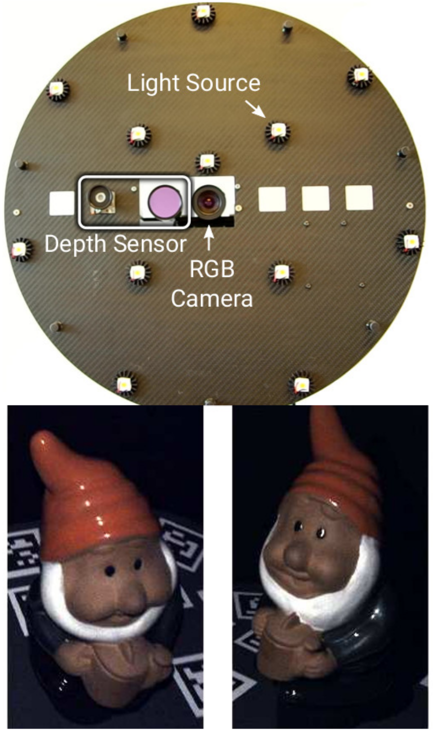
  - Calibrated cameras, distortion and vignetting are removed



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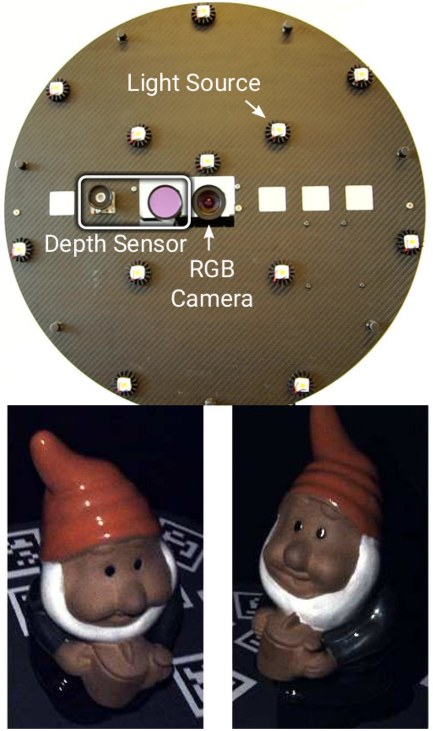

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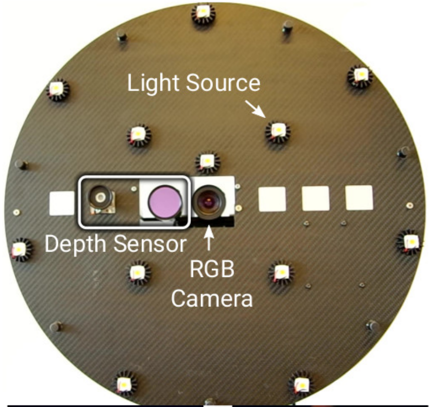

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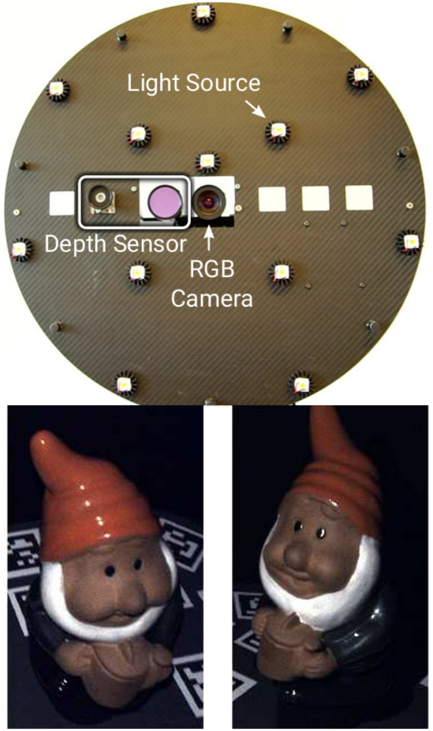

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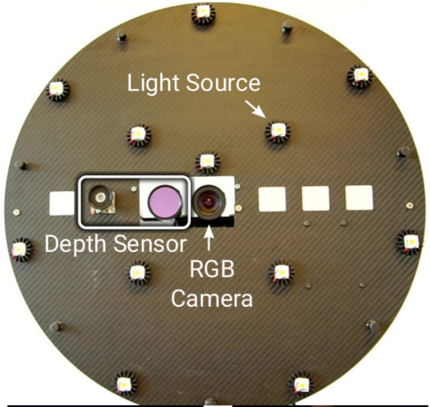

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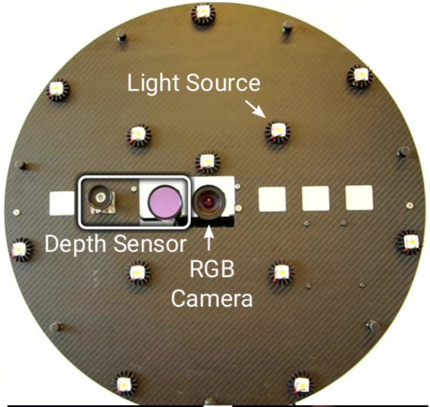

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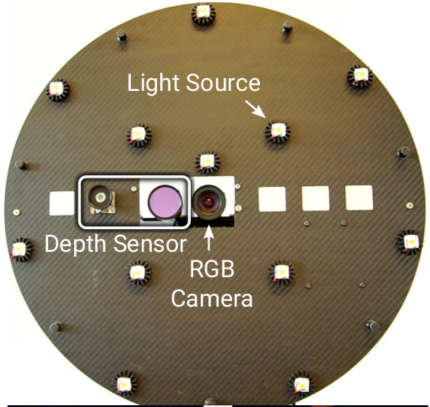
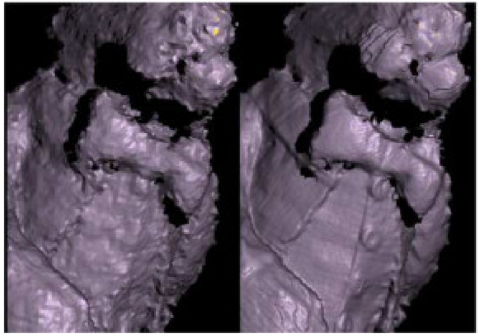


Results



Results

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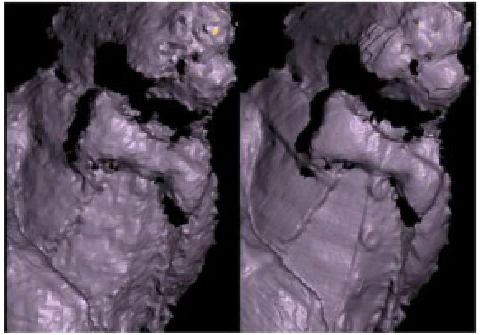

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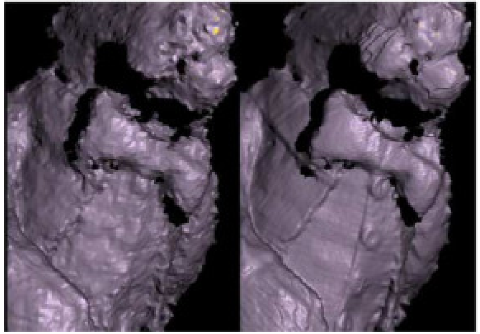

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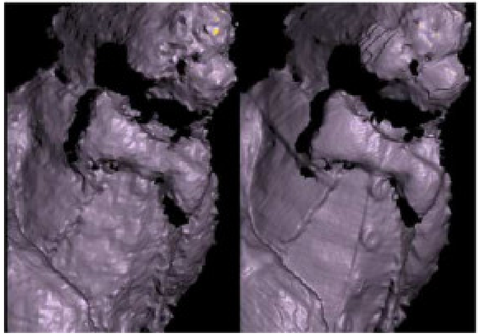

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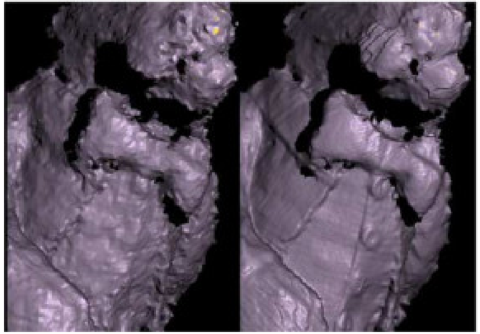

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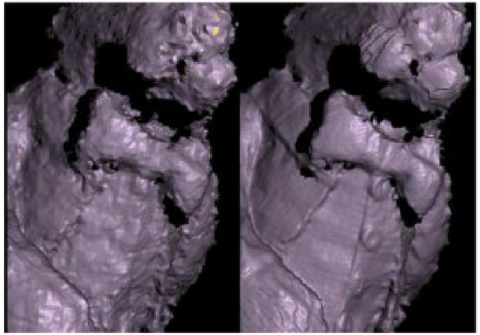

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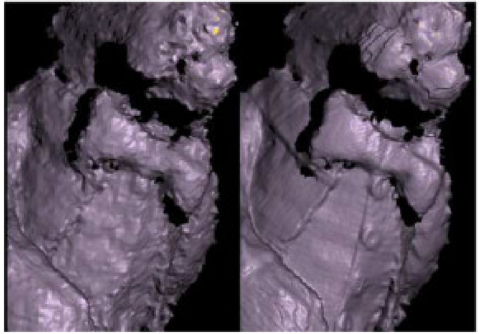

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Questions!