Optimizing Photoconsistency in image-based 3D and appearance modeling

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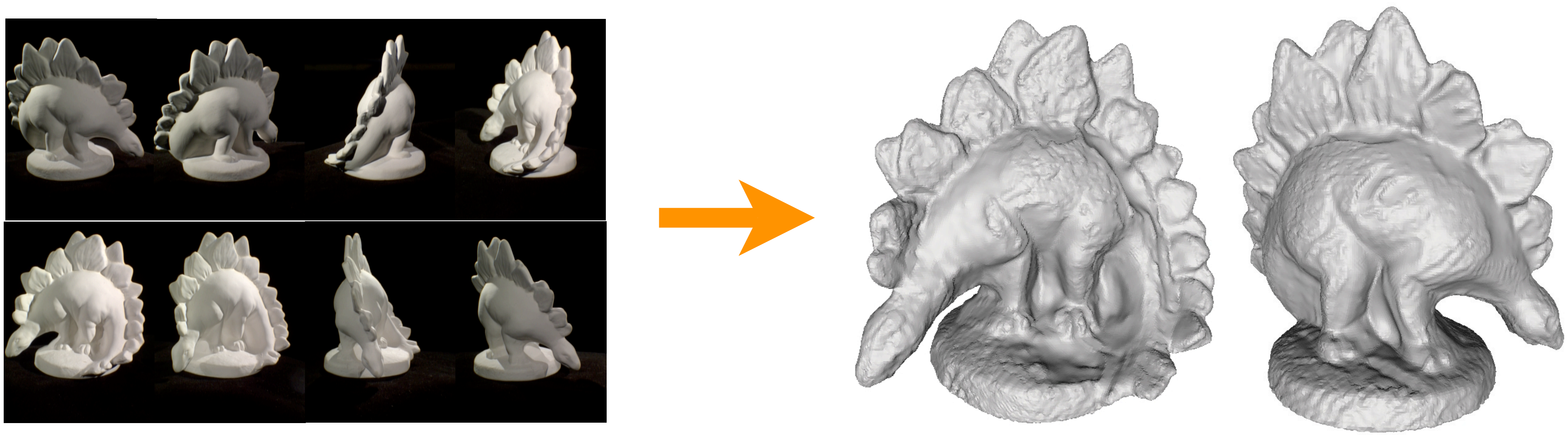
with Pau Gargallo, KukJin Yoon, Amaël Delaunoy, Emmanuel Prados, Visesh Chari, J.-P. Pons

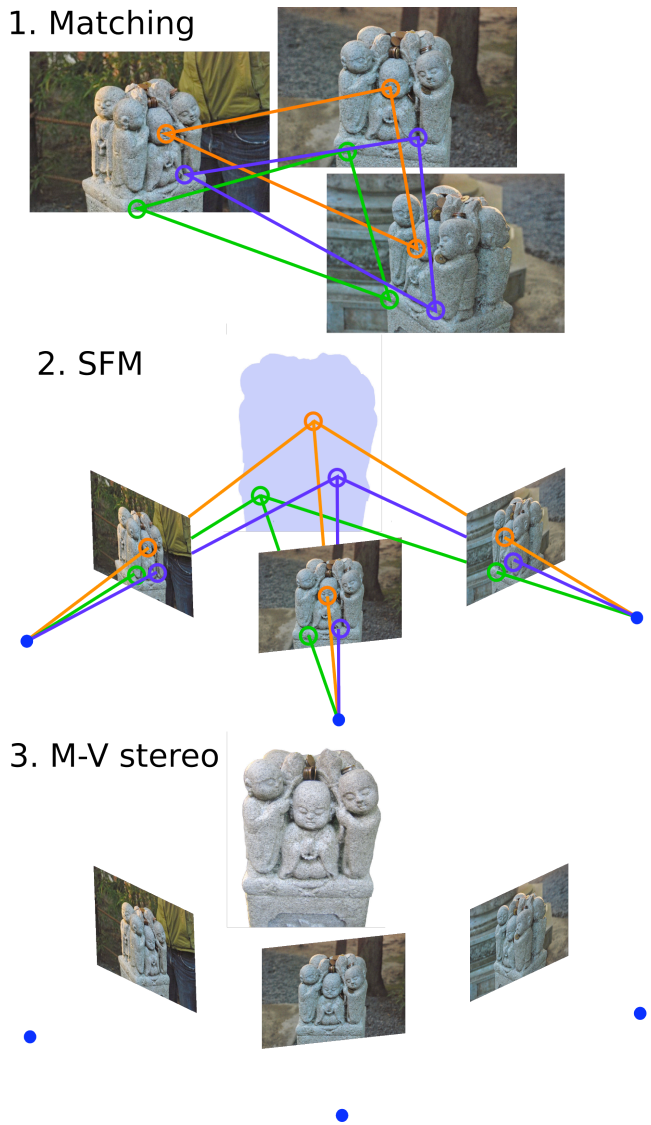
3D Reconstruction from Images



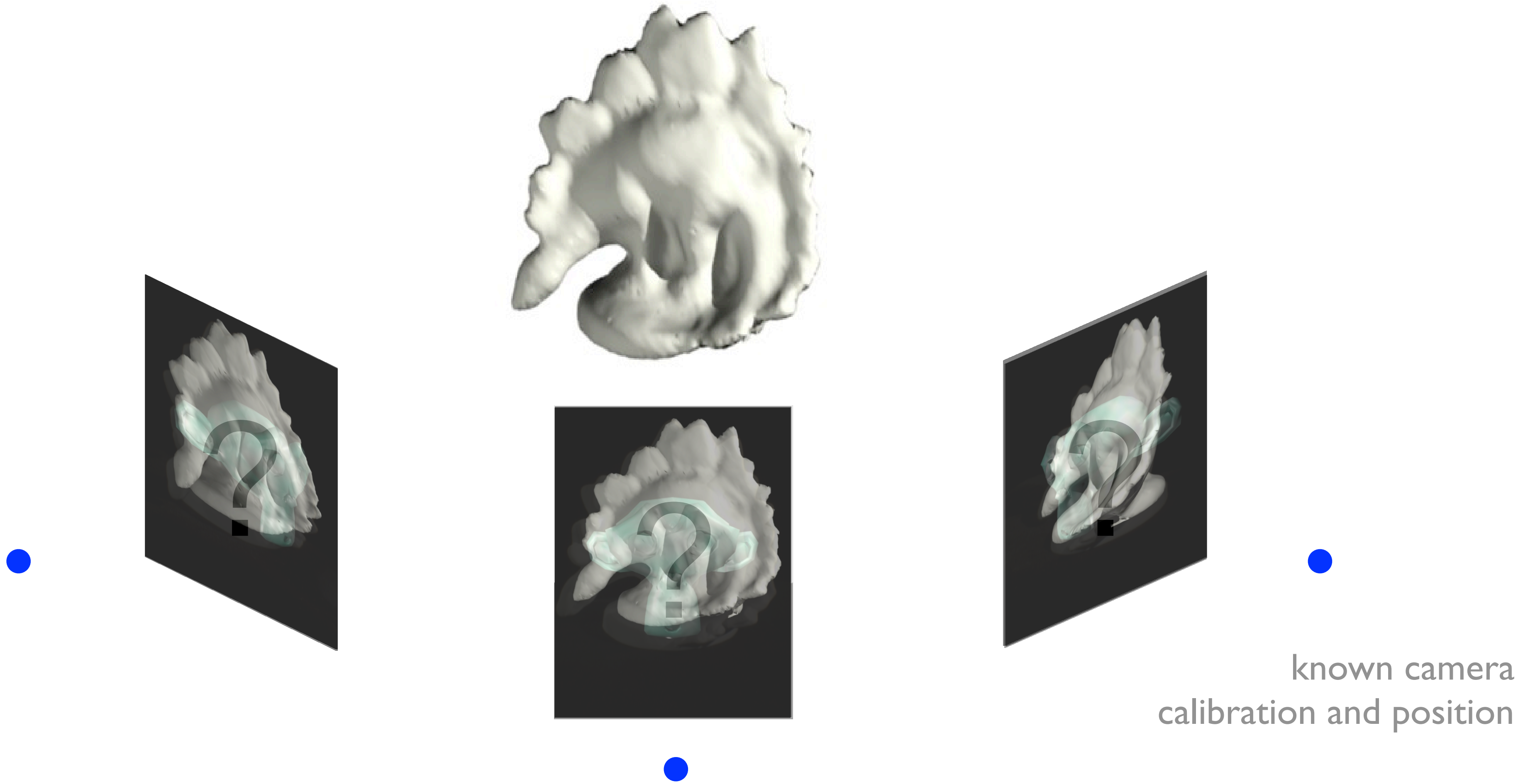
- Building 3D models from images
- Applications:
    - Cinema post-production, special FX and games
    - Archeology and cultural heritage preservation
    - Telecommunication
    - Robotics...

3D Reconstruction Pipeline

- **Matching**
  Finding point correspondences
- **Structure from Motion**
  Locating the cameras and the point locations
- **Multi-View Stereo**
  Dense Reconstruction



Multi-View Stereo



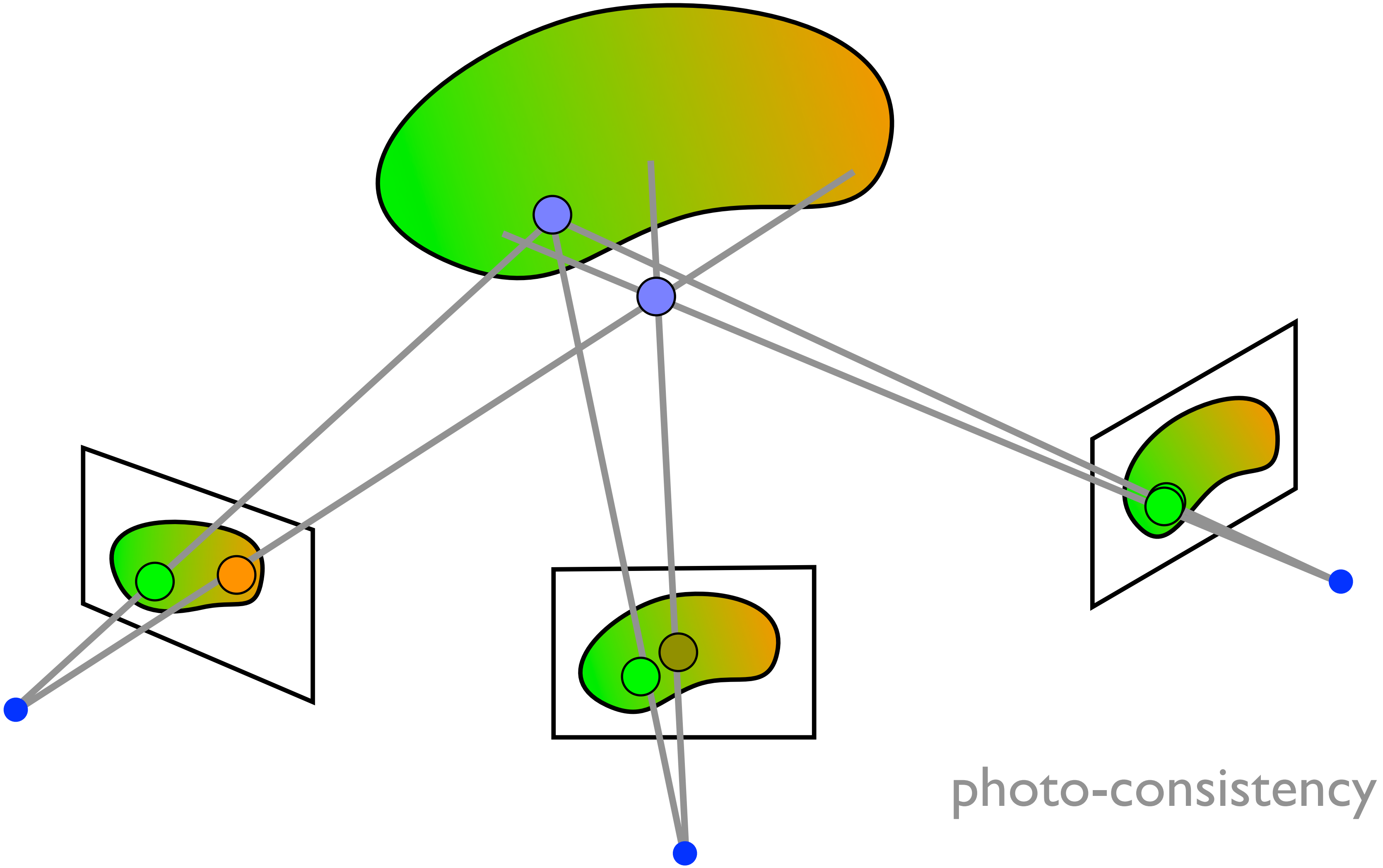
Stereo is the inverse problem of rendering

Quality measure: reprojection error (photoconsistency)

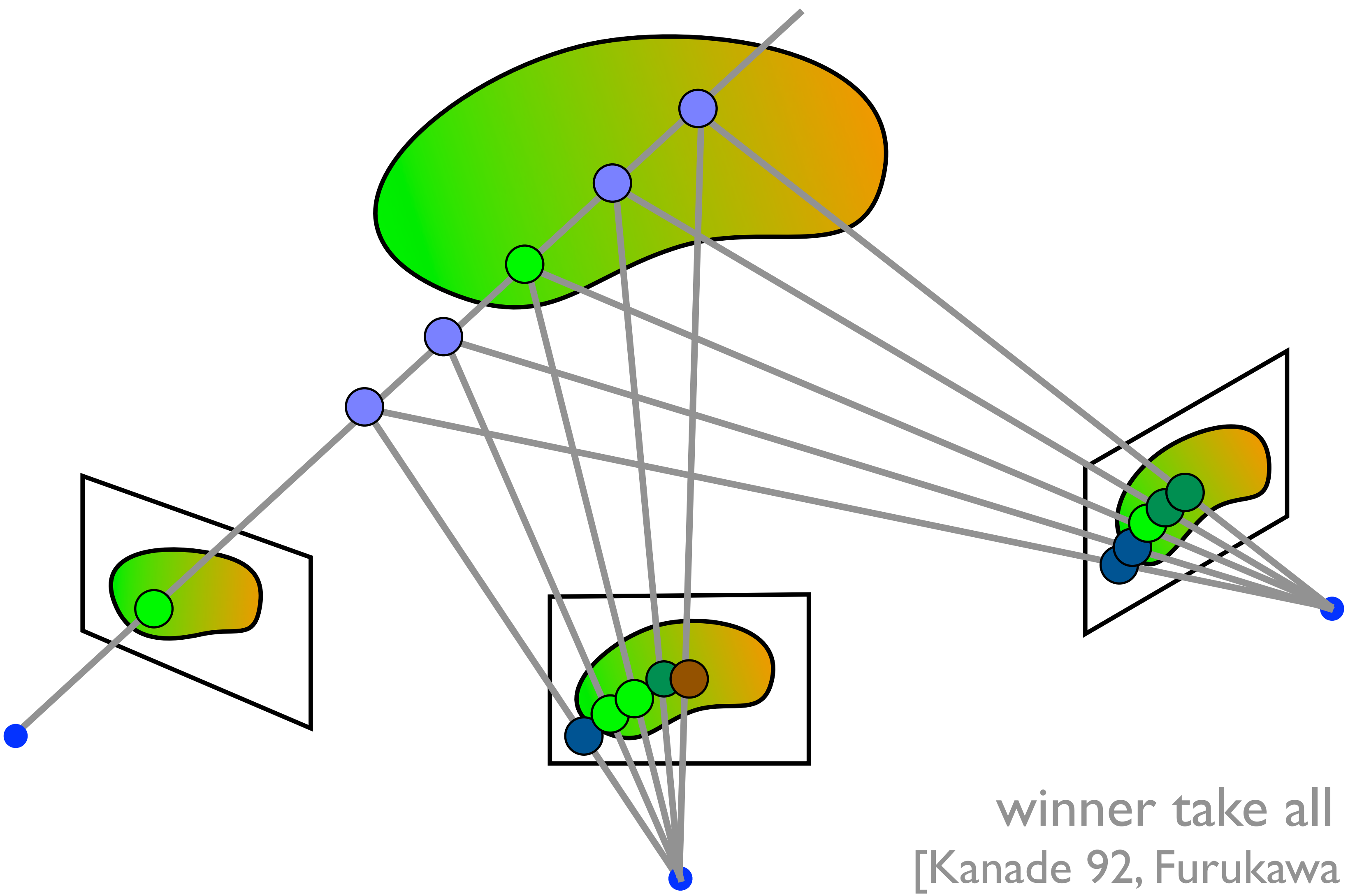
Existing Approaches

- Bottom-up: Direct Methods
- Top-down: Energy Minimization
- Hybrids

Approaches: Bottom-up

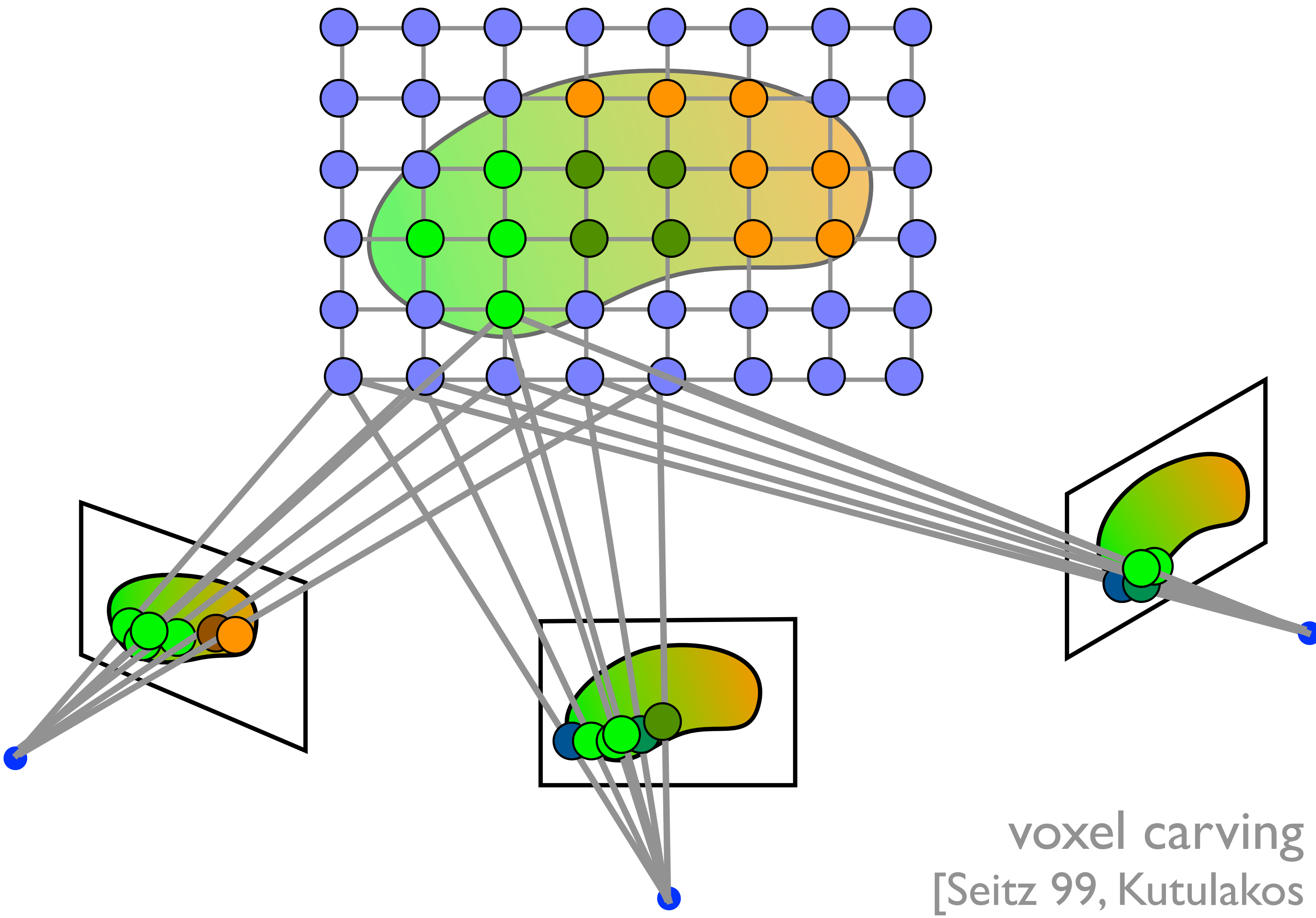


Approaches: Bottom-up



winner take all
[Kanade 92, Furukawa 07]

Approaches: Bottom-up



voxel carving
[Seitz 99, Kutulakos 00]

Approaches: Bottom-up

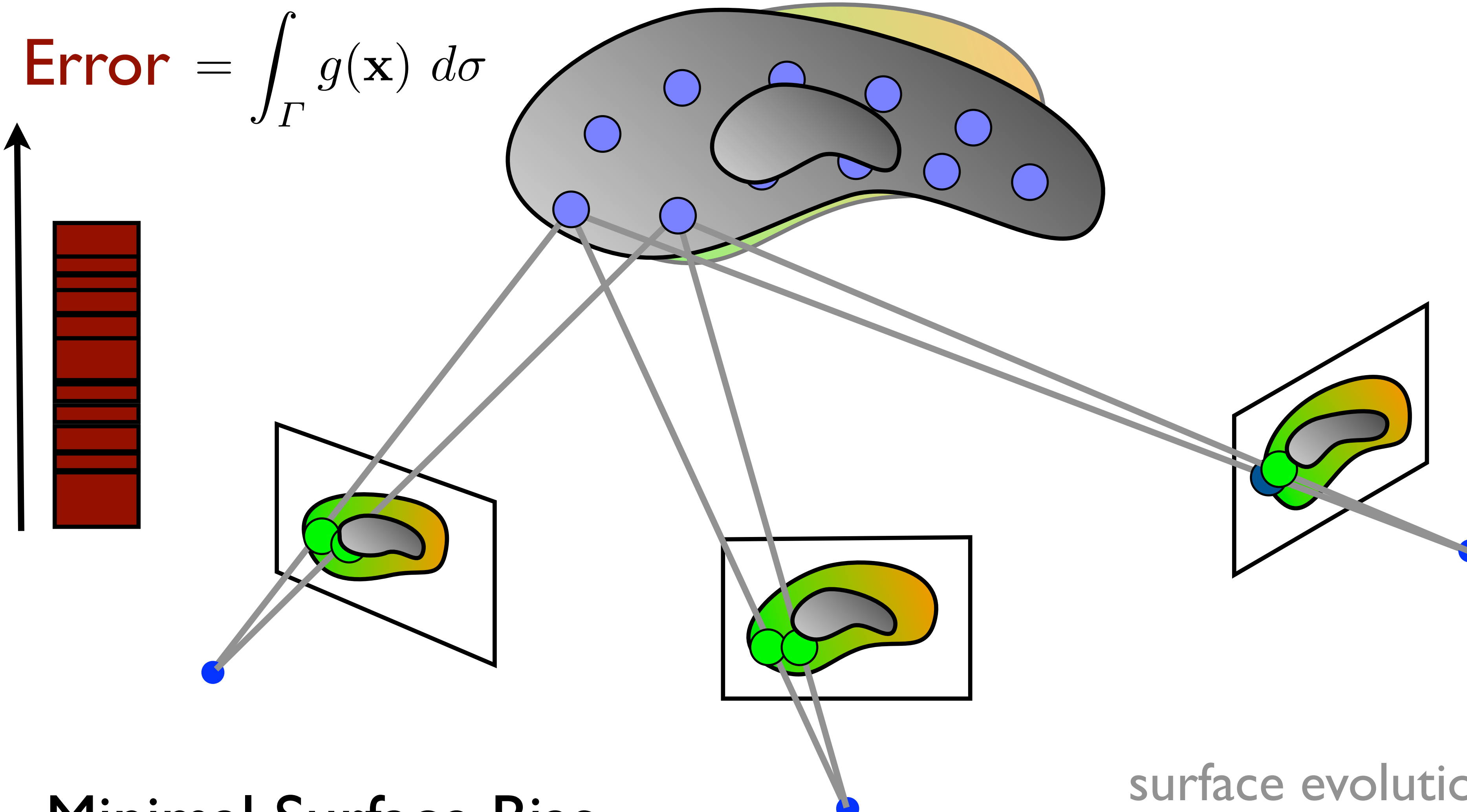
- Problems:
  - False detections: photo-consistent but not on surface
    - Needs regularization
  - Missing detections: on surface but not photo-consistent due to occlusions
    - Need to take care of occlusions

Existing Approaches

- Bottom-up: Direct Methods
- Top-down: Energy Minimization
- Hybrids

Top-Down: Energy Minimization

Error $= \int_{\Gamma} g(\mathbf{x}) \; d\sigma$



Minimal Surface Bias

Silhouette constraints

[Keriven 02, Hernández 04, Sinha 05, Furukawa 06]

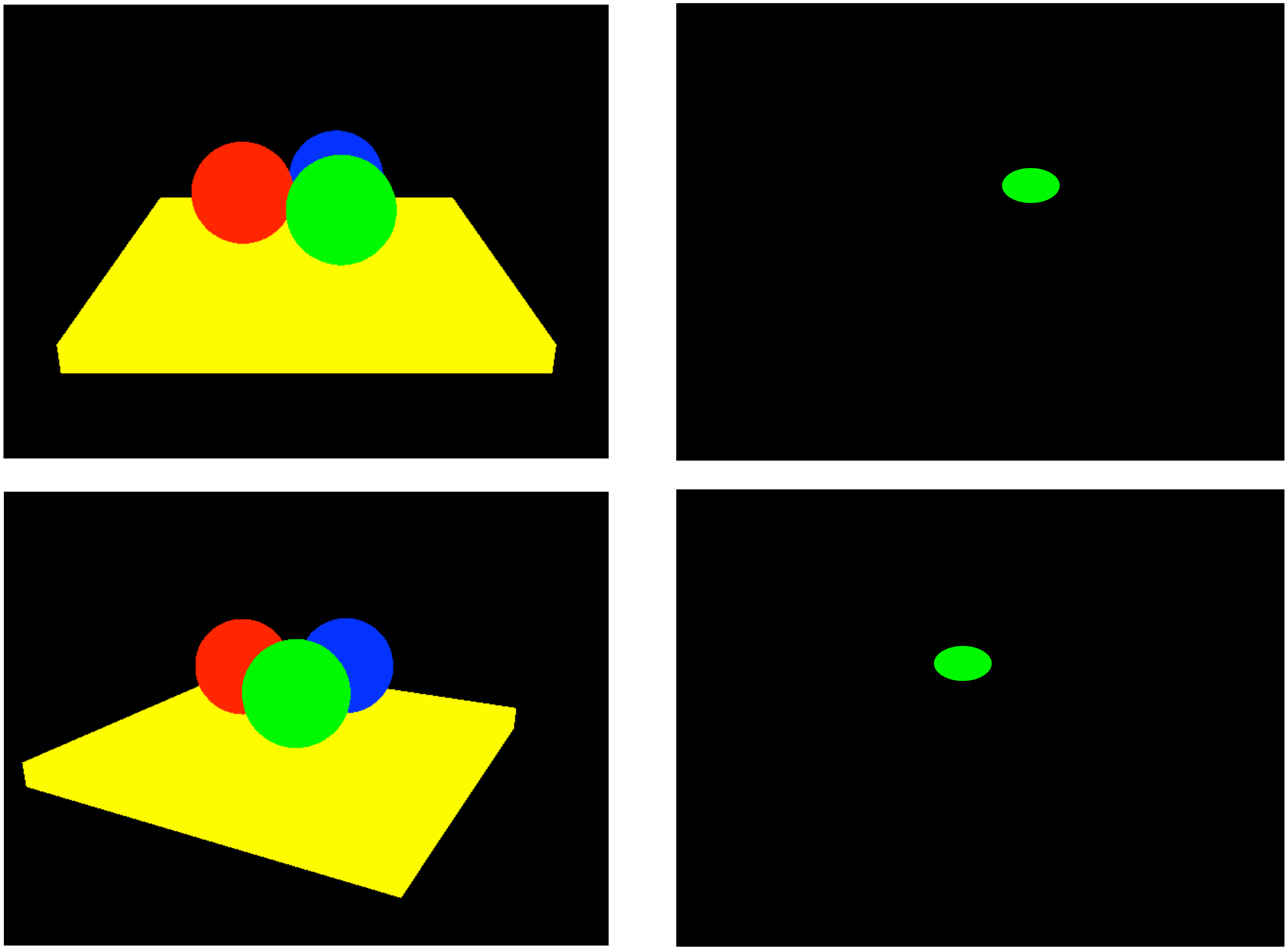
surface evolution

[Faugeras 98, Jin 03]

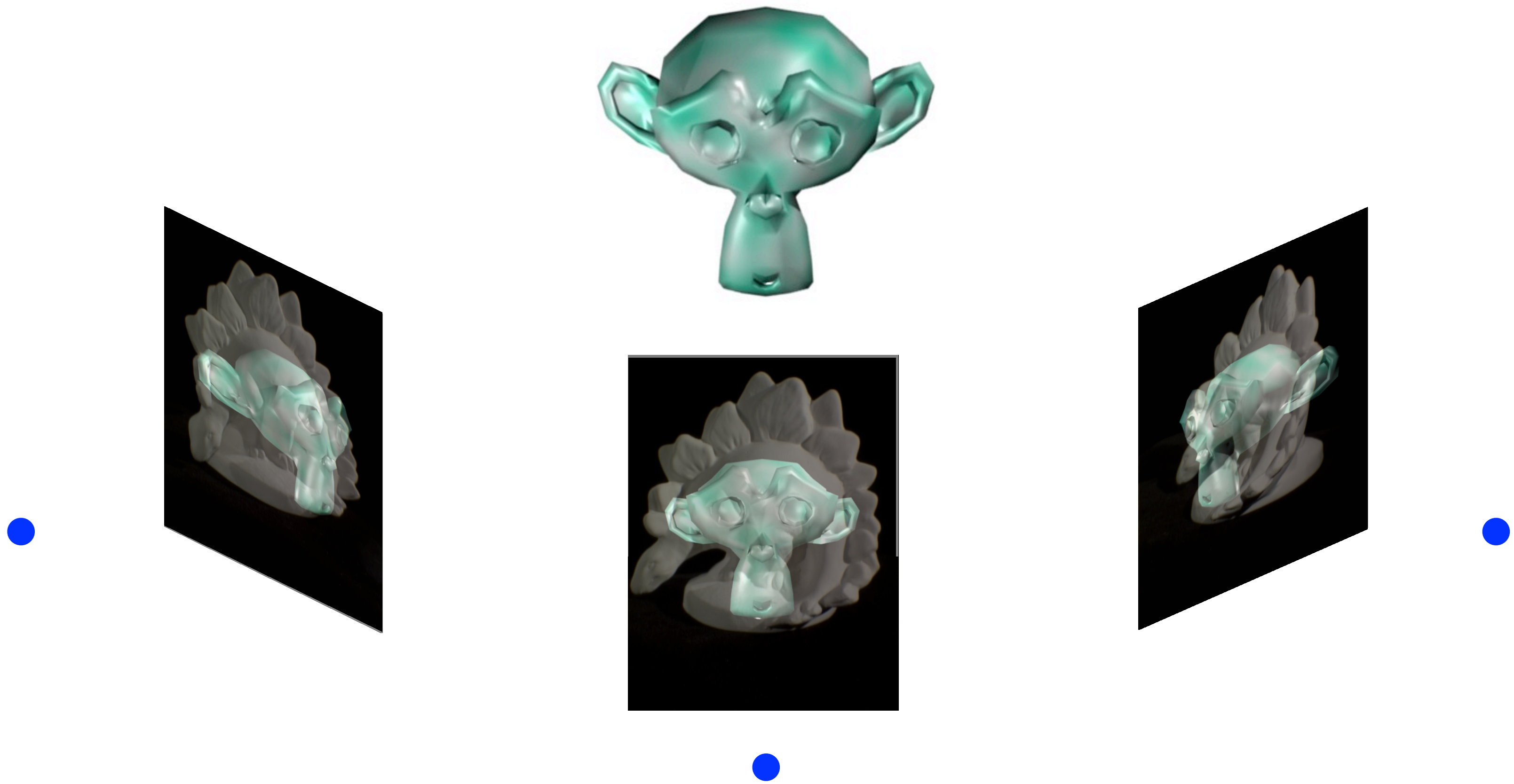
graph cuts

[Paris 04, Vogiatzis 05]

Top-Down: The Reprojection Error



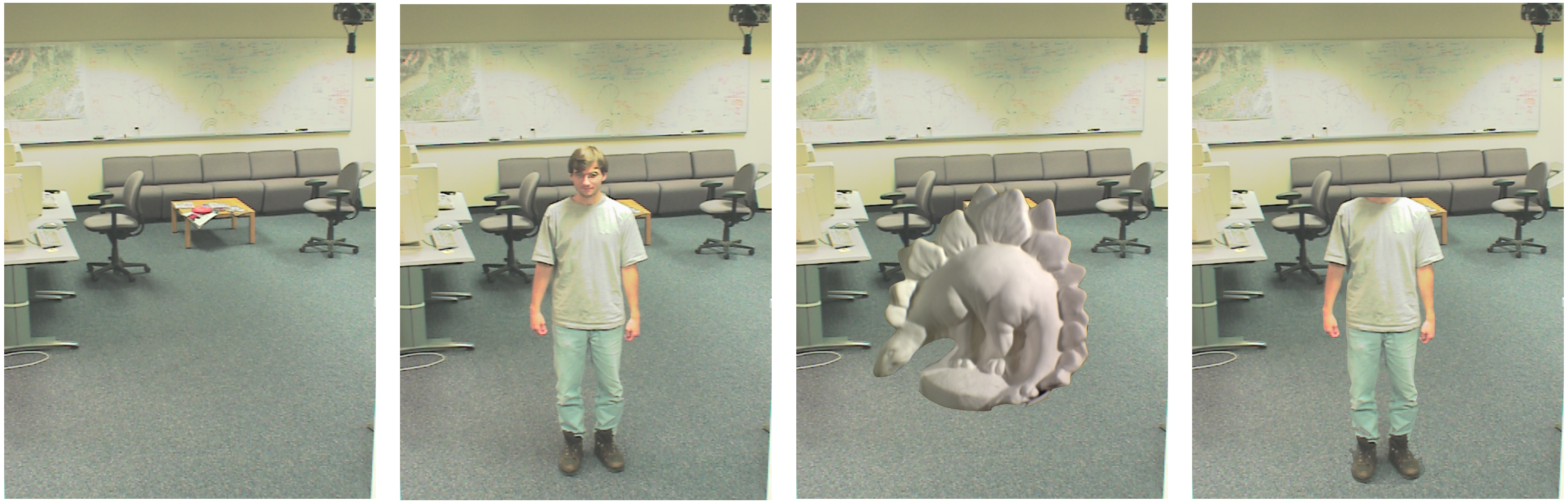
The Reprojection Error – Remarks

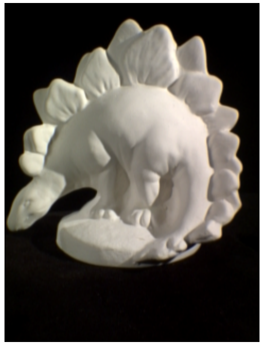


- Need to model shape and color (constant brightness assumption)
- Compare all the pixels of the input images
- Need to model the background
- Predicting the images involves dealing with occlusions

The Reprojection Error – Remarks

- Need to model the background
  - Use actual background images





  - Reconstruct background mosaic
  - Use knowledge that background is of given color
  - Assume that background has similar colors in all images
  - ...

The Bayesian Rationale

What is the most probable object given the images?

likelihood prior

posterior

$$p(w|I) = \frac{p(I|w)\ p(w)}{p(I)}$$

evidence

Energy formulation

$$E(w|I) = E(I|w) + E(w)$$

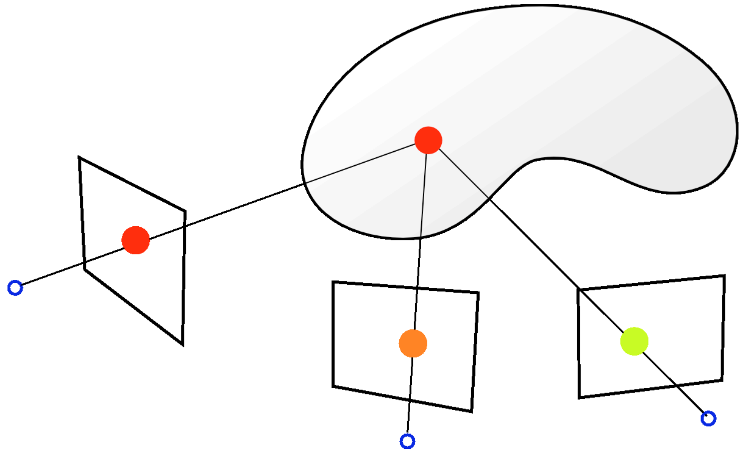
data term prior

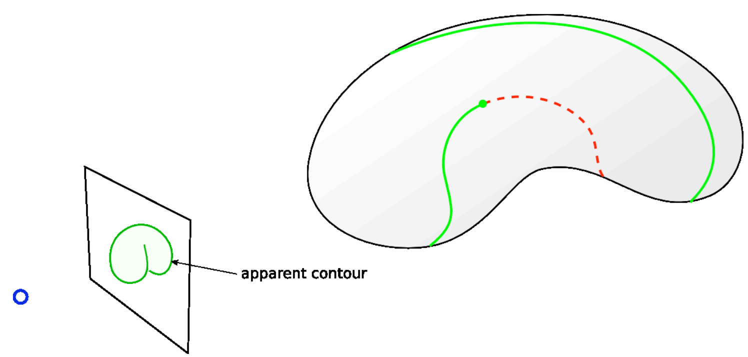
reprojection error

The Weighted Area Functional

$$A(\Gamma) = \int_{\Gamma} g(\mathbf{x})\ d\sigma$$

- Sum over the surface of a photo-consistency measure
- It can be optmized! (graph cuts, surface evolution and others)
- Problem: minimal surface bias. Bias towards small surfaces
- Palliatives: silhouettes and occluding contour constraints, ballooning forces





Reprojection Error vs. Weighted Area

- The weighted area is a sum over the surface

$$A(\Gamma) = \int_{\Gamma} g(\mathbf{x}) \; d\sigma$$

- The reprojection error is a sum over the image

$$E(\Gamma) = \int_{\mathcal{I}} g\big(\pi_{\Gamma}^{-1}(\mathbf{u})\big) \; d\mathbf{u}$$

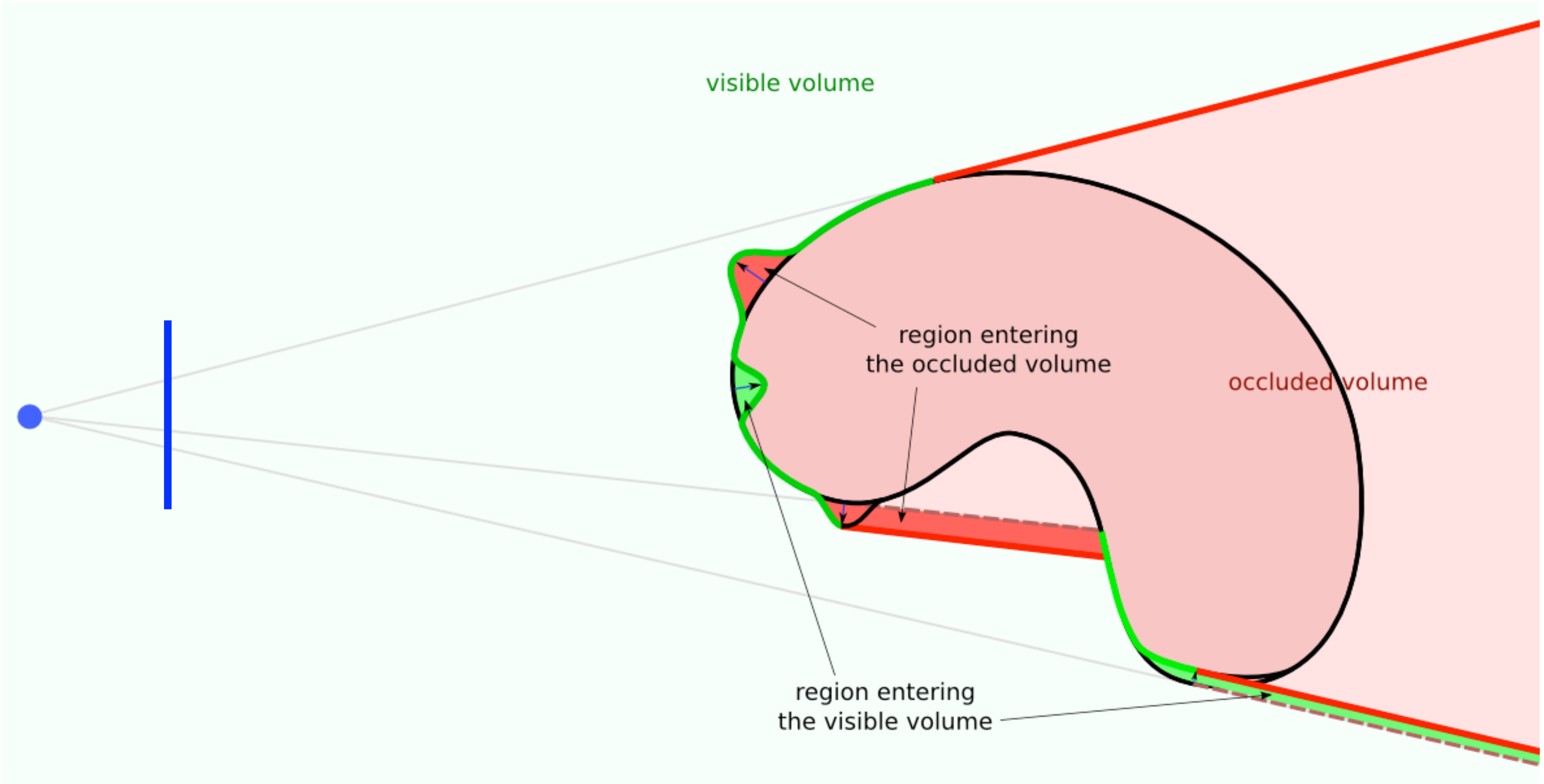
Another way to write the reprojection error

$$E(\Gamma) = -\int_{\Gamma \cup B} g(\mathbf{x}) \; \frac{\mathbf{x} \cdot \mathbf{n}}{\mathbf{x}_z^3} \; \nu_{\Gamma}(\mathbf{x}) \; d\sigma$$

Difference: the visibility term (depends on the surface globally)

Consequence: weighted area minimization methods not applicable

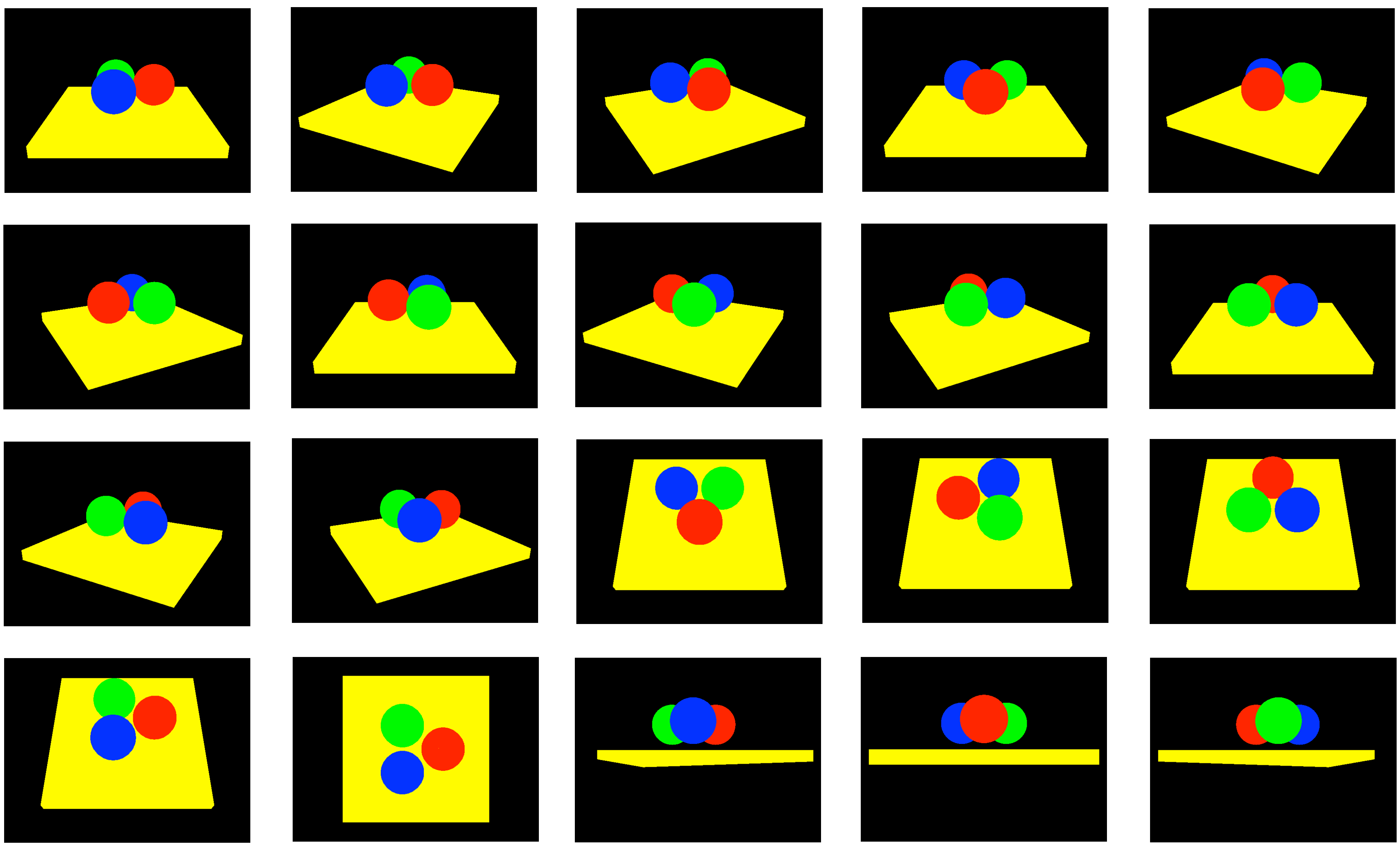
Derivative of a Quantity Integrated over the Visible Volume



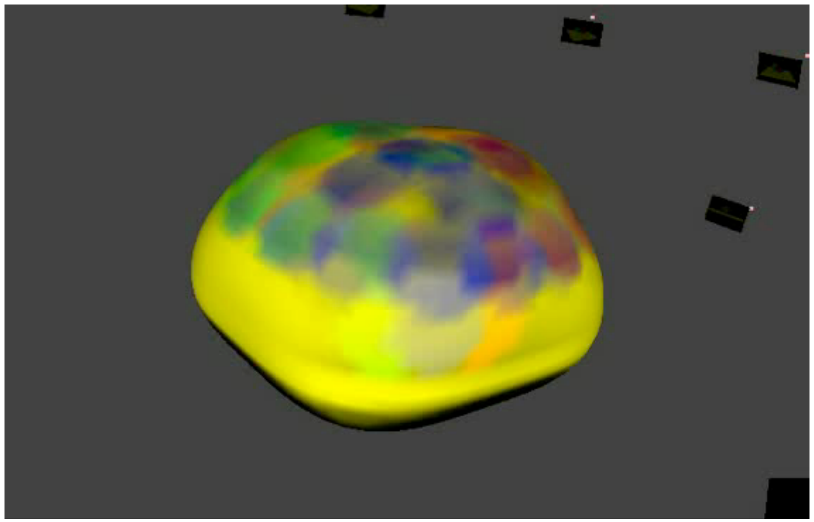
$$E(\Gamma) = -\int_{\Gamma \cup B} g(\mathbf{x}) \; \frac{\mathbf{x} \cdot \mathbf{n}}{\mathbf{x}_z^3} \; \nu_\Gamma(\mathbf{x}) \; d\sigma$$

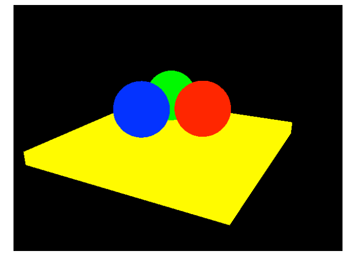
$$dE(\Gamma) = -\nabla g \cdot \frac{\mathbf{x}}{\mathbf{x}_z^3} \nu_\Gamma + (g - g') \frac{\mathbf{x}^t \nabla \mathbf{n} \mathbf{x}}{\mathbf{x}_z^3} \delta(\mathbf{x} \cdot \mathbf{n}) \nu_\Gamma$$

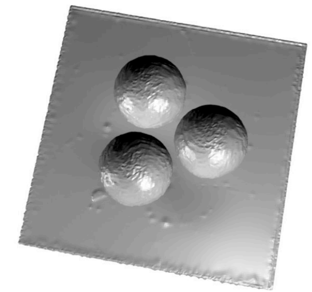
Synthetic Images

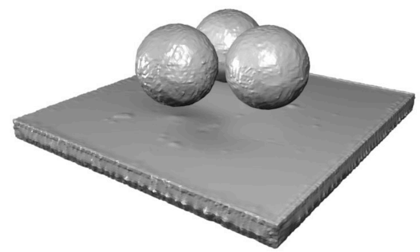


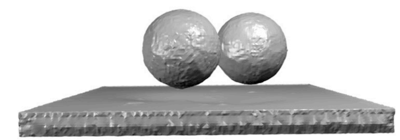
Synthetic Images

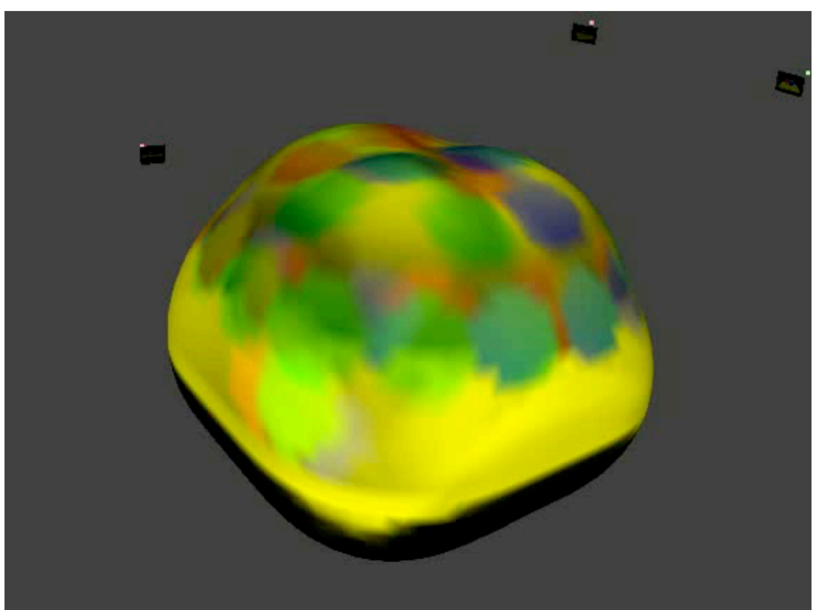


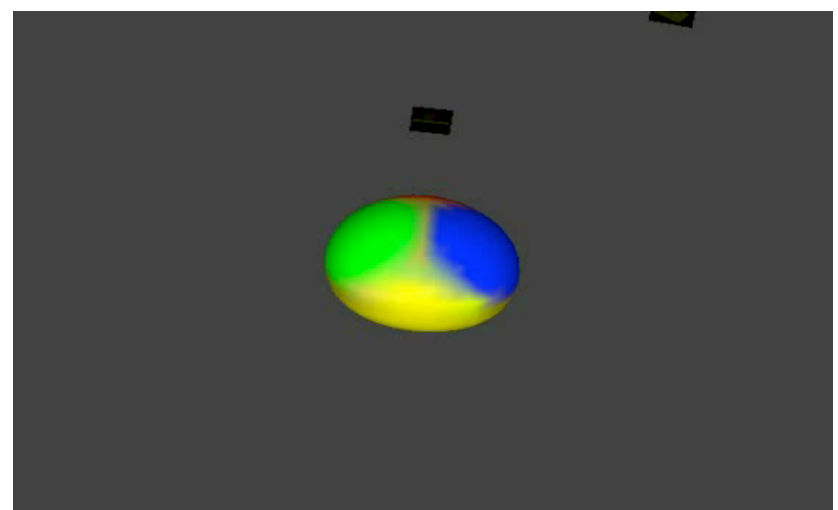




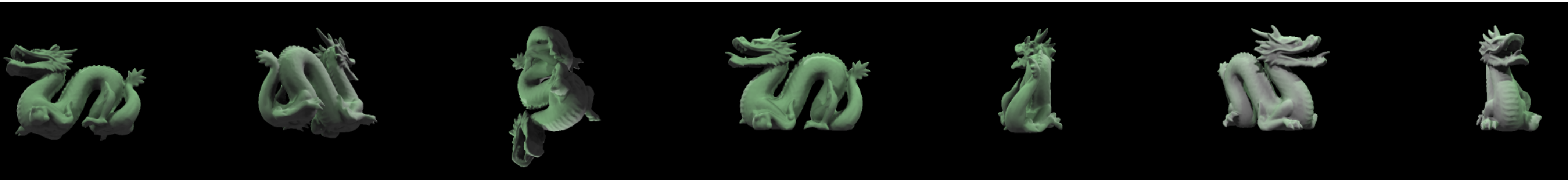


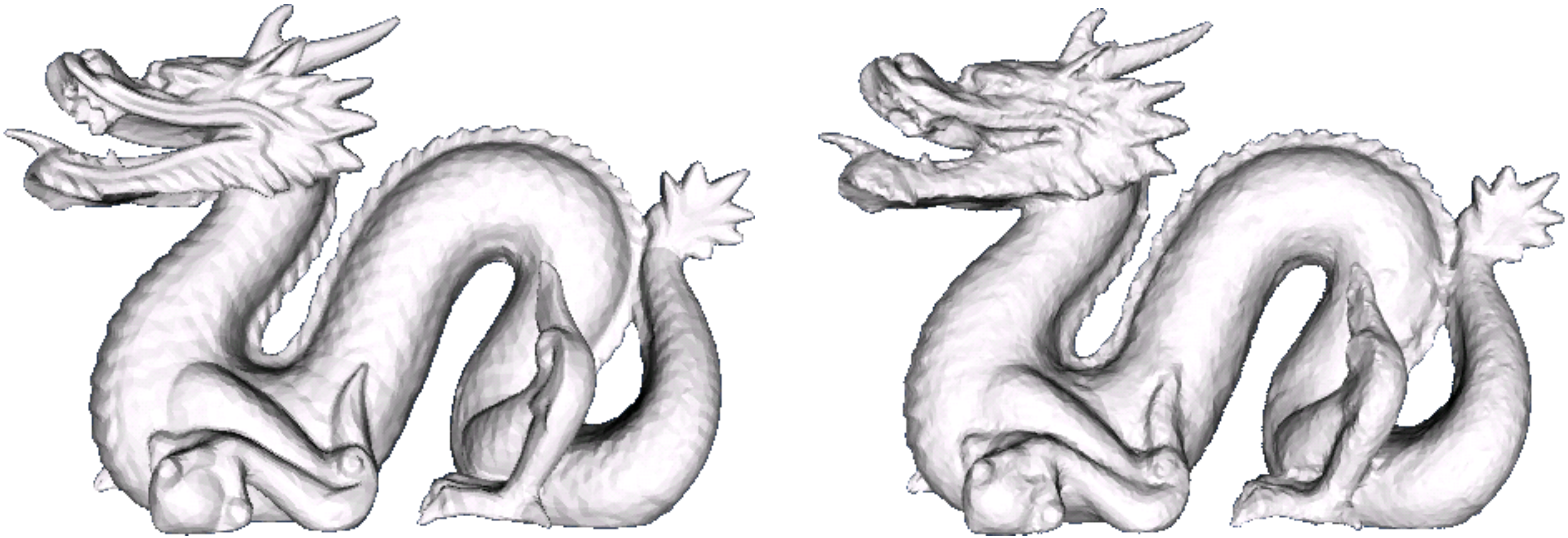






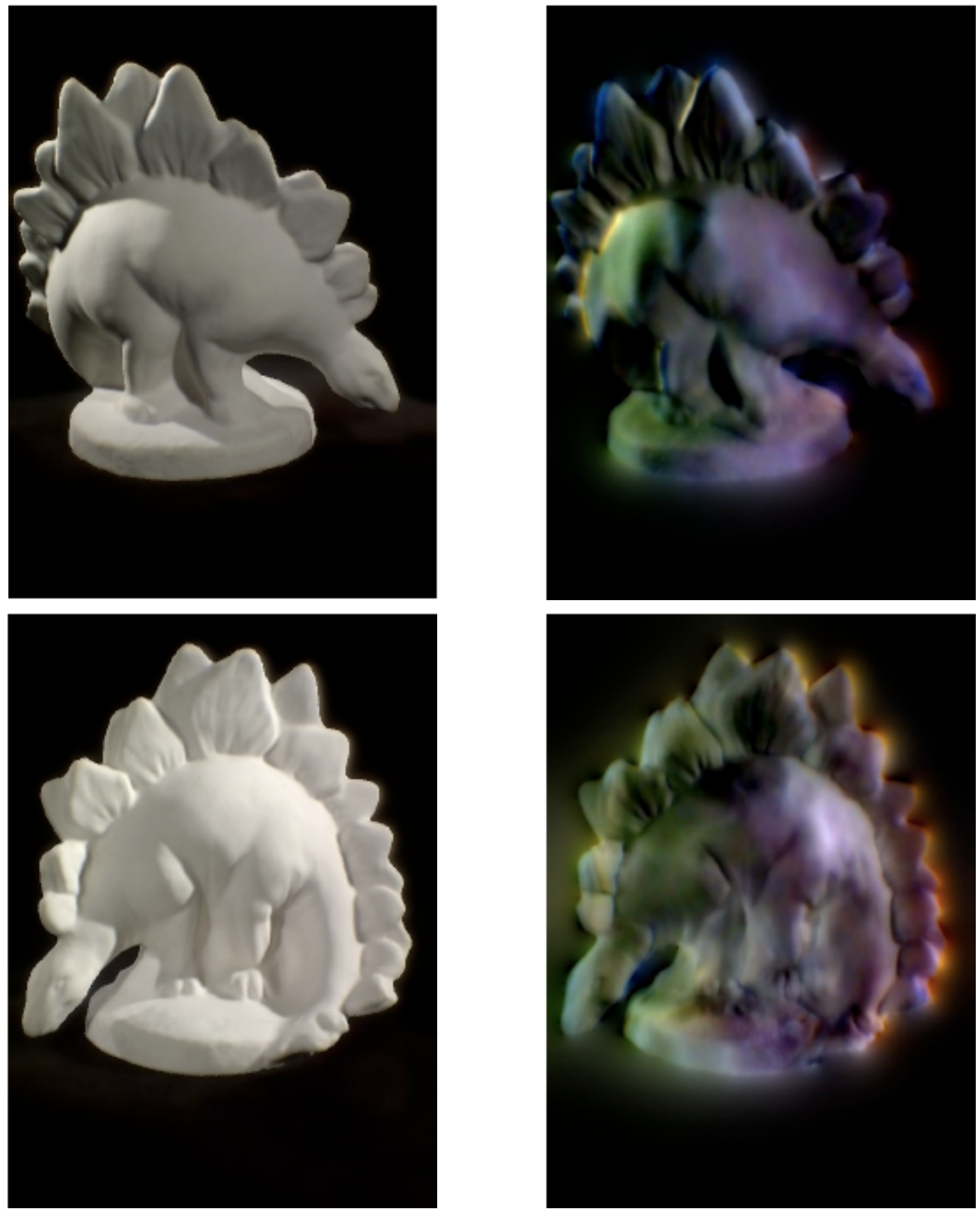
Results – Synthesized Lambertian Data





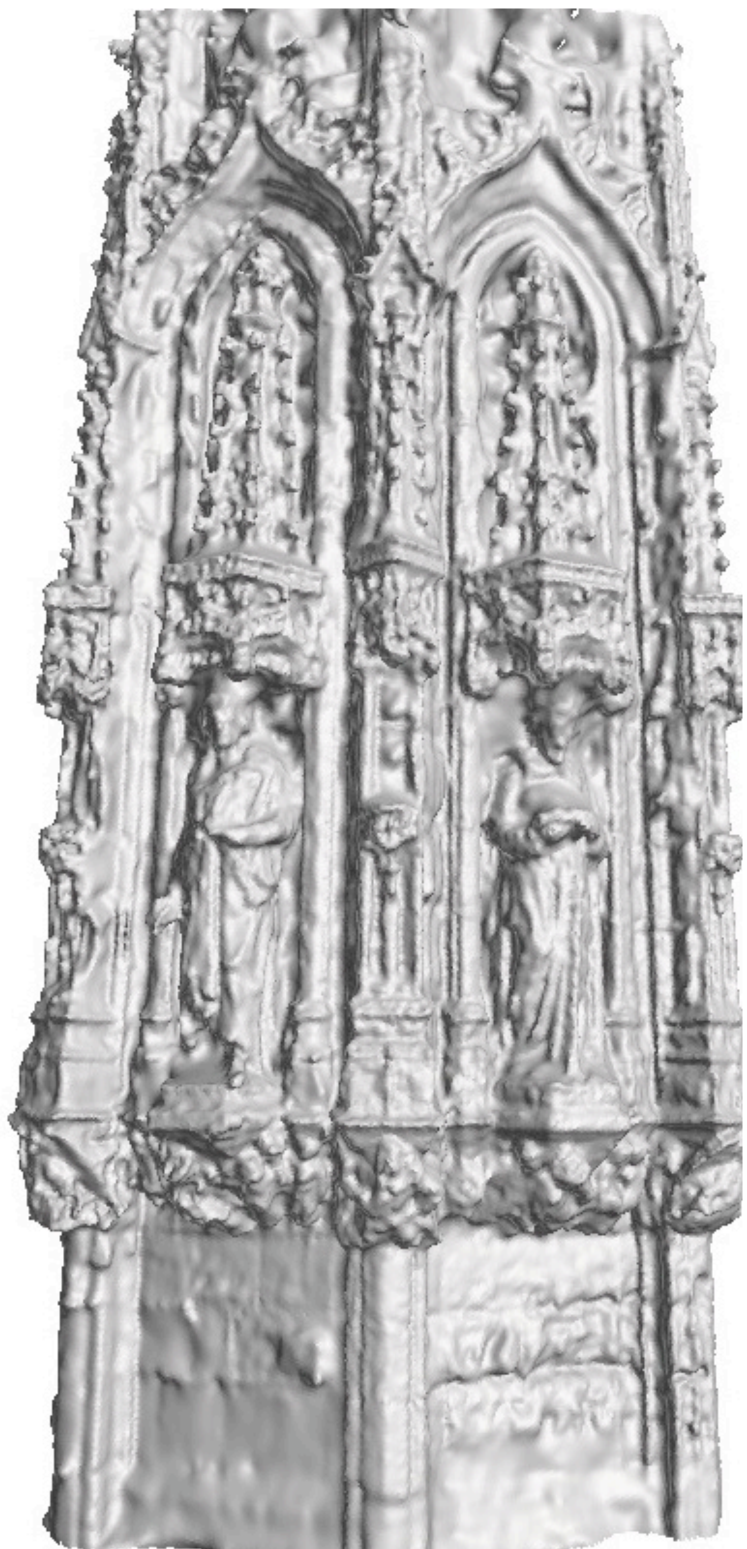
The Constant Brightness Assumption

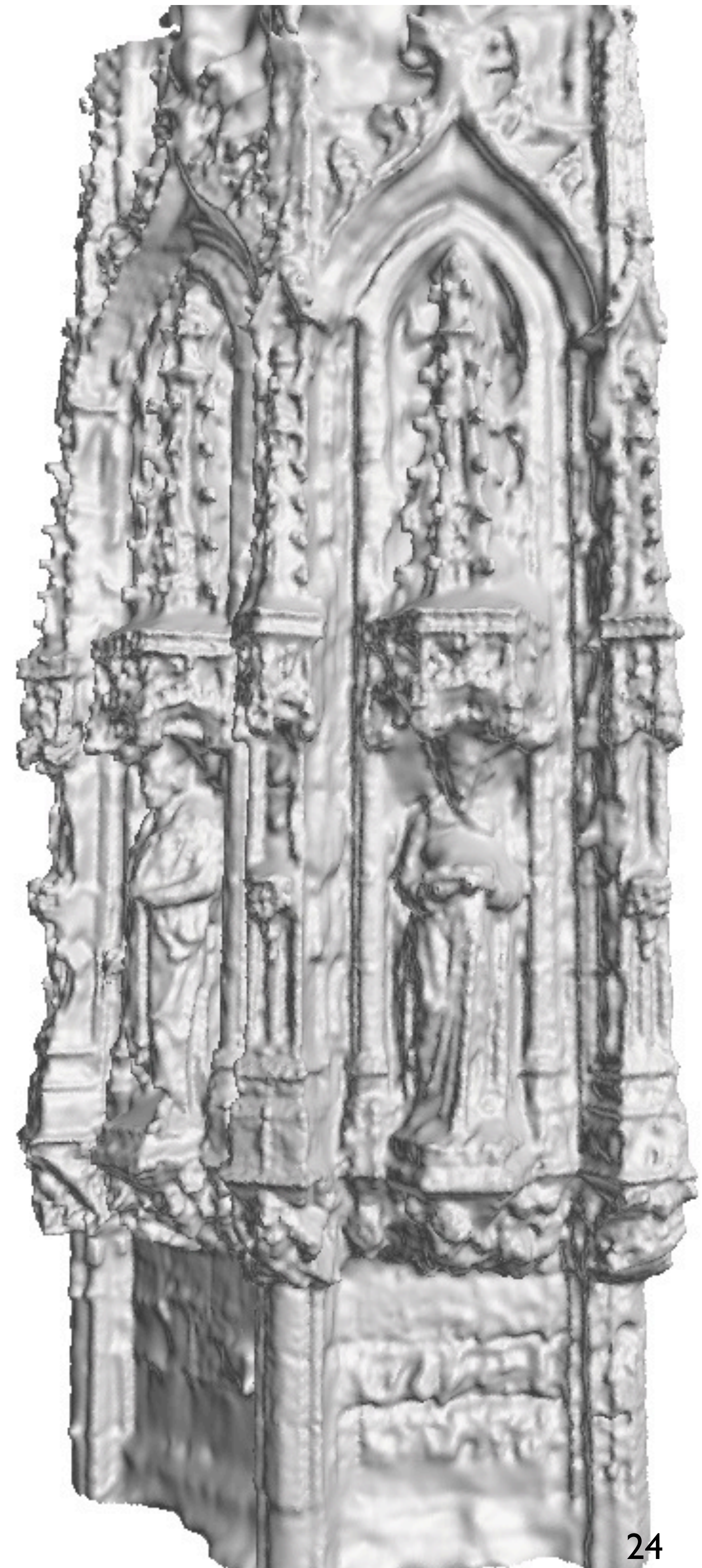
The Constant Brightness Assumption

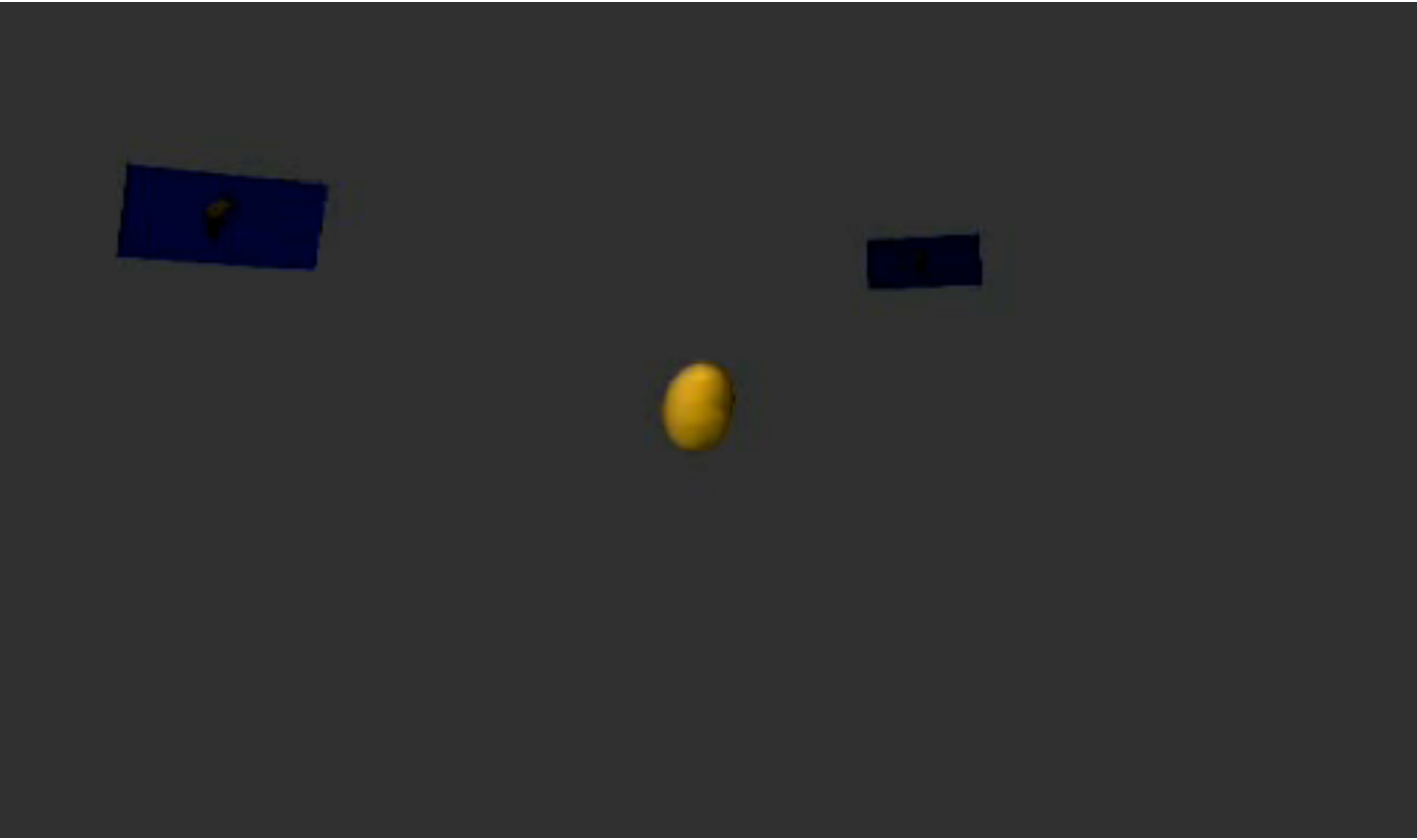


Leuven

750x500x500 voxels
2M+ triangles







[Hilton and Starck]

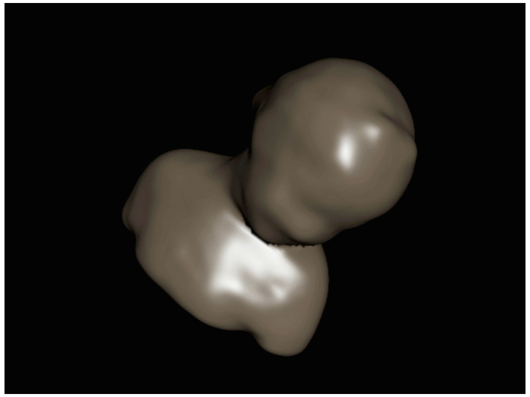
Extensions

- Specialize continuous formulation [ICCV'07] to discrete formulation (meshes) [BMVC'08]
- Go from Lambertian to more complex appearance models [IJCV'10,SSVM'09].
- Application to:
    - Shape from shading
    - Photometric stereo
    - Specular surfaces

Experiments

3

- **Textureless non-Lambertian surface**
  - Varying illumination
  - Specular reflection varying according to the viewing direction
  - Uniform specular/diffuse reflectance



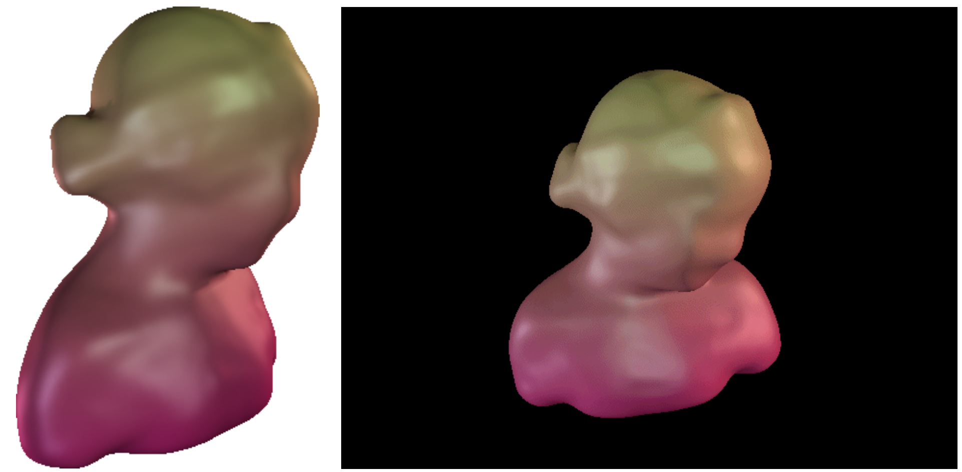
input image	estimated shape	diffuse image	specular image	synthesized image

Result for the smoothed “bimba” image set (36 images) - textureless non-Lambertian surface case (uniform specular reflectance, varying illumination and viewpoint). 95% accuracy (0.33mm, 0.047, 0.040, 0.032, 0.095, 8.248), 1.0mm completeness (100%, 0.048, 0.041, 0.032, 0.095, 8.248), image diff 1.63

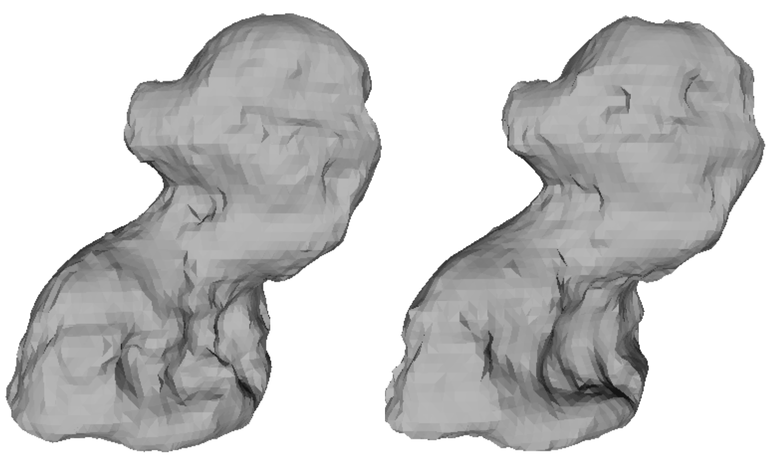
Experiments

3

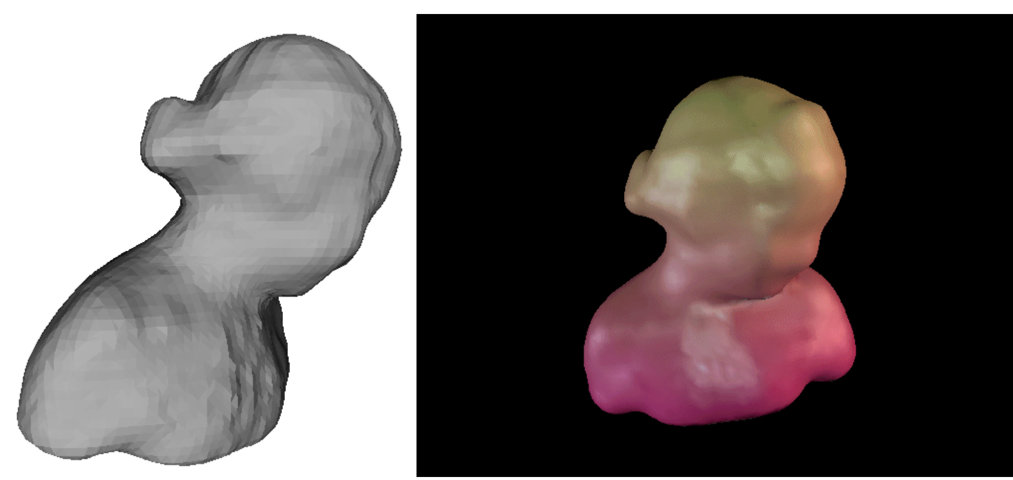
- **Comparison for non-Lambertian surfaces**
  - Specular reflection varying according to the viewing direction
  - Uniform specular reflectance but varying diffuse reflectance



input images



results using Pons et al (2007) (MI and CCL)



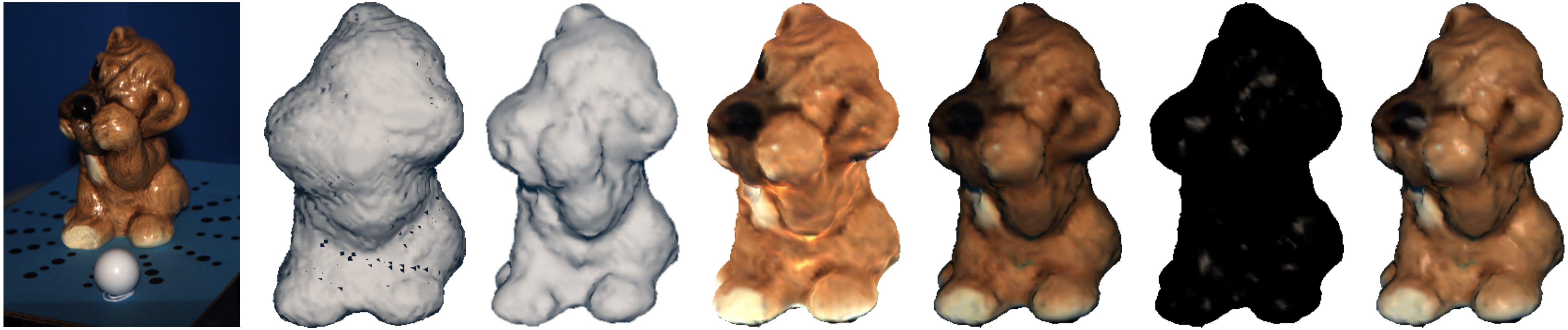
our result

Result comparisom using the smoothed “bimba” image set (16 images)

Experiments

3

- **Real images of glossy objects**
  - A fixed camera/light but a rotating object (= a fixed object and a rotating camera/light)
  - Uniform specular reflectance but varying diffuse reflectance

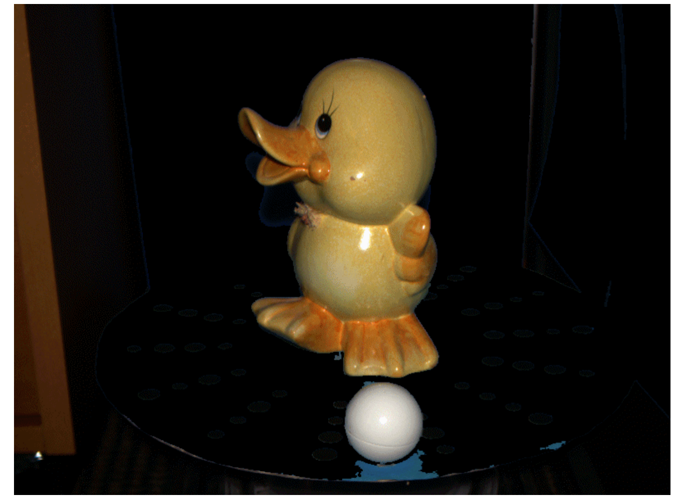


input image | initial shape | estimated shape | diffuse reflectance | diffuse image | specular image | synthesized image

Result for the “saddog” image set (58 images)

Experiments

- **Real images of glossy objects**
  - A fixed camera/light but a rotating object (= a fixed object and a rotating camera/light)
  - Uniform specular reflectance but varying diffuse reflectance



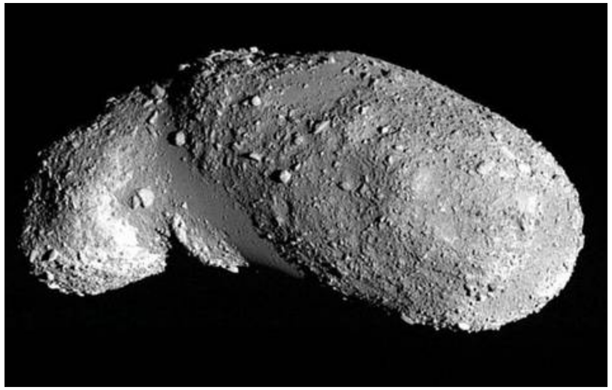
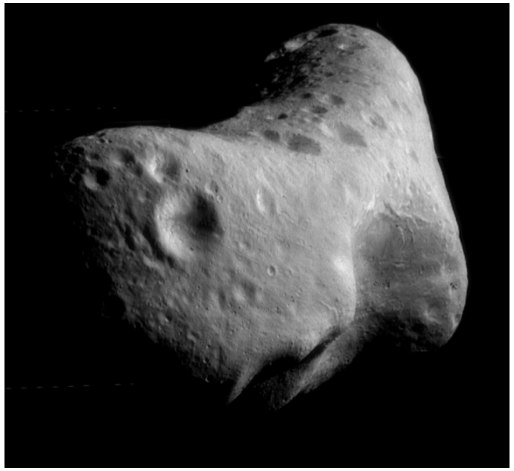
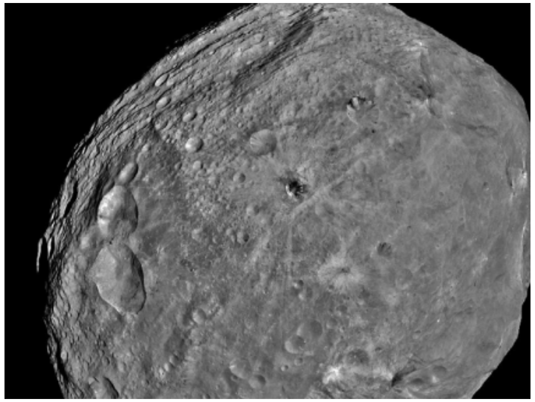
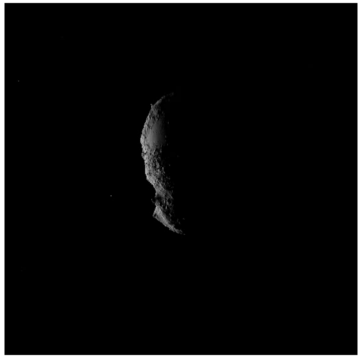
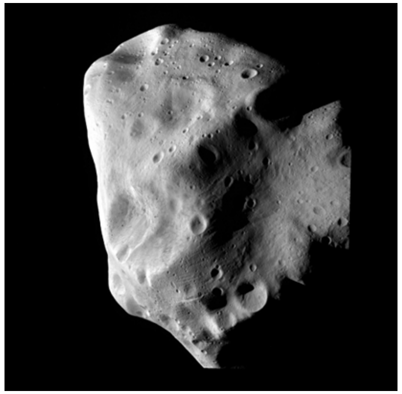
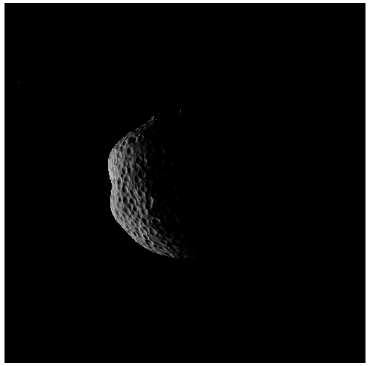
input image | initial shape | estimated shape | diffuse reflectance | diffuse image | specular image | synthesized image

Result for the “saddog” image set (58 images)

Experiments

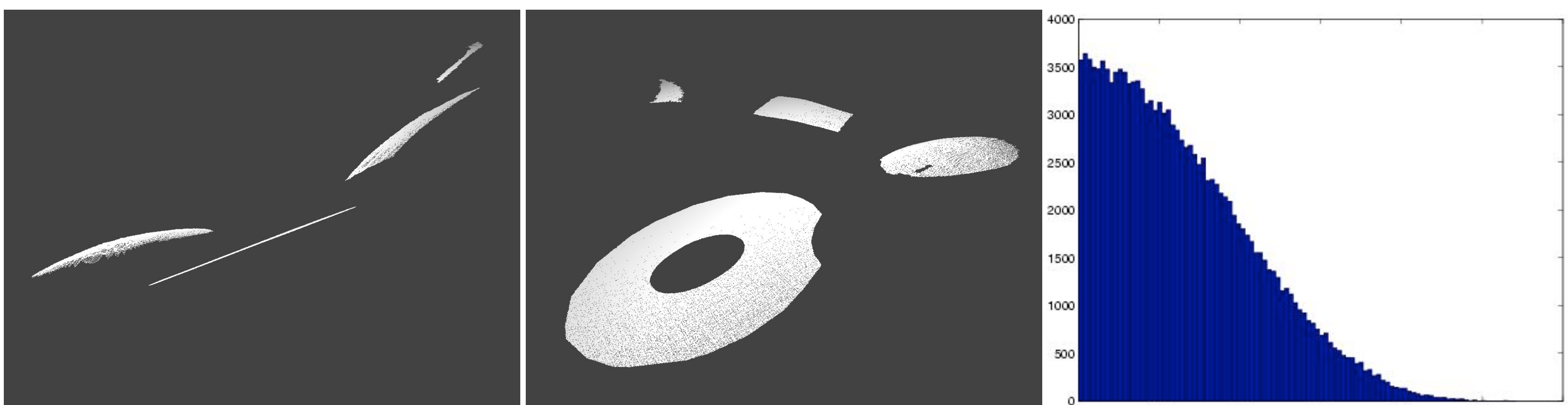
3

Application: reconstruction of asteroids

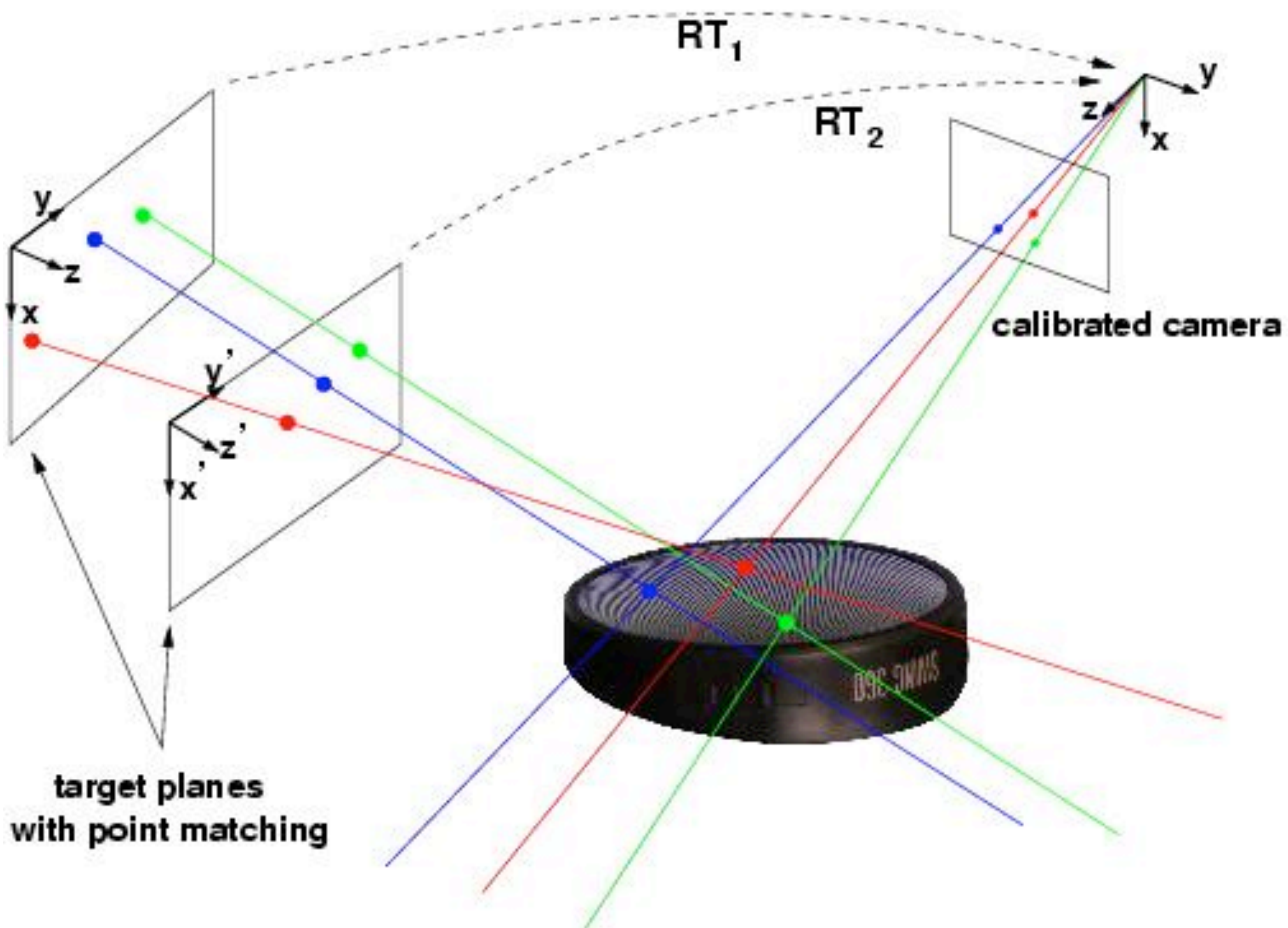
Other related works

- Reconstruction of mirror surfaces



Other related works

- Reconstruction of **specular** or **semi-transparent** surfaces taking into account photometry



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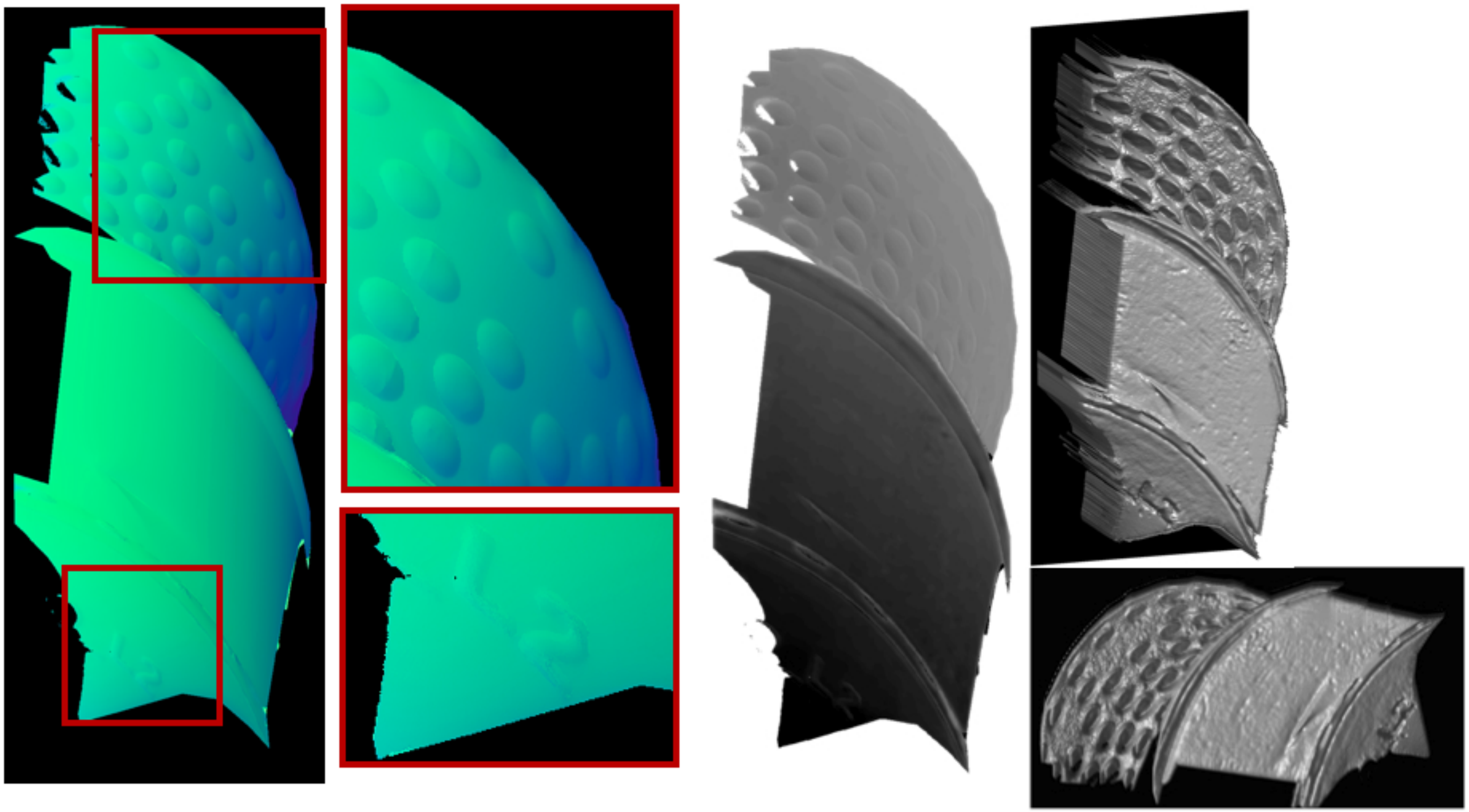

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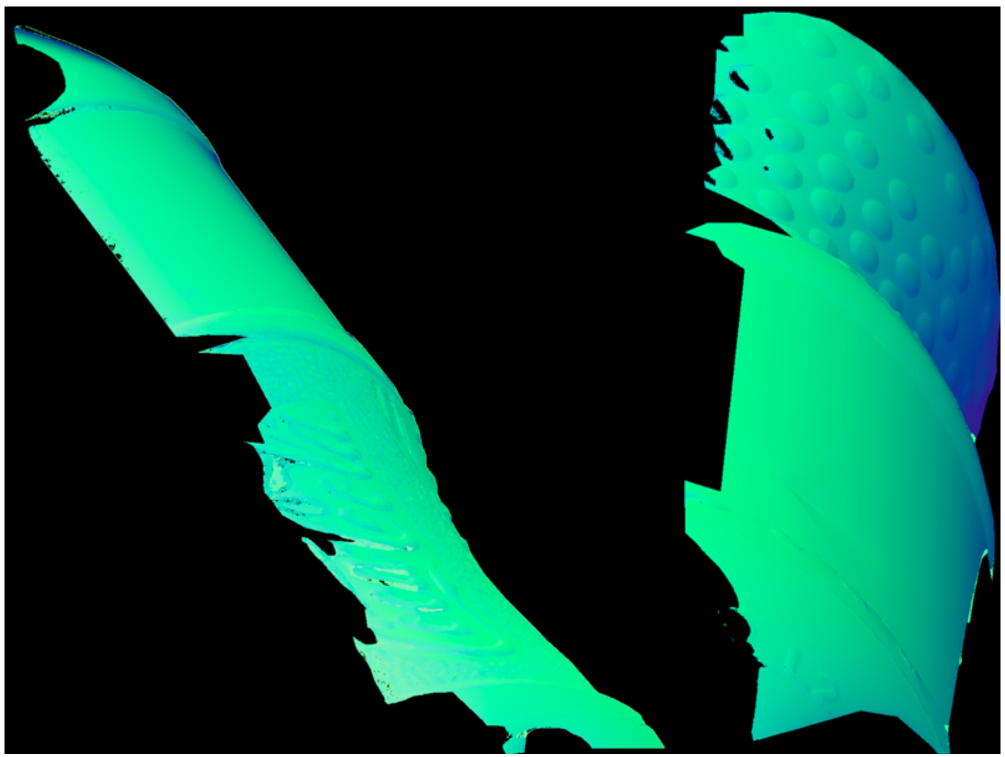

normals

depths

Conclusions

- A study of the intuitive cost function for multi-view stereo
- Findings applicable to various surface representations and other cost functions *(cost functions should be related to image generation process and noise)*
- Natural fusion of stereo, silhouettes, and apparent contours
- Applicable for generative models for multi-view stereo, shape-from-shading, photometric stereo, ...
- Conceptual link to object recognition...
- References: Gargallo et al. ICCV'07, Delaunoy et al. BMVC'08, Yoon et al. IJCV'10, Delaunoy et al. IJCV'11

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