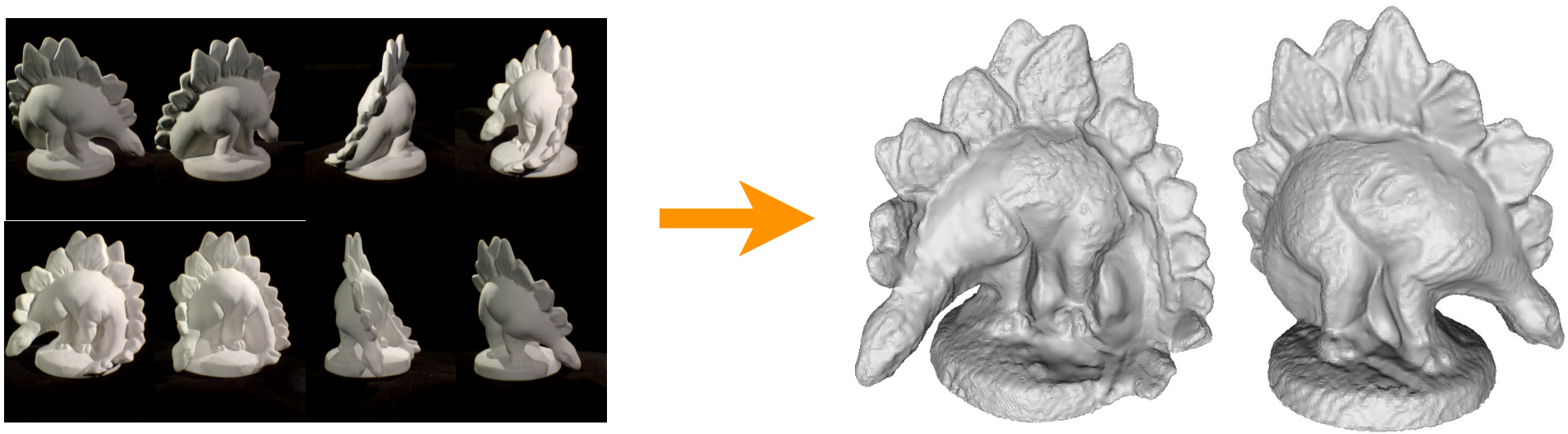
Contributions to the Bayesian Approach to Multi-View Stereo

Pau Gargallo i Piracés

Supervised by Peter Sturm
at the PERCEPTION team of INRIA Rhône-Alpes



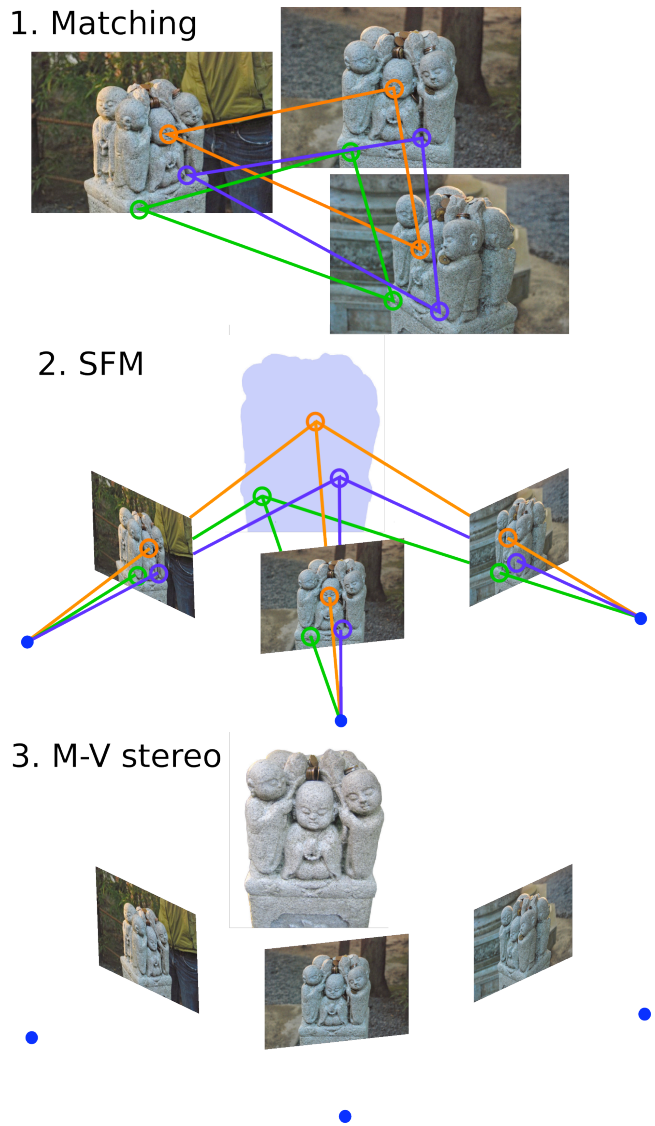
3D Reconstruction from Images



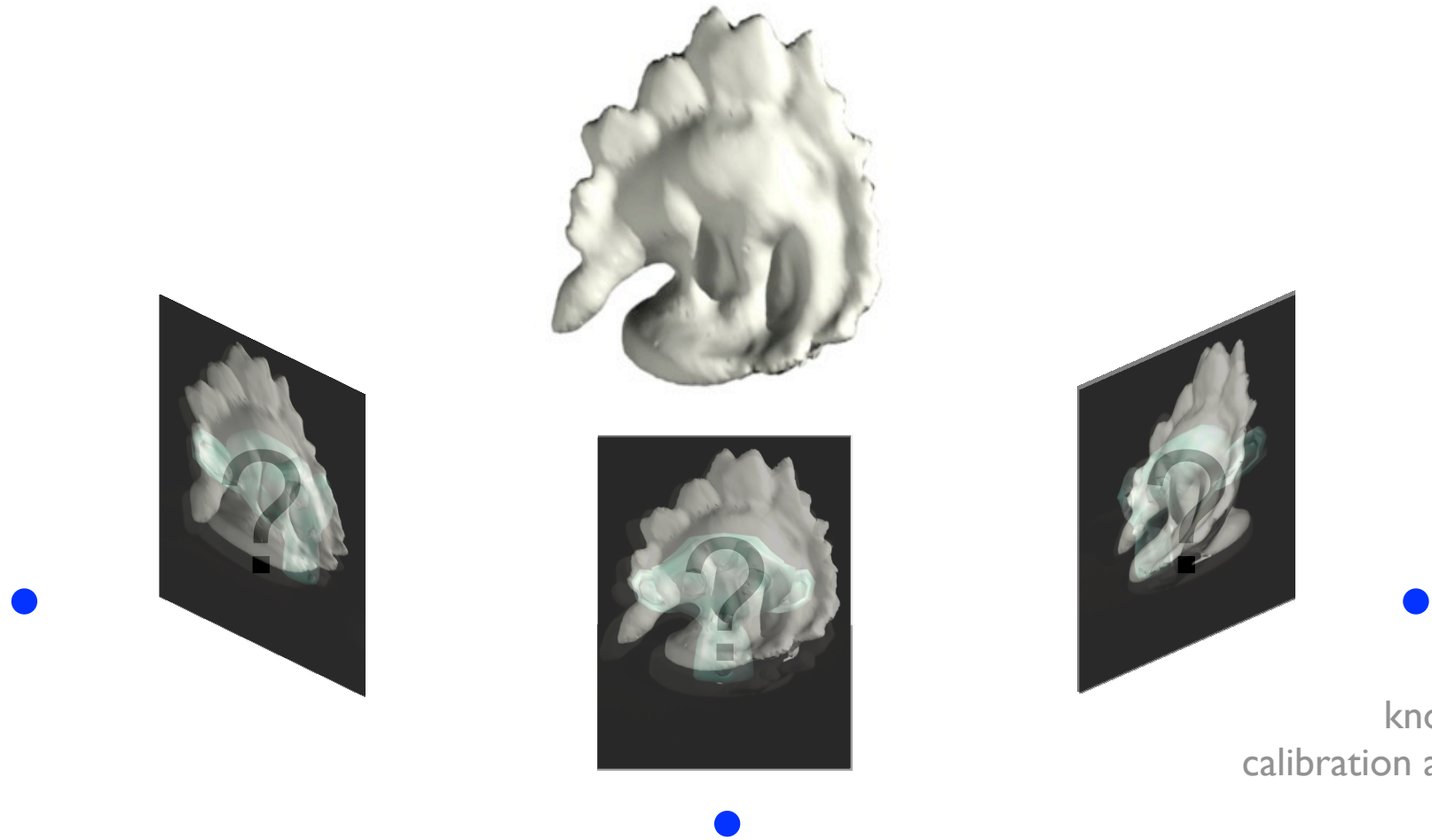
- Building 3D models from images
- Applications:
  - Cinema post-production, special FX and games
  - Archeology and cultural heritage preservation
  - Telecommunication
  - Robotics...

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



known camera
calibration and position

Stereo is the inverse problem of rendering

Quality measure: reprojection error

Outline of the Presentation

- Introduction
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- Conclusion

Existing Approaches

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

Approaches: Bottom-up

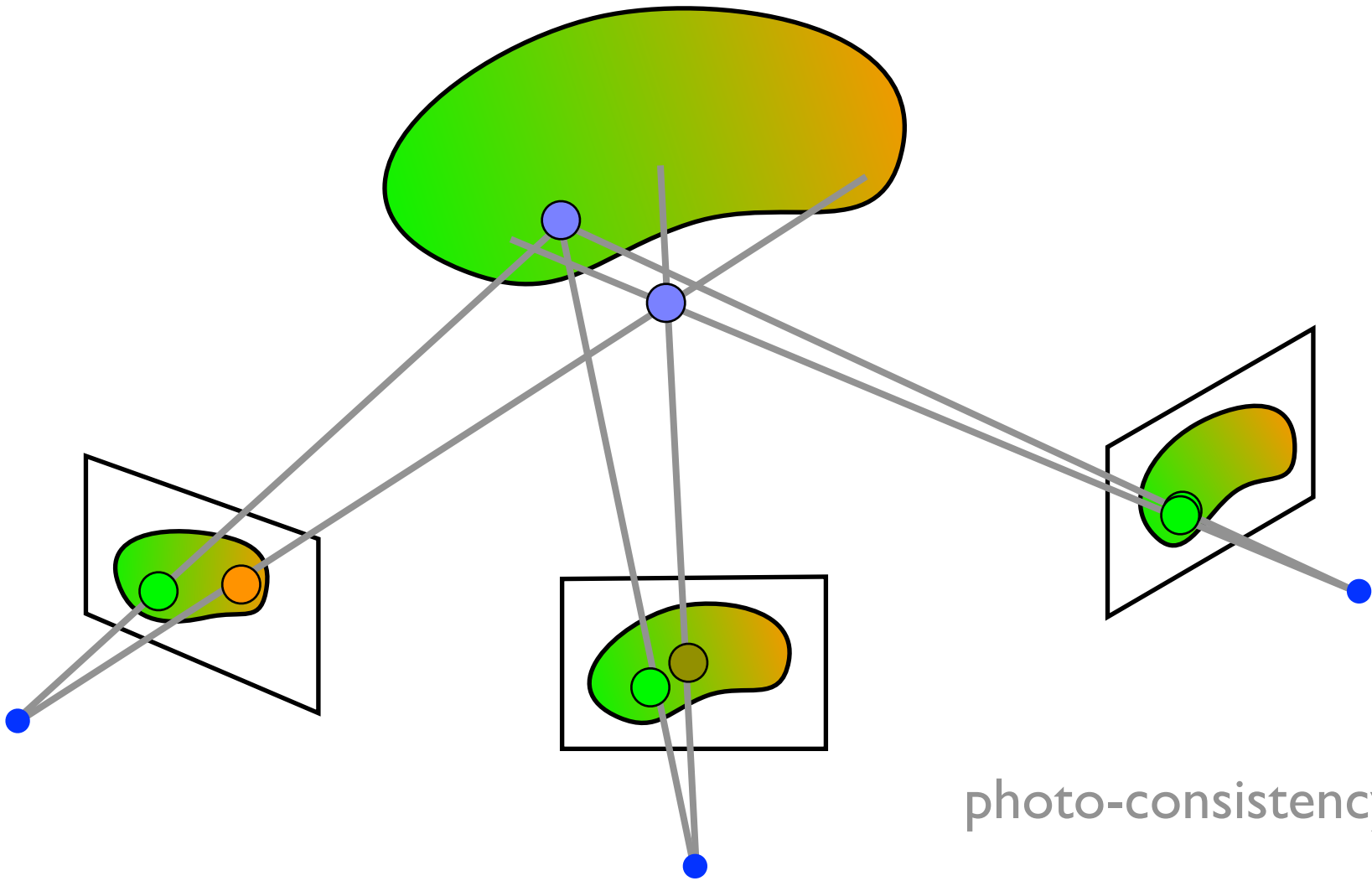
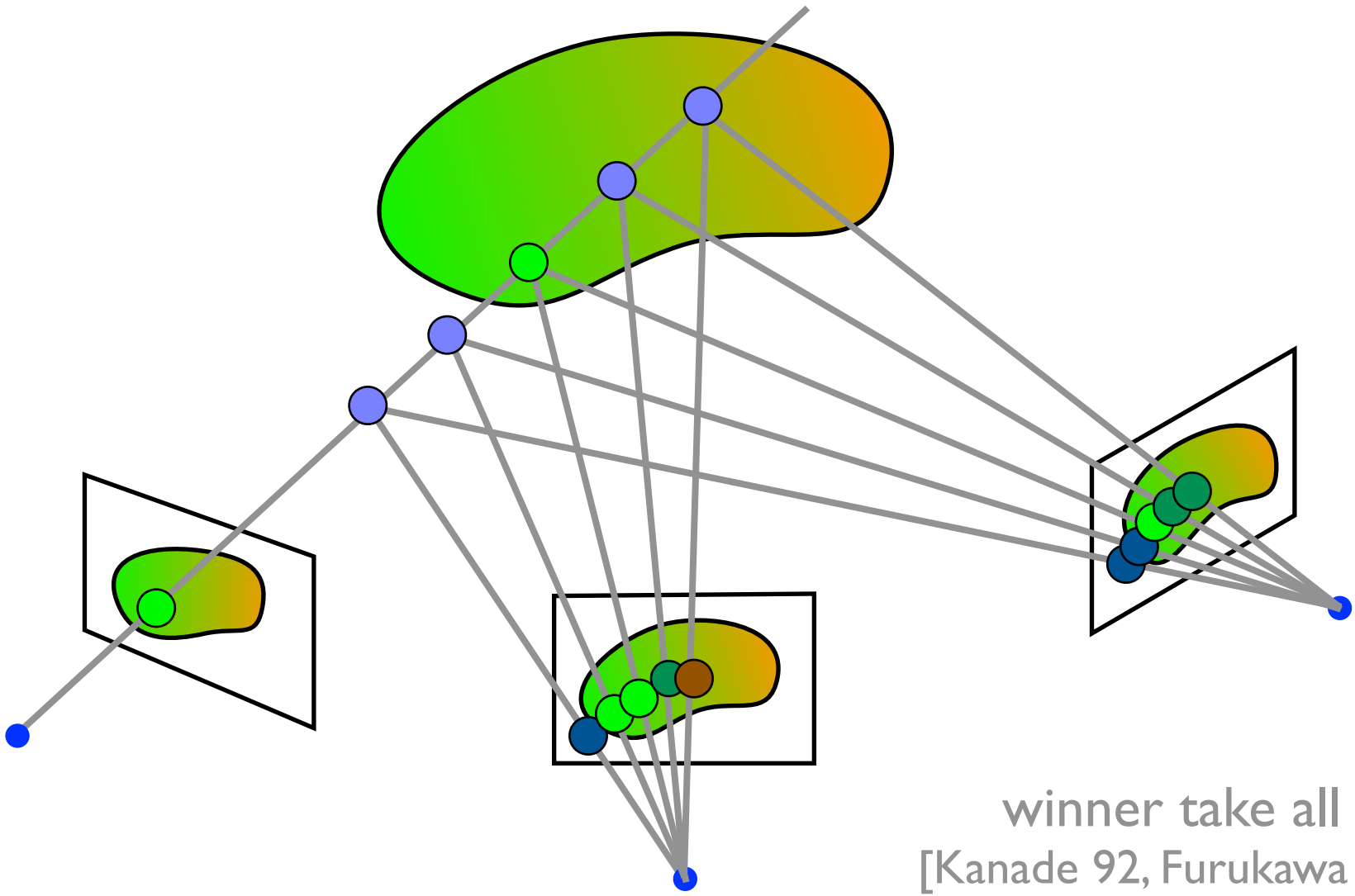


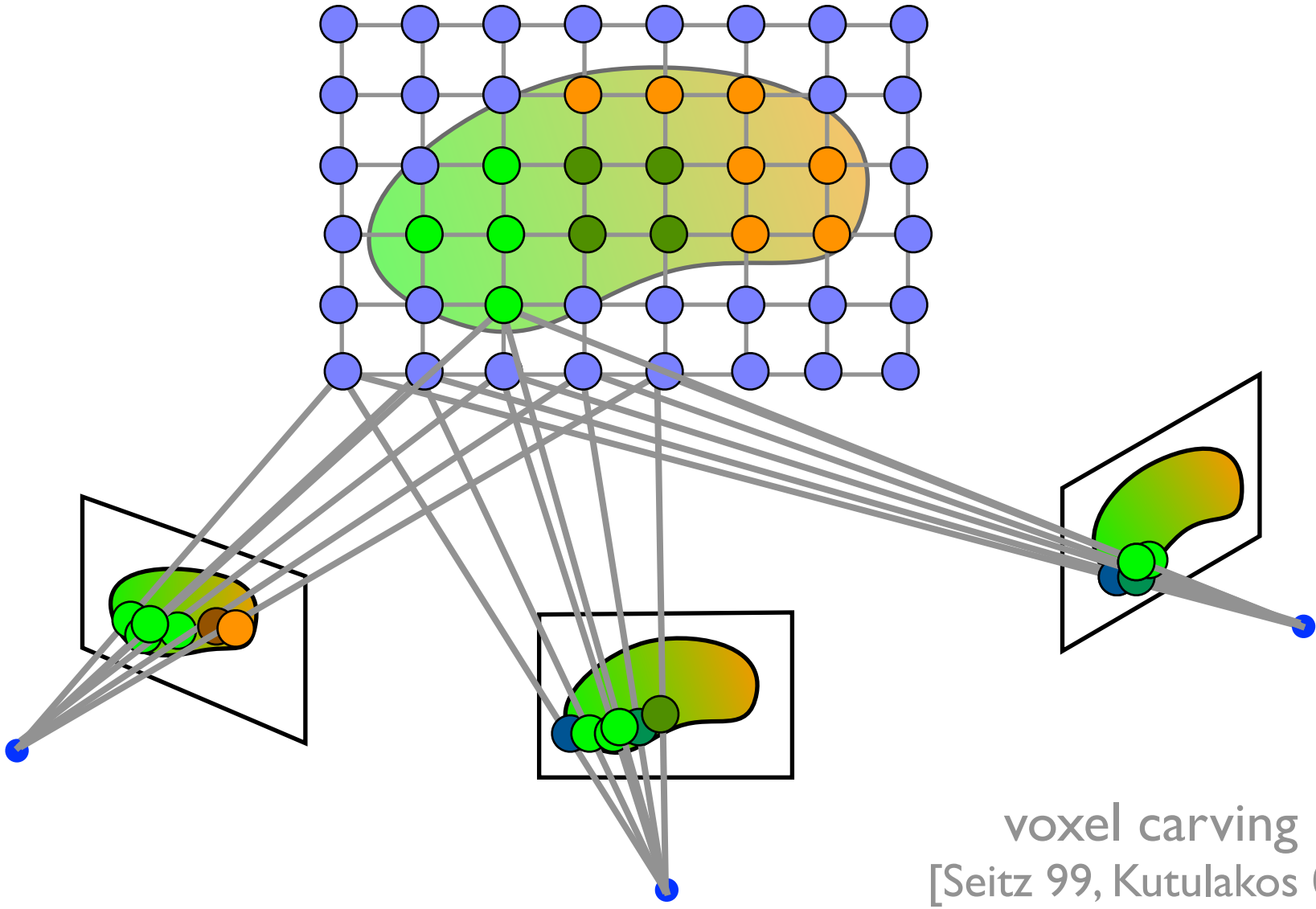
photo-consistency

Approaches: Bottom-up



winner take all
[Kanade 92, Furukawa 07]

Approaches: Bottom-up



voxel carving
[Seitz 99, Kutulakos 00]

Approaches: Bottom-up

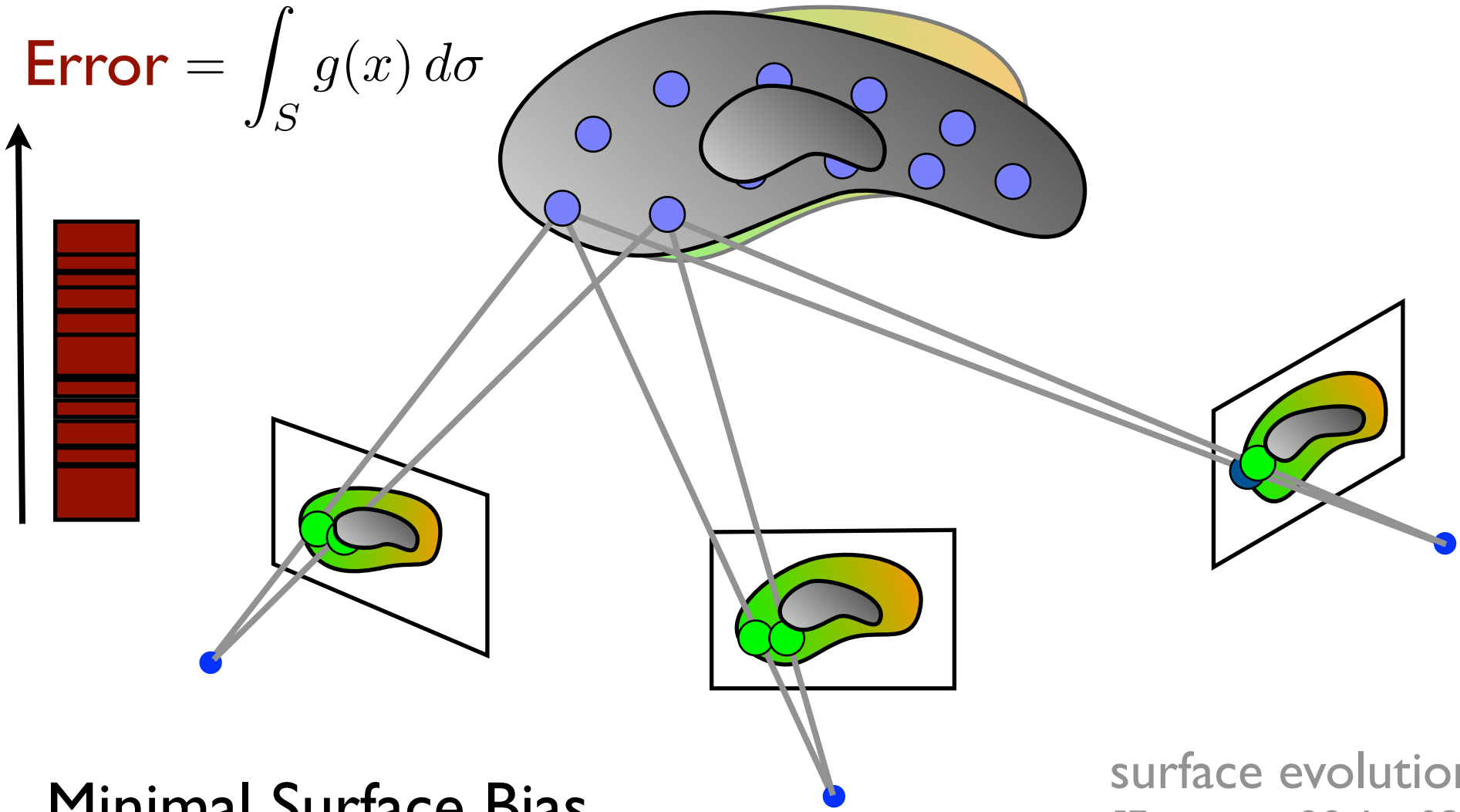
- Problems:
  - False detections: photo-consistent but not on surface
    - Need regularization
  - Missing detections: on surface but not photo-consistent due to occlusions
    - Need to take care of occlusions

Existing Approaches

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

Top-Down: Energy Minimization

$$\text{Error} = \int_S g(x)\, d\sigma$$



Minimal Surface Bias

Silhouette constraints

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

surface evolution

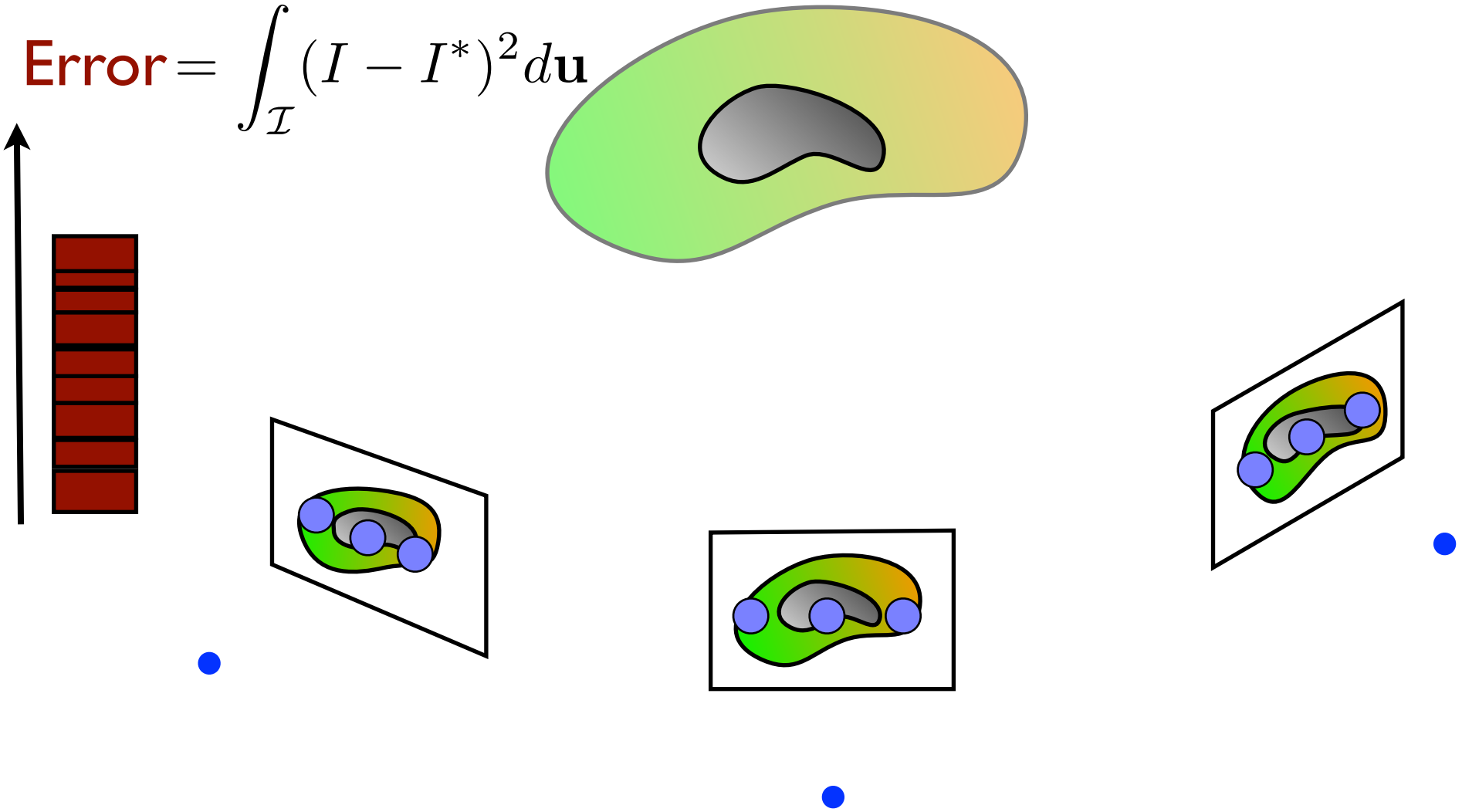
[Faugeras 98, Jin 03]

graph cuts

[Paris 04, Vogiatzis 05]

Top-Down: The Reprojection Error

$$\text{Error} = \int_{\mathcal{I}} (I - I^*)^2 d\mathbf{u}$$



No bias

Need to deal with occlusions

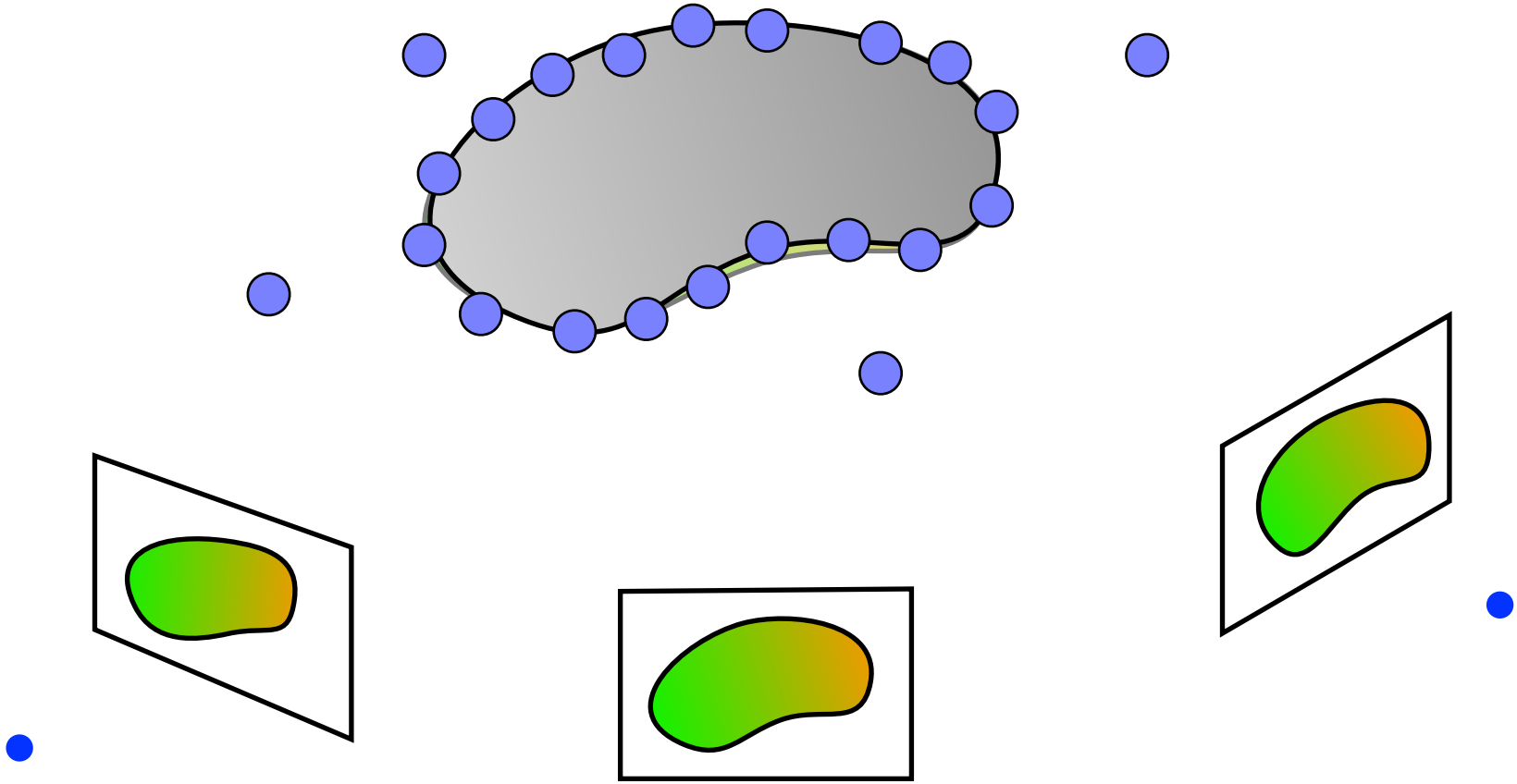
surface evolution

[Yezzi 03, Strecha 03, Pons 05]

Existing Approaches

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

Hybrid



1. Detect surface point using a direct method
2. Robustly fit a surface to the points

depth map integration [Koch 98, Merrel 07, Zach 07]

surface to points fitting [Lhuillier 05, Furukawa 07]

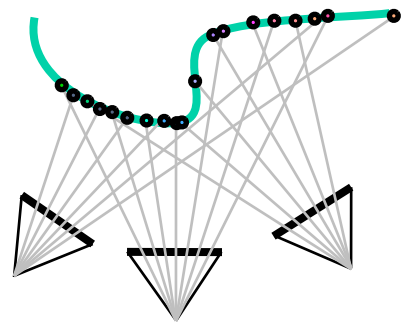
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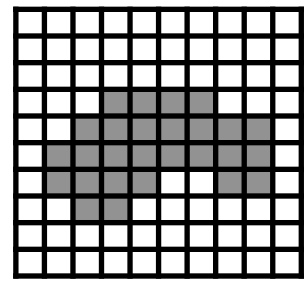
Proposed Models

Bayesian formulation → minimize the reprojection error

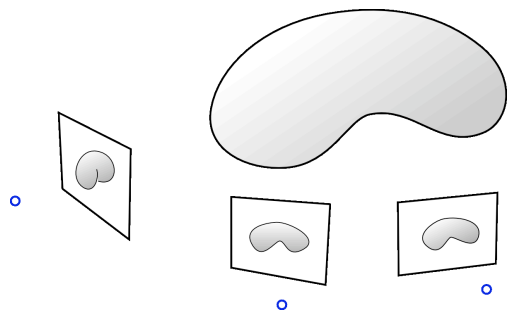
- Multiple Depth Maps



- Occupancy of a discreet grid (voxels)



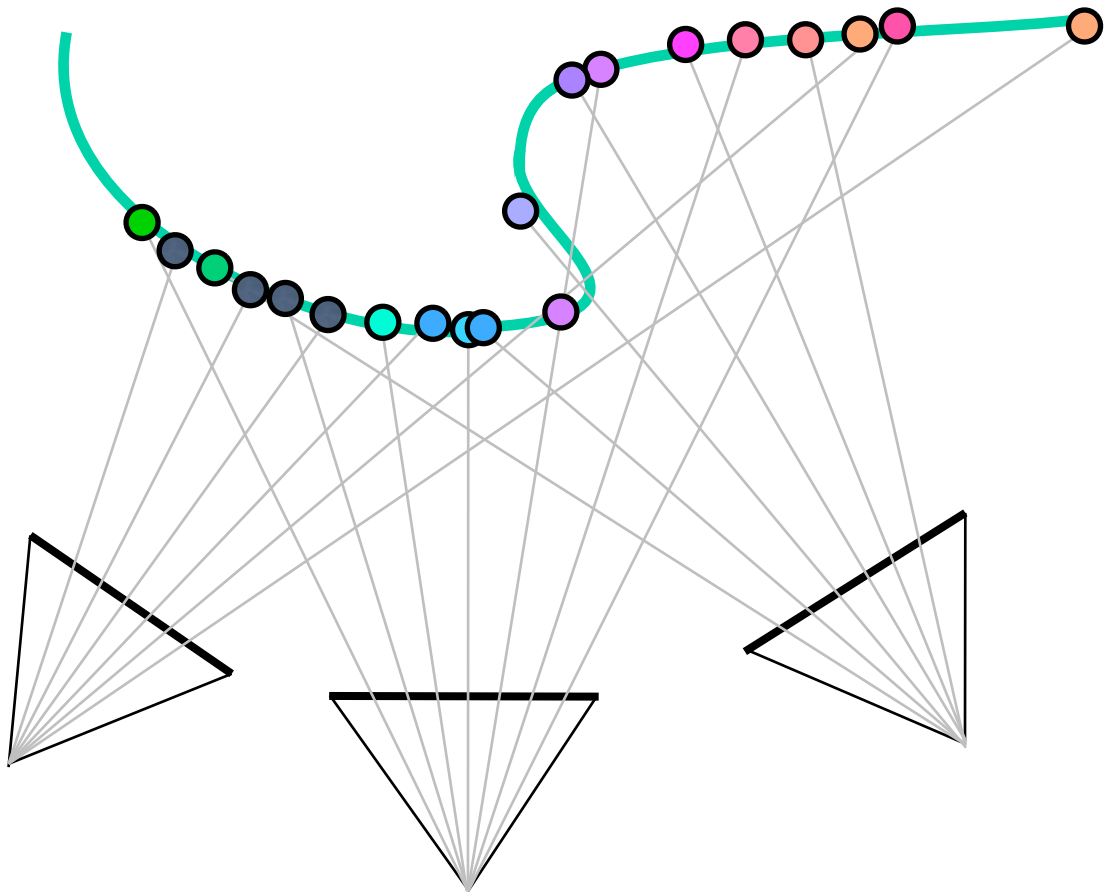
- Smooth surface



Outline of the Presentation

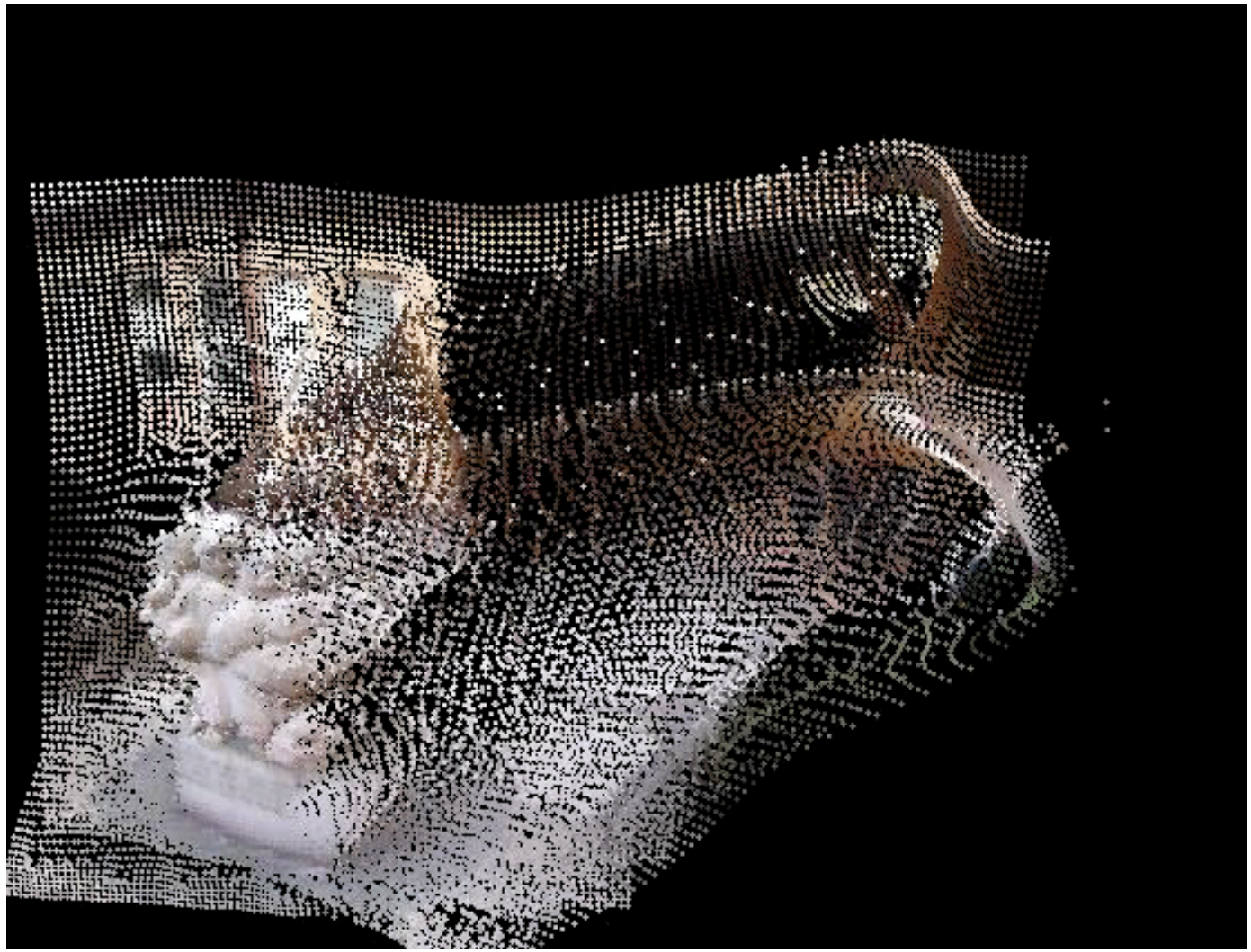
- Introduction
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Multiple Colored Depth Maps



- Motivation:
  - High resolution [Strecha 03]
  - Explain all pixels
  - Occlusions can be efficiently detected
- Drawbacks:
  - Over-parameterization
  - Small shape changes require large changes of depth [Kolmogorov 03]

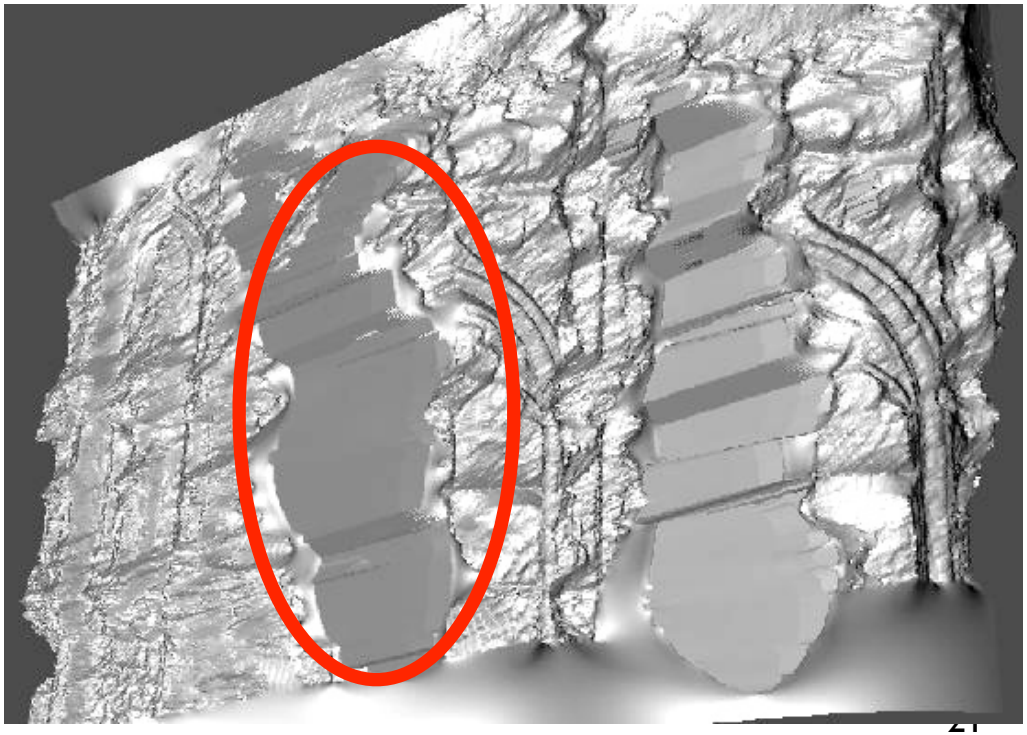








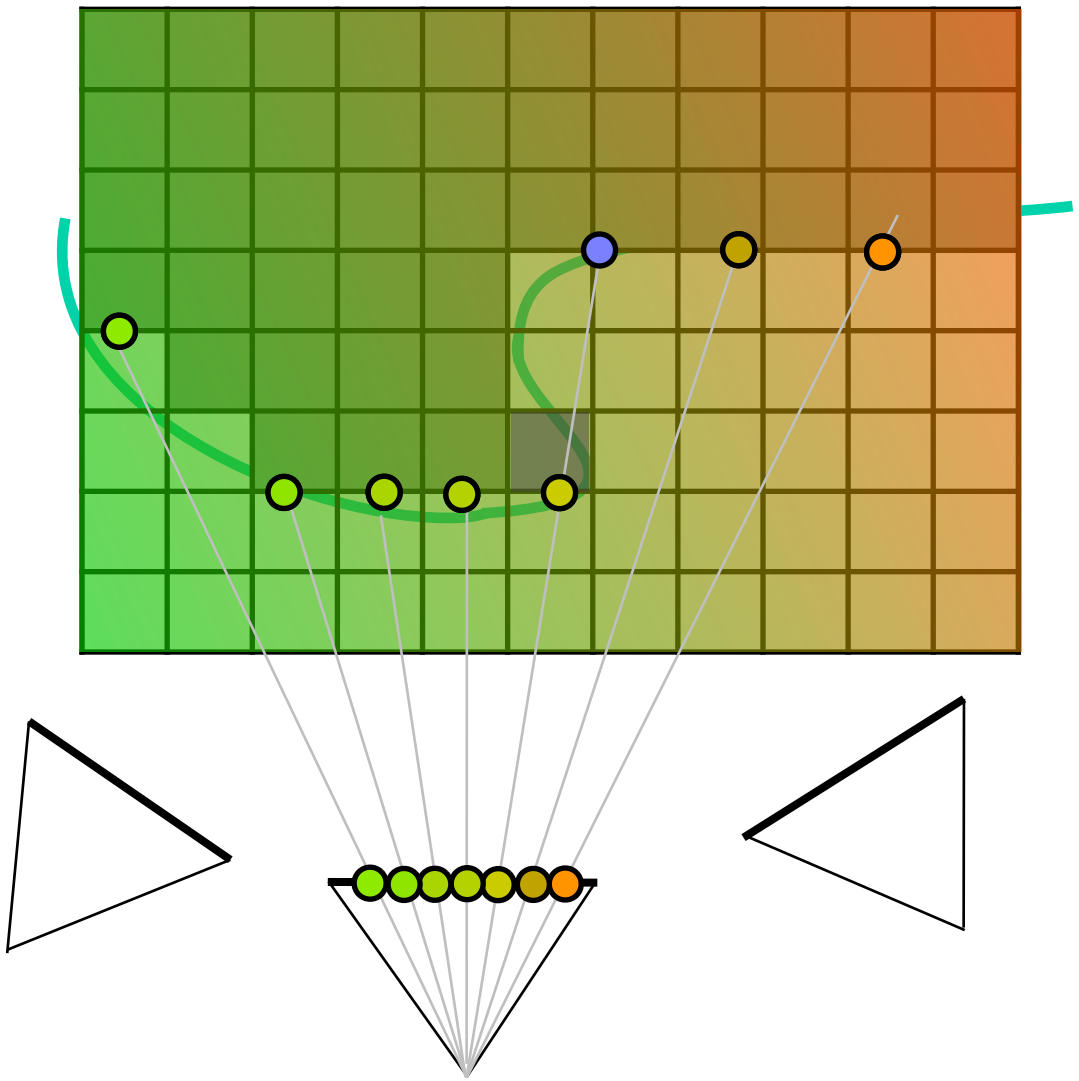




Outline of the Presentation

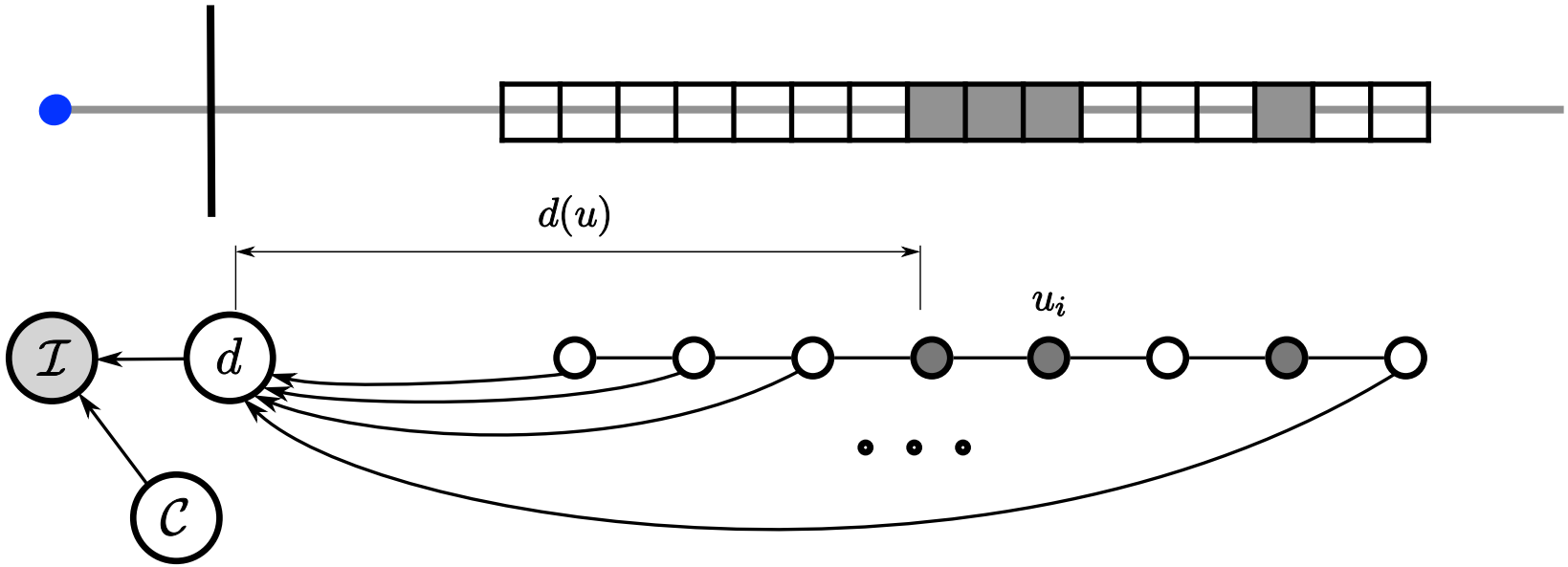
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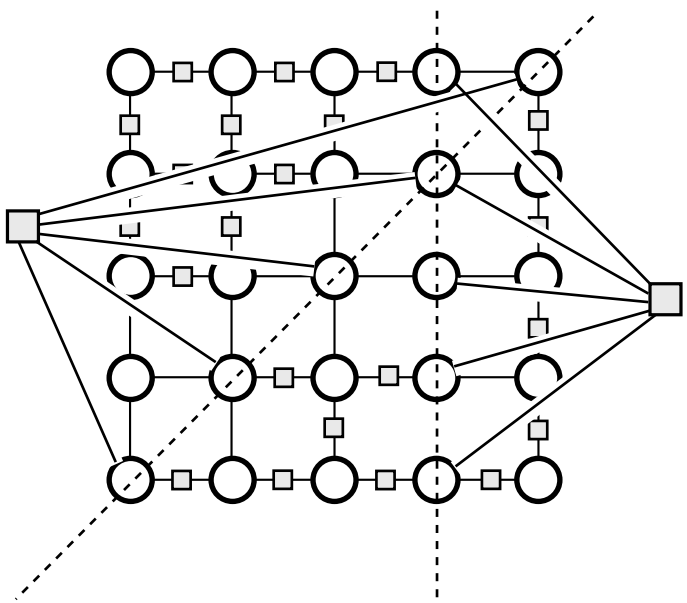
The Occupancy–Depth Model

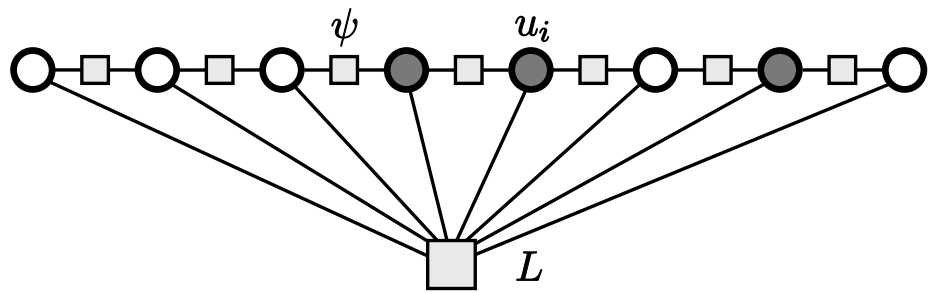


- Motivation:
  - Fair representation of reality
  - Occlusions taken into account by the model
- Drawbacks:
  - Yields a difficult combinatorial optimization problem

The Graphical Model



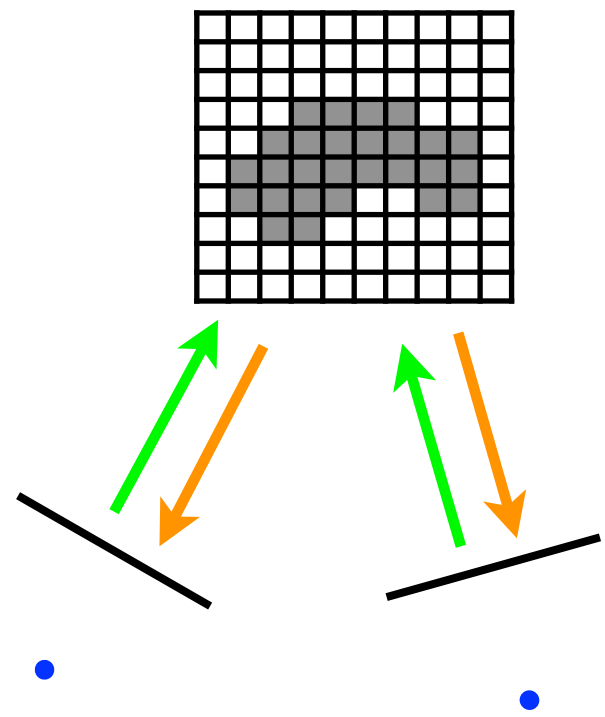




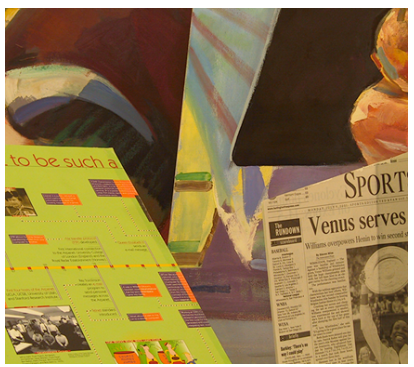
Huge and very loopy factor graph

Inference

- Expectation Maximization
  - E-step: estimate occupancy
    - Message Passing
  - M-step: estimate color
    - weighted average or gradient descent

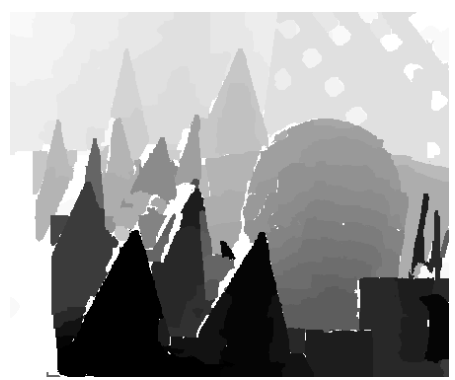


Small Baseline Stereo Pairs

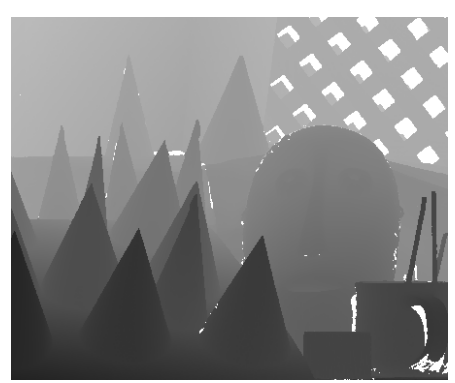





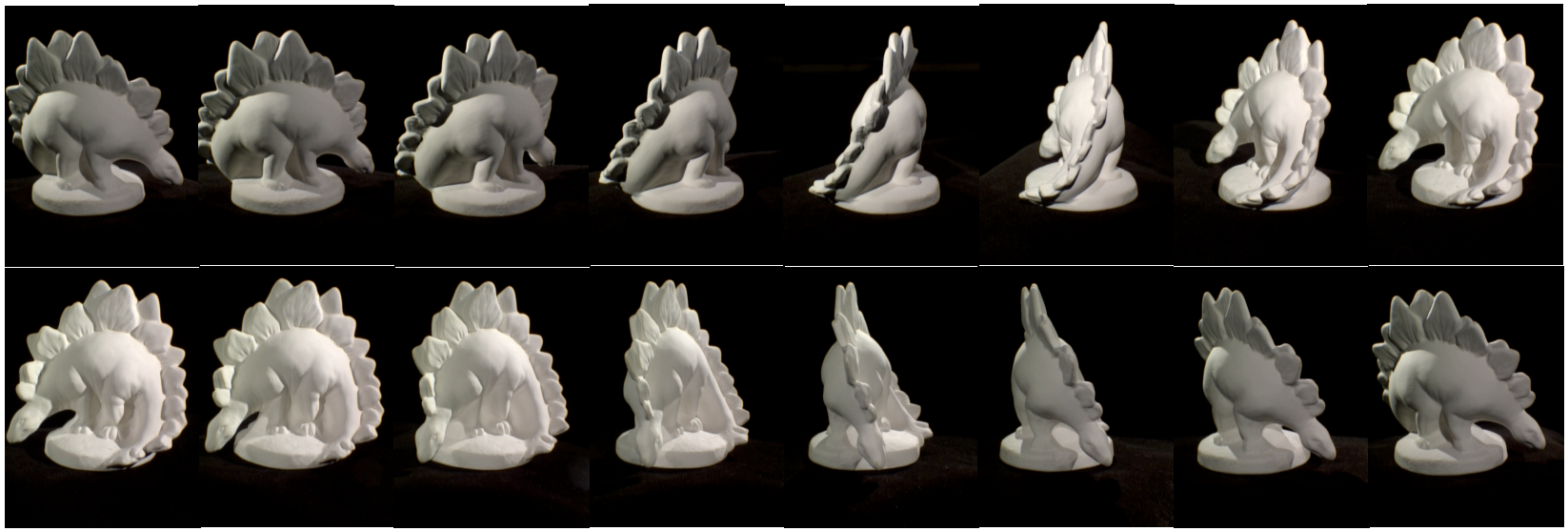


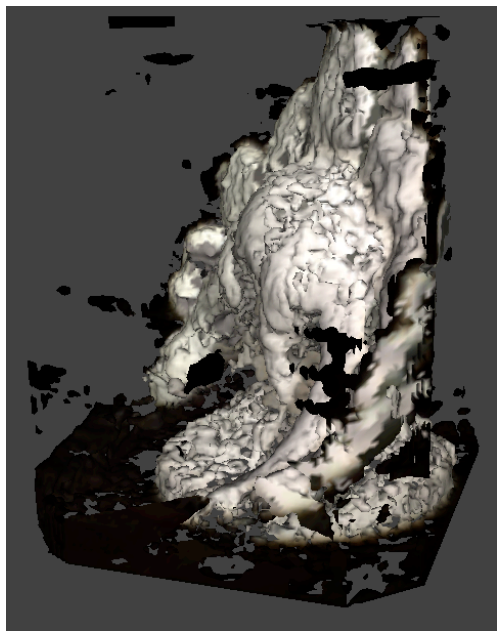



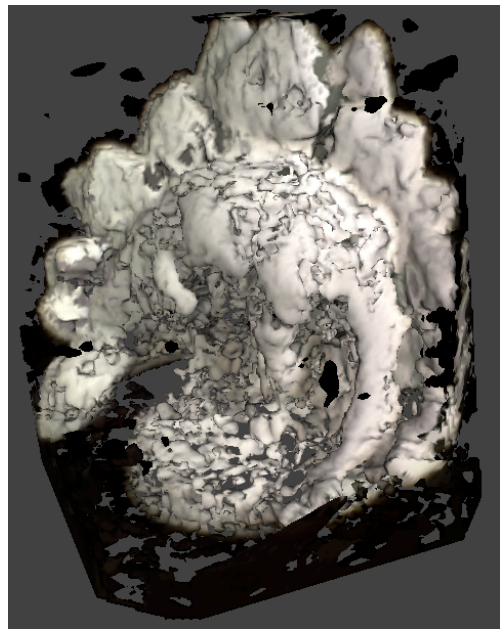


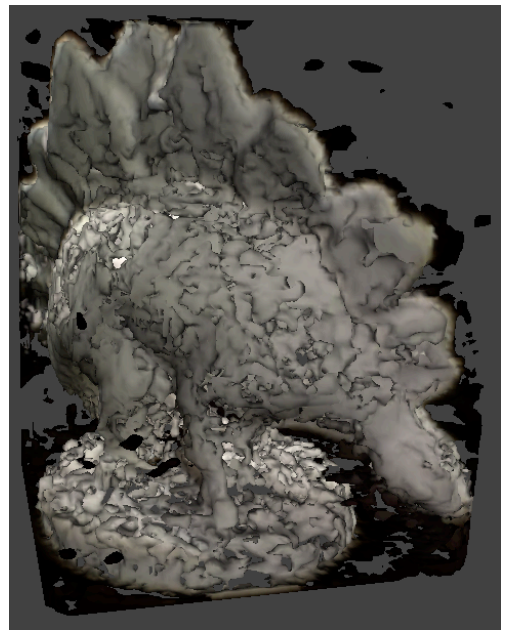


Multi-View Stereo









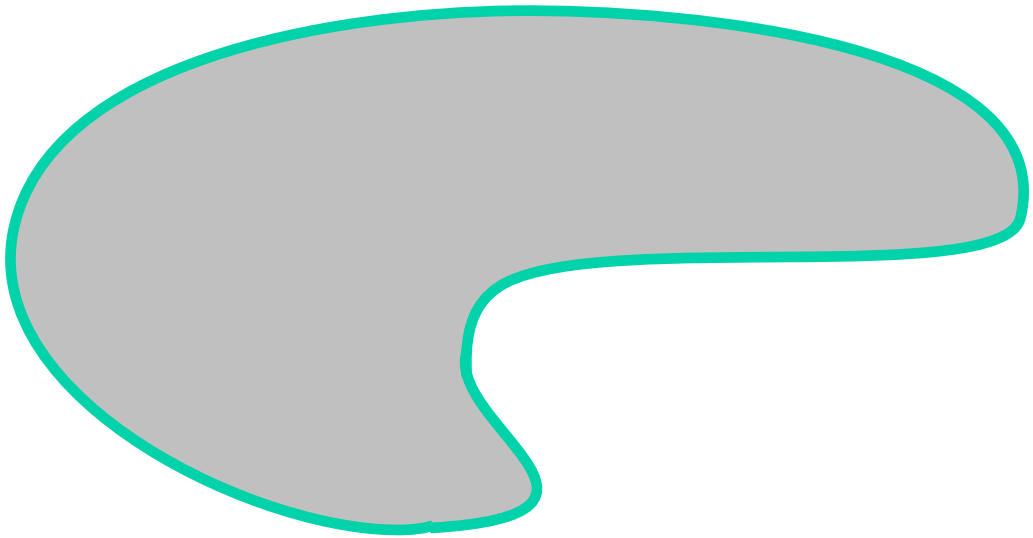
Conclusion on the Occupancy–Depth Model

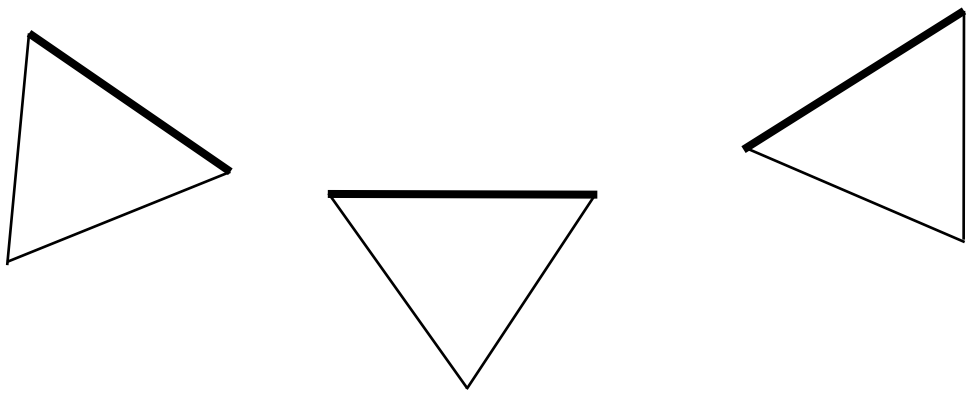
Need better optimization algorithms

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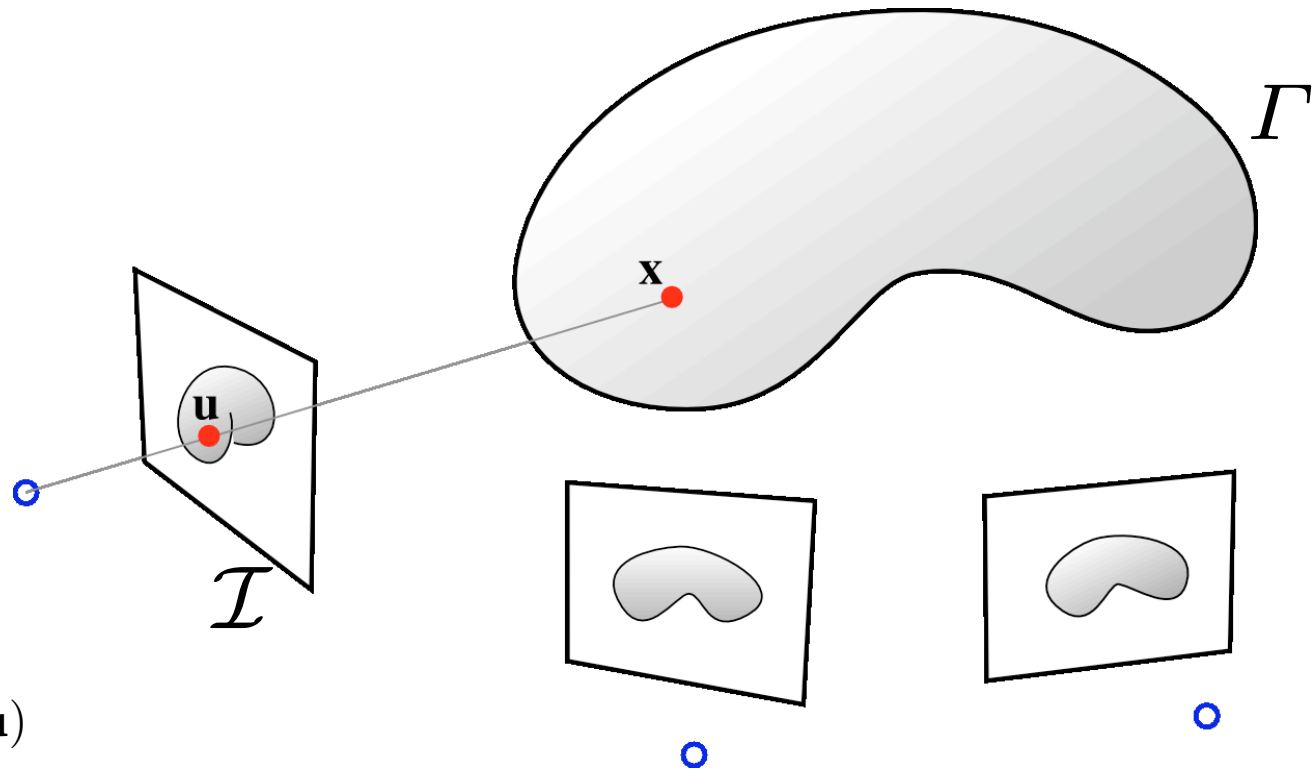
Smooth Surface Representation





- Representation:
  - Generic smooth surface
- Optimization:
  - Gradient descent surface evolution

The Reprojection Error



$$\mathbf{u} = \pi(\mathbf{x})$$

$$\mathbf{x} = \pi_\Gamma^{-1}(\mathbf{u})$$

$$E(\Gamma, C) = \int_{\mathcal{I}} \left(I(\mathbf{u}) - C(\pi_\Gamma^{-1}(\mathbf{u}))\right)^2 d\mathbf{u}$$

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

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

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

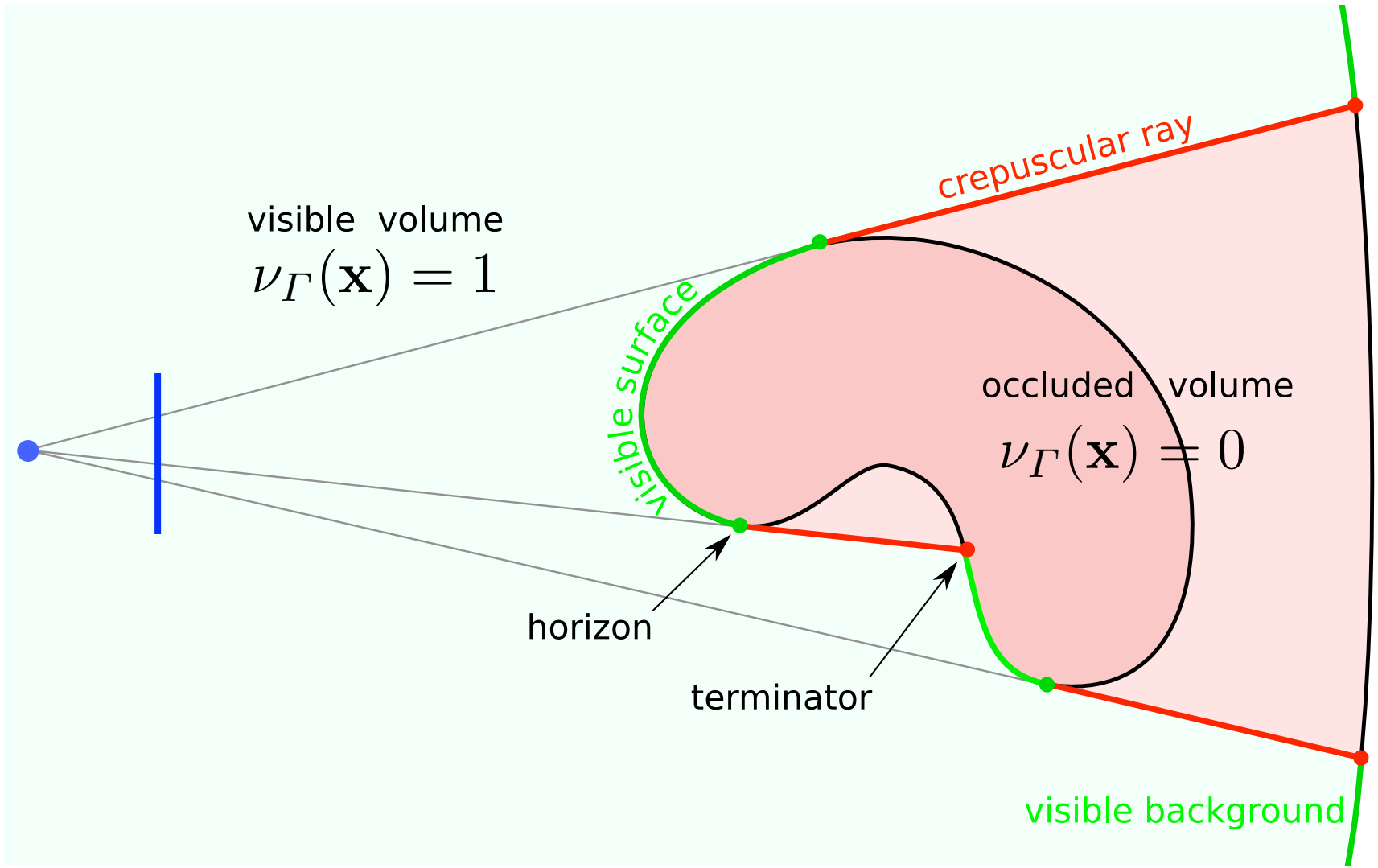
Another way to write the reprojection error

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

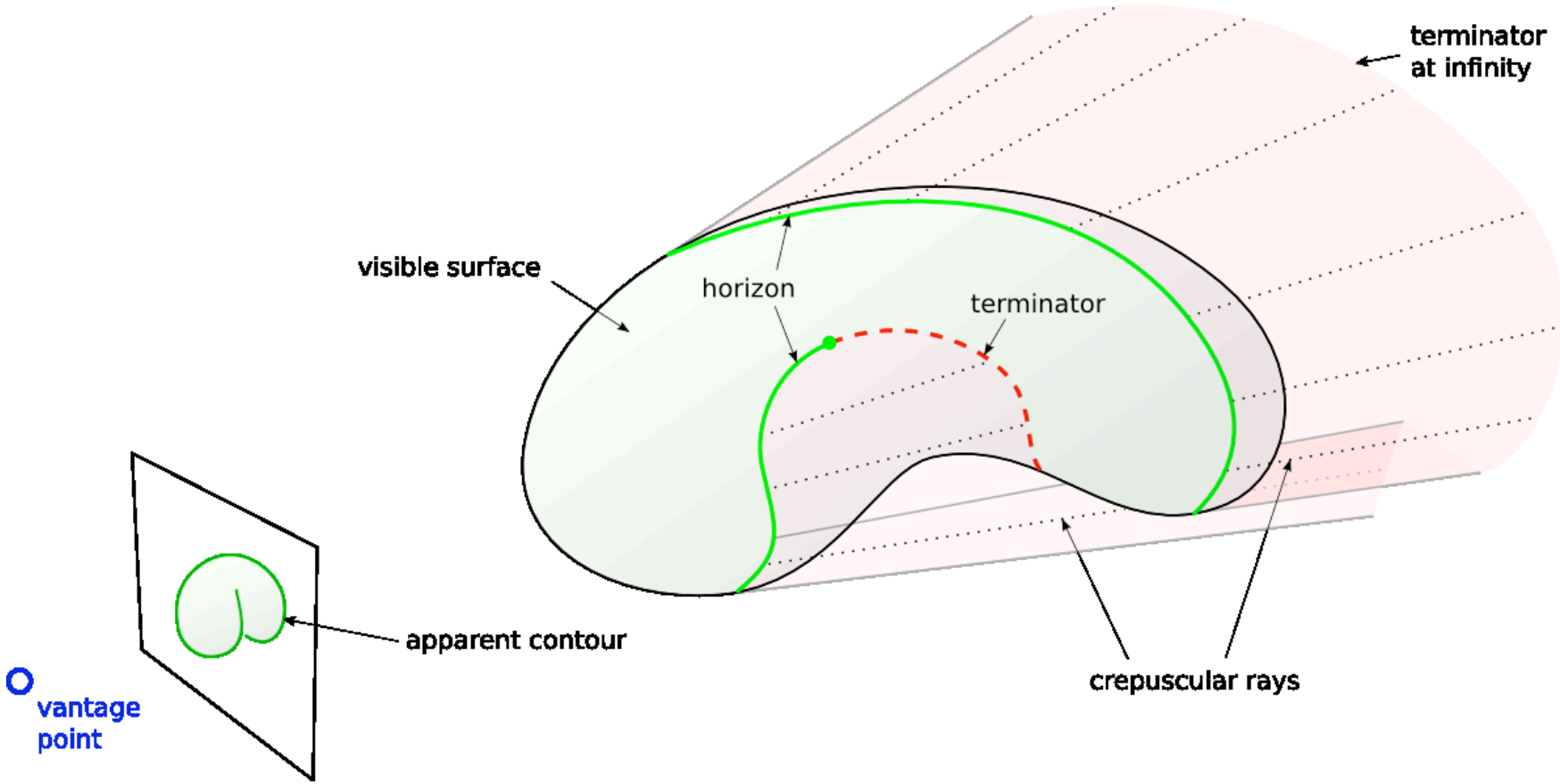
Difference: the visibility term (depends on the surface globally)

Concequence: weighed area minimization methods not applicable

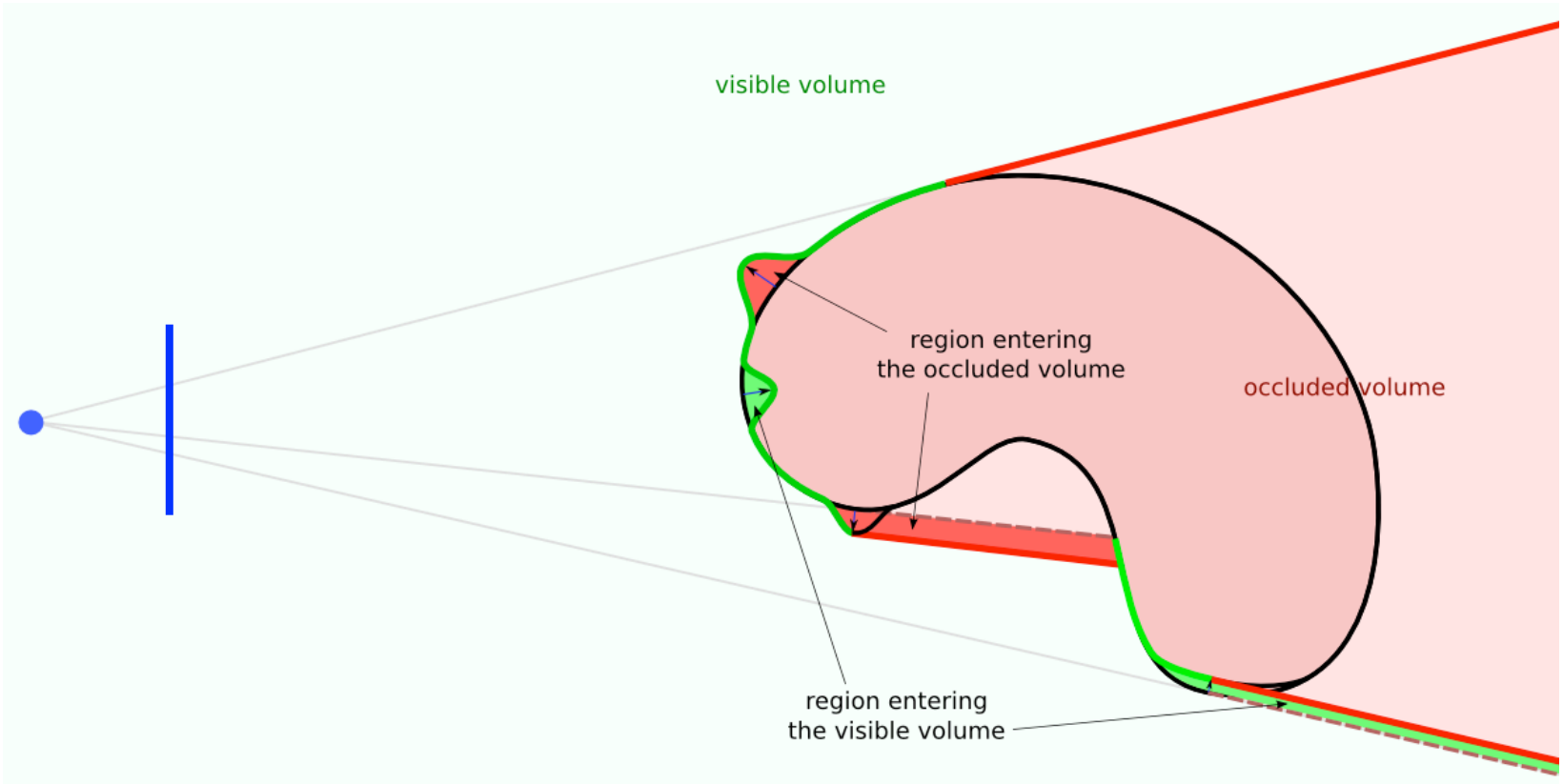
Visible Volume Geometry



Visible Volume Geometry



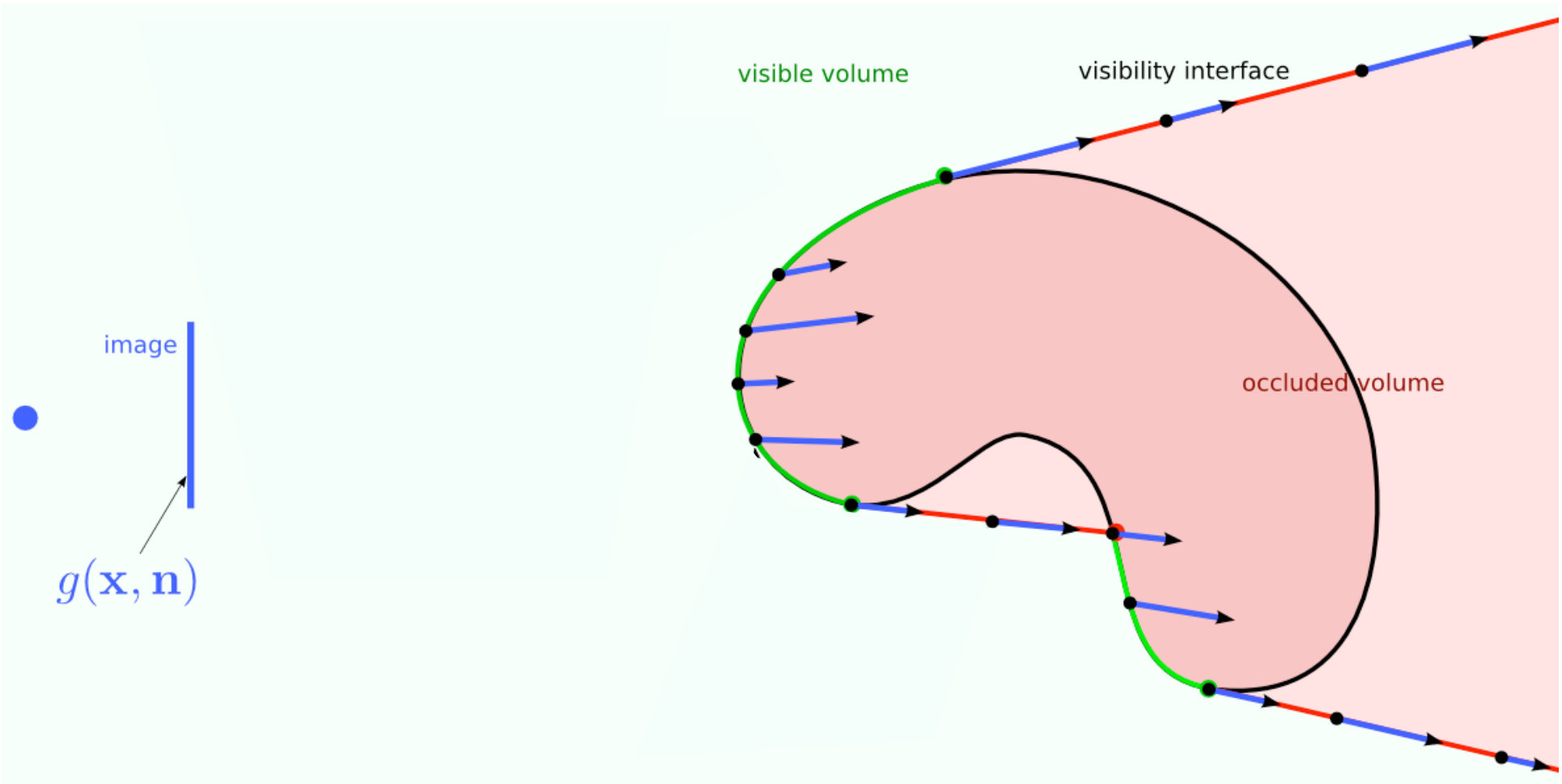
Derivative of a Quantity Integrated over the Visible Volume



$$F(\Gamma) = \int_{\mathbb{R}^3} f(\mathbf{x}) \nu_\Gamma(\mathbf{x}) d\mathbf{x}$$

$$dF(\Gamma) = -f\ \nu_\Gamma\ -\ L\ \mathbf{x}^t D\mathbf{n}\mathbf{x}\ \delta(\mathbf{x}\cdot\mathbf{n})\ \nu_\Gamma \qquad L(\mathbf{x}) = \int_1^{T_\mathbf{x}} f(r\mathbf{x}) r^2\, dr$$

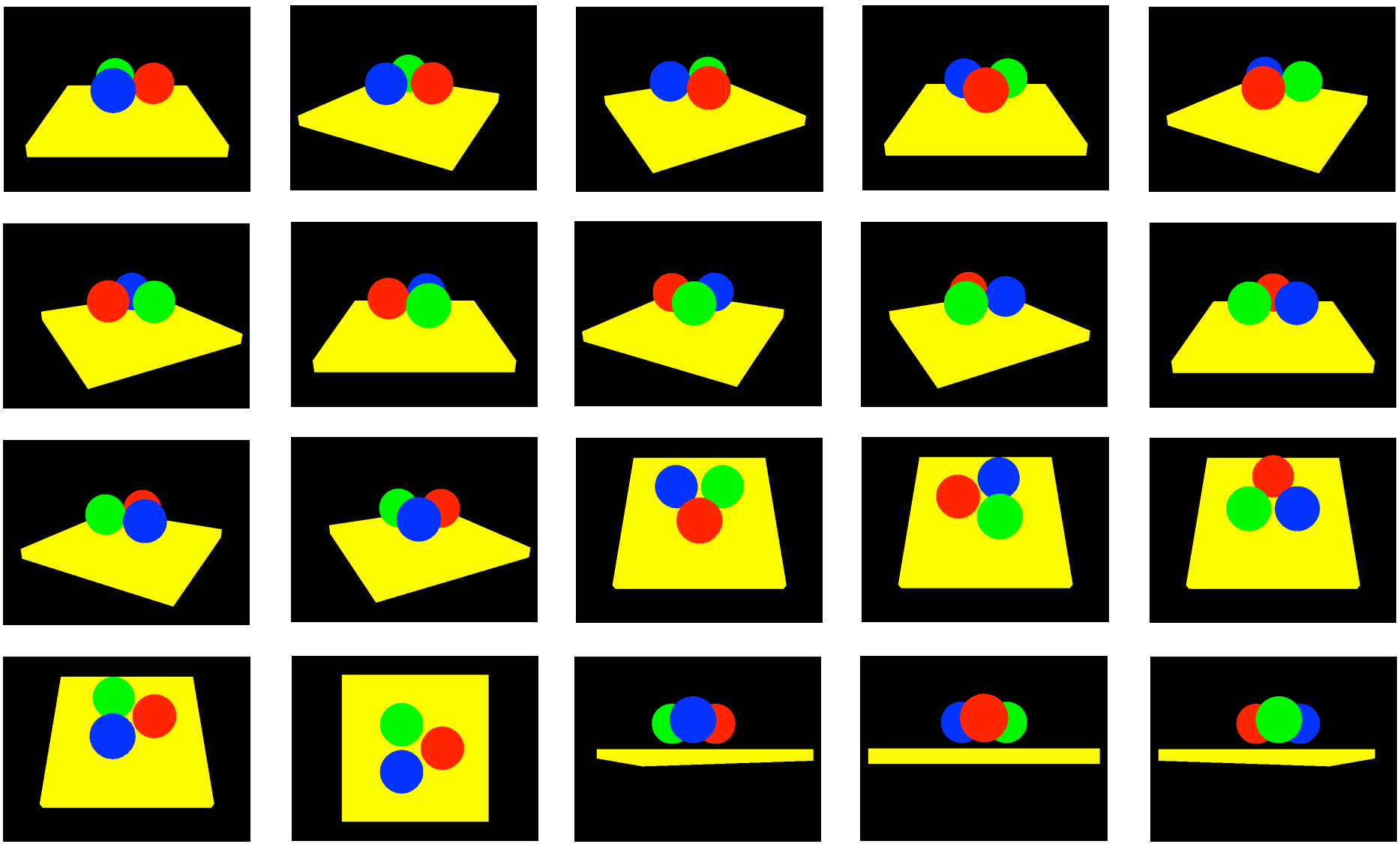
Derivative of the Reprojection Error



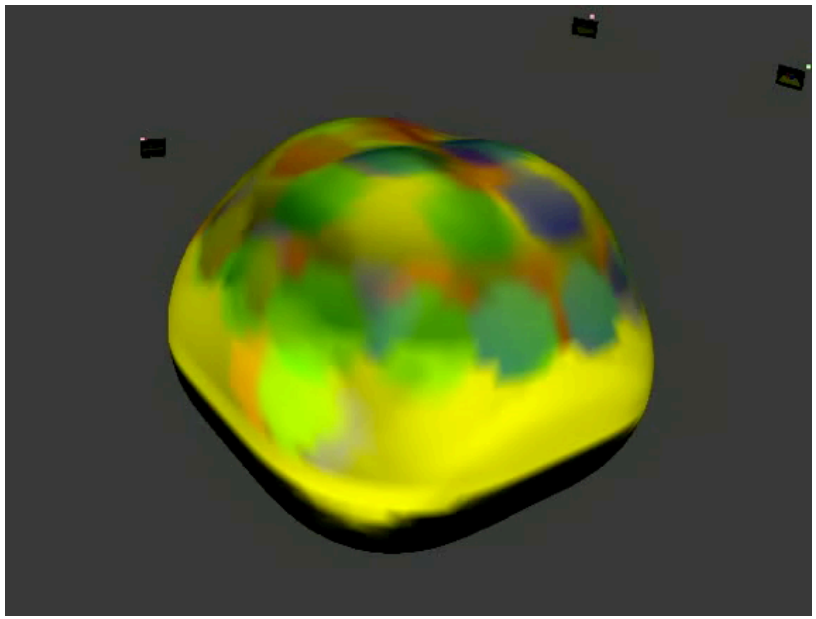
$$dE(\Gamma) = -\nabla g \cdot \frac{\mathbf{x}}{\mathbf{x}_z^3}\nu_\Gamma + (g - g')\frac{\mathbf{x}^t \nabla \mathbf{n}\mathbf{x}}{\mathbf{x}_z^3}\delta(\mathbf{x}\cdot\mathbf{n})\nu_\Gamma$$

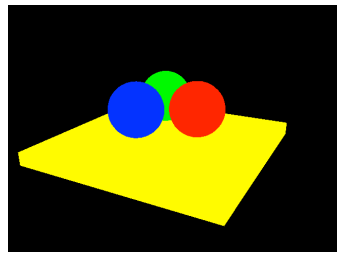
Recall: $dF(\Gamma) = -f\ \nu_\Gamma\ -\ L\ \mathbf{x}^t D\mathbf{n}\mathbf{x}\ \delta(\mathbf{x}\cdot\mathbf{n})\ \nu_\Gamma$

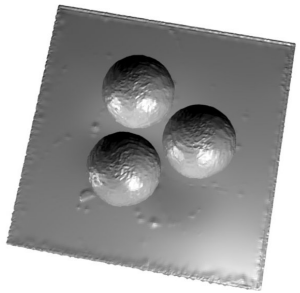
Synthetic Images

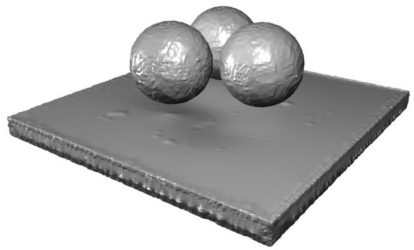


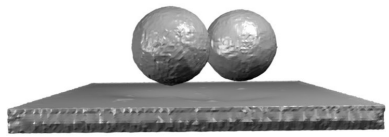
Synthetic Images

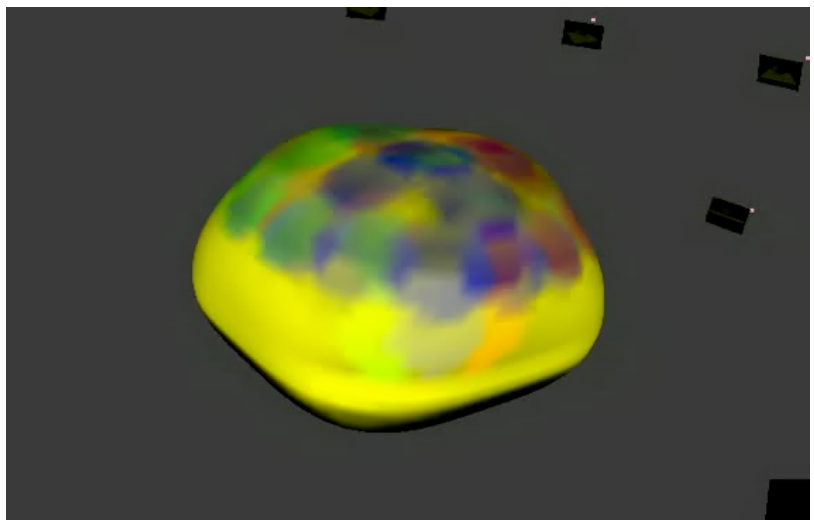


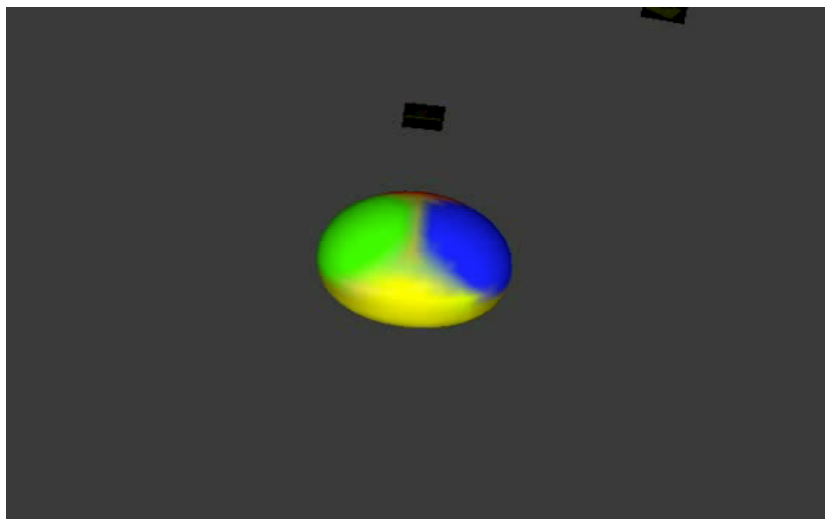






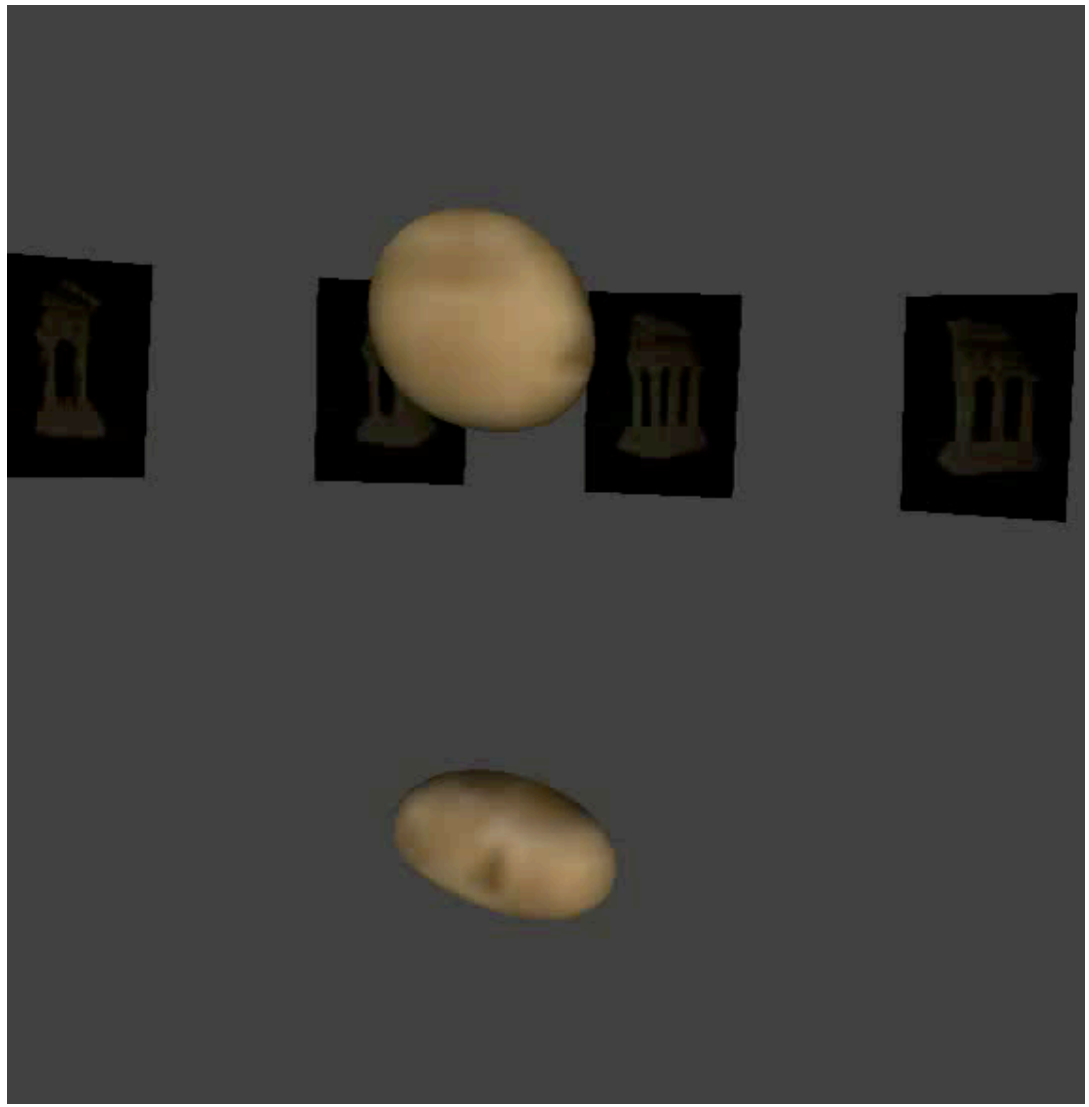






Temple Sparse Ring



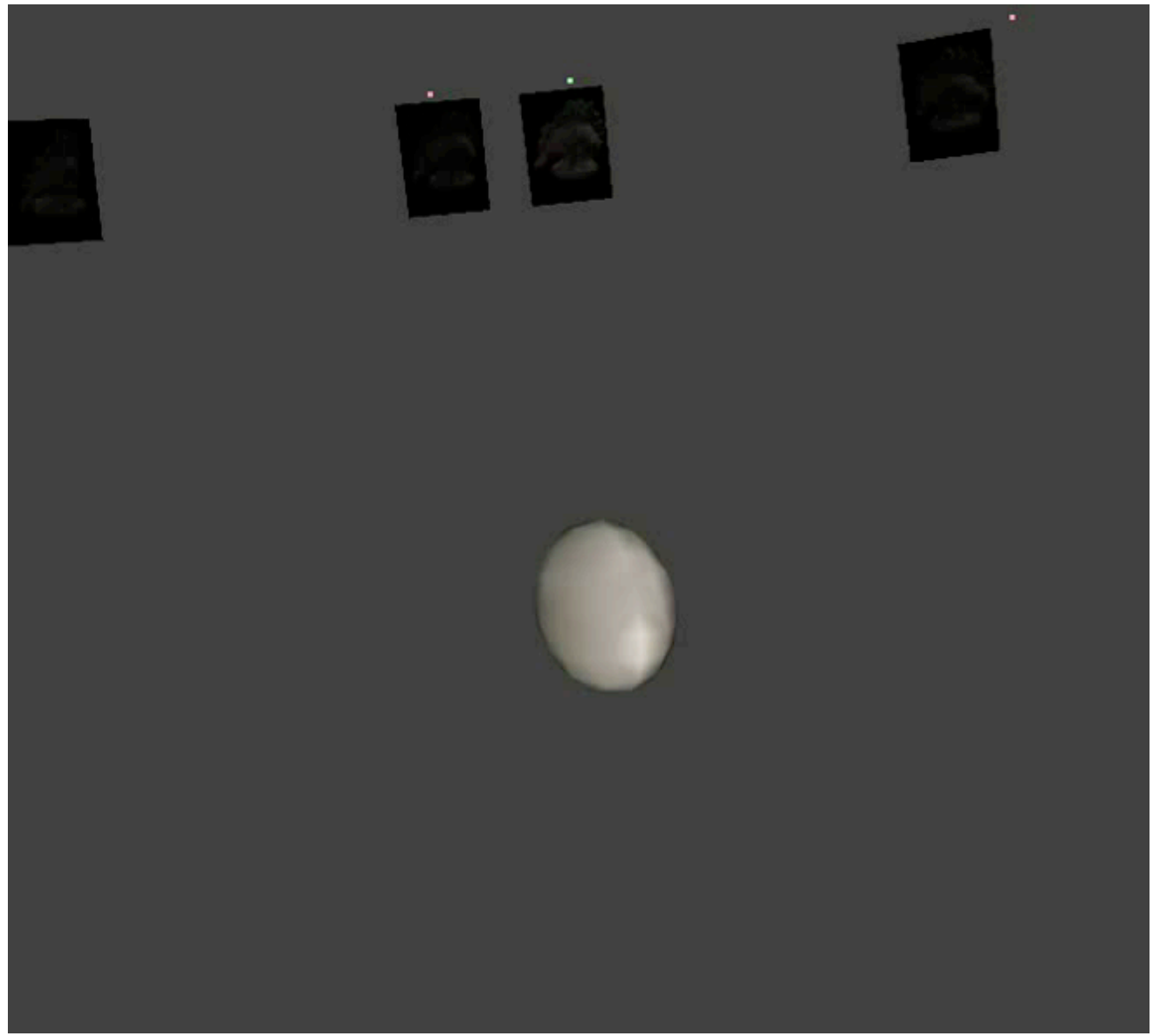


Dino Sparse Ring









The Constant Brightness Assumption

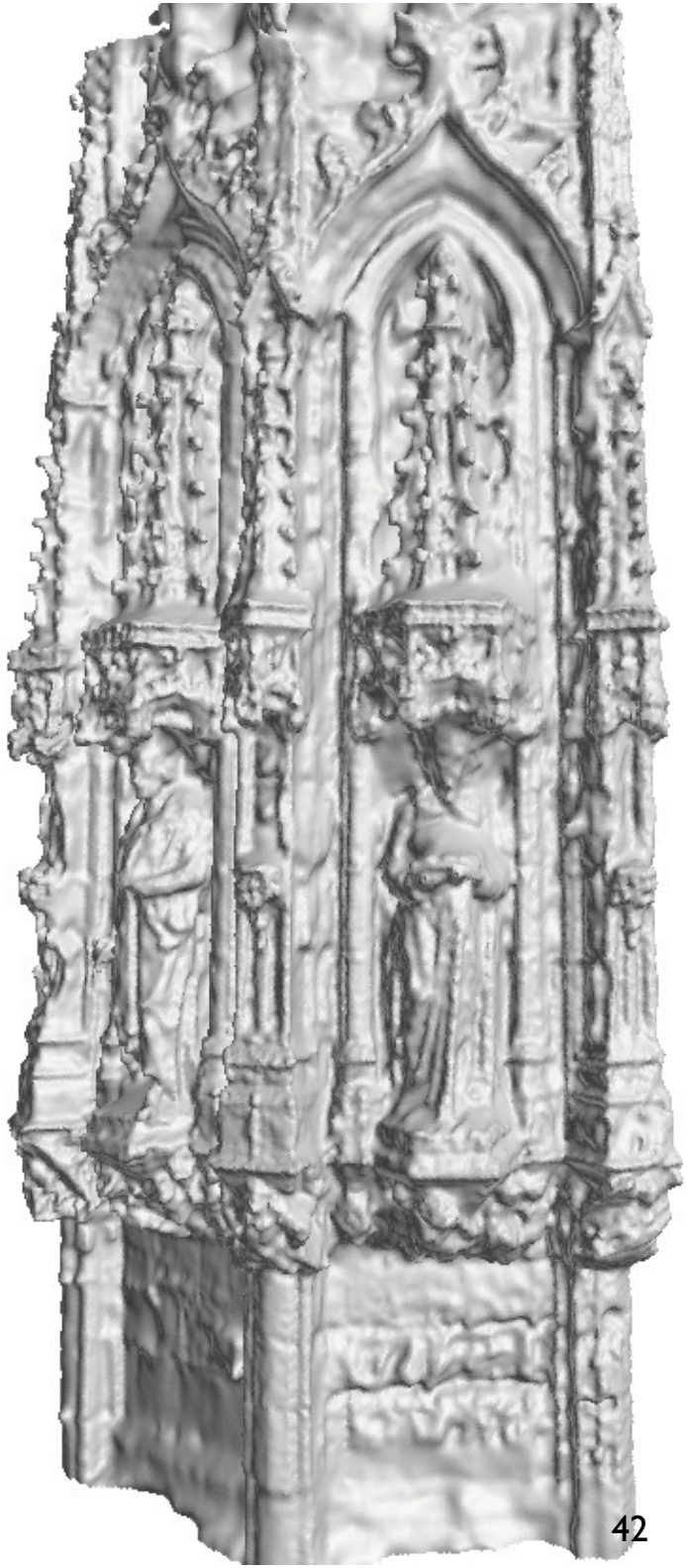


Leuven

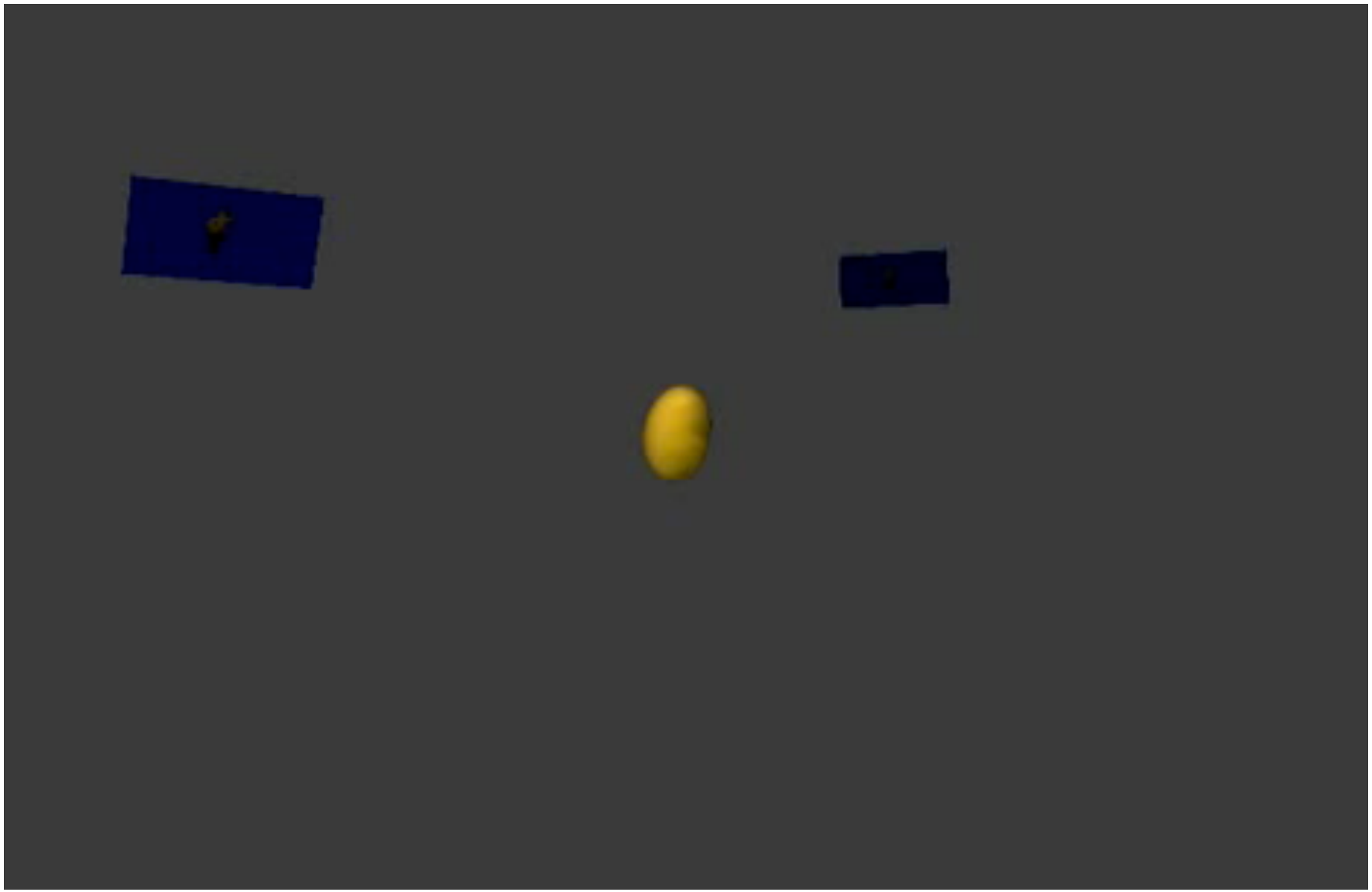


750x500x500 voxels
2M+ triangles





Break



[Hilton and Starck]

Conclusion

- The reprojection error is not equivalent to the weighted area
- Minimizing it implies taking into account visibility changes
- Consequence: The surface's contour generators tend to align with the images' apparent contours
  - No need for additional silhouettes or apparent contour constraints

Summary and Conclusion

- Summary:
  - Multiple Depth Maps
  - Occupancy–Depth discreet
  - Occupancy–Depth continuous

Image likelihood must be computed on the image domain

Avoids biases and the need for additional constraints

- Visibility has to be included in the modeling and the optimization

Future Work

- Better algorithms:
  - could be graph cuts or relaxation methods
- Better models:
  - Better likelihood:
    - Model light reflections
  - Better prior:
    - Specially relating shape and color

The end