

# Practical SVBRDF Acquisition of 3D Objects with Unstructured Flash Photography

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† KAIST

§ Universidad de Zaragoza, I3A

# Input & Output



Unstructured flash photographs



3D geometry

# Input & Output



Unstructured flash photographs



Spatially-varying BRDF

# Input & Output



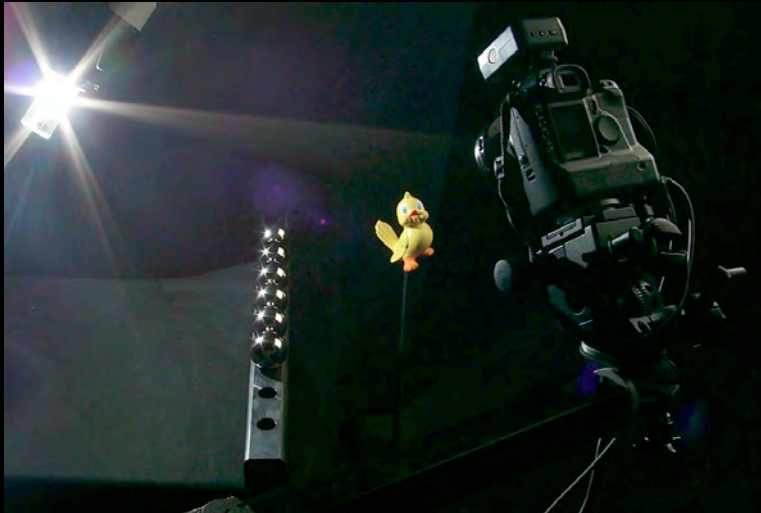
Unstructured flash photographs



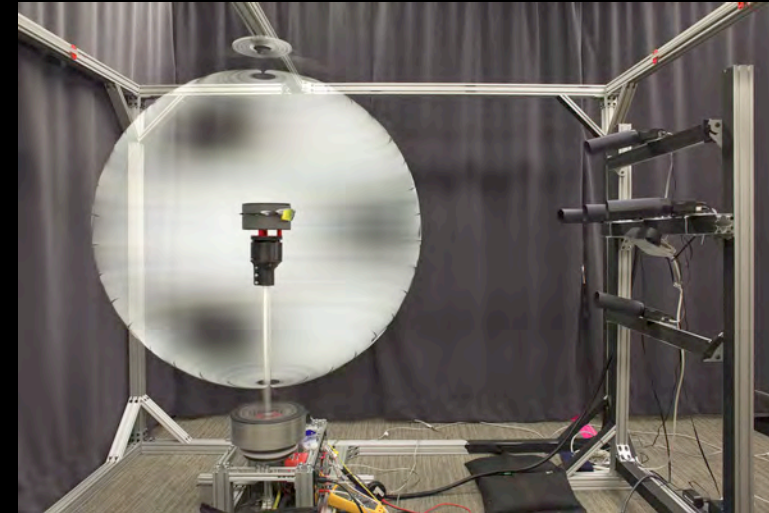
Reproduction in a virtual environment



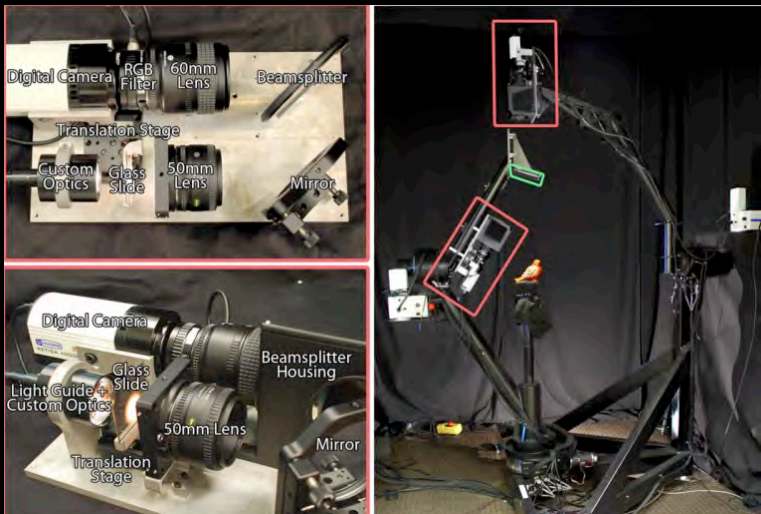
# Previous Work



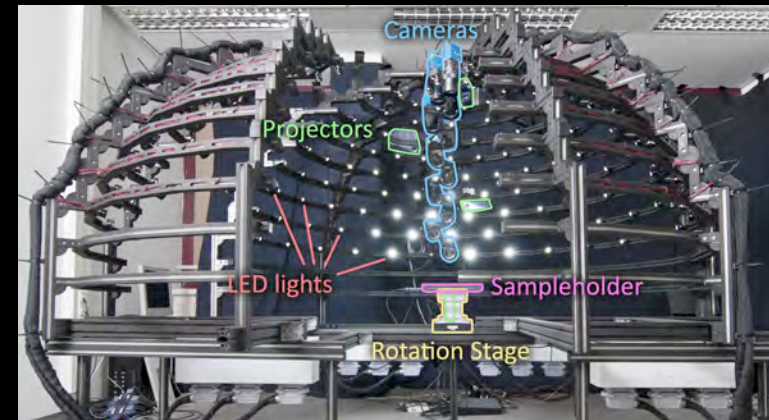
[Lensch et al., 2003]



[Tunwattanapong et al., 2013]

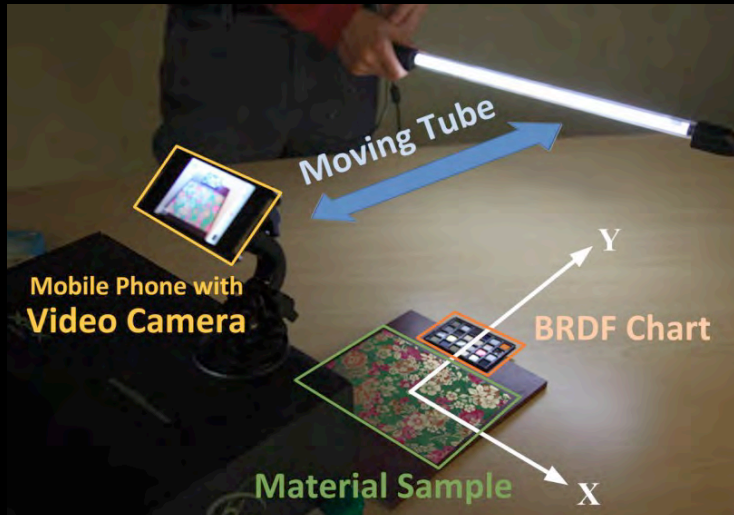


[Holroyd et al., 2010]



[Schwartz et al., 2013]

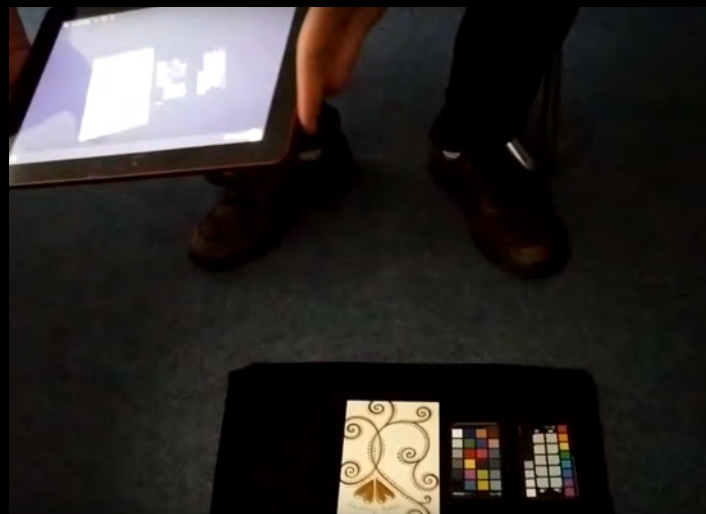
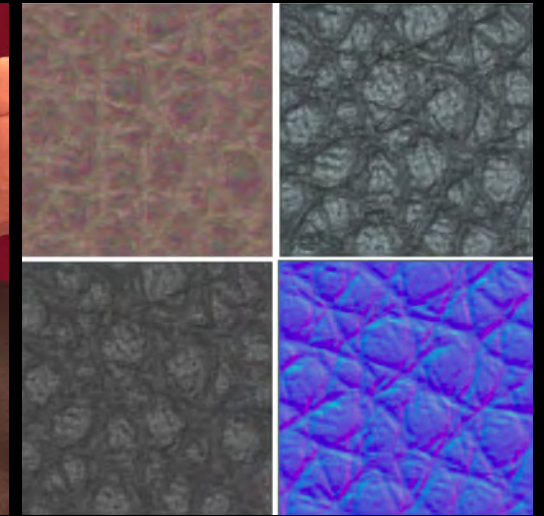
# Previous Work



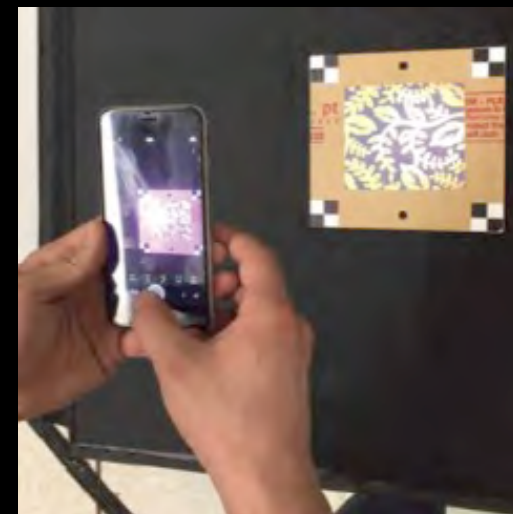
[Ren et al., 2011]



[Aittala et al., 2015]



[Riviere et al., 2015]



[Hui et al., 2017]

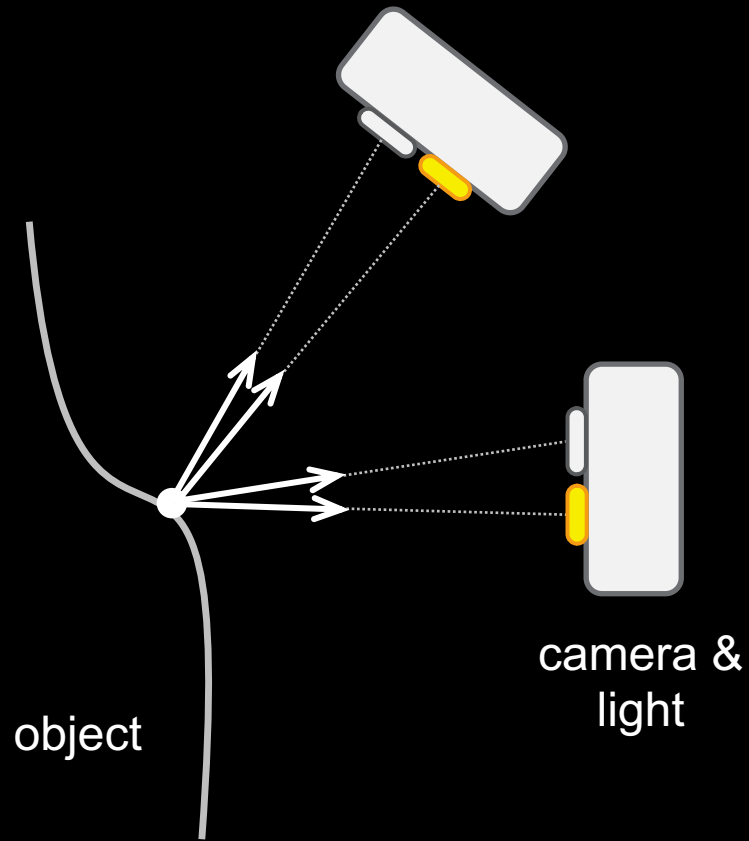




# Challenges

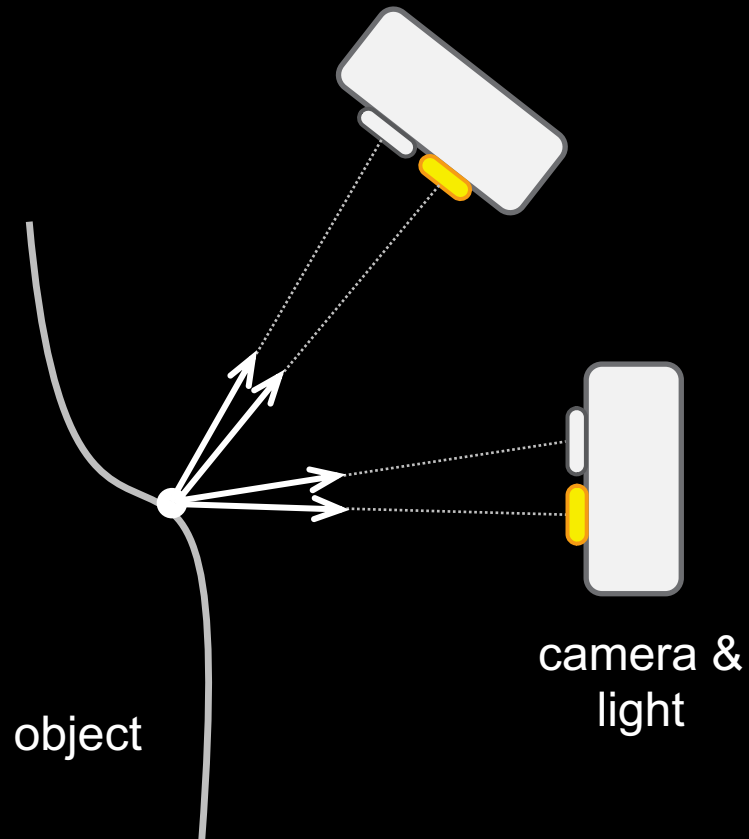
- Limited sampling angles for BRDF acquisition

How can we reconstruct a full BRDF from retro-reflected observations?



# Challenges

- Simultaneous acquisition of SVBRDF and 3D geometry



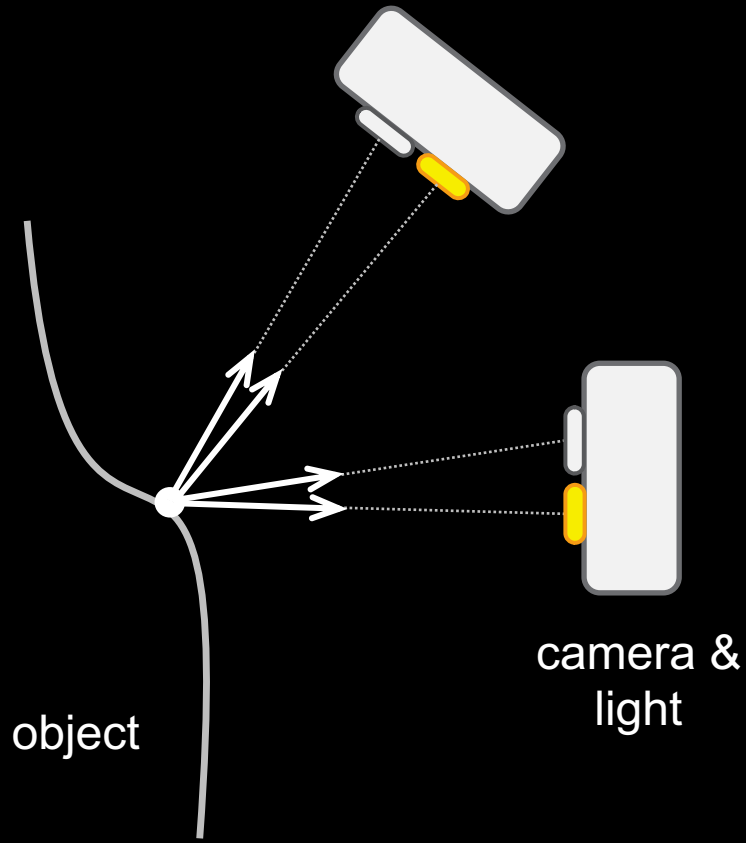
How can we ensure 3D-2D correspondence?



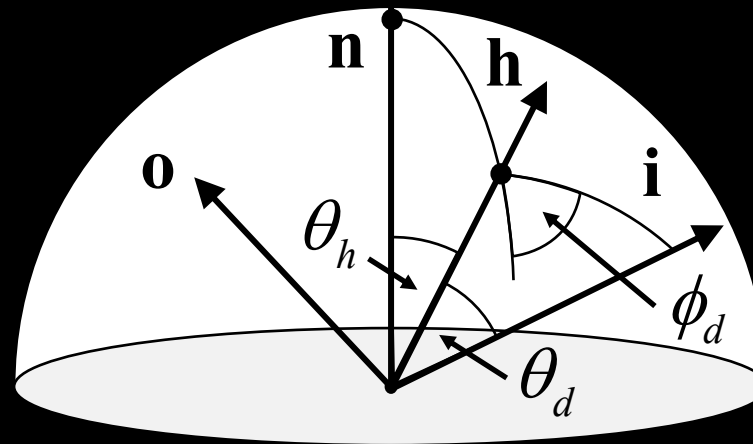


# BRDF Acquisition from Flash Photography

- Parameter space for isotropic BRDFs

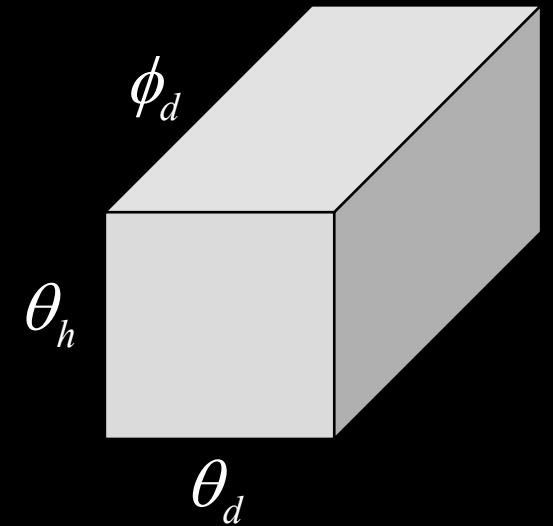


$$f(\mathbf{i}, \mathbf{o}) = f(\theta_h, \theta_d, \phi_d)$$



[Rusinkiewicz 98]

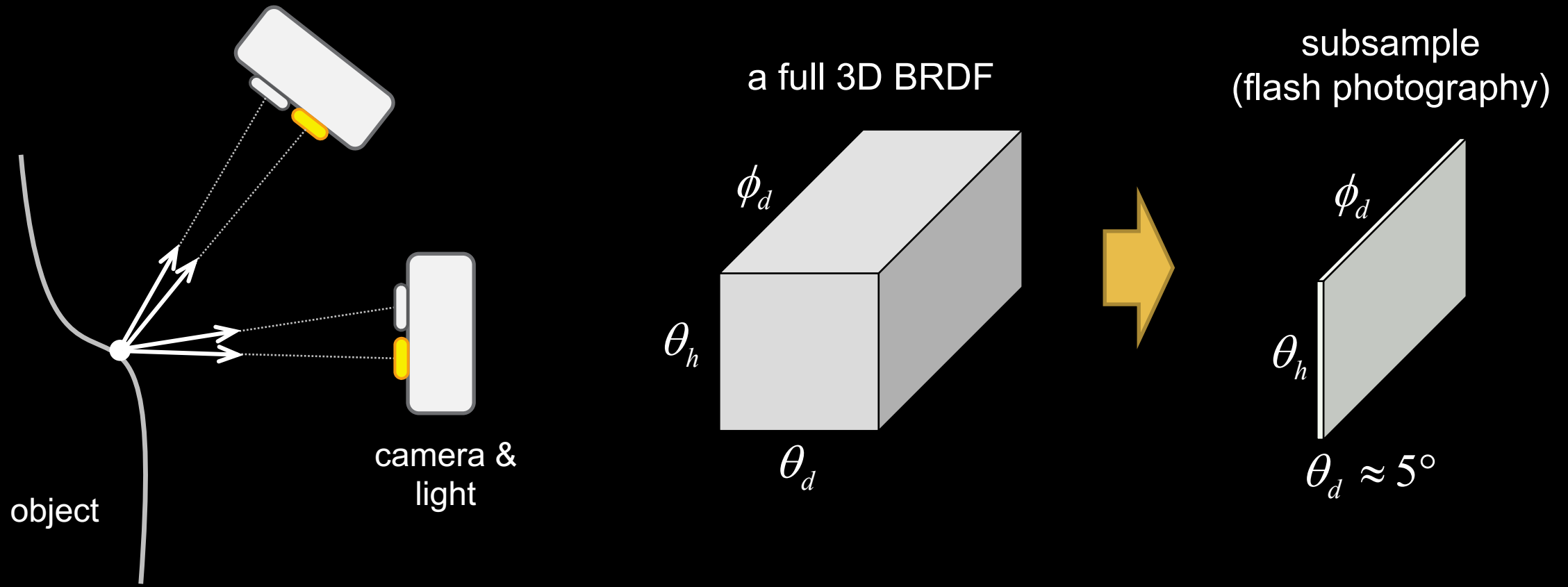
a 3D BRDF data



[Matusik 02]

# BRDF Acquisition from Flash Photography

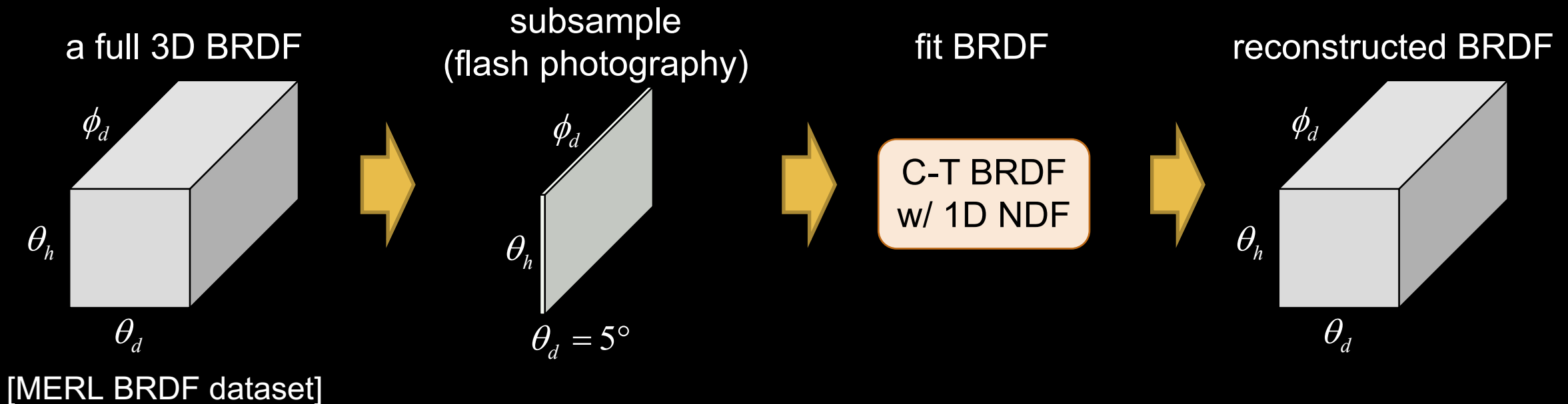
- Limited BRDF sampling angle in flash photography



# BRDF Model Validation

- Cook-Torrance BRDF with 1D data-driven NDF

$$f(\mathbf{i}, \mathbf{o}) = \frac{\rho_d}{\pi} + \rho_s \frac{D(\mathbf{h})G(\mathbf{n}, \mathbf{i}, \mathbf{o})F(\mathbf{h}, \mathbf{i})}{4(\mathbf{n} \cdot \mathbf{i})(\mathbf{n} \cdot \mathbf{o})}$$

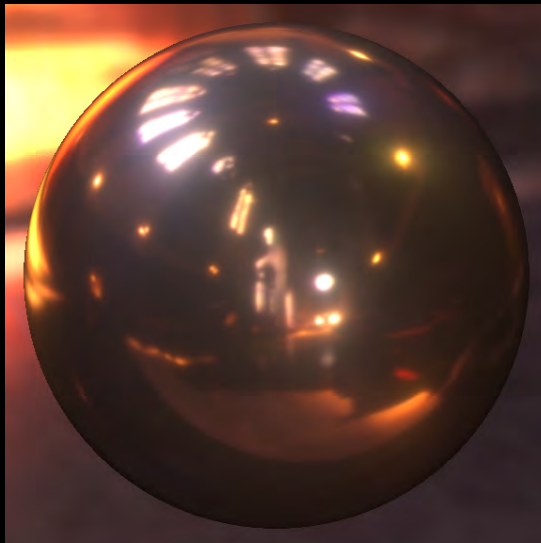




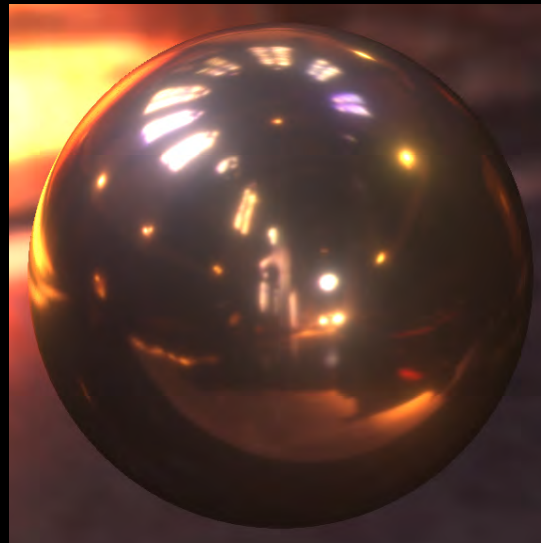
# BRDF Model Validation

- Cook-Torrance BRDF with 1D data-driven NDF

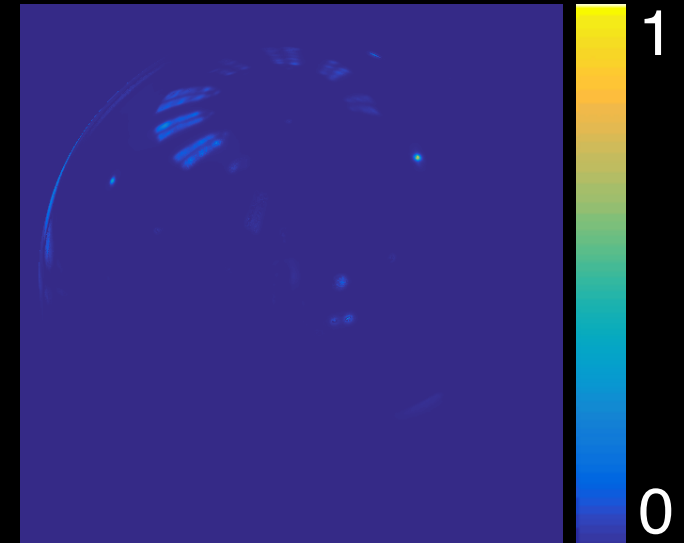
$$f(\mathbf{i}, \mathbf{o}) = \frac{\rho_d}{\pi} + \rho_s \frac{D(\mathbf{h})G(\mathbf{n}, \mathbf{i}, \mathbf{o})F(\mathbf{h}, \mathbf{i})}{4(\mathbf{n} \cdot \mathbf{i})(\mathbf{n} \cdot \mathbf{o})}$$



reference



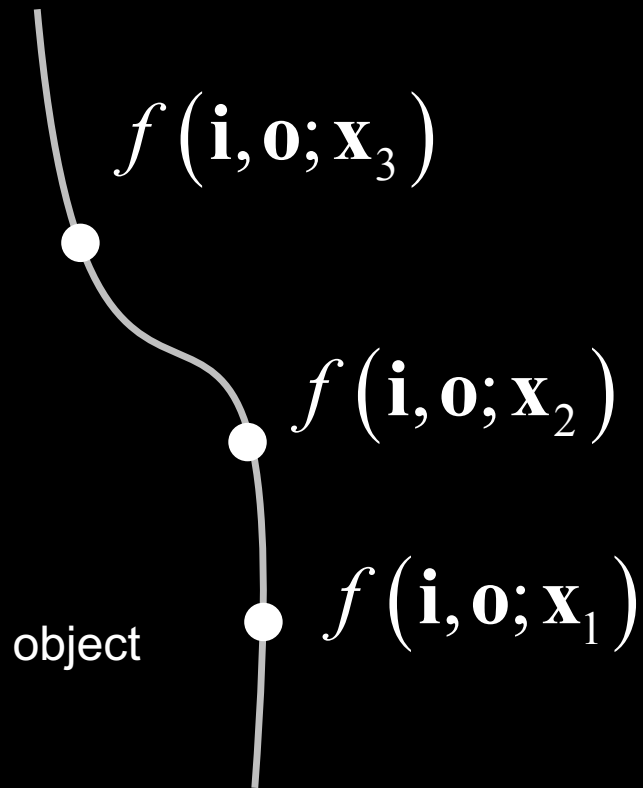
reconstructed



difference

# SVBRDF Representation

- Basis BRDFs and spatial blending weights



$$f(\mathbf{i}, \mathbf{o}; \mathbf{x}) = \sum_{b=1}^B \omega_b f_b(\mathbf{i}, \mathbf{o})$$

$f(\mathbf{i}, \mathbf{o}; \mathbf{x})$ : SVBRDF

$f_b(\mathbf{i}, \mathbf{o})$ : basis BRDF

$\omega$ : blending weight

$B$ : # of basis BRDFs

# Problem Definition

- Objective function using photometric consistency

minimize  
 $\mathbf{X}, \mathbf{N}, \mathbf{W}, \mathbf{F}_b$



photographs

—



rendering

2

$\mathbf{X}$ : 3D vertices

$\mathbf{N}$ : surface normals

$\mathbf{W}$ : blending weights

$\mathbf{F}_b$ : basis BRDFs



# Problem Definition

- Objective function using photometric consistency

$$\underset{\mathbf{X}, \mathbf{N}, \mathbf{W}, \mathbf{F}_b}{\text{minimize}} \sum_{p=1}^P \sum_{k=1}^K \left( L(\mathbf{o}; \mathbf{x}) - f(\mathbf{i}, \mathbf{o}; \mathbf{x}) L(-\mathbf{i}; \mathbf{x}) (\mathbf{n} \cdot \mathbf{i}) \right)^2$$

for all images &  
for all 3D vertices

captured radiance

reconstructed radiance

$\mathbf{X}$ : 3D vertices

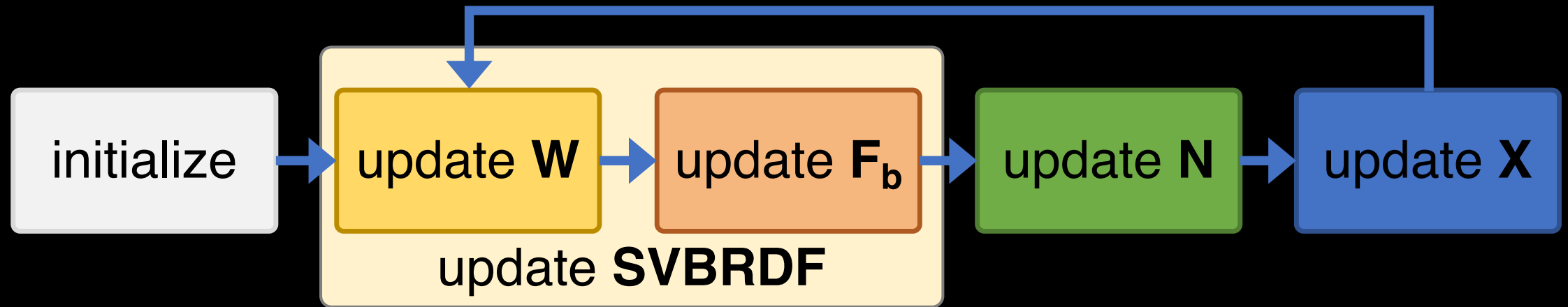
$\mathbf{N}$ : surface normals

$\mathbf{W}$ : blending weights

$\mathbf{F}_b$ : basis BRDFs

# Overview

- Iterative & alternating optimization of  $\{\mathbf{X}, \mathbf{N}, \mathbf{W}, \mathbf{F}_b\}$



$\mathbf{X}$ : 3D vertices

$\mathbf{N}$ : surface normals

$\mathbf{W}$ : blending weights

$\mathbf{F}_b$ : basis BRDFs

# Data Capture

- Any camera with a flash will work
- We test two types of cameras
  - Mobile phone with built-in LED
  - DSLR with built-in flash
- 100 - 200 images (still/video)

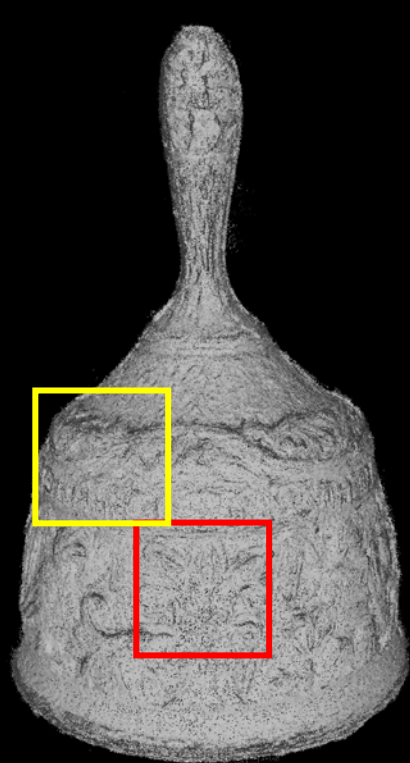


example images

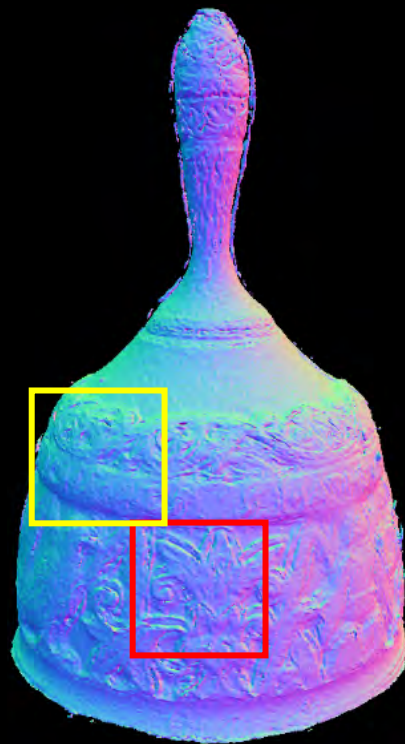


# Initialization

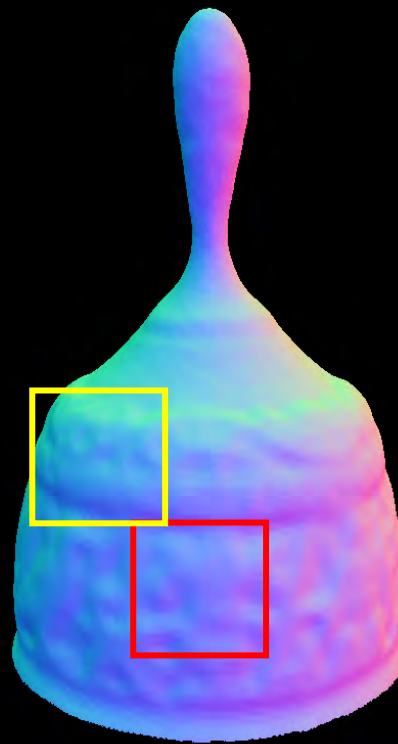
- Initial geometry from image-based 3D modeling  
COLMAP [Schönberger 2016]: SfM  $\rightarrow$  MVS  $\rightarrow$  meshing



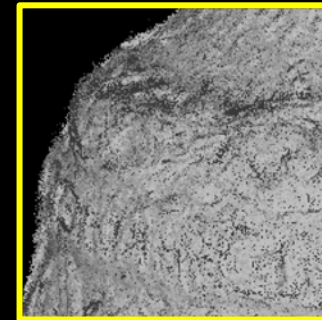
point cloud



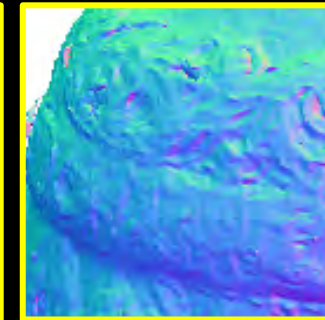
high-res mesh



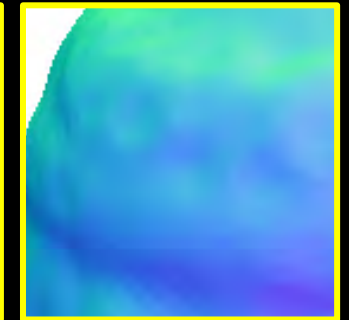
low-res mesh  
(our initial geo.)



point cloud



high-res mesh

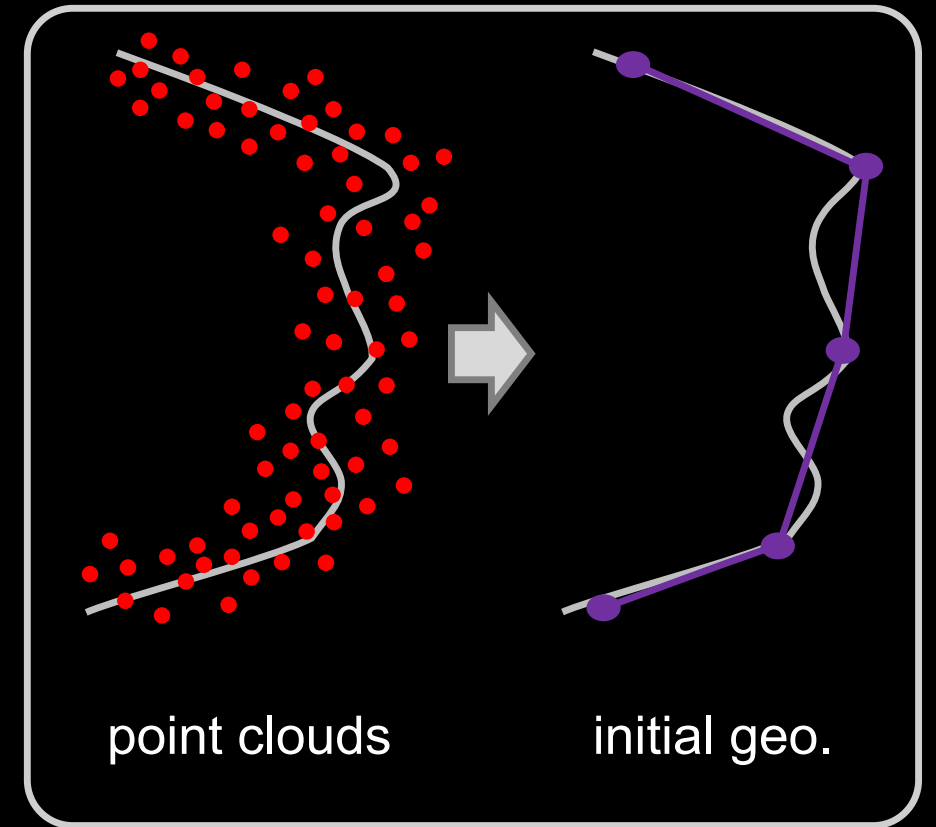
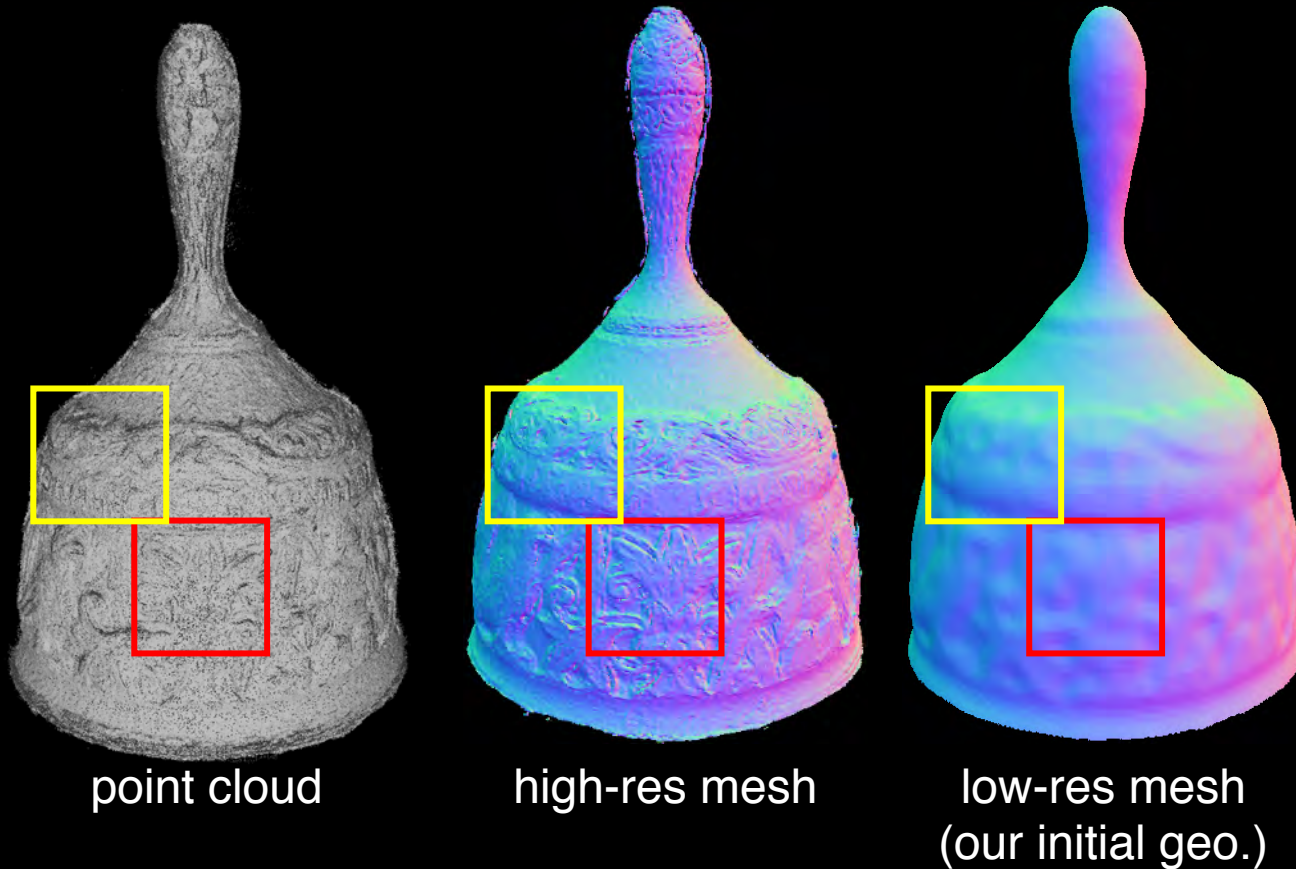


low-res mesh

# Initialization

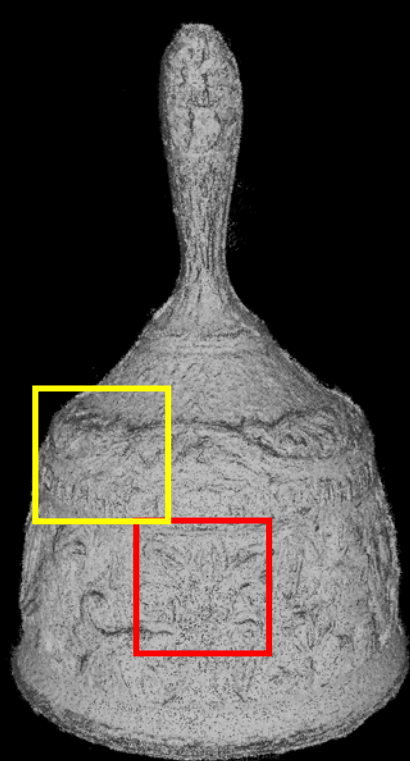
- Initial geometry from image-based 3D modeling

COLMAP [Schönberger 2016]: SfM  $\rightarrow$  MVS  $\rightarrow$  meshing

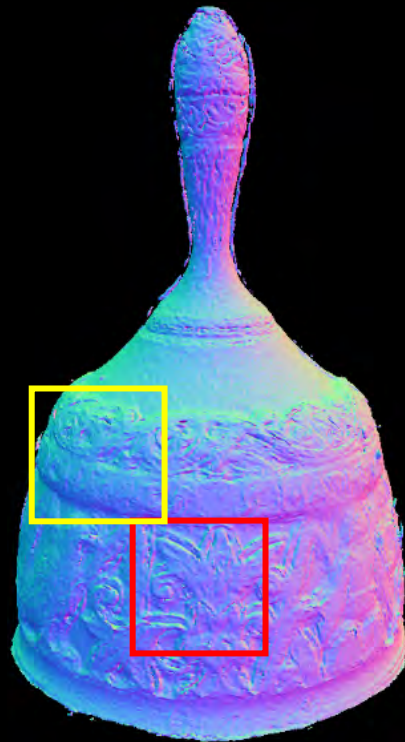


# Initialization

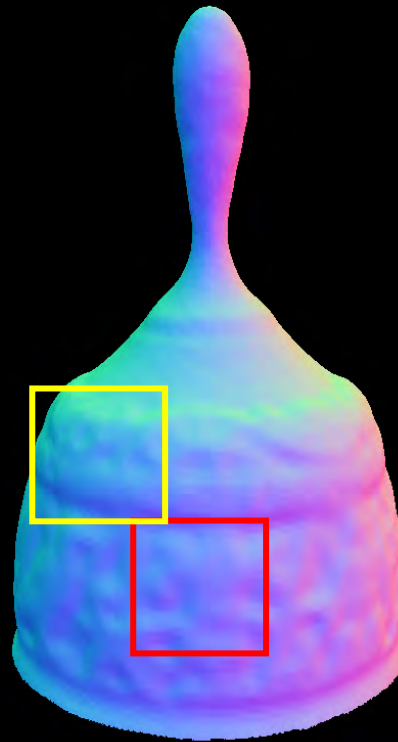
- Initial geometry from image-based 3D modeling  
COLMAP [Schönberger 2016]: SfM  $\rightarrow$  MVS  $\rightarrow$  meshing



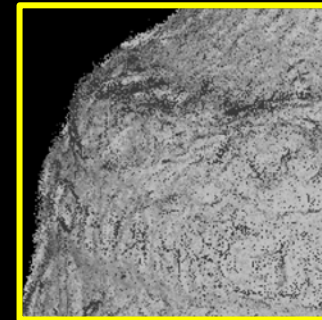
point cloud



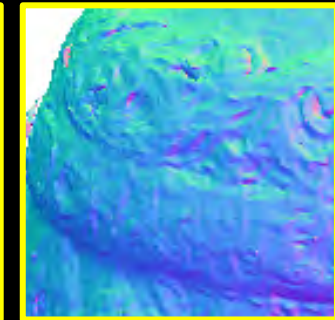
high-res mesh



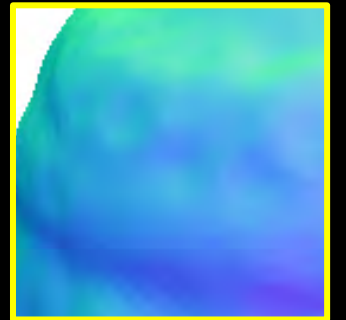
low-res mesh  
(our initial geo.)



point cloud



high-res mesh

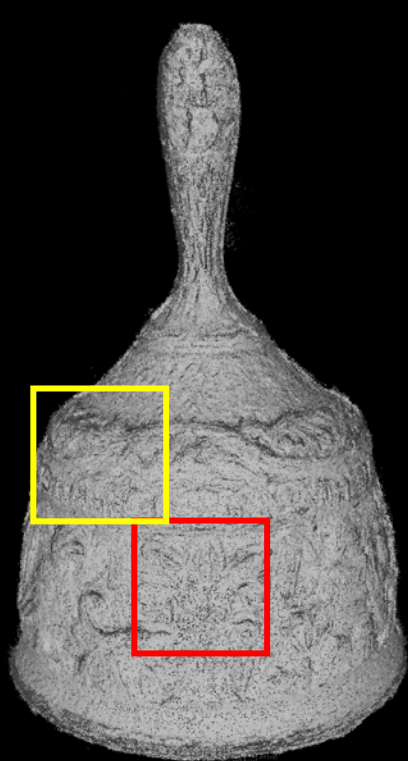


low-res mesh

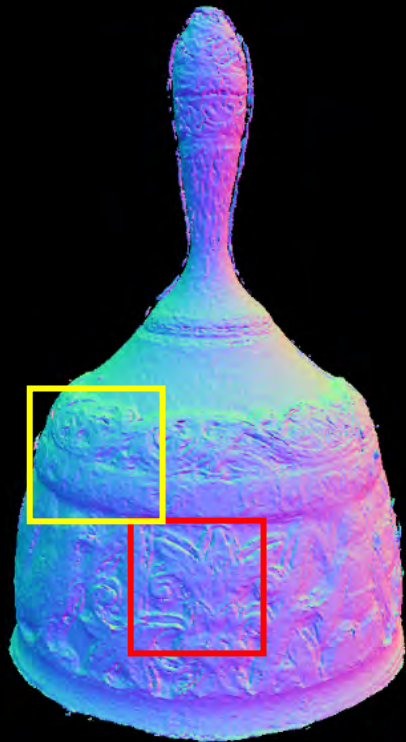


# Initialization

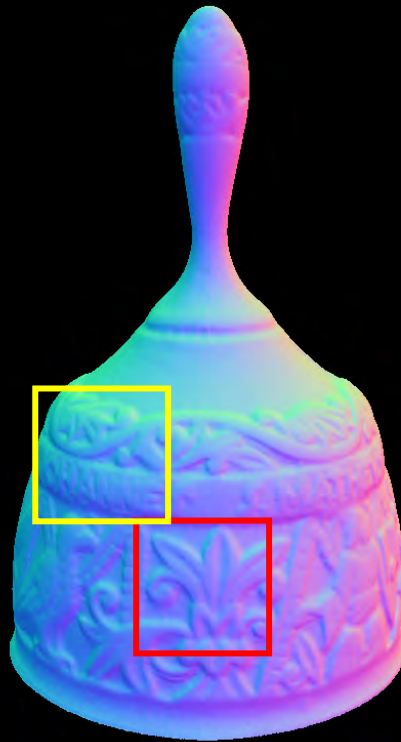
- Initial geometry from image-based 3D modeling  
COLMAP [Schönberger 2016]: SfM  $\rightarrow$  MVS  $\rightarrow$  meshing



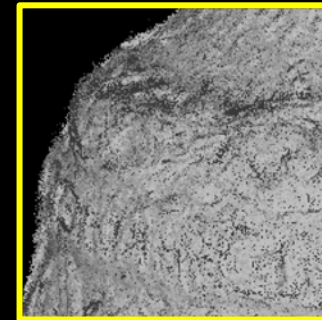
point cloud



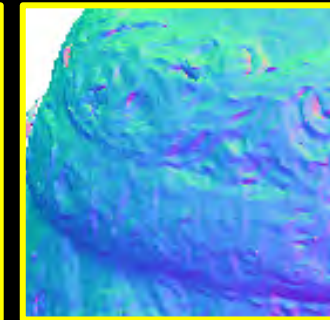
high-res mesh



our result



point cloud



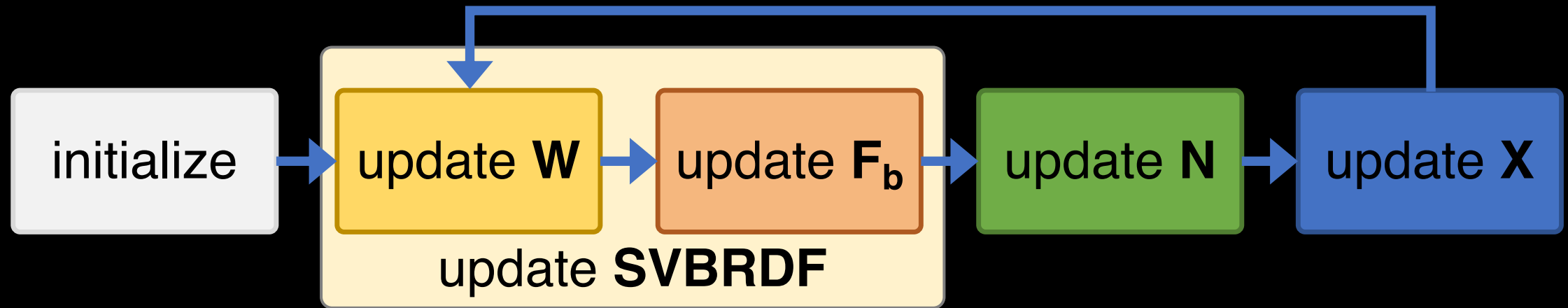
high-res mesh



our result

# Overview

- Iterative & alternating optimization of  $\{\mathbf{X}, \mathbf{N}, \mathbf{W}, \mathbf{F}_b\}$



$\mathbf{X}$ : 3D vertices

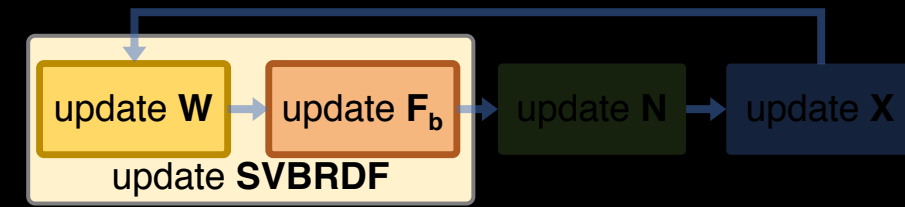
$\mathbf{N}$ : surface normals

$\mathbf{W}$ : blending weights

$\mathbf{F}_b$ : basis BRDFs



# Update SVBRDF



- Re-formulate the equation w.r.t. the reflectance

$$\underset{\mathbf{X}, \mathbf{N}, \mathbf{W}, \mathbf{F}_b}{\text{minimize}} \sum_{p=1}^P \sum_{k=1}^K \left( L(\mathbf{o}; \mathbf{x}) - f(\mathbf{i}, \mathbf{o}; \mathbf{x}) L(-\mathbf{i}; \mathbf{x}) (\mathbf{n} \cdot \mathbf{i}) \right)^2$$



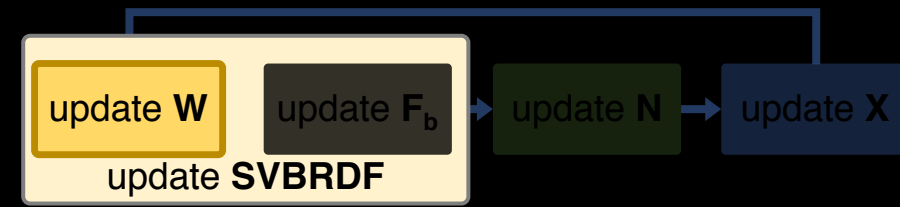
$$\underset{\mathbf{W}, \mathbf{F}_b}{\text{minimize}} \sum_{p=1}^P \sum_{k=1}^K v_{p,k} \left( \underbrace{f'_{p,k}}_{\text{captured reflectance}} - \Phi_{p,k} \sum_{b=1}^B \underbrace{\omega_{p,b} \mathbf{f}_b}_{\text{reconstructed reflectance}} \right)^2$$

$\mathbf{W}$ : blending weights  
 $\mathbf{F}_b$ : basis BRDFs

captured reflectance

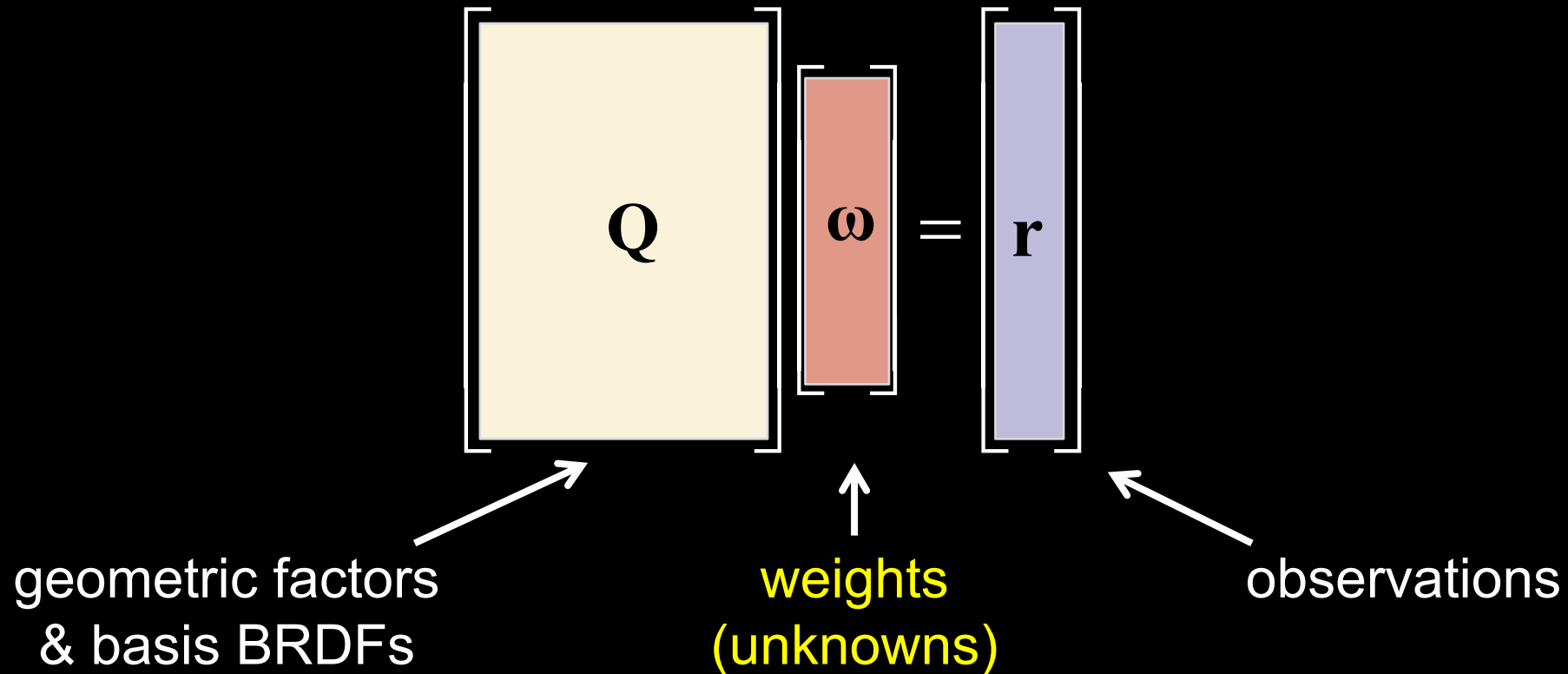
reconstructed reflectance

# Update SVBRDF: Blending Weights

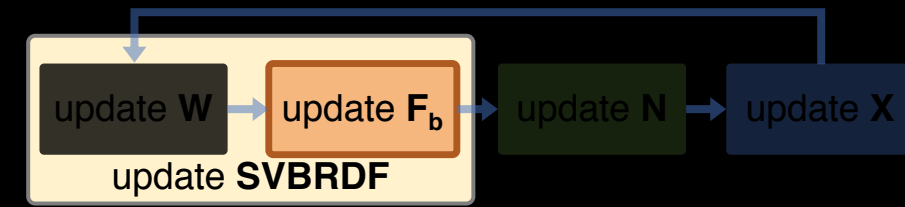


- Per-vertex optimization

$$\underset{\omega}{\text{minimize}} \frac{1}{2} \|\mathbf{Q}\omega - \mathbf{r}\|^2 \quad \text{s.t.} \quad \omega_b > 0, \quad \sum_{b=1}^B \omega_{p,b} = 1$$



# Update SVBRDF: Basis BRDFs

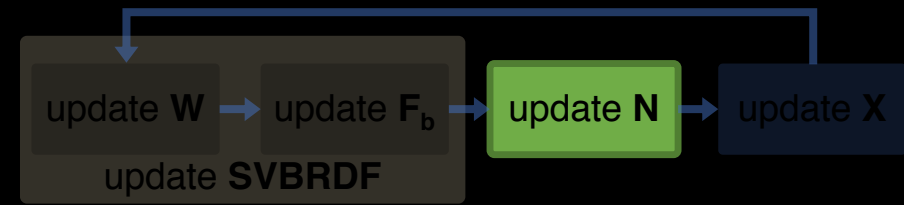


- Optimize for all observations (NOT per-vertex)
- Hold  $\mathbf{W}$  fixed and solve for  $\mathbf{F}_b$
- Sparse quadratic programming

$$\underset{\mathbf{F}_b}{\text{minimize}} \sum_{p=1}^P \sum_{k=1}^K v_{p,k} \left( \underbrace{f'_{p,k}}_{\text{observation}} - \underbrace{\Phi_{p,k}}_{\text{estimated weights}} \sum_{b=1}^B \underbrace{\omega_{p,b} \mathbf{f}_b}_{\text{basis BRDFs (unknowns)}} \right)^2$$

The equation shows the minimization of a squared error term. The term  $f'_{p,k}$  is labeled as 'observation'. The term  $\Phi_{p,k}$  is labeled as 'estimated weights'. The term  $\omega_{p,b} \mathbf{f}_b$  is labeled as 'basis BRDFs (unknowns)'. The entire expression is squared.

# Update Normals



- Per-vertex optimization

$$\underset{\mathbf{n}}{\text{minimize}} \sum_{k=1}^K \left( L(\mathbf{o}; \mathbf{x}) - f(\mathbf{i}, \mathbf{o}; \mathbf{x}, \mathbf{n}) L(-\mathbf{i}; \mathbf{x}) (\mathbf{n} \cdot \mathbf{i}) \right)^2$$

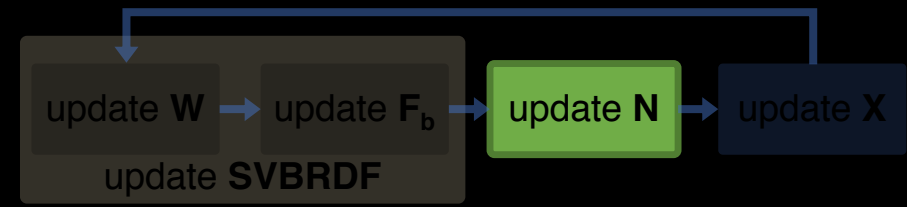
$K$ : # of images

normal for BRDF

normal for irradiance

- Non-linear optimization → hard to solve!

# Update Normals



- Per-vertex optimization

$$\underset{\mathbf{n}}{\text{minimize}} \sum_{k=1}^K \left( L(\mathbf{o}; \mathbf{x}) - f(\mathbf{i}, \mathbf{o}; \mathbf{x}, \mathbf{n}) L(-\mathbf{i}; \mathbf{x}) (\tilde{\mathbf{n}} \cdot \mathbf{i}) \right)^2$$

$K$ : # of images

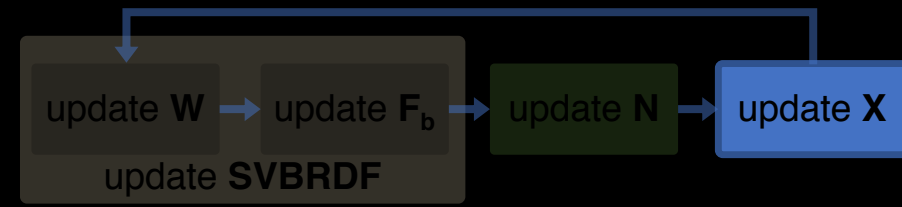
geometric normal  
( $\mathbf{n}$ , known)

shading normal  
( $\tilde{\mathbf{n}}$ , unknown)

- Linear regression → easy to solve!



# Update Geometry



- Screened Poisson surface reconstruction [Kazhdan 2015]

$$\underset{\chi}{\text{minimize}} \int \left\| \mathbf{V}(\mathbf{x}_p) - \nabla \chi(\mathbf{x}_p) \right\|^2 d\mathbf{x}_p + \alpha \sum_{\mathbf{x}_p \in \mathbf{X}} \chi^2(\mathbf{x}_p)$$

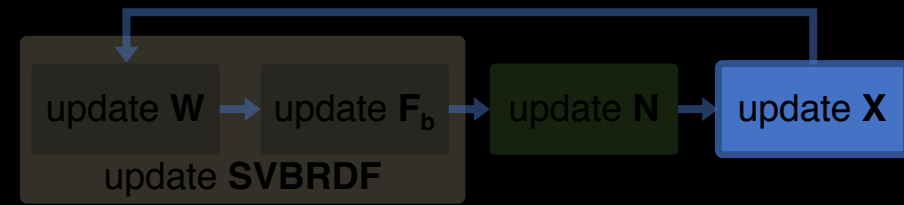
3D vector field from shading normals

gradient of new geometry

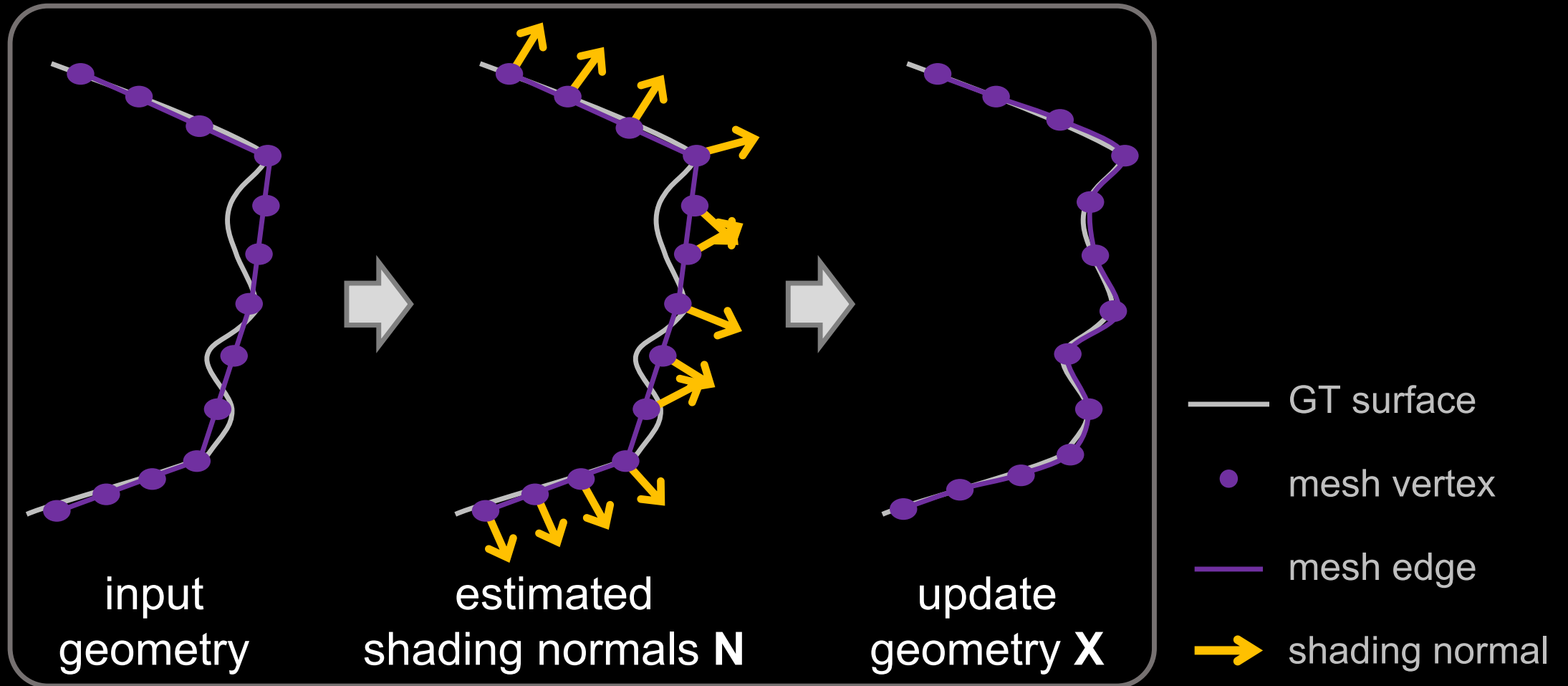
squared distance of current and new geometry

$\chi$  : new geometry (unknown)

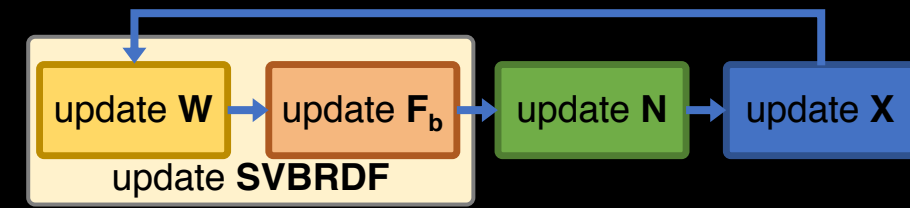
# Update Geometry



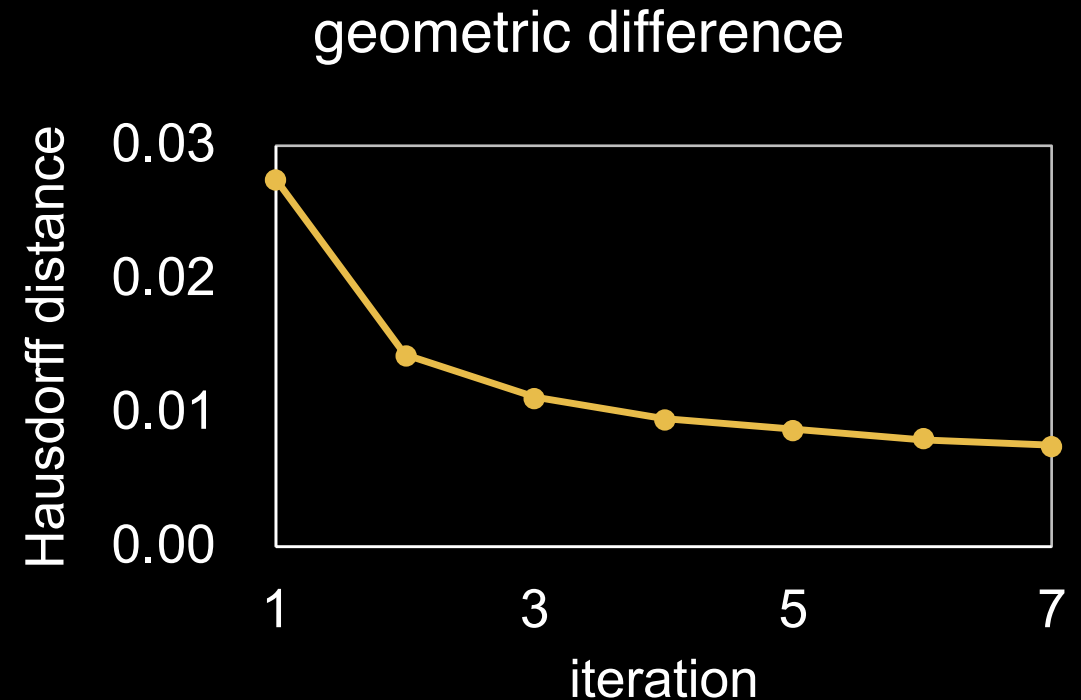
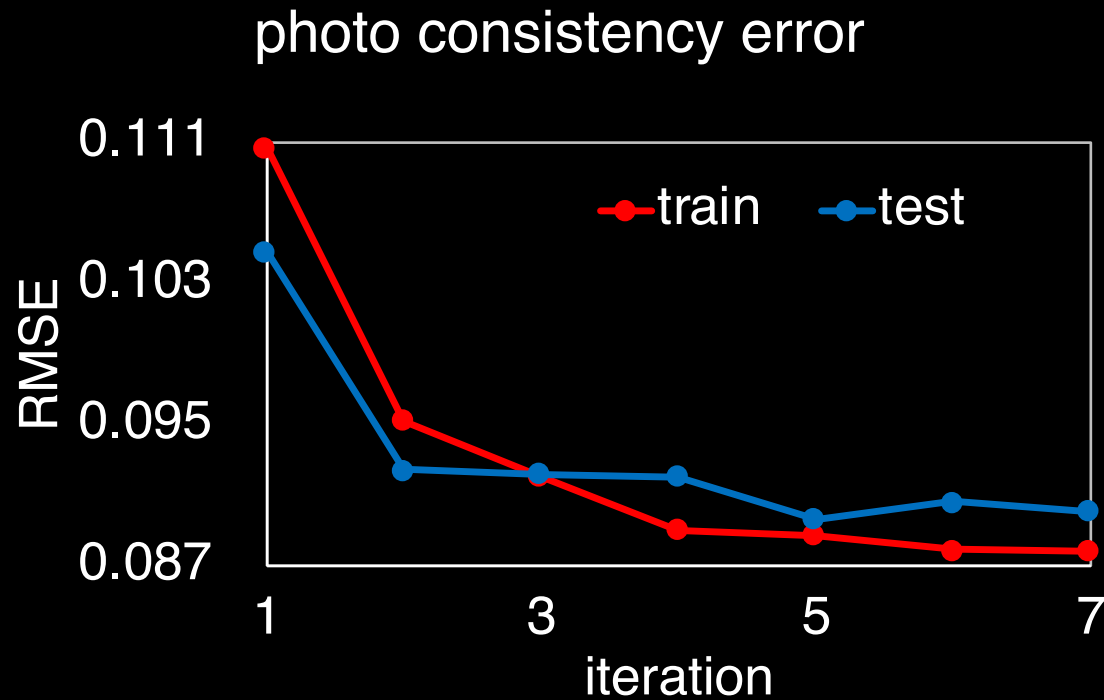
- Screened Poisson surface reconstruction [Kazhdan 2015]



# Iterative Optimization



- Iterate the whole process until RMSE of the test set starts to increase



# Results



point-light rendering



geometry



Env. rendering

# Results



point-light rendering



geometry



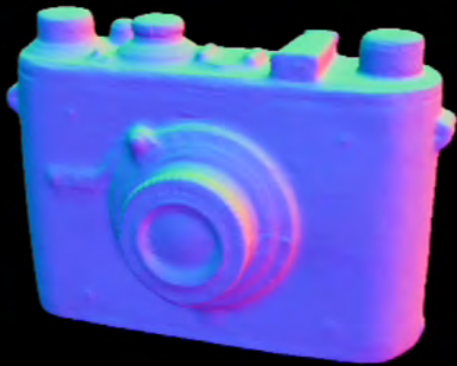
Env. rendering



# Results



point-light rendering



geometry

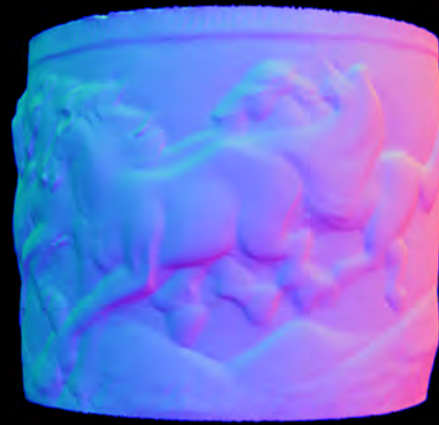


Env. rendering

# Comparison with Previous Work



reference  
(NextEngine)



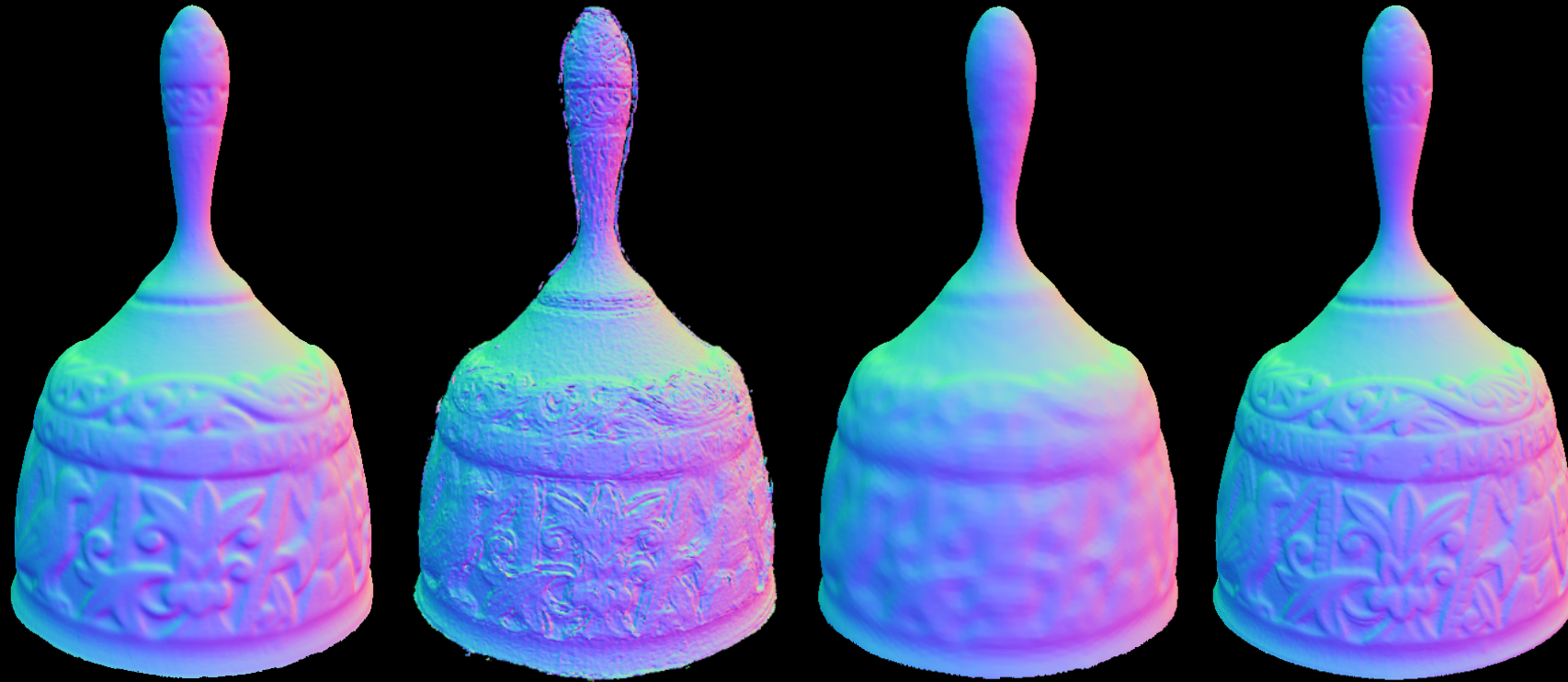
Xia SIGA'16  
(passive env. lighting)



Ours  
(active flashlight)



# Evaluation: Geometry Refinement



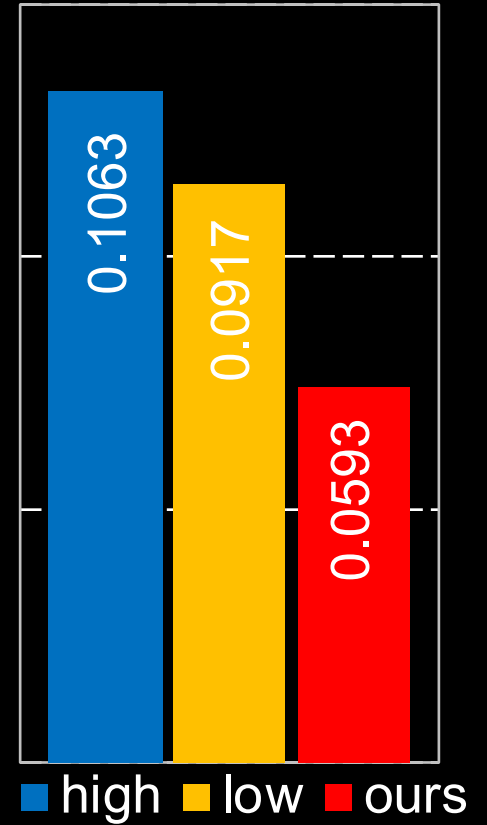
reference  
(NextEngine)

COLMAP  
(high res.)

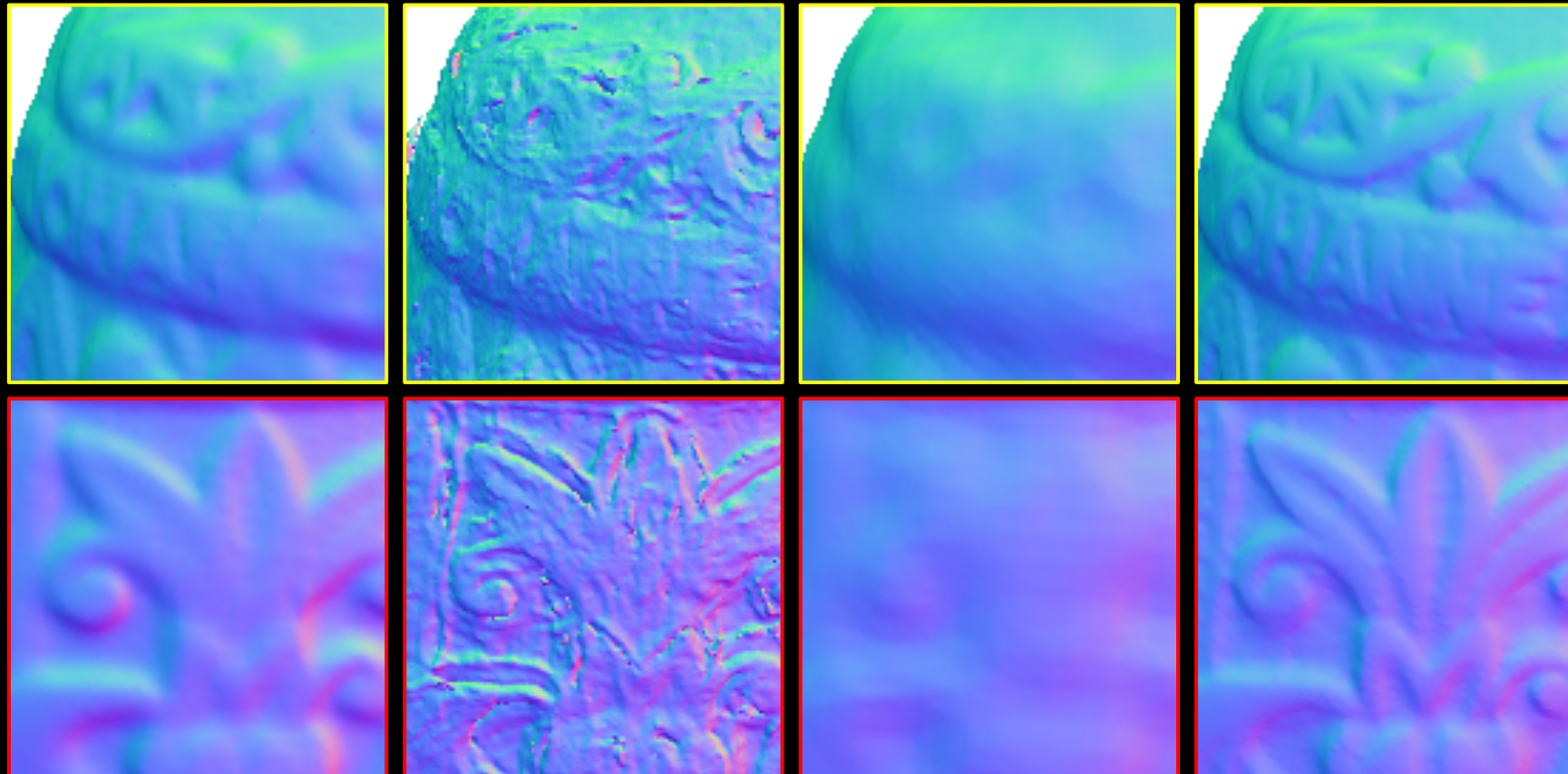
COLMAP  
(low res.)

ours

avg. geo. diff. [mm]



# Evaluation: Geometry Refinement



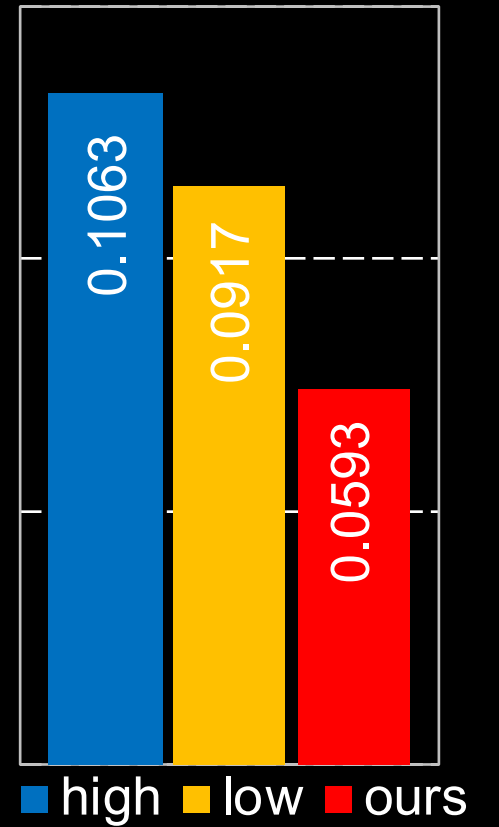
reference  
(NextEngine)

COLMAP  
(high res.)

COLMAP  
(low res.)

ours

avg. geo. diff. [mm]



# Discussion: DLSR vs. Mobile Phone

- DLSRs
  - Higher sensor signal-to-noise ratio
  - Brighter flashlight intensity
  - Does not need a darkroom



experiment setup



flash in a darkroom



flash + indoor light





# Discussion: DLSR vs. Mobile Phone

- Mobile phones
  - Better portability
  - Record a video with the LED light on



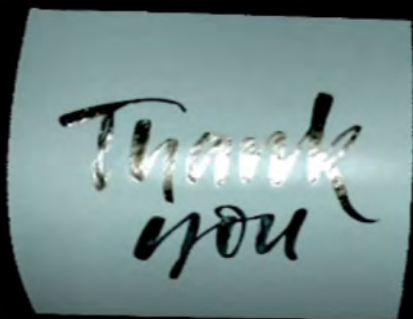
# Limitation

- Geometry
  - Complex geometries cannot be reconstructed accurately from image-based 3D modeling.
    - Pinecones, hair strands, etc.
- Material Appearance
  - Inter-reflections
  - Subsurface scattering
  - Transparency

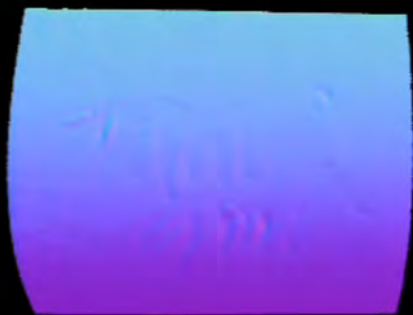
# Conclusion

- Capture images using commercial cameras with flash lights
- You will get high-quality 3D geometry & SVBRDF!





point-light rendering



geometry



Env. rendering