Practical SVBRDF Acquisition of 3D Objects with Unstructured Flash Photography

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Seminar: The Evolution of Motion Estimation and Real-time 3D Reconstruction

Technische Universität München

Fakulty of Informatics

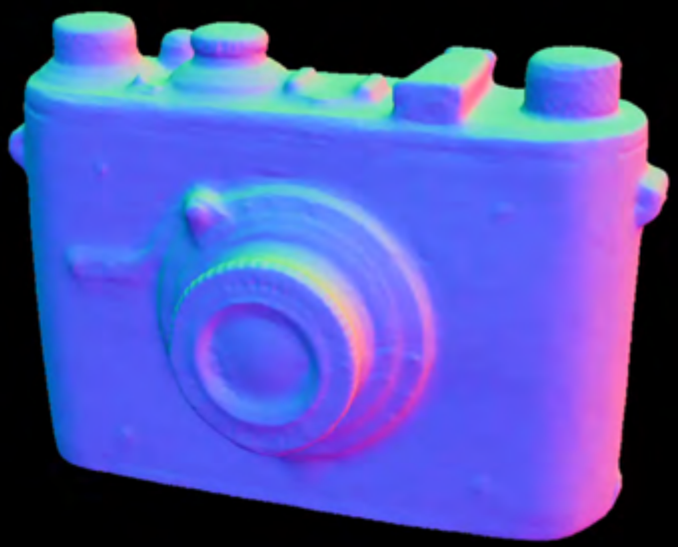
Chair of Computer Vision & Artificial Intelligence

München, 15.04.2020

Introduction: Input

Unstructured flash photographs

MVS



Initial 3D Geometry

Lehrstuhl für Computer Vision
Fakultät für Informatik
Technische Universität München

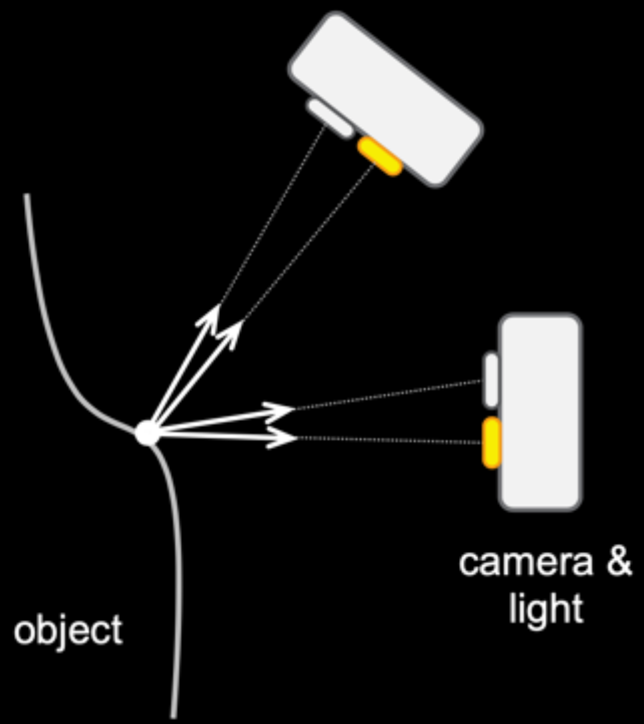
Introduction: Outputs

Spatially-varying BRDF

Reproduction in a virtual environment

Challenges

Limited sampling angles for BRDF acquisition



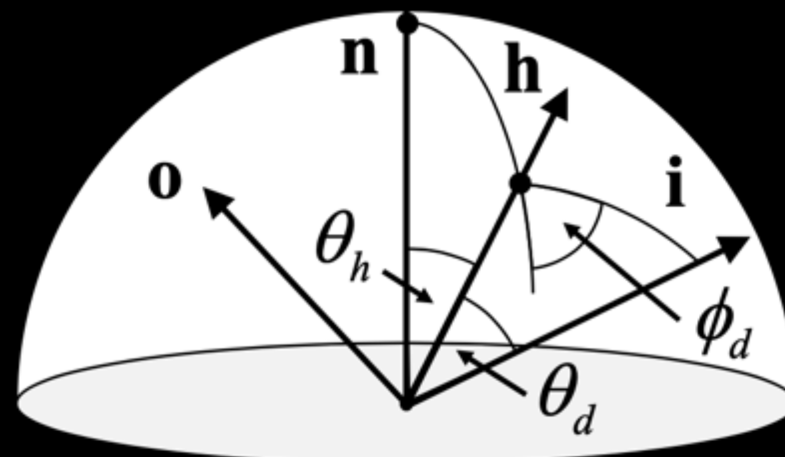
How can we ensure 3D-2D correspondence?

BRDF Acquisition from Flash Photography

BRDF: Bidirectional reflectance distribution

Parameter space for isotropic BRDFs

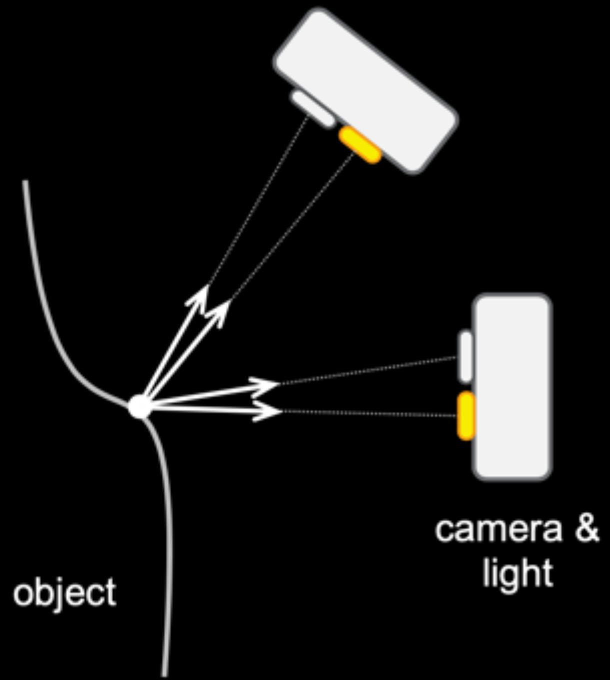
$$f(\mathbf{i},\mathbf{o}) = f(\theta_h, \theta_d, \phi_d)$$

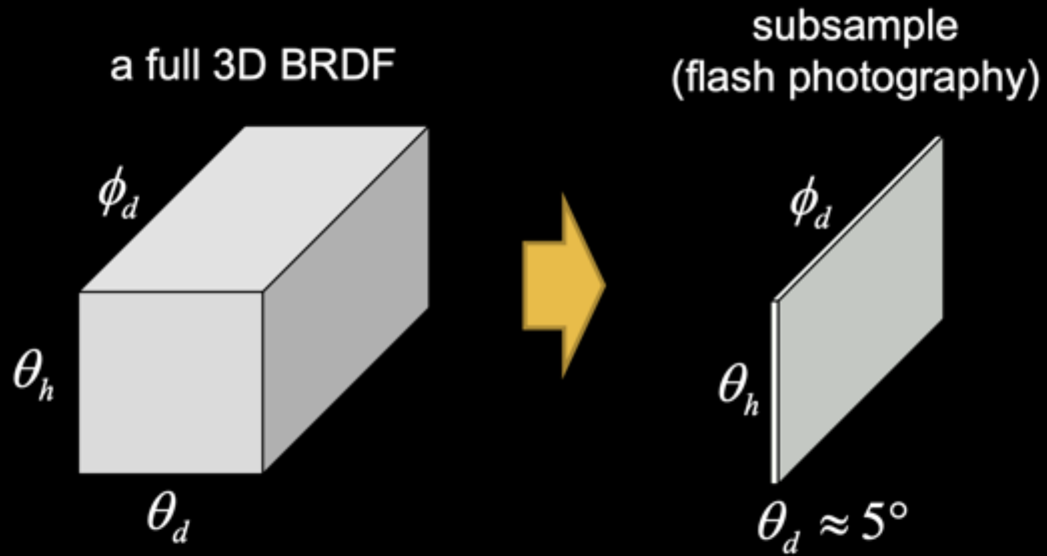


[Rusinkiewicz 98]

BRDF Acquisition from Flash Photography

Limited BRDF sampling angle in flash photography





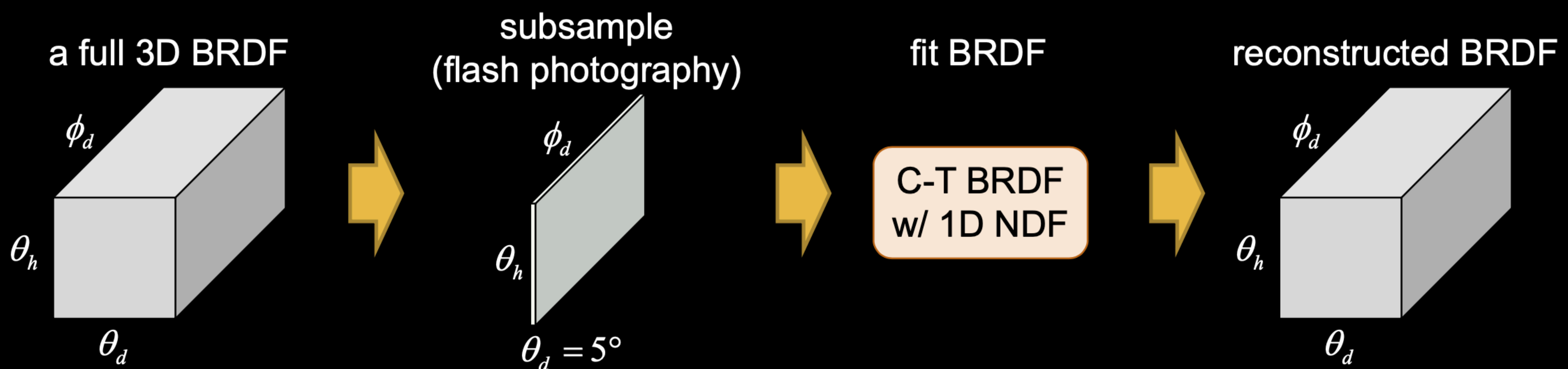
$$f(\mathbf{i}, \mathbf{o}) = f(\theta_h, \theta_d, \phi_d)$$

BRDF Model Validation

Cook-Torrance BRDF with 1D data-driven NDF
NDF: Normal Distribution Function

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

[Bagher et al. 2016]



[MERL BRDF dataset]

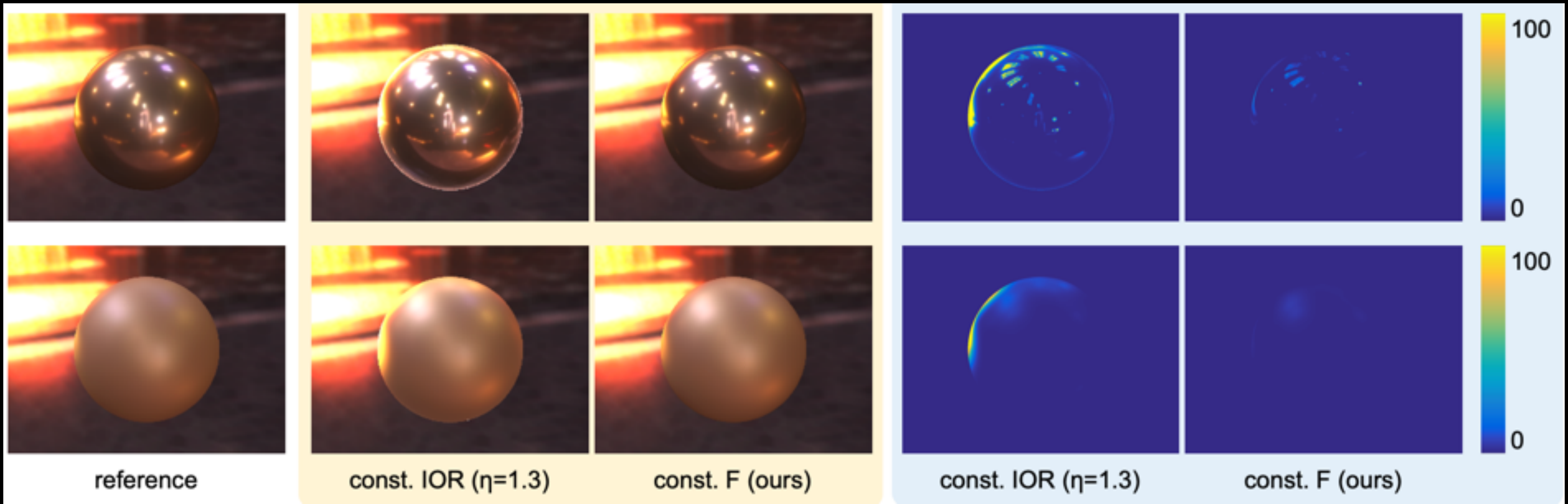
BRDF Model Validation

Cook-Torrance BRDF with 1D data-driven NDF

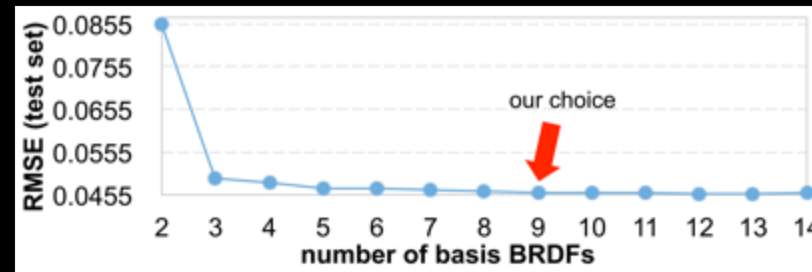
$$\theta_d = cos^{-1}(\boldsymbol{h} \cdot \boldsymbol{i})$$

Fresnel Effects

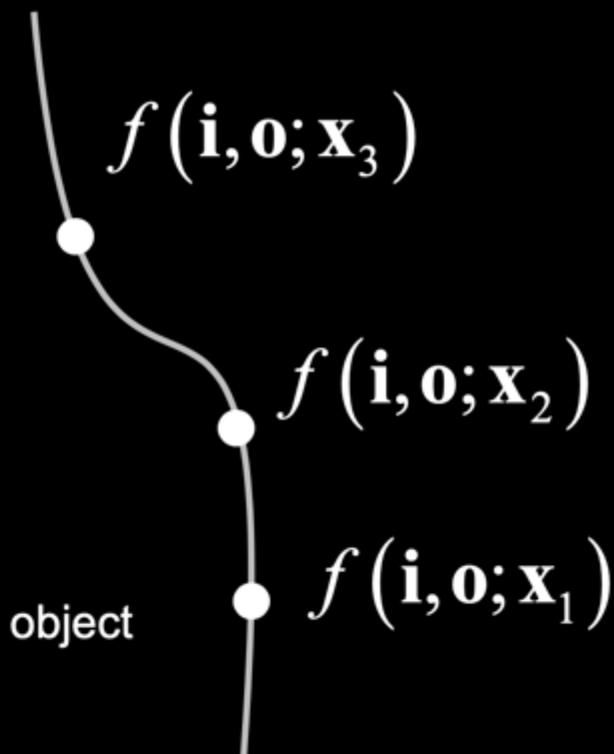
$$f(\mathbf{i},\mathbf{o}) = \frac{\rho_d}{\pi} + \rho_s \frac{D(\mathbf{h})G(\mathbf{n},\mathbf{i},\mathbf{o})F(\mathbf{h},\mathbf{i})}{4(\mathbf{n}\cdot\mathbf{i})(\mathbf{n}\cdot\mathbf{o})}$$



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

ω : blending weight

B : # of basis BRDFs

Problem Definition

Objective function using photometric consistency

$$I(\boldsymbol{u}) = L(\boldsymbol{o};\boldsymbol{x})\Delta t \Delta g$$

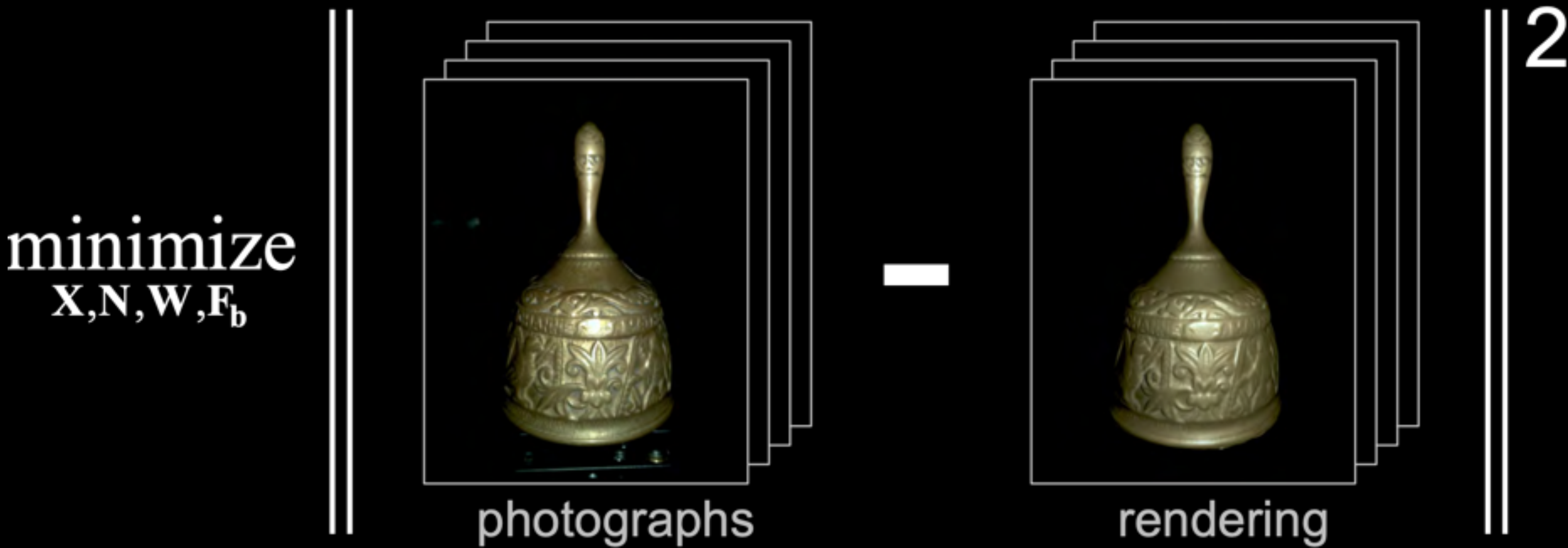
- $I(\boldsymbol{u})$: captured image, u: pixel position
- $L(\boldsymbol{o};\boldsymbol{x})$: outgoing radiance
- Δt: exposure time; Δg: flash intensity

$$L(\boldsymbol{o};\boldsymbol{x}) = f(\boldsymbol{i},\boldsymbol{o};\boldsymbol{x},\boldsymbol{n})L(-\boldsymbol{i};\boldsymbol{x})(\boldsymbol{n}\cdot\boldsymbol{i})$$

- $f(\boldsymbol{i},\boldsymbol{o};\boldsymbol{x},\boldsymbol{n})$: reflectance function at point **x**
- $L(-\boldsymbol{i};\boldsymbol{x})$: incident light at **x**

Problem Definition

Objective function using photometric consistency



X: 3D vertices
N: surface normals
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

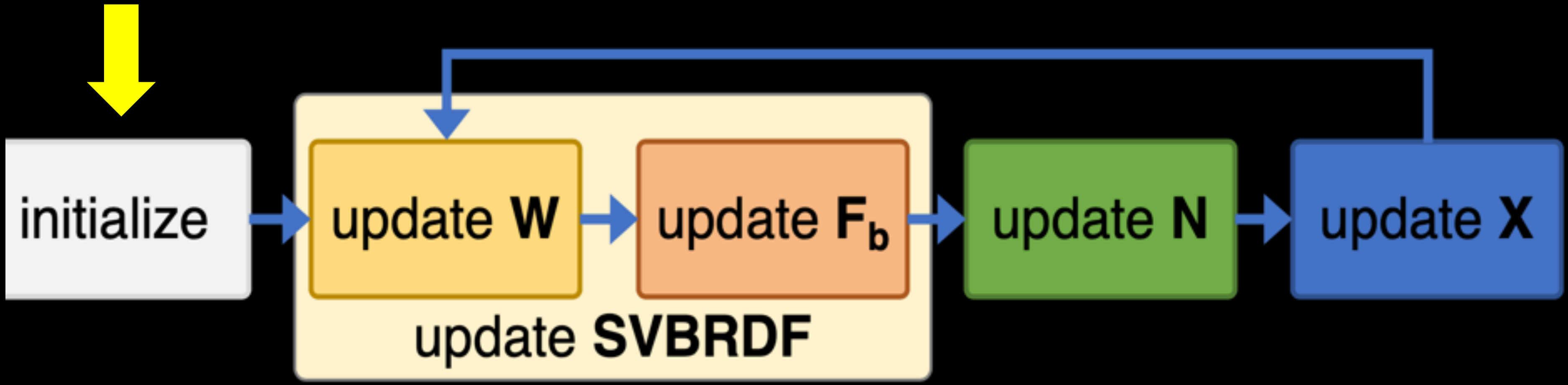
$\mathbf{N}$: surface normals

$\mathbf{W}$: blending weights

$\mathbf{F_b}$: basis BRDFs

Overview

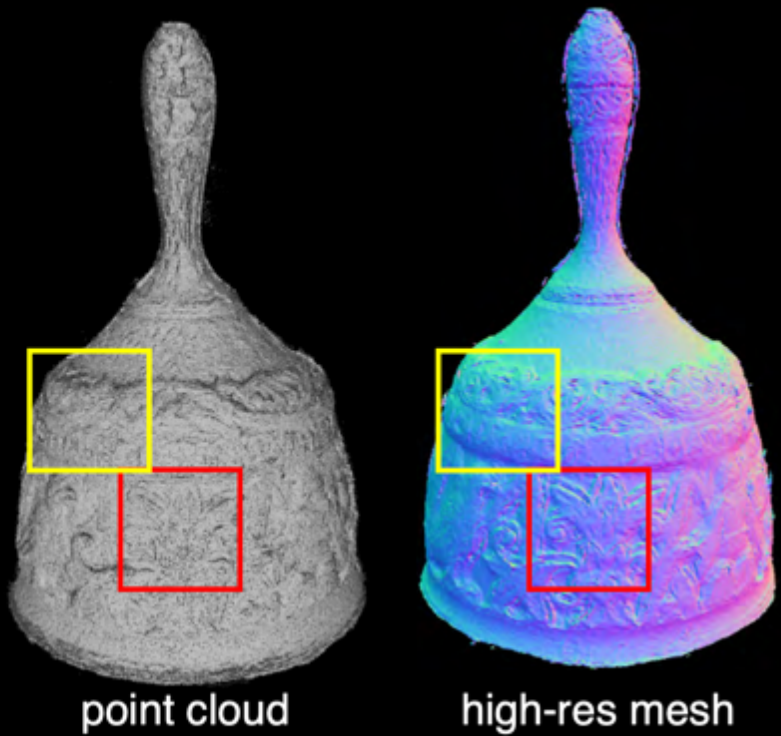
Iterative & alternating optimization of {X, N, W, Fb}

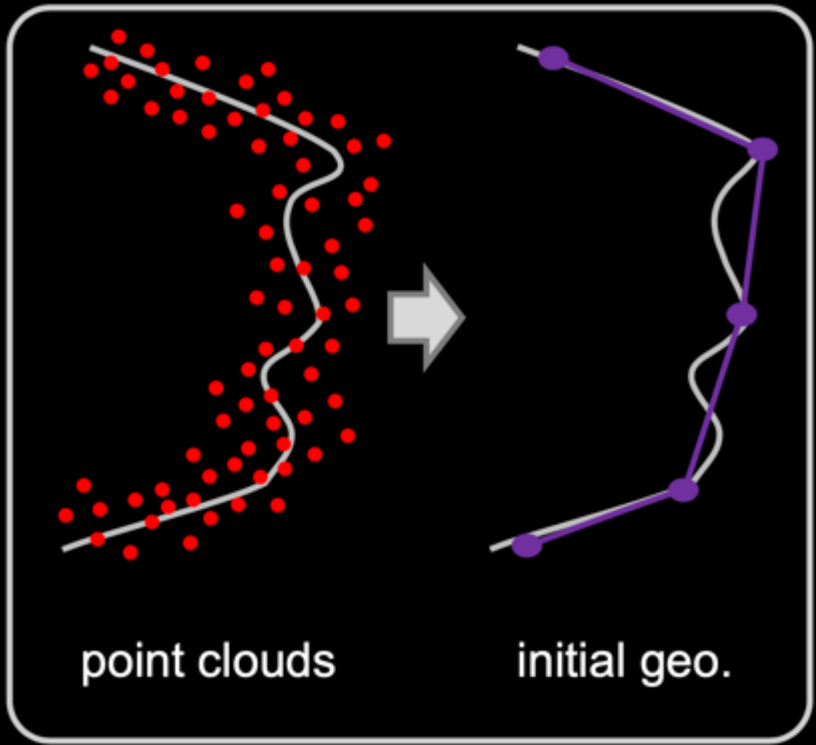


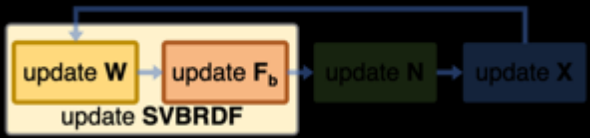
X: 3D vertices
N: surface normals
W: blending weights
$\mathbf{F_b}$: basis BRDFs

Initialization

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







Update SVBRDF

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

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

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

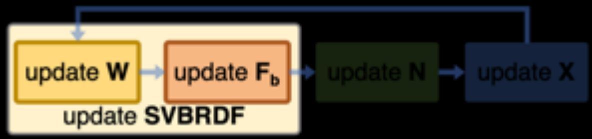
$$\underset{\mathbf{W},\mathbf{F_b}}{\text{minimize}} \sum_{p=1}^{P} \sum_{k=1}^{K} v_{p,k} \left(f'_{p,k} - \Phi_{p,k} \sum_{b=1}^{B} \omega_{p,b} \mathbf{f}_b \right)^2$$

captured reflectance

reconstructed reflectance

W: blending weights

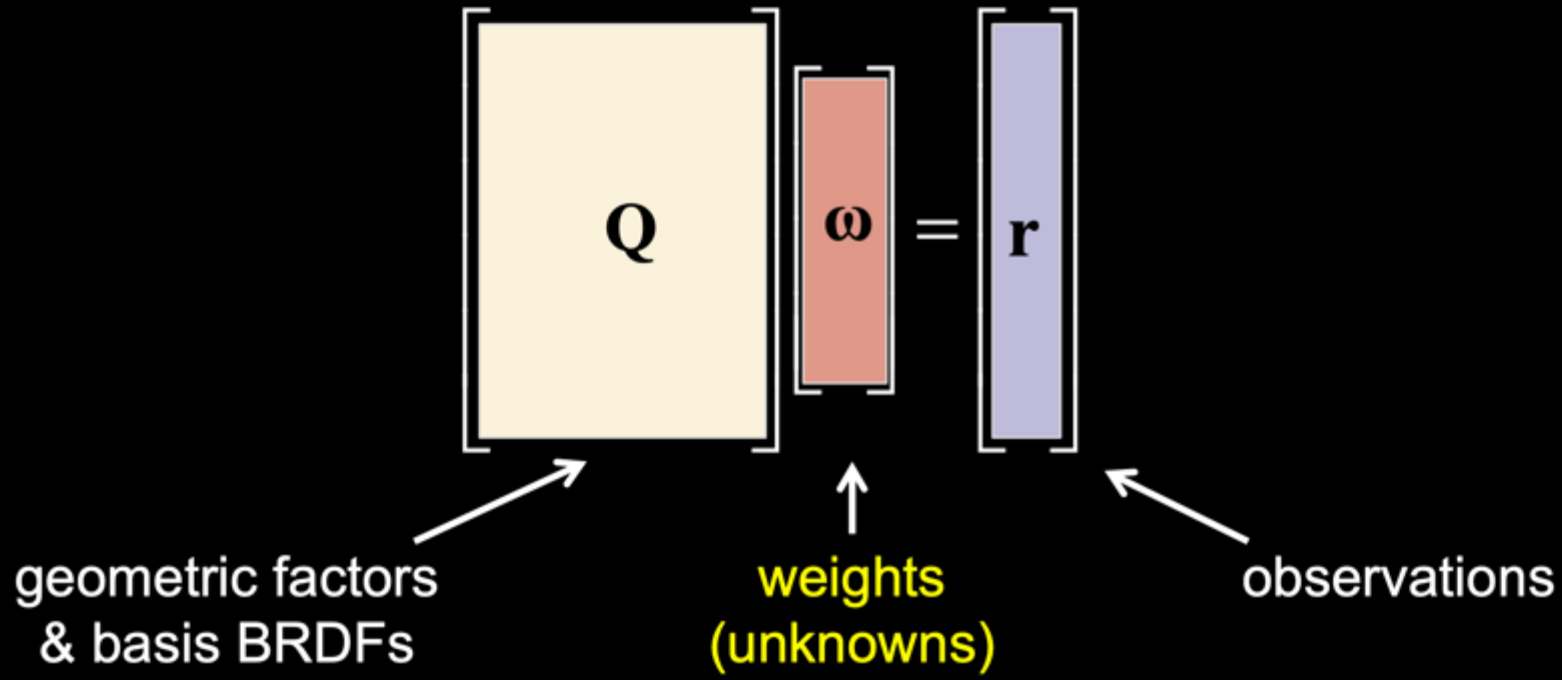
$\mathbf{F_b}$: basis BRDFs

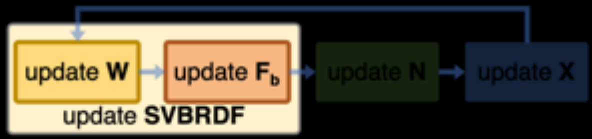


Update SVBRDF: blending Weights W

Per-vertex optimization

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





Update SVBRDFs: basisBRDFs

Hold W fixed and solve for F_b
Convex quadratic programming

$$\underset{\mathbf{F_b}}{\text{minimize}} \sum_{p=1}^{P} \sum_{k=1}^{K} v_{p,k} \left(f'_{p,k} - \mathbf{\Phi}_{p,k} \sum_{b=1}^{B} \omega_{p,b} \mathbf{f}_b \right)^2$$

observation

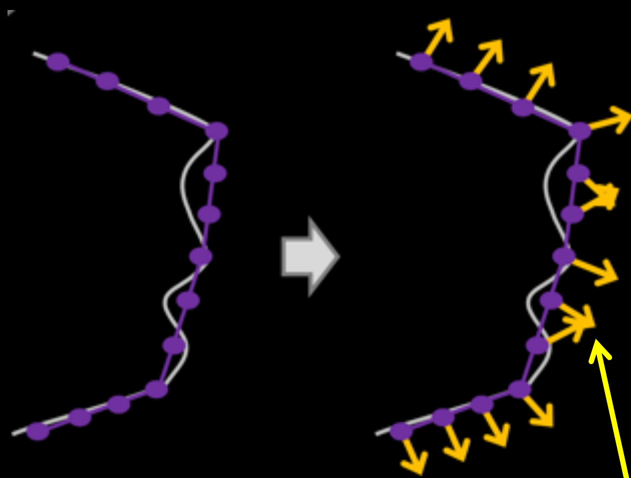
estimated weights

basis BRDFs (unknowns)

$$\boldsymbol{f_b} = [\rho_d, \rho_s F D(\theta_h)]^T$$

Update Normals

Per-vertex optimization
Linear regression easy to solve!

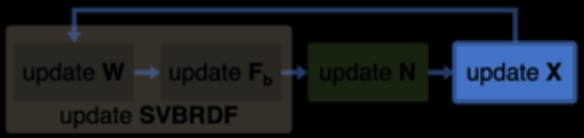


$$\underset{\tilde{\mathbf{n}}}{\text{minimize}} \sum_{k=1}^{K} \left(L(\mathbf{o};\mathbf{x}) - f(\mathbf{i},\mathbf{o};\mathbf{x},\mathbf{n}) L(-\mathbf{i};\mathbf{x}) (\tilde{\mathbf{n}} \cdot \mathbf{i}) \right)^2$$

K: # of images

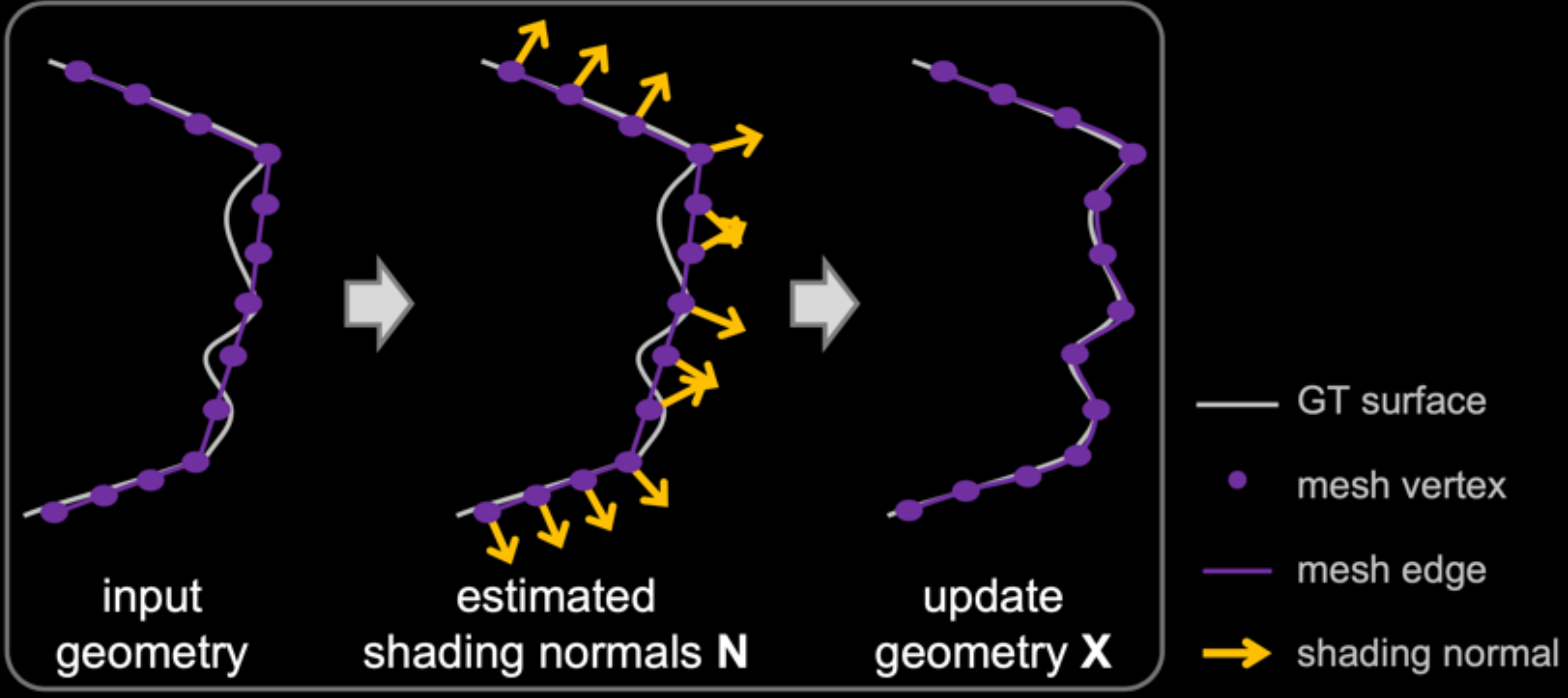
geometric normal
($\mathbf{n}$, known)

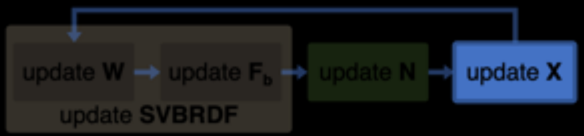
shading normal
($\tilde{\mathbf{n}}$, unknown)



Update Geometry

Screened Poisson surface reconstruction [Kazhdan2015]





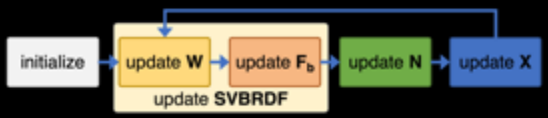
Update Geometry

Screened Poisson surface reconstruction [Kazhdan2015]

X: new geometry (unknown)

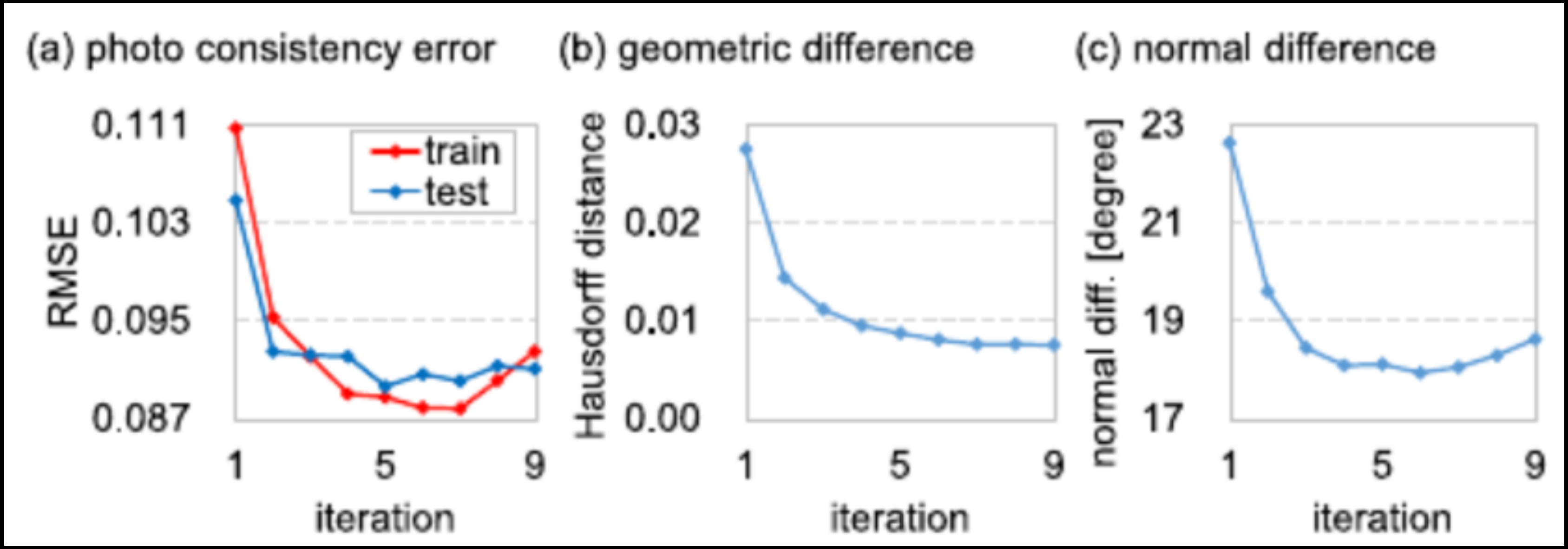
$$\underset{\chi}{\text{minimize}} \int \left\| \mathbf{V}(\mathbf{x}_p) - \nabla \chi(\mathbf{x}_p) \right\|^2 d\mathbf{x}_p + \alpha \sum_{\mathbf{x}_p \in \mathbf{X}} \chi^2(\mathbf{x}_p)$$

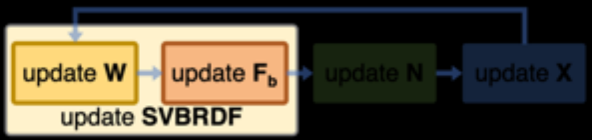
- $\mathbf{V}(\mathbf{x}_p)$: 3D vector field from shading normals
- $\nabla \chi(\mathbf{x}_p)$: gradient of new geometry
- $\sum_{\mathbf{x}_p \in \mathbf{X}} \chi^2(\mathbf{x}_p)$: squared distance of current and new geometry



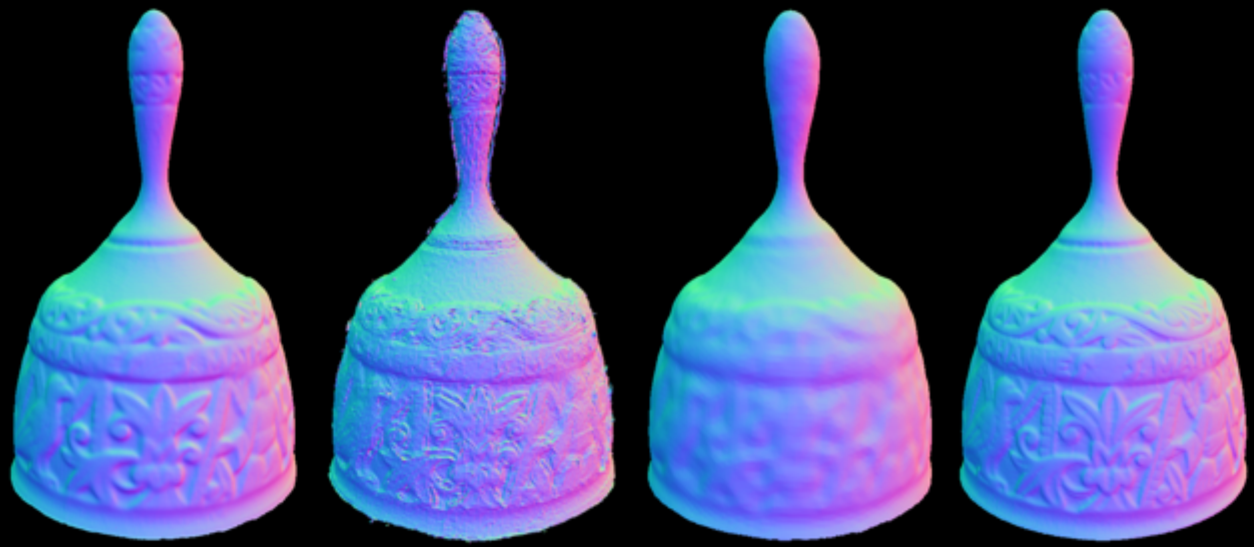
Iterative Optimization Result

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

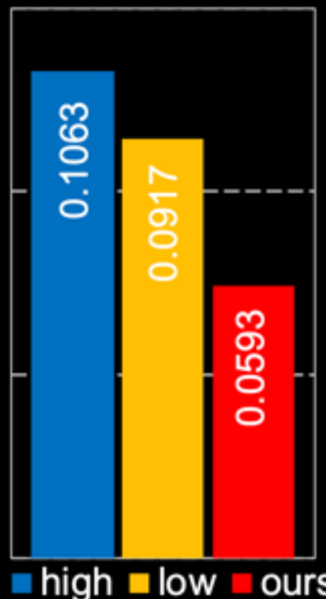


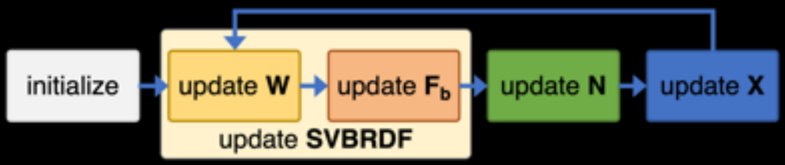


Evaluation: Geometry Refinement



reference (NextEngine) | COLMAP (high res.) | COLMAP (low res.) | ours



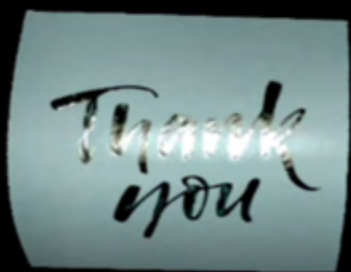


Personal Comments

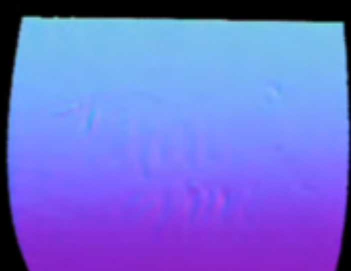
- Creative and novel idea to optimize the reconstruct of 3D geometry
- Get high-quality 3D geometry & SVBRDF simultaneously
- Capture images using just commercial cameras with flash lights
- Dark room is not a must
- No additional complex hardware, suitable for wider public
- Not real-time

Summary

- Comparable quality to commercial 3D desktop scanning systems
- Complex geometries cannot be reconstructed accurately from image-based 3D modeling, Pinecones, hair strands, etc.
- Missing specular highlights at mirror reflection angles
- Future works: material appearance, inter-reflections, subsurface scattering, transparency in light transport model



point-light rendering



geometry