Re-rendering from a Dense/Sparse Set of Images

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Virtual/Augmented/Mixed Reality

- Three consistencies
  - Photometric
  - Geometric
  - Time

Photometric Object Modeling

Observation

Display

Approaches: Appearance-based

- Image-based Rendering
  - Light rays as a ?(<7)D function
  - Compression
  - Interpolation
  - Unknown geometry

Approaches: Appearance-based
cont'd

- 3D Photography
  - Surface light fields
  - Compression
  - Interpolation
  - Known geometry

Approaches: Model-based

- Inverse Rendering
  - Extract photometric information from images
    - Texture
    - BRDF
    - Lighting
  - Render

Our Approach

Take full advantage of knowing the geometry of the target

1. From a dense set of images
2. From a sparse set of images

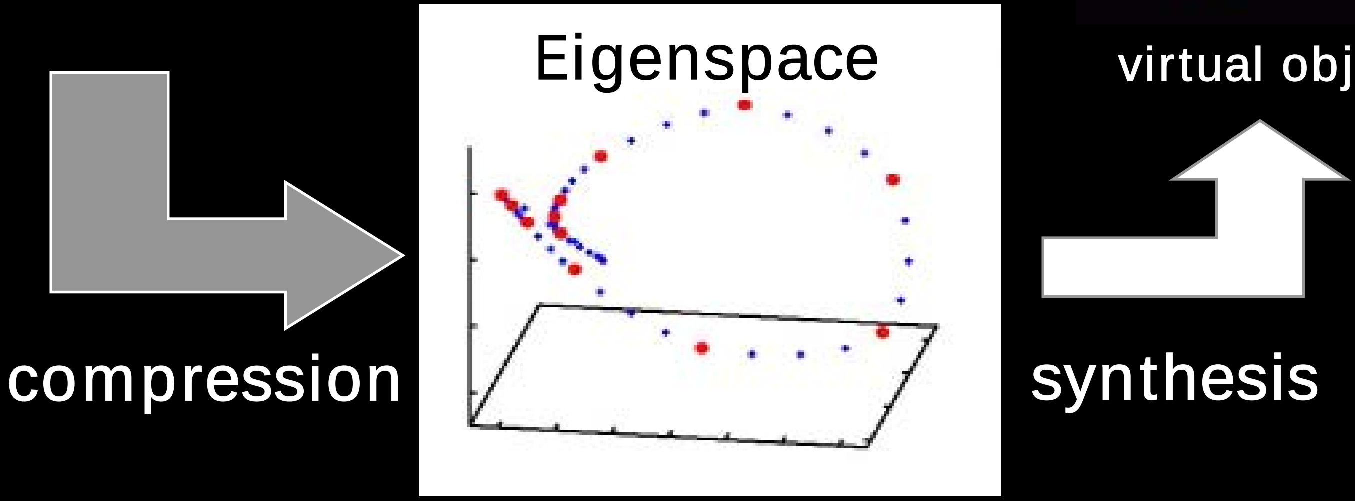
Eigen-Texture Rendering

Re-rendering from a Dense Set of Images

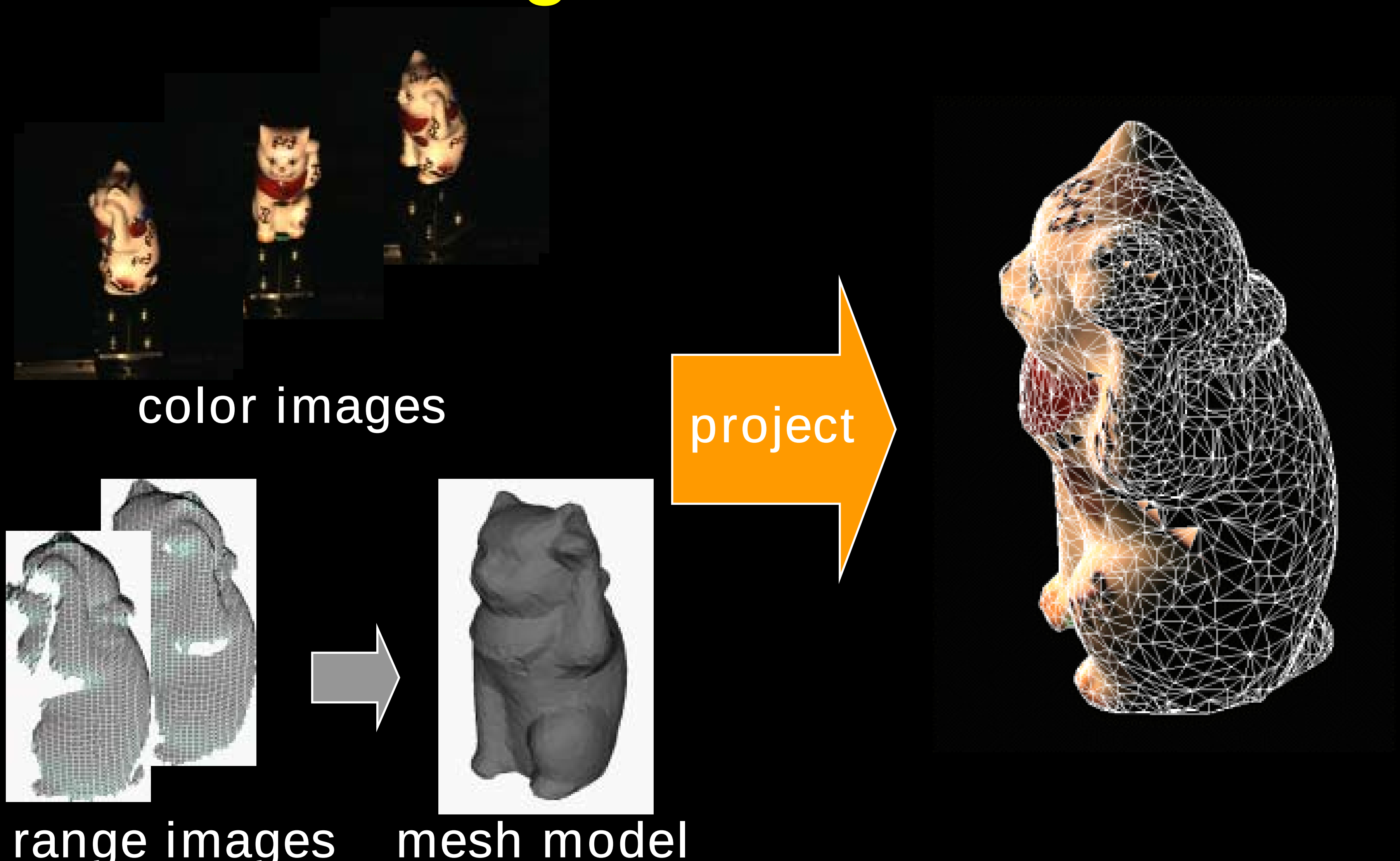
color images

geometric model

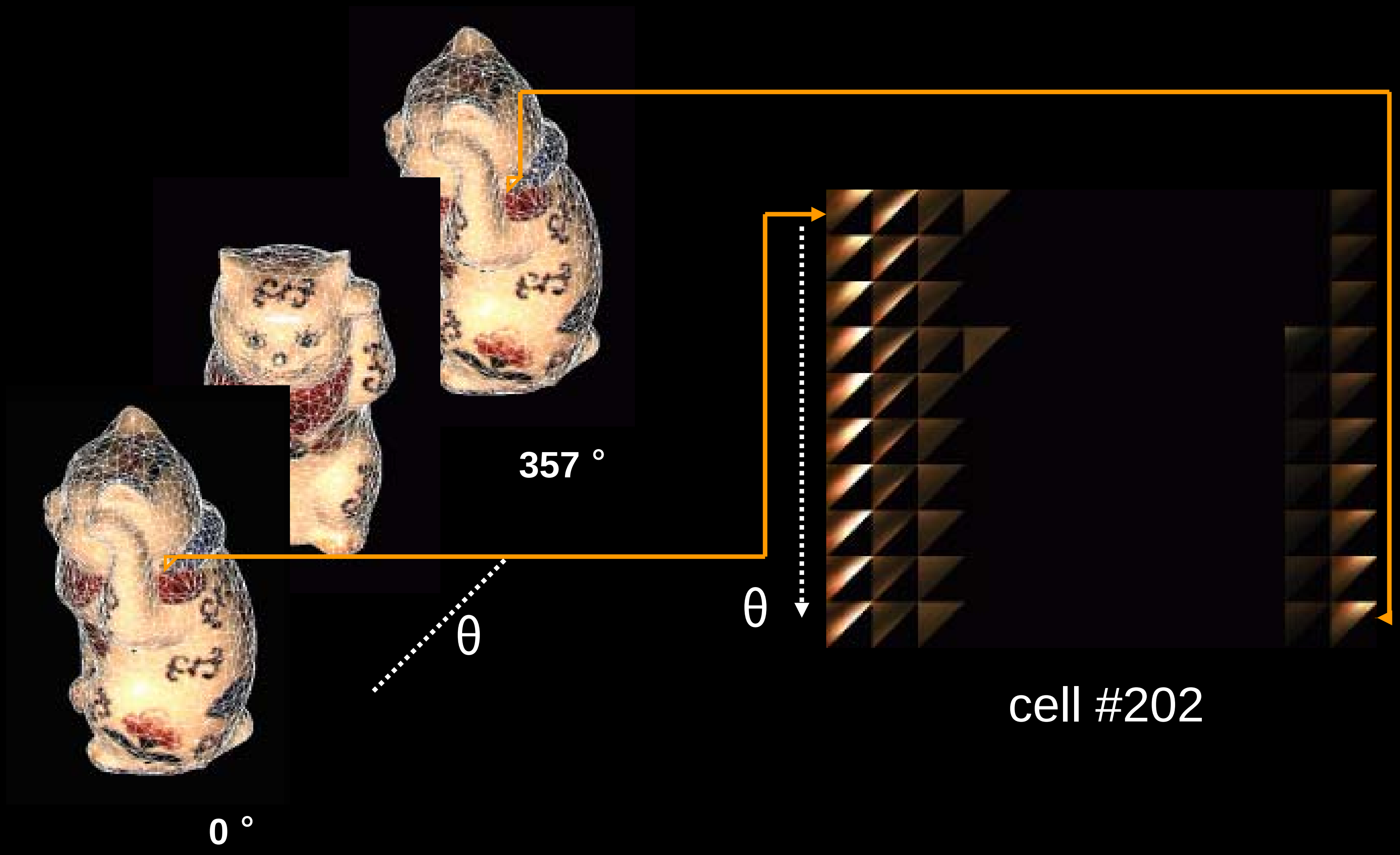
virtual object



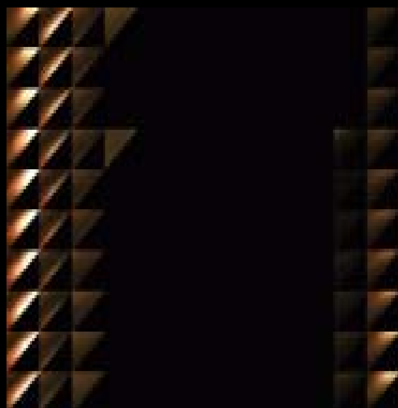
Cutting Out Texture



Cell Image Sequence



Compression

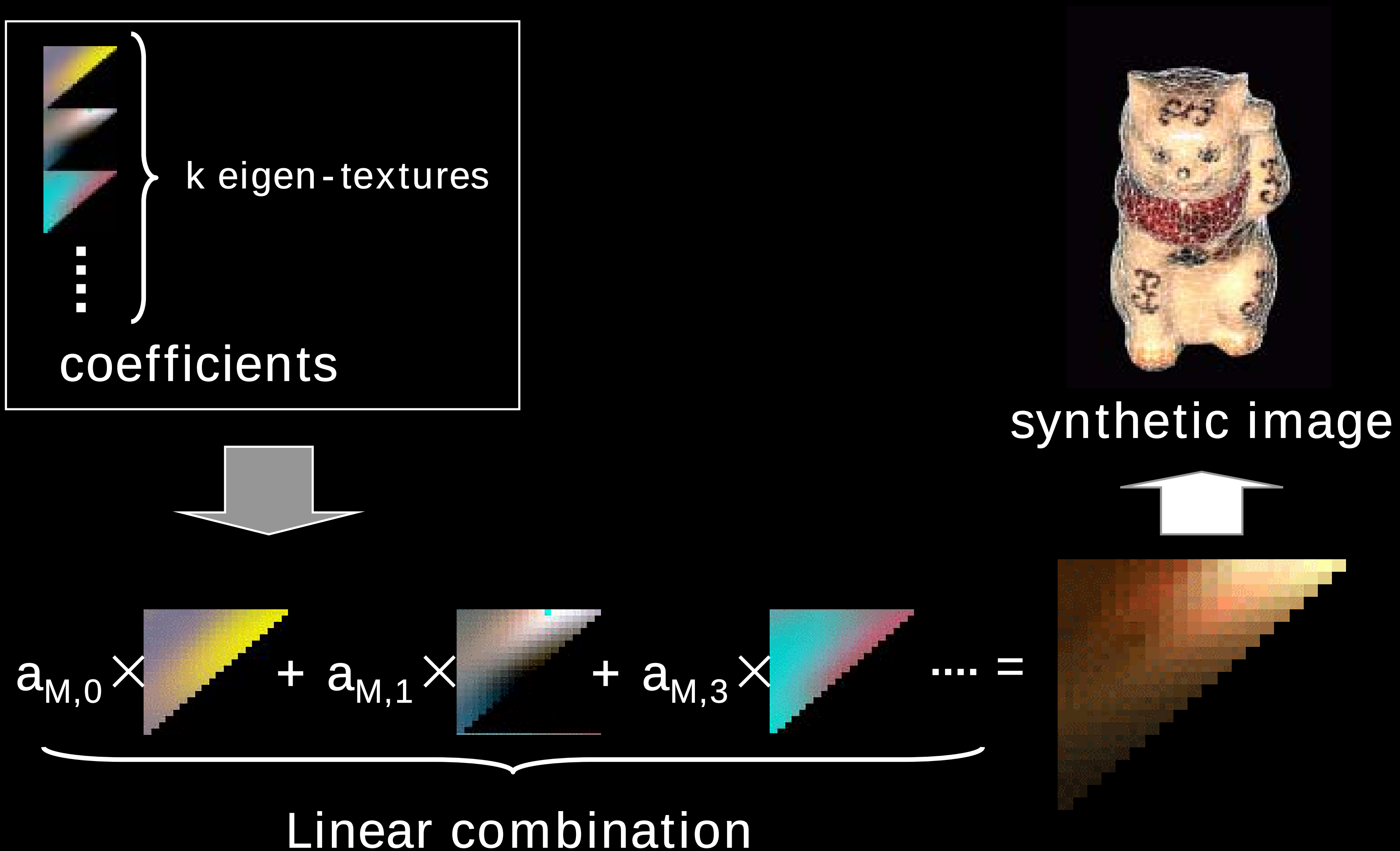


Cell image sequence

$$\begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,3N} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,3N} \\ & \cdots\cdots\cdots & & \\ x_{M,1} & x_{M,2} & \cdots & x_{M,3N} \end{pmatrix} \updownarrow M \;\Rightarrow\; \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,3N} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,3N} \\ & \cdots\cdots\cdots & & \\ x_{k,1} & x_{k,2} & \cdots & x_{k,3N} \end{pmatrix} \updownarrow k$$

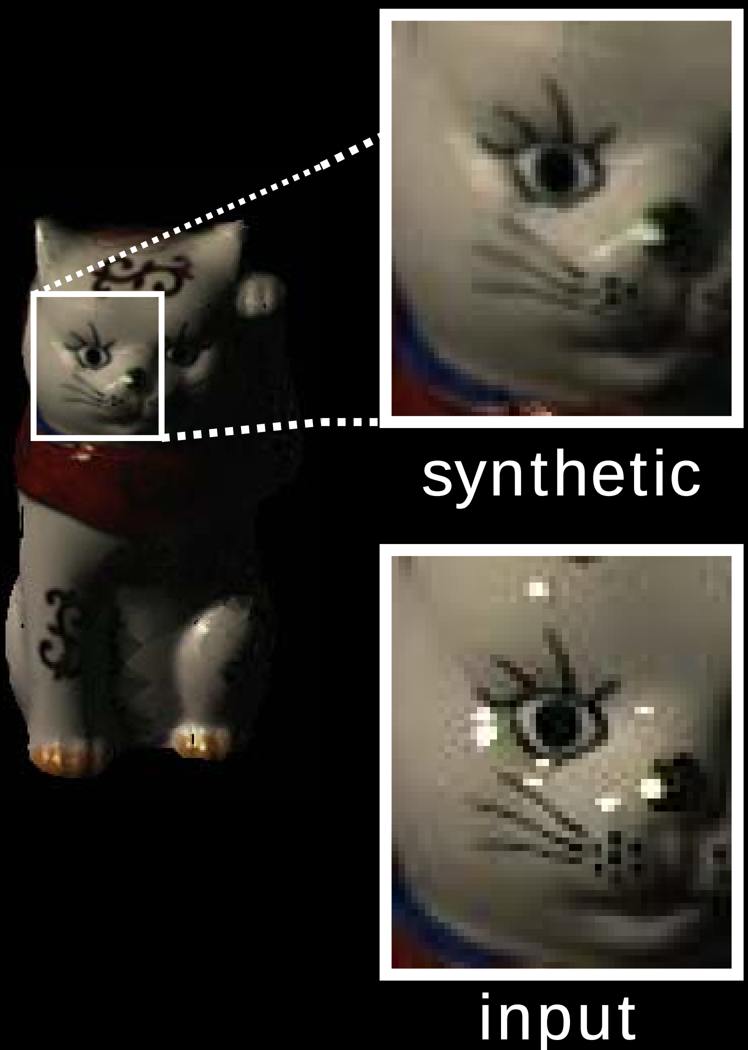
coefficients

Synthesis



k eigen-textures
coefficients
synthetic image
$a_{M,0} \times$ + $a_{M,1} \times$ + $a_{M,3} \times$ .... =
Linear combination

Determining the Dimensions



- If planar and Lambertian→3
  - Photometric Stereo[Woodham 78]
- In real life
  - Non-planar
  - Specularity
  - Interreflections
  - Selfshadows

Adaptive dimensions based on eigen-ratios

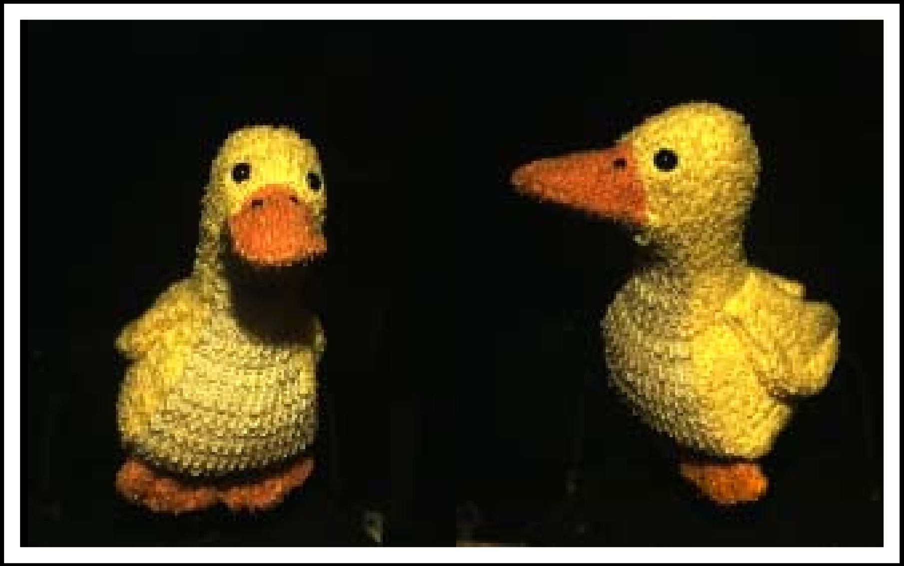
Cell-adaptive Compression

Input

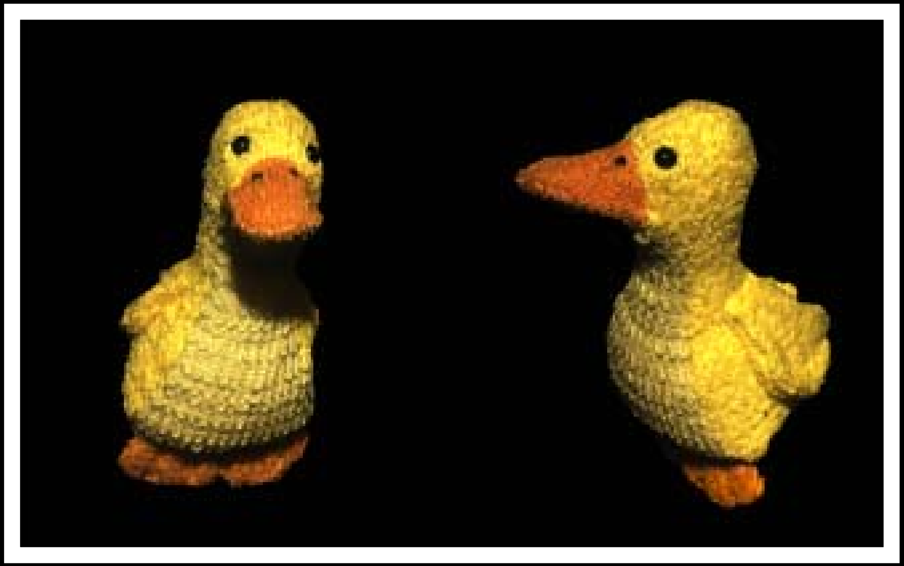
Synthetic

Average dimensions 6.6   Compression ratio 15.3:1   RMS error 1.5

Cell-adaptive Compression



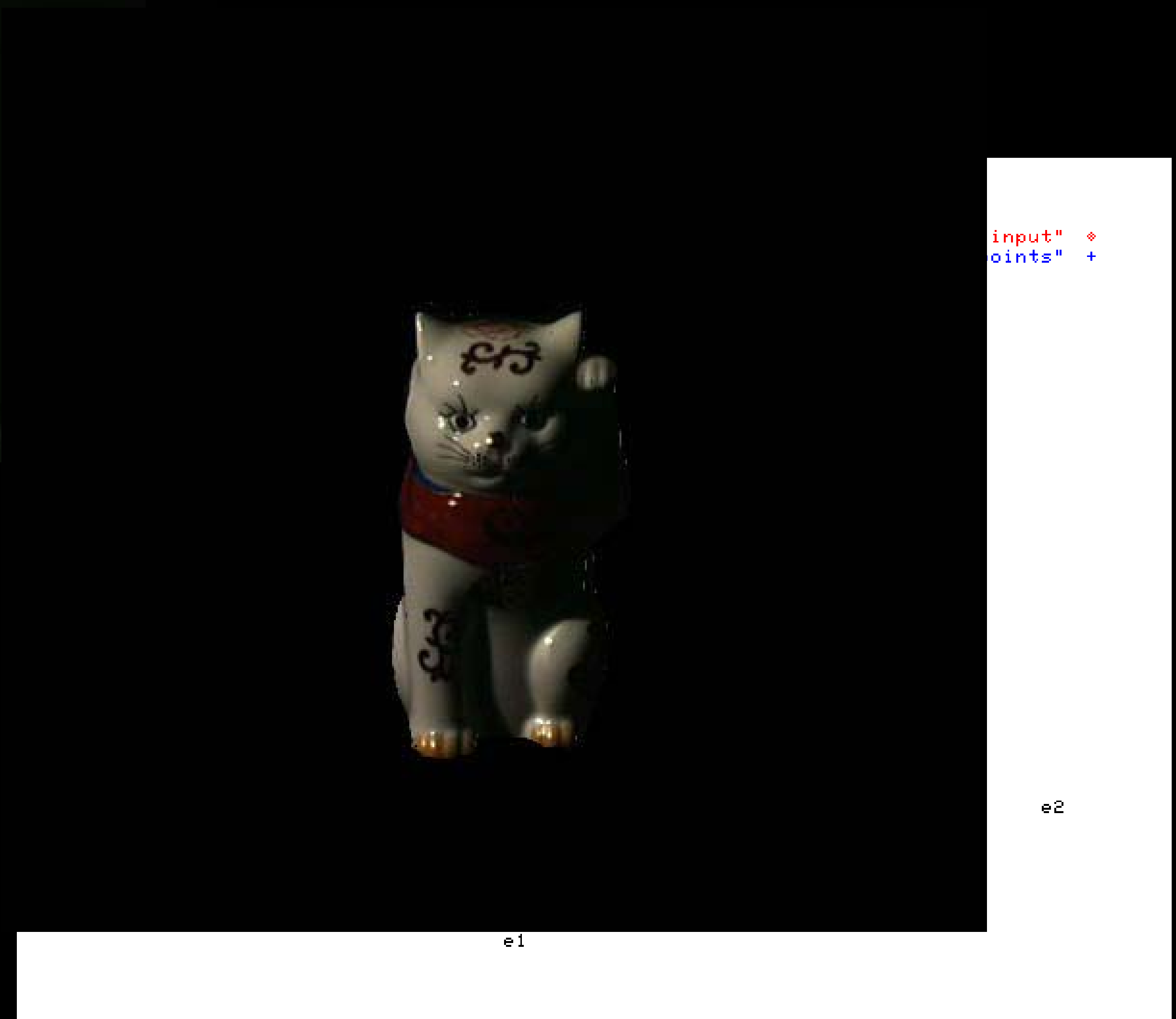
Input



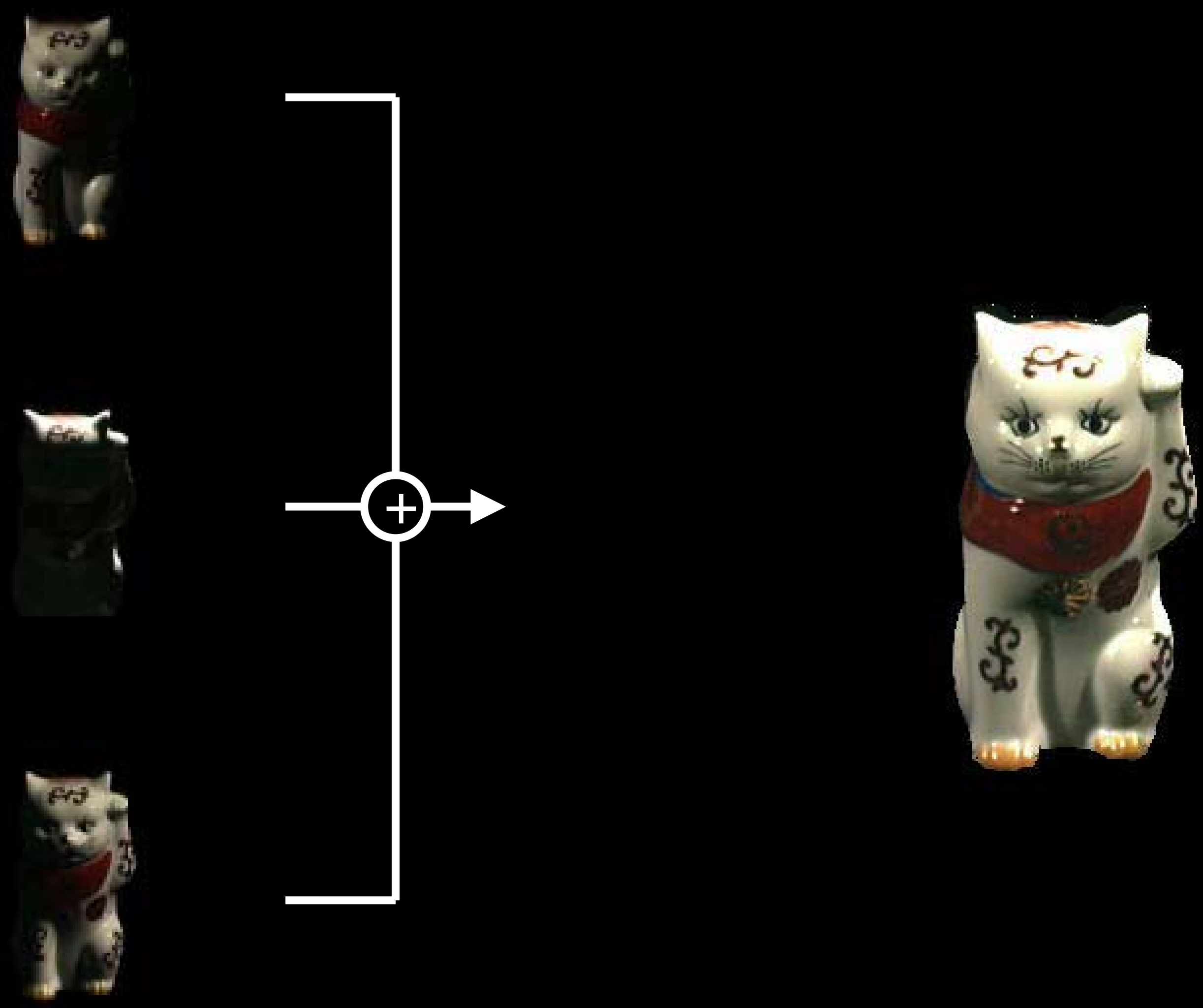
Synthetic

Average dimensions 17.6   Compression ratio 5.7:1   RMS error 1.8

Interpolation in Eigenspace



Sampling Lights



Integration

Re-rendering from a Sparse Set of Images

- As less input images as possible?

  - Assumptions on BRDF
- Inverse rendering (a hard one)
  - Estimate all three elements

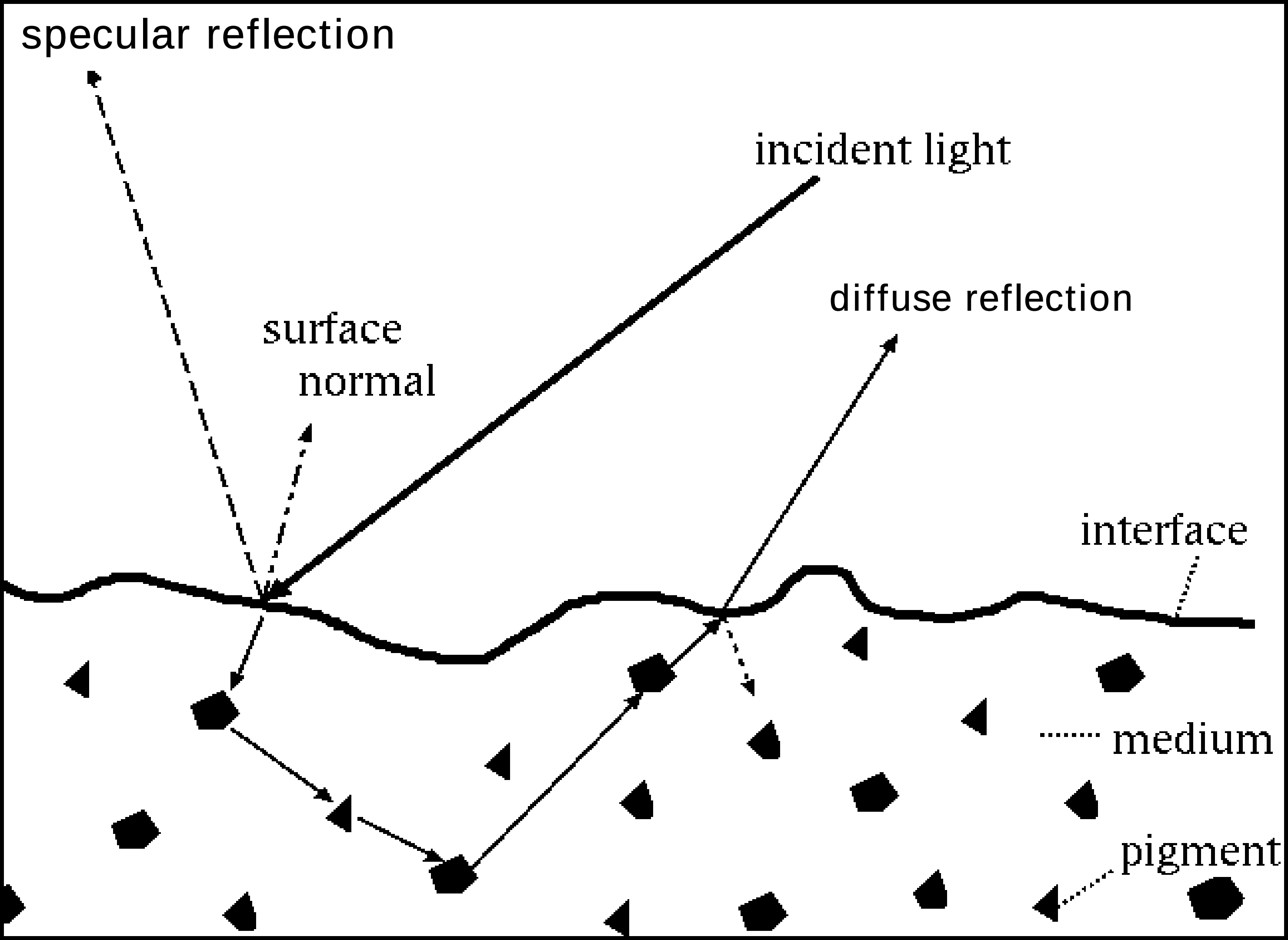
Inputs

6 HDR images

Mesh model

Camera params

Reflection on a Surface



Reflection Components

Radiance of a object surface point

$$\mathbf{I} = \mathbf{I}_D + \mathbf{I}_S$$

diffuse component   specular component

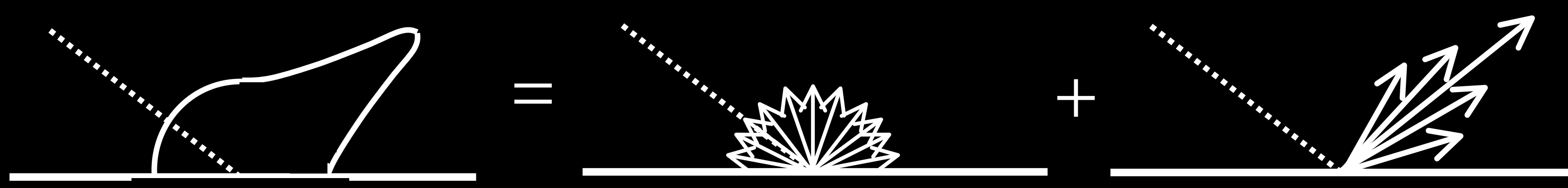
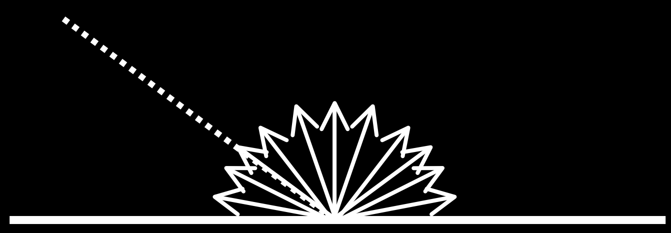
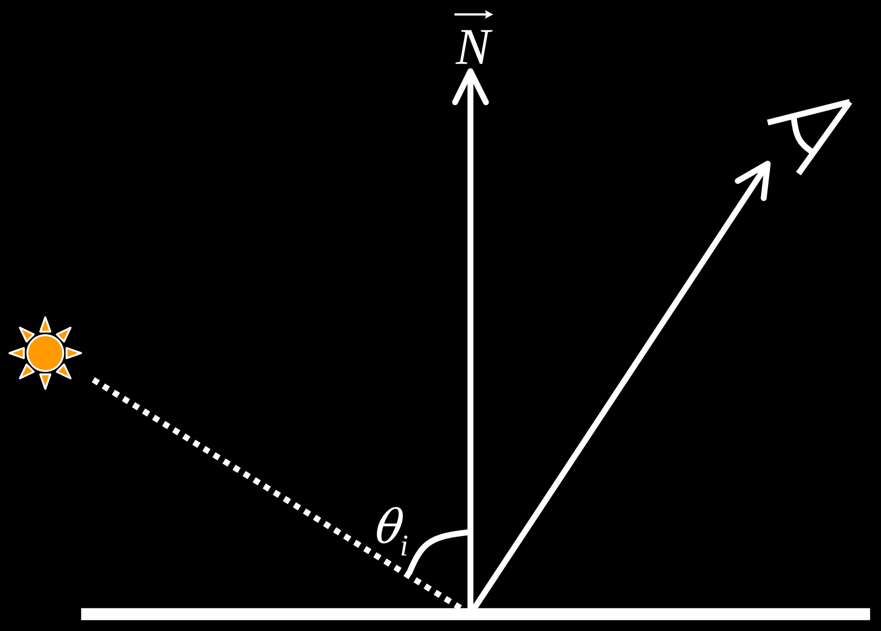


Image irradiance $\propto$ Scene radiance

Diffuse Component

- Lambertian model
  - isotropic

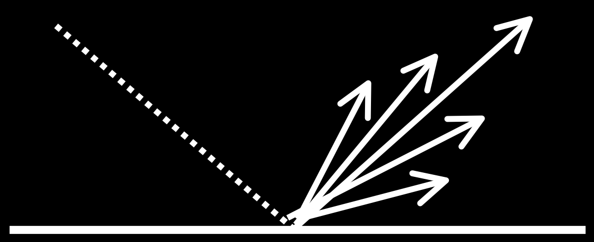


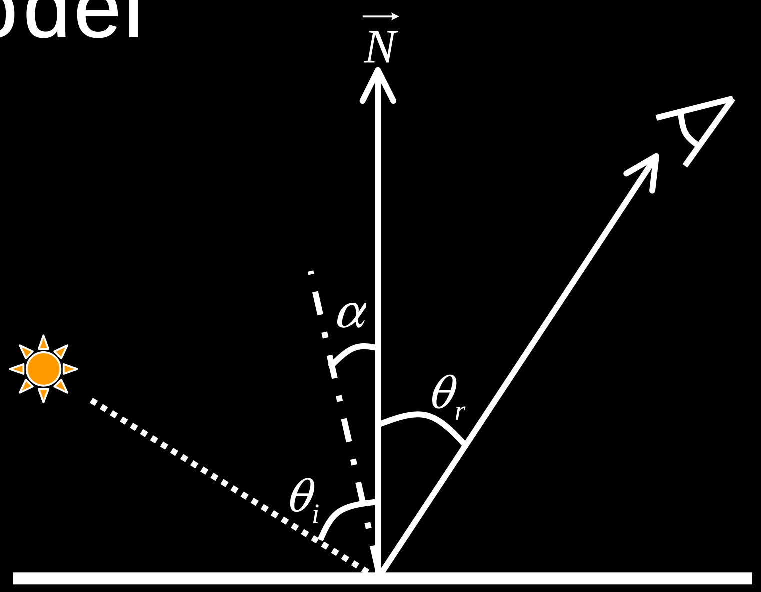


$$\mathbf{I}_D = \max[0, \mathbf{K}_D \int_\Omega L_i(\theta_i, \phi_i) \cos\theta_i d\omega_i]$$

Specular Component

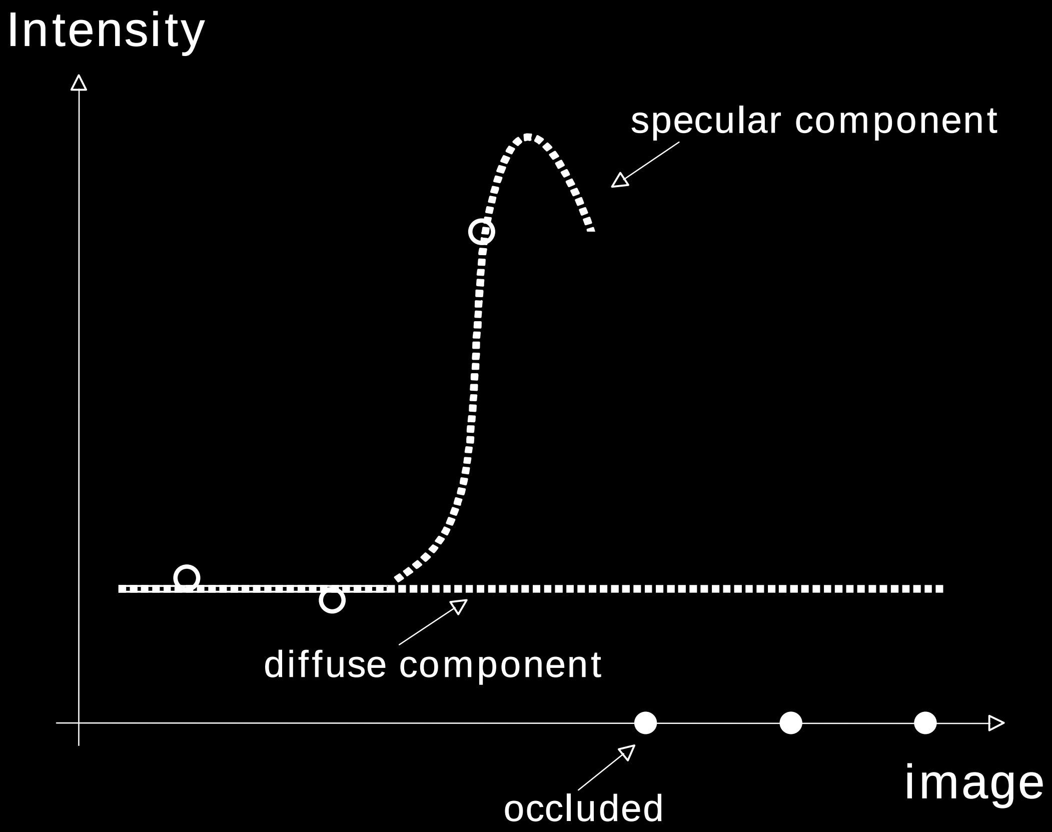
- Torrance-Sparrow model
  - Micro-facets
    - Gaussian dist.





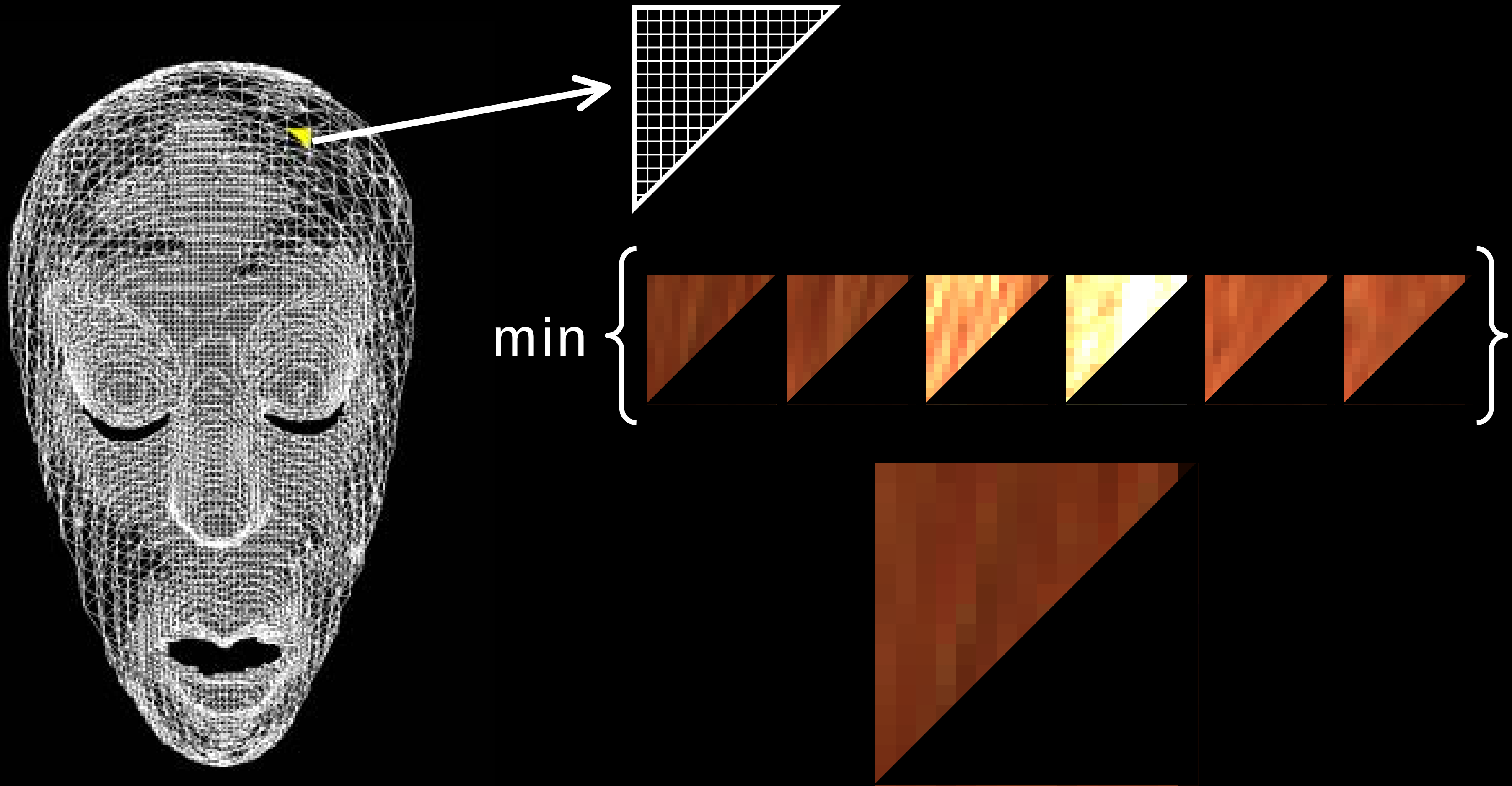
$$\mathbf{I}_S = \int_{\Omega} \frac{\mathbf{K}_S F G}{\cos\theta_r} L_i(\theta_i, \phi_i) \exp\left[-\frac{\alpha^2}{2\sigma^2}\right] d\omega_i$$

Reflection Component Separation



Diffuse Texture Map

- 3D grids in each triangular patch

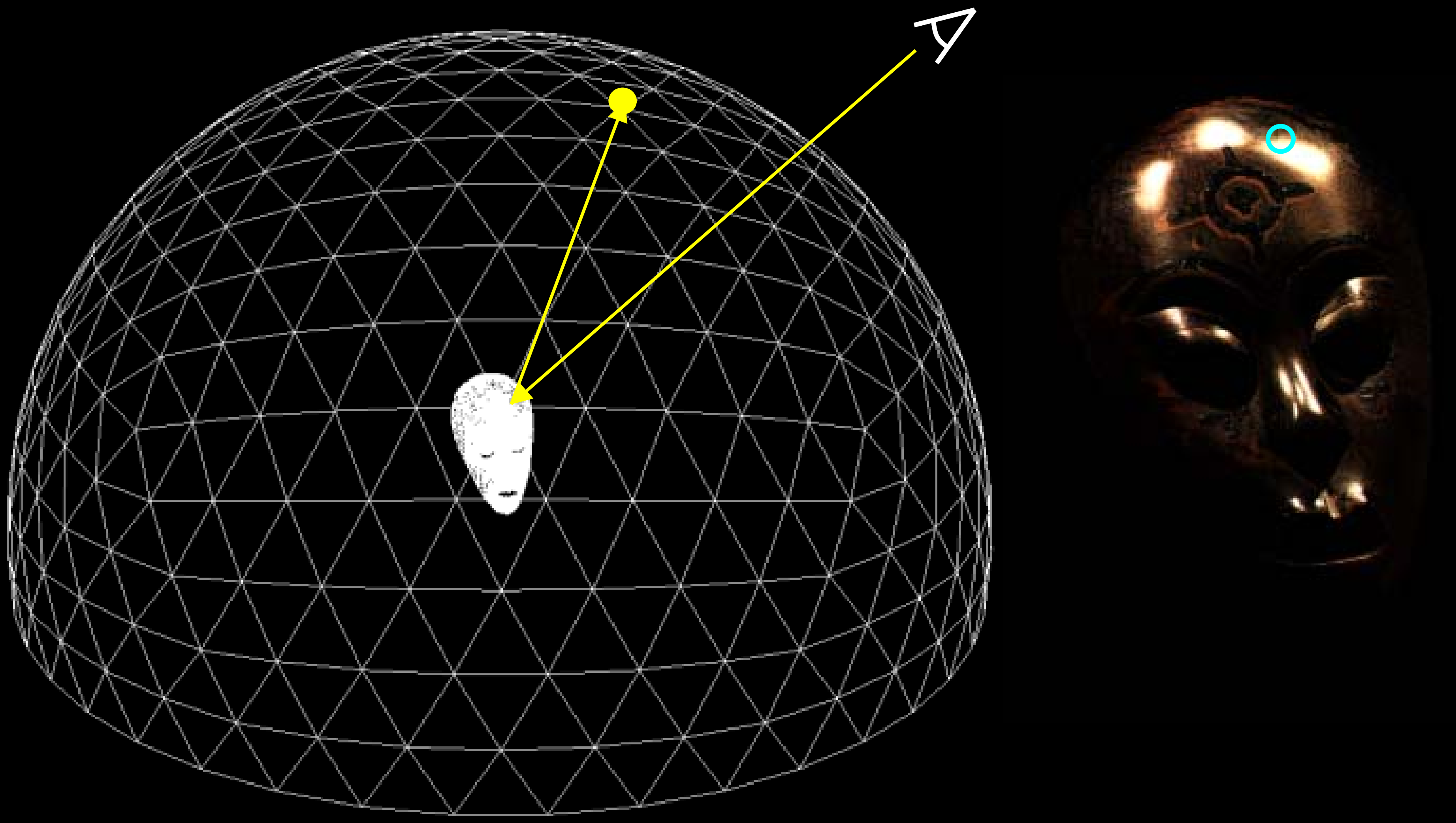


Diffuse-texture-mapped Images

Specular Images

Ignore interreflections

Illumination Hemisphere



Initial Illumination Hemisphere

Simplify and Discretize T-S

$$\mathbf{I}_S(v) = \int_\Omega \frac{\mathbf{K}_{S,v} F G}{\cos\theta_r} L_i(\theta_i, \phi_i) \exp\left[-\frac{\alpha^2}{2\sigma^2}\right] d\omega_i$$

- Assume F and G are constant
- Uniform illuminant color L
- Illumination as a set of point light sources

$$\mathbf{I}_S(v) = I_S(v)\mathbf{L}$$

$$I_S(v) = \frac{2\pi}{N_L} \frac{K_S}{\cos\theta_r} \sum_l^{N_L} L_l(\theta_l, \phi_l) \exp\left[-\frac{\alpha^2}{2\sigma^2}\right]$$

Illumination and Reflectance Parameter Estimation

Straightforward minimization ?

$$\arg\min_{\sigma, K_S, L_l} \sum_{k}^{N_K} \sum_{s,t}^{N_S, N_T} \left| I(s,t,k) - I_S(s,t,k) \right|^2$$

s,t : image coords
k: image number

Specular Reflection as Convolution

$$I_S(s,t,k) = \frac{2\pi}{N_L}\frac{K_S}{\cos\theta_r}\sum_{l}^{N_L} L_l(\theta_l,\phi_l)\, g_{\frac{1}{2\sigma^2}}\left(\left\| BS(s,t,k,\theta_l,\phi_l) - C(s,t,k)\right\|\right)$$

specular images

$$z = h * u + \eta$$

filter

true lighting

noise

2D convolution on the surface of the illumination hemisphere

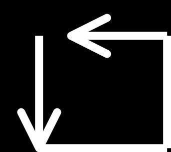
Illumination and Reflectance Parameter Estimation

$$\min_{L,\sigma} f(L,\sigma) = \min_{L,\sigma} \sum_{k}^{N_K} \sum_{l}^{N_L} \left\| I_S(s,t,k) - I(s,t,k) \right\|_{L^2}^2 + \rho \sum_{l}^{N_L} \left| \nabla L(\theta_l, \phi_l) \right|$$

- Alternative Minimization

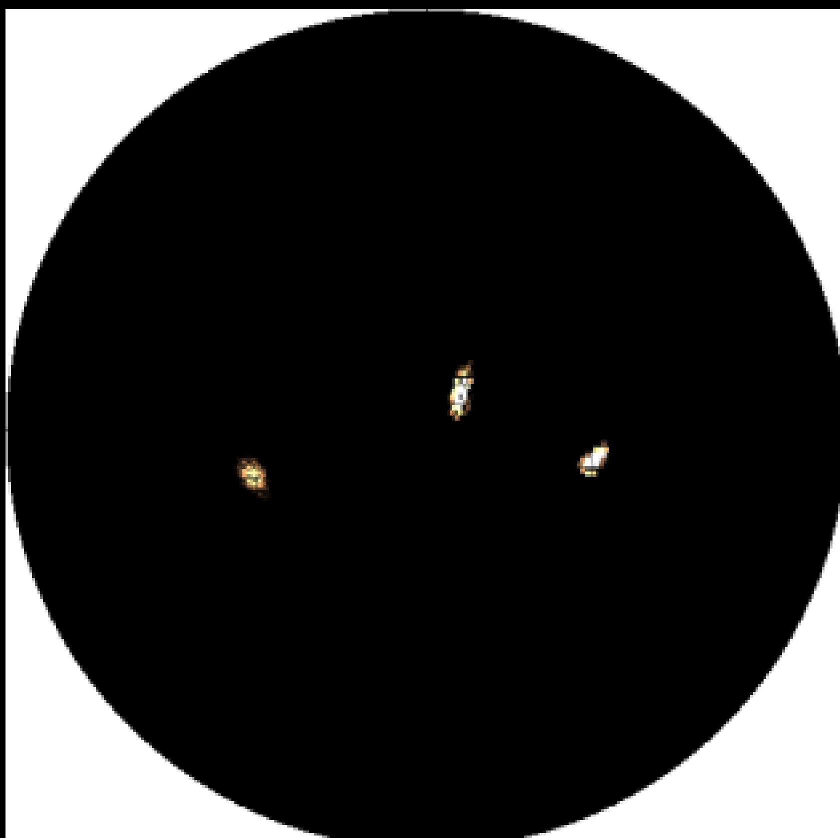
  fix σ estimate L

  fix L estimate σ



- Robustness
  - M-estimation
  - Conjugate gradient

Estimated Results



$\sigma = 0.075$

fisheye view

View-dependent Rendering

1. Render diffuse reflection image
2. Construct shadow maps
   - Shadow z-buffer
3. Render specular reflection image
4. Add 1 and 3

View-dependent Rendering Result

Relighting

Diffuse reflection under the original ill-hemipshere

$$\mathbf{I}_{D,v} = \mathbf{K}_{D,v} \sum_{l}^{N_L} M_{l,v} L_l \cos\theta_{l,v}$$

Diffuse reflection under a new ill-hemisphere

$$\tilde{\mathbf{I}}_{D,v} = \mathbf{K}_{D,v} \sum_{l}^{\tilde{N}_L} \tilde{M}_{l,v} \tilde{L}_l \cos\theta_{l,v}$$

$$\frac{\mathbf{I}_{D,v}}{\tilde{\mathbf{I}}_{D,v}} = \frac{\sum_{l}^{N_L} M_{l,v} L_l \cos\theta_{l,v}}{\sum_{l}^{\tilde{N}_L} \tilde{M}_{l,v} \tilde{L}_l \cos\theta_{l,v}}$$

Relighting Result

Relighting Result

Relighting Result

Rendering from a Sparse Set of Images

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Rendering from a Sparse Set of Images

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Conclusion

- Re-rendering from a Dense Sampling
  - Appearance-based
  - On the object surface (triangular patch based)
- Re-rendering from a Sparse Sampling
  - Estimate texture, parametric BRDF and lighting
  - Deconvolution on a spherical surface

Pros and Cons

- Appearance-based
  - ☺ Any kind of BRDFs
  - ☹ Requires dense sampling
- Model-based
  - ☺ Less input images & compact representation
  - ☹ Assumptions on BRDFs
  - ☹ Assumptions on lighting

Future Work

- From a dense sampling
  - Higher correlation

    (global eigenspace?)
- From a sparse sampling
  - Relighting under different color illuminants

    (spatio-spectral distribution)

Collaborators

Katsushi Ikeuchi Yoichi Sato

The Univ. of Tokyo

Zhengyou Zhang

Microsoft Research

More Info.

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Moving soon (Columbia Univ.)

Alternating Minimization

Joint regularization

$$\min_{u,h} f\left(u,h\right) = \min_{u,h} \left\| h * u - z \right\|^2_{L^2(\Omega)} + \alpha_1 TV\left(u\right) + \alpha_2 TV\left(h\right)$$

Total Variation (TV) norm

$$TV\left(u\right) \equiv \int_\Omega \left|\nabla u\right| dxdy$$

AMUH (AMHU)

initialize h^0 →

$$0 = \nabla_u f\left(u, h^{k-1}\right) \rightarrow u^{k-1}$$

↓

$$0 = \nabla_h f\left(u^{k-1}, h\right) \rightarrow h^k$$

Convergence?