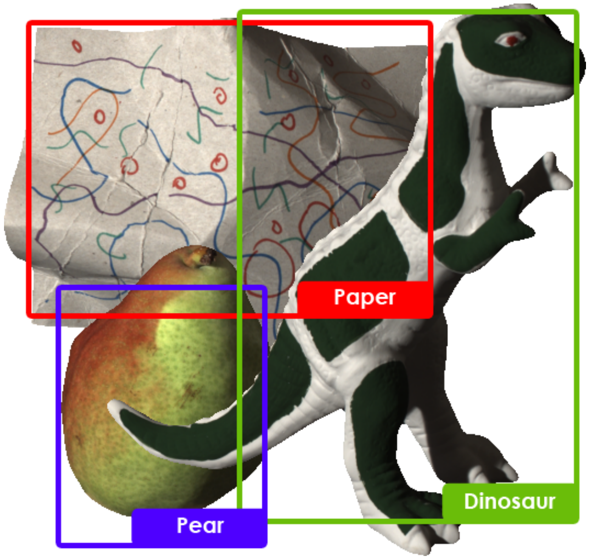
Shape, Illumination, and Reflectance from Shading

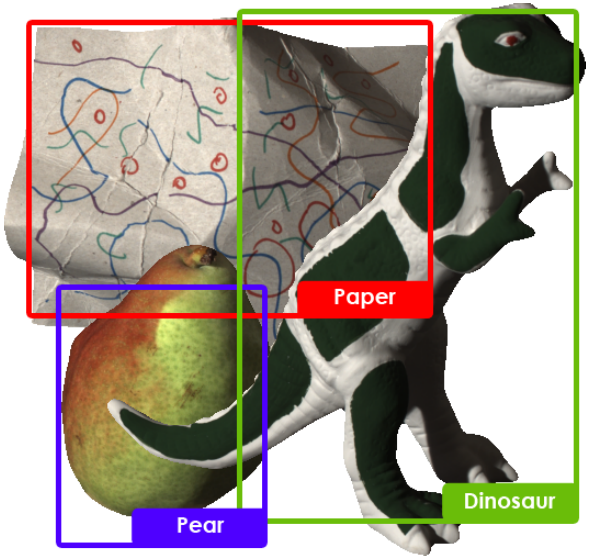
Jonathan Barron & Jitendra Malik

UC Berkeley

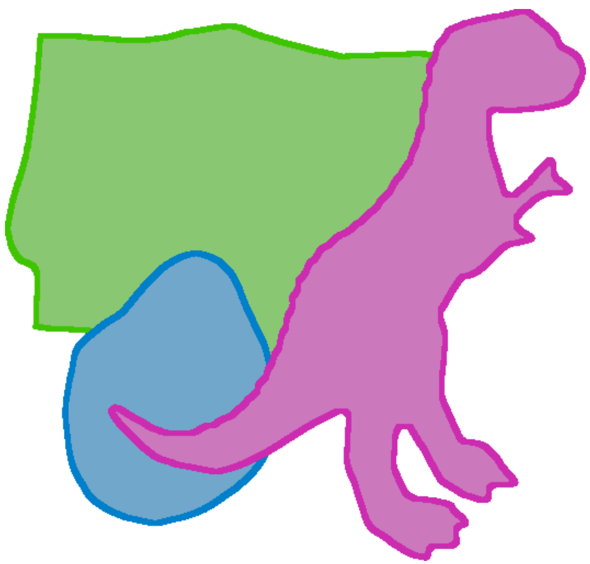
Computer Vision: A Taxonomy



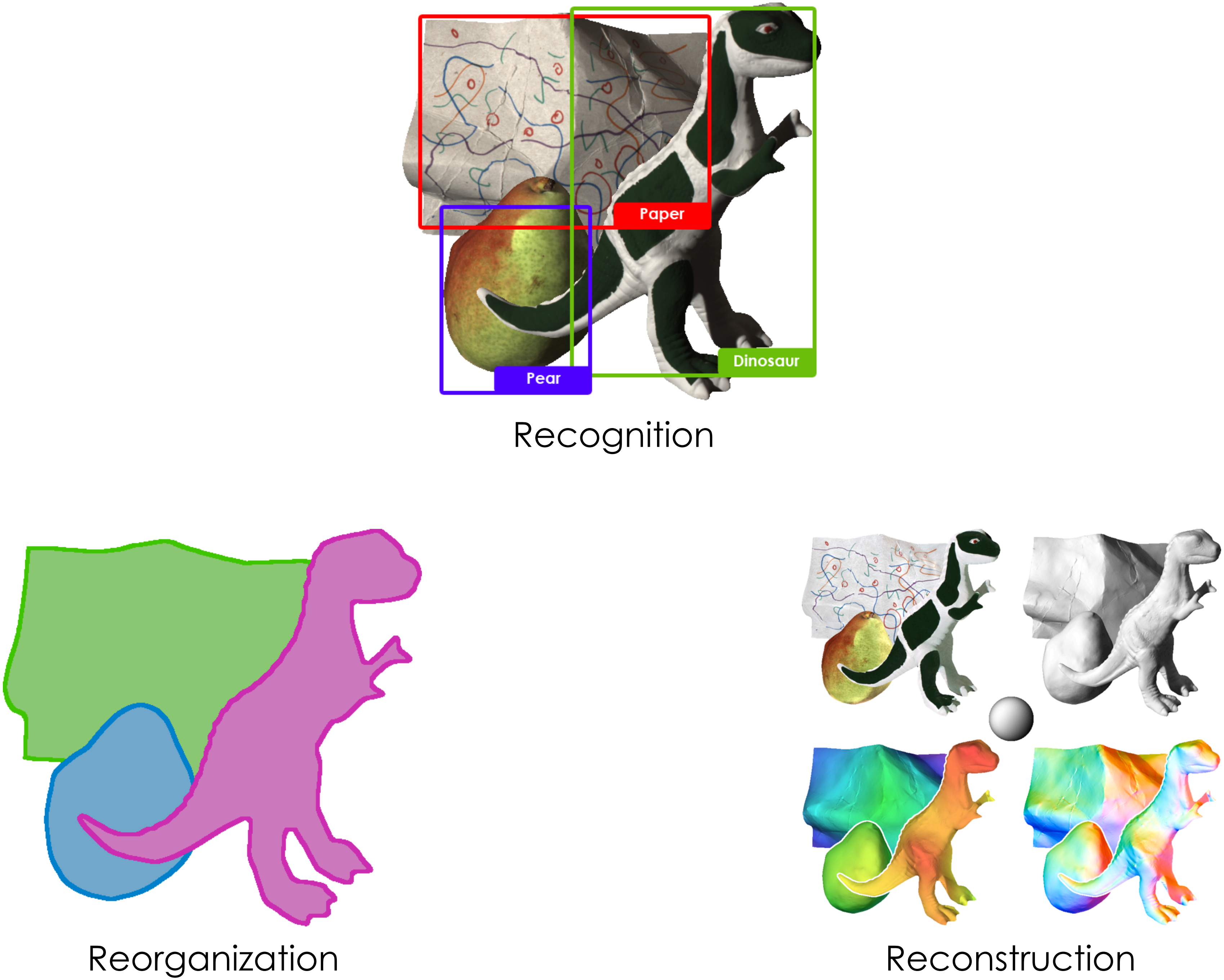
Recognition



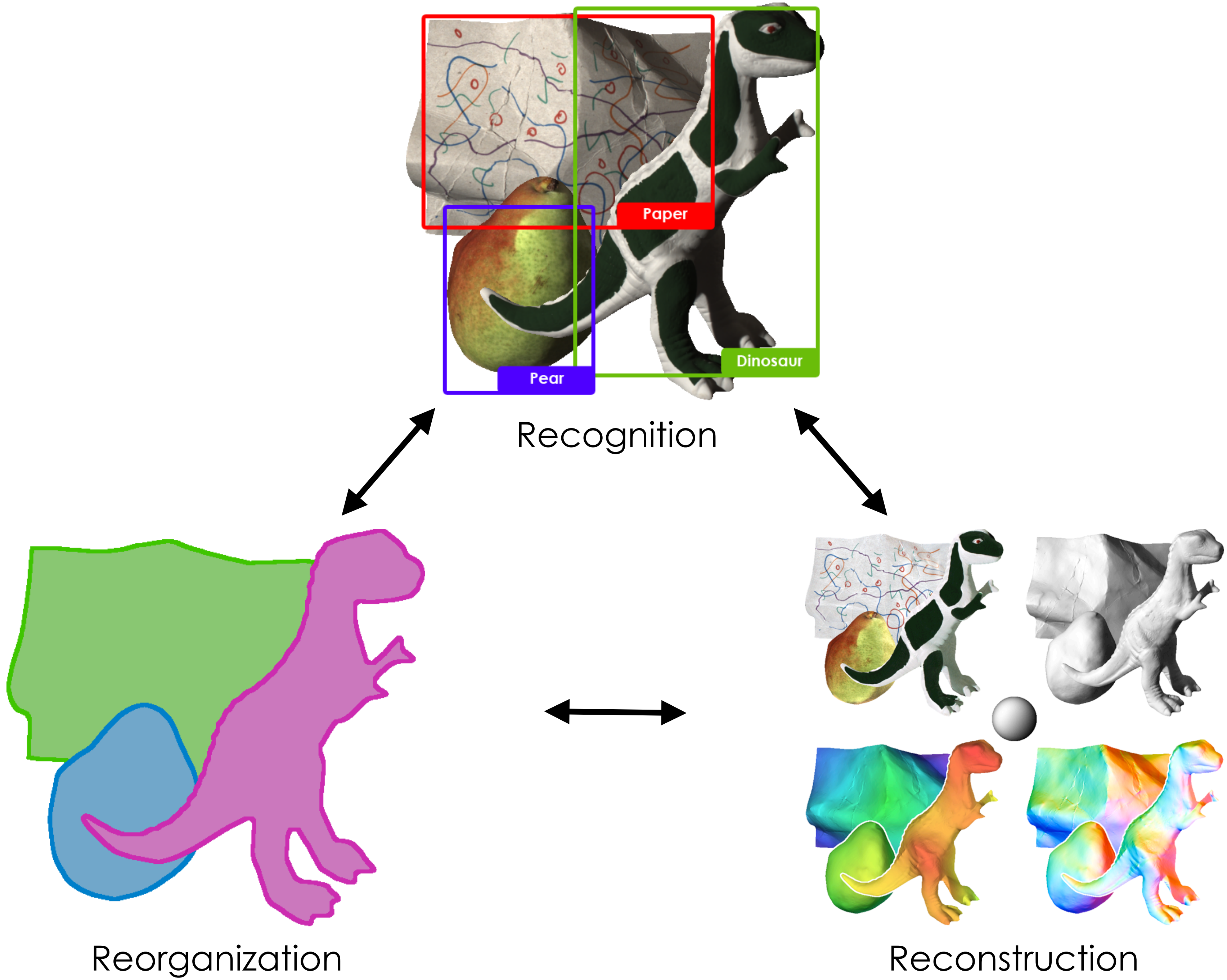
Recognition



Reorganization



Paper
Pear
Dinosaur
Recognition
Reorganization
Reconstruction



Paper
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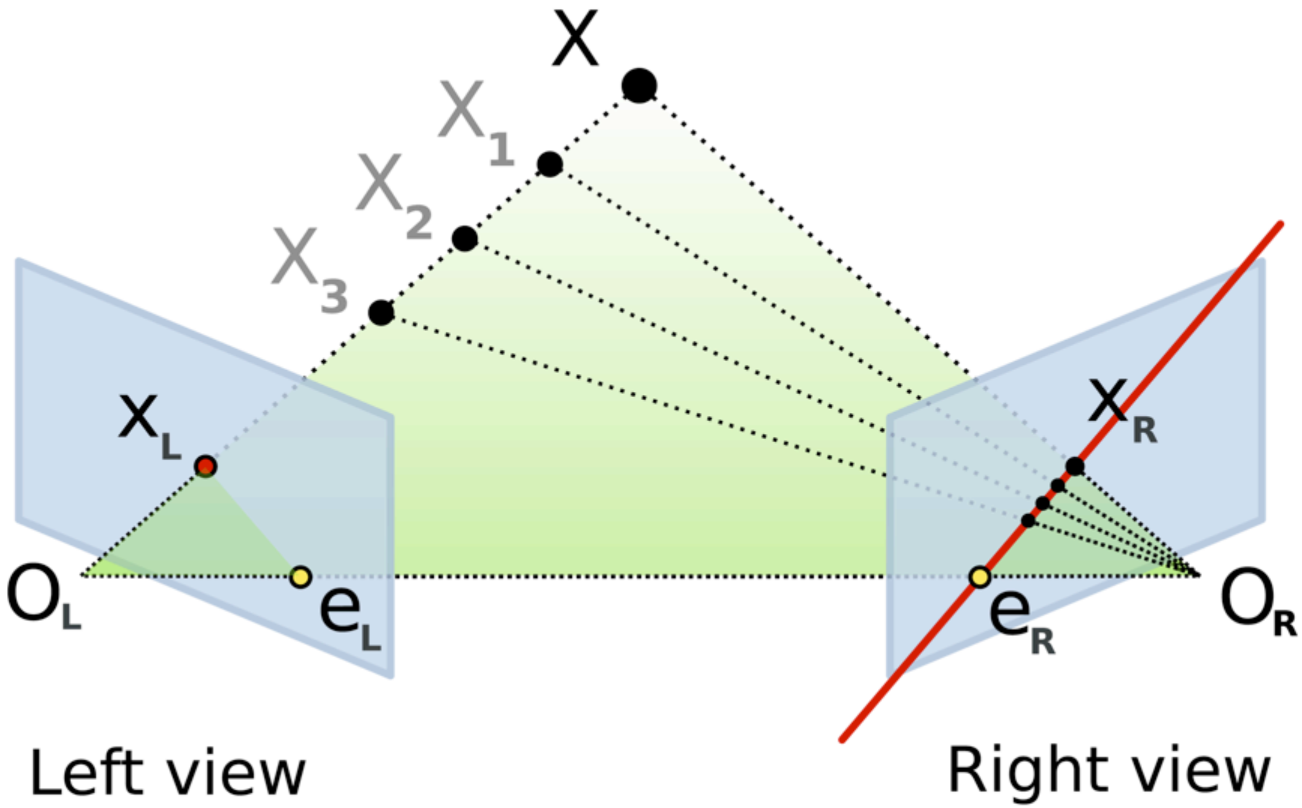
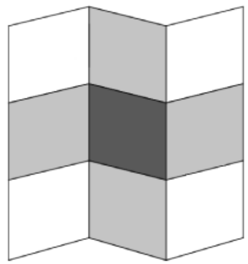
Reconstruction



Reconstruction

Reconstruction?

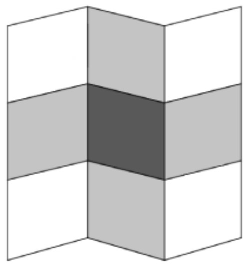
The Workshop Metaphor



(a) an image

E. Adelson and A. Pentland, "The perception of shading and reflectance," *Perception as Bayesian inference*, 1996.

The Workshop Metaphor



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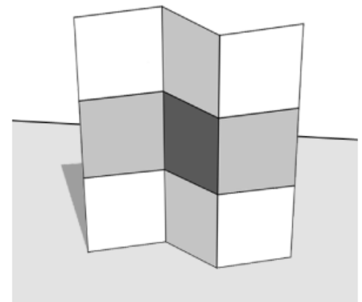

(b) a likely explanation

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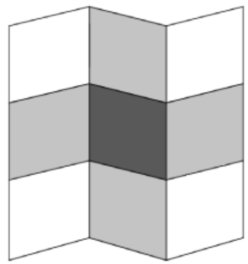
The Workshop Metaphor



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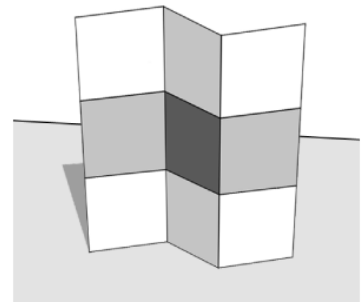
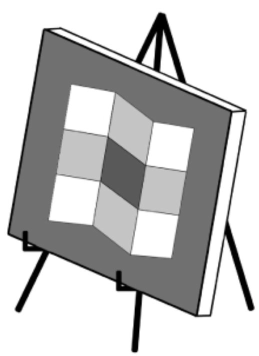


(b) a likely explanation



(c) painter's explanation

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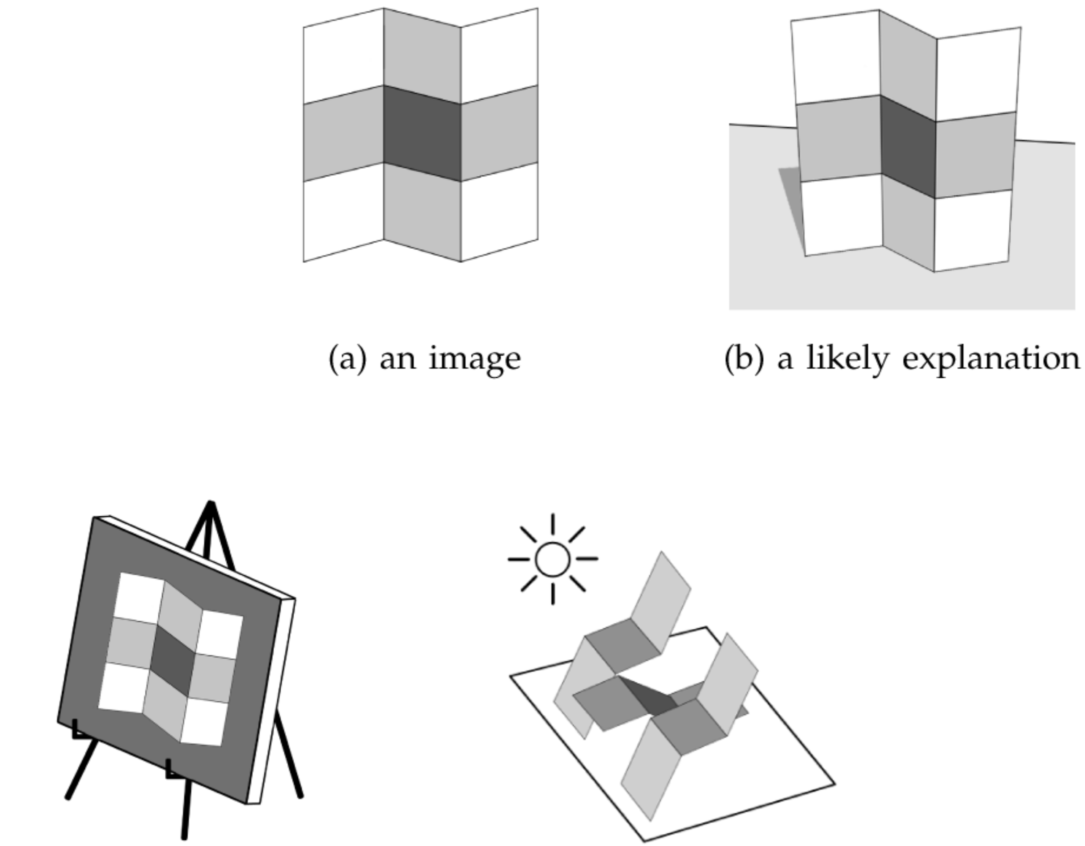

(a) an image
(b) a likely explanation
(c) painter's explanation
(d) sculptor's explanation

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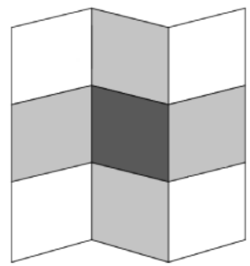
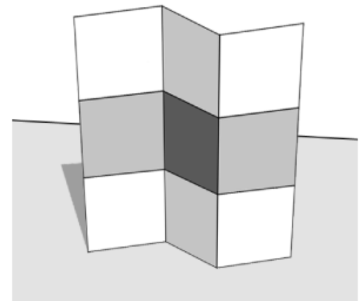
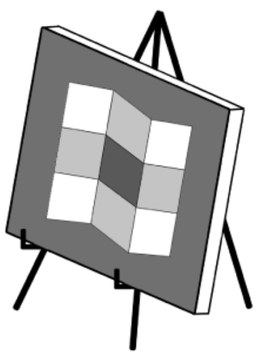
The Workshop Metaphor



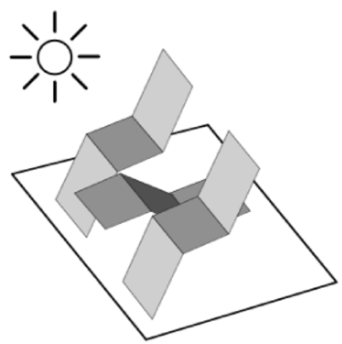
(a) an image



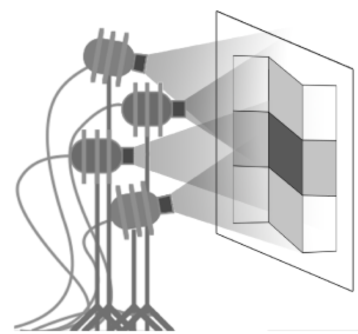
(b) a likely explanation



(c) painter's explanation



(d) sculptor's explanation



(e) gaffer's explanation

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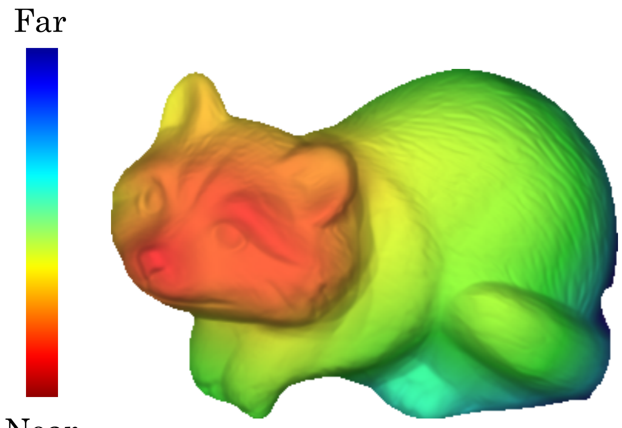
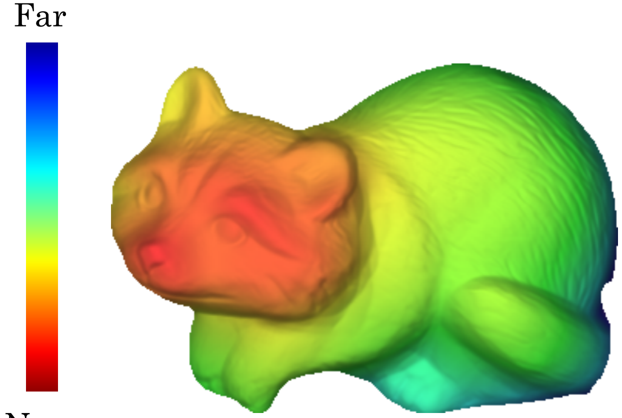
Forward Optics



Z
shape / depth

Forward Optics



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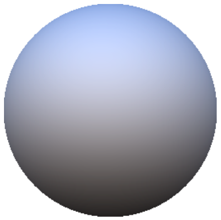
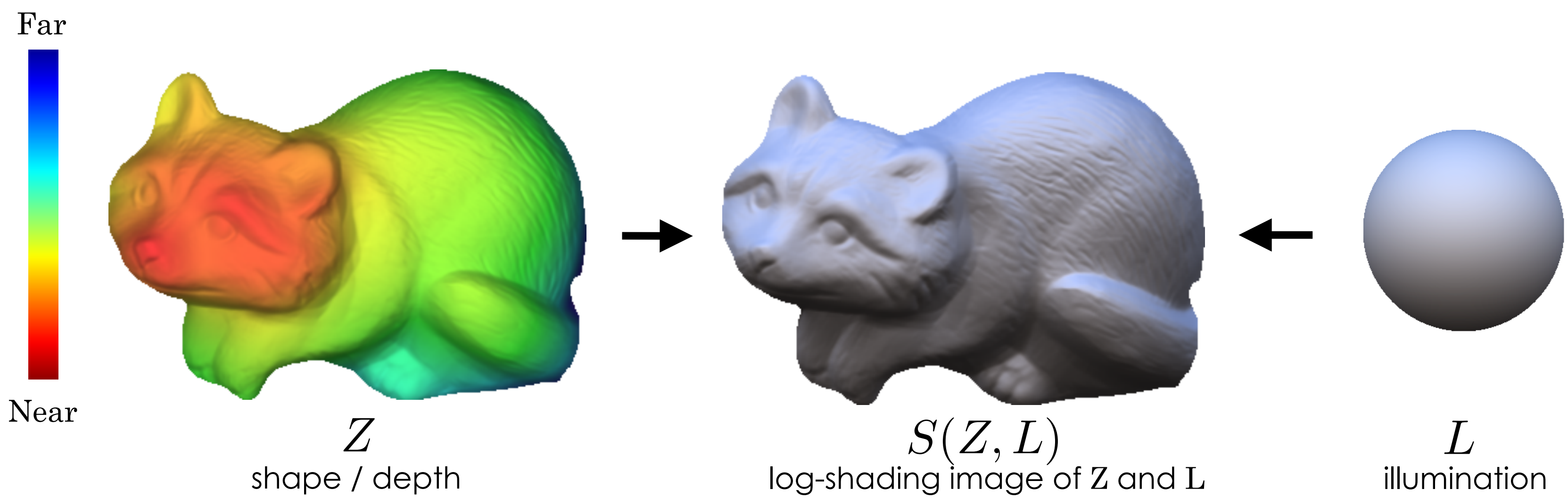


L
illumination

Forward Optics



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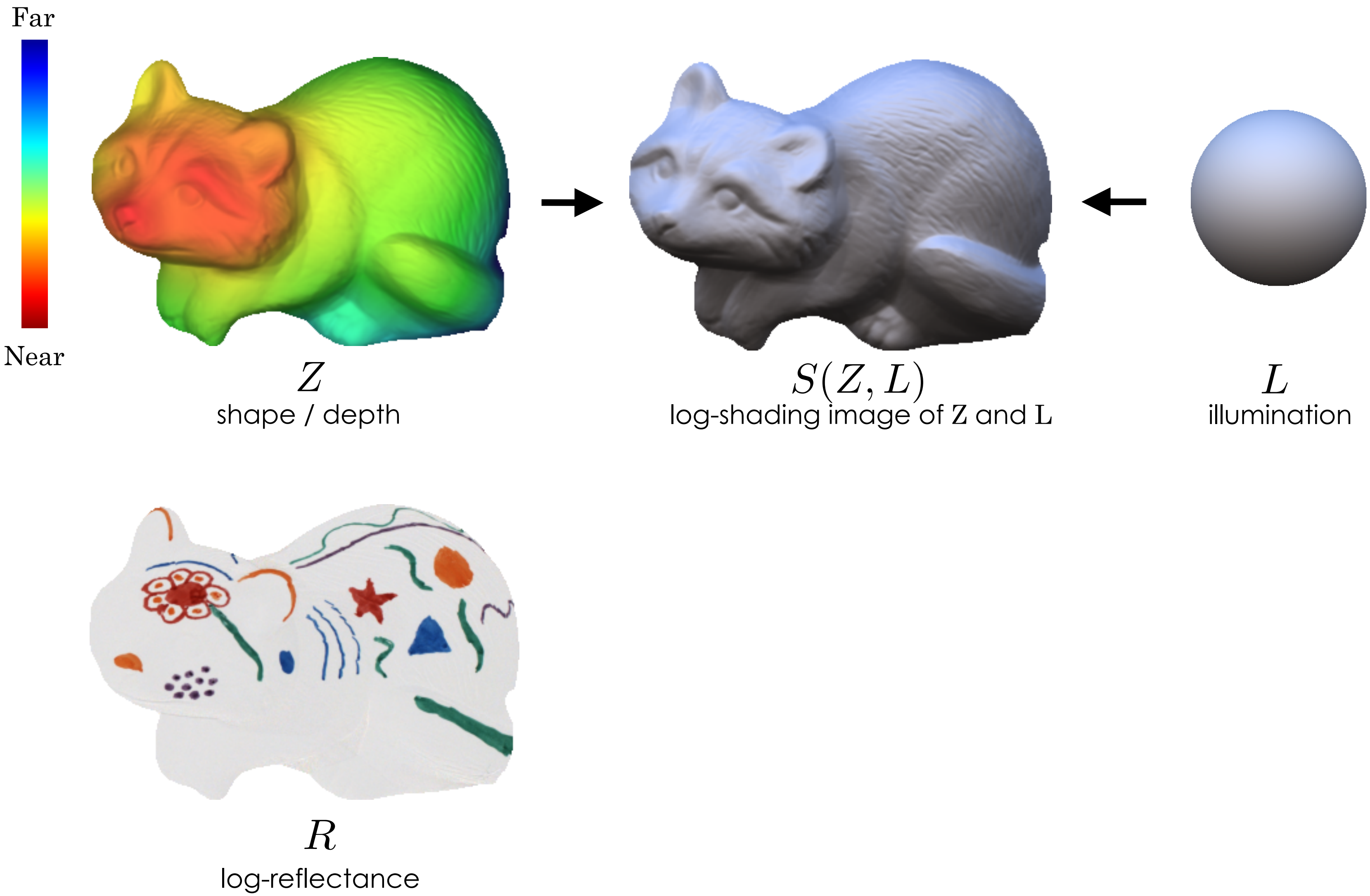

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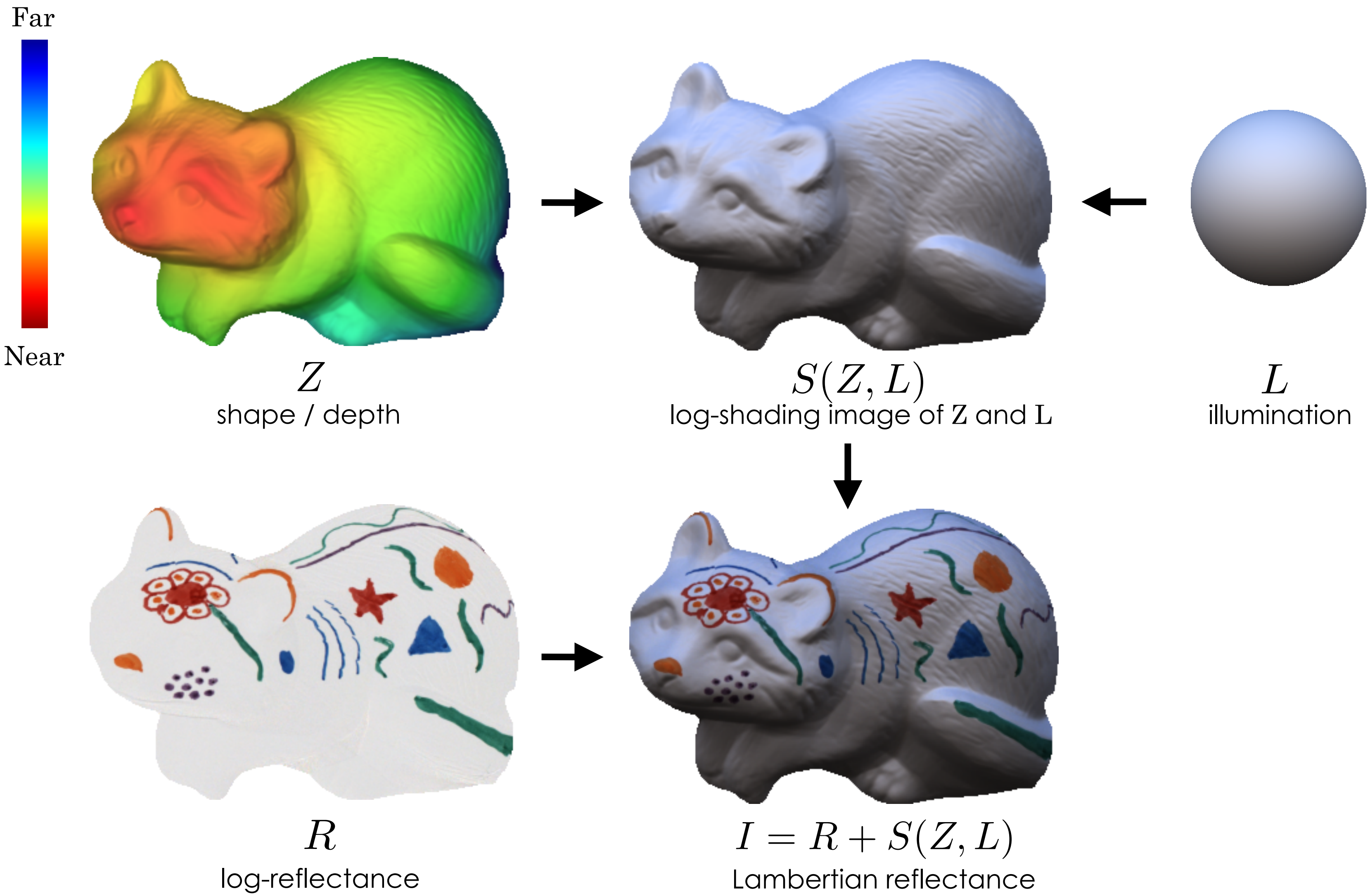
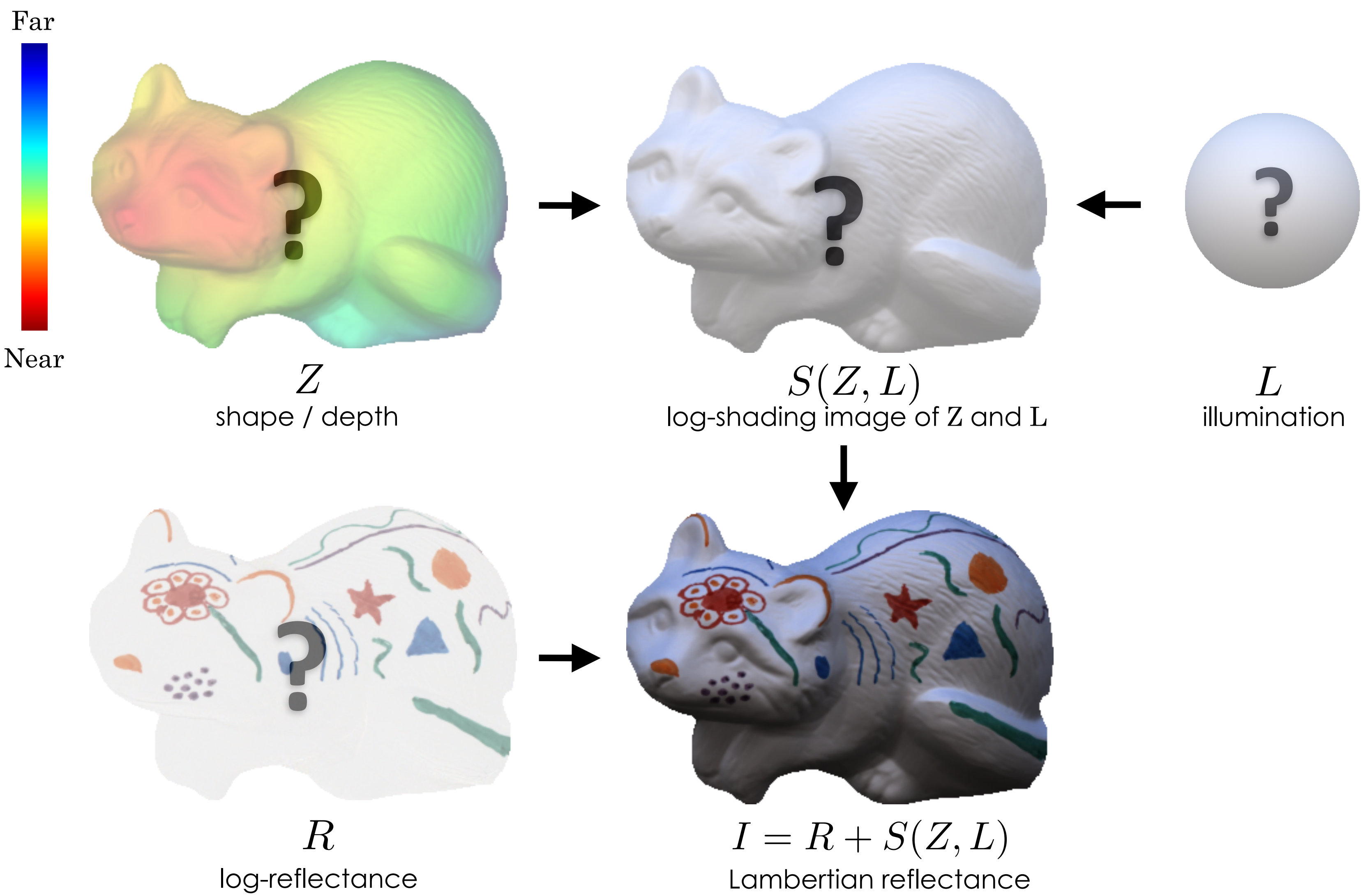
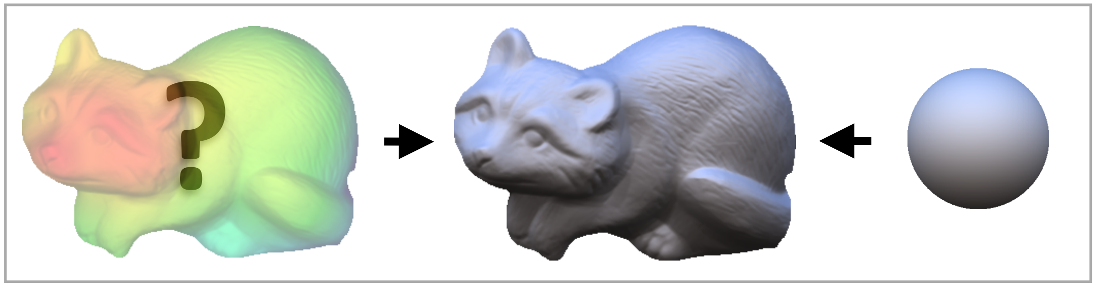


Our problem


Far
Near
Z
shape / depth
$S(Z, L)$
log-shading image of Z and L
L
illumination
R
log-reflectance
$I = R + S(Z, L)$
Lambertian reflectance

Past Work: Shape from Shading



Basic Assumption: illumination and albedo are known.

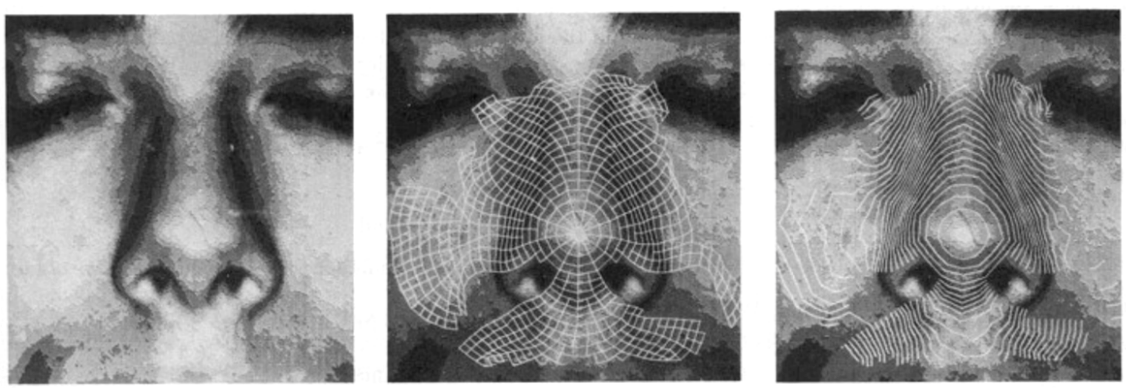
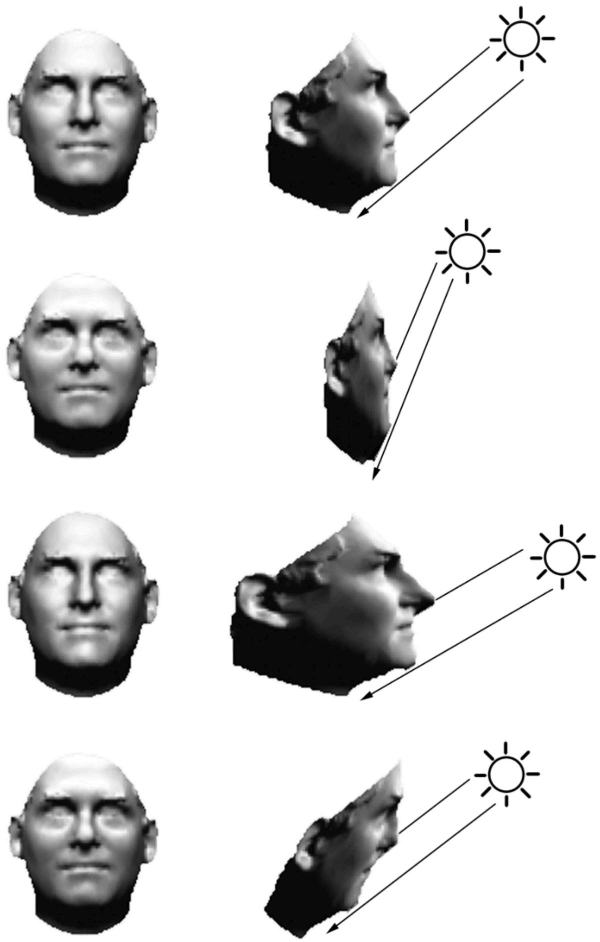


Figure 11-7. The shape-from-shading method is applied here to the recovery of the shape of a nose. The first picture shows the (crudely quantized) gray-level image available to the program. The second picture shows the base characteristics superimposed, while the third shows a contour map computed from the elevations found along the characteristic curves.

B. K. P. Horn. Shape from shading: A method for obtaining the shape of a smooth opaque object from one view. Technical report, MIT, 1970.

Past Work: Shape from Shading



P. Belhumeur, D. Kriegman, and A. Yuille.
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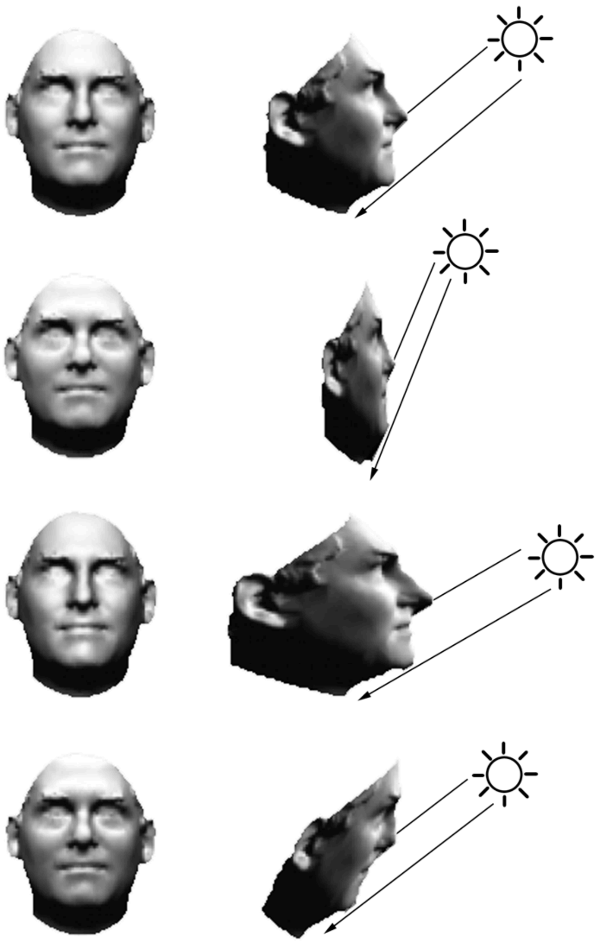
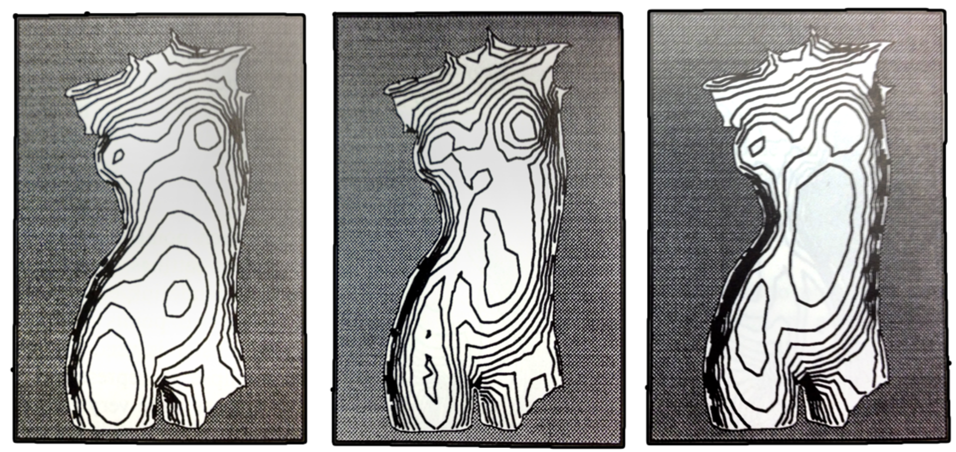




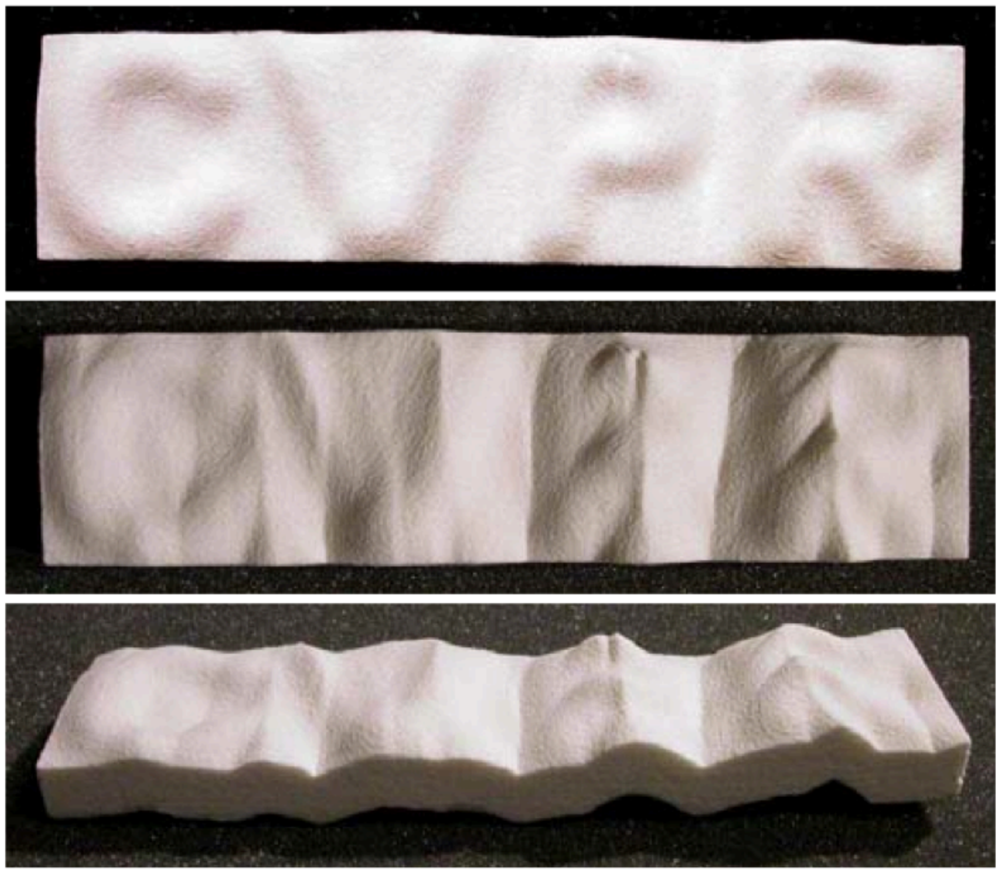
P. Belhumeur, D. Kriegman, and A. Yuille. The Bas-Relief Ambiguity. *IJCV*, 1999.

J. Koenderink, A. van Doorn, C. Christou, and J. Lappin. Shape constancy in pictorial relief. *Perception*, 1996.

Past Work: Shape from Shading

Ecker & Jepson, Polynomial Shape from Shading, *CVPR* 2010

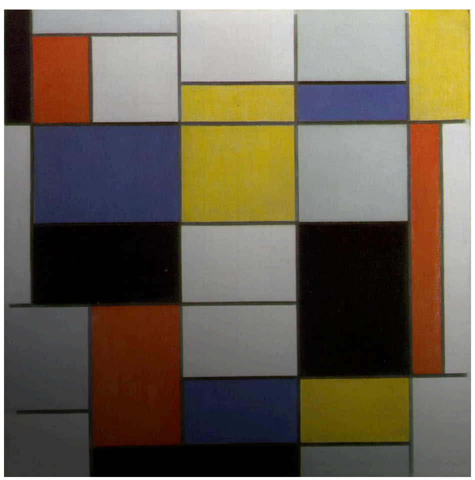
Past Work: Shape from Shading



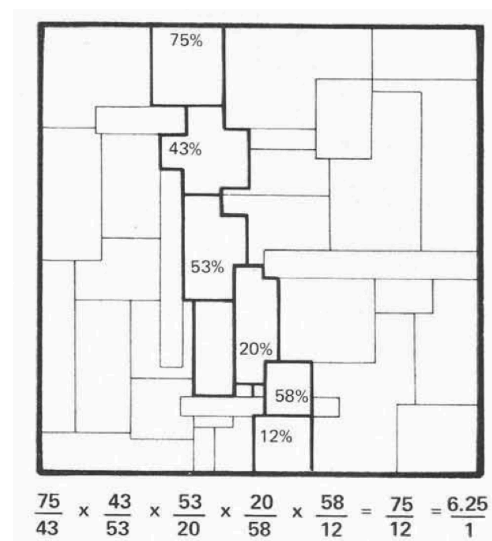
Ecker & Jepson, Polynomial Shape from Shading, *CVPR* 2010

Past Work: Intrinsic Images

Basic assumption: Shape and illumination are ignored, shading varies slowly, reflectance varies quickly.

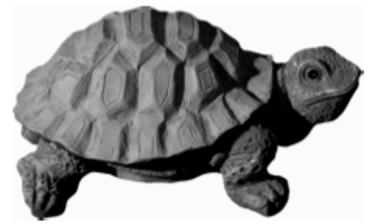


Piet Mondrian, Composition A. Oil on Canvas, 1920.



E. H. Land and J. J. McCann.
Lightness and retinex theory. *JOSA*, 1971.

Past Work: Intrinsic Images



Horn. Determining lightness from an image. CGIP, 1974
Grosse et el., Ground-truth dataset and baseline evaluations for intrinsic image algorithms, ICCV, 2009

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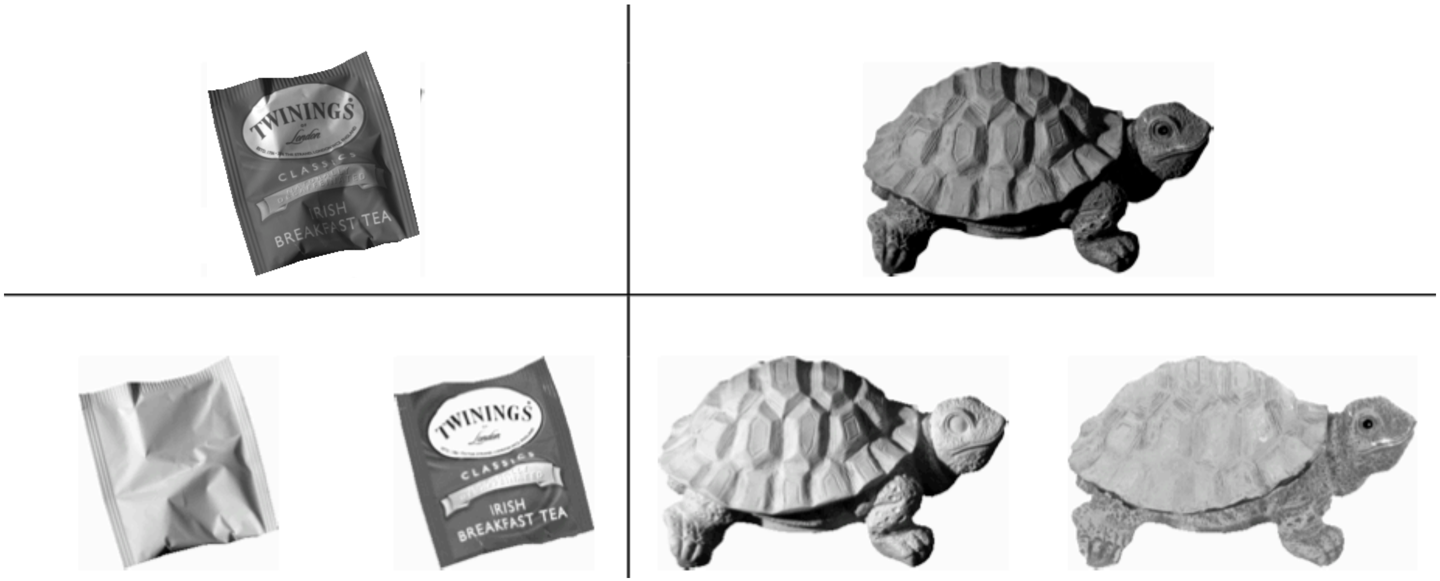

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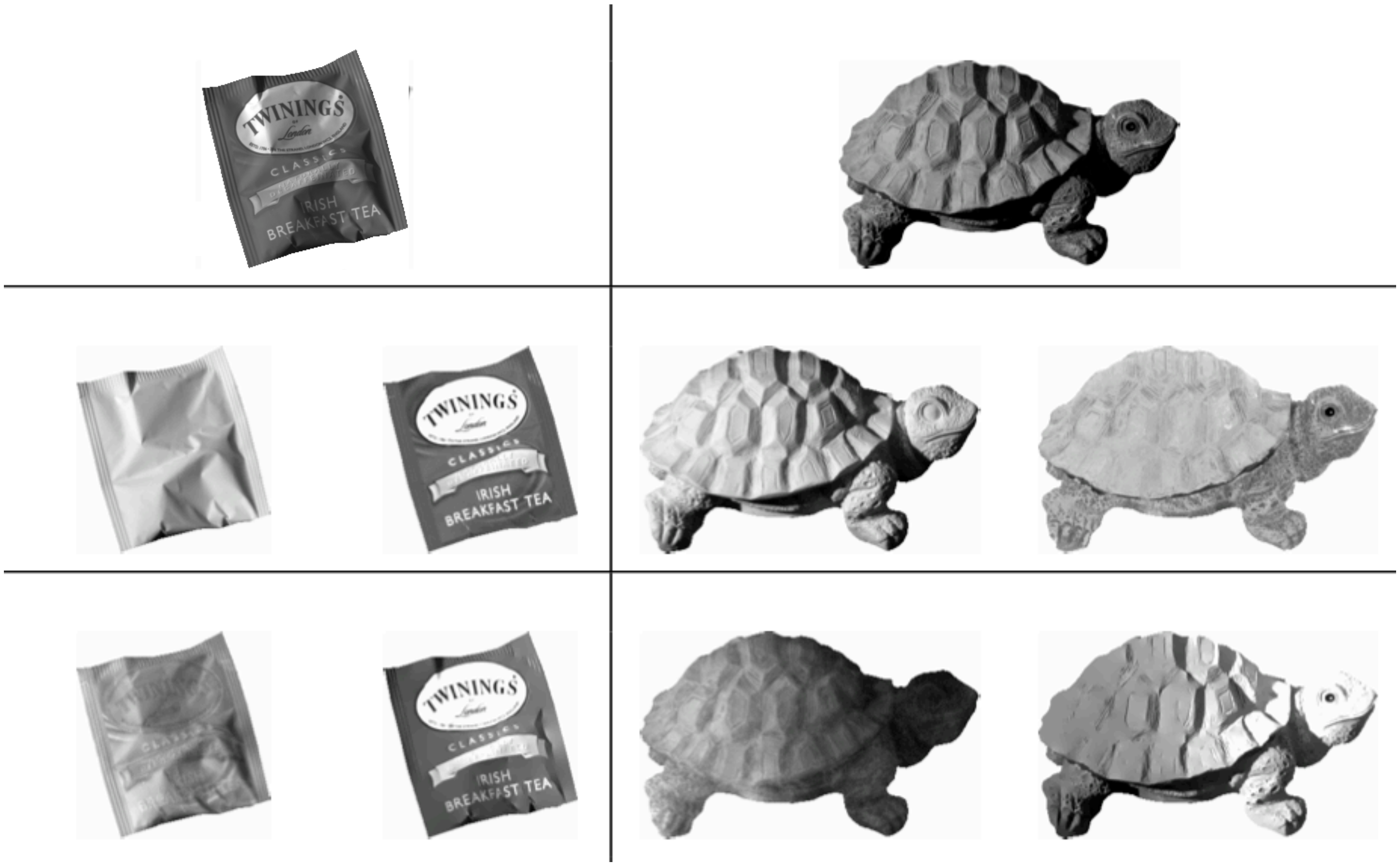


Horn. Determining lightness from an image. CGIP, 1974

Grosse et el., Ground-truth dataset and baseline evaluations for intrinsic image algorithms, ICCV, 2009

Past Work: Color Constancy

Past Work: Natural Image Statistics

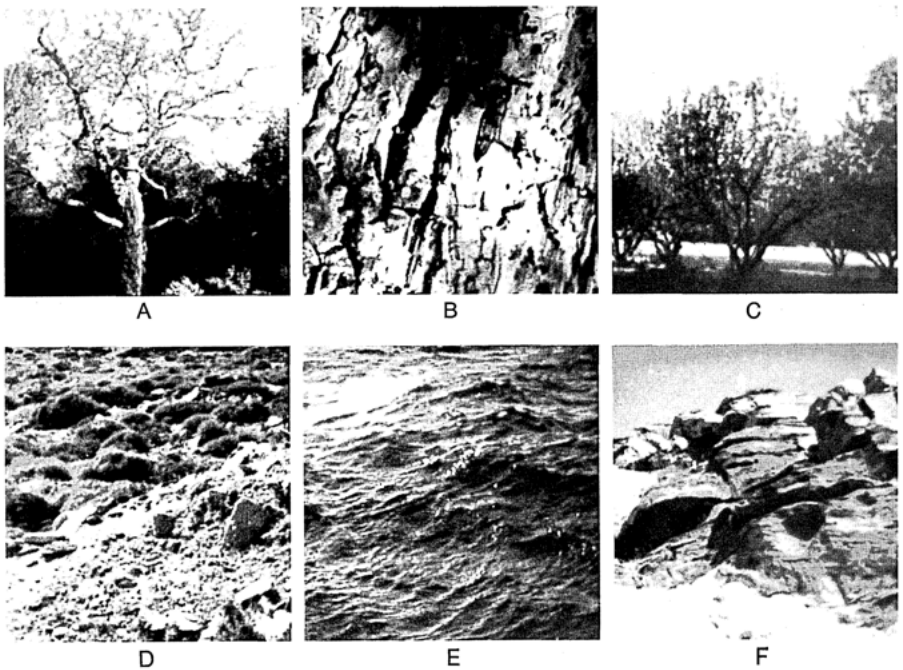
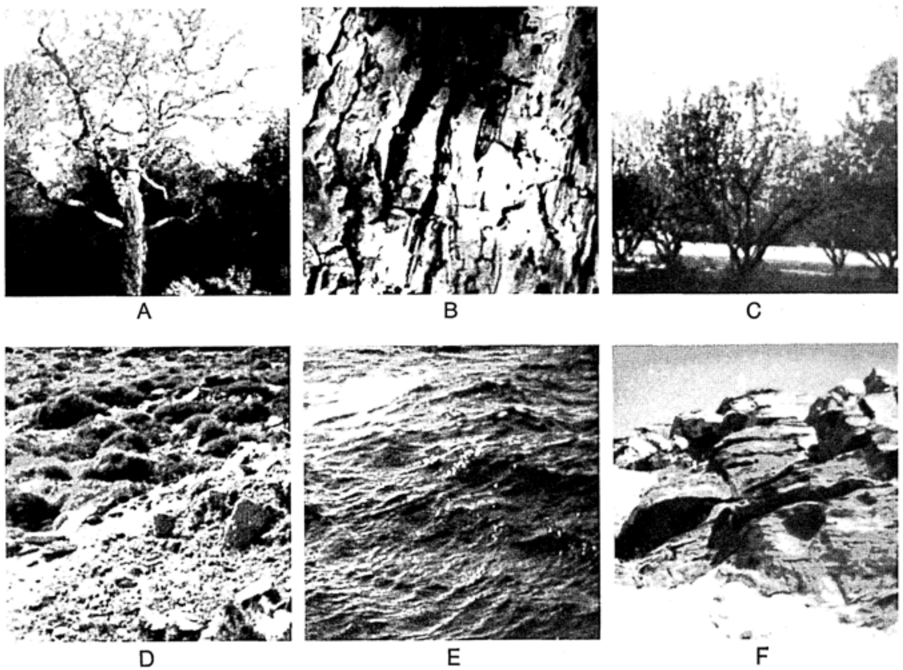


Fig. 6. Examples of the six images (A–F) in this study. Each image consists of 256×256 pixels with 256 gray levels (8 bits). However, only the central region was directly analyzed (160×160). See the text or details.

D. Field. Relations between the statistics of natural images and the response properties of cortical cells. JOSA A, 1987.

Past Work: Natural Image Statistics



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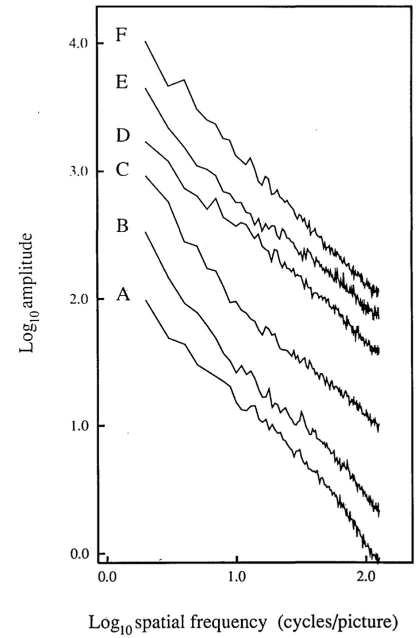

Fig. 8. Amplitude spectra for the six images A–F, averaged across all orientations. The spectra have been shifted up for clarity. On these log–log coordinates the spectra fall off by a factor of roughly $1/f$ (a slope of -1). Therefore the power spectra fall off as $1/f^2$.

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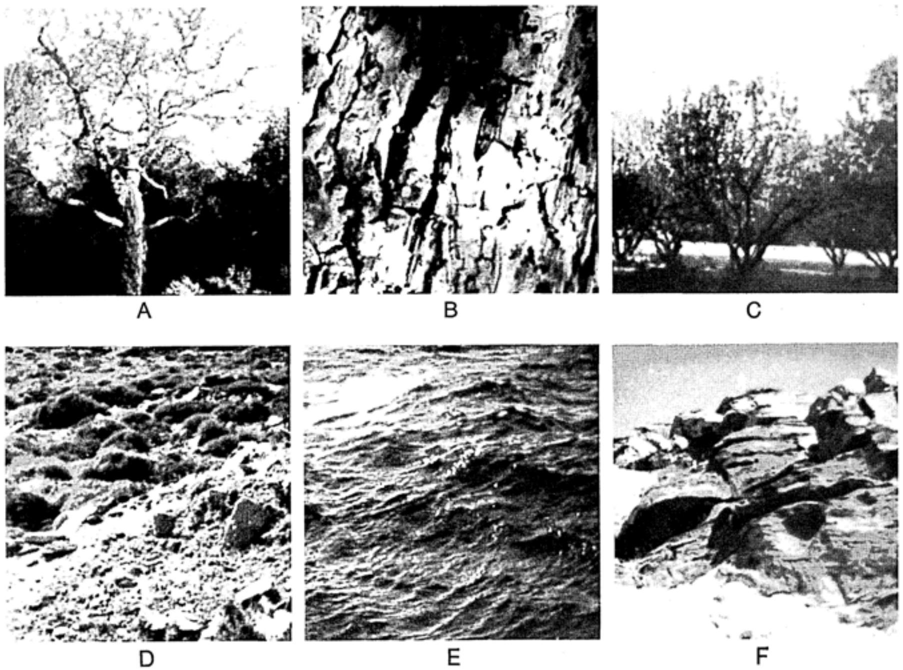

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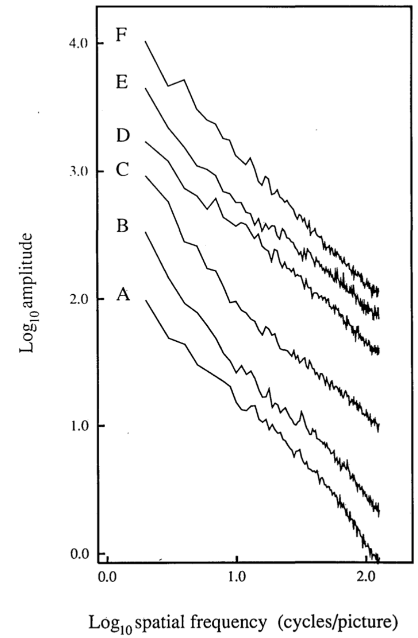

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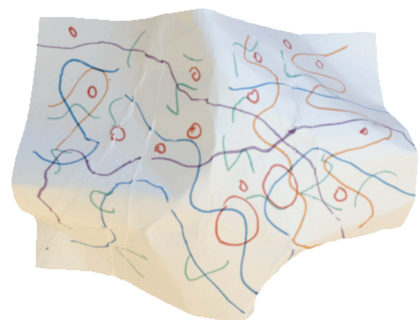
Statistical regularities arise in natural images (mostly) because of statistical regularities in natural environments!

Our Work

SIRFS:
Shape, Illumination and Reflectance from Shading

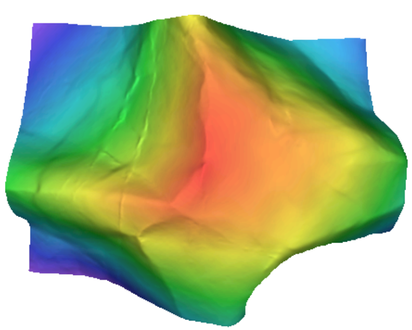
Barron & Malik, CVPR 2011, CVPR 2012, ECCV 2012

Input:

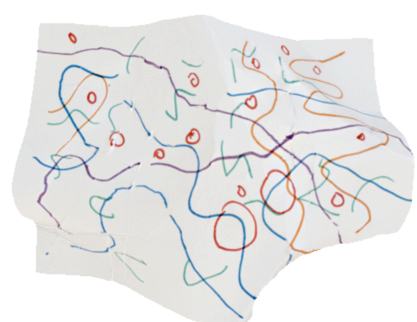


Image

Output:



Shape



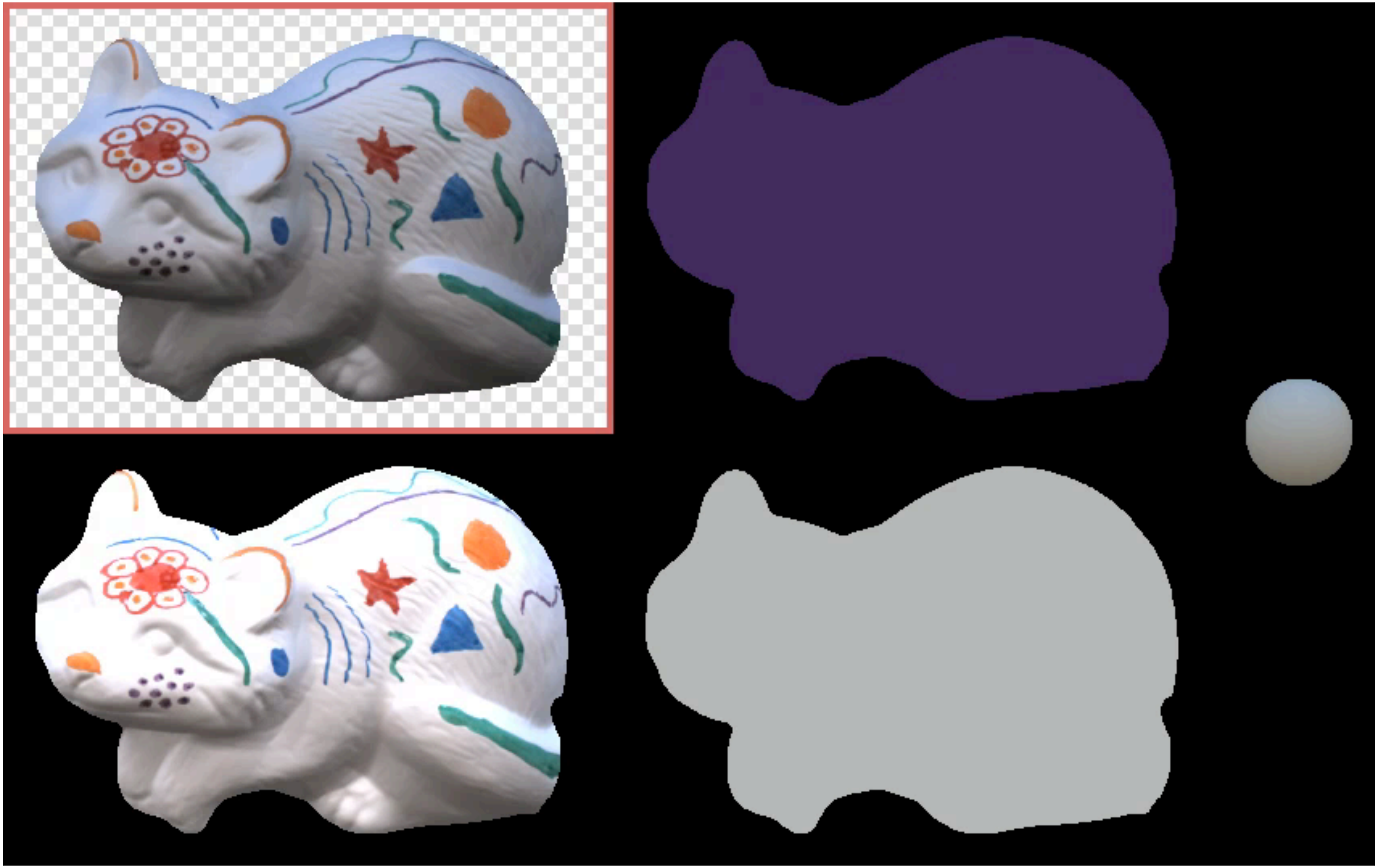
Reflectance

Shading

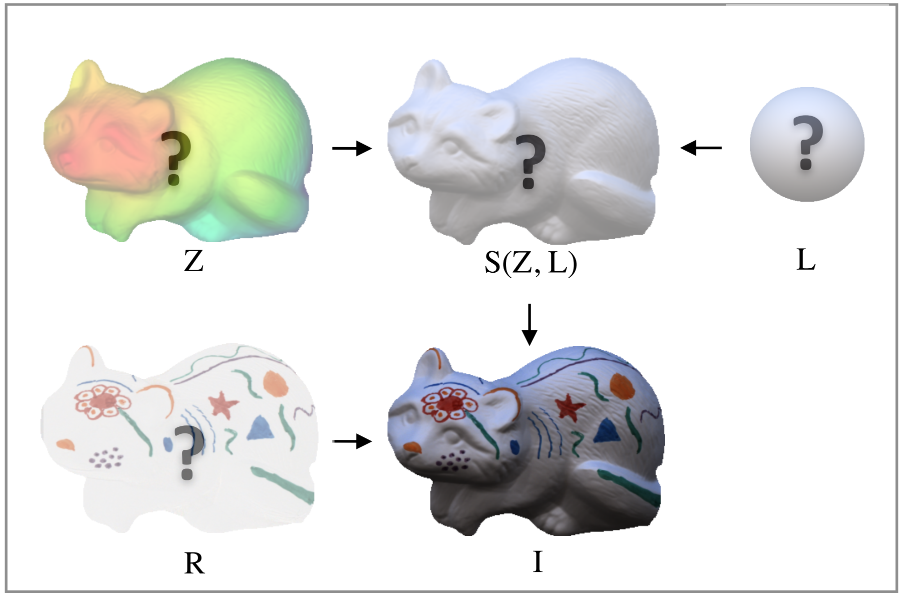
Illumination

Demo!

Demo!



SIRFS

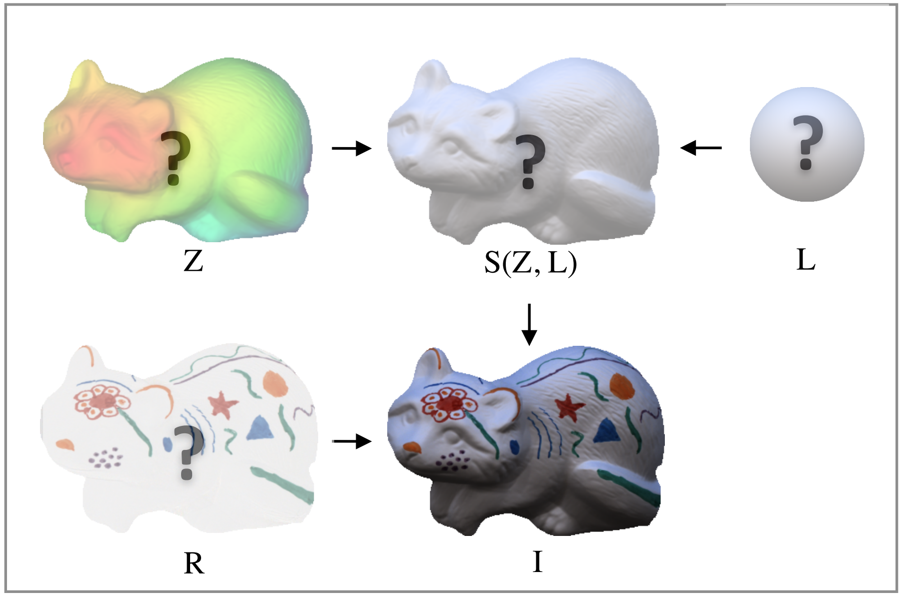


$$\underset{Z,R,L}{\text{maximize}} \quad P(R)P(Z)P(L)$$

$$\text{subject to} \quad I = R + S(Z, L)$$

"Search for the most likely explanation
(shape Z, log-reflectance R and illumination L)
that together exactly reconstructs log-image I"

SIRFS

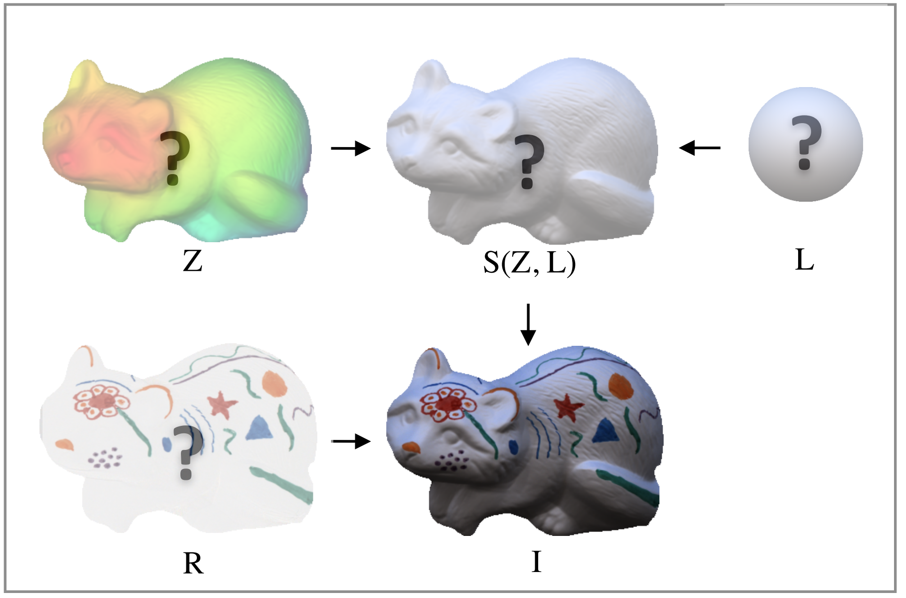


$$\underset{Z,R,L}{\text{minimize}} \quad g(R) + f(Z) + h(L)$$

$$\text{subject to} \quad I = R + S(Z, L)$$

"Search for the least costly explanation
(shape Z, log-reflectance R and illumination L)
that together exactly reconstructs log-image I"

SIRFS



$$\underset{Z,R,L}{\text{minimize}} \quad \boxed{g(R)} + f(Z) + h(L)$$

$$\text{subject to} \quad I = R + S(Z, L)$$

"Search for the least costly explanation
(shape *Z*, log-reflectance *R* and illumination *L*)
that together exactly reconstructs log-image *I*"

What do we know about **reflectance**?

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1) **Smoothness:** reflectance rarely changes.

→ Minimize local variation

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What do we know about **reflectance**?

1) **Smoothness:** reflectance rarely changes.

→ Minimize local variation

2) **Parsimony:** the palette of a scene tends to be small

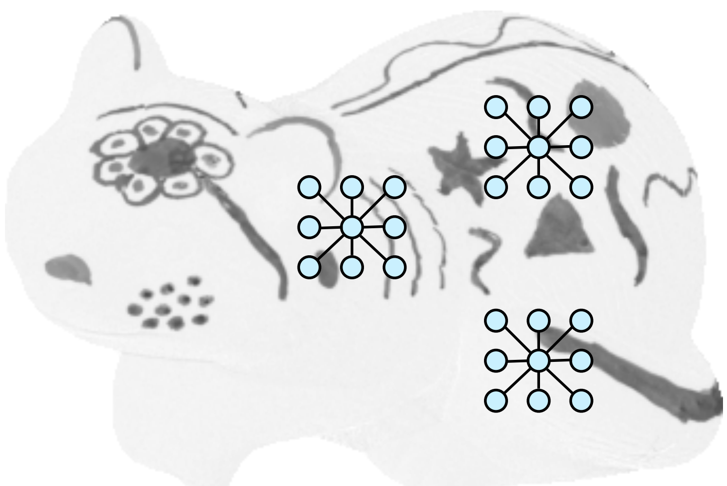
→ Minimize global entropy

3) **Color:** some colors are more likely than others

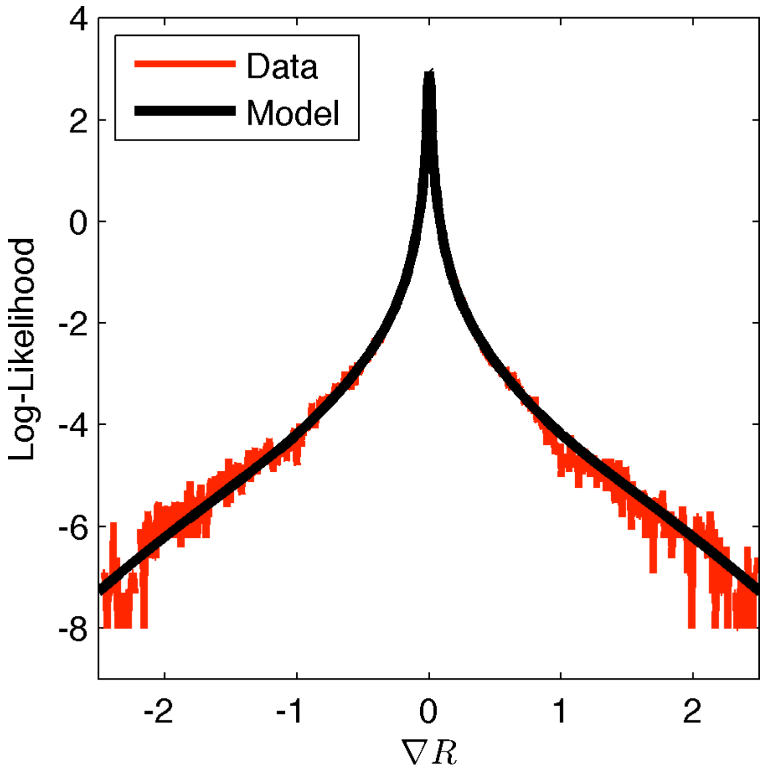
→ Maximize likelihood under some density model

Reflectance: Smoothness

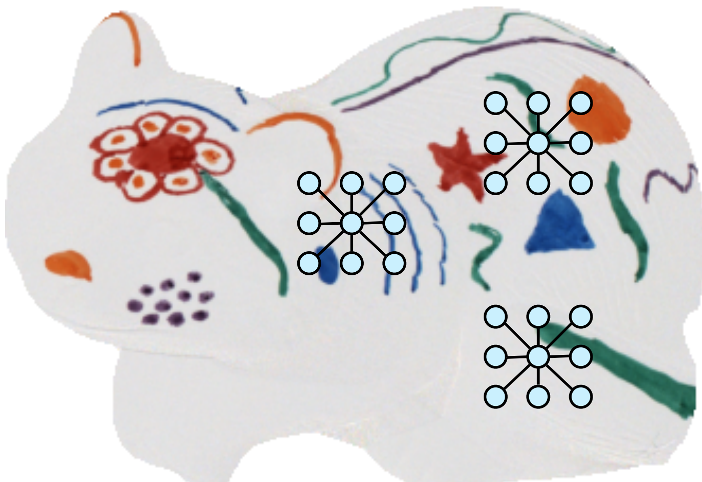
Reflectance: Smoothness

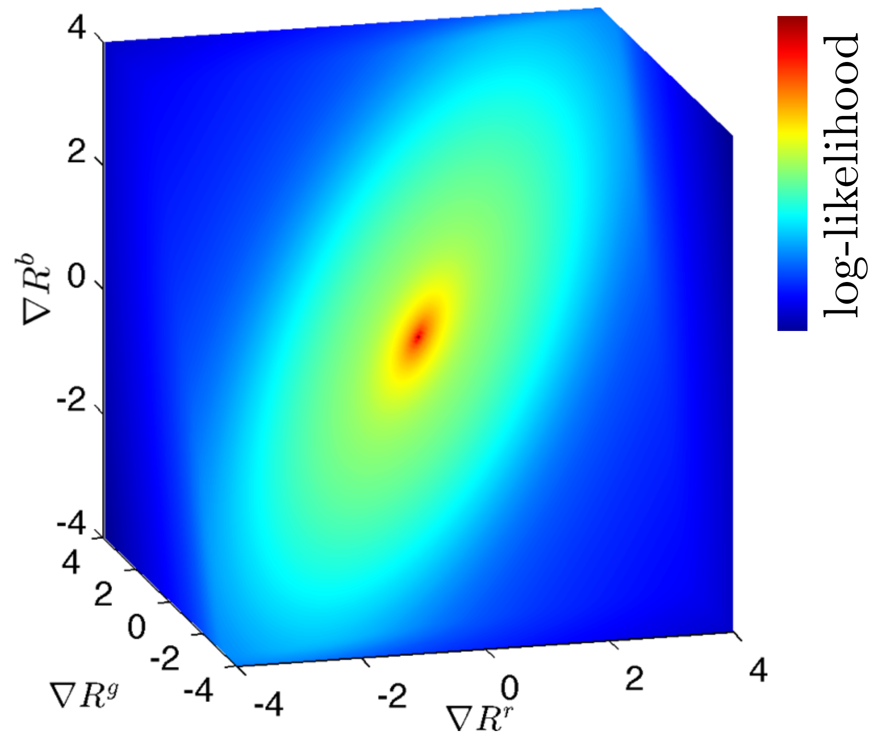


Reflectance: Smoothness

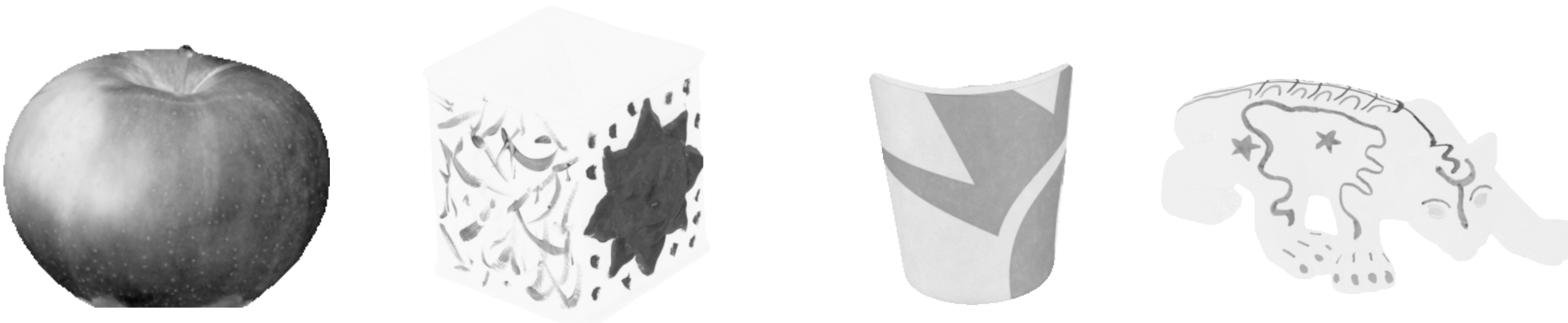


Reflectance: Smoothness

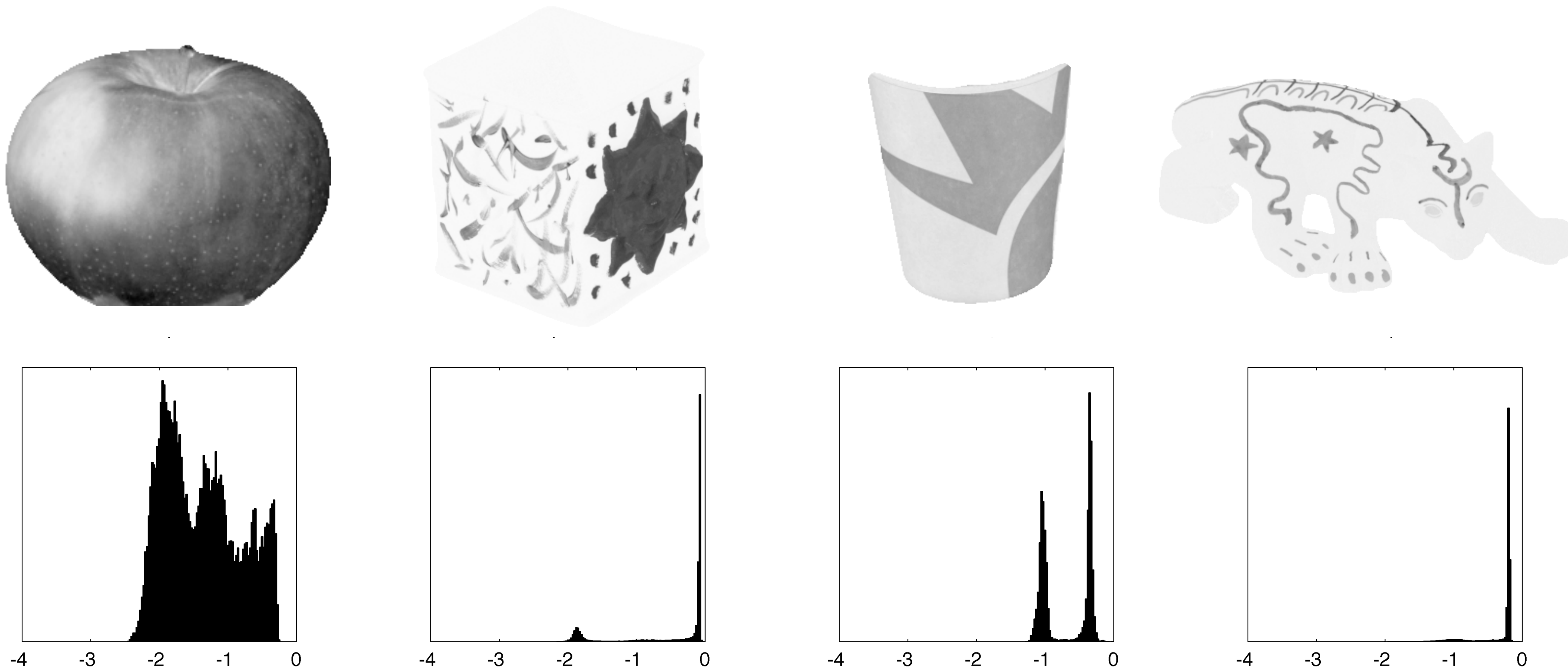




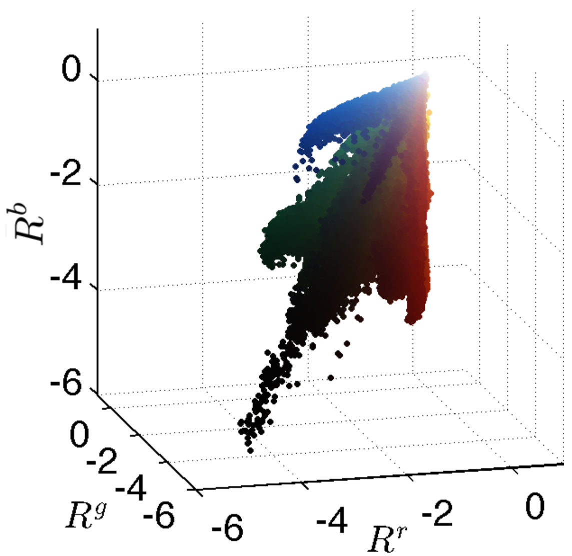
Reflectance: Parsimony



Reflectance: Parsimony

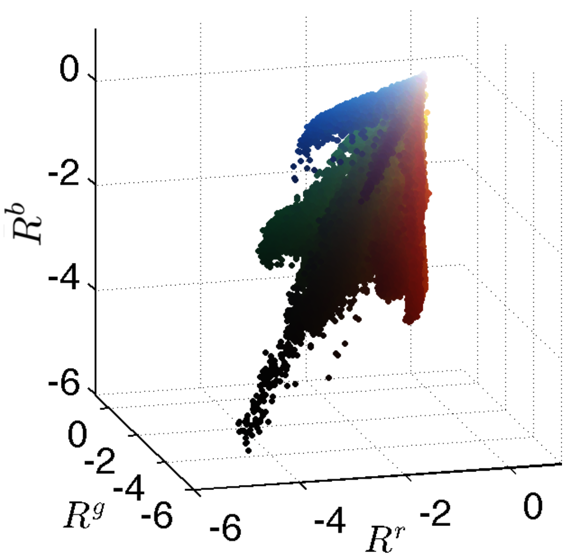


Reflectance: Color



Training Reflectances

Reflectance: Color



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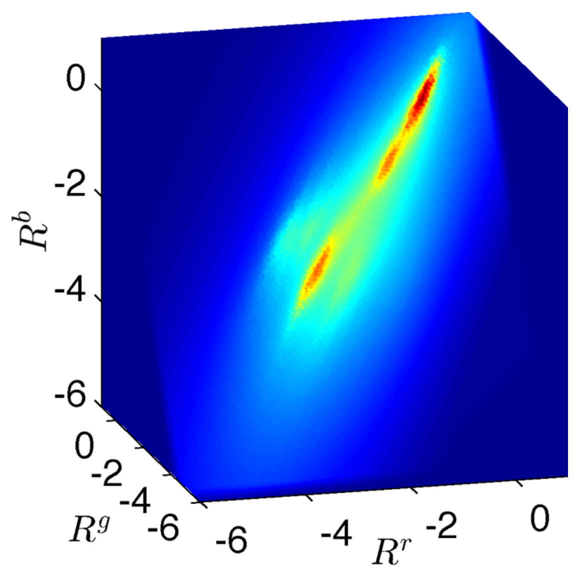
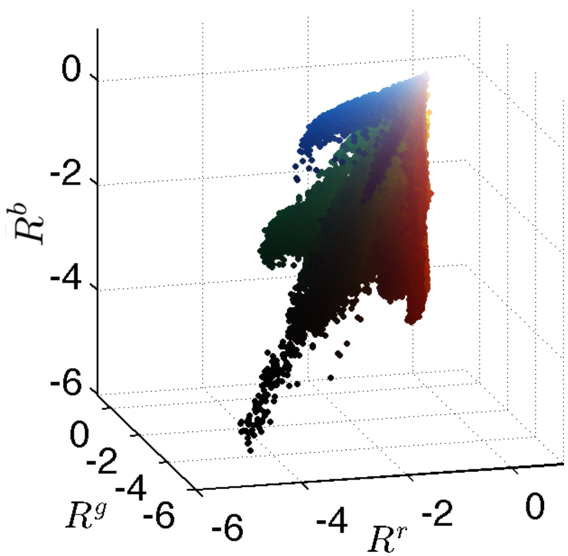
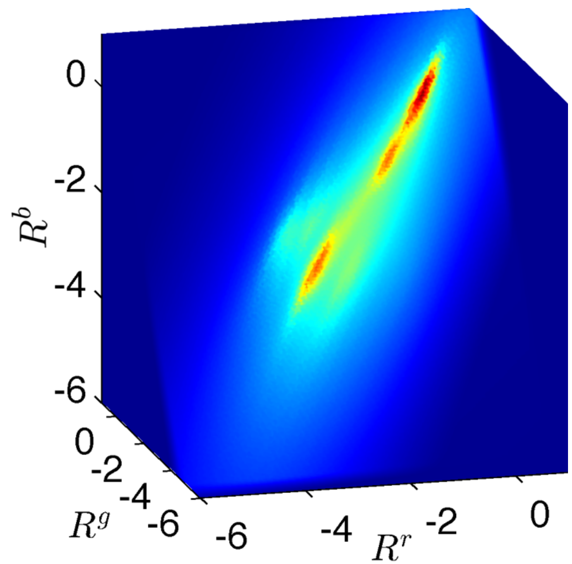


Our PDF of reflectance

Reflectance: Color



Training Reflectances



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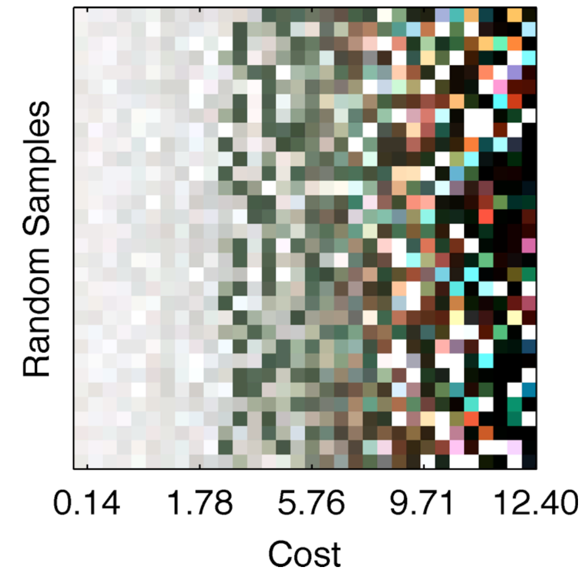
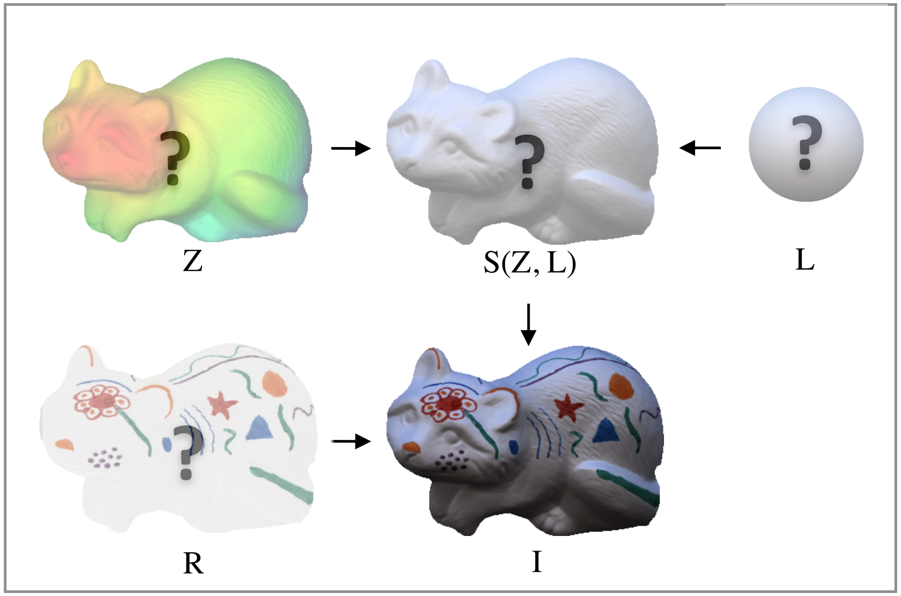


Samples from our PDF,
sorted by cost

SIRFS



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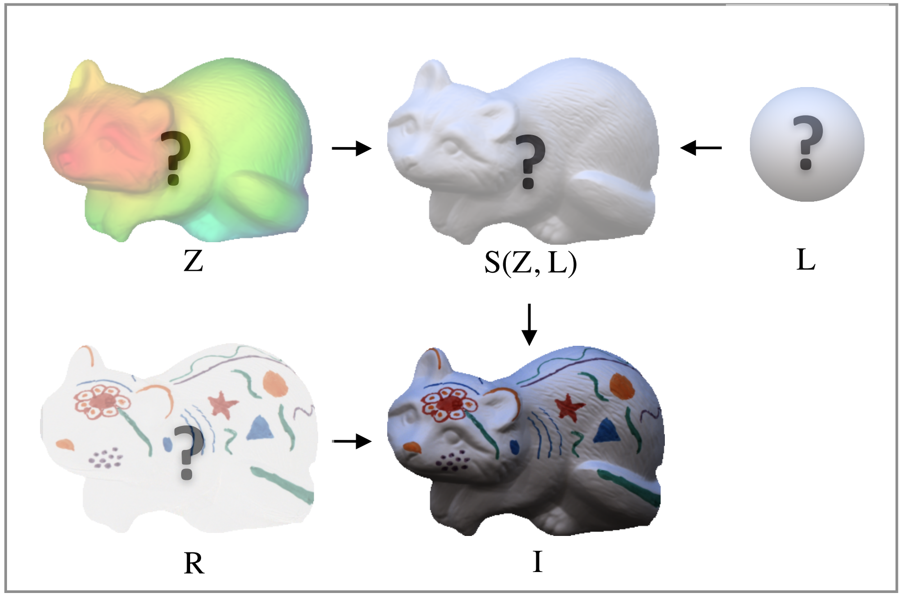

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→Minimize variation in mean curvature

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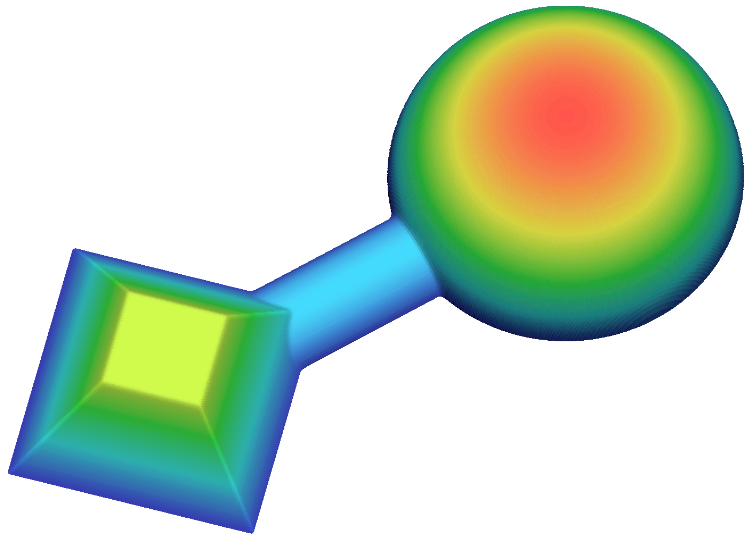
1) **Smoothness:** surfaces rarely bend.
   →Minimize variation in mean curvature

2) **Isotropy:** surface orientations in the world are isotropic.
   → Minimize slant

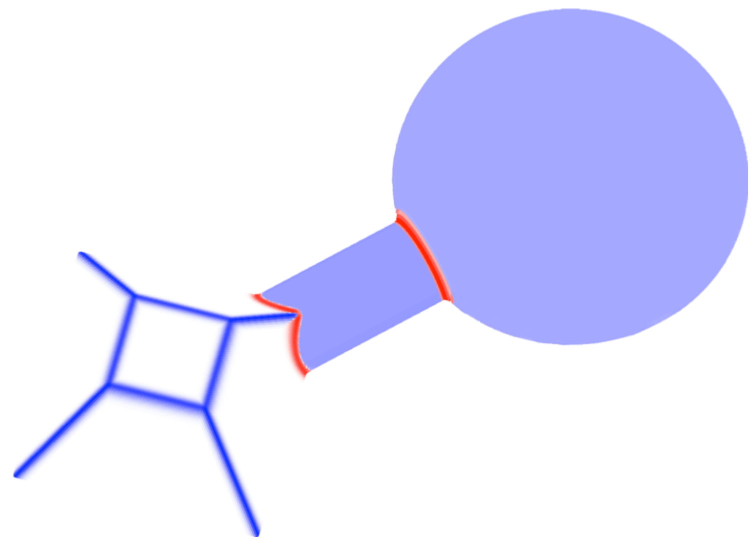
Shapes: Smoothness



$$Z$$

What's a good representation of shape for imposing priors?

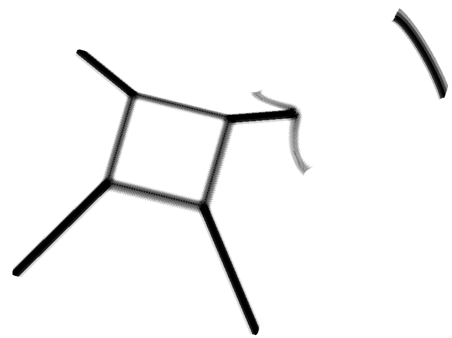
Shapes: Smoothness



$$H(Z)$$

Mean Curvature of Z
(zero on planes, constant on cylinders and spheres)

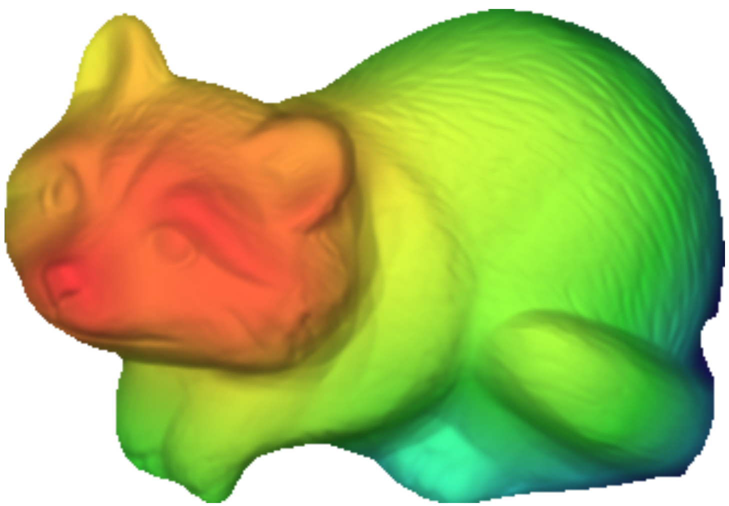
Shapes: Smoothness



$$\nabla H(Z)$$

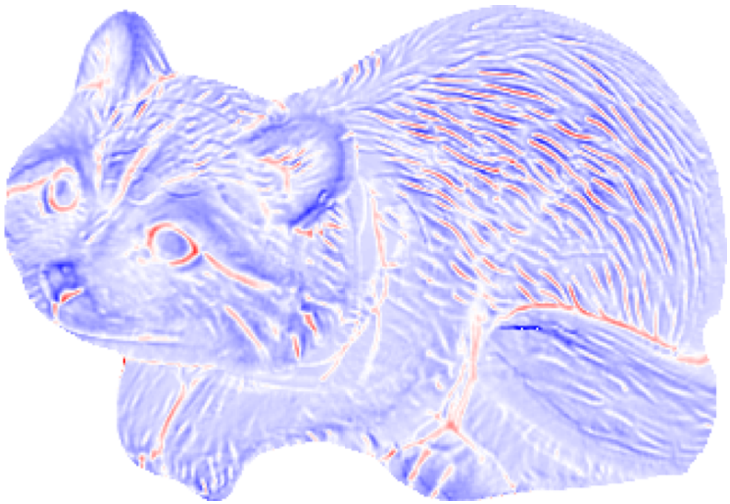
Variation of Mean Curvature of Z
"bending"

Shapes: Smoothness



Z

Shapes: Smoothness



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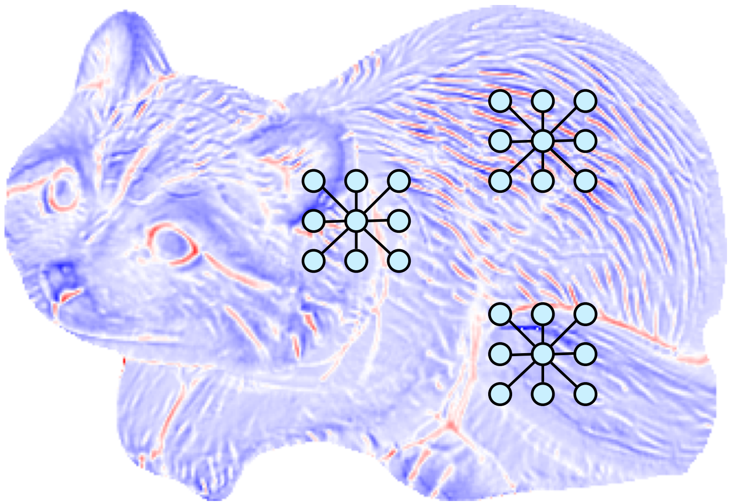

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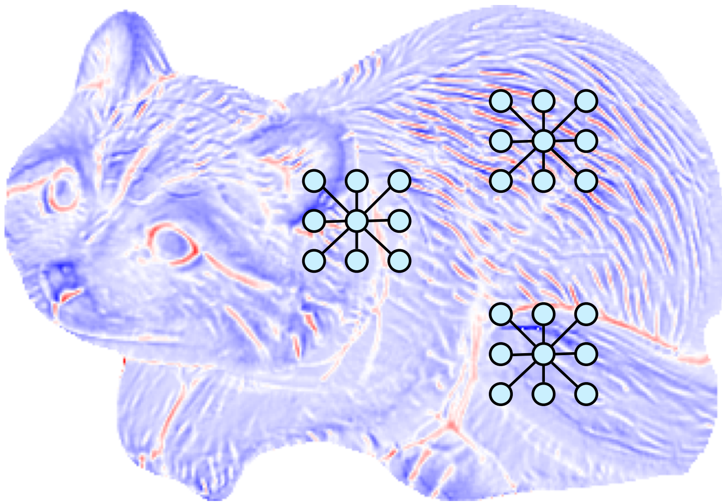

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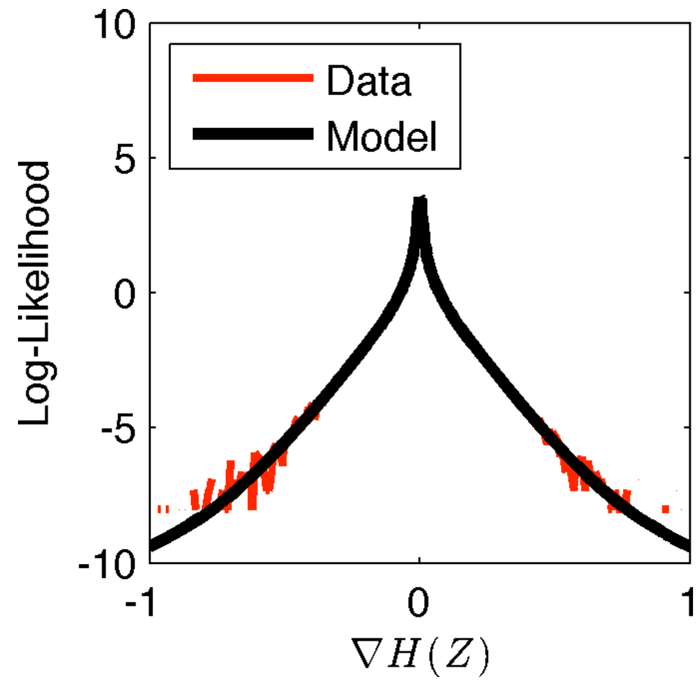
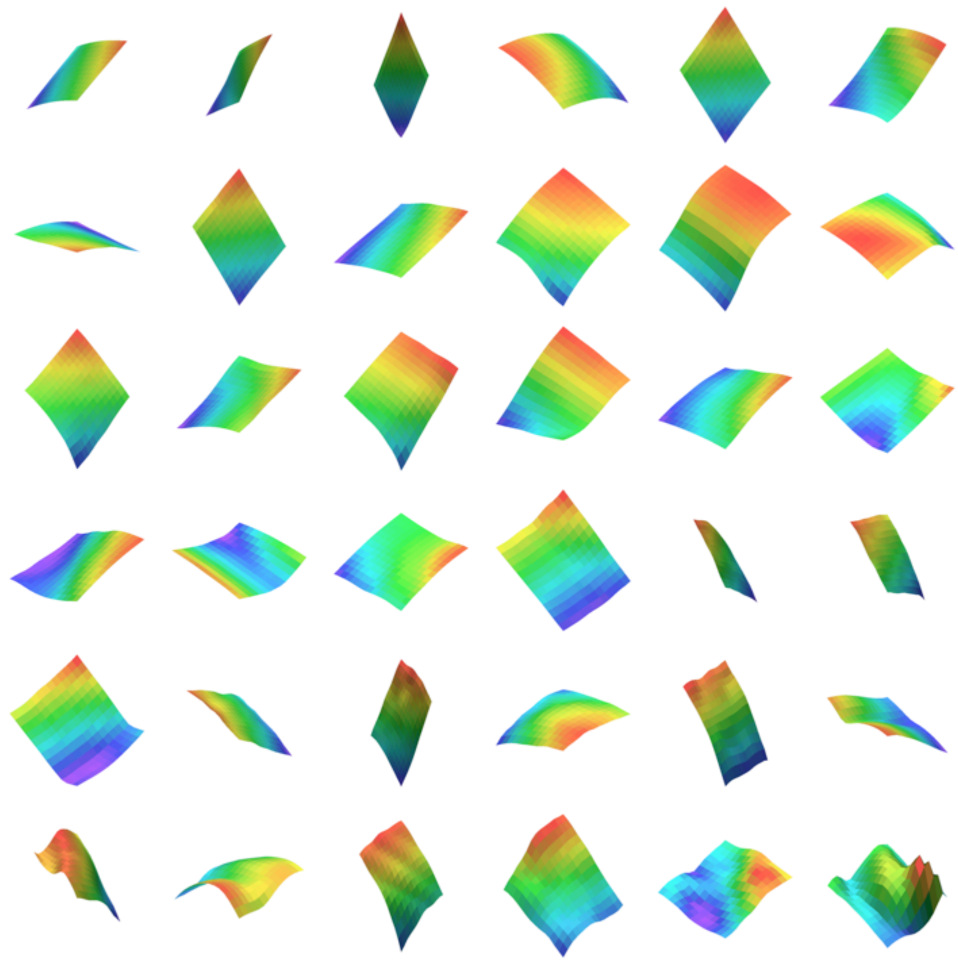


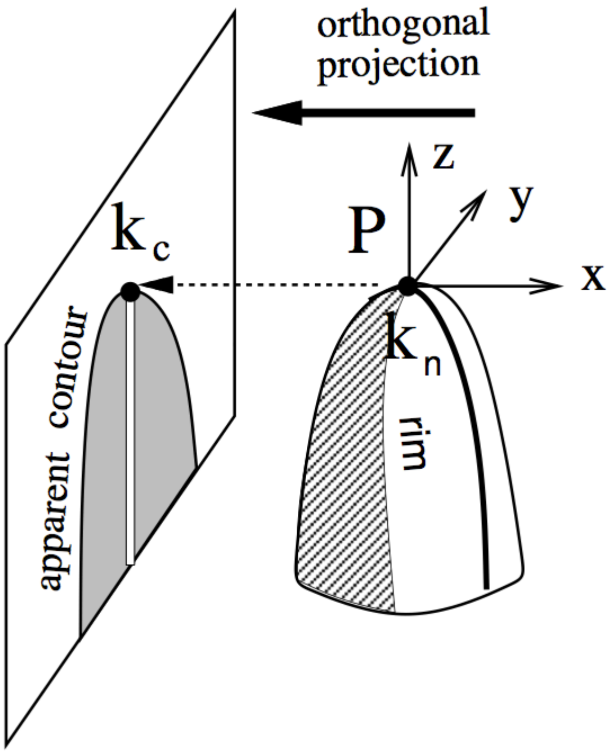
Shapes: Smoothness

Likely



Unlikely

Shapes: Occluding Contours



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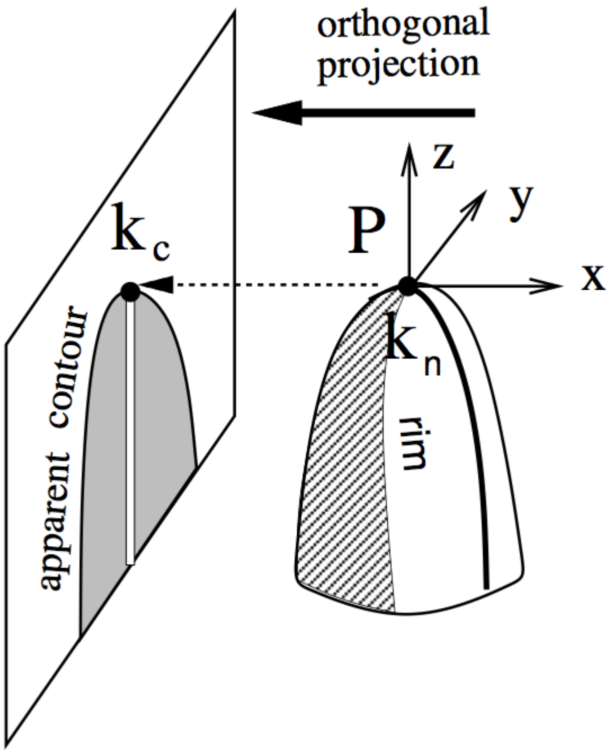

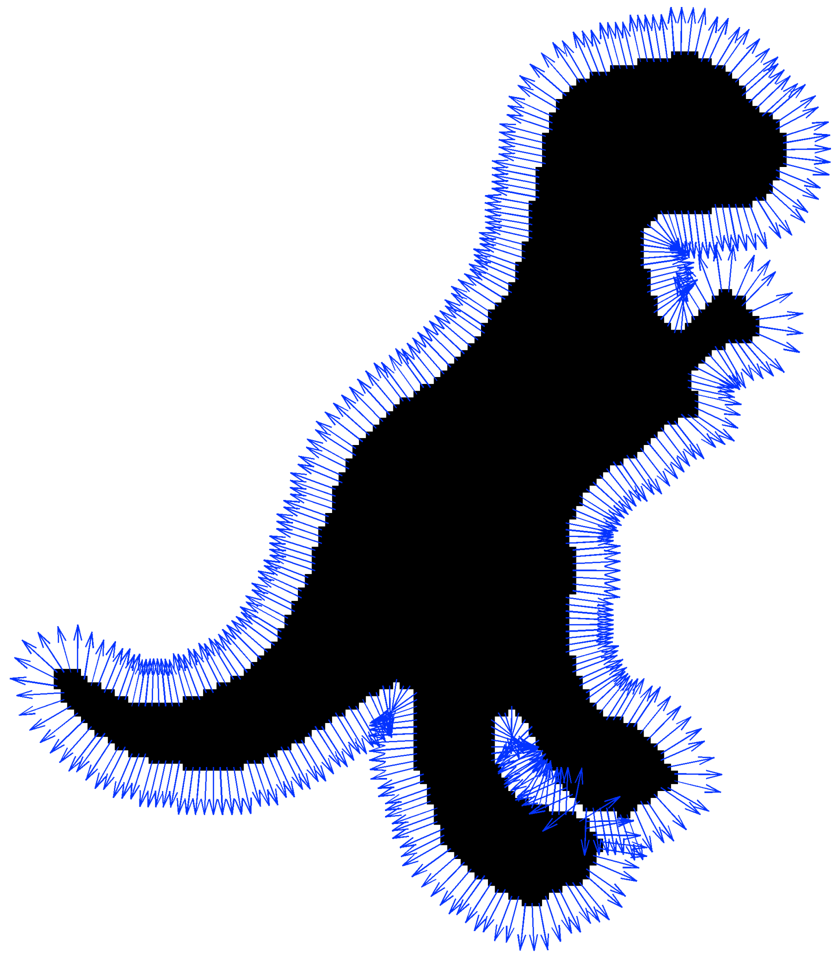

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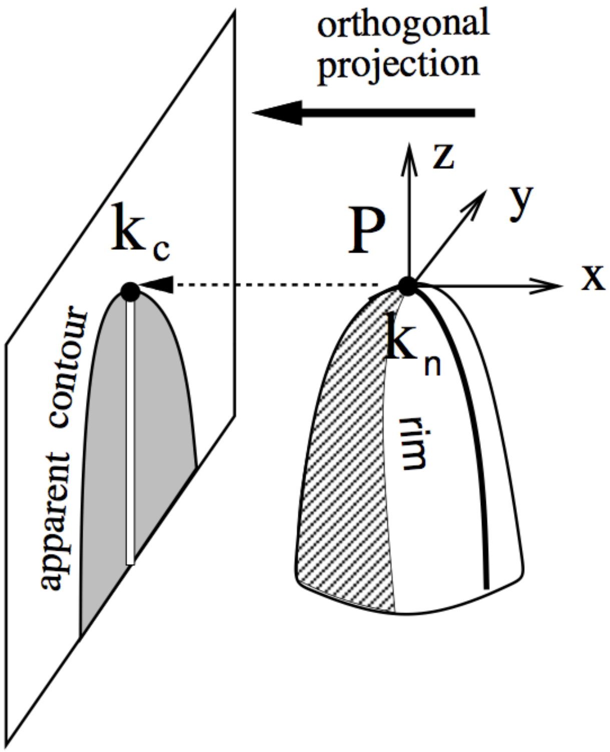

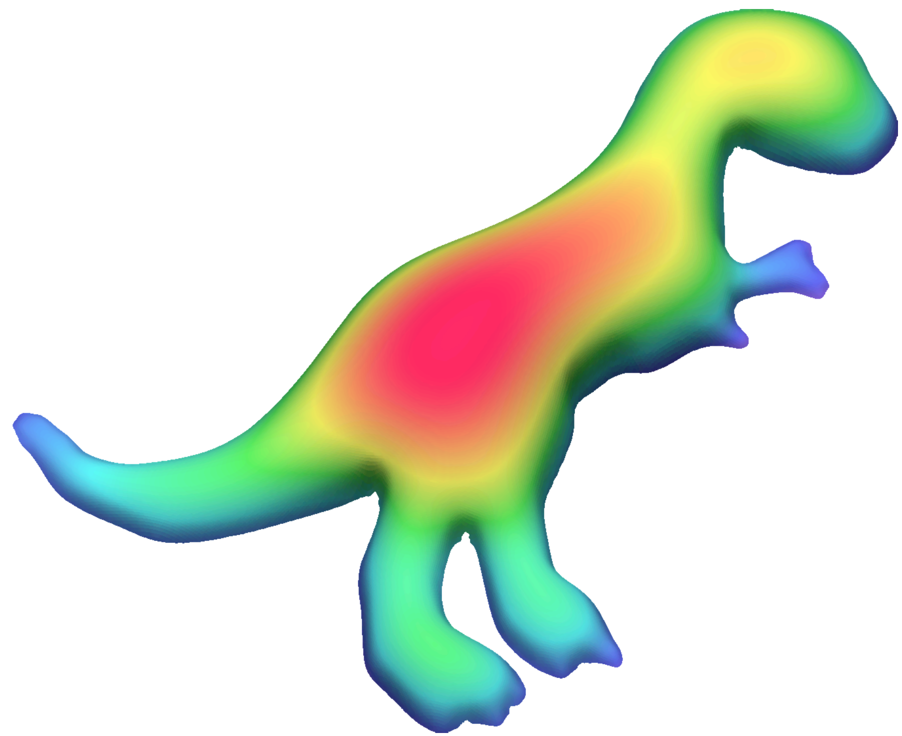

Shapes: Isotropy

Surfaces tend to be oriented isotropically in the world,

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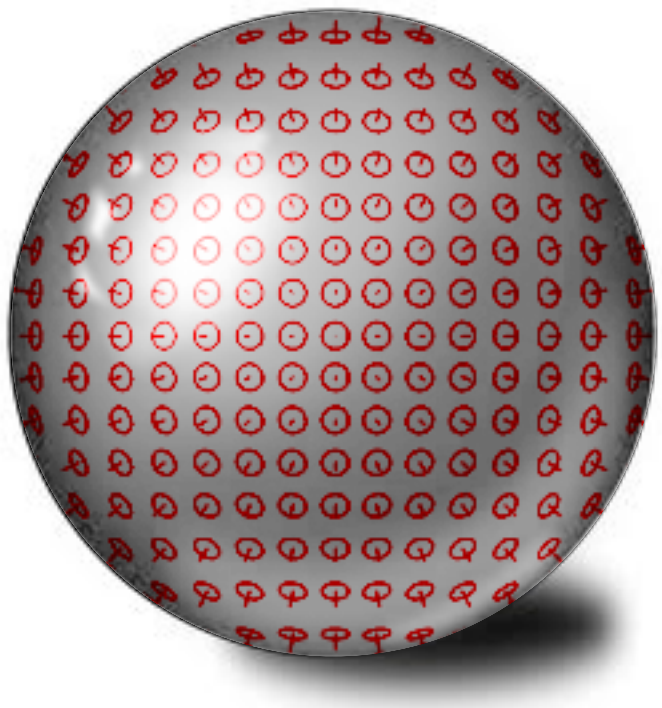
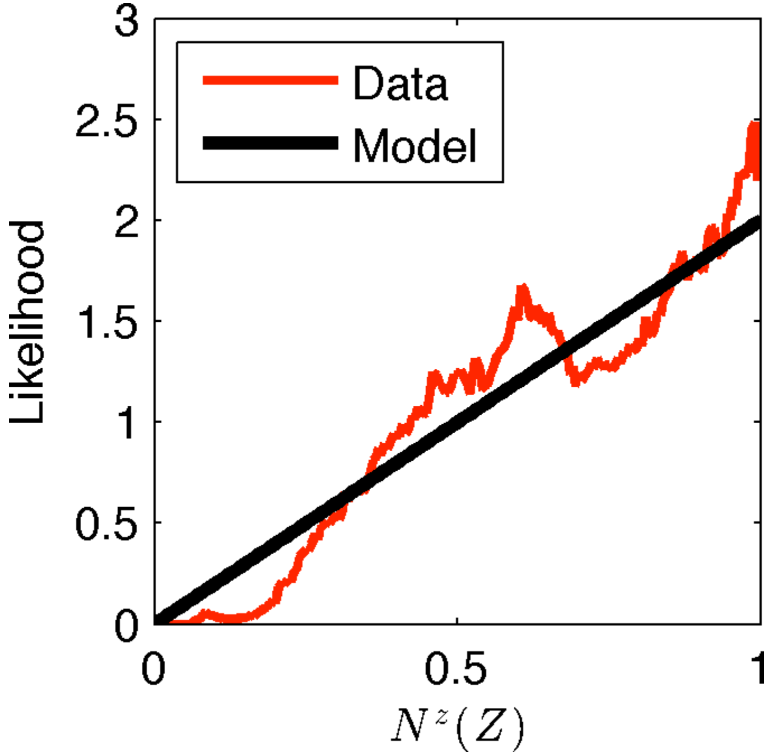


Surfaces tend to be oriented isotropically in the world,
but given that we've observed a surface, it's much more likely
that it faces us $(N^z \approx 1)$ than faces away from us $(N^z \approx 0)$

Shapes: Isotropy



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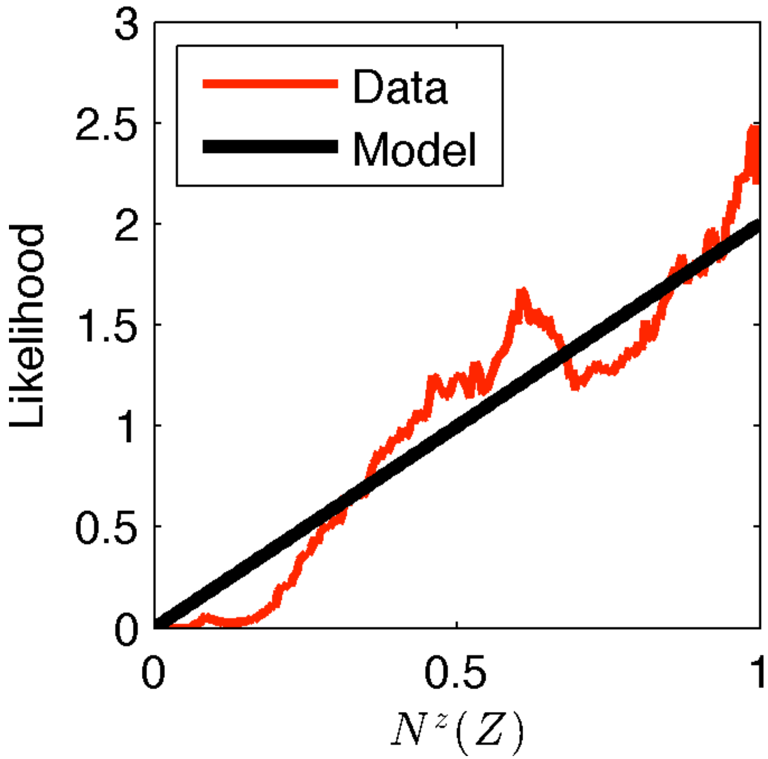
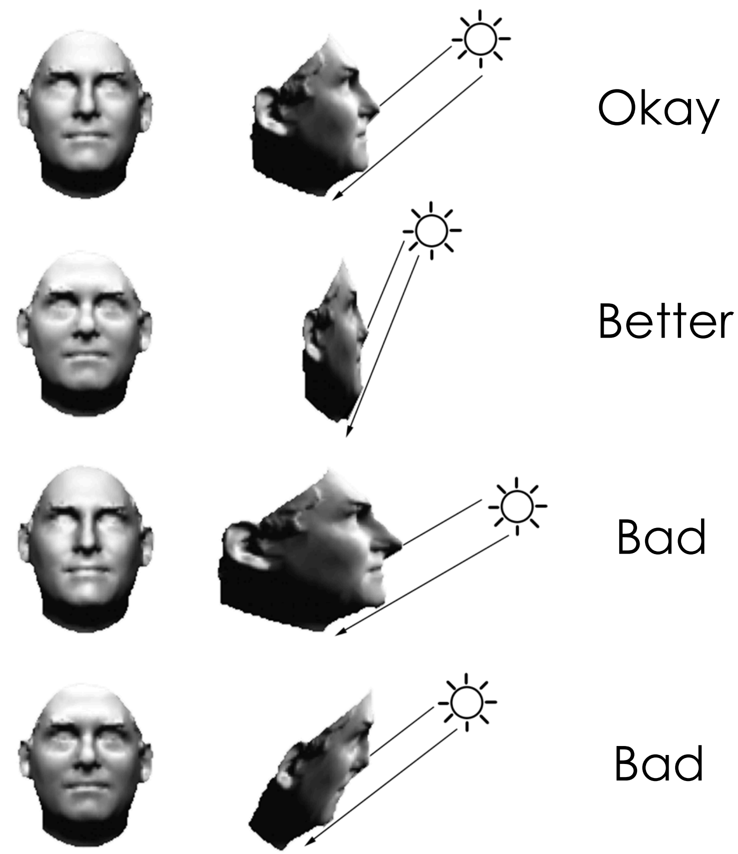
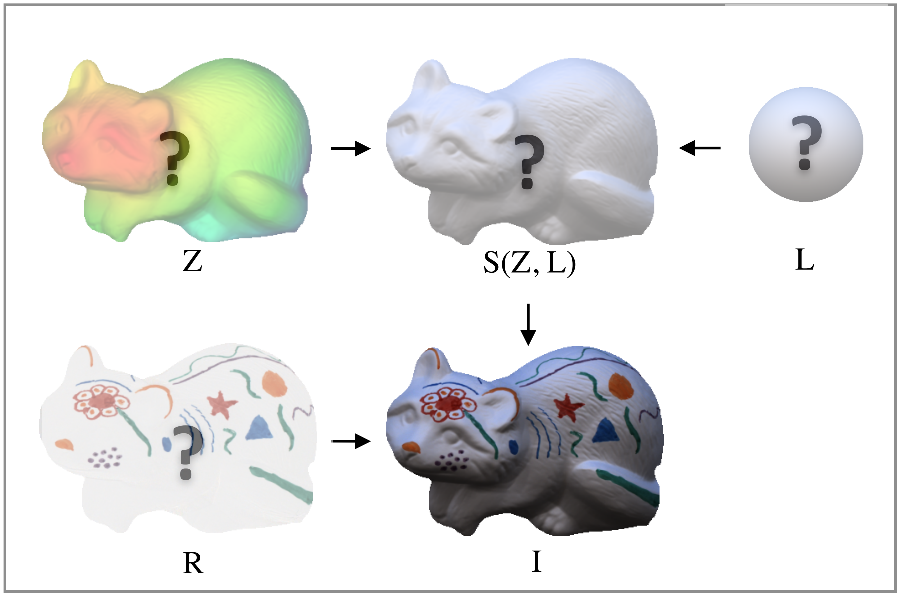




SIRFS



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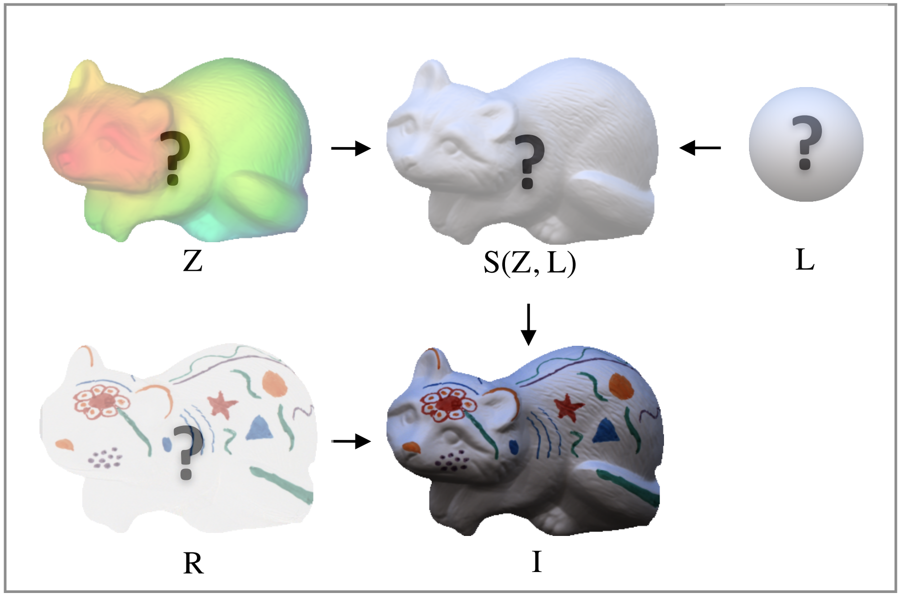

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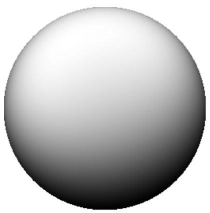
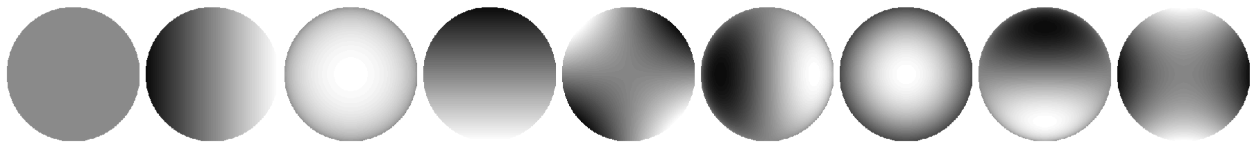
1) Global illumination is well modeled with spherical harmonics:

 $= < L,$  $>$

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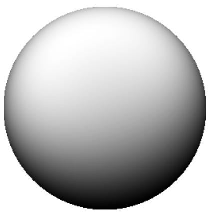
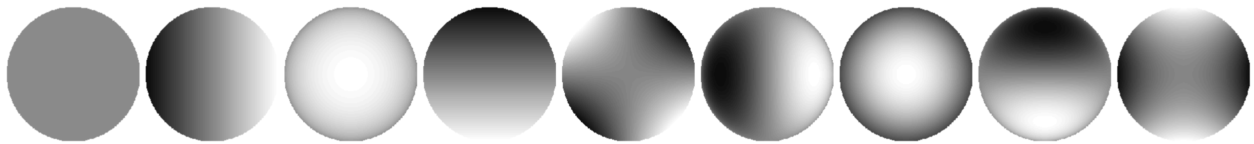
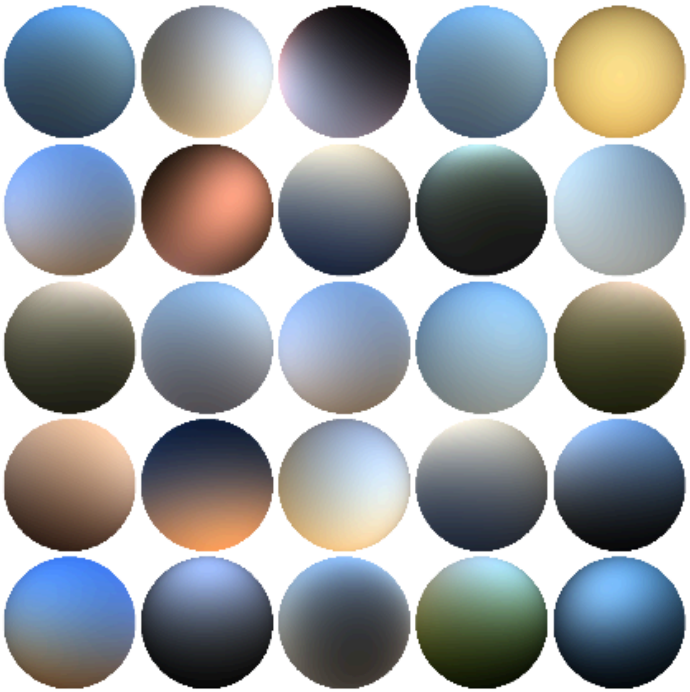
 $= < L,$  $>$

2) Spherical harmonic coefficients are well-modeled with a Gaussian

$$h(L) = \lambda_L (L - \boldsymbol{\mu}_L)^{\mathrm{T}} \Sigma_L^{-1} (L - \boldsymbol{\mu}_L)$$

What do we know about **light**?



Natural Illuminations from our dataset

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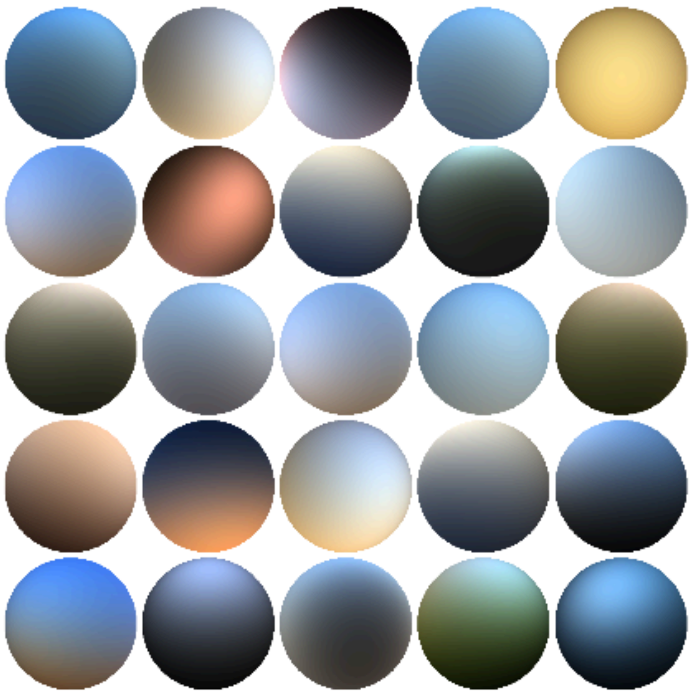

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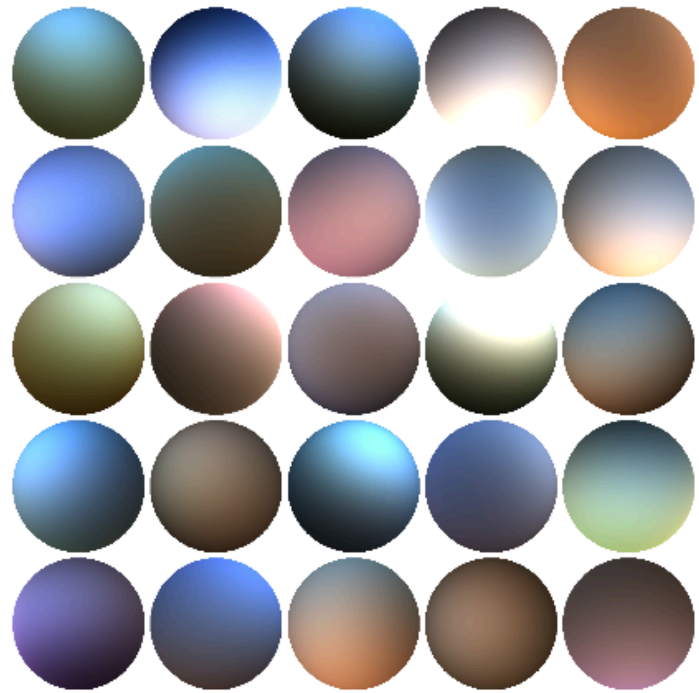
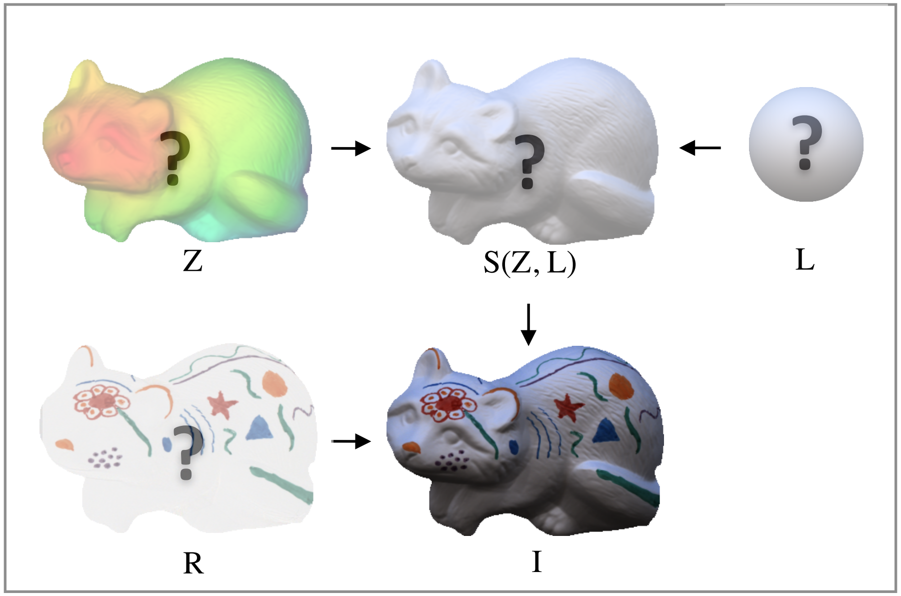


Samples from a Gaussian fit to the training set

SIRFS



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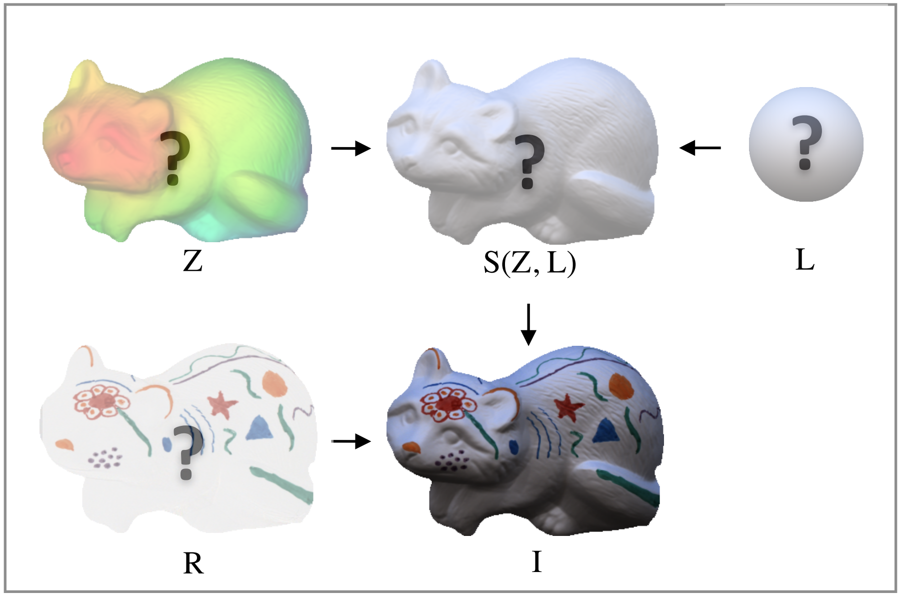

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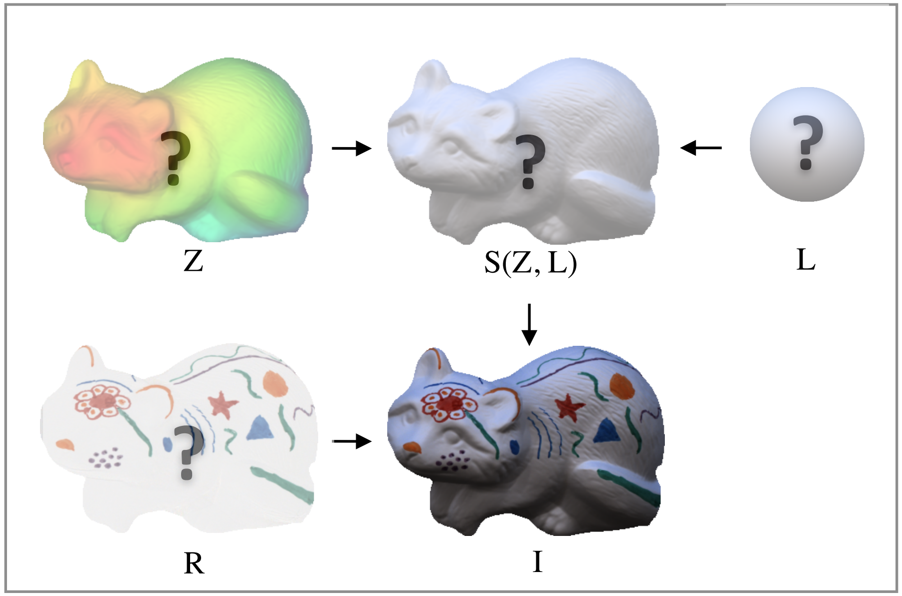

$$\underset{Z,L}{\text{minimize}} \quad g(I - S(Z,L)) + f(Z) + h(L)$$

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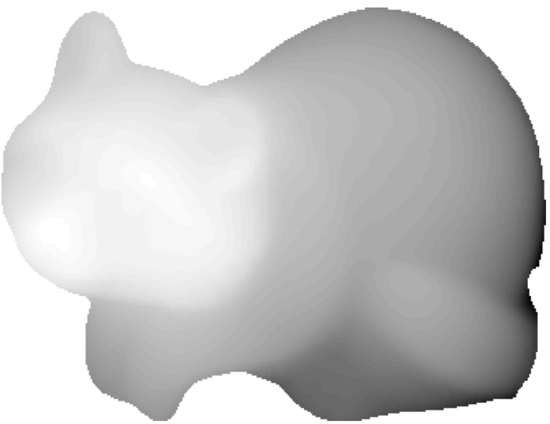
Optimization

Straightforward L-BFGS with respect to Z fails!



Z

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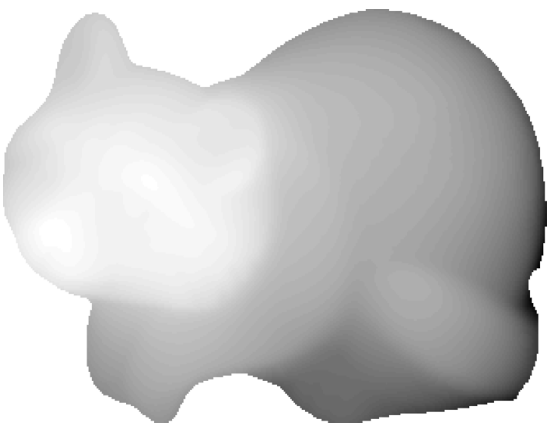
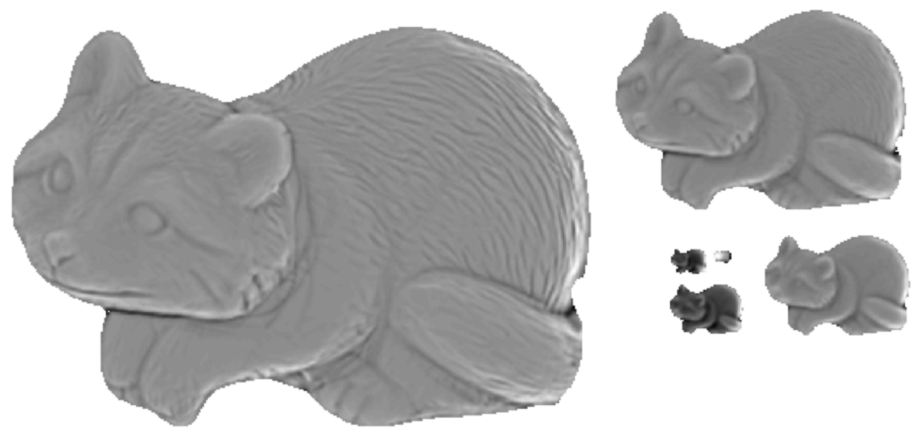


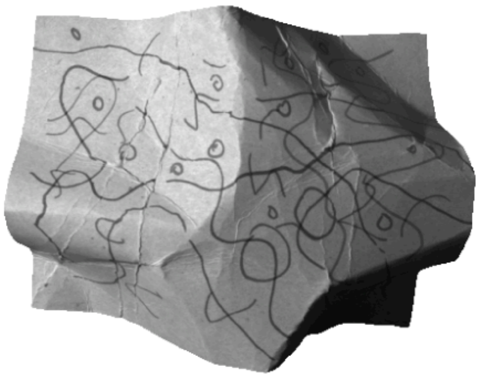
Z



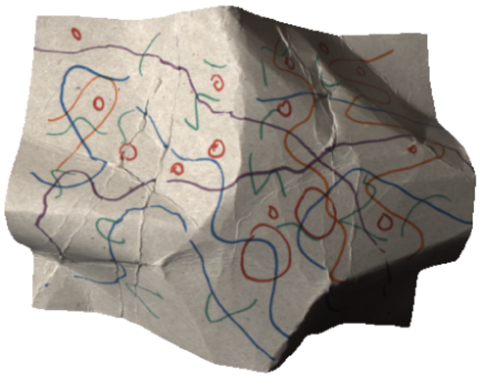
$\mathcal{L}(Z)$

Instead, optimize over $\mathcal{L}(Z)$, a Laplacian pyramid of Z

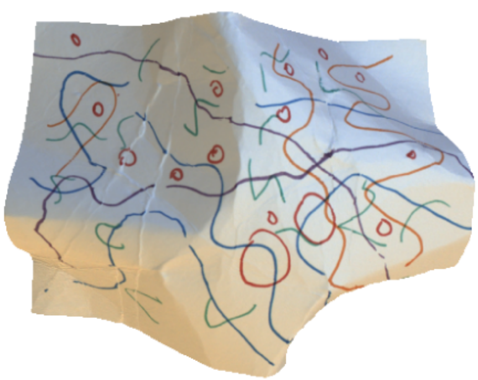
Results: MIT Intrinsic Images Dataset



Grayscale Image
"Laboratory" Illumination



Color Image
"Laboratory" Illumination



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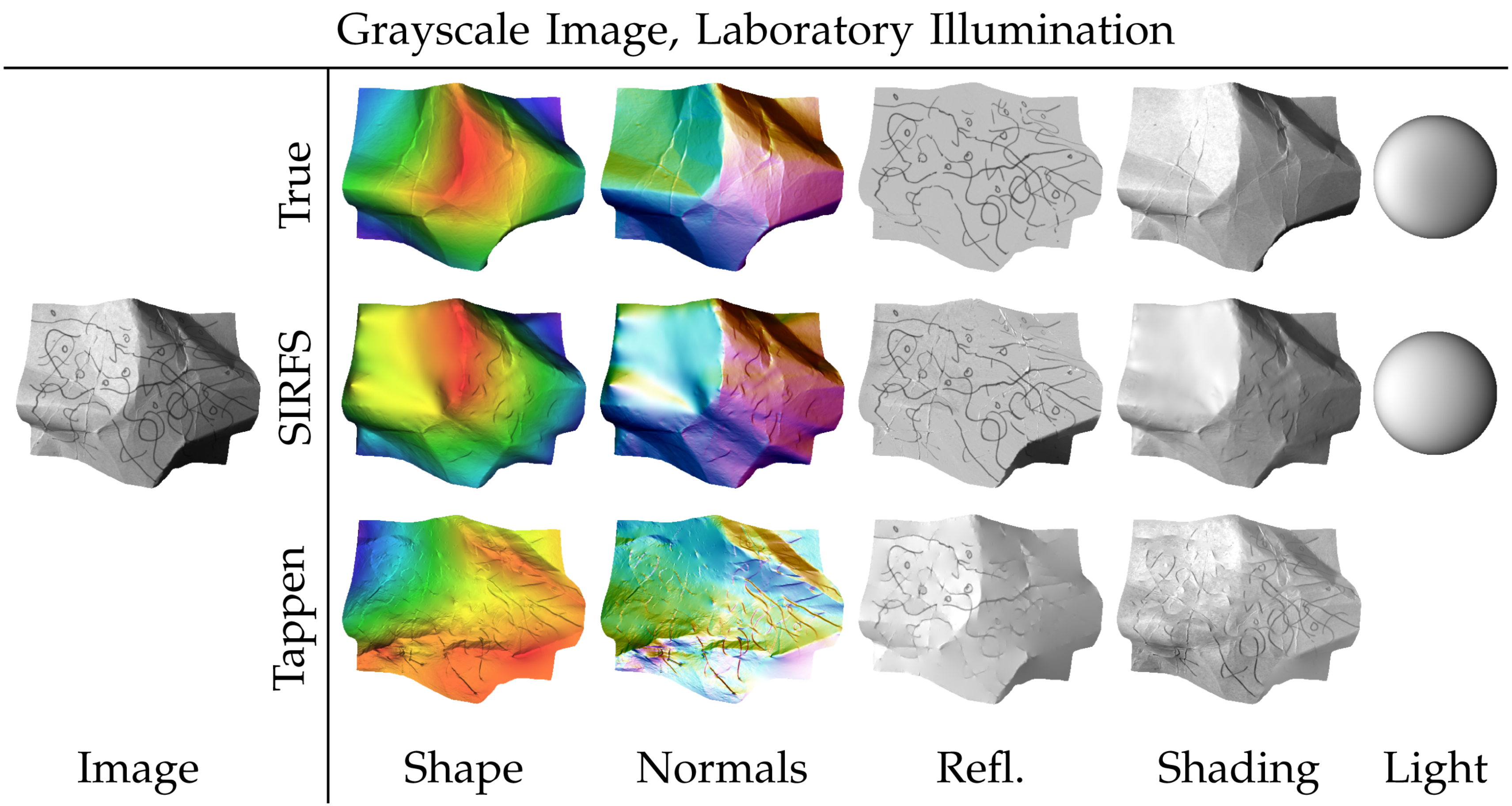

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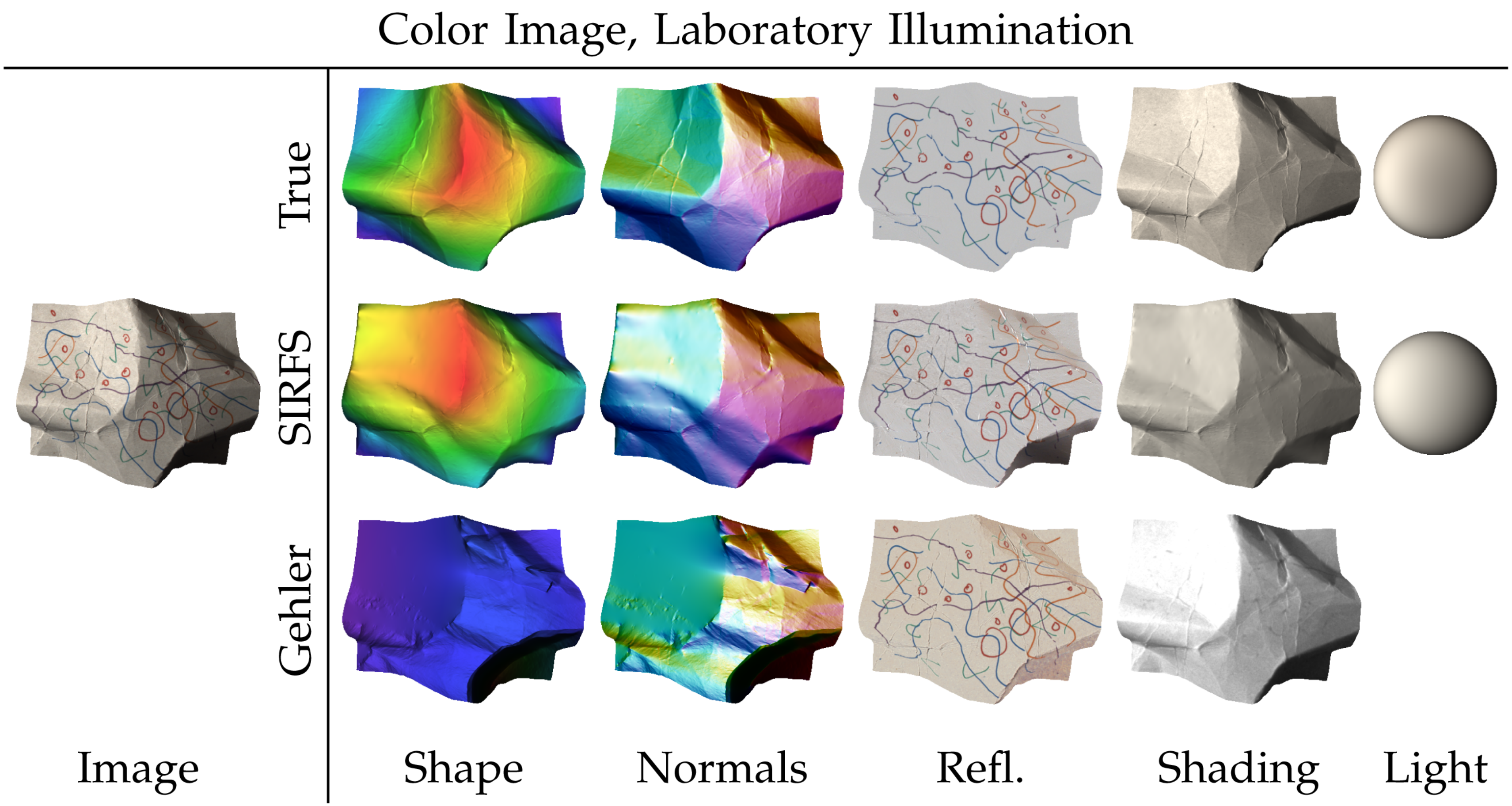

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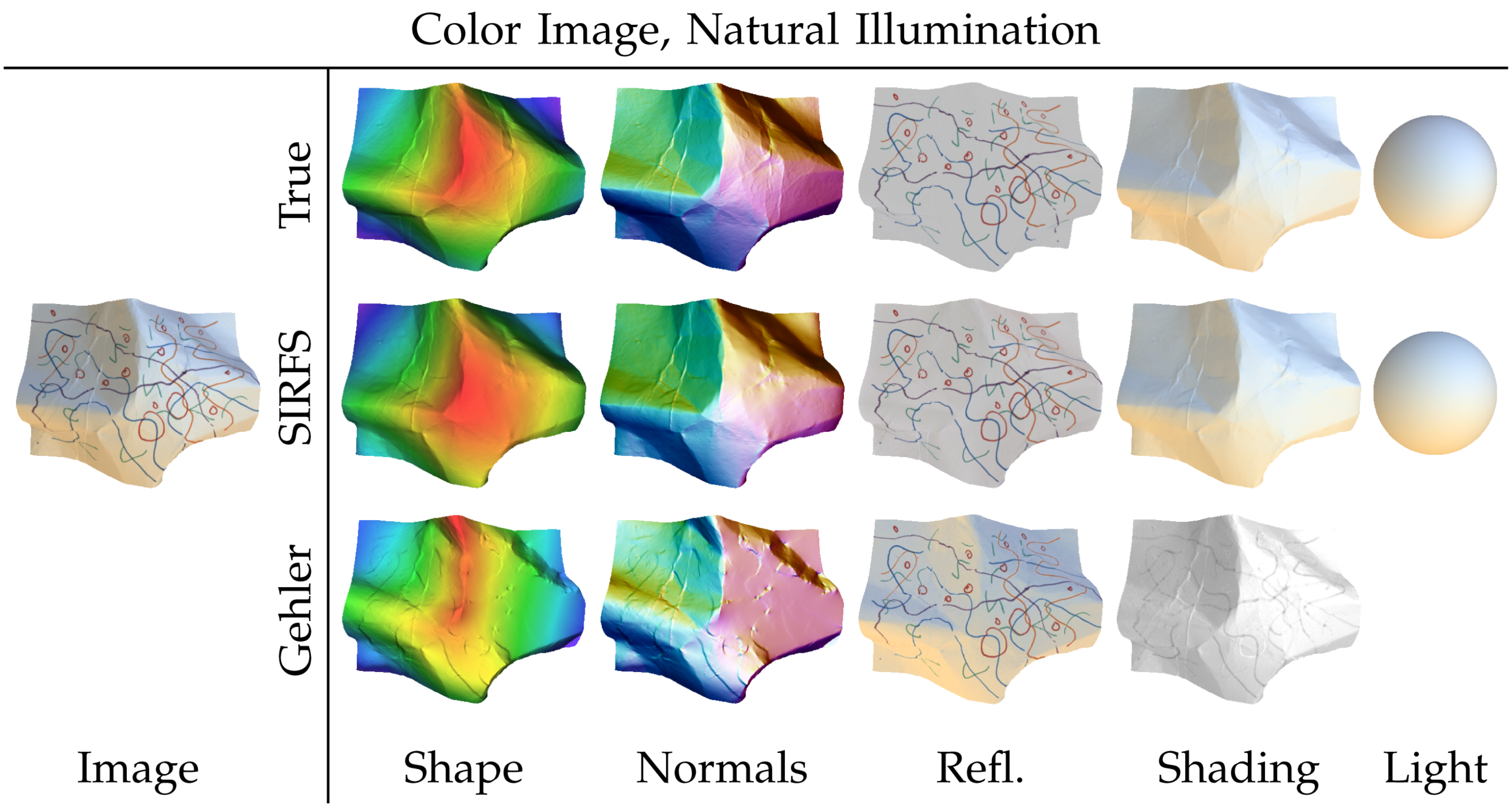

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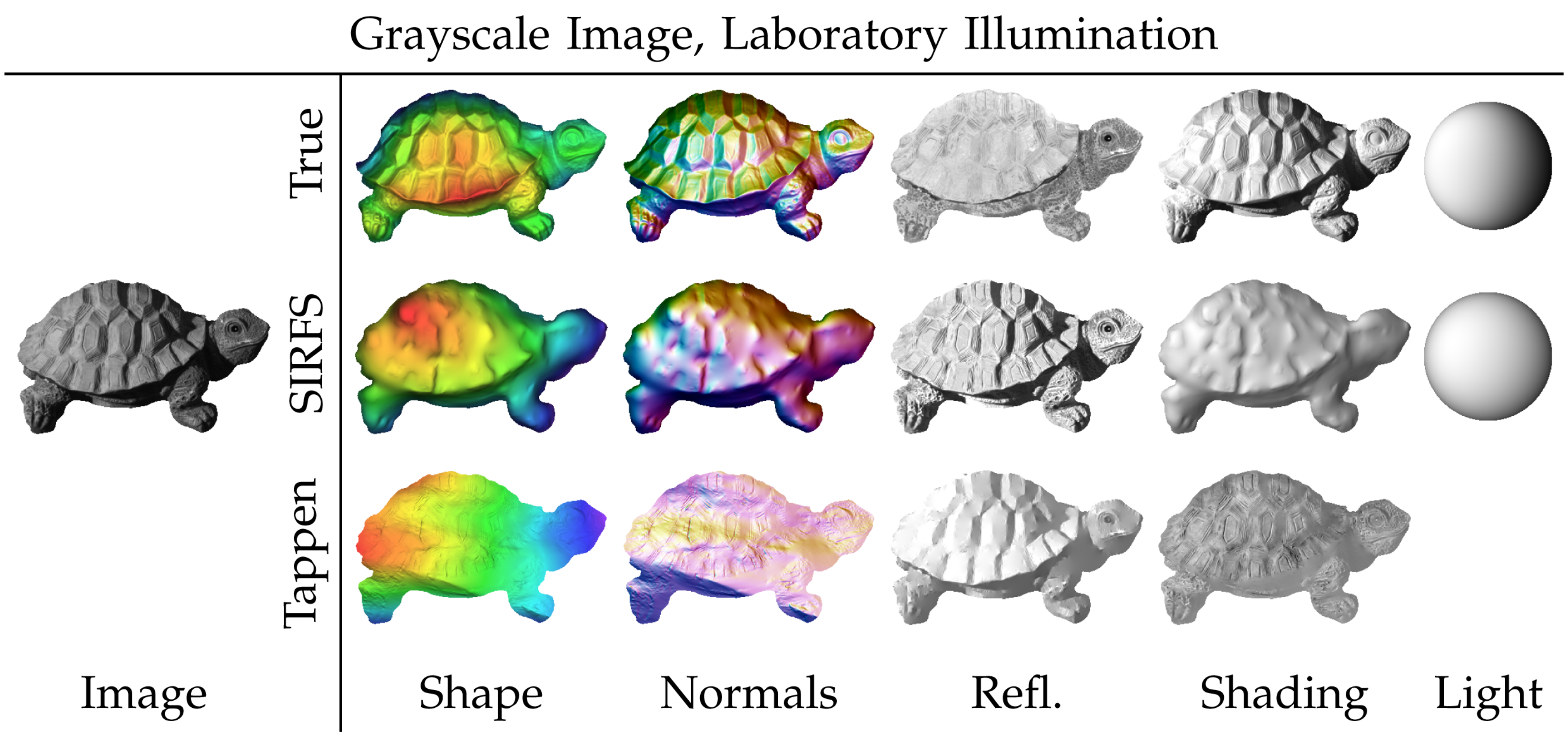

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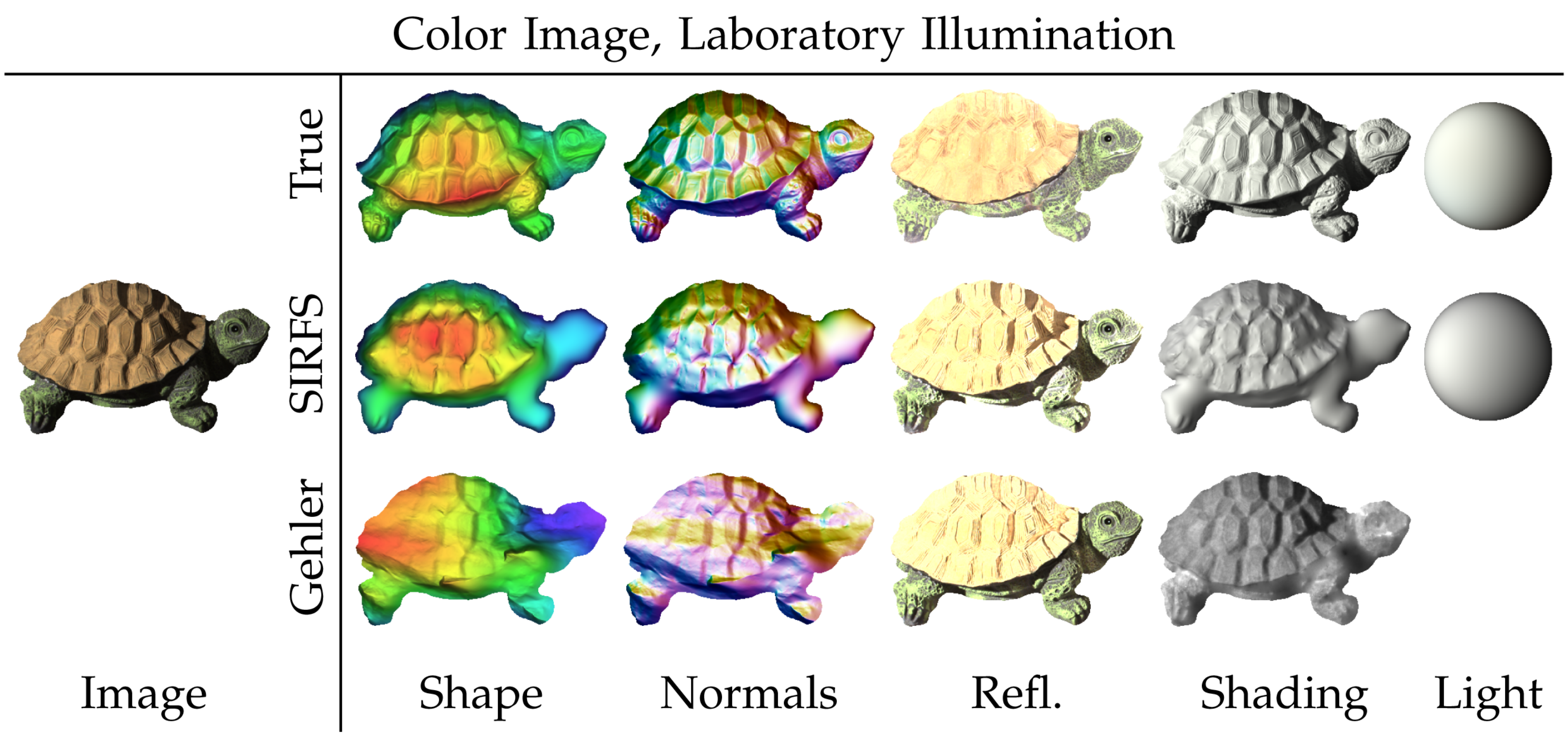

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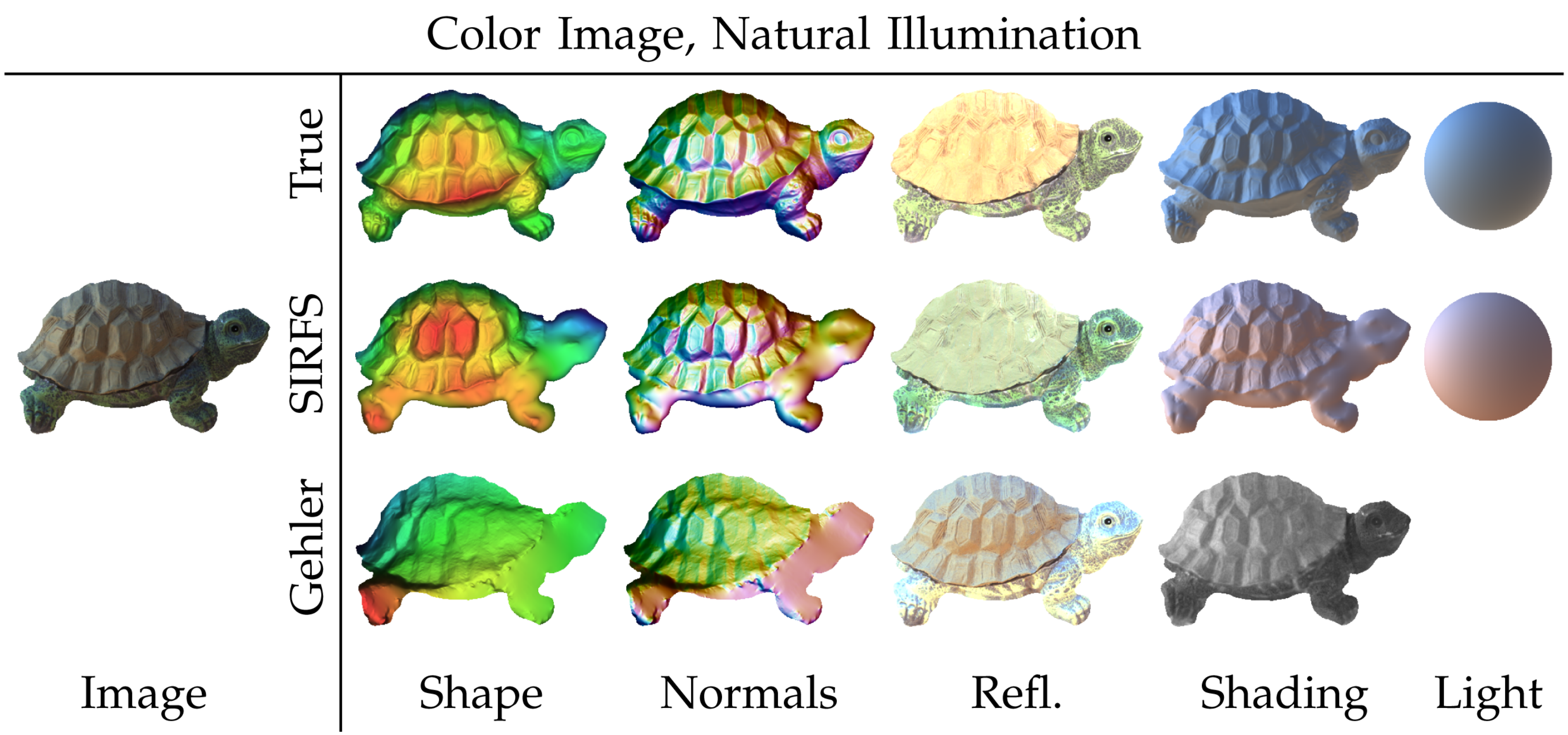

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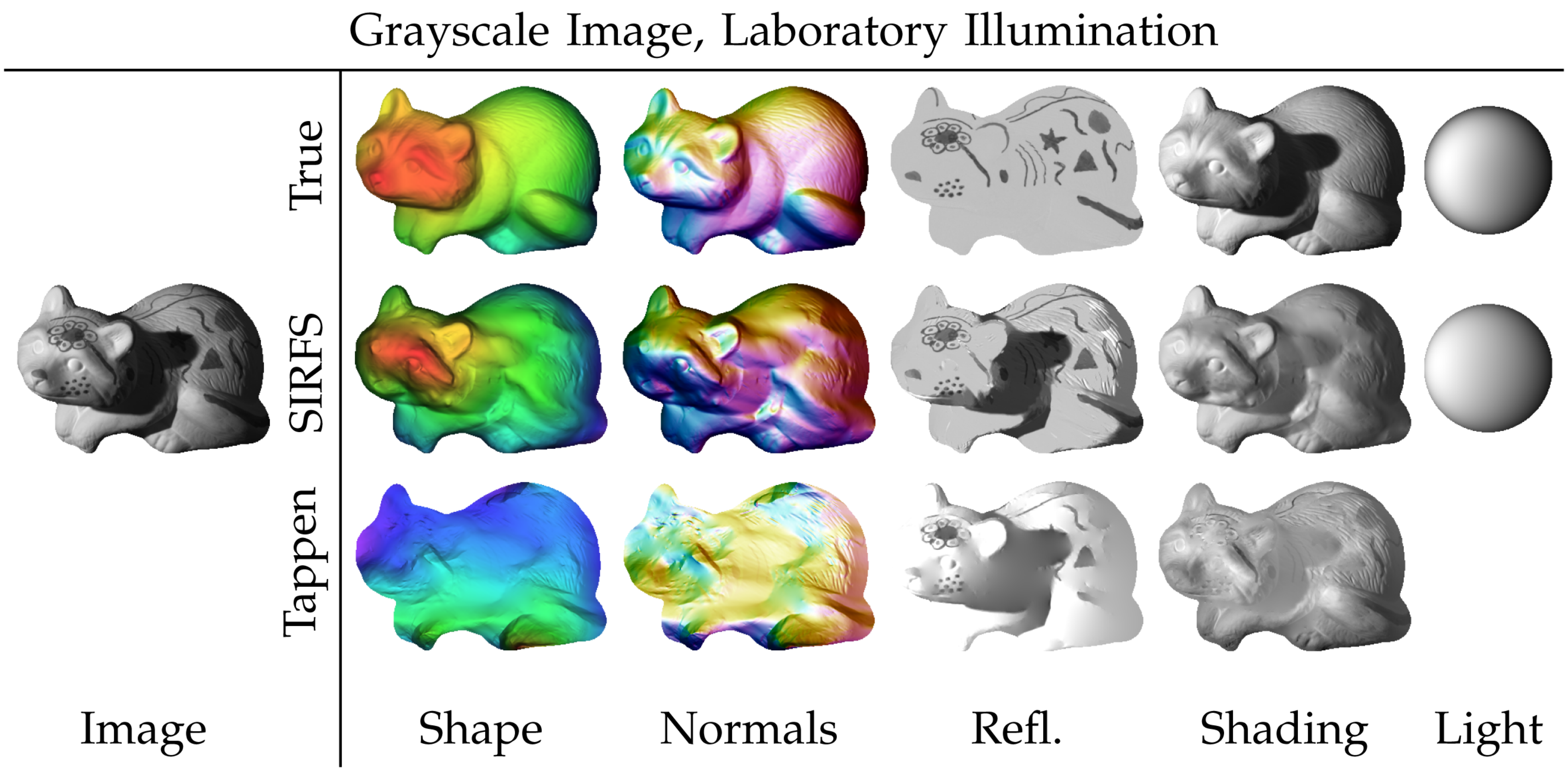

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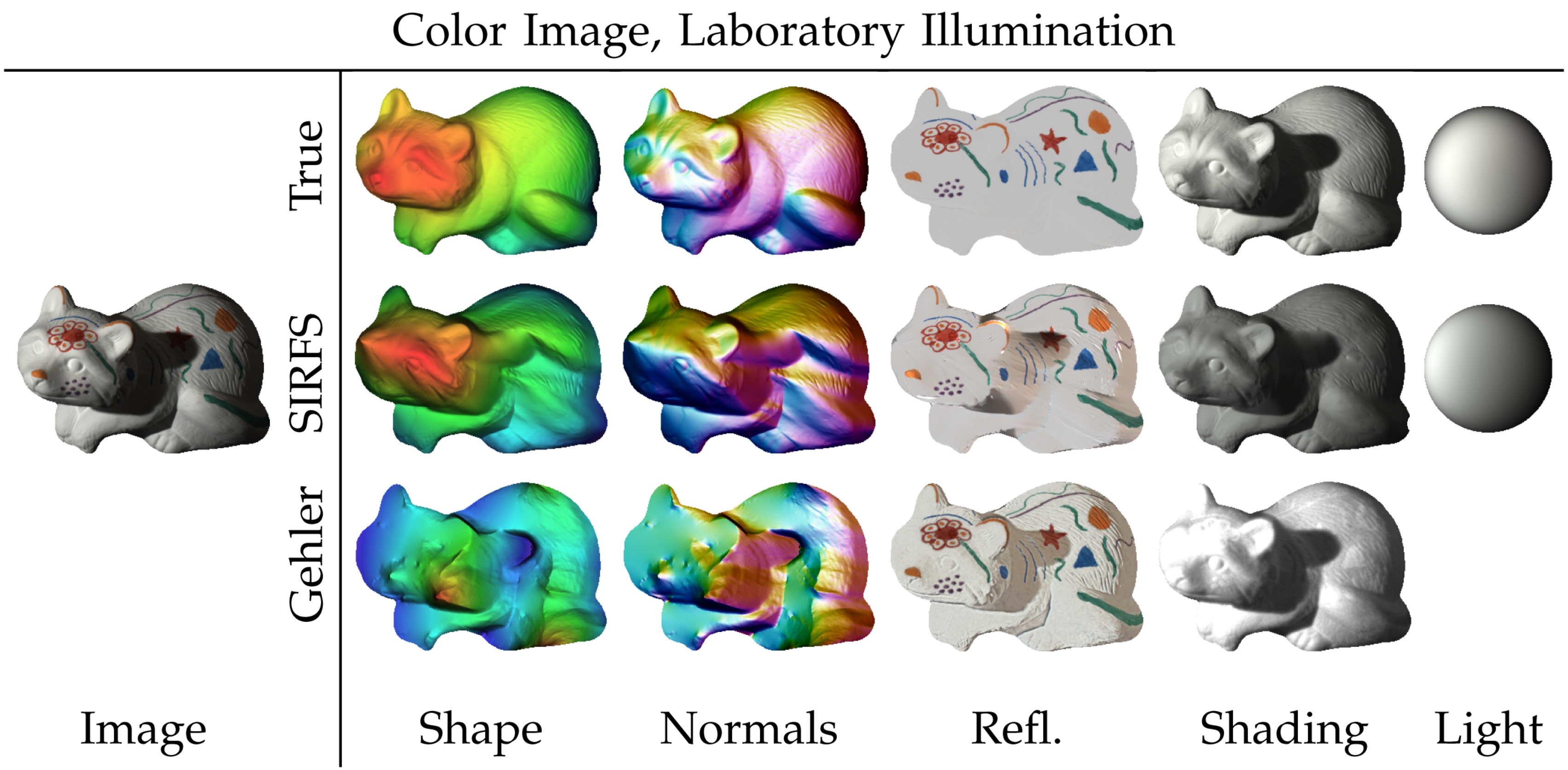

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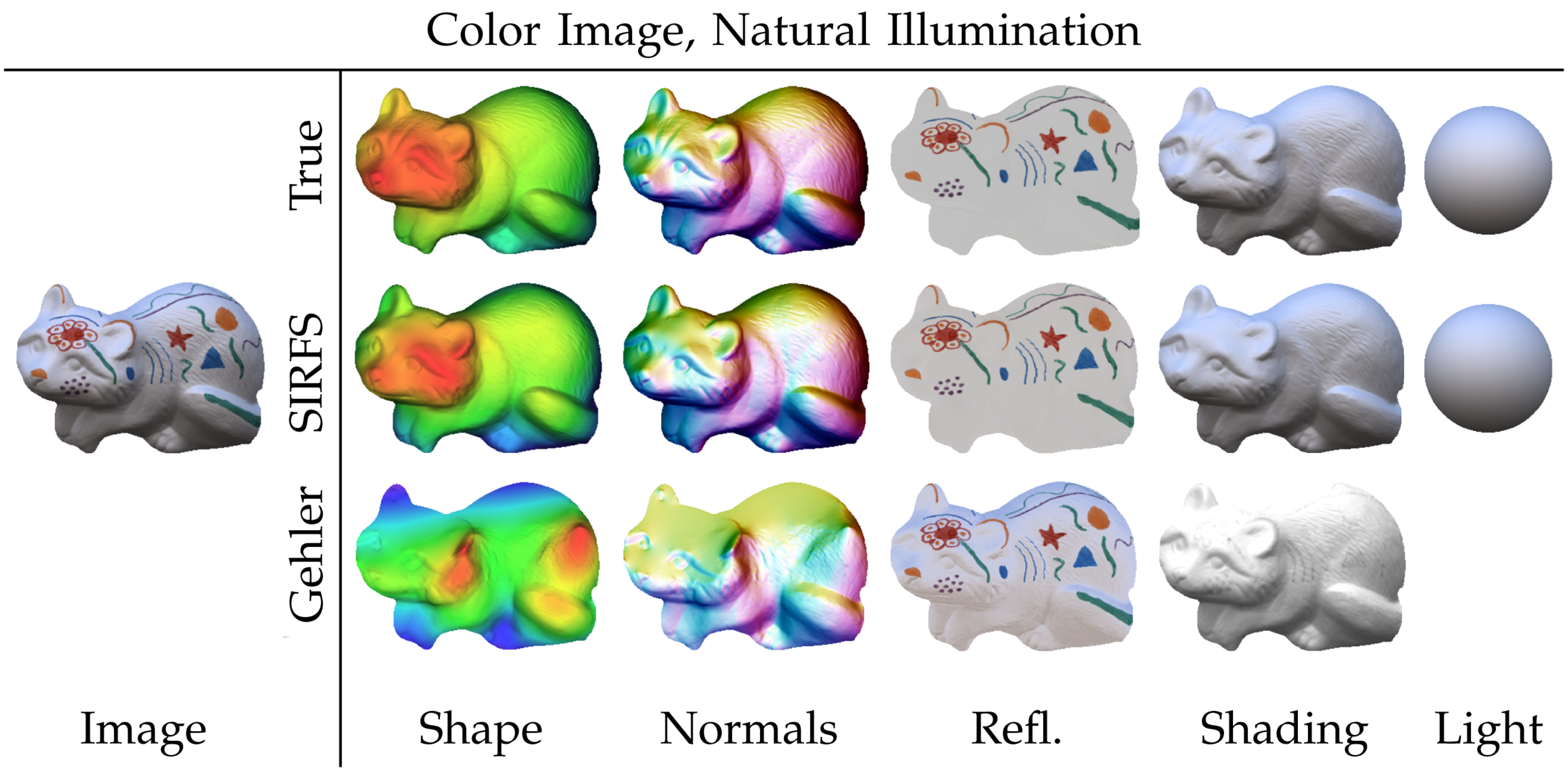

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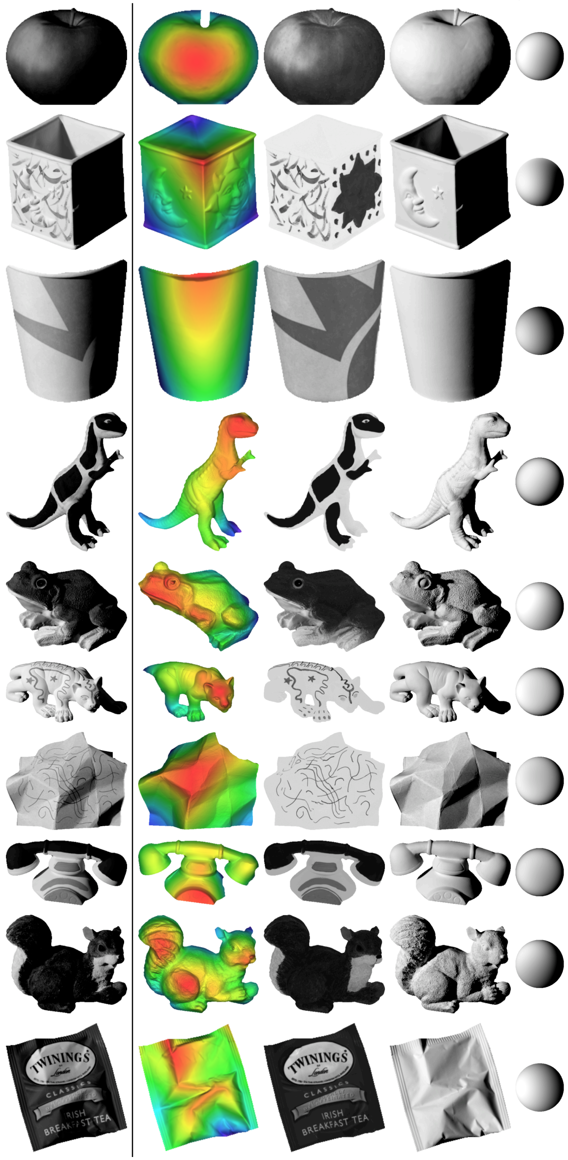

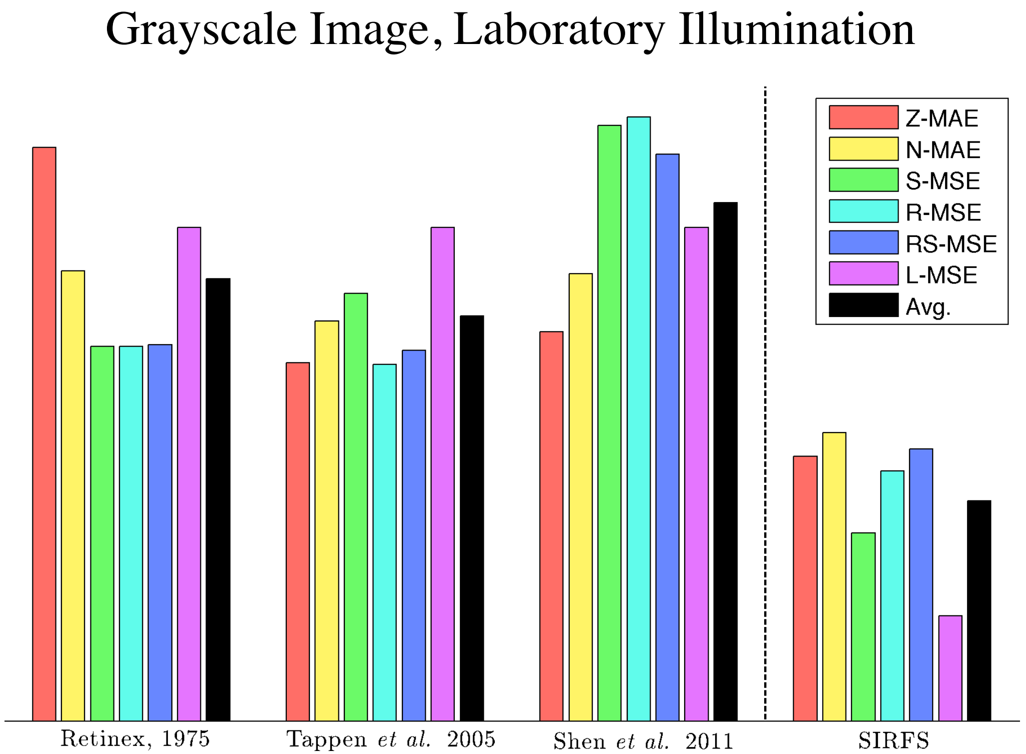

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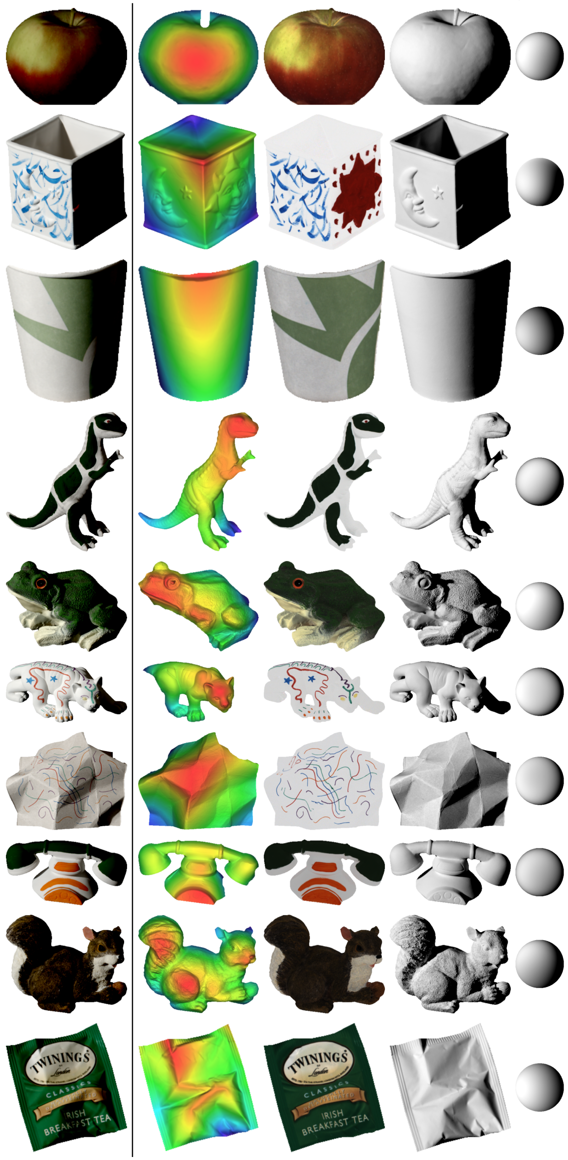

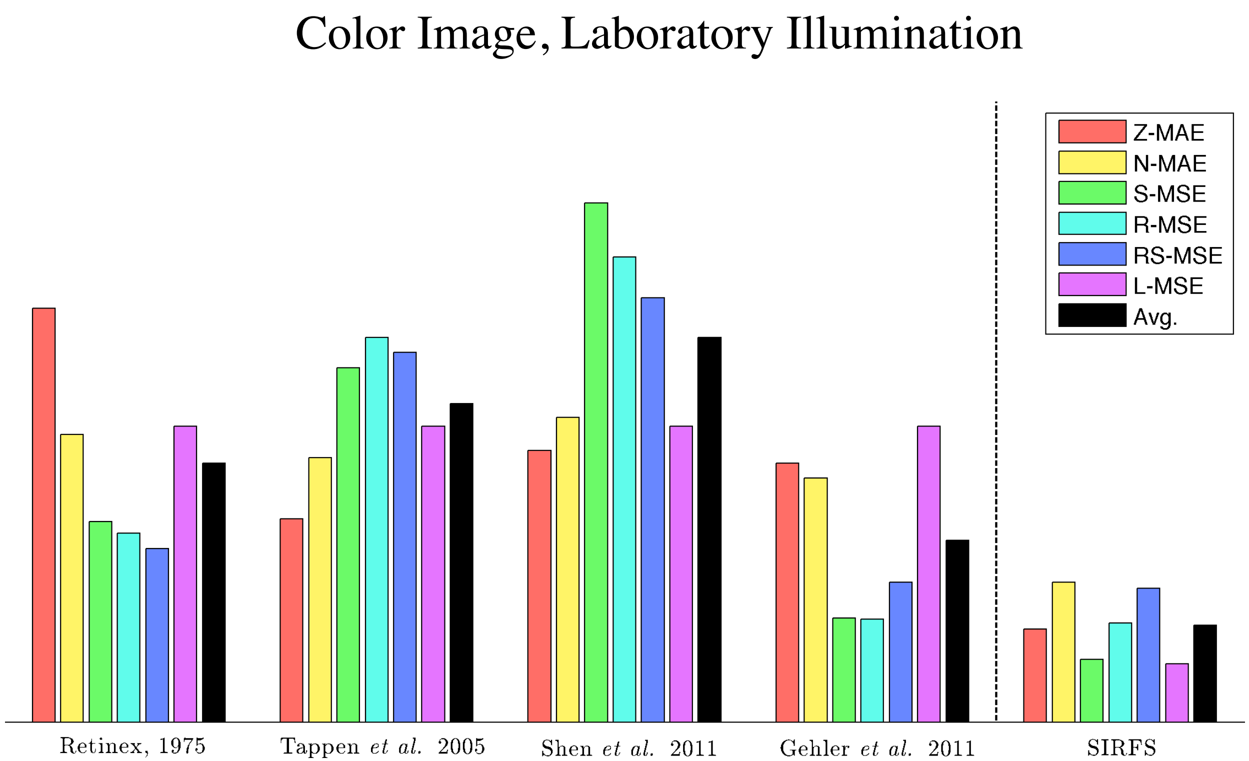

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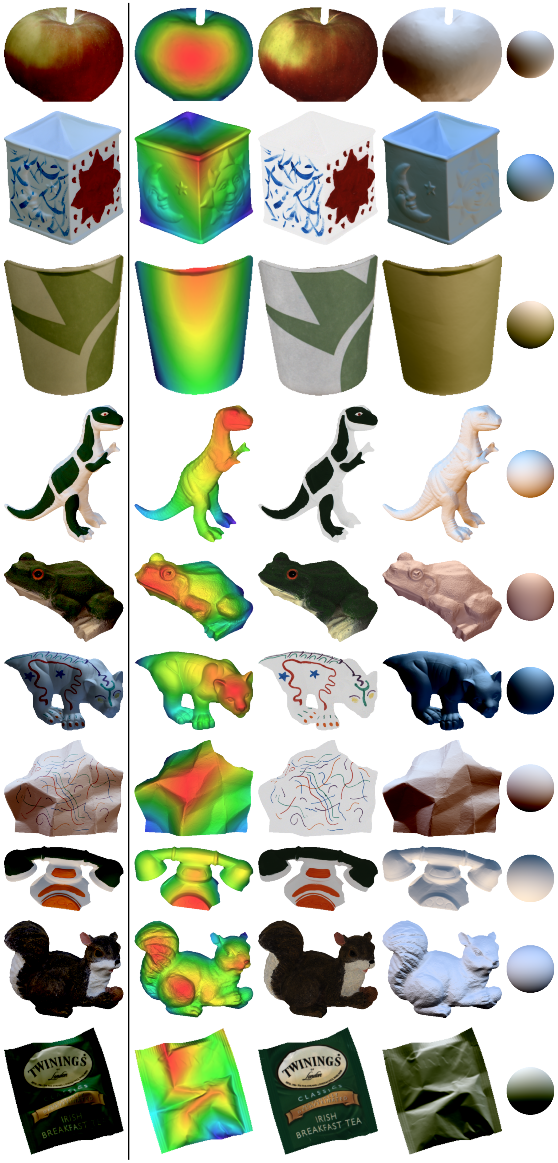
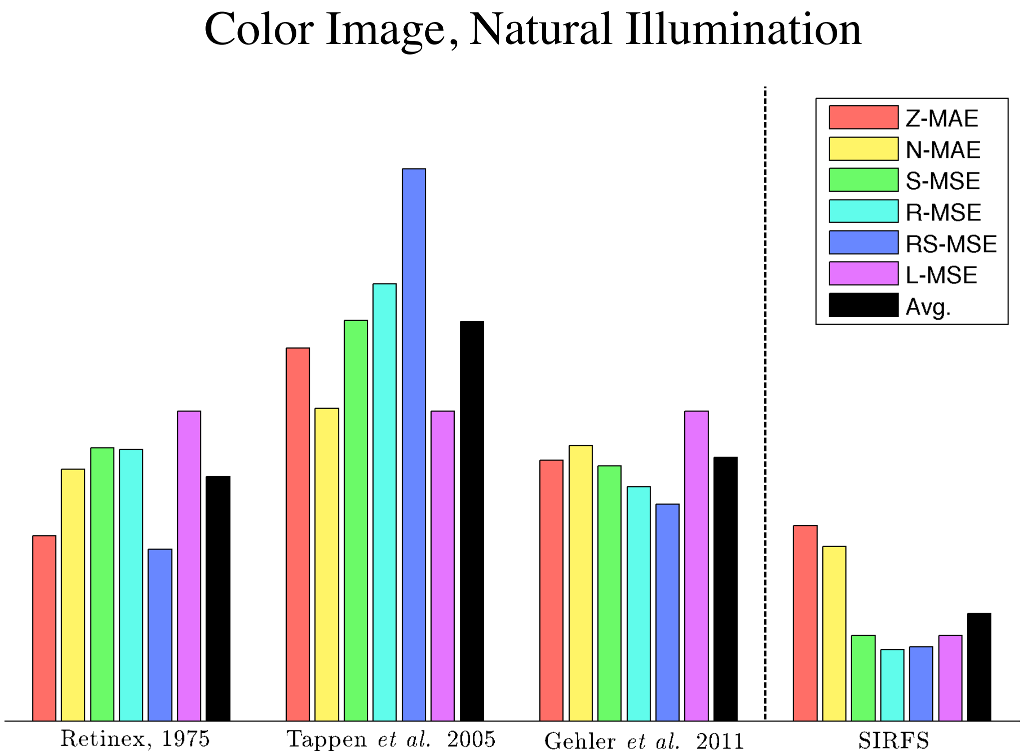
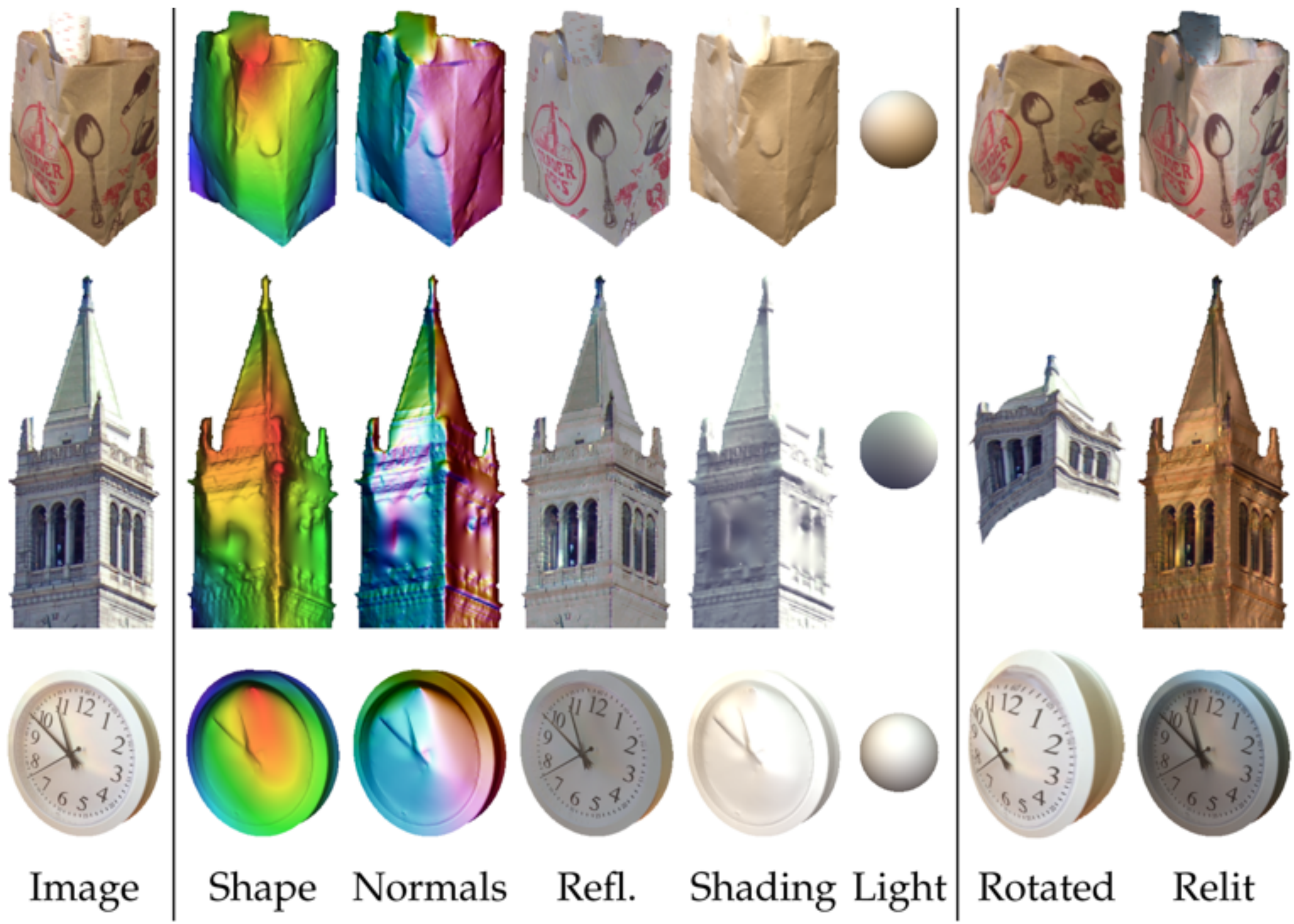




Results: Real Images



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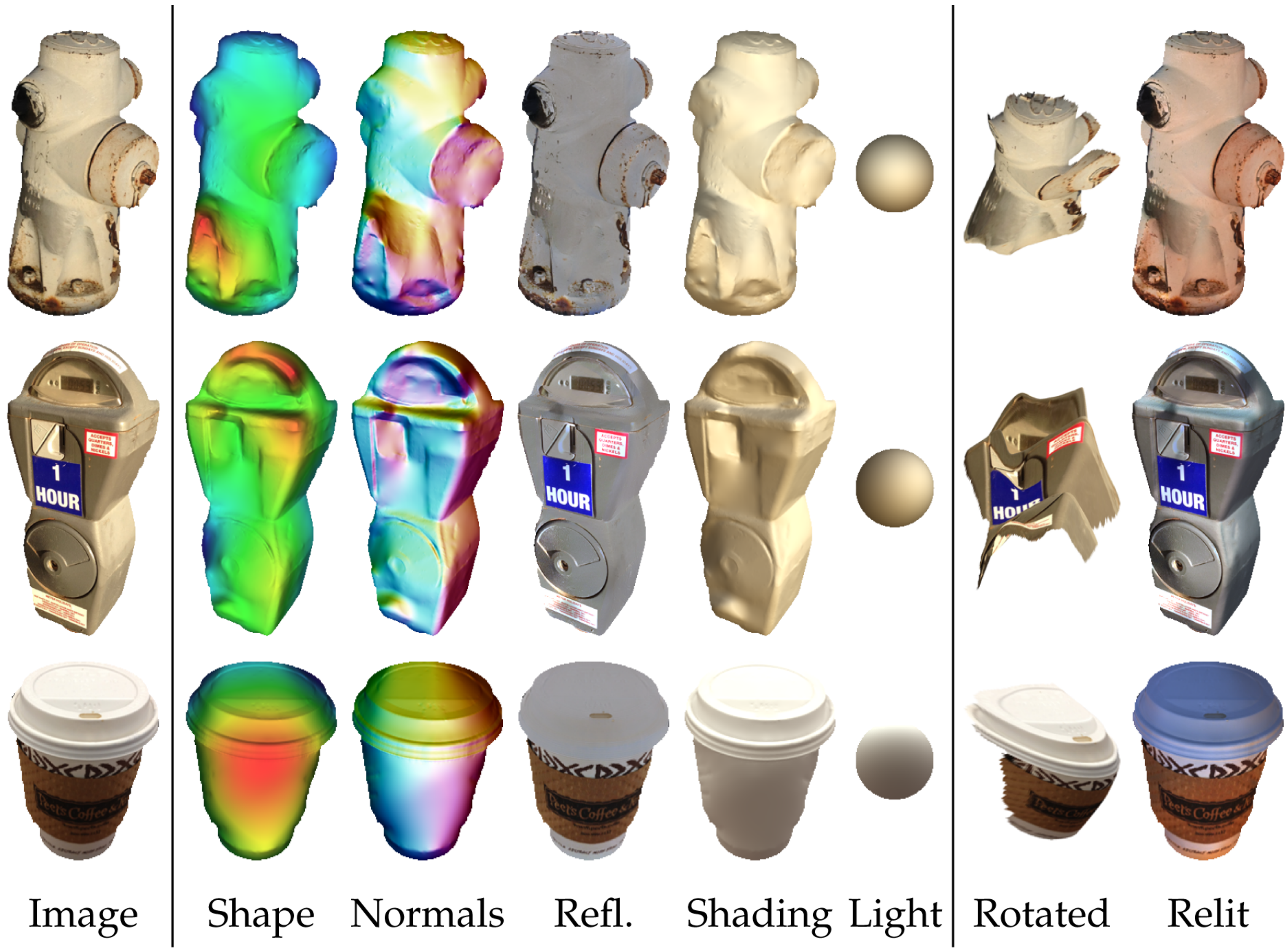

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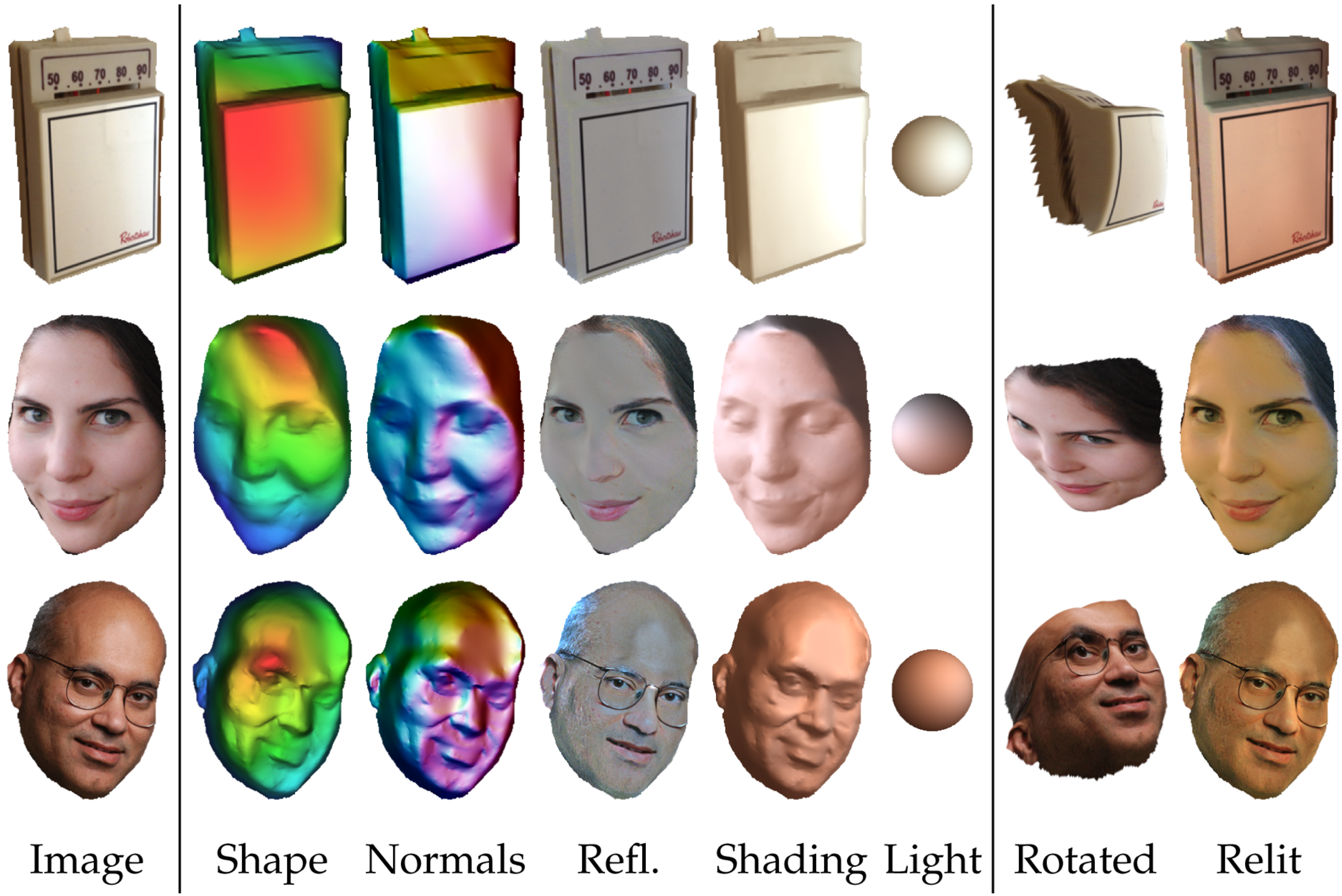

Graphics Applications

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Conclusions

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- Solving the unified problem > Solving any sub-problem
- Not a toy! Works on real-world images
- Has implications for reorganization, recognition, graphics, etc

Thanks!