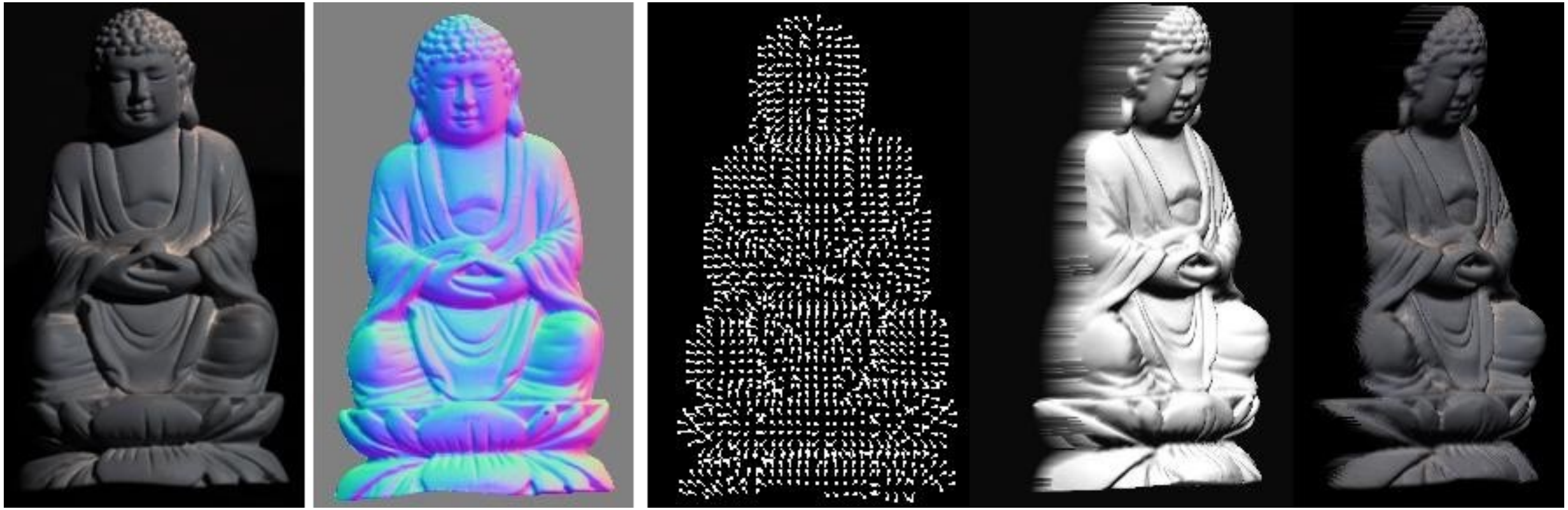
CS5670 : Computer Vision

Reflectance & Photometric stereo



Reading

- Szeliski 2nd Edition: Chapter 2.2 & 13.1

Announcements

- Project 3 (Panorama) artifact due tonight at 8pm
- Project 4 (Stereo) released today due Friday, March 31, at 8pm
  - To be done in groups of 2

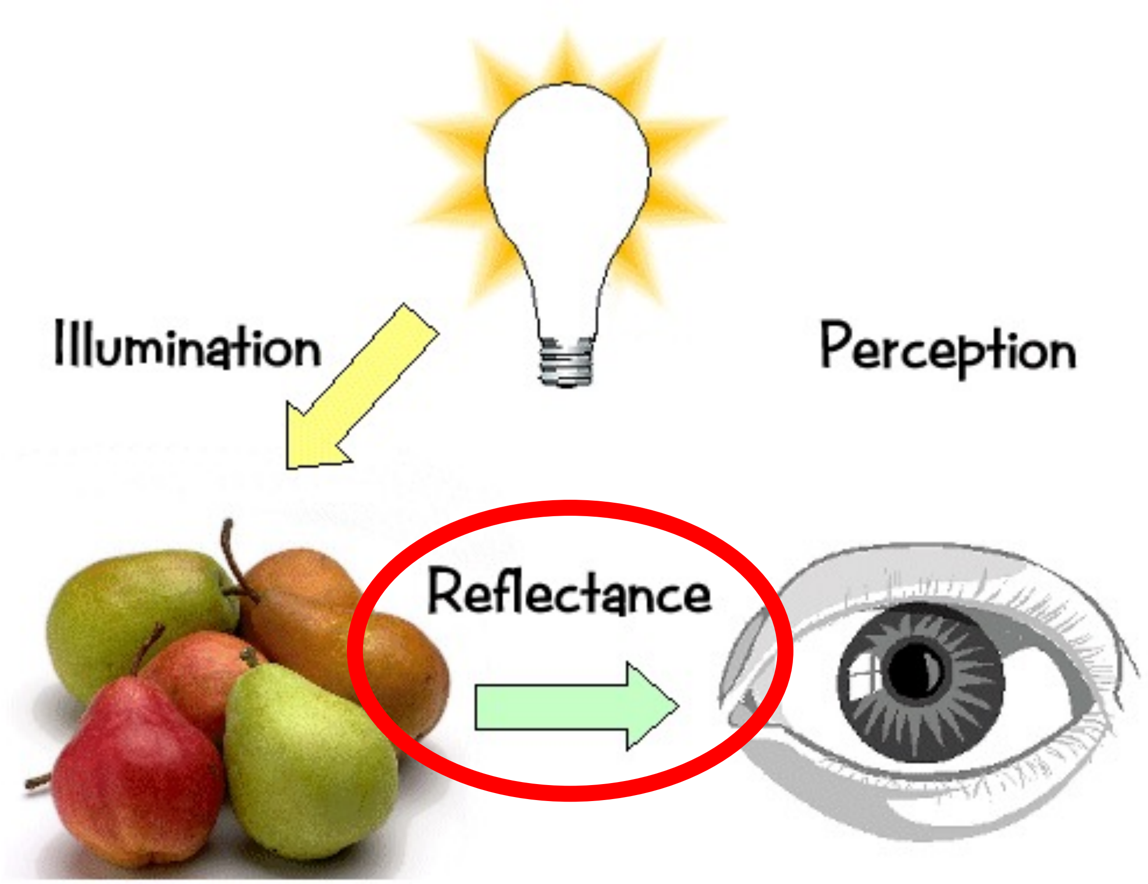
Roadmap for the rest of the course

- The next three lectures will finish up geometry and image formation
  - Next up (after Spring Break): deep learning, image recognition, neural radiance fields, image synthesis
- Coming up
  - Reflectance and Photometric Stereo (today)
  - Two-view geometry
  - Multi-view geometry

Project 4 Demo

Last time: Light & Perception

- Now: Reflectance



Light sources

- Basic types
  - point source
  - directional source
    - a point source that is infinitely far away
  - area source
    - a union of point sources

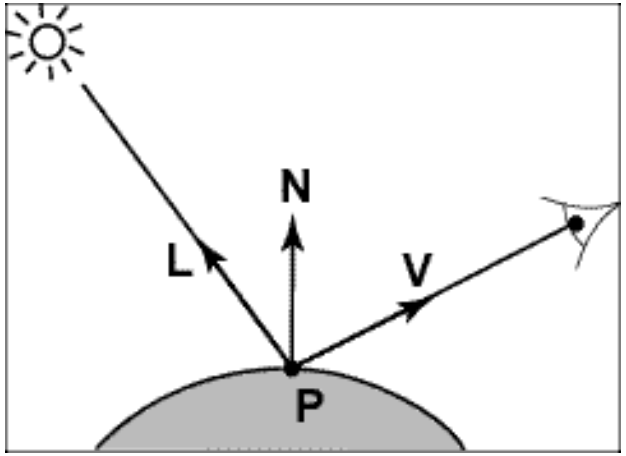
- More generally
  - a light field can describe *any* distribution of light sources

- What happens when light hits an object?

Modeling Image Formation

We need to reason about:

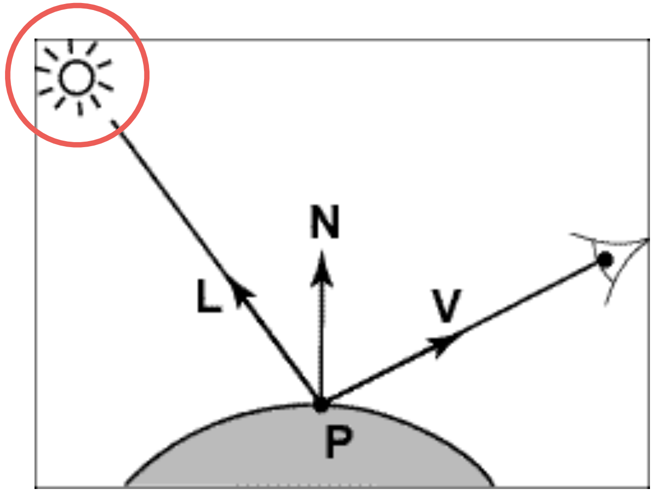
- How light interacts with the scene
- How a pixel value is related to light energy in the world



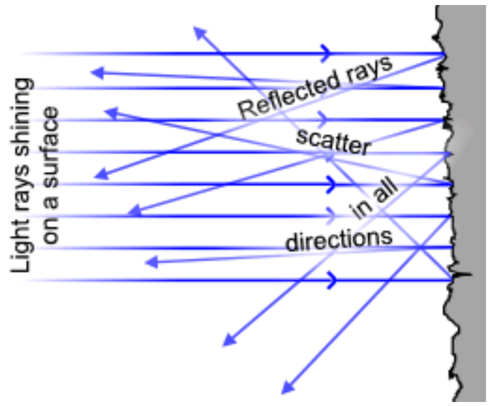
Track a “ray” of light all the way from light source to the sensor

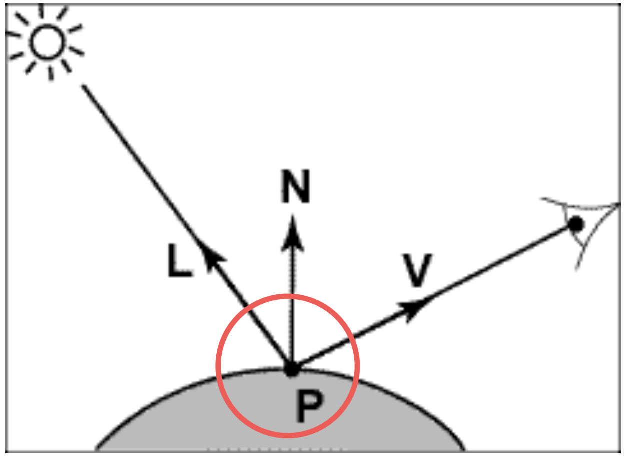
Directional Lighting

- Key property: all rays are parallel
- Equivalent to an infinitely distant point source



Lambertian Reflectance



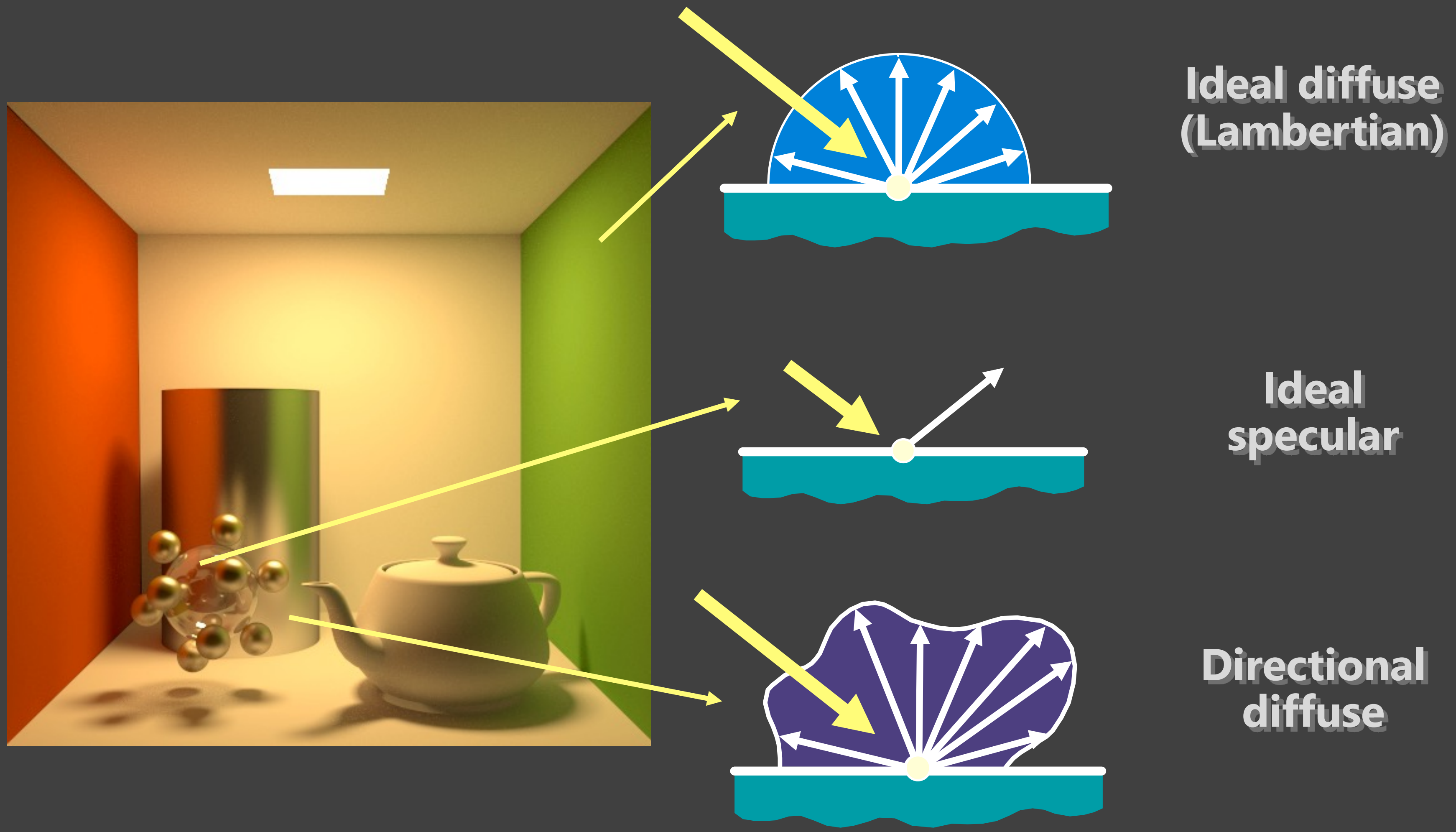


$$I = N \cdot L$$

Image intensity = Surface normal • Light direction

Image intensity $\propto$ cos(angle between N and L)

Materials - Three Forms

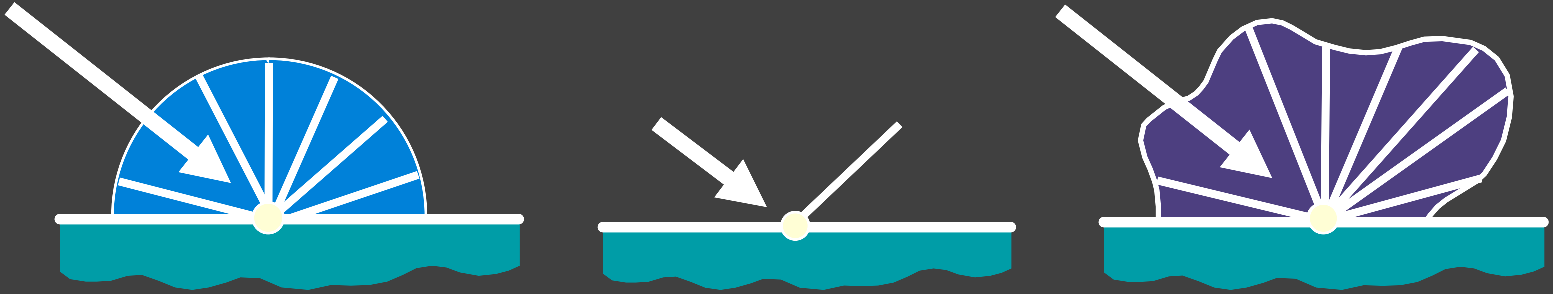


Refle

Ideal diffuse (Lambertian)

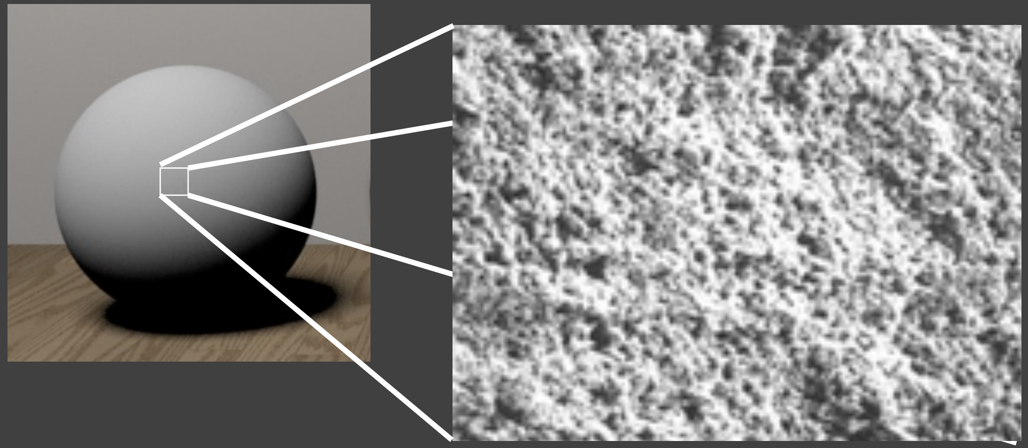
Ideal specular

Directional diffuse

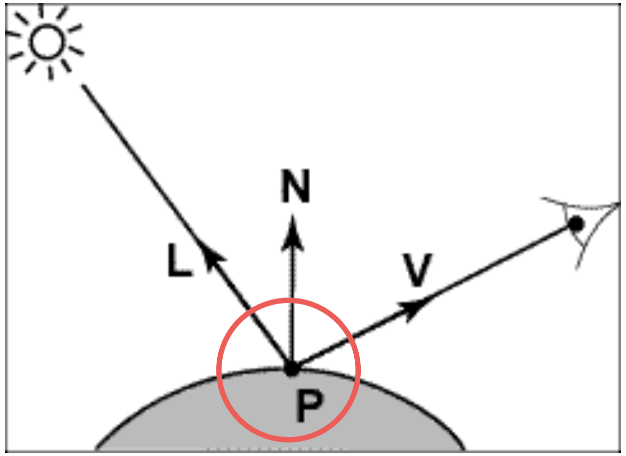


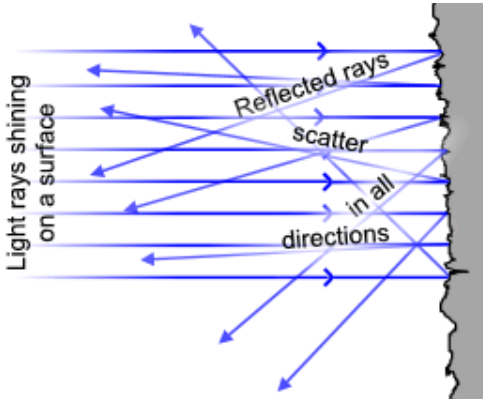
Ideal Diffuse Reflection

- Characteristic of multiple scattering materials
- An idealization but reasonable for matte surfaces



Lambertian Reflectance





1. Reflected energy is proportional to cosine of angle between L and N **(incoming)**

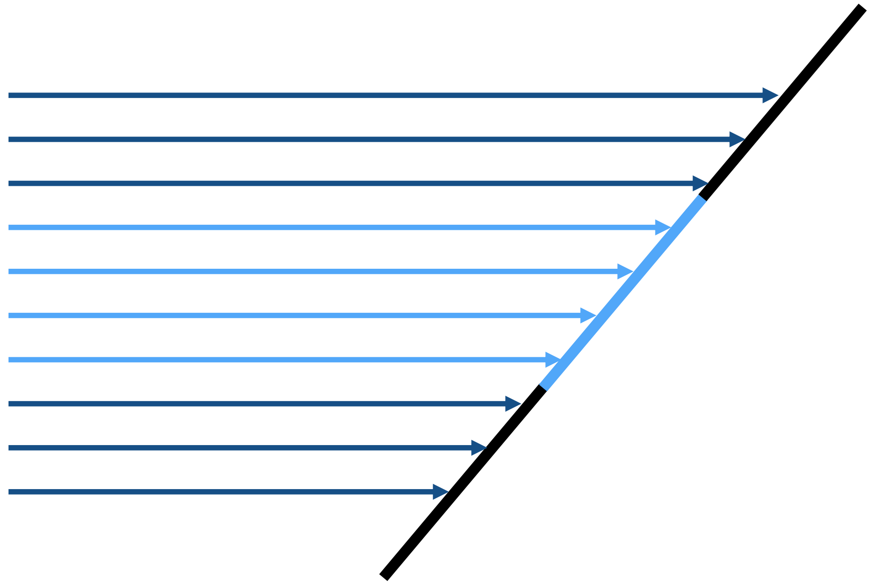
2. Measured intensity is viewpoint-independent **(outgoing)**

Lambertian Reflectance: Incoming

- Reflected energy is proportional to cosine of angle between L and N

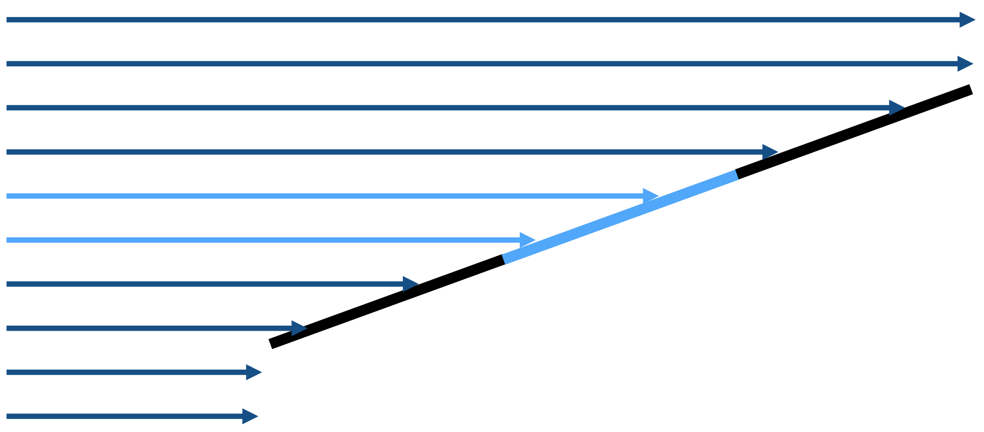
Lambertian Reflectance: Incoming

- Reflected energy is proportional to cosine of angle between L and N



Lambertian Reflectance: Incoming

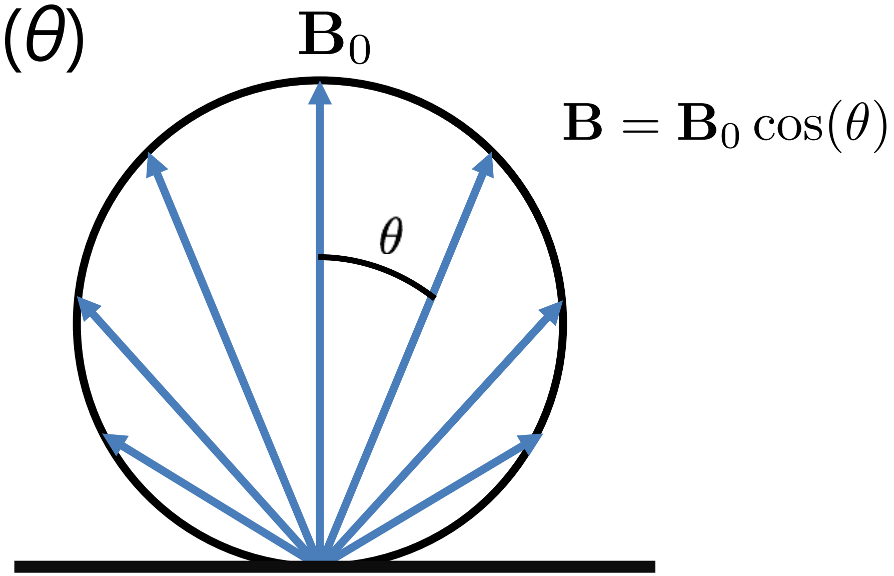
- Reflected energy is proportional to cosine of angle between L and N



Light hitting surface is proportional to the **cosine**

Lambertian appearance is view-independent

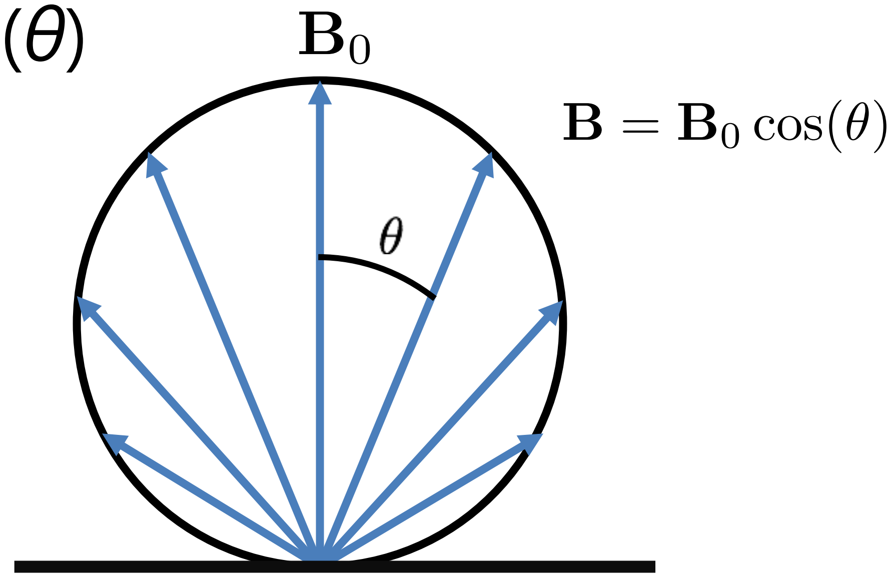
- Number of photons reflected to a given angle θ is proportional to $\cos(\theta)$



Lambert's cosine law: $\mathbf{B} = \mathbf{B}_0 \cos(\theta)$

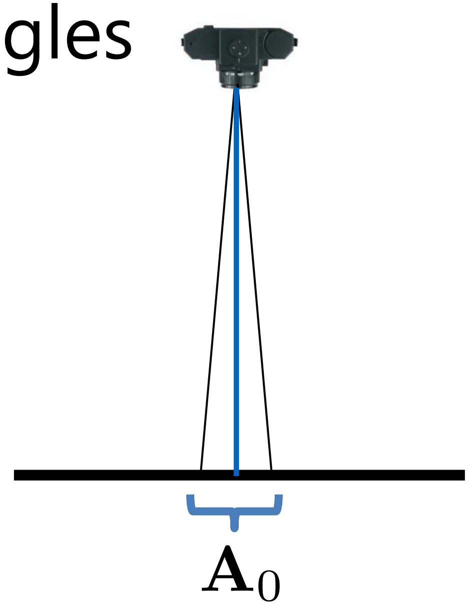
Lambertian appearance is view-independent

- Number of photons reflected to a given angle θ is proportional to $\cos(\theta)$



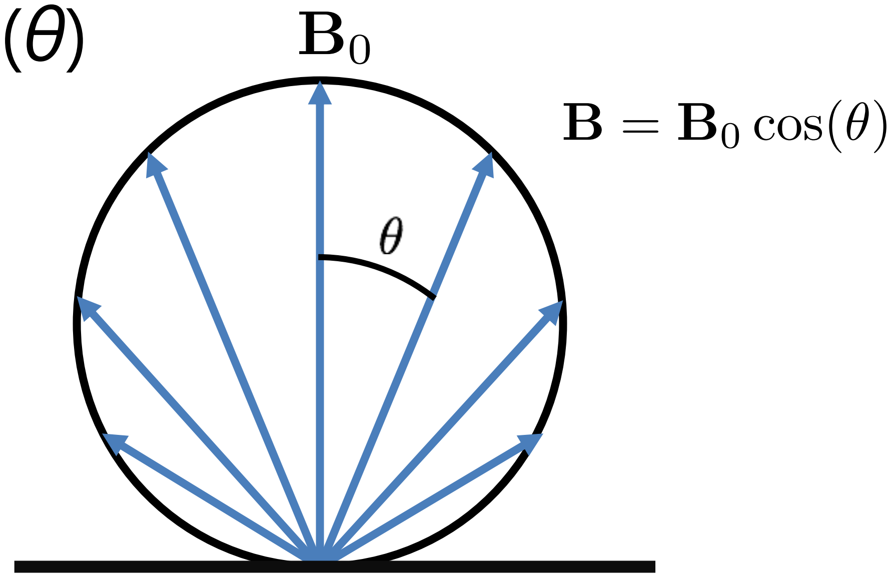
Lambert's cosine law: $\mathbf{B} = \mathbf{B}_0 \cos(\theta)$

- But appearance is the same from every angle due to larger pixel footprint at larger angles



Lambertian appearance is view-independent

- Number of photons reflected to a given angle θ is proportional to $\cos(\theta)$



Lambert's cosine law: $\mathbf{B} = \mathbf{B}_0 \cos(\theta)$

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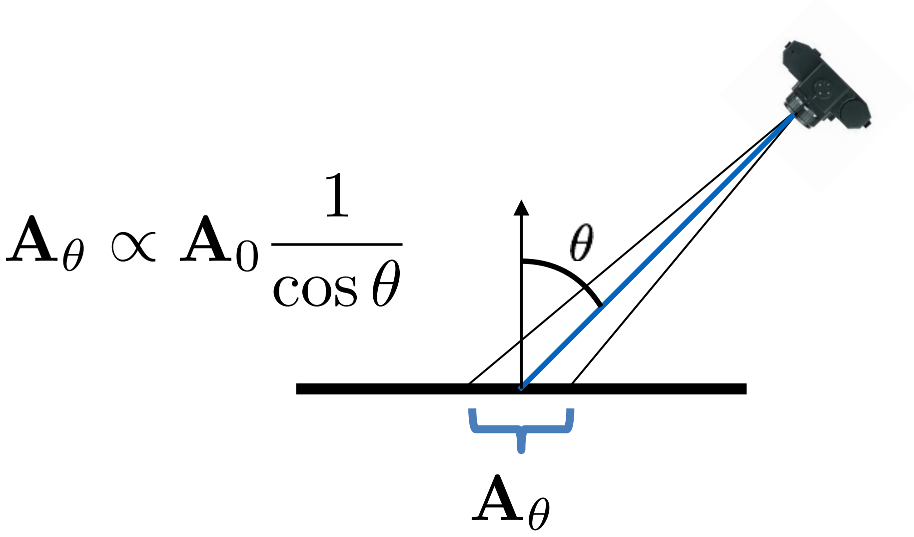
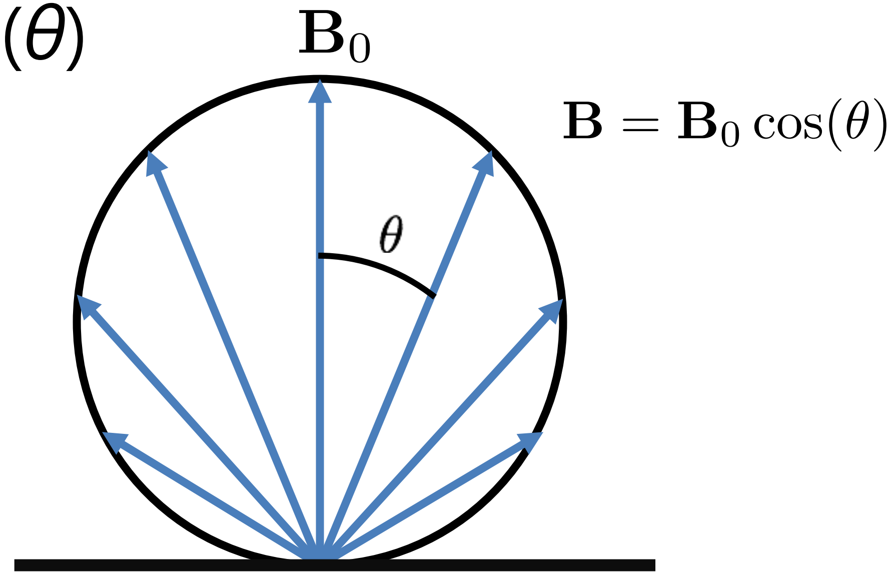


Lambertian appearance is view-independent

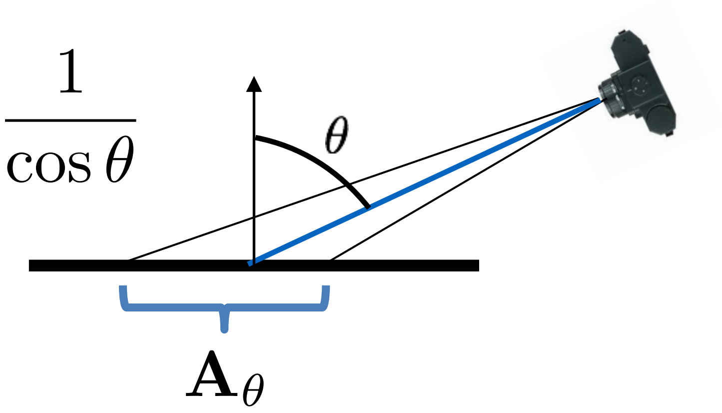
- Number of photons reflected to a given angle θ is proportional to cos(θ)



Lambert's cosine law: $\mathbf{B} = \mathbf{B}_0 \cos(\theta)$

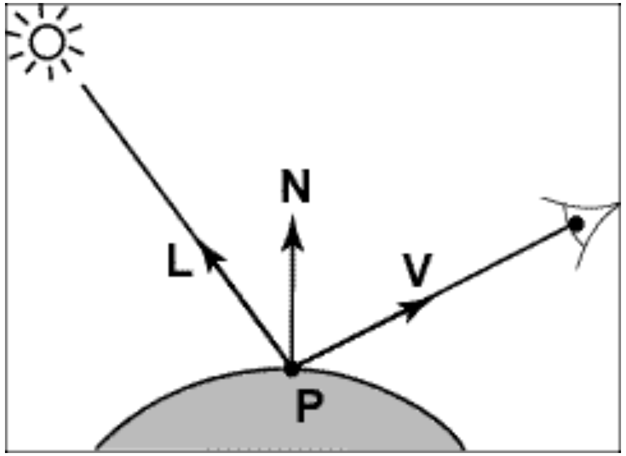
- But appearance is the same from every angle due to larger pixel footprint at larger angles

$$\mathbf{A}_\theta \propto \mathbf{A}_0 \frac{1}{\cos\theta}$$

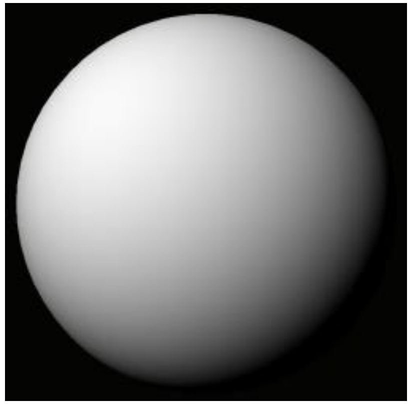


Radiance (what eye sees) $\propto \mathbf{B}_0 \mathbf{A}_0 \cancel{\cos(\theta)} \frac{1}{\cancel{\cos(\theta)}}$

Final Lambertian image formation model



$$I = k_d \mathbf{N} \cdot \mathbf{L}$$

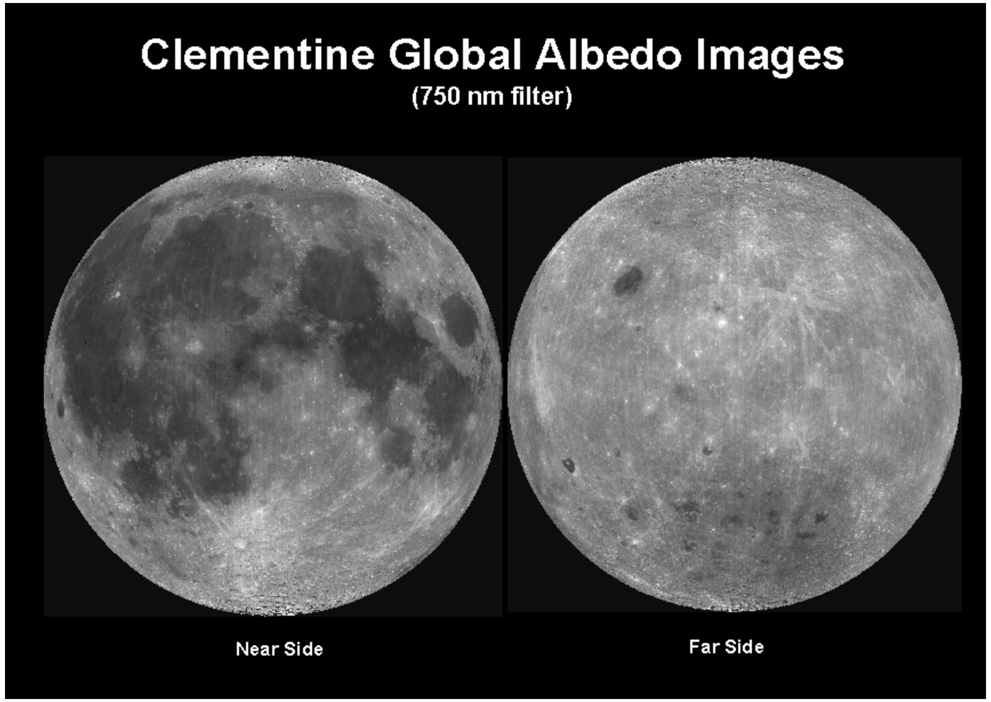


1. Diffuse **albedo**: what fraction of incoming light is reflected?
   - Introduce scale factor k_d
2. Light intensity: how much light is arriving?
   - Compensate with camera exposure (global scale factor)
3. Camera response function
   - Assume pixel value is linearly proportional to incoming energy (perform radiometric calibration if not)

Albedo

Sample albedos

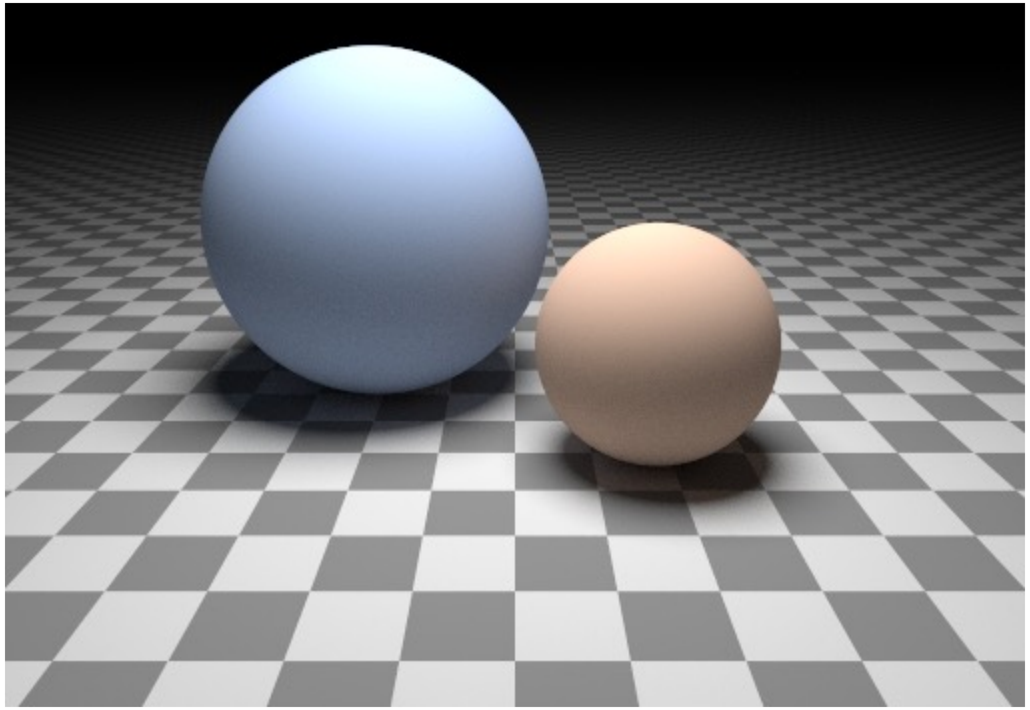
Surface	Typical albedo
Fresh asphalt	0.04[4]
Open ocean	0.06[5]
Worn asphalt	0.12[4]
Conifer forest (Summer)	0.08,[6] 0.09 to 0.15[7]
Deciduous trees	0.15 to 0.18[7]
Bare soil	0.17[8]
Green grass	0.25[8]
Desert sand	0.40[9]
New concrete	0.55[8]
Ocean ice	0.5–0.7[8]
Fresh snow	0.80–0.90[8]



Objects can have varying albedo and albedo varies with wavelength

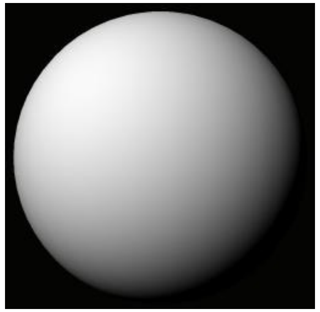
Source: https://en.wikipedia.org/wiki/Albedo

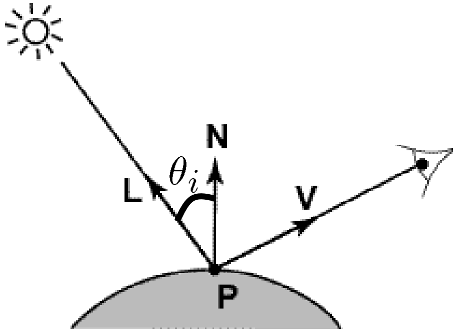
Can we determine shape from lighting?



- Are these spheres?
  - Or just flat discs painted with varying albedo?

A Single Image: Shape from shading





Suppose (for now) $k_d = 1$

$$\begin{aligned} I &= k_d \mathbf{N} \cdot \mathbf{L} \\ &= \mathbf{N} \cdot \mathbf{L} \\ &= cos\ \theta_i \end{aligned}$$

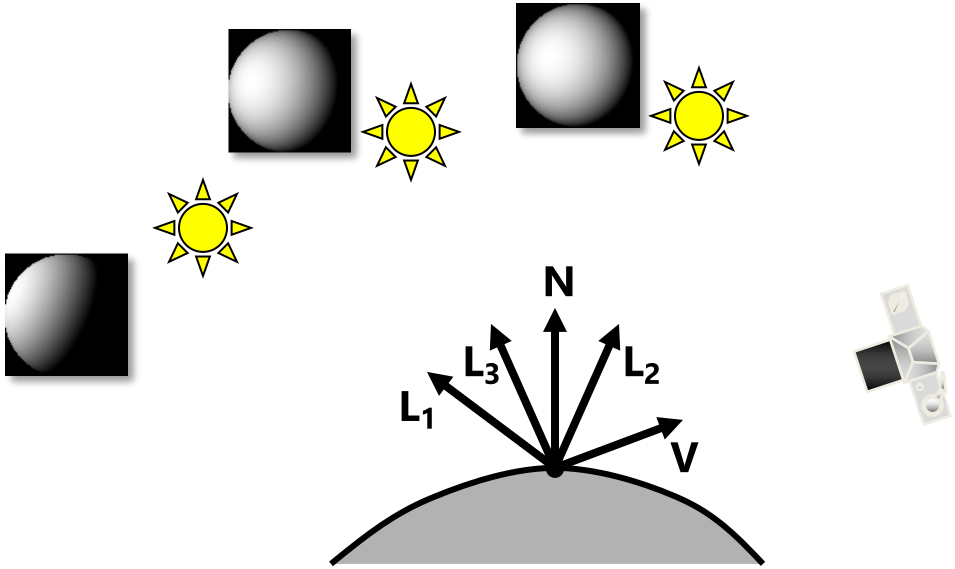
You can directly measure angle between normal and light source

- Not quite enough information to compute surface shape
- But can be if you add some additional info, for example
  - assume a few of the normals are known (e.g., along silhouette)
  - constraints on neighboring normals—"integrability"
  - smoothness
- Hard to get it to work well in practice
  - plus, how many real objects have constant albedo?
  - But, deep learning can help

https://www.good.is/optical-illusion-plates-and-bowls-upside-down-or-not

Let’s take more than one photo!

Photometric stereo



$$I_1 = k_d \mathbf{N} \cdot \mathbf{L_1}$$
$$I_2 = k_d \mathbf{N} \cdot \mathbf{L_2}$$
$$I_3 = k_d \mathbf{N} \cdot \mathbf{L_3}$$

Can write this as a matrix equation:

$$\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix} = k_d \begin{bmatrix} \mathbf{L_1}^T \\ \mathbf{L_2}^T \\ \mathbf{L_3}^T \end{bmatrix} \mathbf{N}$$

Solving the equations

$$\underbrace{\begin{bmatrix} I_1 \\ I_2 \\ I_3 \end{bmatrix}}_{\substack{\mathbf{I} \\ 3 \times 1}} = \underbrace{\begin{bmatrix} \mathbf{L_1}^T \\ \mathbf{L_2}^T \\ \mathbf{L_3}^T \end{bmatrix}}_{\substack{\mathbf{L} \\ 3 \times 3}} \underbrace{k_d \mathbf{N}}_{\substack{\mathbf{G} \\ 3 \times 1}}$$

$$\mathbf{G} = \mathbf{L}^{-1}\mathbf{I}$$

$$k_d = \|\mathbf{G}\|$$

$$\mathbf{N} = \frac{1}{k_d}\mathbf{G}$$

Solve one such linear system **per pixel** to solve for that pixel's surface normal

More than three lights

Can get better results by using more than 3 lights

$$\begin{bmatrix} I_1 \\ \vdots \\ I_n \end{bmatrix} = \begin{bmatrix} \mathbf{L_1} \\ \vdots \\ \mathbf{L_n} \end{bmatrix} k_d \mathbf{N}$$

Least squares solution:

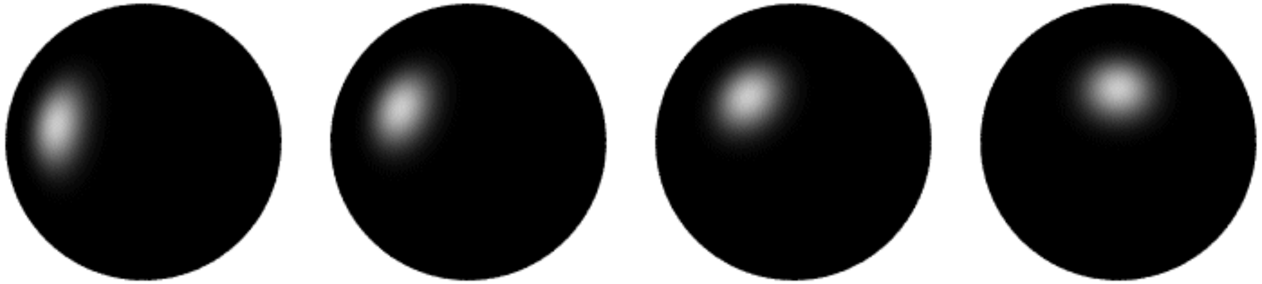
$$\begin{aligned} \mathbf{I} &= \mathbf{L}\mathbf{G} \\ \mathbf{L^T I} &= \mathbf{L^T L G} \\ \mathbf{G} &= (\mathbf{L^T L})^{-1}(\mathbf{L^T I}) \end{aligned}$$

Solve for N, k_d as before

What's the size of $\mathbf{L^T L}$?

Computing light source directions

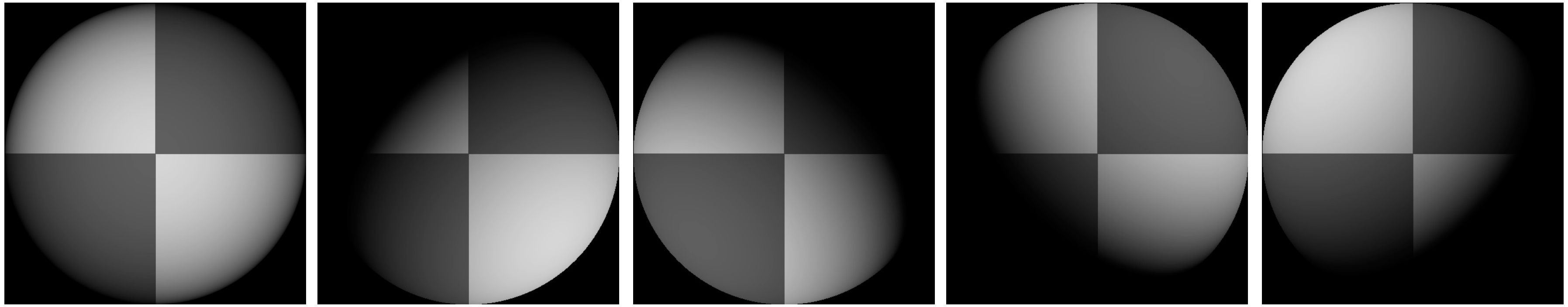
Trick: place a chrome sphere in the scene



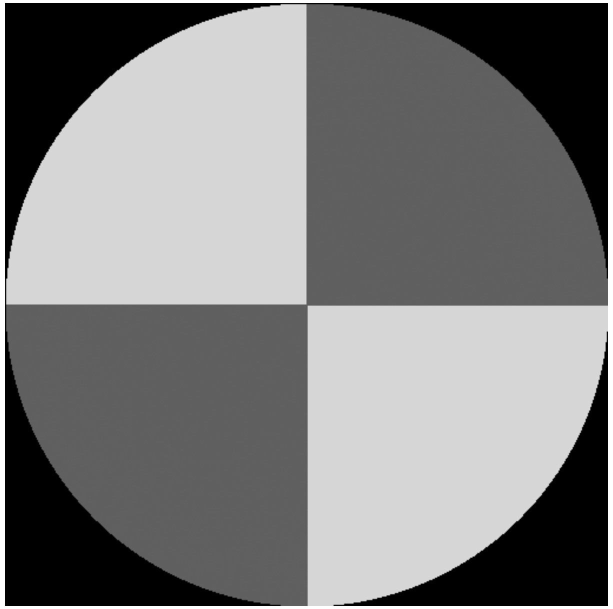
– the location of the highlight tells you where the light source is

Example

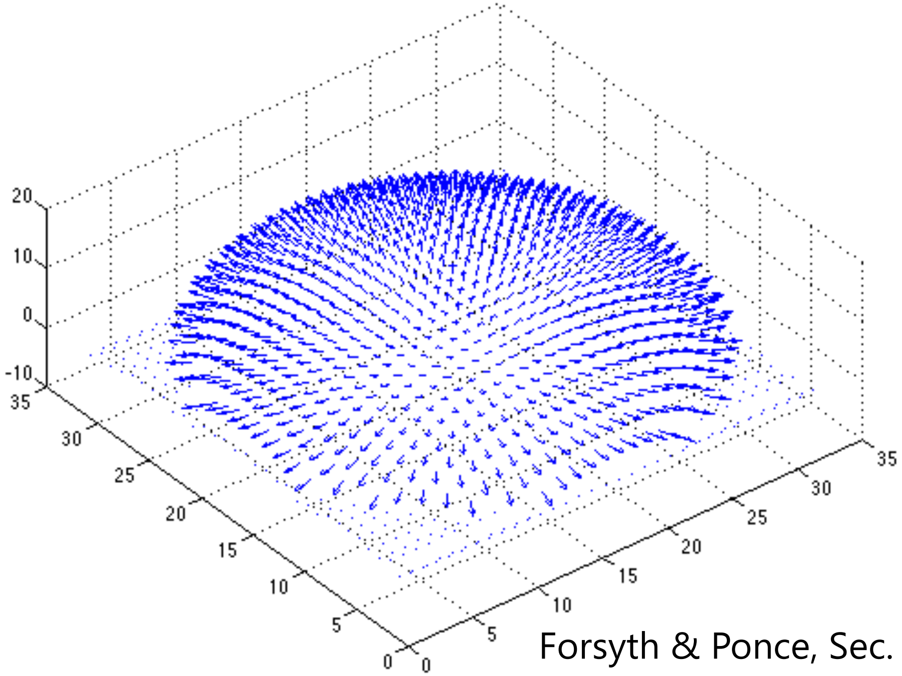
Input views



Recovered albedo



Recovered normal field

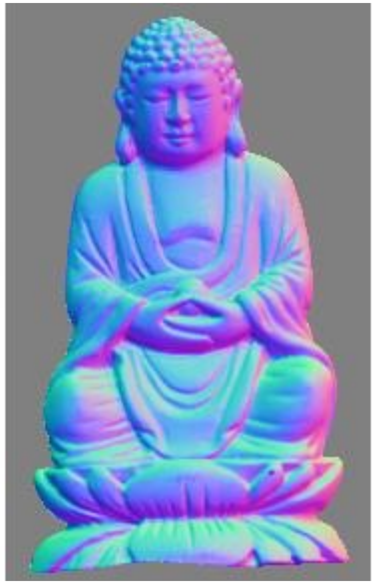


Forsyth & Ponce, Sec. 5.4

Depth from normals

- Solving the linear system per-pixel gives us an estimated surface normal for each pixel
- How can we compute depth from normals?
  - Normals are like the "derivative" of the true depth

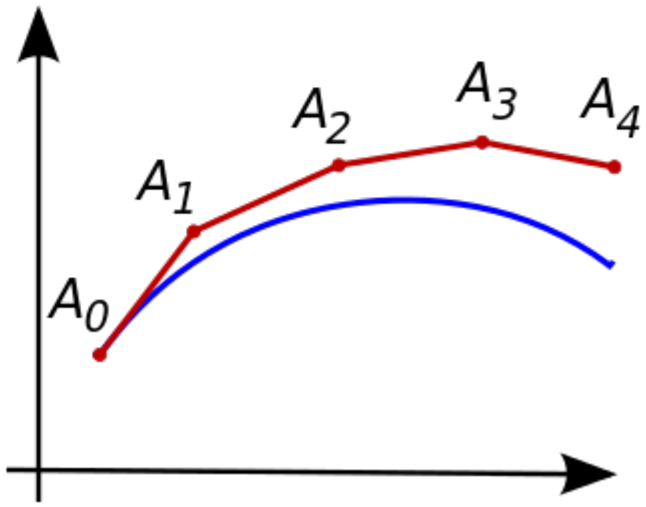

Input photo


Estimated normals


Estimated normals (needle diagram)

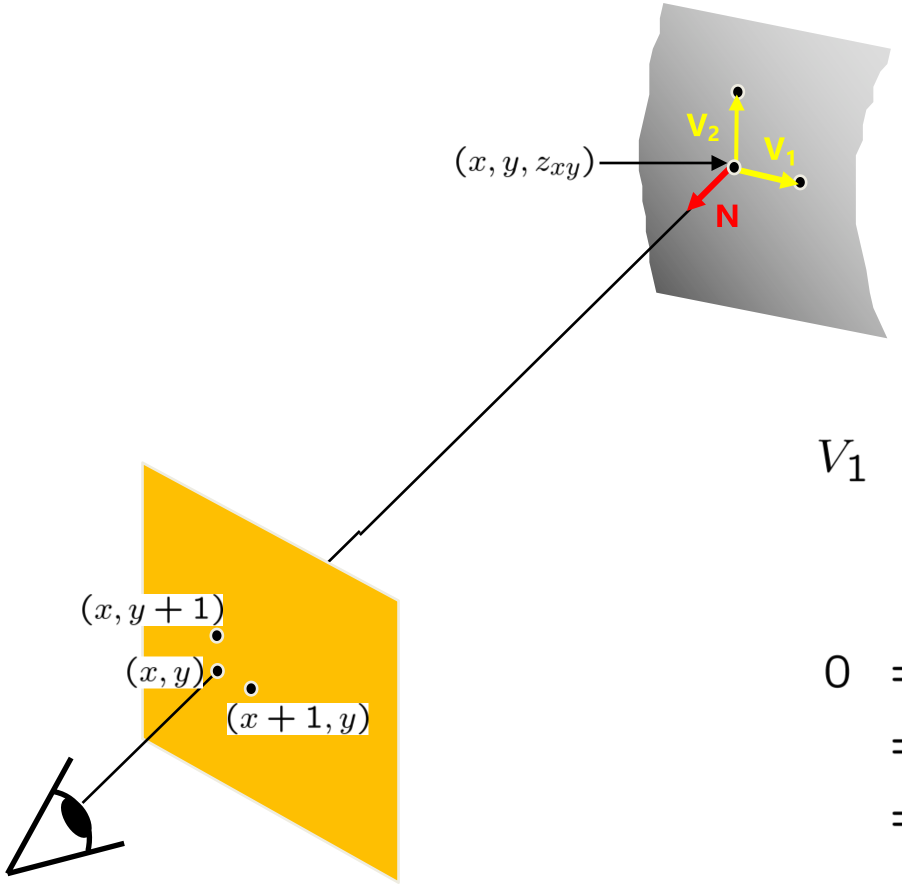
Normal Integration

- Integrating a set of derivatives is easy in 1D
  - (similar to Euler's method from diff. eq. class)



- Could integrate normals in each column / row separately
  - Wouldn't give a good surface
- Instead, we formulate as a linear system and solve for depths that *best agree with the surface normals*

Depth from normals



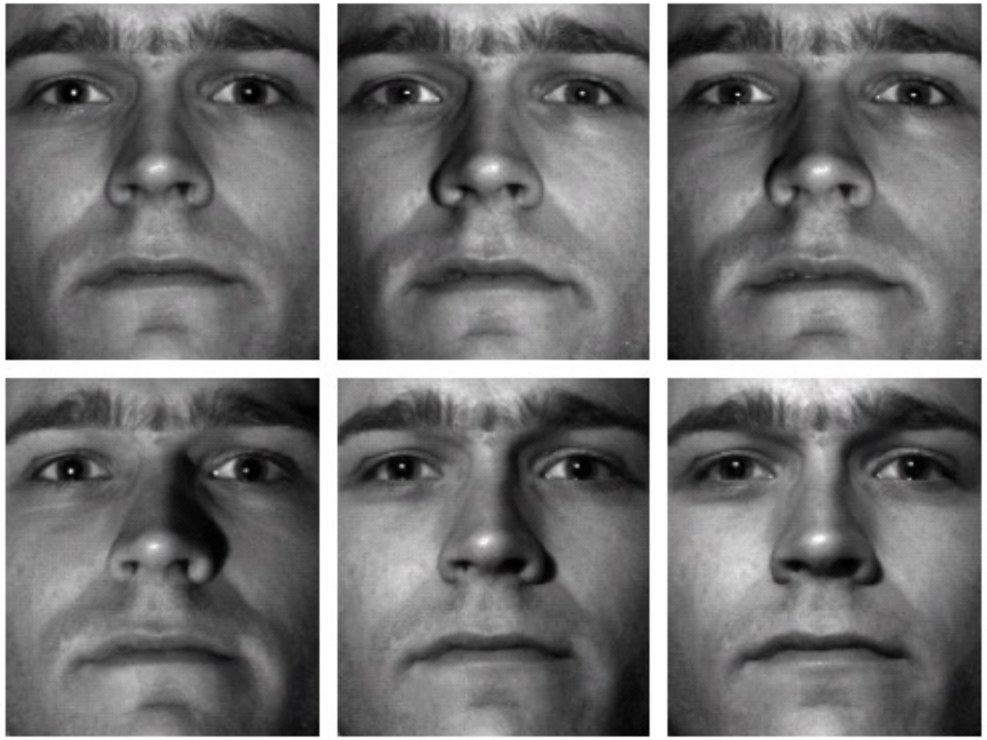
$$
\begin{aligned}
V_1 &= (x+1, y, z_{x+1,y}) - (x, y, z_{xy}) \\
&= (1, 0, z_{x+1,y} - z_{xy})
\end{aligned}
$$

$$
\begin{aligned}
0 &= N \cdot V_1 \\
&= (n_x, n_y, n_z) \cdot (1, 0, z_{x+1,y} - z_{xy}) \\
&= n_x + n_z(z_{x+1,y} - z_{xy})
\end{aligned}
$$

Get a similar equation for $\mathbf{V_2}$

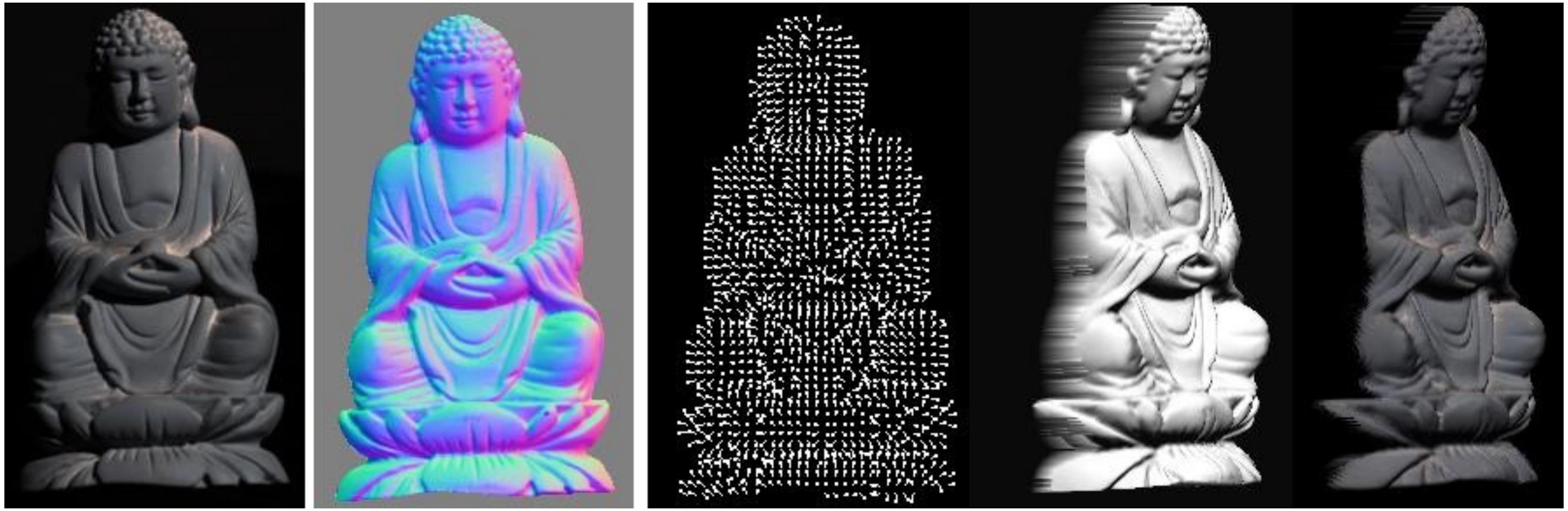
- Each normal gives us two linear constraints on z
- compute z values by solving a matrix equation

Results



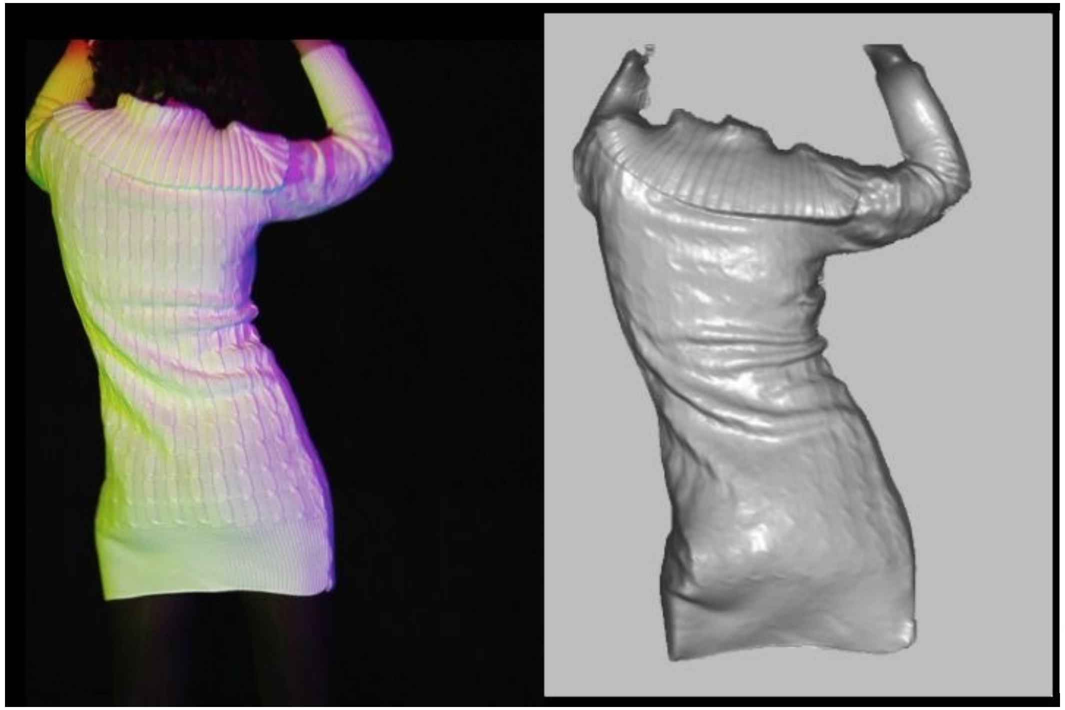
from Athos Georghiades

Results



Extension

- Photometric Stereo from Colored Lighting



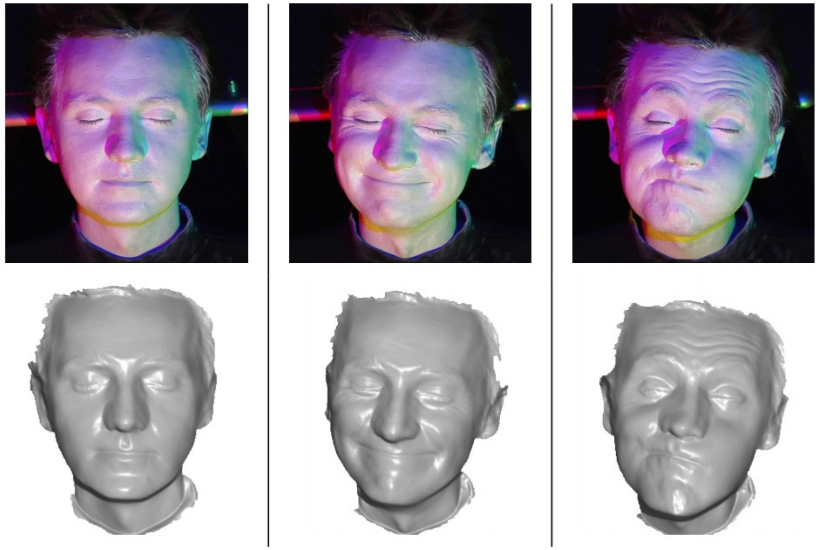


Fig. 2. **Applying the original algorithm to a face with white makeup.** Top: example input frames from video of an actor smiling and grimacing. Bottom: the resulting integrated surfaces.

Video Normals from Colored Lights
Gabriel J. Brostow, Carlos Hernández, George Vogiatzis, Björn Stenger, Roberto Cipolla
IEEE TPAMI, Vol. 33, No. 10, pages 2104-2114, October 2011.

Questions?

For now, ignore specular reflection

Slides from Photometric Methods for 3D Modeling, Matsushita, Wilburn, Ben-Ezra

And Refraction…

Slides from Photometric Methods for 3D Modeling, Matsushita, Wilburn, Ben-Ezra

And Interreflections…

Slides from Photometric Methods for 3D Modeling, Matsushita, Wilburn, Ben-Ezra

And Subsurface Scattering…

Slides from Photometric Methods for 3D Modeling, Matsushita, Wilburn, Ben-Ezra

Limitations

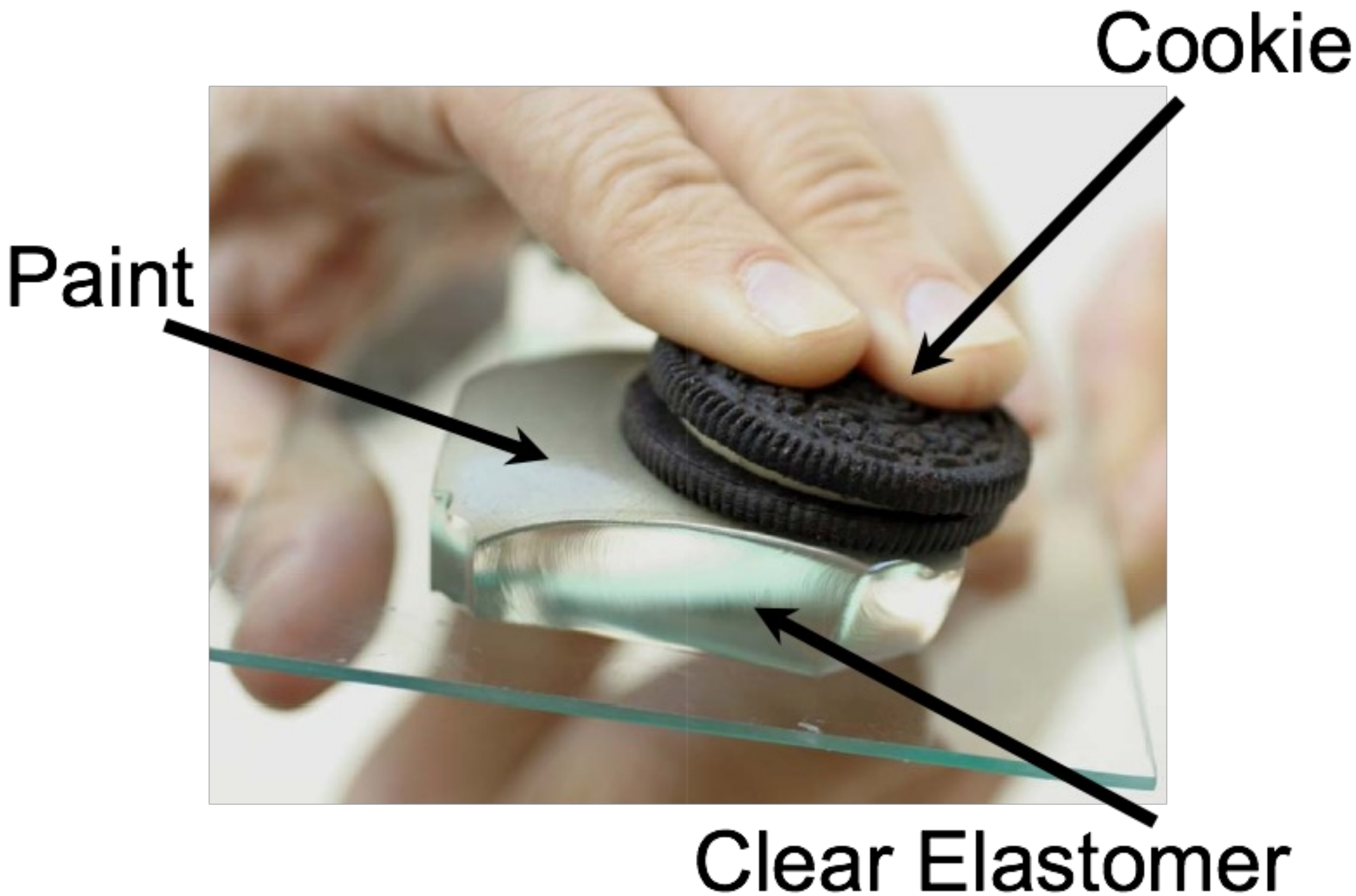
Bigger problems
- doesn't work for shiny things, semi-translucent things
- shadows, inter-reflections

Smaller problems
- camera and lights have to be distant
- calibration requirements
  - measure light source directions, intensities
  - camera response function

Newer work addresses some of these issues

Some pointers for further reading:
- Zickler, Belhumeur, and Kriegman, "*Helmholtz Stereopsis: Exploiting Reciprocity for Surface Reconstruction*." IJCV, Vol. 49 No. 2/3, pp 215-227.
- Hertzmann & Seitz, "*Example-Based Photometric Stereo: Shape Reconstruction with General, Varying BRDFs*." IEEE Trans. PAMI 2005

Johnson and Adelson, 2009

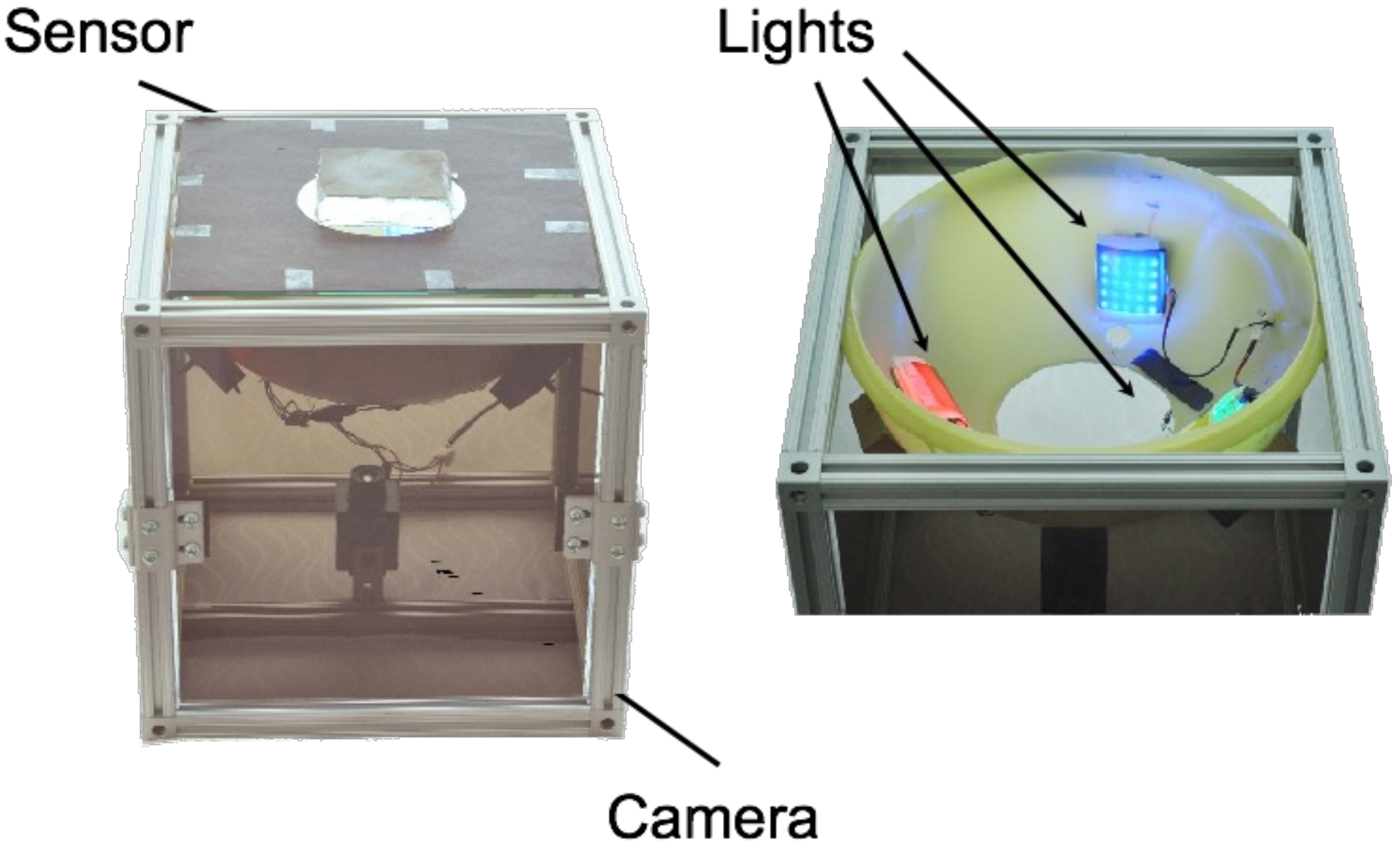


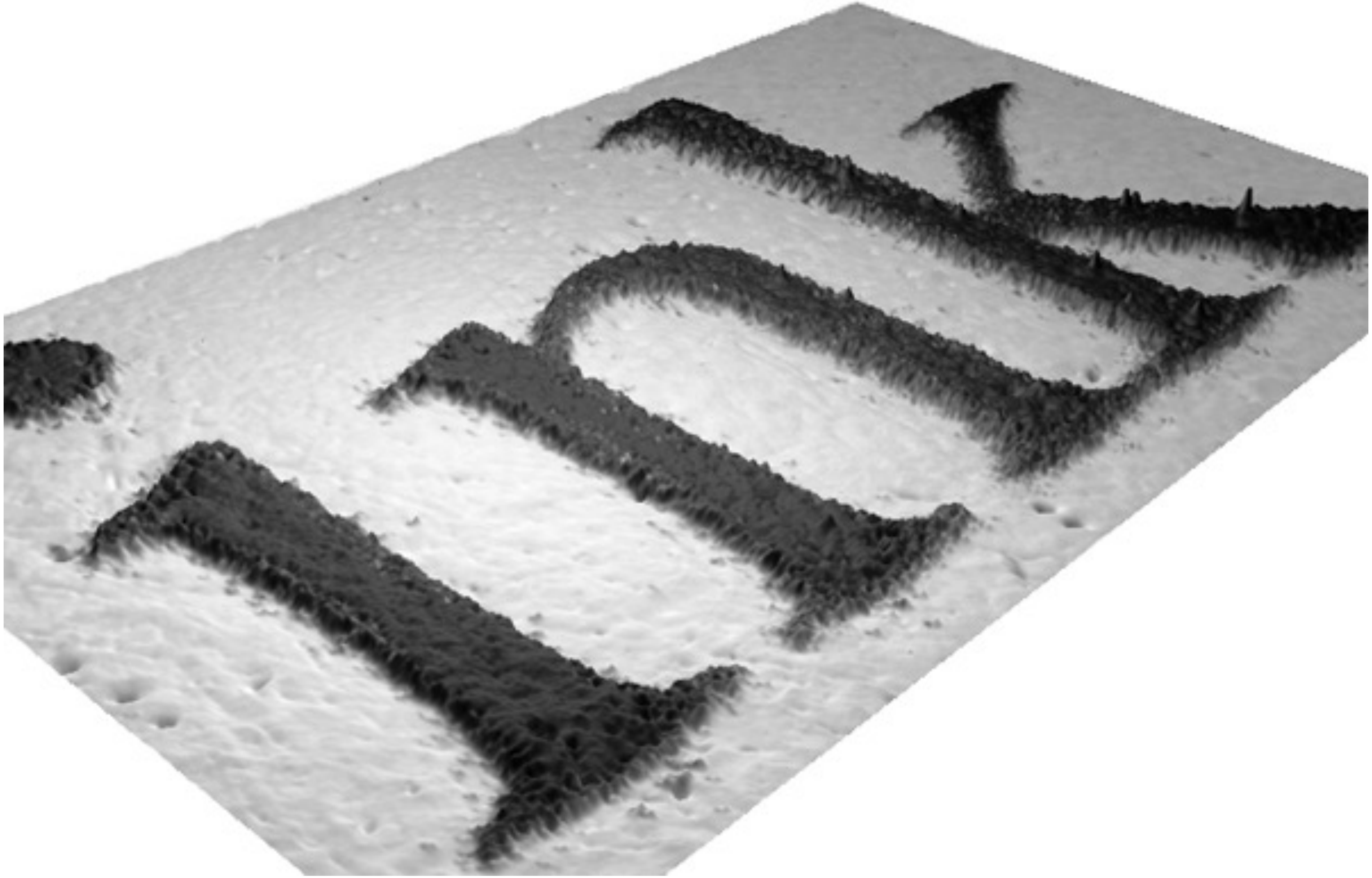
Johnson and Adelson, 2009

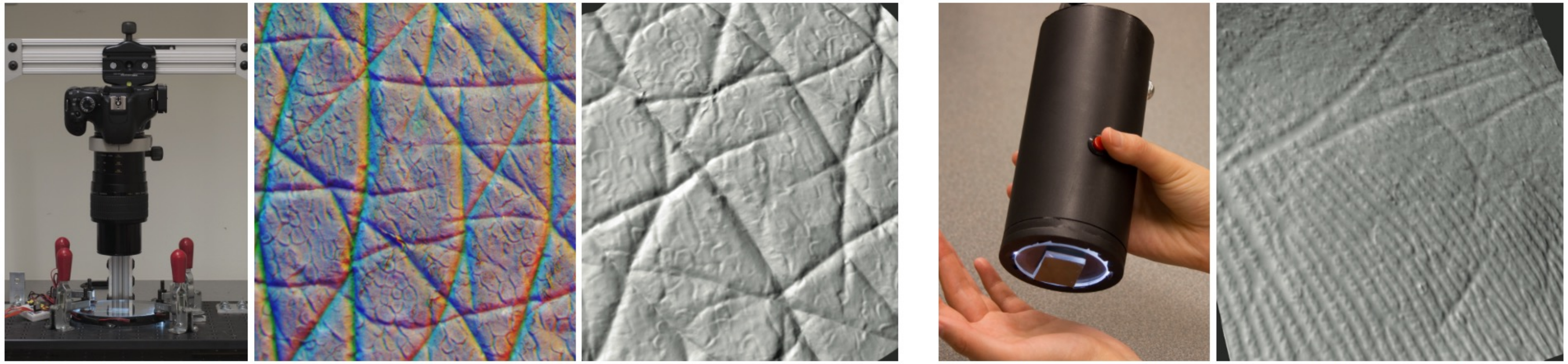

OREO


OREO

Lights, camera, action




ink



(a) bench configuration (b) captured (c) reconstruction (d) portable configuration (e) reconstruction

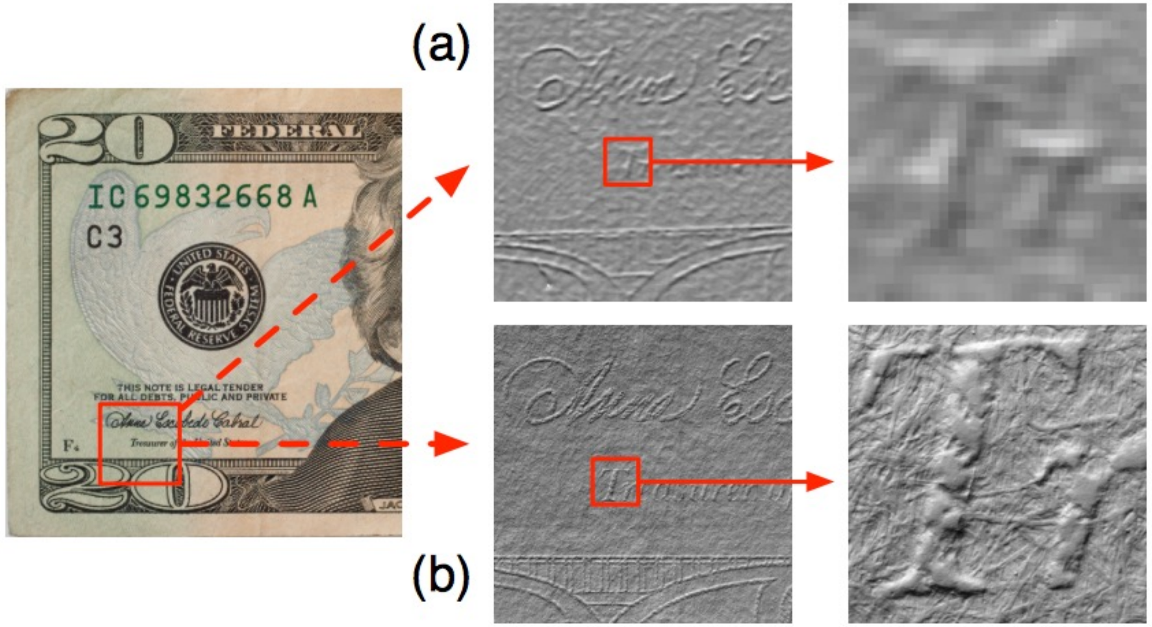


Figure 7: *Comparison with the high-resolution result from the original retrographic sensor. (a) Rendering of the high-resolution $20 bill example from the original retrographic sensor with a close-up view. (b) Rendering of the captured geometry using our method.*

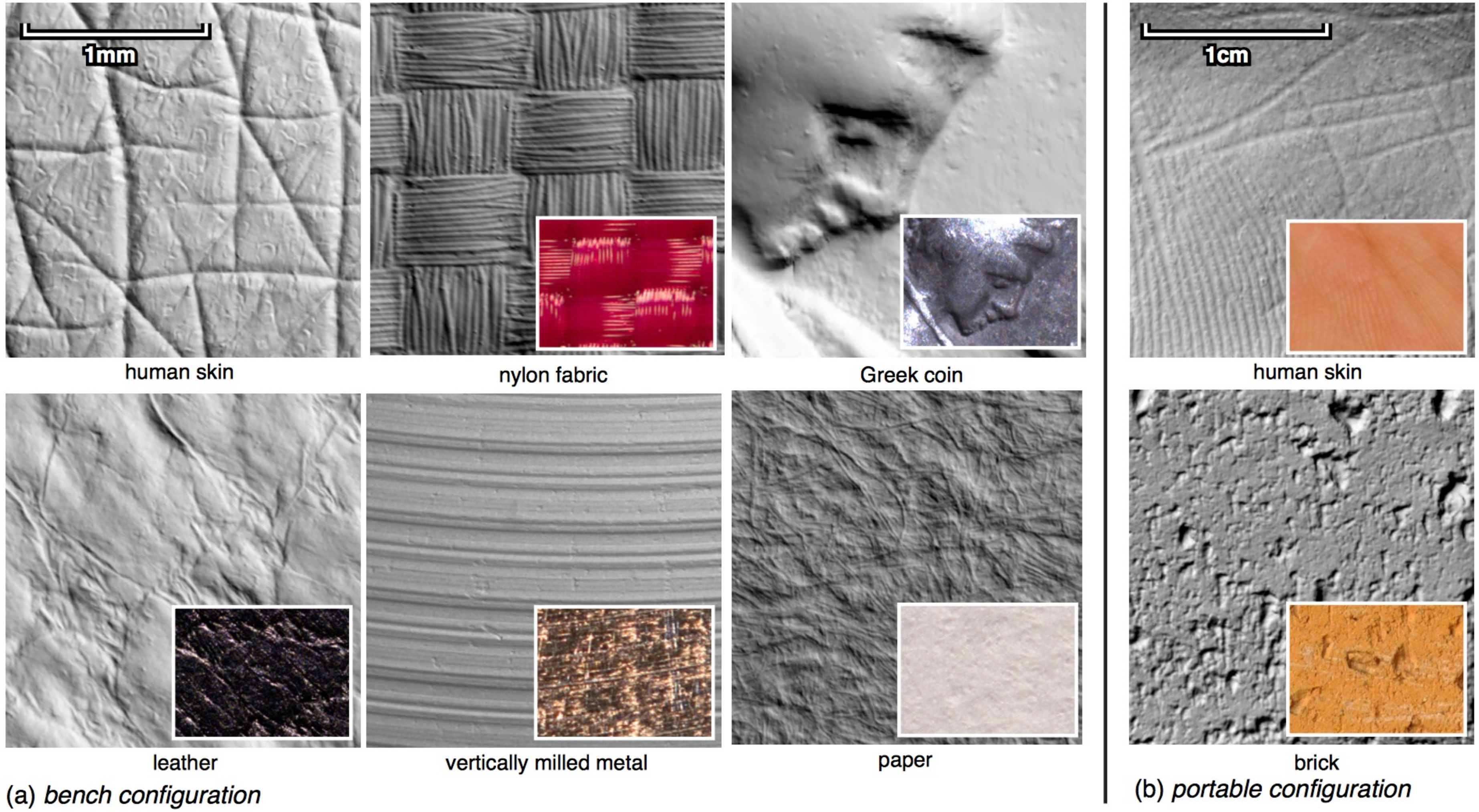
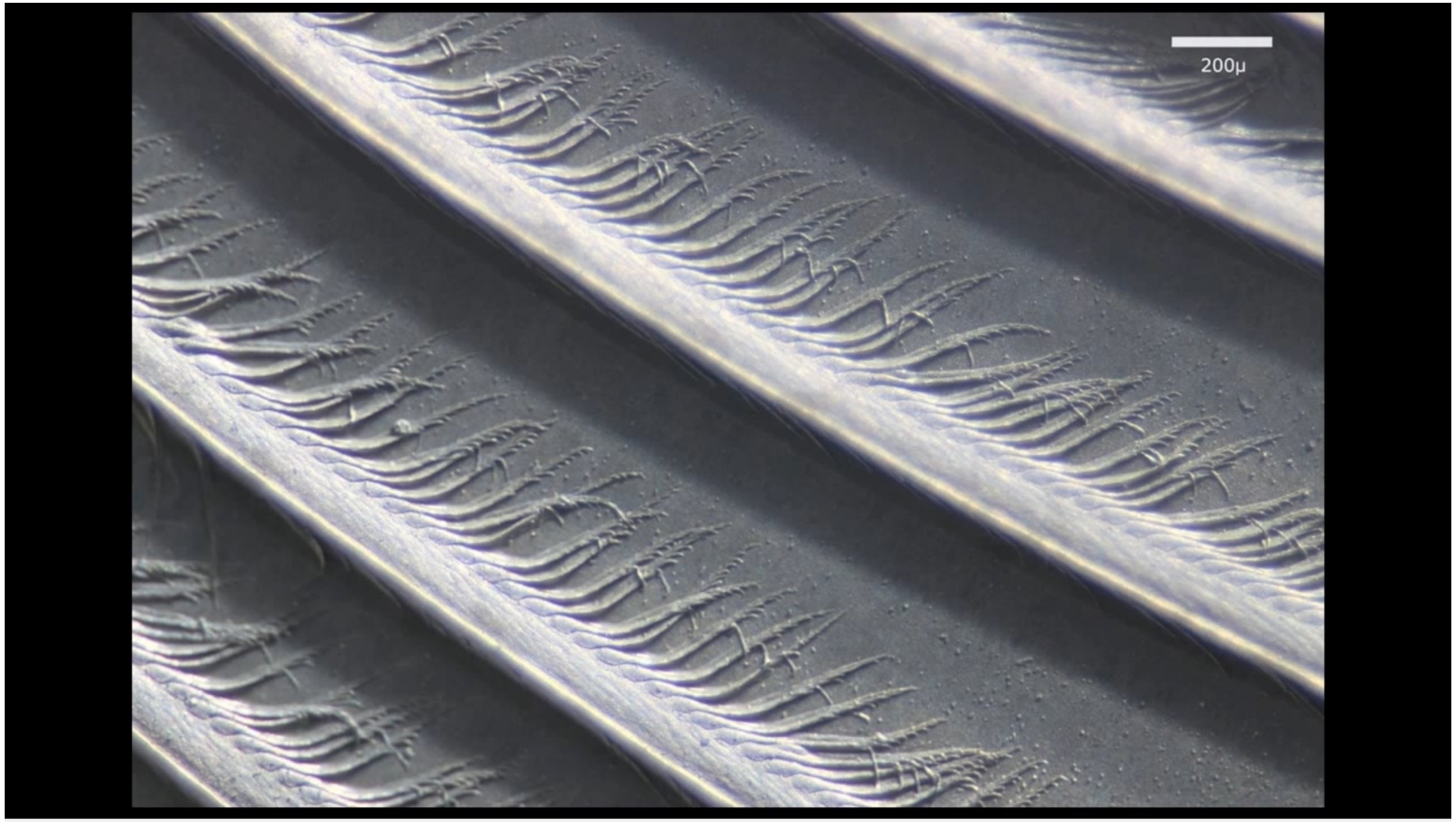


Figure 9: *Example geometry measured with the bench and portable configurations. Outer image: rendering under direct lighting. Inset: macro photograph of original sample. Scale shown in upper left. Color images are shown for context and are to similar, but not exact scale.*



Sensing Surfaces with GelSight

kimoatmit

Subscribe 64

138,850 views

https://www.youtube.com/watch?v=S7gXih4XS7A

InverseRenderNet: Learning single image inverse rendering

Ye Yu and William A. P. Smith
Department of Computer Science, University of York, UK
{yy1571,william.smith}@york.ac.uk

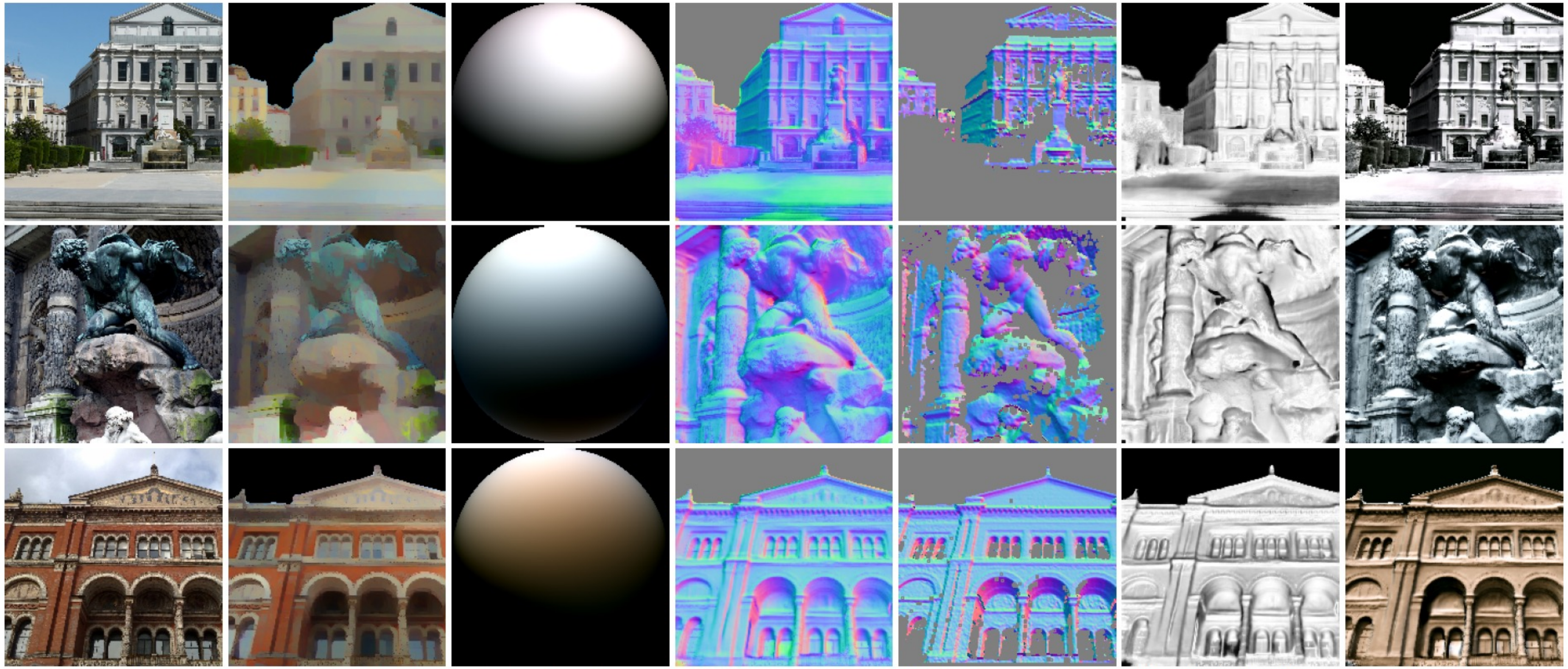


Figure 1: From a single image (col. 1), we estimate albedo and normal maps and illumination (col. 2-4); comparison multi-view stereo result from several hundred images (col. 5); re-rendering of our shape with frontal/estimated lighting (col. 6-7).

Questions?