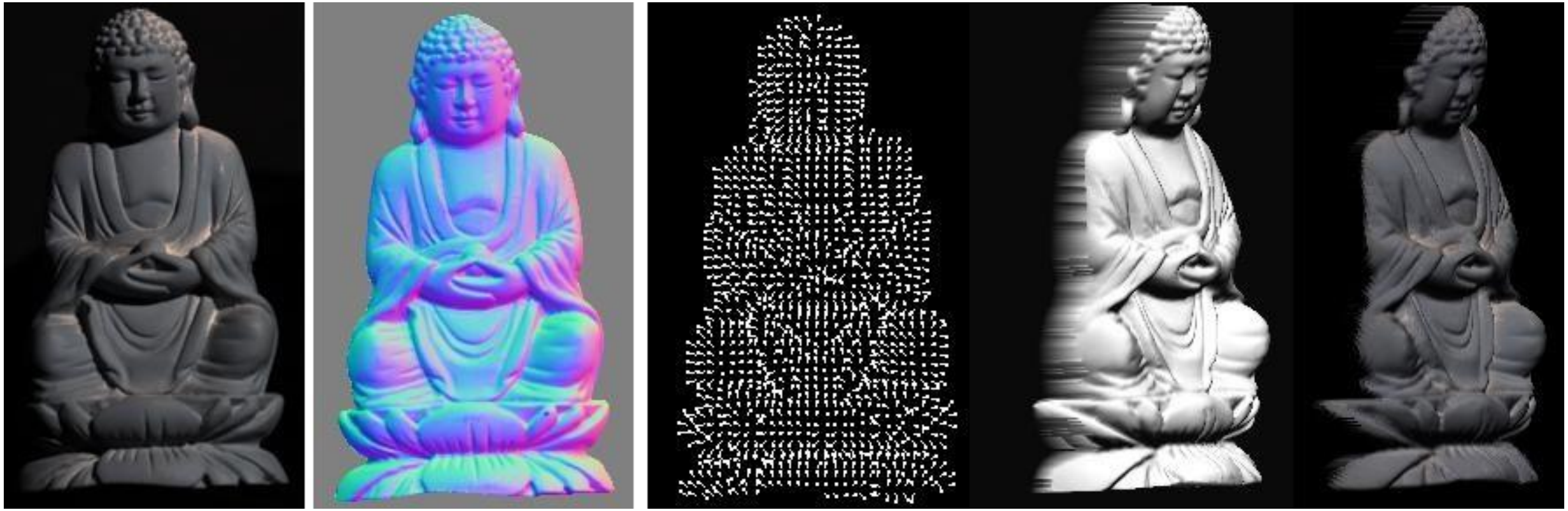
CS5670 : Computer Vision

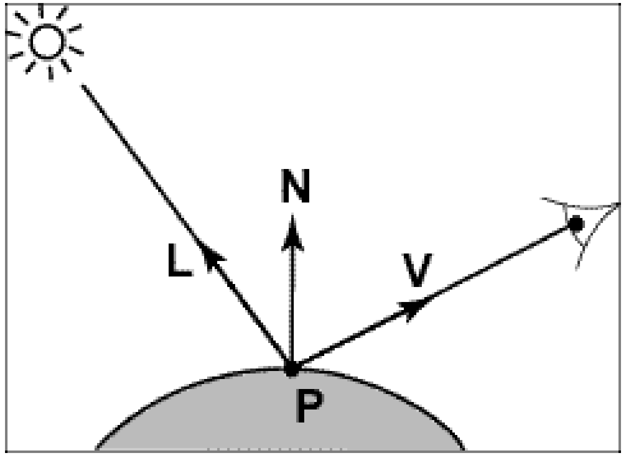
Photometric stereo

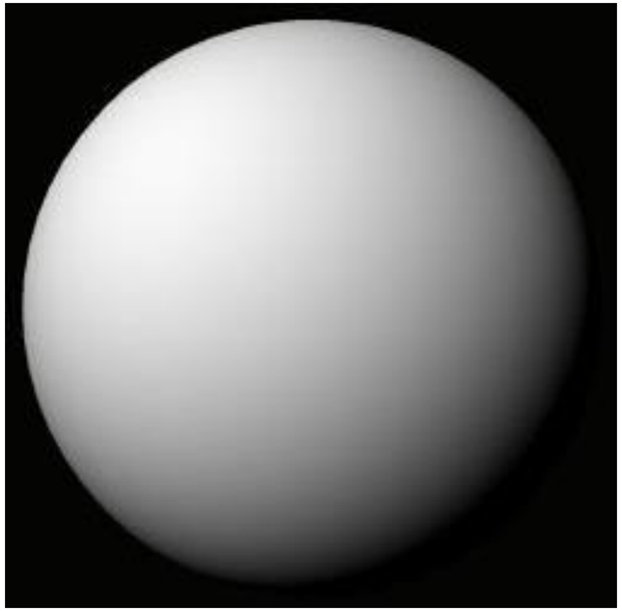


Announcements

- Project 4 (stereo) released today, due Friday, April 1, at 8pm
- To be done in groups of 2

Recap:
Lambertian (Diffuse) Reflectance



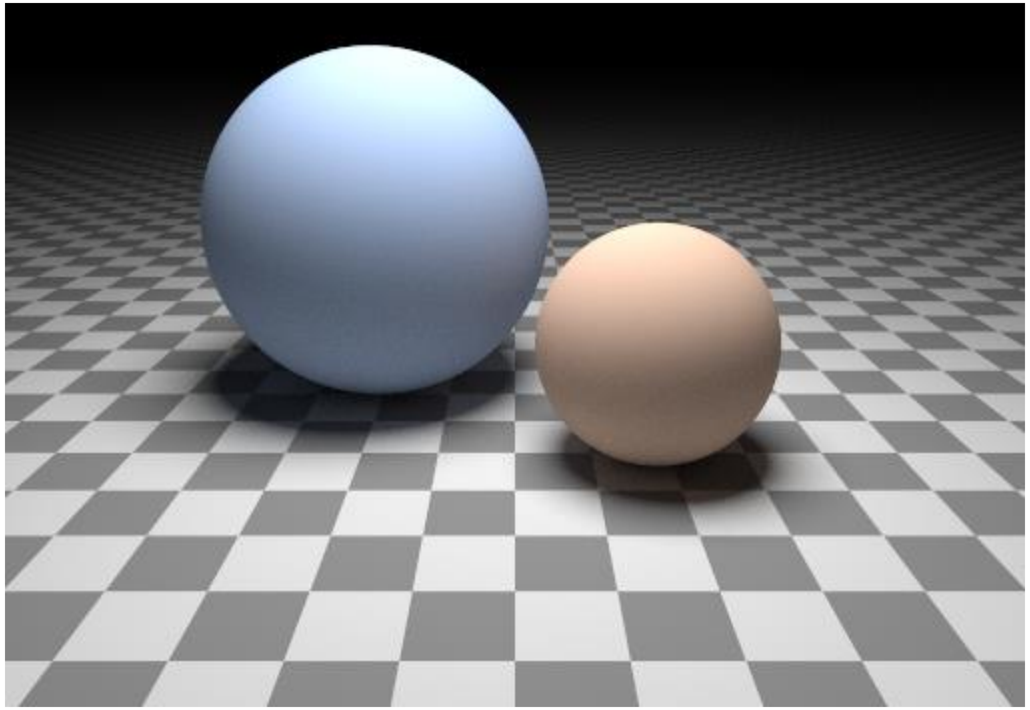


$$I = k_d \mathbf{N} \cdot \mathbf{L}$$

- I : observed image intensity
- k_d : object albedo
- $\mathbf{N}$: surface normal
- $\mathbf{L}$: light source direction

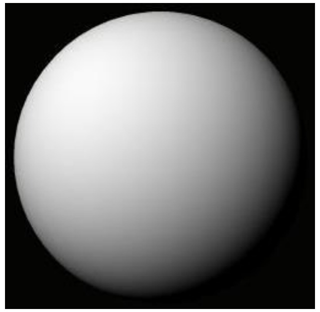
Lambertian sphere with constant albedo lit by a directional light source

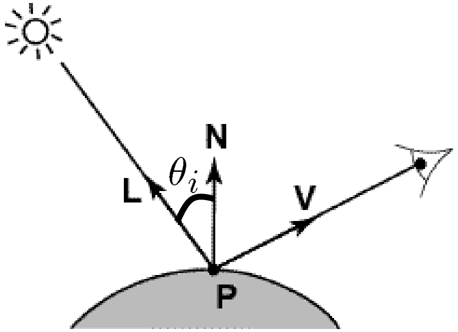
Can we determine shape from lighting?



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

A Single Image: Shape from shading





Suppose (for now) $k_d = 1$

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

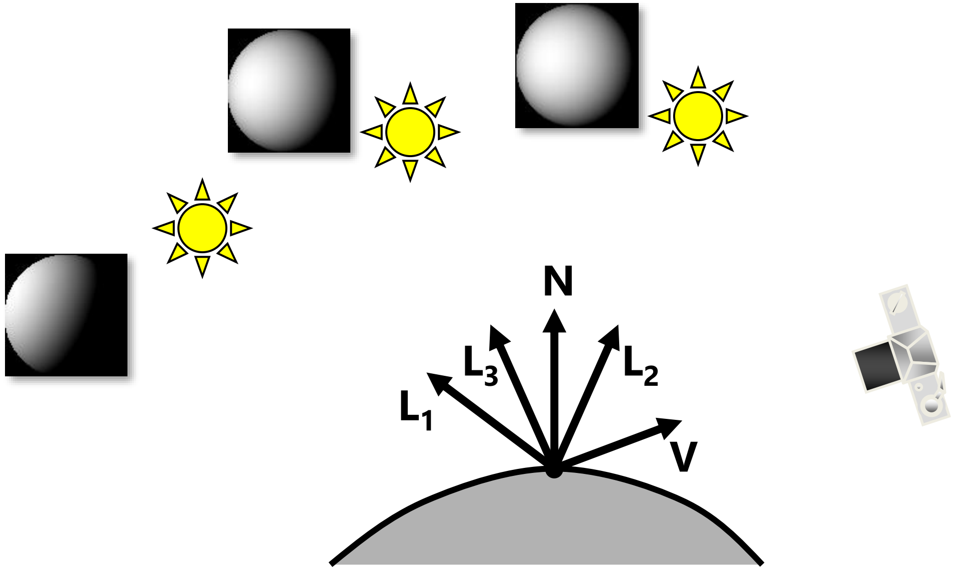
You can directly measure angle between normal and light source

- 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:

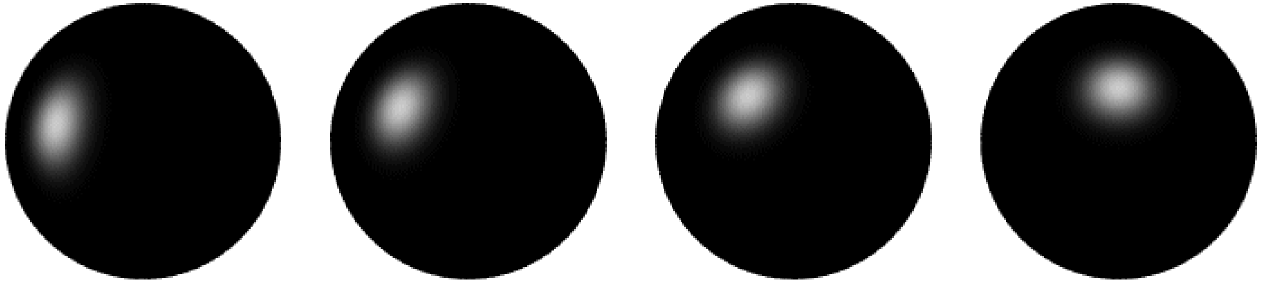
$$\begin{aligned} \mathbf{I} &= \mathbf{LG} \\ \mathbf{L^T I} &= \mathbf{L^T L G} \\ \mathbf{G} &= (\mathbf{L^T L})^{-1} (\mathbf{L^T I}) \end{aligned}$$

Solve for N, k_d as before

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

Computing light source directions

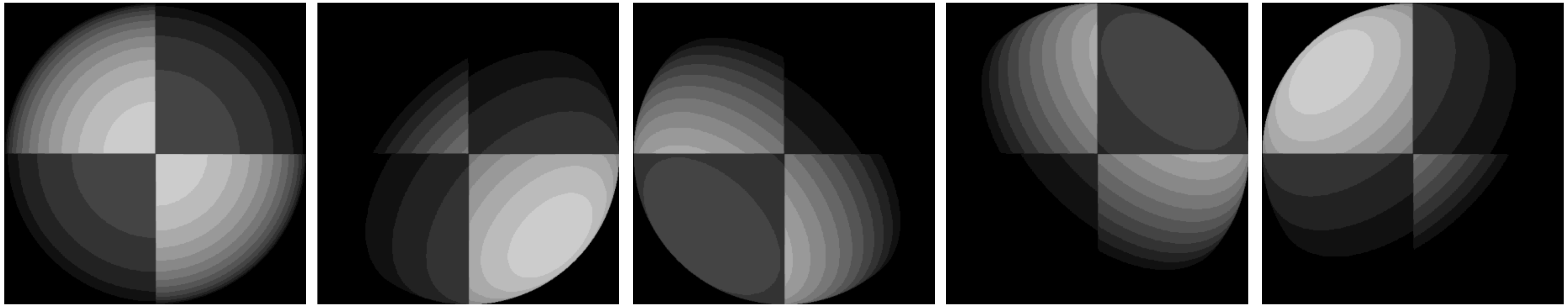
Trick: place a chrome sphere in the scene



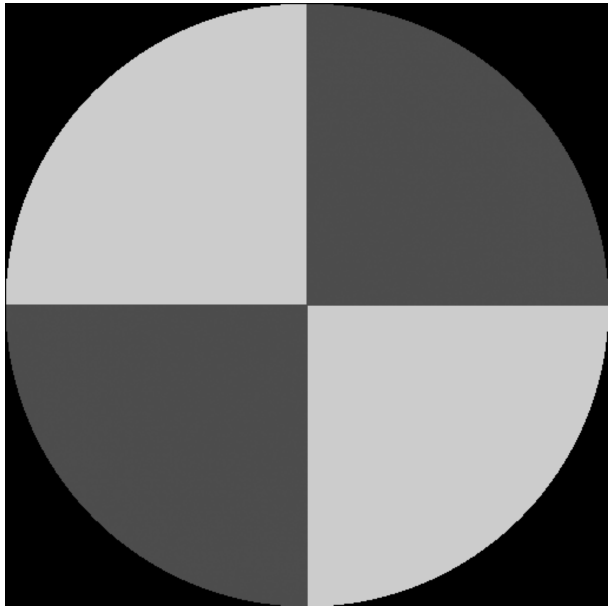
– the location of the highlight tells you where the light source is

Example

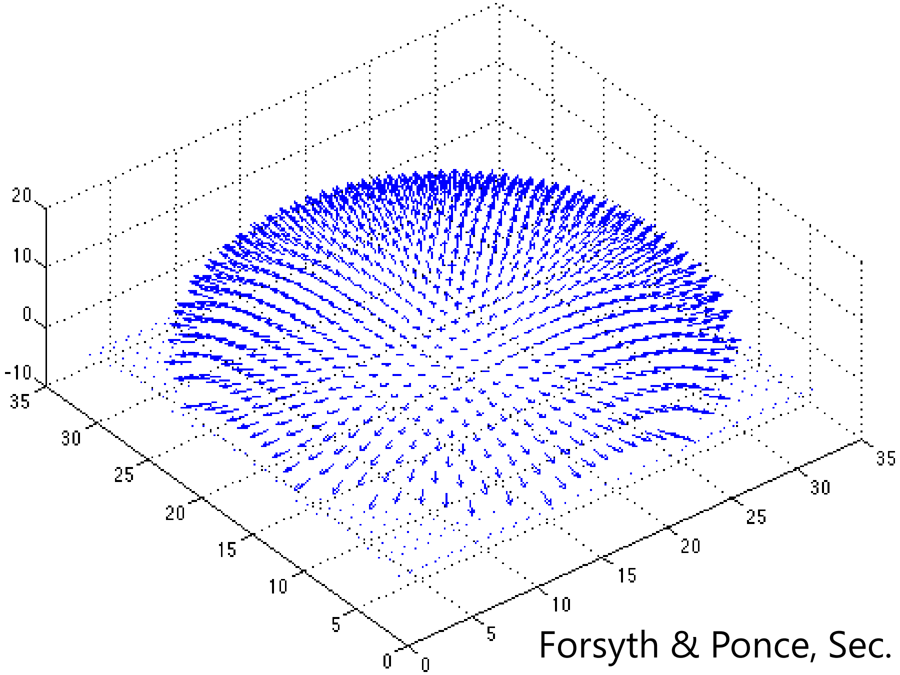
Input views



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

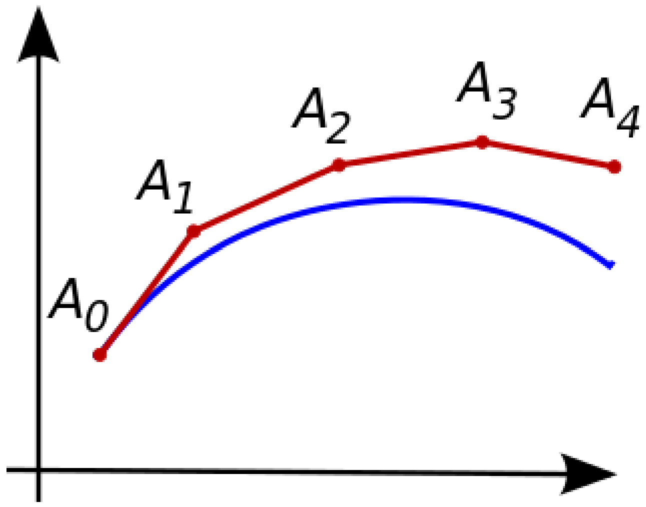
Estimated normals

Estimated normals (needle diagram)

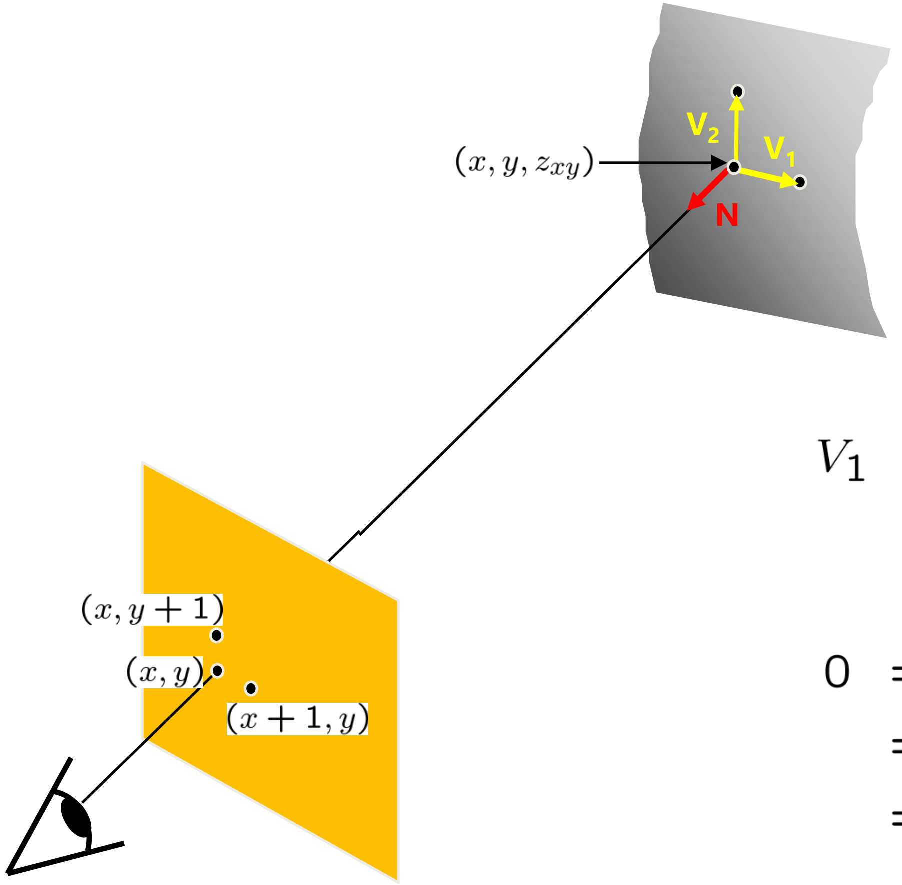
Normal Integration

- 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



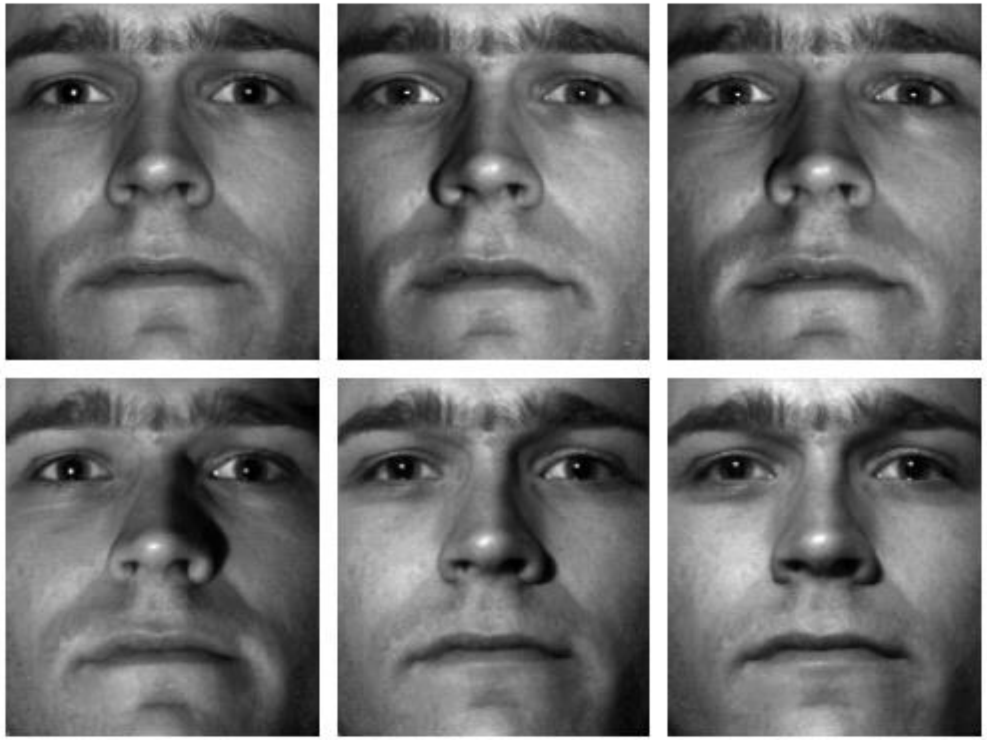
$$
\begin{aligned}
V_1 &= (x+1, y, z_{x+1,y}) - (x, y, z_{xy}) \\
&= (1, 0, z_{x+1,y} - z_{xy})
\end{aligned}
$$

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

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

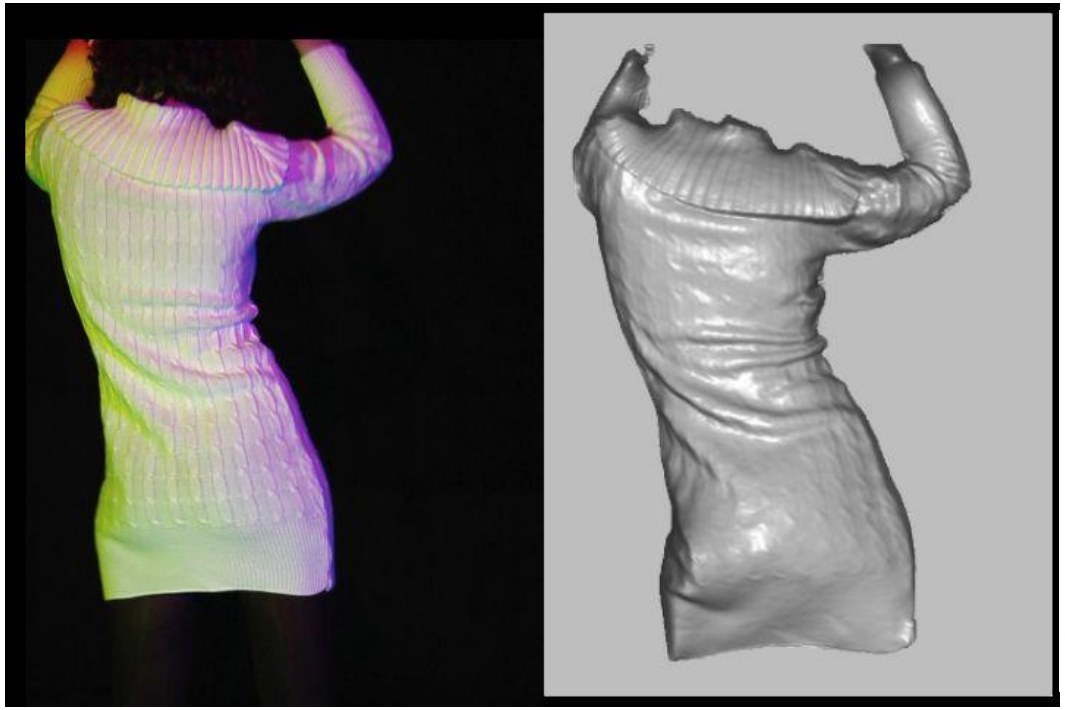


from Athos Georghiades

Results

Extension

- Photometric Stereo from Colored Lighting



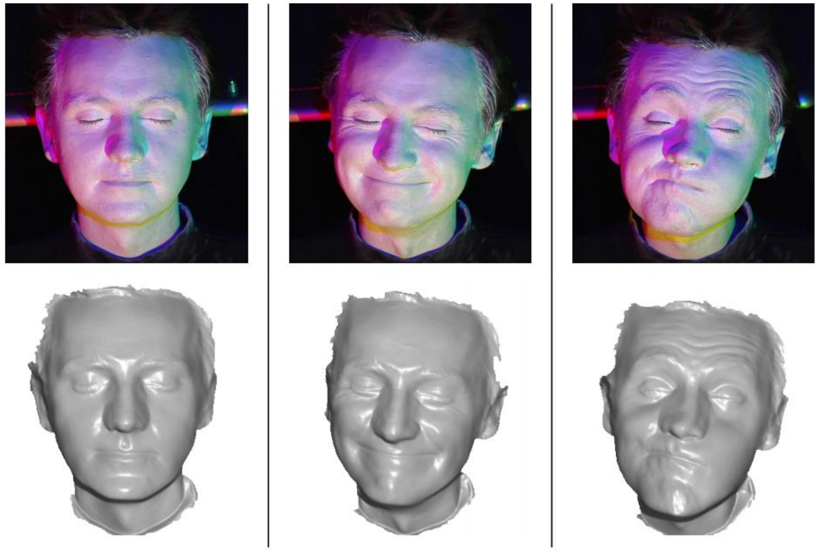


Fig. 2. **Applying the original algorithm to a face with white makeup.** Top: example input frames from video of an actor smiling and grimacing. Bottom: the resulting integrated surfaces.

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

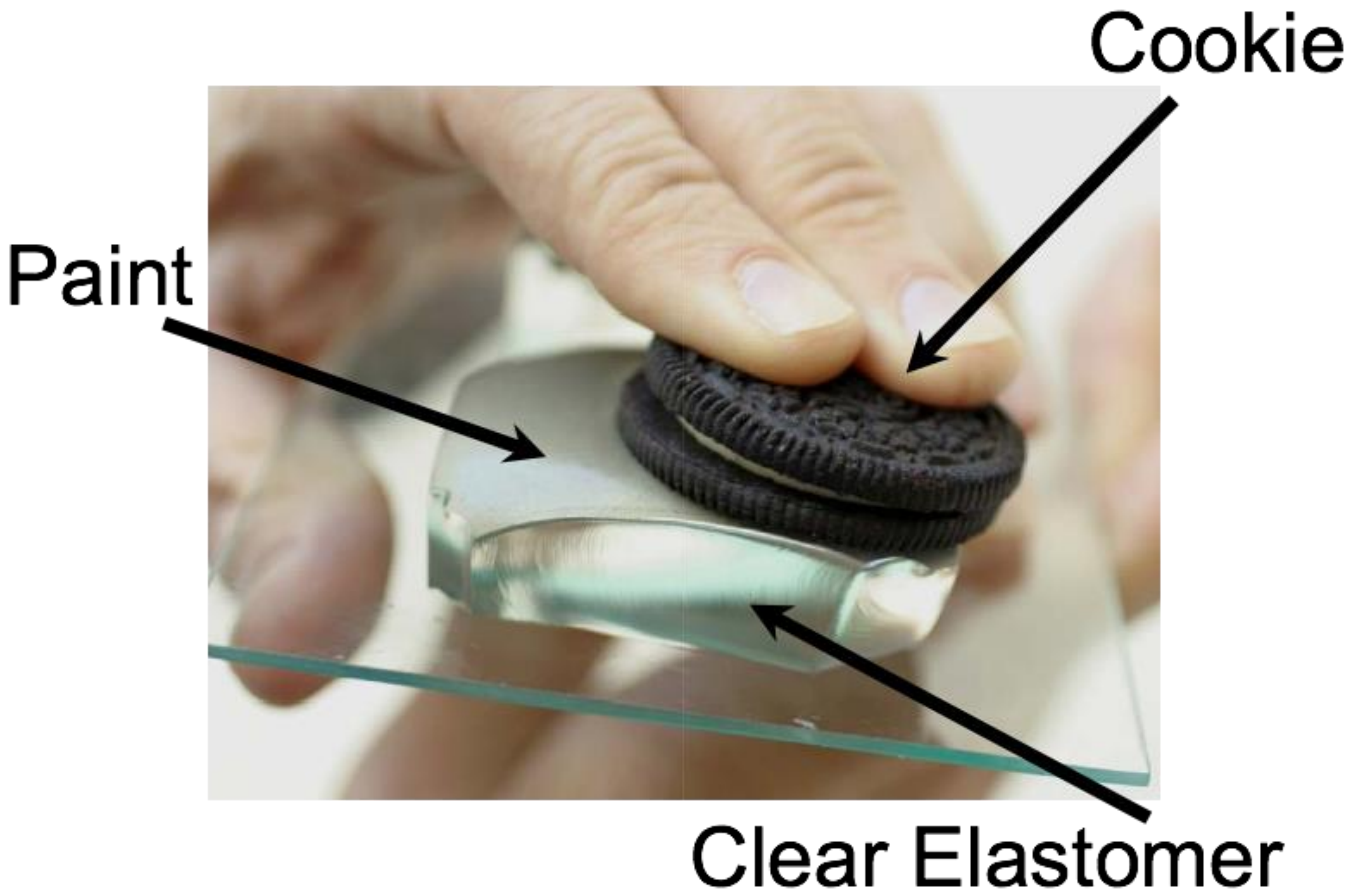
Bigger problems
- doesn’t work for shiny things, semi-translucent things
- shadows, inter-reflections

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

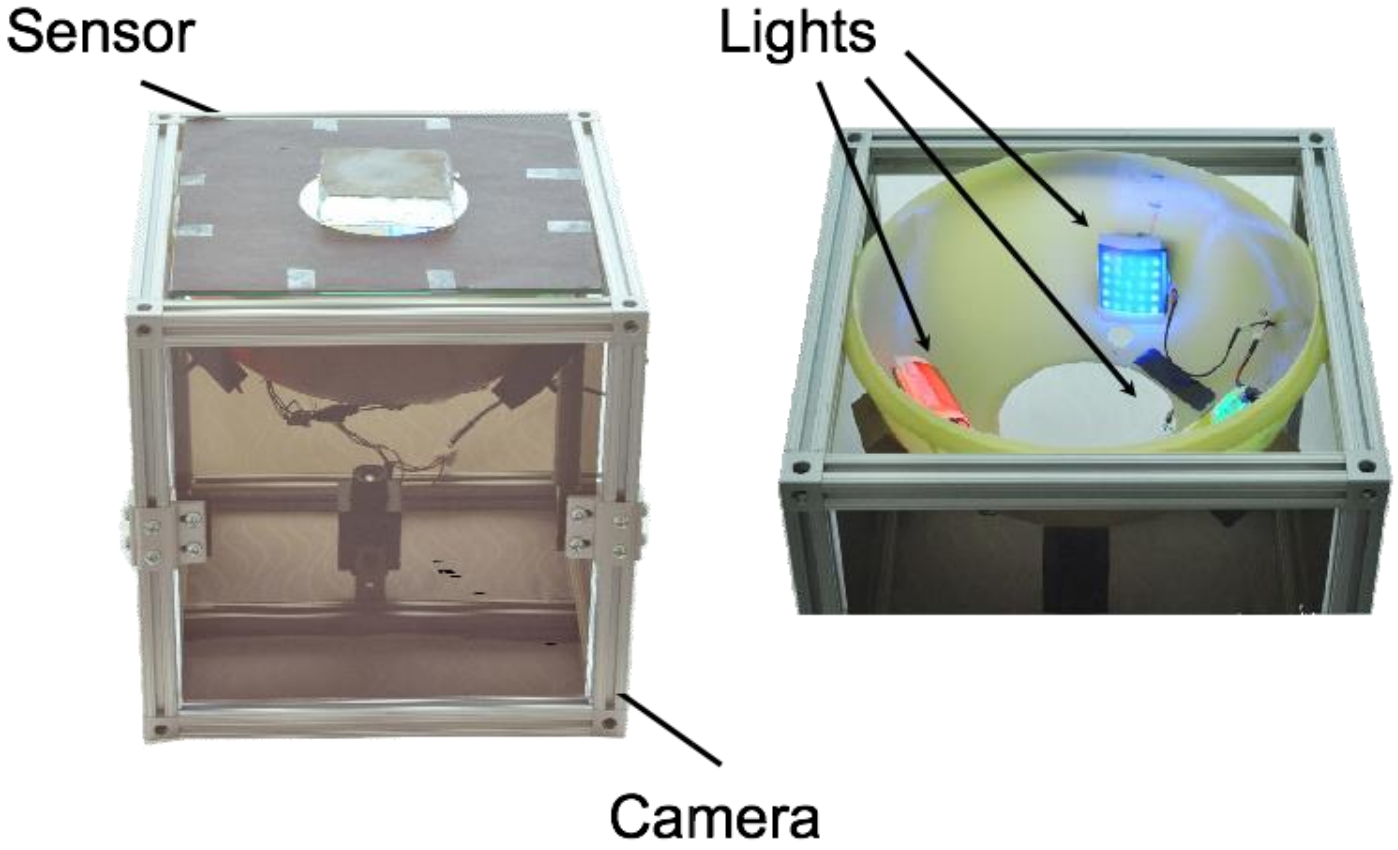


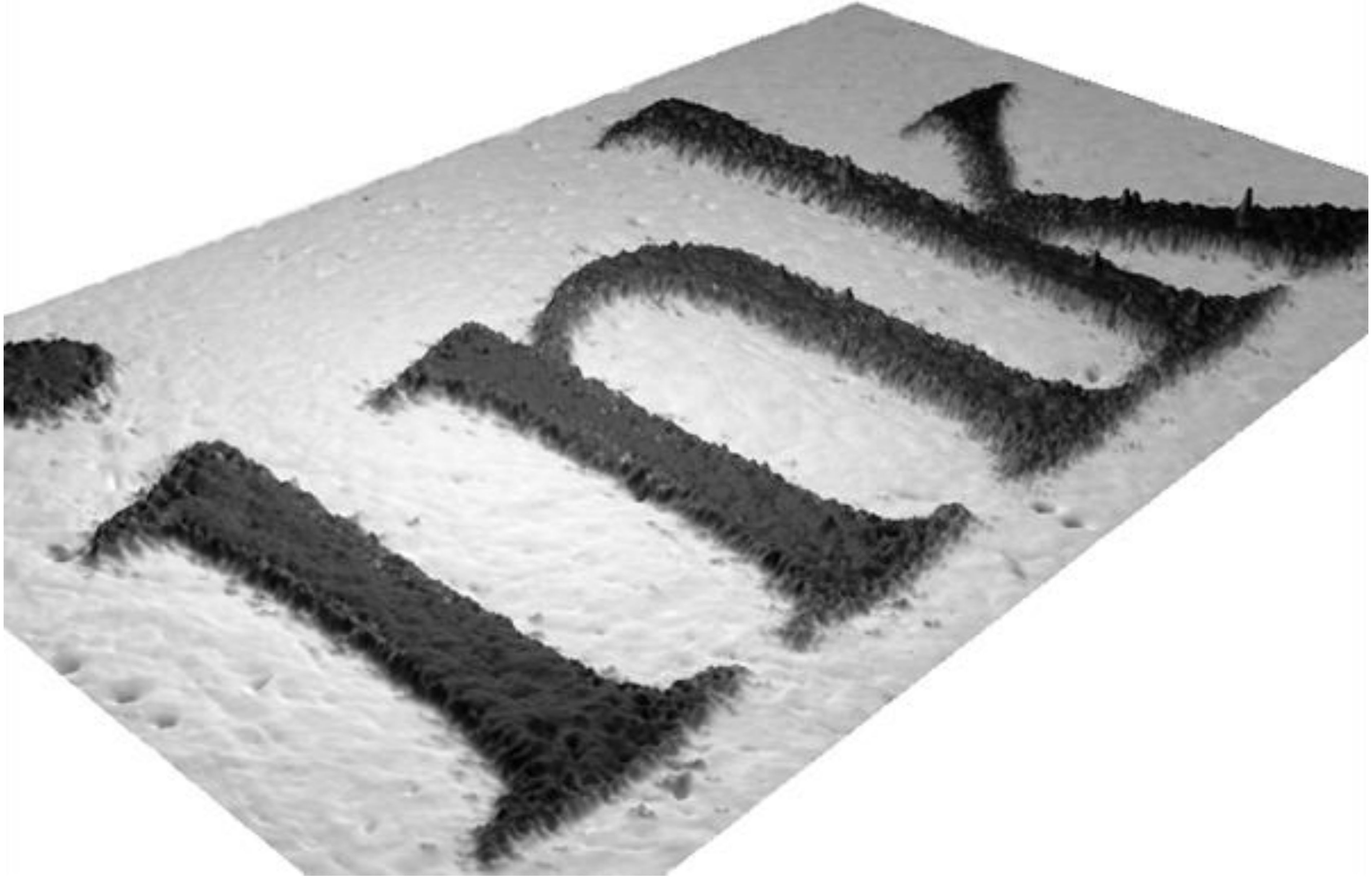
Johnson and Adelson, 2009

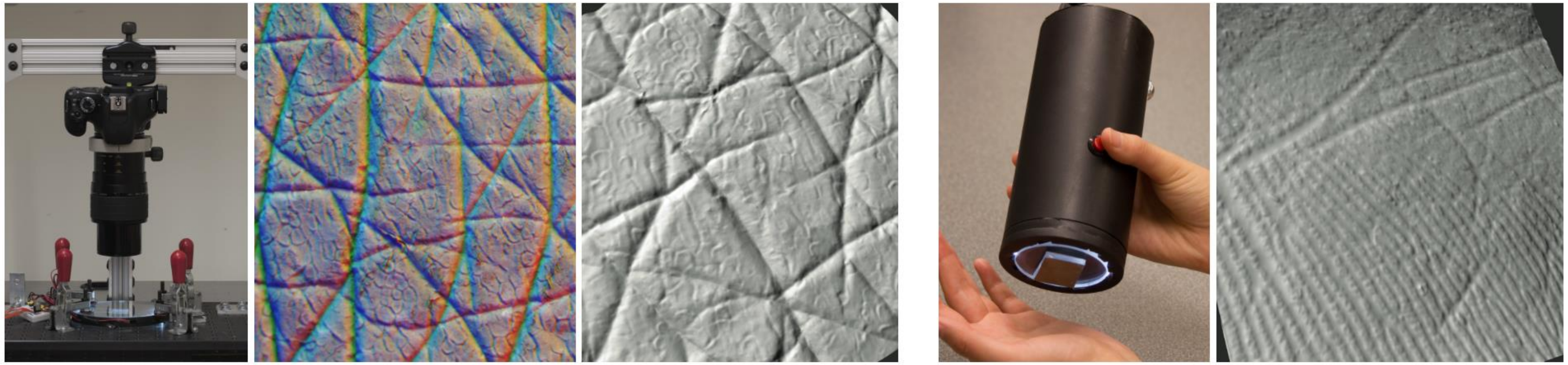

OREO


OREO

Lights, camera, action







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

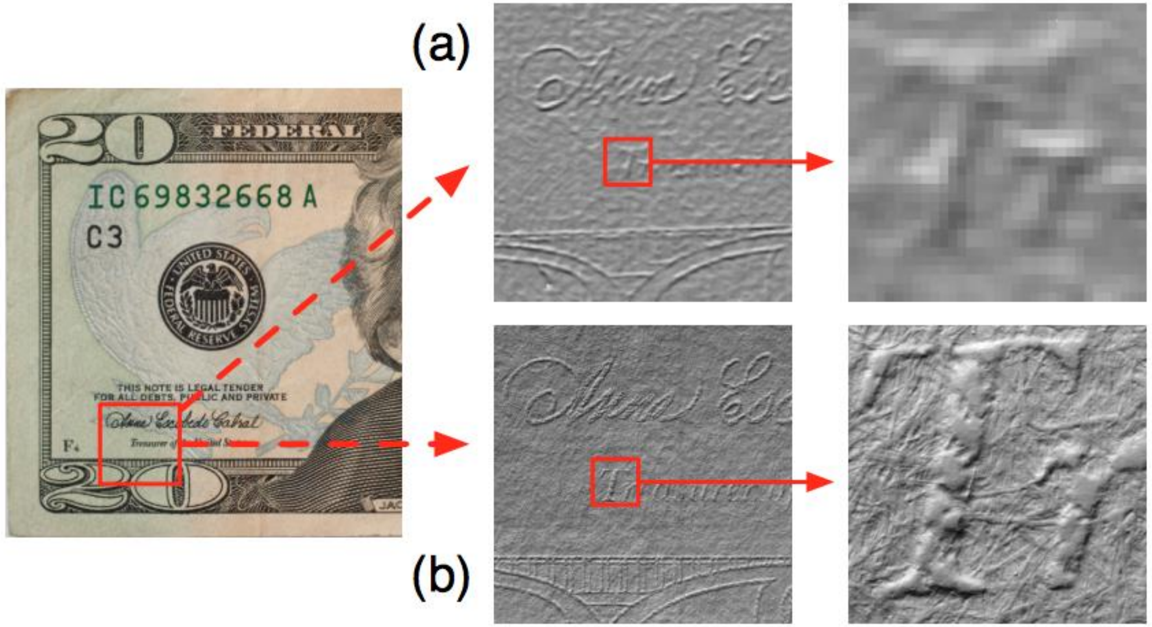


Figure 7: *Comparison with the high-resolution result from the original retrographic sensor. (a) Rendering of the high-resolution \$20 bill example from the original retrographic sensor with a close-up view. (b) Rendering of the captured geometry using our method.*

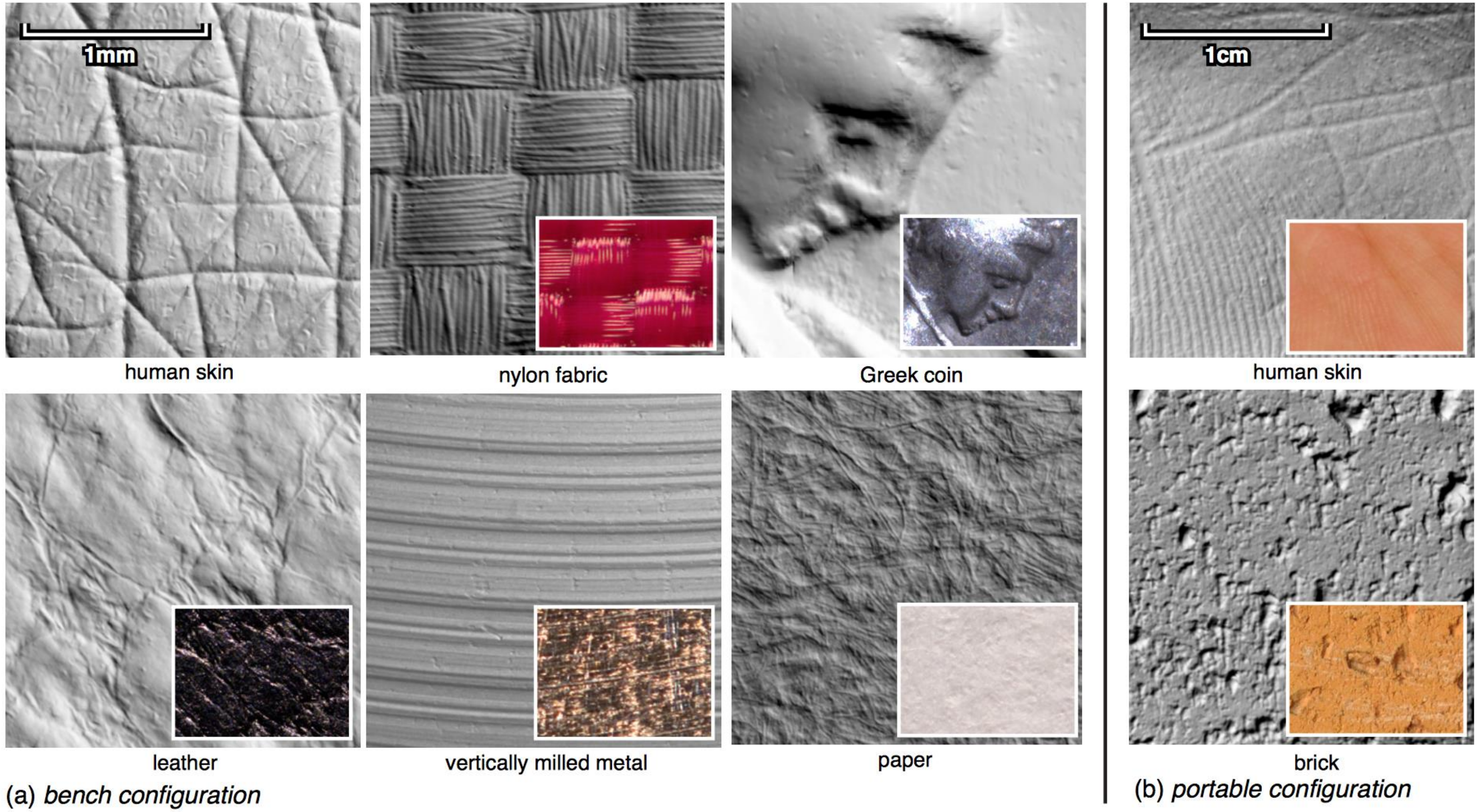
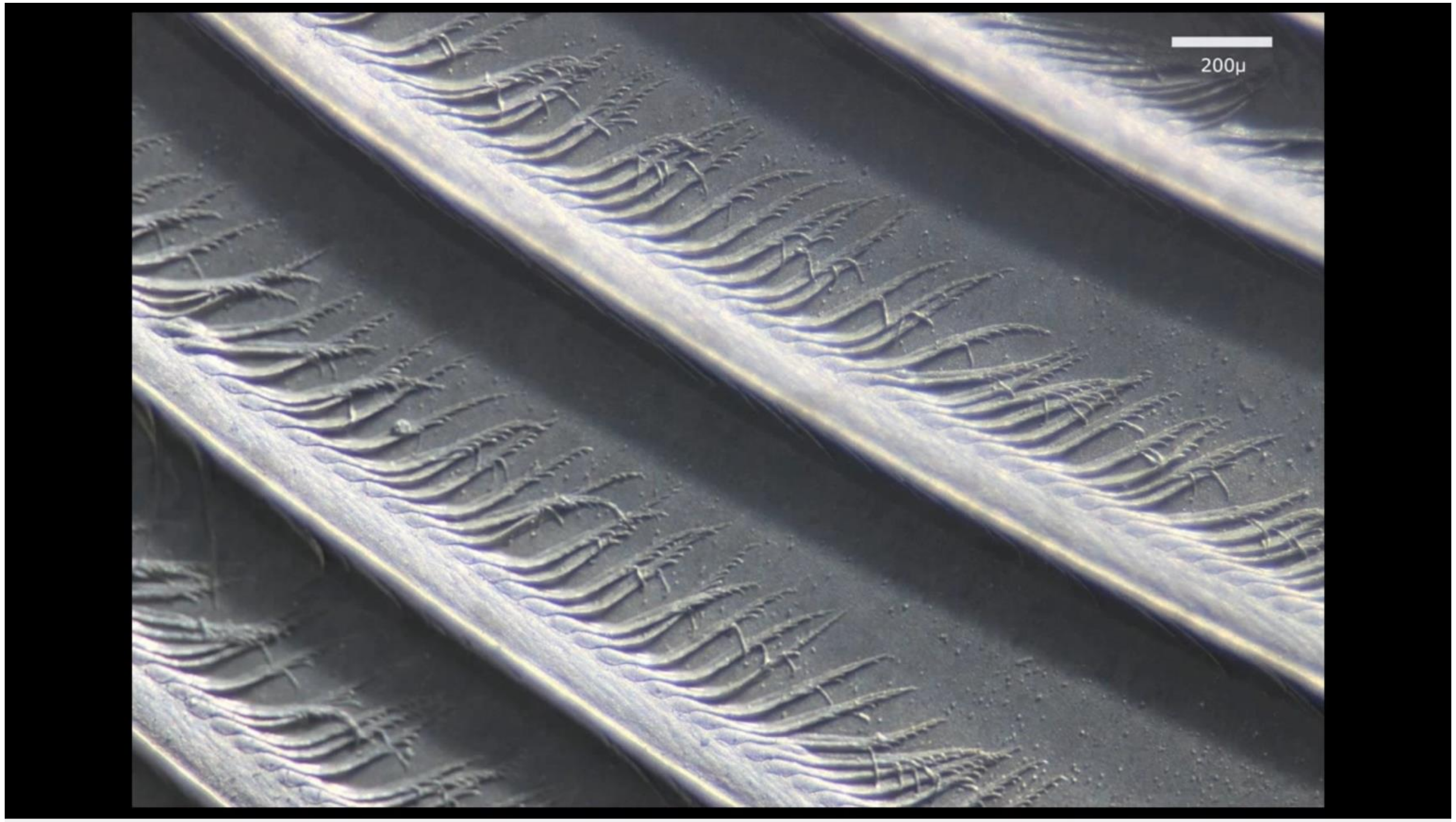


Figure 9: *Example geometry measured with the bench and portable configurations. Outer image: rendering under direct lighting. Inset: macro photograph of original sample. Scale shown in upper left. Color images are shown for context and are to similar, but not exact scale.*



Sensing Surfaces with GelSight

kimoatmit

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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

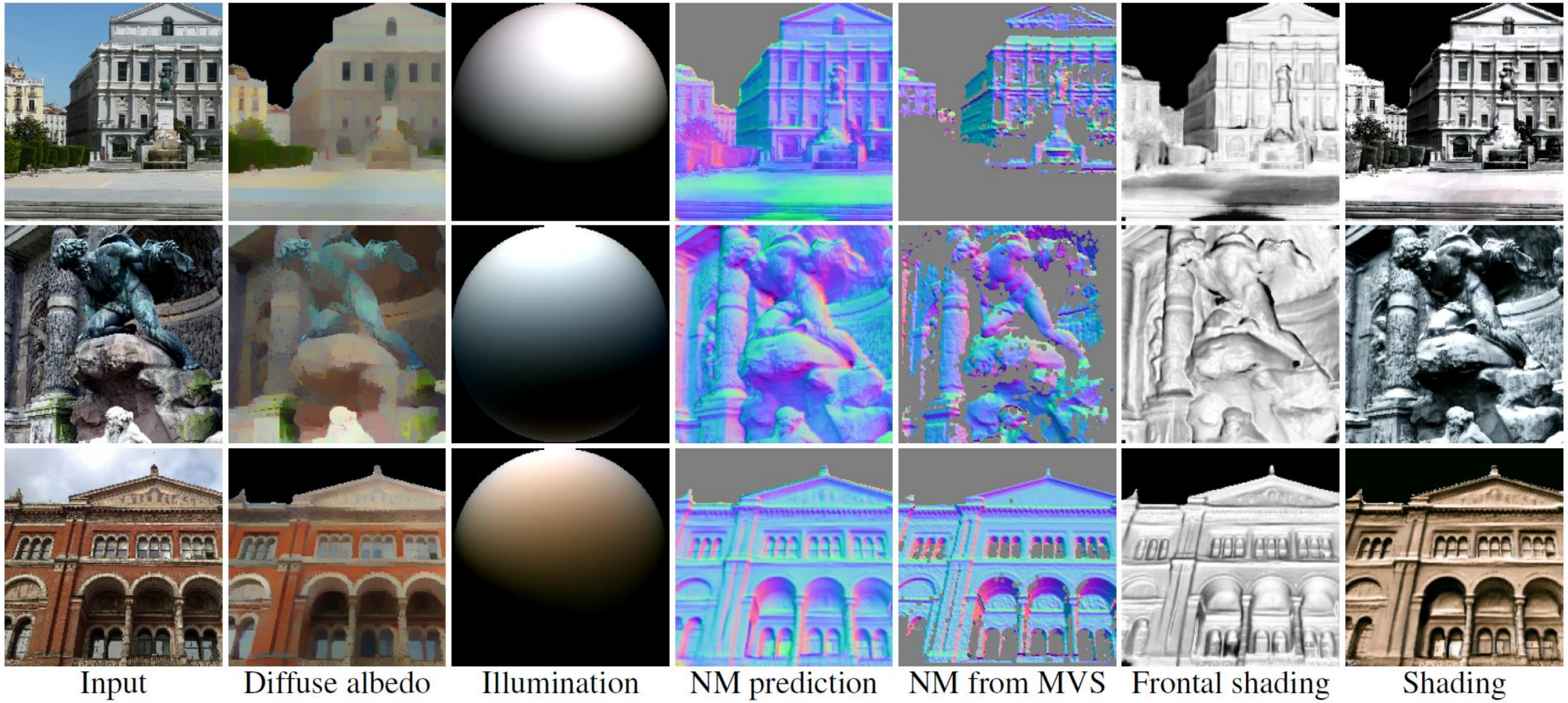

Figure 1: From a single image (col. 1), we estimate albedo and normal maps and illumination (col. 2-4); comparison multi-view stereo result from several hundred images (col. 5); re-rendering of our shape with frontal/estimated lighting (col. 6-7).

Questions?