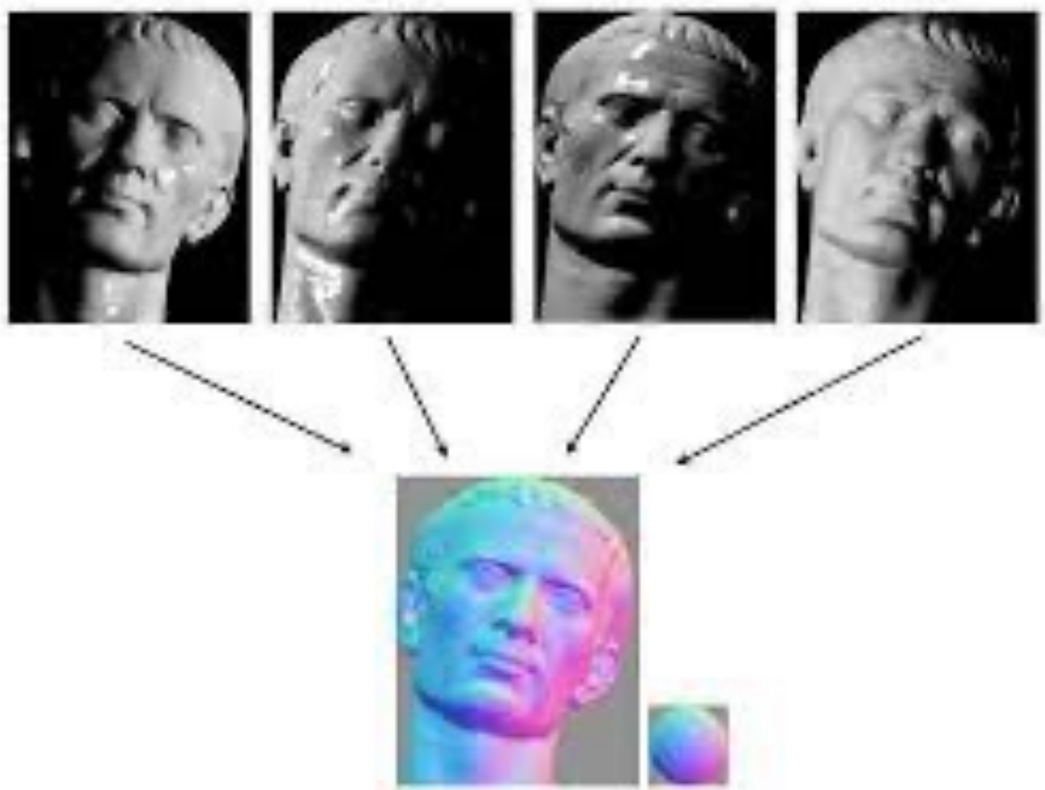
ENGN 8501

Physics based Vision-1:

Photometric Stereo



Today’s lecture duration:
1 hours ~ 1.5 hours

- Guided paper reading : 30~45 minutes
- Breakout room discussion & report: 30 minutes

FYI: ANU covid students support package

1. Opt-in option for students to the CRS/CRN (i.e., Pass/Fail) grading system for Semester 2.

2. Delaying the Semester 2 Census Date to 14 September 2021 (was previously 31 August).

3. Changes to medical certification documentation to allow students to submit a personal statement *in lieu* of a medical certificate.

4. Allowing students to drop course without academic failure up until 3 November 2021.

Downside of CRS/CRN

CRS/CRN grades can have significant unintended impacts, including:

it can negatively impact professional accreditation; students should seek program specific advice from their academic College or School;

it can make an applicant ineligible for particular scholarships;

it can make an applicant ineligible for particular academic programs;

it is unknown how international academic institutions will interpret these grades and this could limit future options;

we are not able to guarantee how employer schemes and graduate work placements will interpret CRS/CRN which could limit future career options.

Students should carefully consider their circumstances before requesting a CRS/CRN.

PLEASE NOTE: Once a CRS or CRN grade has been applied it will not be possible to revert to a numeric grade; only the CRS/CRN will be recorded to the student's academic record.

Some administrative matters

Reading-Report #1 marks will be released in this week.

Reading-Report # 2 due: this Thursday evening.

Project proposal due: next Thursday.

Research Project Q&A

How to form and register project teams ?

- use the GoogleSpread sheet.

How to select paper ?

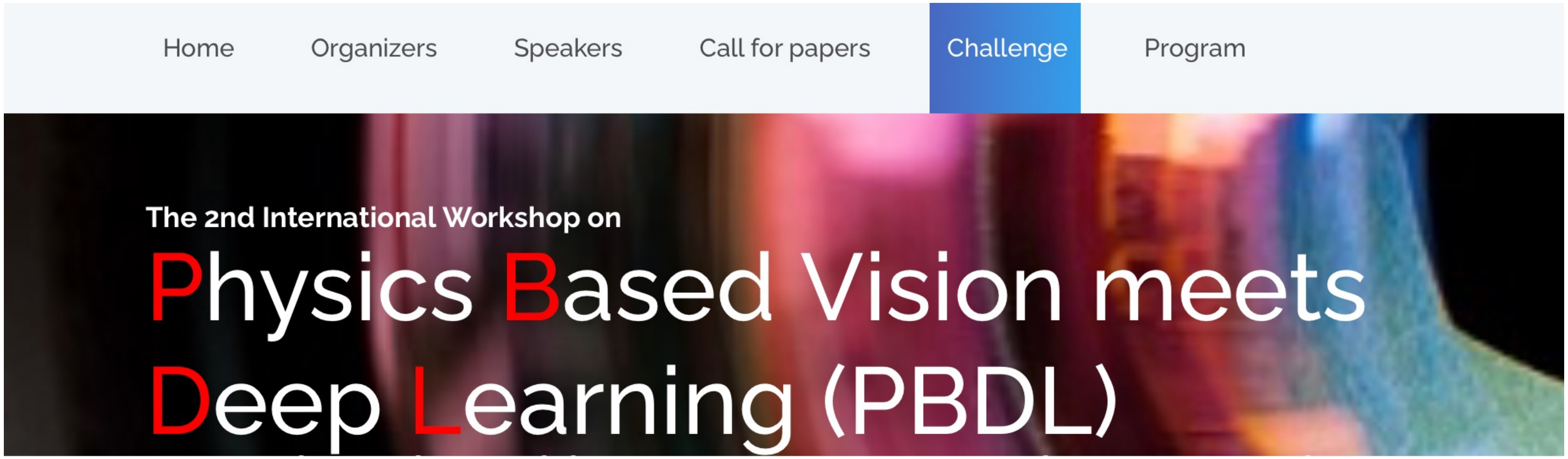
- must skim through all candidate papers and discuss among your project team.

- your project must be based on one or two papers.

What test images or dataset to use ?

- Often the original test images/videos are available on the internet.
- You may also capture/curate your own test dataset.
- Remember your 6-page final report must be complete, self-contained, and read like a mini conference paper.

What is physics based vision ？



Light traveling in the 3D world interacts with the scene through intricate processes before being captured by a camera. These processes result in the dazzling effects like color and shading, complex surface and material appearance, different weathering, just to name a few. Physics based vision aims to invert the processes to recover the scene properties, such as shape, reflectance, light distribution, medium properties, etc., from the images by modeling and analysing the imaging process to extract desired features or information.

PBDL-2021

PBDL 2021 : 3rd ICCV Workshop on Physics Based Vision meets Deep Learning

Link: https://pbdl-ws.github.io/pbdl2021/callforpapers.html

When	Oct 11, 2021 - Oct 11, 2021
Where	Virtual
Submission Deadline	Aug 7, 2021
Notification Due	Aug 12, 2021

Call For Papers

Following the success of 2nd ICCV Workshop on Physics Based Vision Meets Deep Learning (PBDL2019). We propose the 3rd workshop using the same title and topics with ICCV 2021. The goal is to encourage the interplay between physics based vision and deep learning. Physics based vision aims to invert the processes to recover the scene properties, such as shape, reflectance, light distribution, medium properties, etc., from images. In recent years, deep learning shows promising improvement for various vision tasks. When physics based vision meets deep learning, there must be mutual benefits.

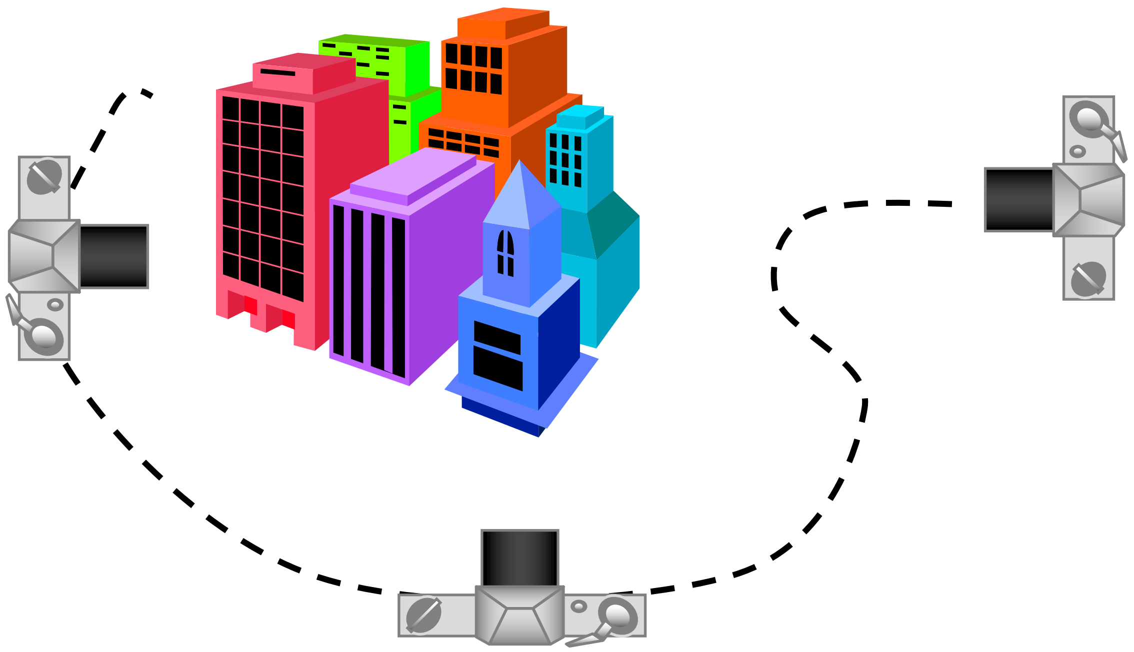
We welcome submissions of new methods in the classic physics based vision problems, but preference will be given to novel insights inspired by utilizing deep learning techniques. Relevant topics include but are not limited to

Deep learning +
- Photometric 3D reconstruction
- Radiometric modeling/calibration of cameras
- Color constancy
- Illumination analysis and estimation
- Reflectance modeling, fitting, and analysis
- Forward/inverse renderings
- Material recognition and classification
- Transparency and multi-layer imaging
- Reflection removal
- Intrinsic image decomposition
- Light field imaging

3D from 2D via SFM (Structure from motion)

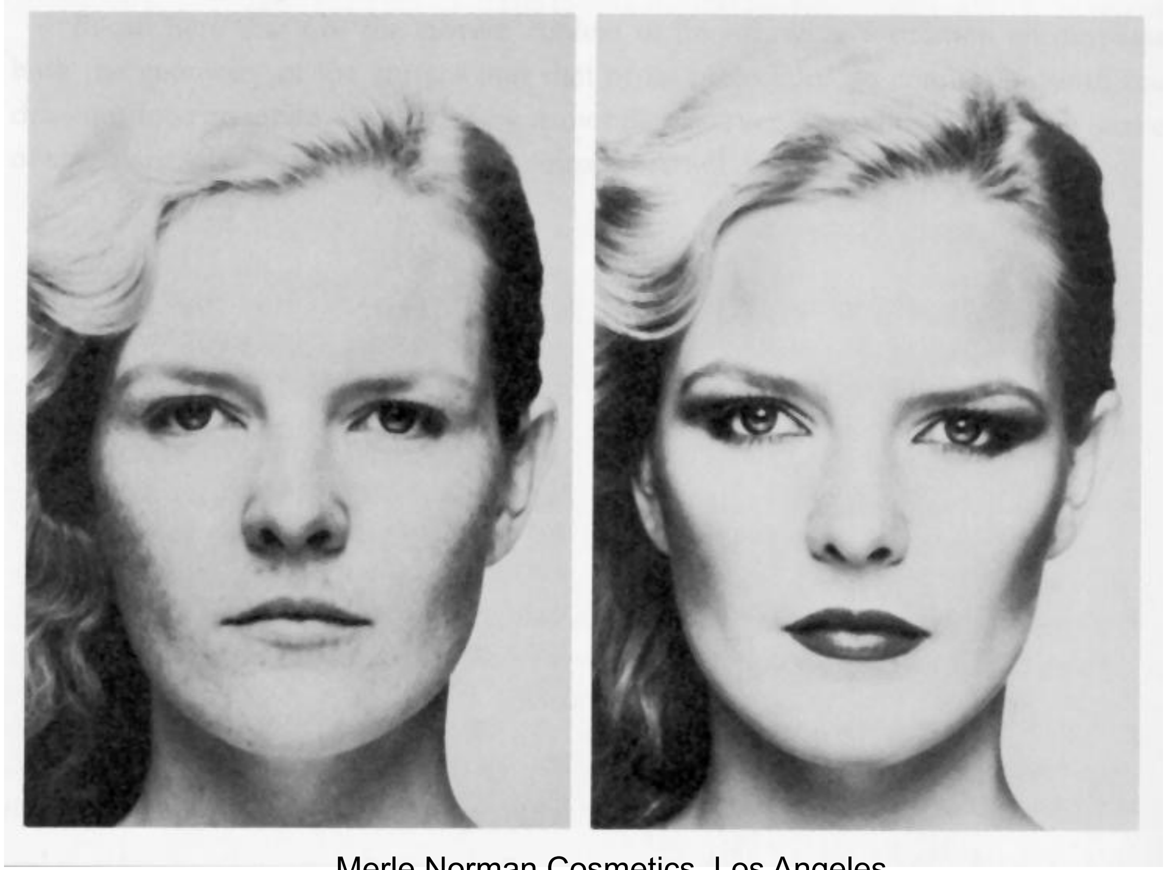
Key Idea: use feature motion to understand shape

SFM: Recovering 3D information from 2D images



Example: Photo-Tourism (Snavely, Agarwal et al.))

Shape from Shading (SfS)



Merle Norman Cosmetics, Los Angeles

Readings

- R. Woodham, *Photometric Method for Determining Surface Orientation from Multiple Images*. Optical Engineering 19(1)139-144 (1980). (PDF)

Photometric Stereo (PS)

- Can you tell the shape of an object from these photos ?



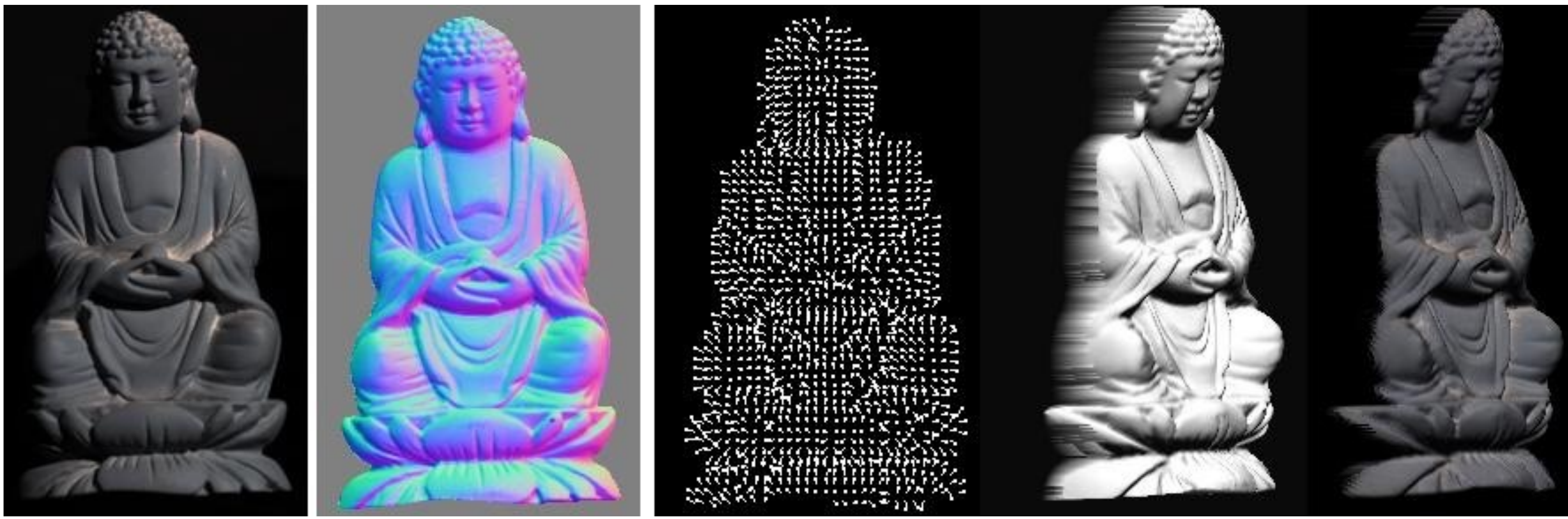
Recap: Structure from motion

Key Idea: use feature correspondences to understand shape

3D from 2D images: Photometric Stereo

Key Idea: use pixel brightness changes to understand shape

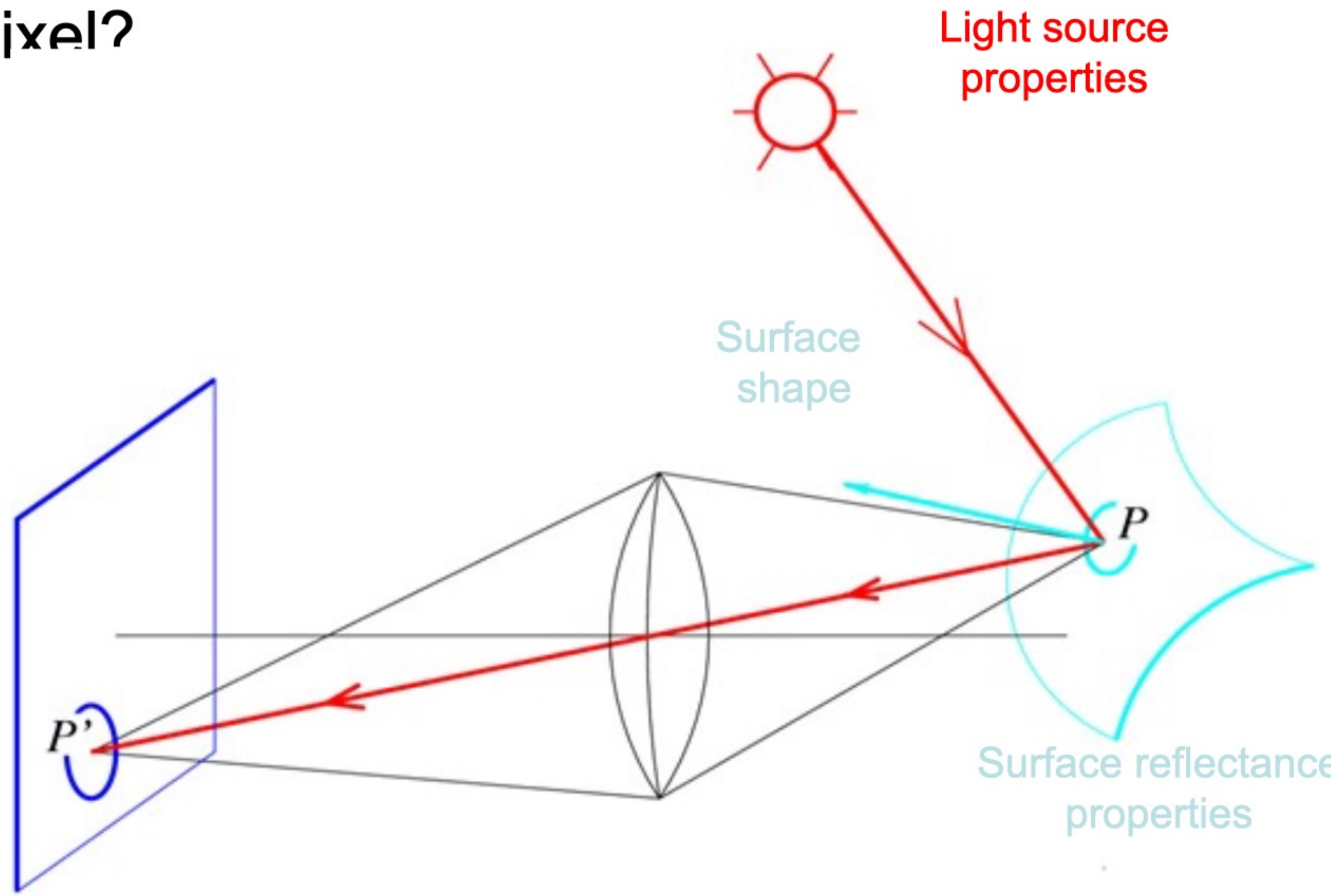
Photometric Stereo



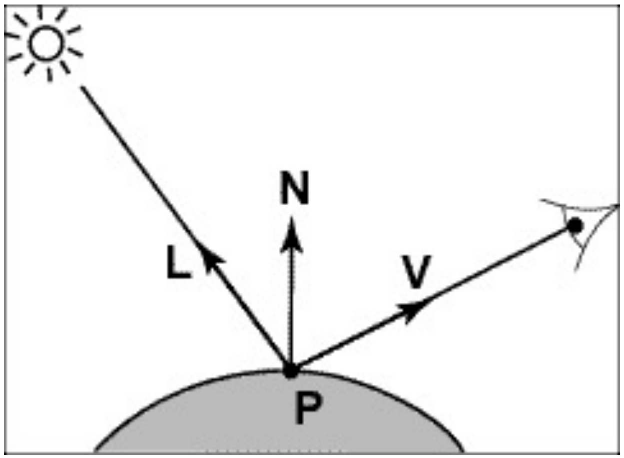
Input (1 of 12) | Normals (RGB colormap) | Normals (vectors) | Shaded 3D rendering | Textured 3D rendering

Physics (photometric) image formation

- What determines the brightness of an image pixel?



Photometric Image Formation

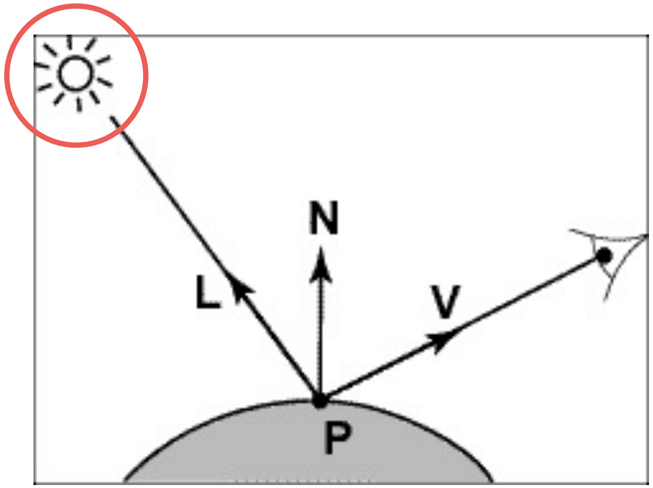


Now we need to reason about:

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

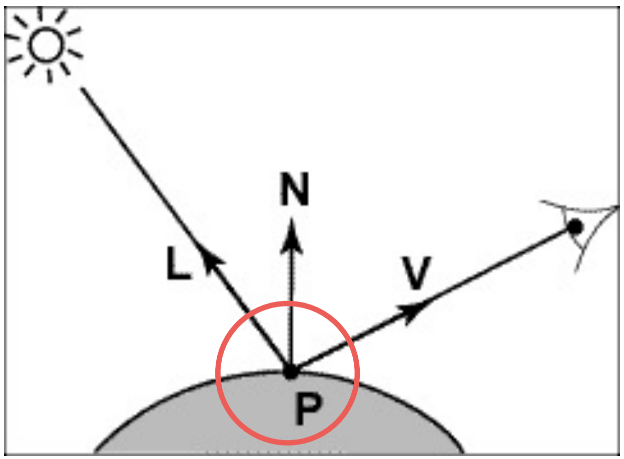
Track a "ray" of light all the way from light source to the sensor

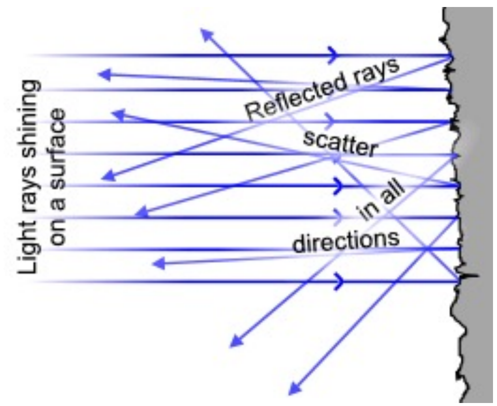
Directional Lighting



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

Lambertian Reflectance



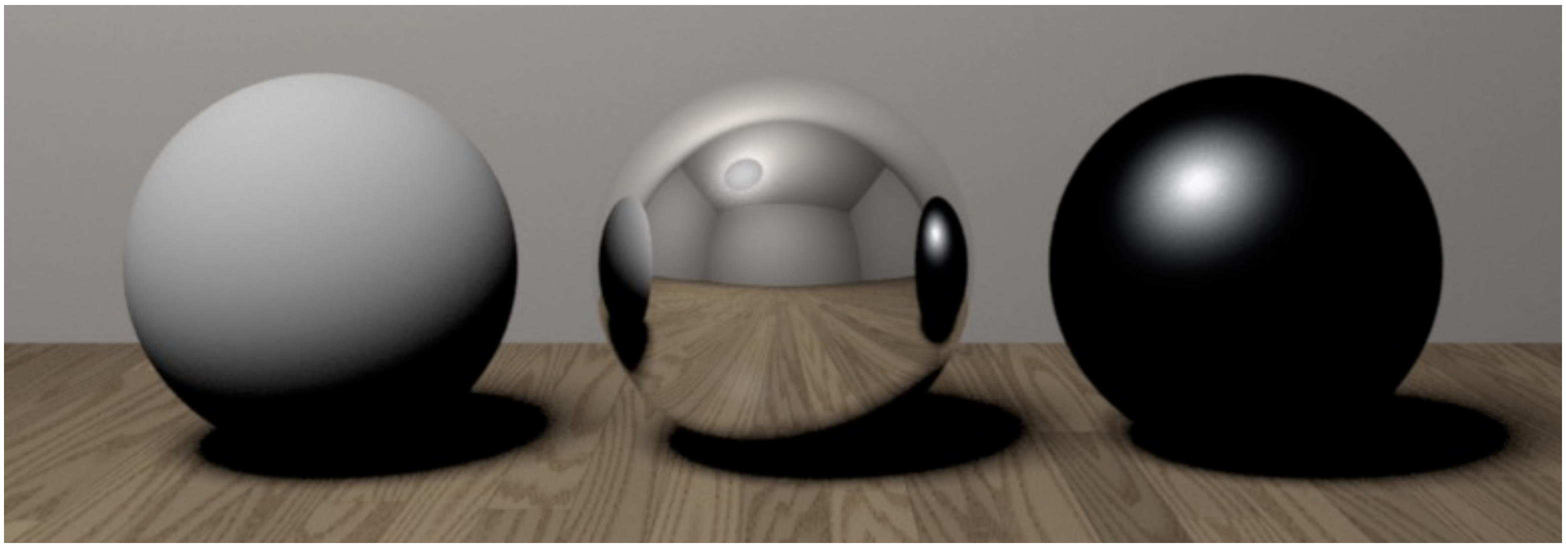


$$I = N \cdot L$$

Image intensity $=$ Surface normal $\cdot$ Light direction

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

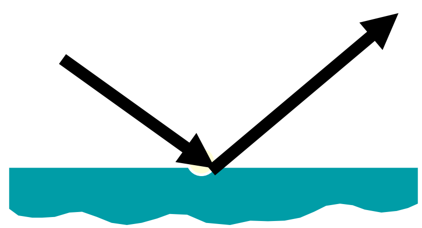
Reflectance—Three Forms



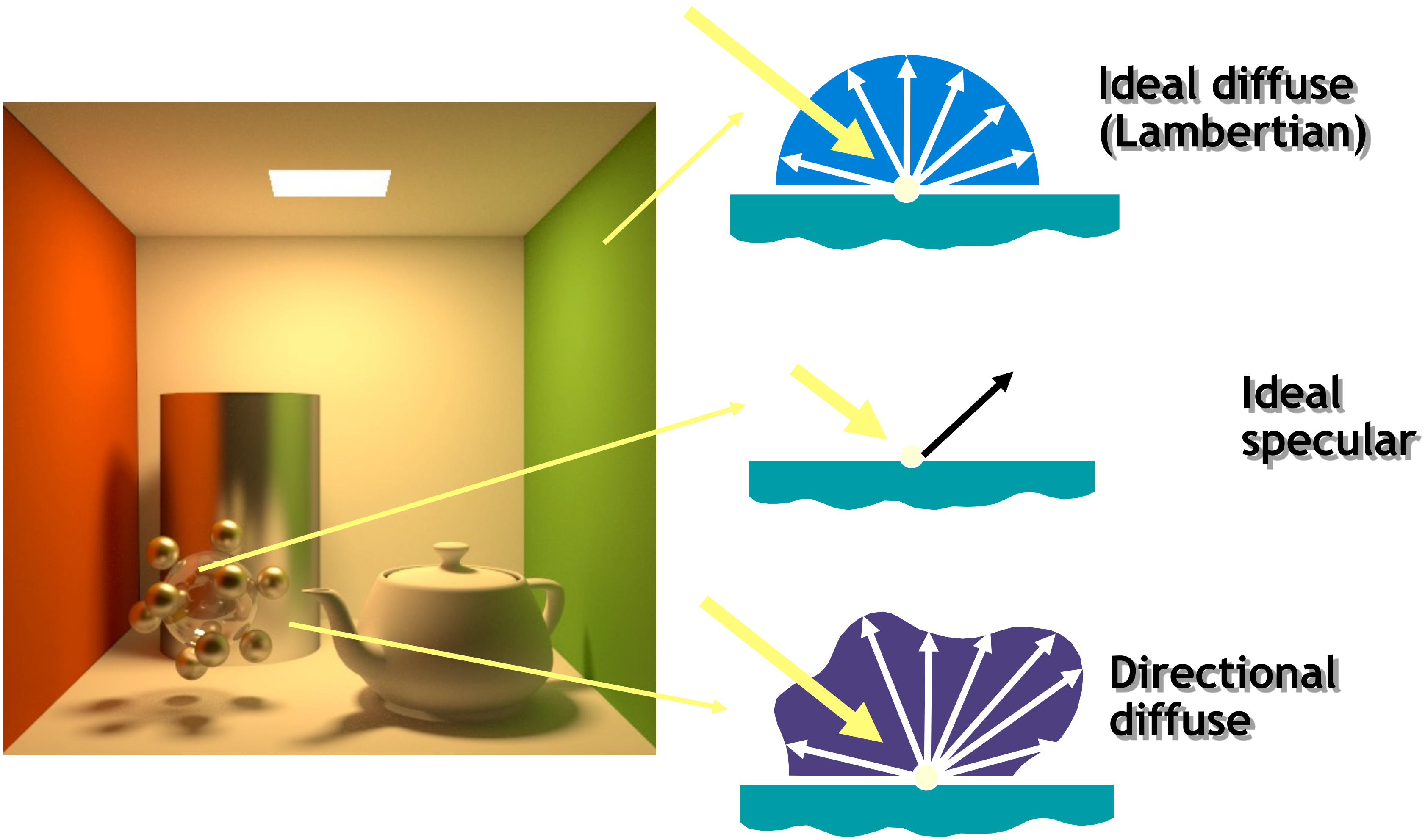
Ideal diffuse (Lambertian)

Ideal specular

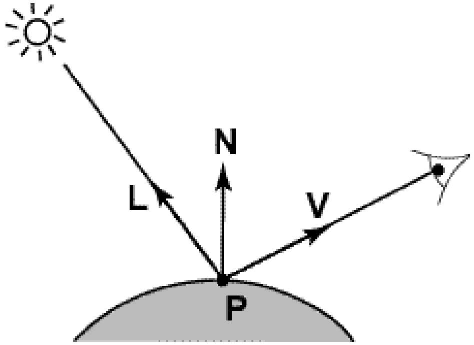
Directional diffuse

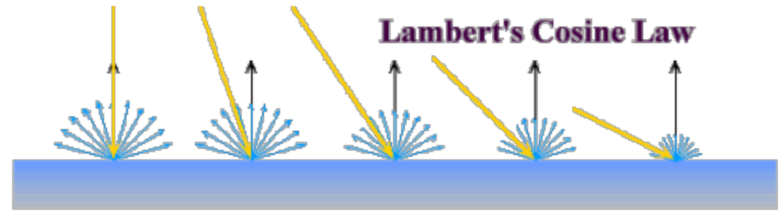


Materials - Three Forms



Lambertian (diffuse) reflection





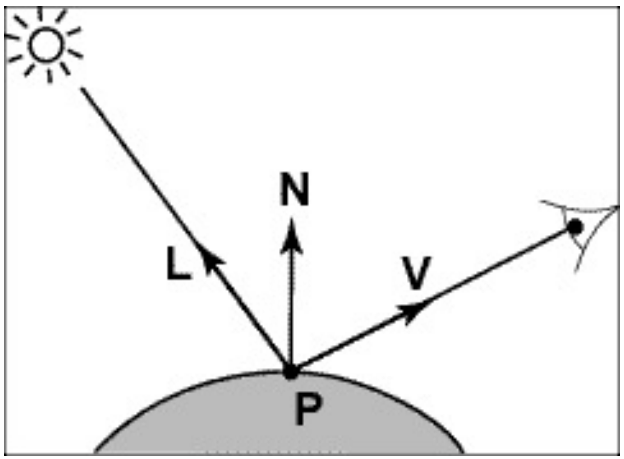
$$R_e = k_d \mathbf{N} \cdot \mathbf{L} R_i$$

image intensity of **P** $\longrightarrow$ $$I = k_d \mathbf{N} \cdot \mathbf{L}$$

Simplifying assumptions

- $I = R_e$: camera response function f is the identity function:
  - can always achieve this in practice by solving for f and applying f^{-1} to each pixel in the image
- $R_i = 1$: light source intensity is 1
  - can achieve this by dividing each pixel in the image by R_i

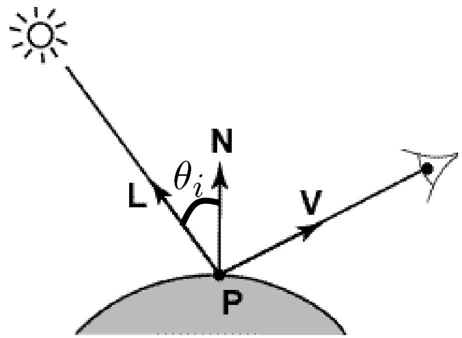
Image Formation Model: Final



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

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)

Shape from Shading



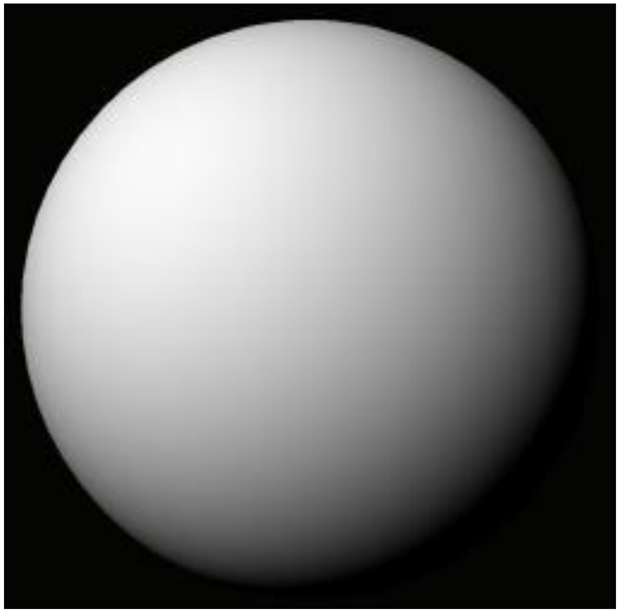
Suppose $k_d = 1$

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

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?

A Single Image: Shape from Shading



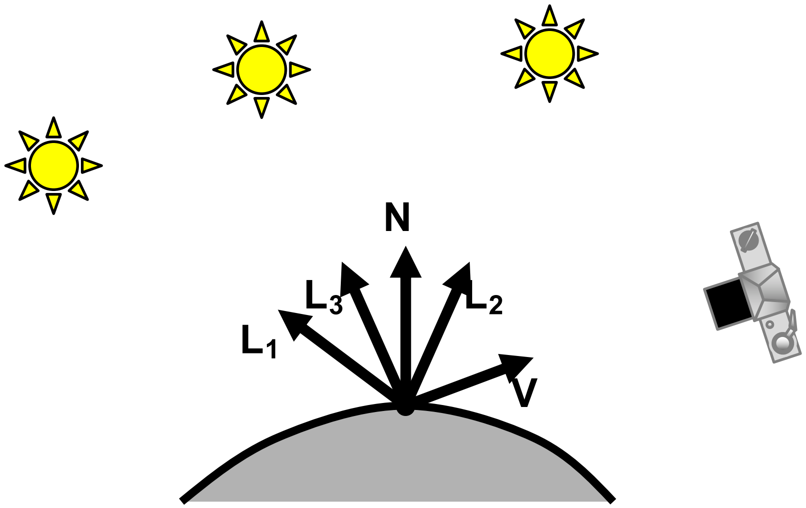
$$I = k_d \mathbf{N} \cdot \mathbf{L}$$

Assume k_d is 1 for now.
What can we measure from one image?

- $\cos^{-1}(I)$ is the angle between N and L
- Add assumptions:
  - A few known normals (e.g. silhouettes)
  - Smoothness of normals

In practice, SFS doesn't work very well:
assumptions are too restrictive,
too much ambiguity in nontrivial scenes.

Multiple Images: Photometric Stereo



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

Write this as a matrix equation:

$$\left[\begin{array}{ccc} I_1 & I_2 & I_3 \end{array}\right] = k_d \mathbf{N}^T \left[\begin{array}{ccc} \mathbf{L_1} & \mathbf{L_2} & \mathbf{L_3} \end{array}\right]$$

Solving the Equations

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

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

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

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

Solving the Equations

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

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

- When is L nonsingular (invertible)?
  - >= 3 light directions are linearly independent, or:
  - All light direction vectors cannot lie in a plane.
- What if we have more than one pixel?
  - Stack them all into one big system.

More than Three Lights

$$\left[\begin{array}{ccc} I_1 & \dots & I_n \end{array}\right] = k_d \mathbf{N}^T \left[\begin{array}{ccc} \mathbf{L_1} & \dots & \mathbf{L_n} \end{array}\right]$$

- Solve using least squares (normal equations):

$$\begin{aligned} \mathbf{I} &= \mathbf{GL} \\ \mathbf{IL^T} &= \mathbf{GLL^T} \\ \mathbf{G} &= (\mathbf{IL^T})(\mathbf{LL^T})^{-1} \end{aligned}$$

- Equivalently use SVD
- Given G, solve for N and k_d as before.

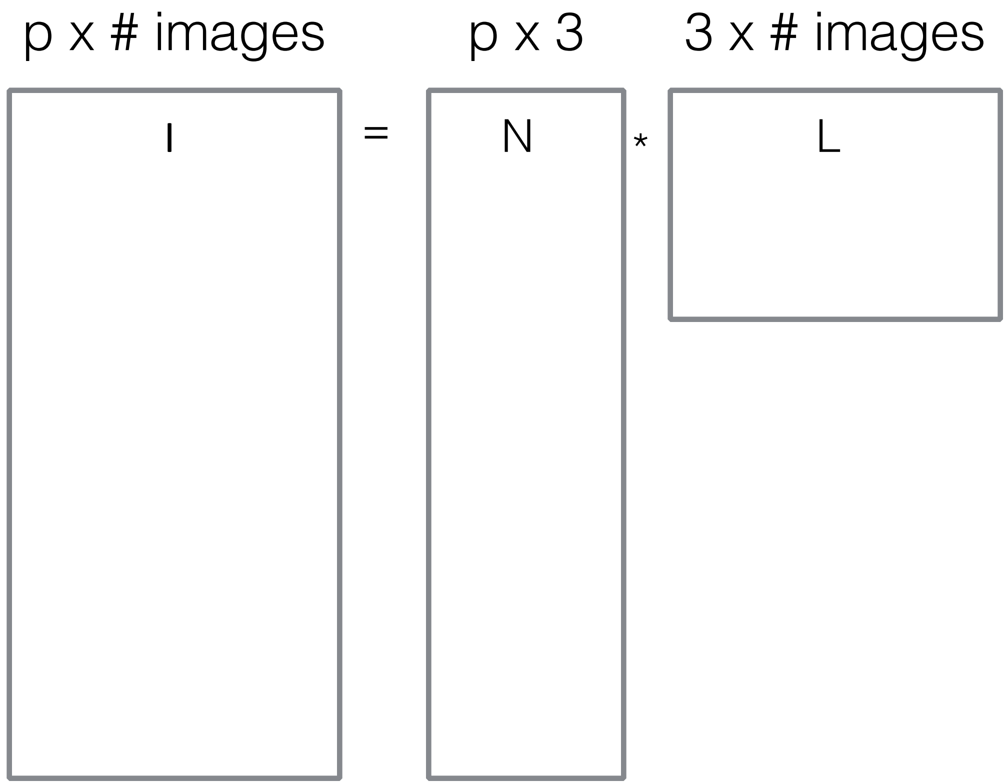
More than one pixel

Previously:

$$\overset{1 \times \#\text{ images}}{\boxed{I}} = \overset{1 \times 3}{\boxed{N}} * \overset{3 \times \#\text{ images}}{\boxed{L}}$$

More than one pixel

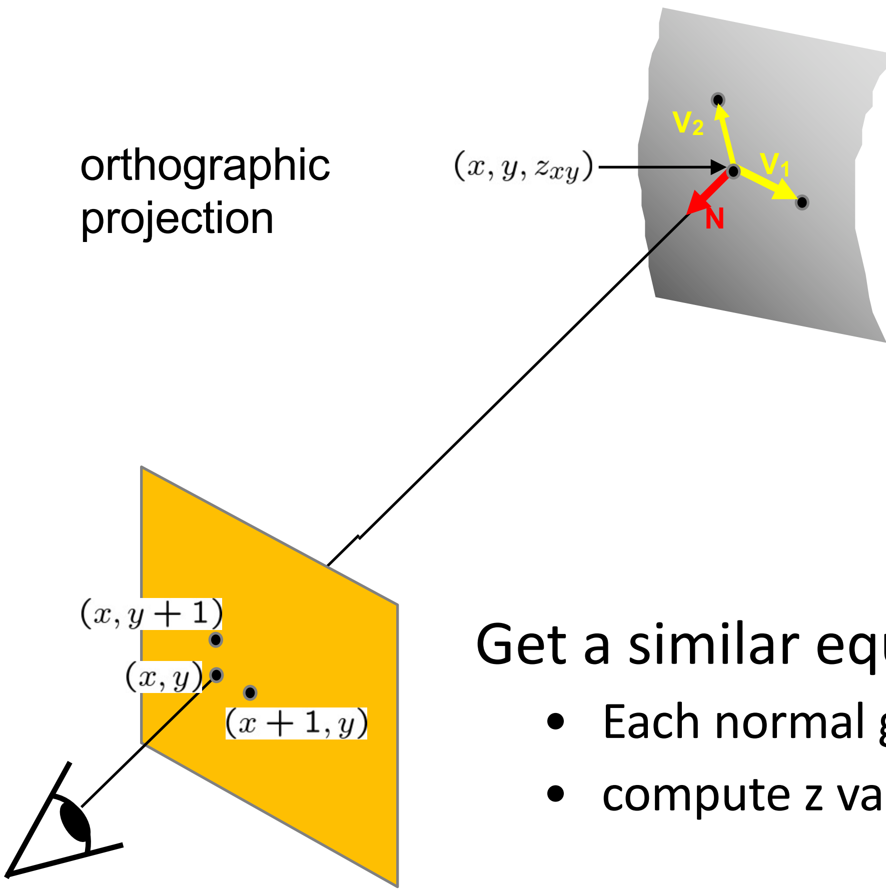
Stack all pixels into one system:



Solve as before.

Depth Map from Normal Map

- We now have a surface normal, but how do we get depth?



Assume a smooth surface

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

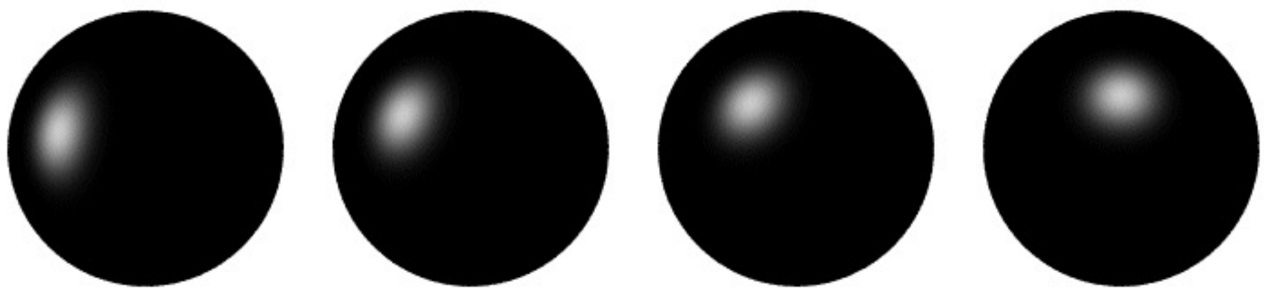
$$
\begin{aligned}
0 &= N \cdot V_1 \\
&= (n_x, n_y, n_z) \cdot (1, 0, z_{x+1,y} - z_{xy}) \\
&= n_x + n_z(z_{x+1,y} - z_{xy})
\end{aligned}
$$

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

Determining Light Directions

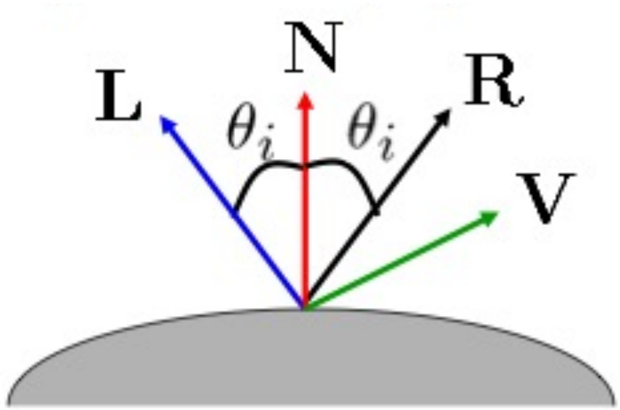
- Trick: Place a mirror ball in the scene.



- The location of the highlight is determined by the light source direction.

Determining Light Directions

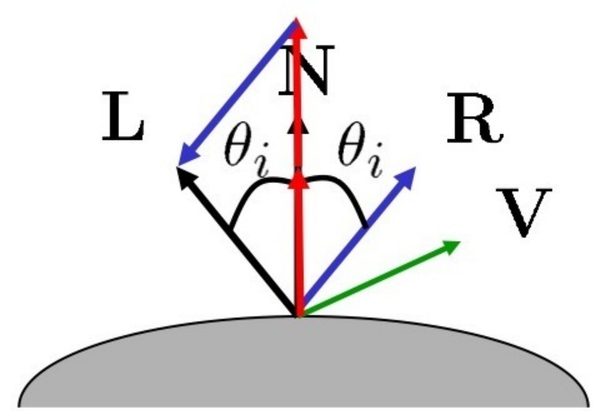
- For a perfect mirror, the light is reflected across N:



$$I_e = \begin{cases} I_i & \text{if } \mathbf{V} = \mathbf{R} \\ 0 & \text{otherwise} \end{cases}$$

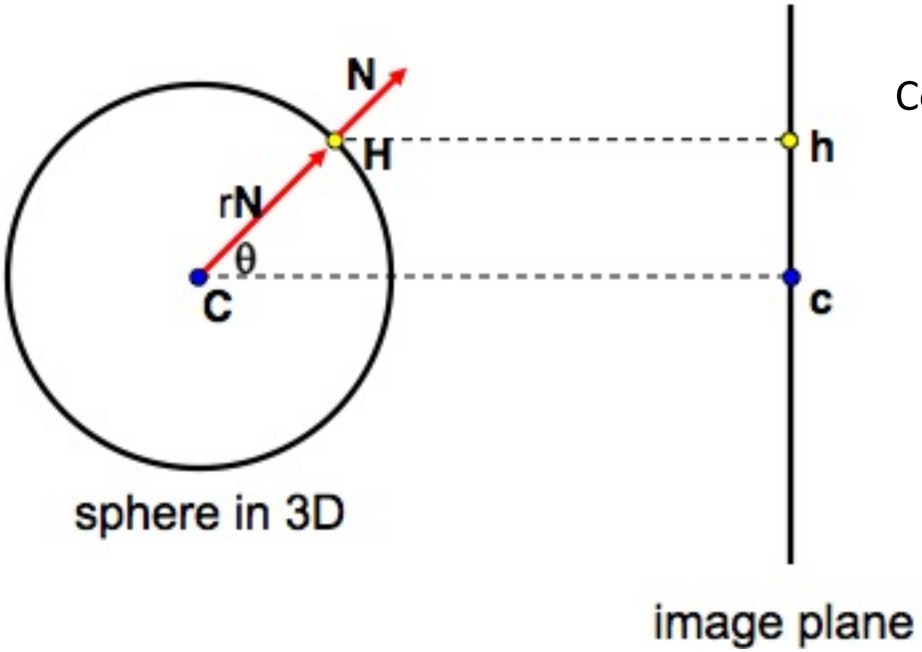
- Sc
  is given by:

$$L = 2(N \cdot R)N - R$$



Determining Light Directions

- For a sphere with highlight at point H:



Compute N:

$$N_x = \frac{x_h - x_c}{r}$$

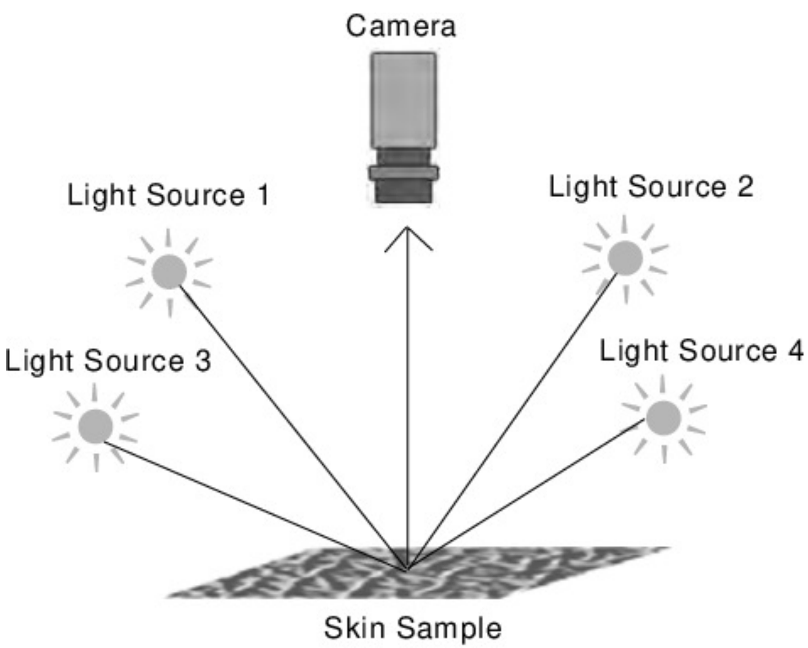
$$N_y = \frac{y_h - y_c}{r}$$

$$N_z = \sqrt{1 - x^2 - y^2}$$

- R = direction of the camera from C = $[0\ 0\ 1]^T$

$$L = 2(N \cdot R)N - R$$

Results…

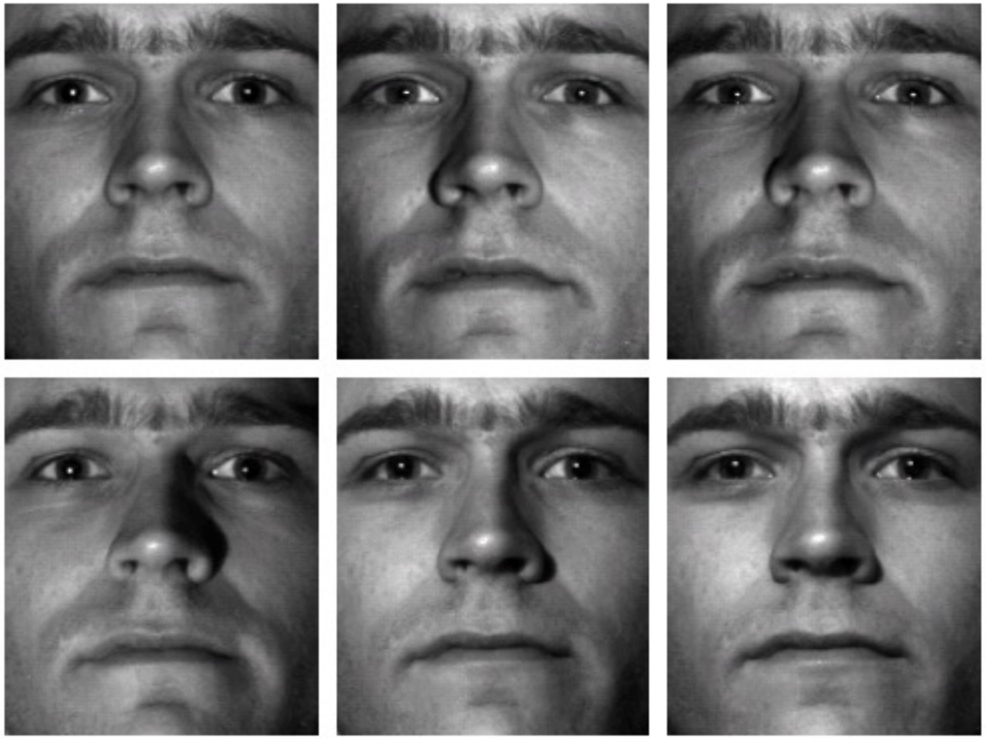


Camera
Light Source 1
Light Source 2
Light Source 3
Light Source 4
Skin Sample

(a)

(b)

Results…

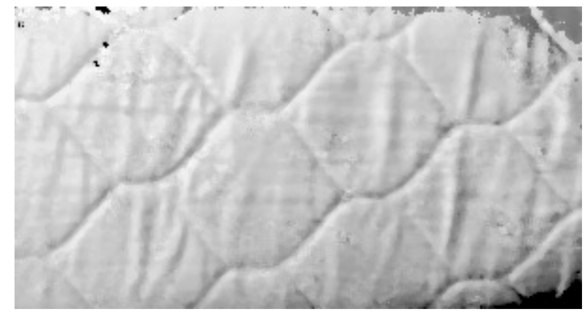


from Athos Georghiades

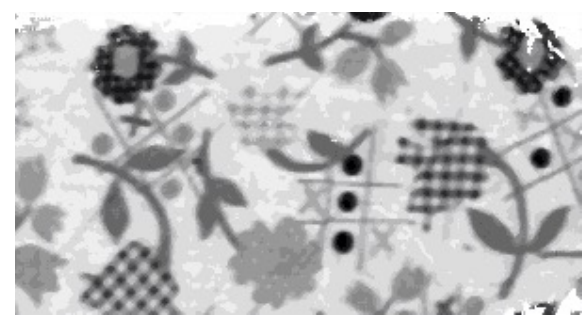
http://cvc.yale.edu/people/Athos.html

Results…

Input images



Recovered normals (re-lit)

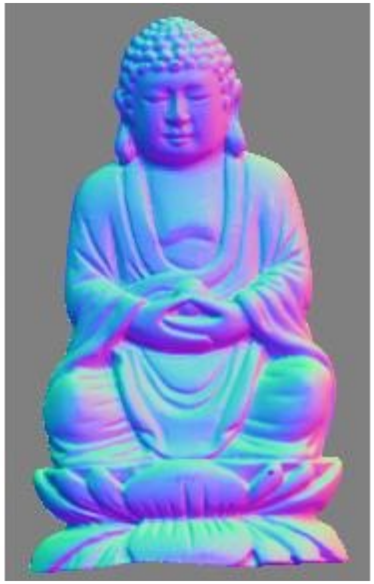


Recovered color

[Rushmeier et al., 1997]

Results…


Input
(1 of 12)


Normals


Normals


Shaded
rendering


Textured
rendering

Video Demo: Photometric Stereo

Dyson Lab; ICL

https://www.youtube.com/watch?v=PdJTIx7d0HA

Limitations

Big problems

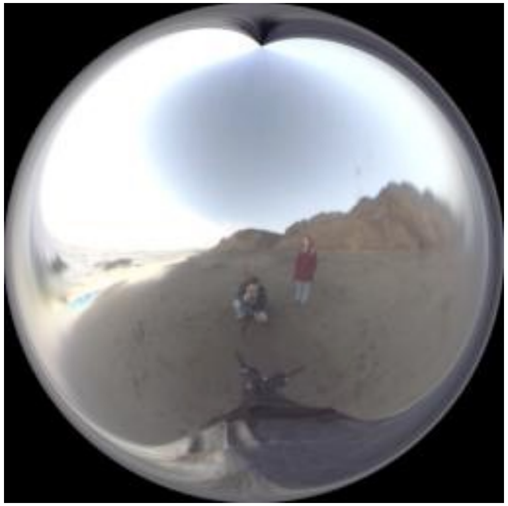
- Do not handle shadows, inter-reflections
- Only works in controlled **indoor lab environment**

Smaller problems

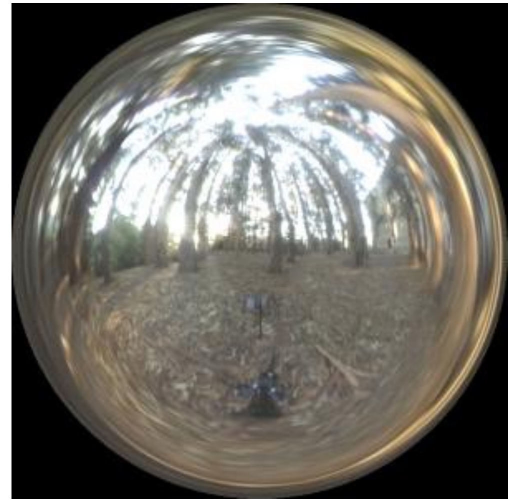
- camera and lights have to be distant
- calibration requirements
  - measure light source directions, intensities
  - camera response function

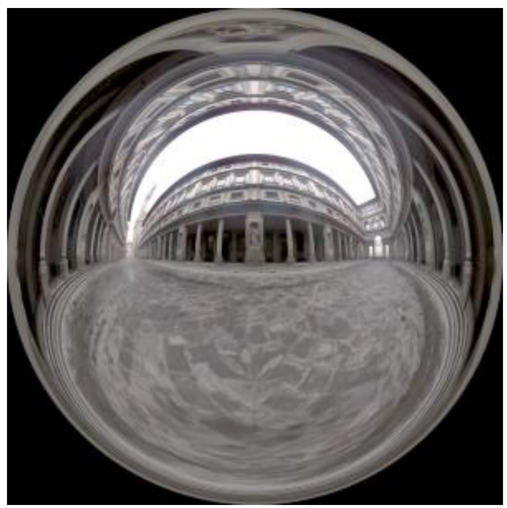
Real-World Lighting Environments

Funston Beach



Eucalyptus Grove





Uffizi Gallery

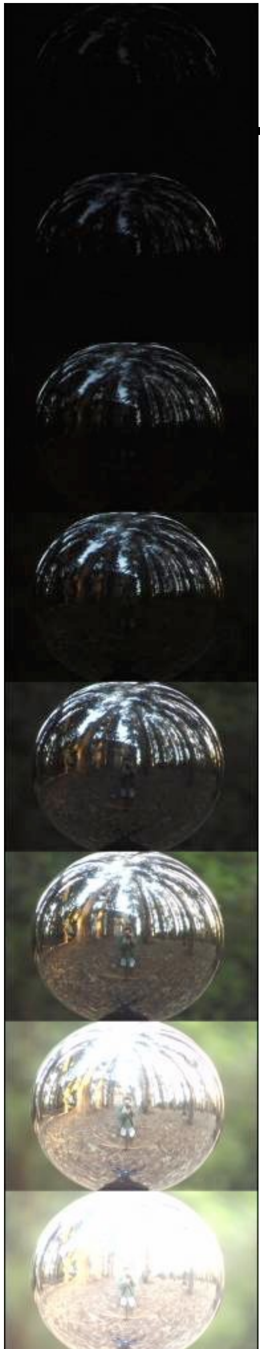
Grace Cathedral

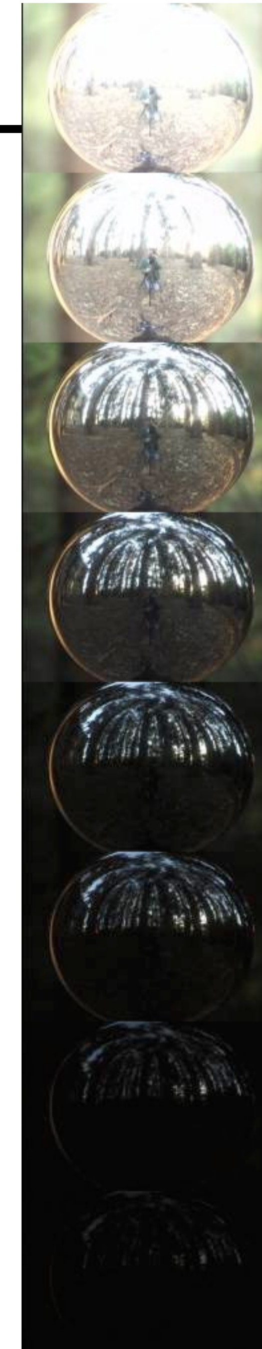
Lighting Environments from the Light Probe Image Gallery:
http://www.debevec.org/Probes/

Mirrored Sphere

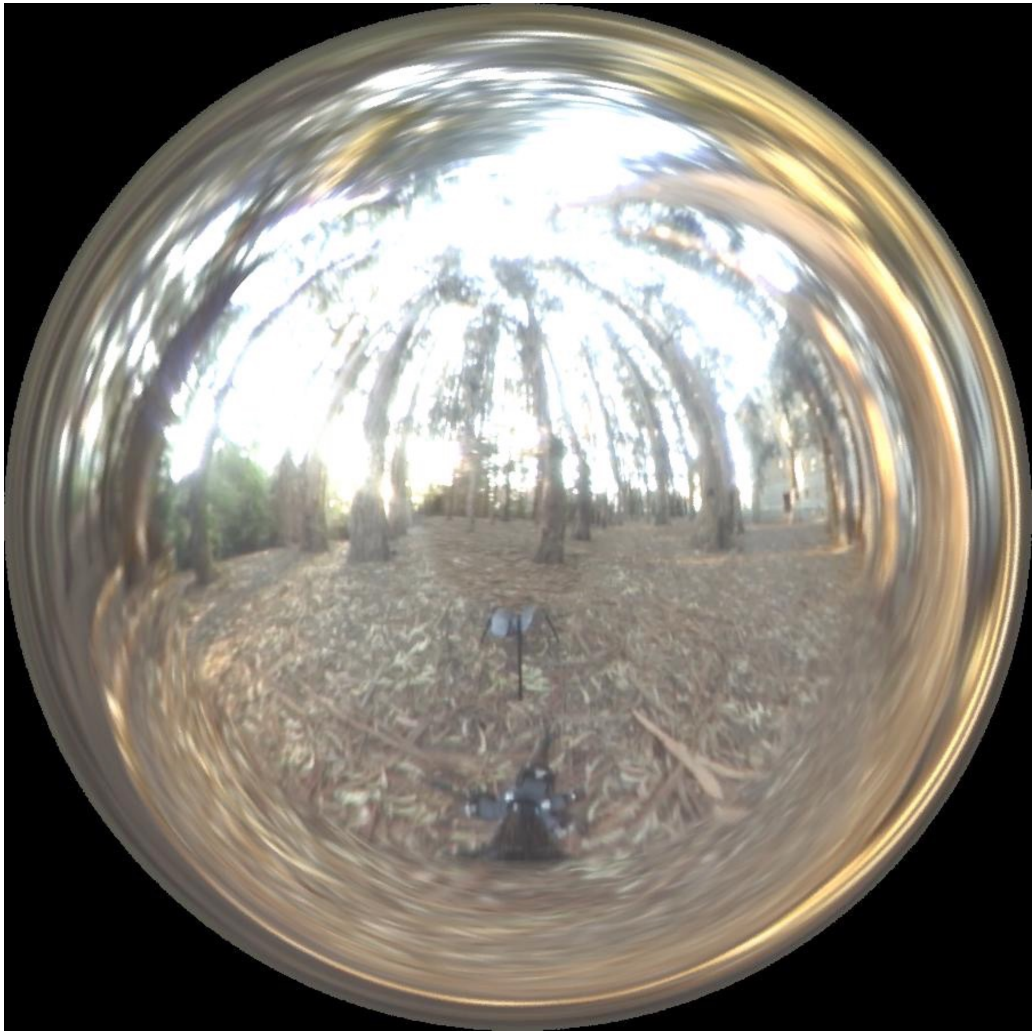

Canon
Canon
REMOTE SWITCH

Acquiring the Light Probe

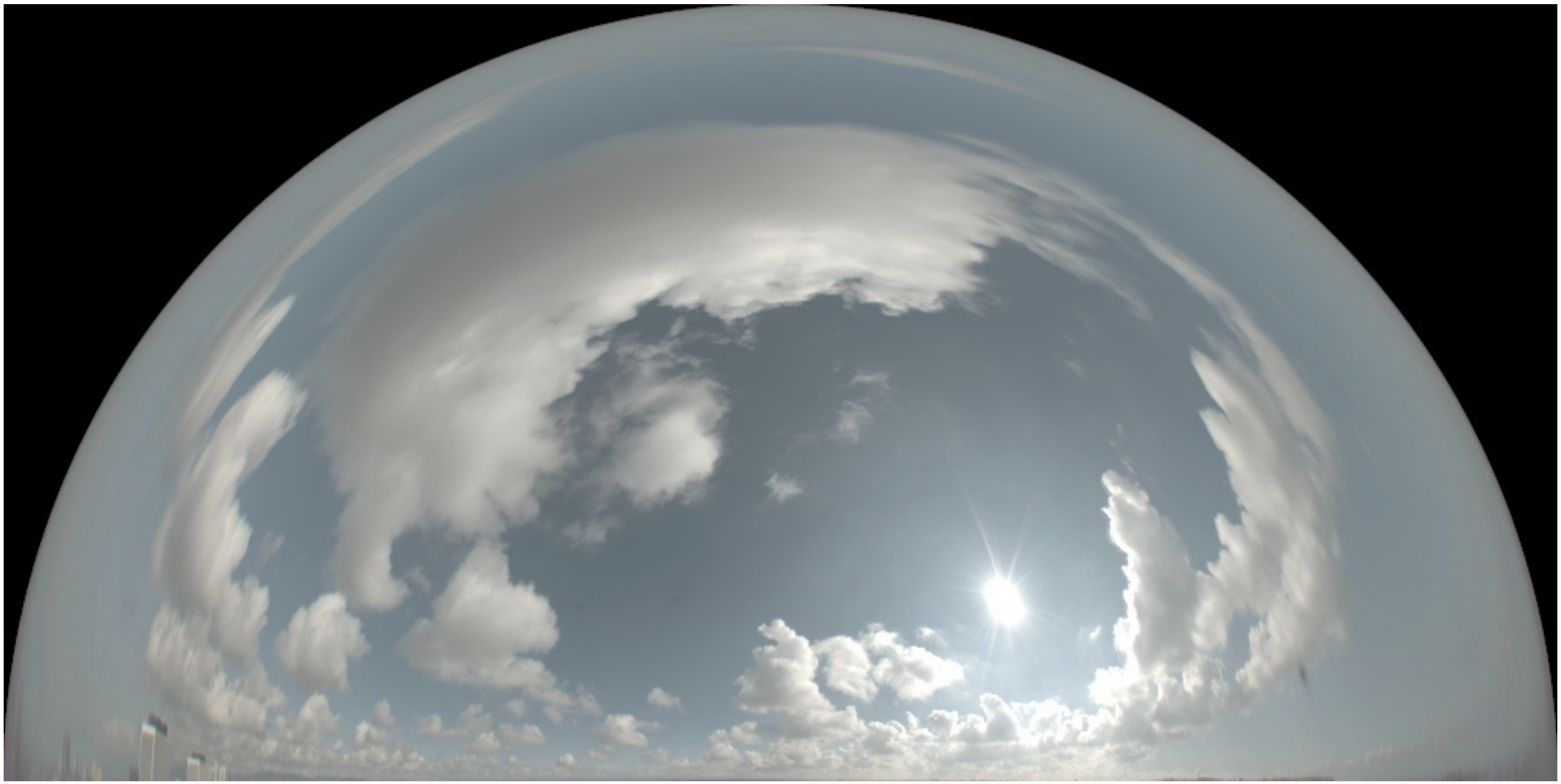




Assembling the Light Probe



HDR Sky Probe



Paper#1 to read today

Outdoor Photometric Stereo

Lap-Fai Yu [1*] Sai-Kit Yeung [2] Yu-Wing Tai [3] Demetri Terzopoulos [1] Tony F. Chan [4]

[1] University of California, Los Angeles [2] Singapore University of Technology and Design
[3] Korea Advanced Institute of Science and Technology [4] Hong Kong University of Science and Technology

Abstract

We introduce a framework for outdoor photometric stereo utilizing natural environmental illumination. Our framework extends beyond existing photometric stereo methods intended for laboratory environments to encompass robust outdoor operation in the real world. In this paper, we motivate our framework, describe the components of its processing pipeline, and assess its performance in synthetic experiments as well as in natural experiments including objects in outdoor environments with complex real-world illuminations.

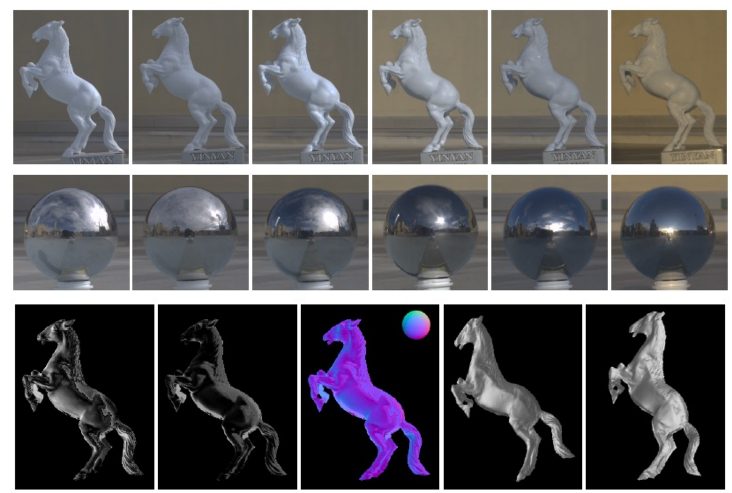


Image formation model

3. Environment Light Photometric Stereo

In this section, we describe the basic model of our environment light photometric stereo and our image data acquisition process.

3.1. Basic model

In the Lambertian surface model (assuming a linear camera response function), the intensity of a pixel I depends on the surface albedo ρ, the illumination direction $\mathbf{l}$, and the surface normal $\mathbf{n}$ according to

$$I(x) = \rho(x)\mathbf{l}(x) \cdot \mathbf{n}(x), \quad (1)$$

where x is the image coordinate. The common photometric stereo setting presumes a distant, directional light source. Thus, $\mathbf{l}$ is spatially invariant and it can easily be estimated

Multiple light sources

When we have multiple directional light sources, we can extend (1) by summing the contribution of each light source to the pixel's intensity, as follows:

$$I(x) = \rho(x) \sum_{i=1}^{K} c_i \mathbf{l}_i \cdot \mathbf{n}(x), \tag{2}$$

where K is the number of light sources in the scene, and c_i is the strength of light source i with direction $\mathbf{l}_i$. In the case where the illumination comes from all directions, we can describe the image intensity using (2) with K tending to infinity; i.e., an integral. Note that in (2) the number of unknowns for $\mathbf{n}$ remains the same as in (1) and (2) remains a linear equation when ρ and $\mathbf{l}_i$ are known.

Data acquisition

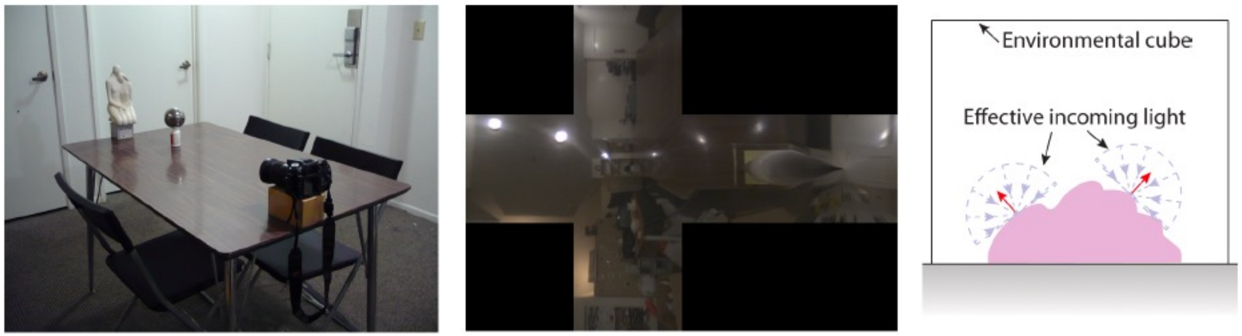


Figure 2. Left: Our simple setup for data acquisition. A mirror sphere is placed near the object. Middle: From the image of the mirror sphere, we estimate the illumination environment map using the method in [8]. Right: For each pixel, we must estimate the illumination directions that contribute to the pixel intensity, which depends on the orientation of the associated surface normal.

Synthetic images

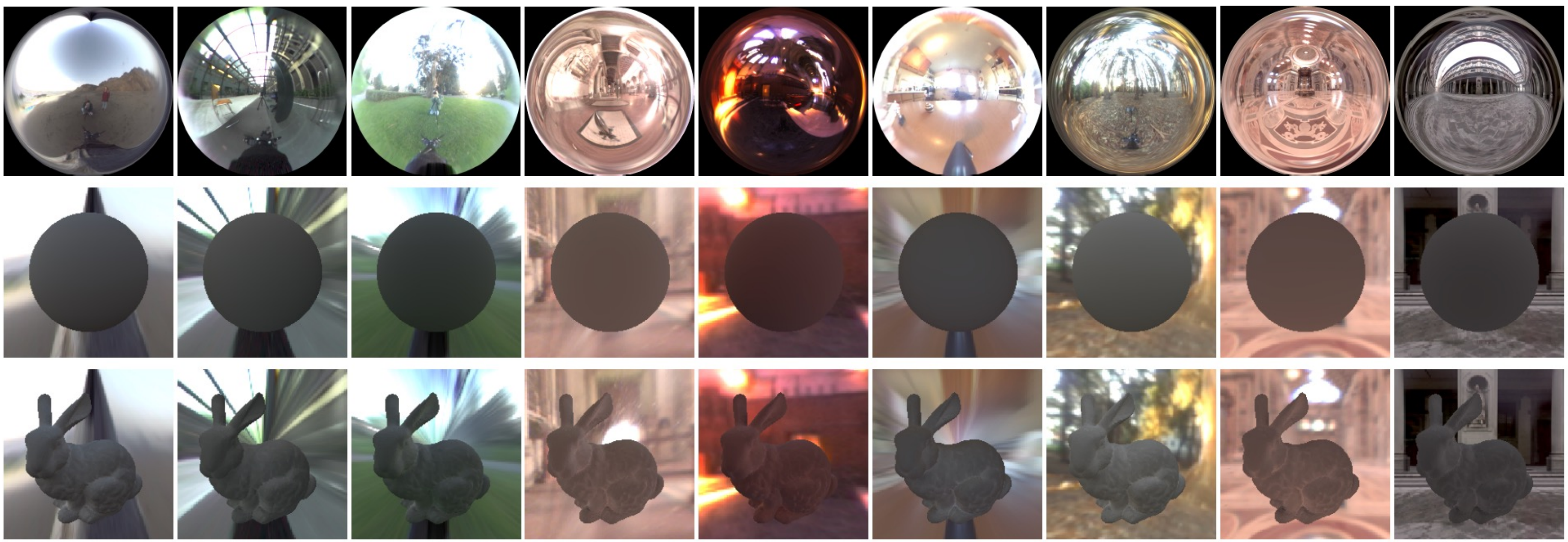
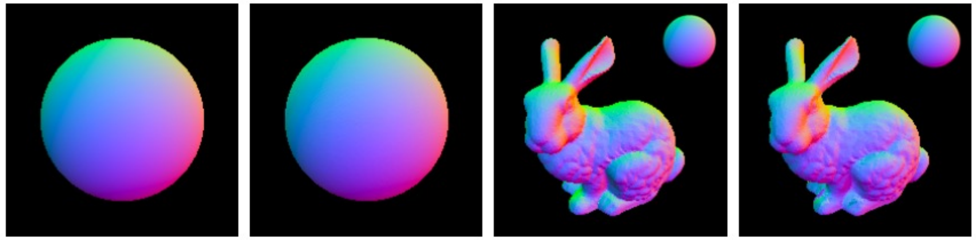


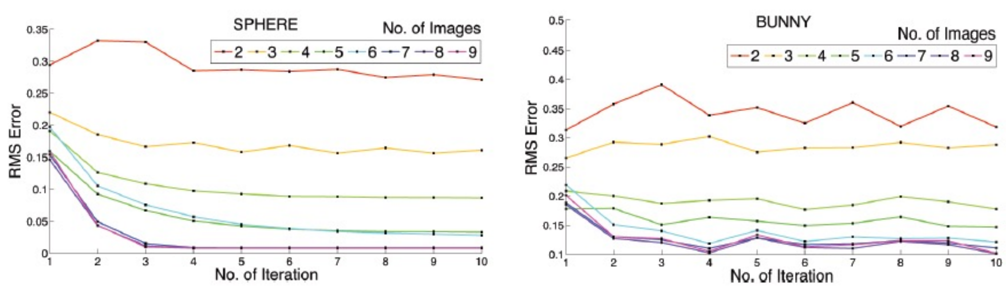
Figure 5. Input environments and images for the synthetic examples SPHERE and BUNNY.

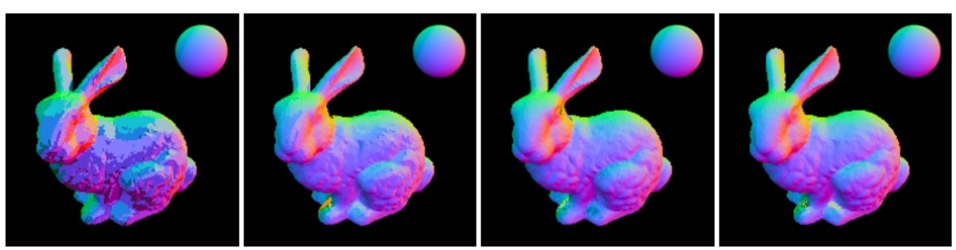
Result



(a) Ground truth (b) Result (c) Ground truth (d) Result

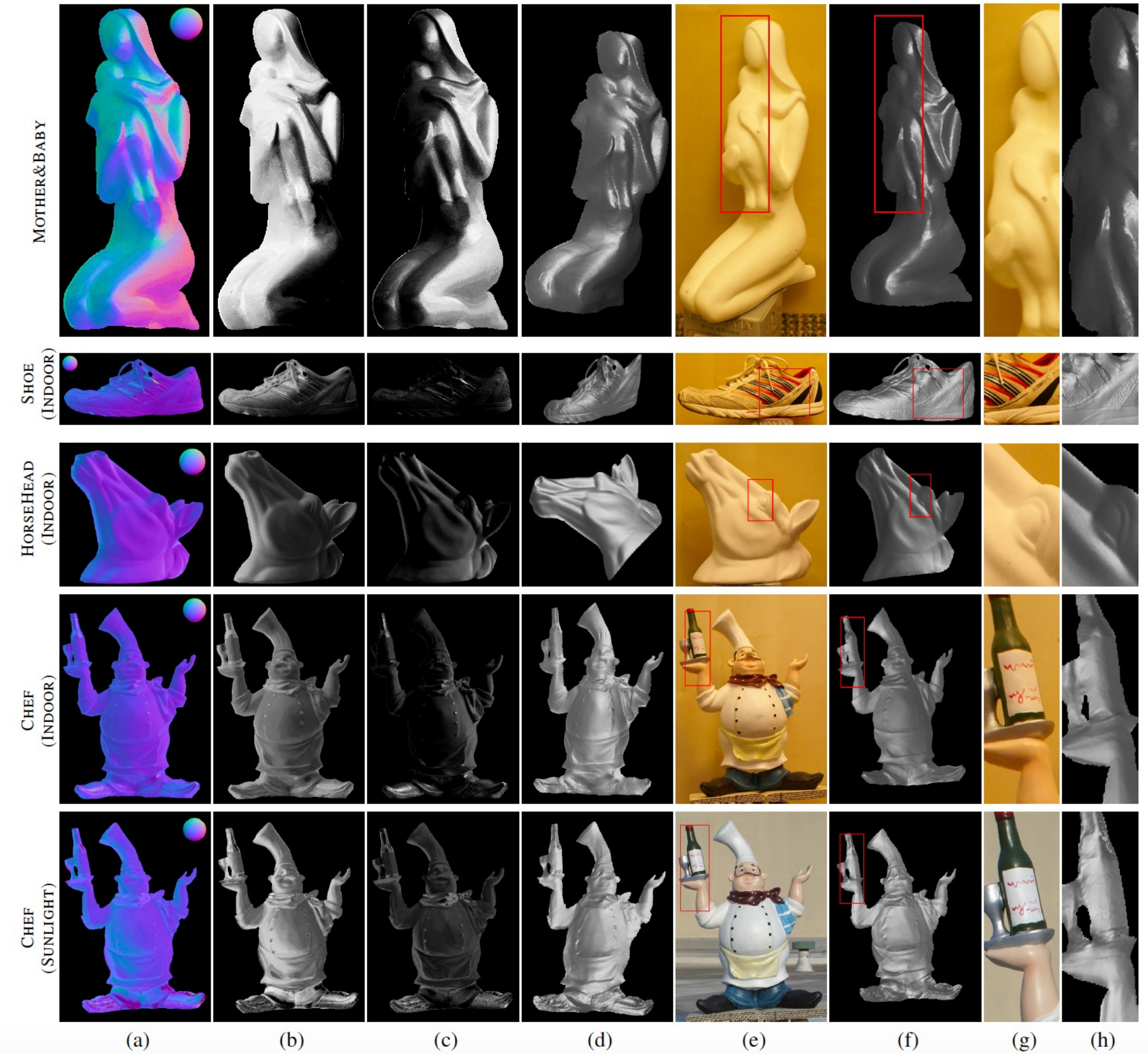
Figure 6. Comparison between ground truth and normal maps obtained using nine environments. The results are obtained after four iterations of the AO process.





Iteration 0 Iteration 1 Iteration 2 Iteration 3

Result



MOTHER&BABY
SHOE (INDOOR)
HORSEHEAD (INDOOR)
CHEF (INDOOR)
CHEF (SUNLIGHT)
(a)
(b)
(c)
(d)
(e)
(f)
(g)
(h)

Paper#2 to read today

Photometric Stereo in the Wild

Chun-Ho Hung[♯] Tai-Pang Wu[†] Yasuyuki Matsushita[§] Li Xu[‡] Jiaya Jia[†] Chi-Keung Tang[◇]
[♯] Quora, Inc. [†] The Chinese University of Hong Kong [‡] Lenovo R&T
[§] Microsoft Research Asia [◇] Hong Kong University of Science and Technology

Abstract

Conventional photometric stereo requires to capture images or videos in a dark room to obstruct complex environment light as much as possible. This paper presents a new method that capitalizes on environment light to avail geometry reconstruction, thus bringing photometric stereo to the wild, such as an outdoor scene, with uncontrolled lighting. We do not make restrictive assumption, and only use simple capture equipments, which include a mirror sphere and a video camera. Qualitative and quantitative experiments indicate the potential and practicality of our system to generalize existing frameworks.

(a) (b)

(c) (d)

Figure 1. Typical scenes that are difficult for photometric stereo.

Abstract

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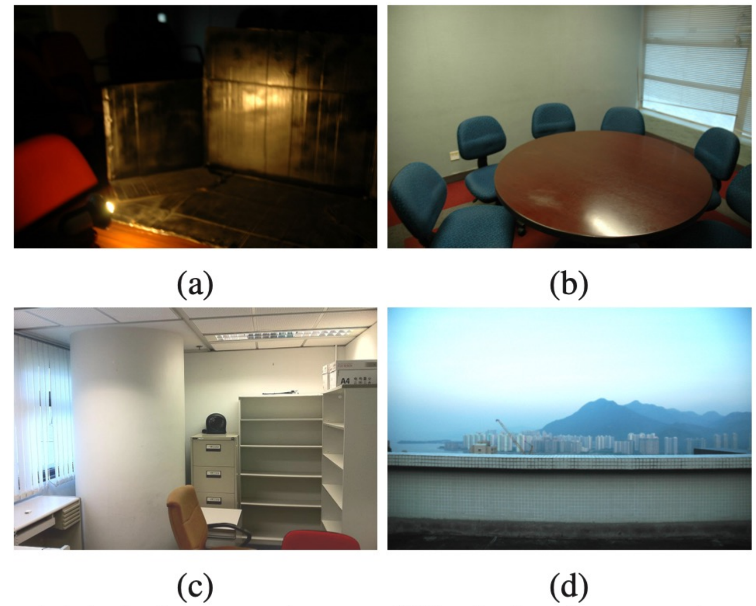
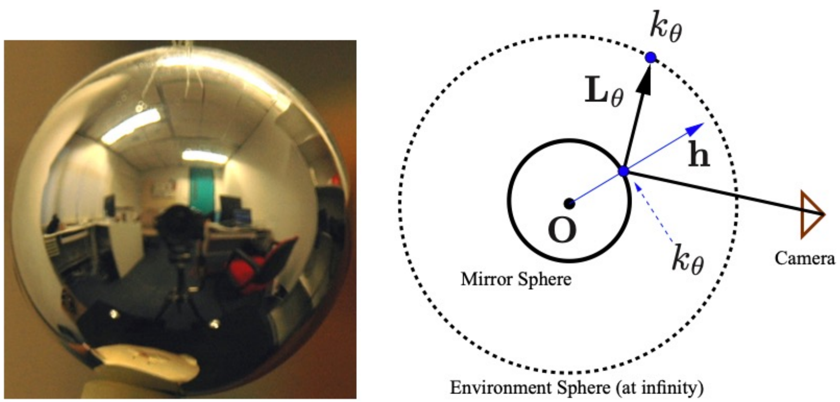


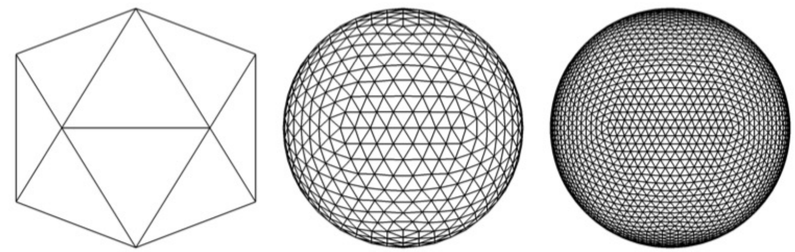
Figure 1. Typical scenes that are difficult for photometric stereo.

Environment light map



(a) (b)

Figure 2. A mirror sphere for capturing environment lighting. (b) shows the relationship between the mirror sphere and environment sphere, where $\mathbf{O}$ is the *ideal* location where the object is placed, $\mathbf{h}$ is the angle bisector between the lighting direction $\mathbf{L}_\theta$ and viewing direction. k_θ is the incident intensity along $\mathbf{L}_\theta$.



(a) (b) (c)

Figure 3. Icosahedron and its subdivision. (a) A 20-face polyhedron, where the vertices are evenly distributed on a 3D unit sphere that encloses and touches the polyhedron. (b) A 3-time subdivided icosahedron. (c) A 4-time subdivided icosahedron. Each subdivision is done by splitting each face into four equilateral triangles followed by reprojecting the vertices onto a unit 3D sphere.

Tan [21] is derived based on cosine kernels and coefficients

Rendering equation

Similar to the notations used in [17], the intensity I observed at a surface point can be modeled as an integration

$$I = \int_{\theta \in \Omega} f(\mathbf{L}_\theta, \mathbf{V}) k_\theta \mathbf{N}^T \mathbf{L}_\theta d\theta, \tag{1}$$

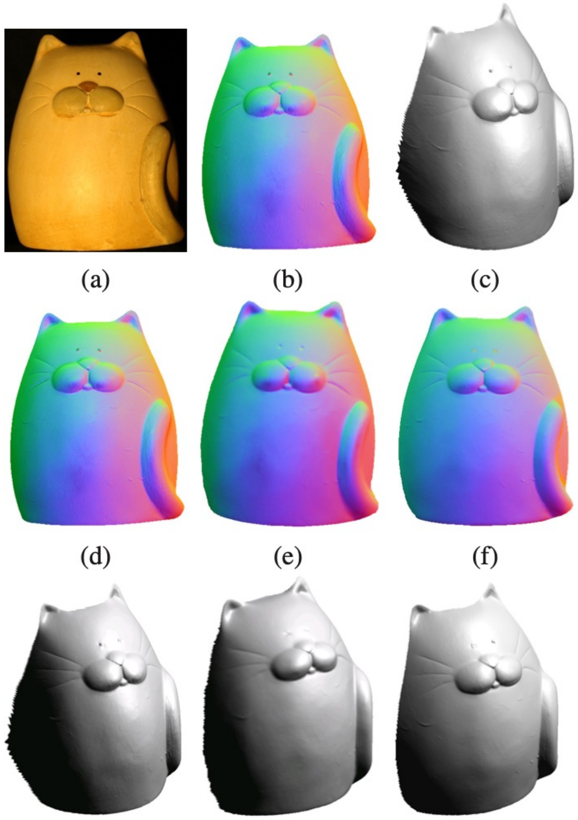
where $f(\cdot)$ is the BRDF at the surface point, Ω is a space containing all possible orientations, $\mathbf{L}_\theta$ is a lighting direction defined by orientation θ, k_θ is the incident intensity at θ, $\mathbf{V}$ is the viewing direction at the surface point, and $\mathbf{N}$ is the corresponding surface normal.

With Eq. (2), our target is to estimate ρ and $\mathbf{N}$ from a set of captured images I_i, indexed by $i = 1 \cdots n \mid n \geq 3$ with a fixed viewing direction. As $\mathbf{N}^T \mathbf{L}_{\theta i}$ cannot be negative, Eq. (2) can be more accurately expressed as

$$I_i = \sum_{\theta \in \Omega'} \rho k_{\theta i} \max(\mathbf{N}^T \mathbf{L}_{\theta i}, 0), \tag{3}$$

where $k_{\theta i}$ and $\mathbf{L}_{\theta i}$ are respectively the incident intensity and the lighting direction defined by θ for image i. The $\max(\cdot)$ operator is used to reject negative energies. Eq. (3) describes a single-pixel color formation.

Result



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure 11. *KitCat* – (a) An input image. (b) Ground truth normal map generated in a dark room. (c) The reconstructed surface from (b). (d)-(f) Color coded normal maps generated by our method with the environments respectively shown in Fig. 1(a)-(c). (g)-(i) Corresponding surfaces.

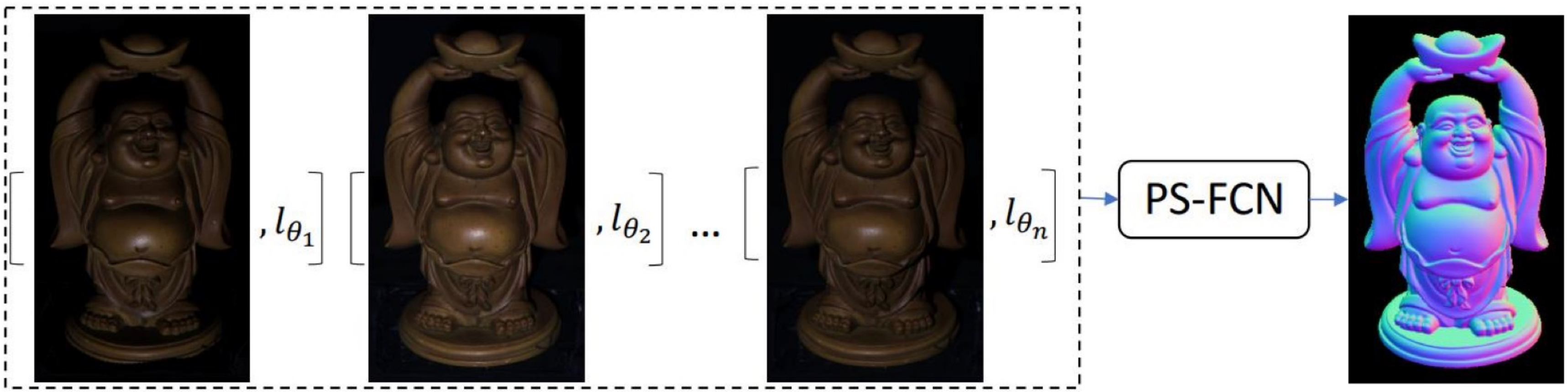
Paper #3 to read today

PS-FCN: A Flexible Learning Framework for Photometric Stereo

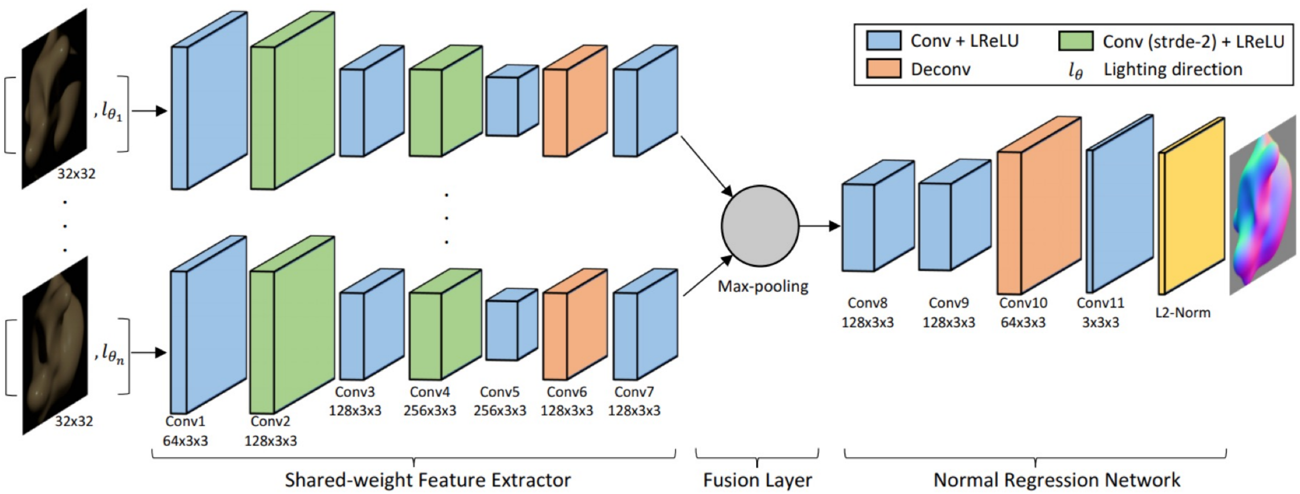
Guanying Chen[1] Kai Han[2] Kwan-Yee K. Wong[1]

[1] The University of Hong Kong
{gychen,kykwong}@cs.hku.hk
[2] University of Oxford
khan@robots.ox.ac.uk

PS-FCN: A Flexible Learning Framework for Photometric Stereo



PS-FCN: Network architecture

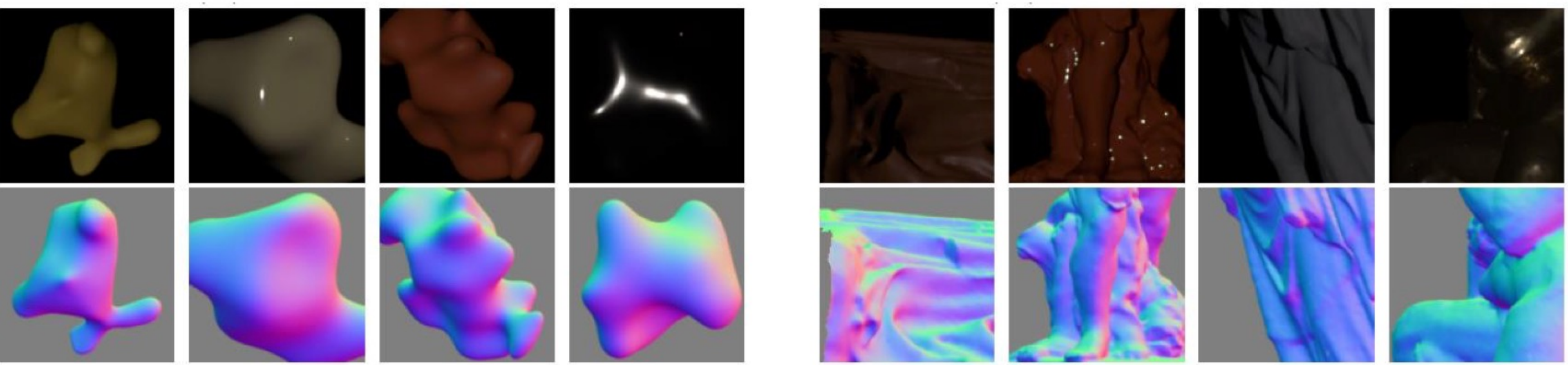


$$Loss = \frac{1}{hw}\sum_{i,j}(1 - \boldsymbol{N}_{ij} \cdot \widetilde{\boldsymbol{N}}_{ij})$$

Training data

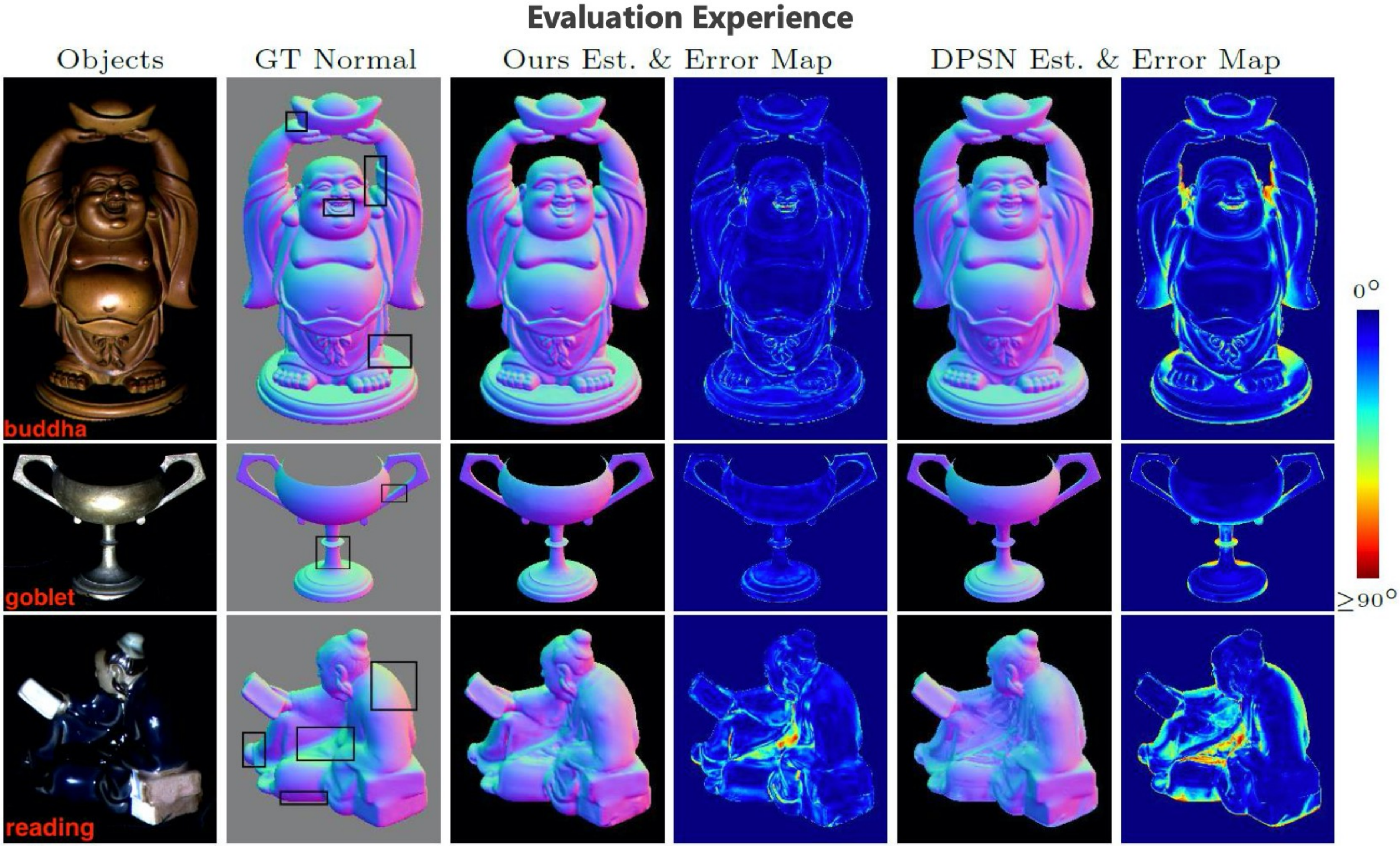
Dataset

Blobby shape | **Sculapture shape**



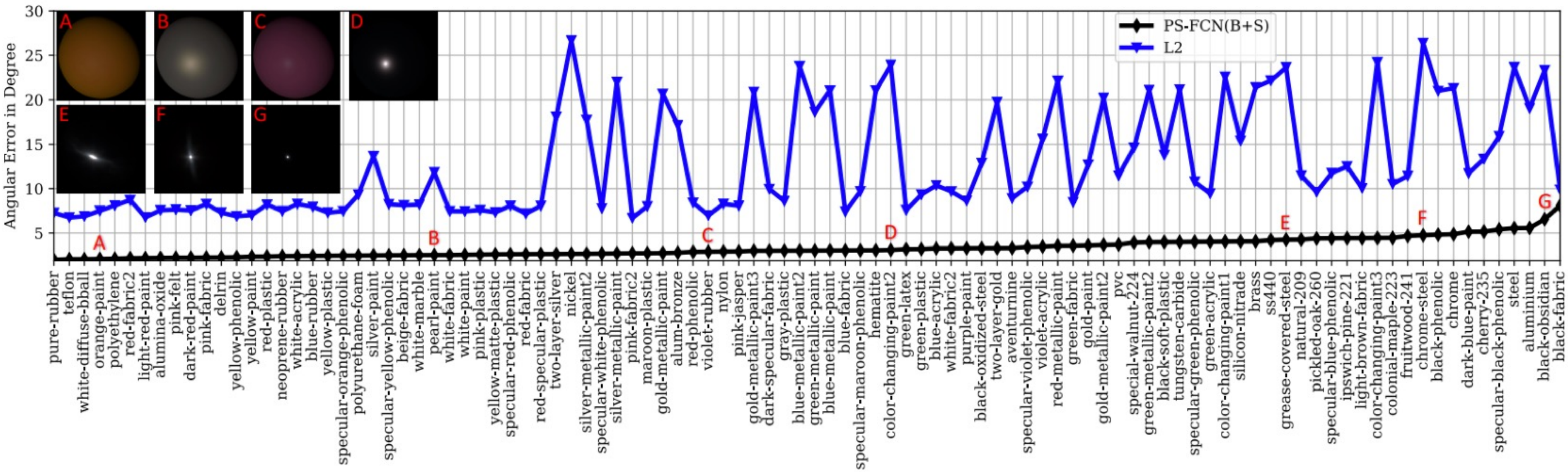
Blobby shape	Sculapture shape
Data size : 25,910 samples	Data size : 59,282 samples
Image size : 128×128	Image size : 128×128
Train : Test = 99 : 1	Train : Test = 99 : 1

Result


Evaluation Experience
Objects
GT Normal
Ours Est. & Error Map
DPSN Est. & Error Map
buddha
goblet
reading
0°
≥90°

Quantitative results

Evaluation Experience



Method	ball	cat	pot1	bear	pot2	buddha	goblet	reading	cow	harvest	Avg.
L2 [1]	4.10	8.41	8.89	8.39	14.65	14.92	18.50	19.80	25.60	30.62	15.39
AZ08 [14]	2.71	6.53	7.23	**5.96**	11.03	12.54	13.93	14.17	21.48	30.50	12.61
WG10 [17]	2.06	6.73	7.18	6.50	13.12	10.91	15.70	15.39	25.89	30.01	13.35
IA14 [23]	3.34	6.74	6.64	7.11	8.77	10.47	9.71	14.19	13.05	25.95	10.60
ST14 [22]	**1.74**	**6.12**	**6.51**	6.12	8.78	10.60	10.09	13.63	13.93	25.44	10.30
DPSN [8]	2.02	6.54	7.05	6.31	7.86	12.68	11.28	15.51	8.01	16.86	9.41
PS-FCN (B+S+32, 16)	3.31	7.64	8.14	7.47	8.22	8.76	9.81	14.09	8.78	17.48	9.37
PS-FCN (B+S+32, 96)	2.82	6.16	7.13	7.55	**7.25**	**7.91**	**8.60**	**13.33**	**7.33**	**15.85**	**8.39**

Paper #4:

Lightweight Photometric Stereo for Facial Details Recovery

Xueying Wang[1] Yudong Guo[1] Bailin Deng[2] Juyong Zhang[1]*
[1]University of Science and Technology of China [2]Cardiff University
{WXY17719, gyd2011}@mail.ustc.edu.cn DengB3@cardiff.ac.uk juyong@ustc.edu.cn

Abstract

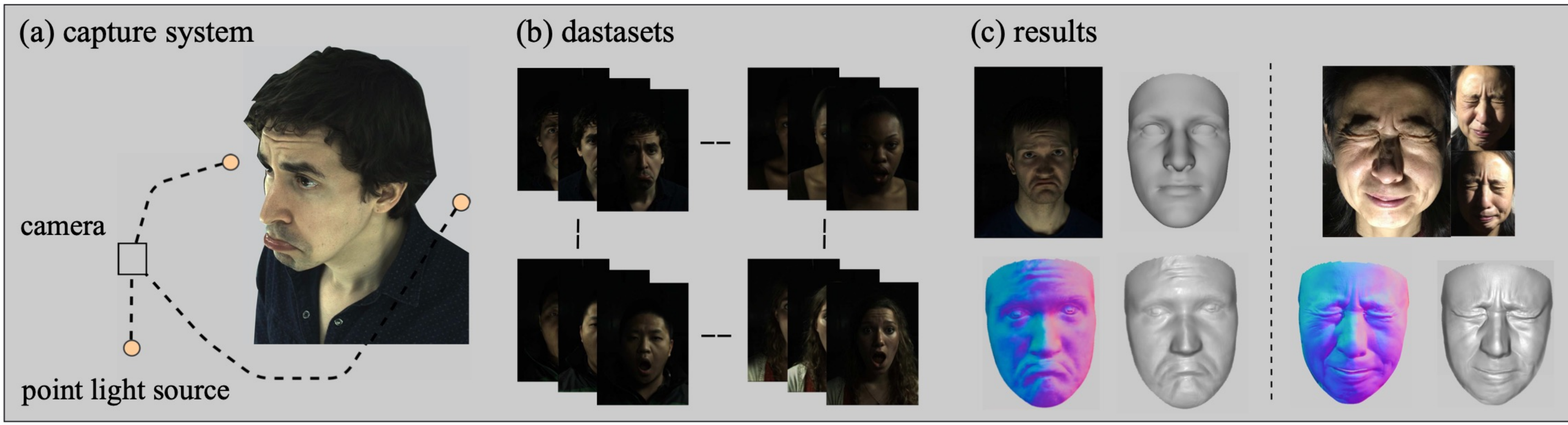


Figure 1. We propose a convolutional neural network based method for face reconstruction under photometric stereo scenario. (a) & (b): Our dataset for network training consists of photos with different expressions, captured using a system composed of three near point light sources and a fixed camera. (c): Our proposed method can recover fine details even with a single image input (left). For images captured by a smartphone, with a hand-held light at locations not seen in our training dataset, our method also works well in this casual setup. (right).

Near field image formation

$$\mathbf{I}_{ij}(\mathbf{V}_i, \mathbf{N}_i, \boldsymbol{\rho}_i) \triangleq \boldsymbol{\rho}_i \left(\mathbf{N}_i \cdot \frac{\beta_j \left(\mathbf{P}_j - \mathbf{V}_i\right)}{\|\mathbf{P}_j - \mathbf{V}_i\|_2^3} \right), \qquad (1)$$

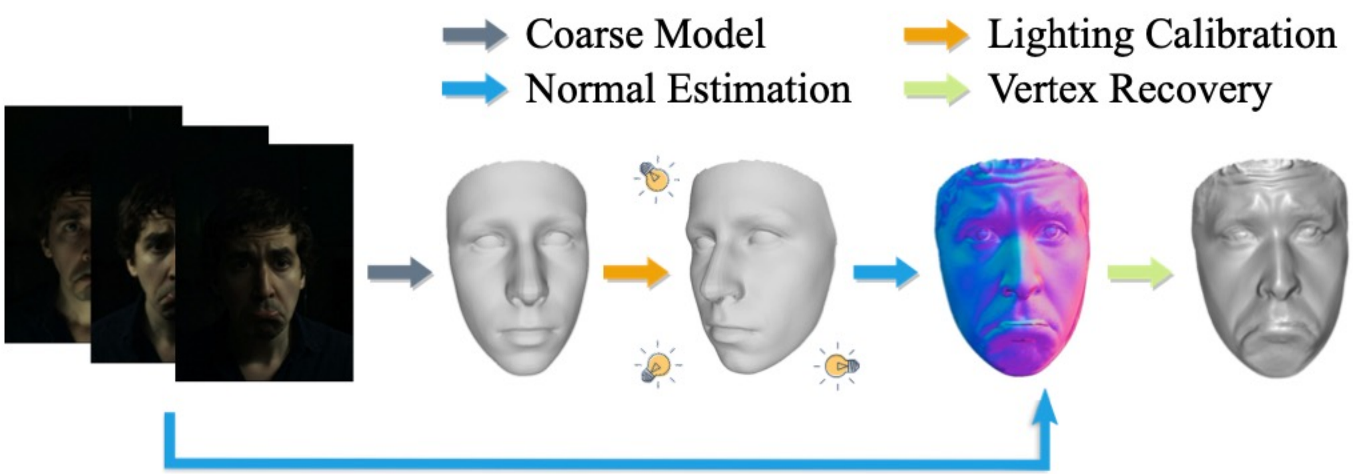


Figure 3. The algorithm pipeline of real dataset construction.

Network structure

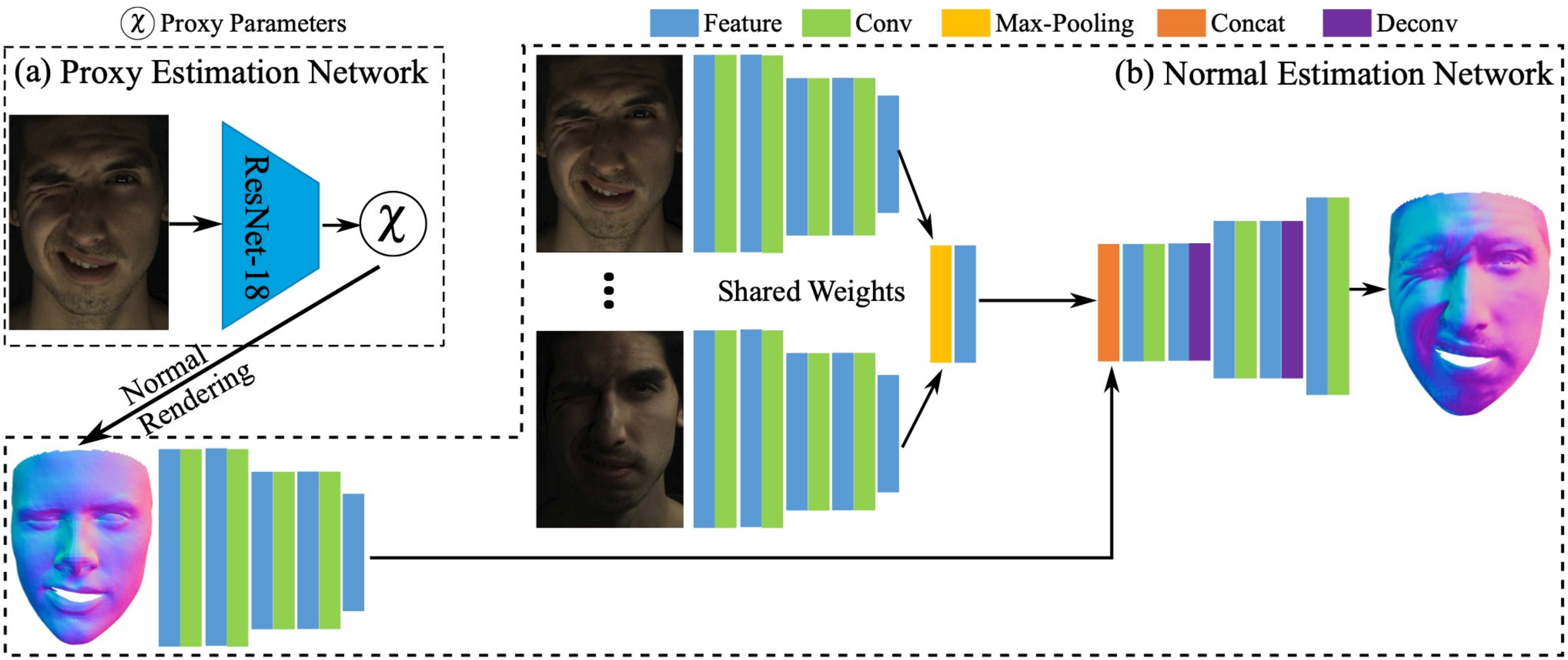
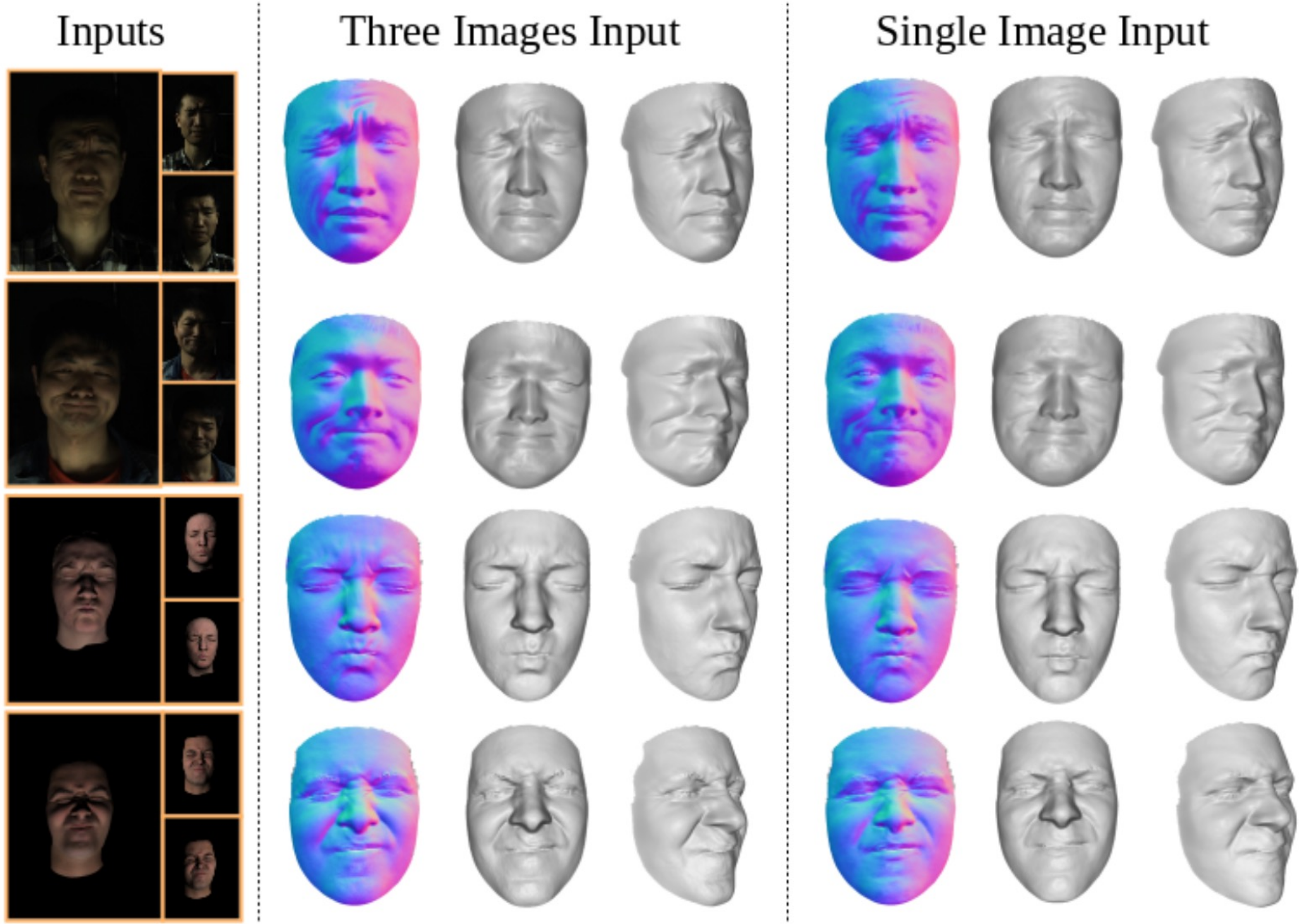


Figure 5. The architecture of our two-stage network which consists of (a) Proxy Estimation Network and (b) Normal Estimation Network. The connection between the two modules is a rendering layer which generates a coarse normal map with the estimated proxy parameters.

Result



Result

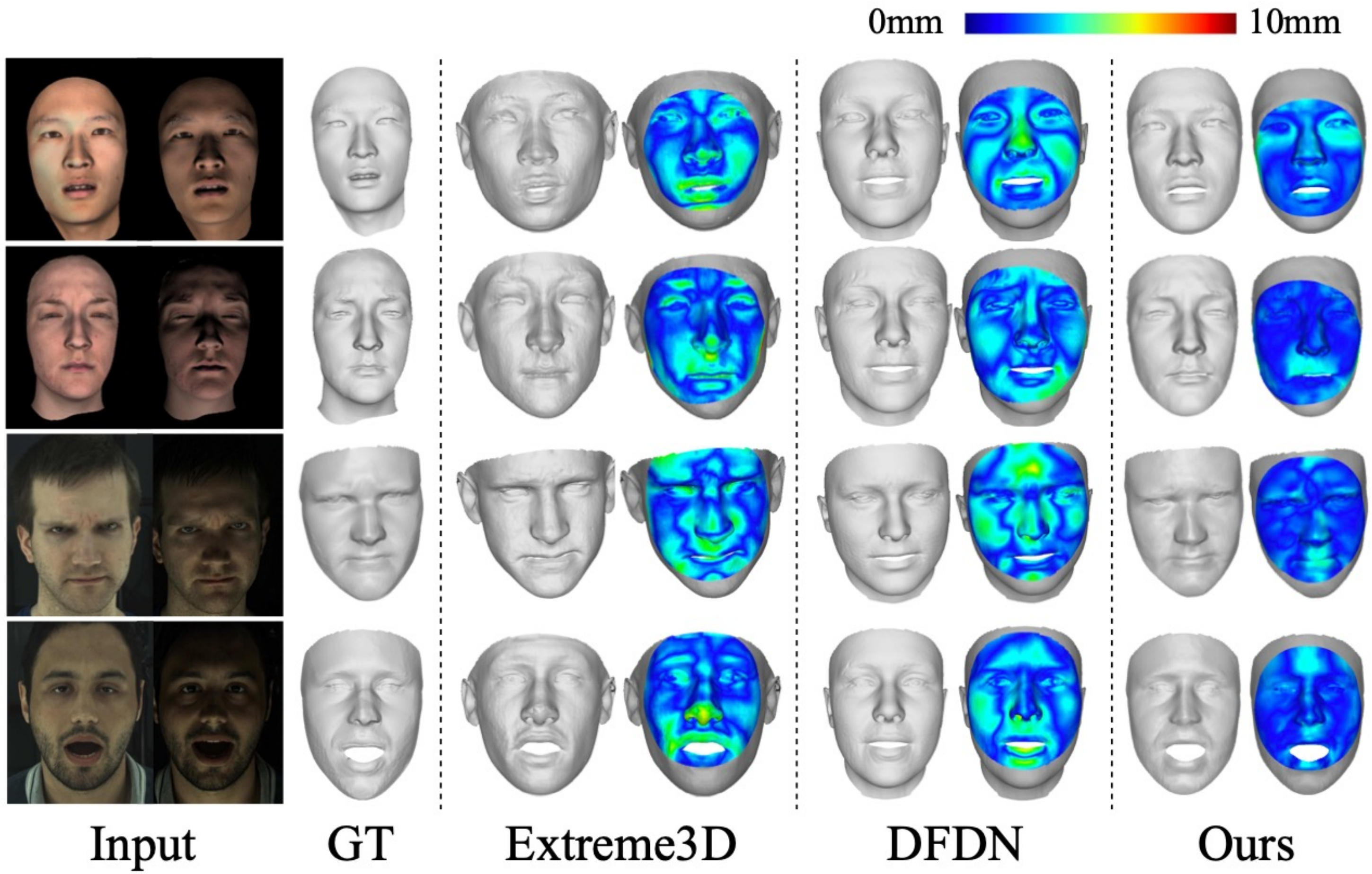


Figure 9. Reconstructed results and geometric error maps of Extreme3D [41], DFDN [10] and ours. Other methods use the left image in the first column as input while ours uses the right image as input.

Breakout room: Now it is your turn.

Breakout room group discussion & report:

Check your name on Zoom

Take note: breakout room ID, room members, “Mr/Ms speaker”.

Your task:

- Recorded your Room ID, and room members’ names, and nominate a “Speaker”.
- Together you discuss and pick one paper, either (1) the ”coded aperture”, or (2) the “coded shutter”;

- Quickly re-read it for about 5 minutes.
- Discuss their limitations/drawbacks, for another 20 minutes.

- Try to answer the following “critical analysis” questions → page turn ..
- Report back in 3 minutes by the “Mr/Ms speaker”. Tutor may record your report.