

Photometric Stereo

Introduction to Computer Vision
CSE 152
Lecture 4

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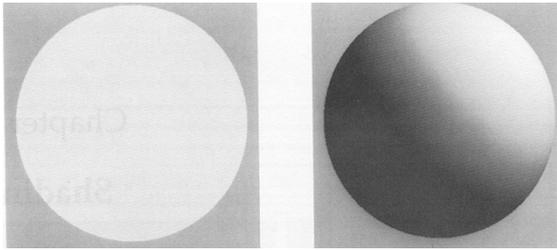
Announcements

- Homework 1 is due today by 11:59 PM
- Homework 2 will be assigned today
 - Due Wed, Apr 26, 11:59 PM
 - To be completed individually, not in groups
- Reading:
 - Section 2.2.4: Photometric Stereo
 - Shape from Multiple Shaded Images

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Shading reveals 3-D surface geometry

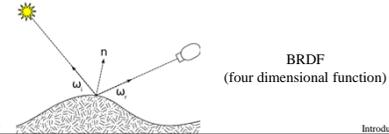


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Two shape-from-X methods that use shading

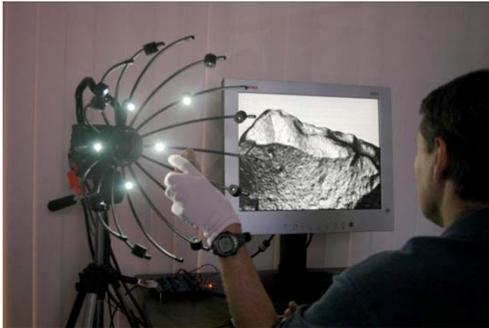
- Shape-from-shading: Use just one image to recover shape. Requires knowledge of light source direction and BRDF everywhere. Too restrictive to be useful.
- Photometric stereo: Single viewpoint, multiple images under different lighting.



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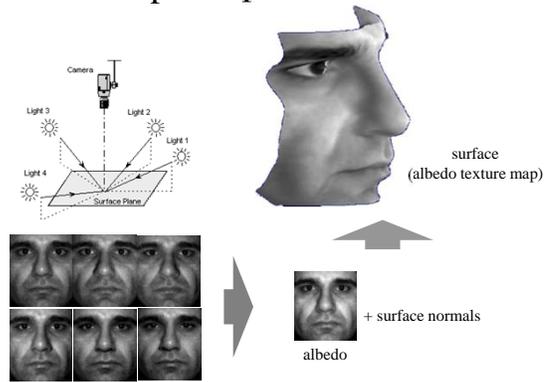
Photometric Stereo Rigs: One viewpoint, changing lighting



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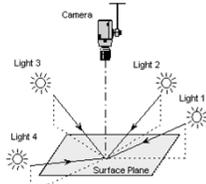
An example of photometric stereo



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Photometric stereo



- Single viewpoint, multiple images under different lighting.
 1. Arbitrary known BRDF, known lighting
 2. Lambertian BRDF, known lighting
 3. Lambertian BRDF, unknown lighting.

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1. Photometric Stereo: General BRDF and Reflectance Map

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BRDF

- Bi-directional Reflectance Distribution Function

$$\rho(\theta_{in}, \phi_{in}; \theta_{out}, \phi_{out})$$

- Function of

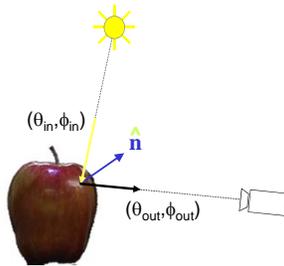
– Incoming light direction:

$$\theta_{in}, \phi_{in}$$

– Outgoing light direction:

$$\theta_{out}, \phi_{out}$$

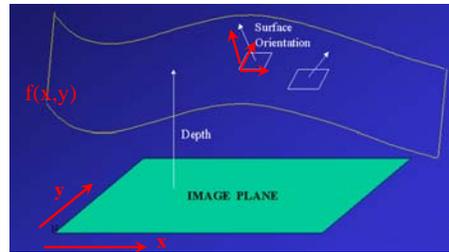
- Ratio of incident irradiance to emitted radiance



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Coordinate system



Surface: $s(x,y) = (x,y, f(x,y))$

Tangent vectors: $\frac{\partial s(x,y)}{\partial x} = \left(1, 0, \frac{\partial f}{\partial x}\right)$

$$\frac{\partial s(x,y)}{\partial y} = \left(0, 1, \frac{\partial f}{\partial y}\right)$$

Normal vector

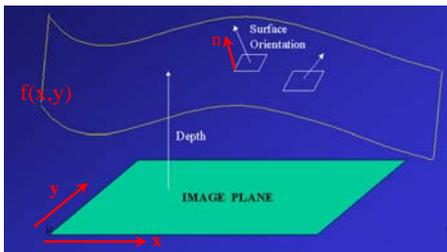
$$\mathbf{n} = \frac{\partial s}{\partial x} \times \frac{\partial s}{\partial y}$$

$$= \left(-\frac{\partial f}{\partial x}, -\frac{\partial f}{\partial y}, 1\right)$$

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Gradient Space (p,q)



Gradient Space : (p,q)

$$p = \frac{\partial f}{\partial x}, \quad q = \frac{\partial f}{\partial y}$$

Normal vector

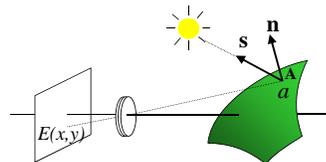
$$\mathbf{n} = \frac{\partial s}{\partial x} \times \frac{\partial s}{\partial y} = \left(-\frac{\partial f}{\partial x}, -\frac{\partial f}{\partial y}, 1\right)^T$$

$$\hat{\mathbf{n}} = \frac{1}{\sqrt{p^2 + q^2 + 1}} (-p, -q, 1)^T$$

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Image Formation



For a given point A on the surface a, the image irradiance $E(x,y)$ is a function of

1. The BRDF at A
2. The surface normal at A
3. The direction of the light source

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Reflectance Map

Let the BRDF be the same at all points on the surface, and let the light direction s be a constant.

1. Then image irradiance is a function of only the direction of the surface normal.
2. In gradient space, we have $E(p,q)$.

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Example Reflectance Map: Lambertian surface

For lighting from front

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LAMBERTIAN REFLECTANCE MAP

$$E = L\rho \frac{1 + pp_1 + qq_1}{\sqrt{1+p^2+q^2}\sqrt{1+p_1^2+q_1^2}}$$

$p = s_x, q = s_y$
Light Source Direction, expressed in gradient space.

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Reflectance Map of Lambertian Surface

What does the intensity (irradiance) of one pixel in one image tell us?
It constrains the surface normal projecting to that point to a curve

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Two Light Sources Two reflectance maps

A third image would disambiguate match

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Three Source Photometric stereo: Step 1

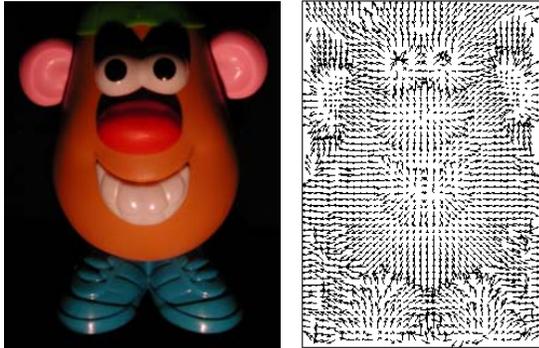
Offline:
Using source directions & BRDF, construct reflectance map for each light source direction. $R_1(p,q), R_2(p,q), R_3(p,q)$

Online:

1. Acquire three images with known light source directions. $E_1(x,y), E_2(x,y), E_3(x,y)$
2. For each pixel location (x,y) , find (p,q) as the intersection of the three curves
 - $R_1(p,q) = E_1(x,y)$
 - $R_2(p,q) = E_2(x,y)$
 - $R_3(p,q) = E_3(x,y)$
3. This is the surface normal at pixel (x,y) . Over image, the normal field is estimated

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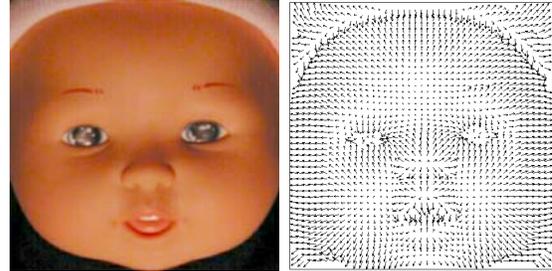
Normal Field



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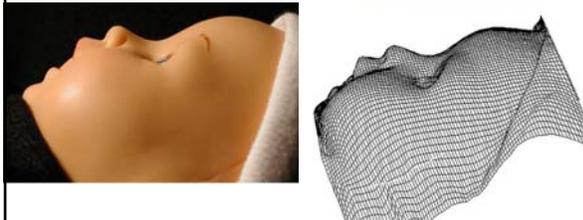
Plastic Baby Doll: Normal Field



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Next step:
Go from normal field to surface



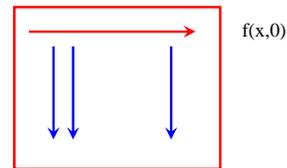
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Recovering the surface $f(x,y)$

Many methods: Simplest approach

1. From estimate $\mathbf{n}=(n_x, n_y, n_z)$, $p=n_x/n_z$, $q=n_y/n_z$
2. Integrate $p=df/dx$ along a row $(x,0)$ to get $f(x,0)$
3. Then integrate $q=df/dy$ along each column starting with value of the first row



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What might go wrong?



- Height $z(x,y)$ is obtained by integration along a curve from (x_0, y_0) .

$$z(x,y) = z(x_0, y_0) + \int_{(x_0, y_0)}^{(x,y)} (pdx + qdy)$$

- If one integrates the derivative field along any closed curve, one expects to get back to the starting value.
- Might not happen because of noisy estimates of (p,q)

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What might go wrong?

Integrability. If $f(x,y)$ is the height function, we expect that

$$\frac{\partial}{\partial y} \frac{\partial f}{\partial x} = \frac{\partial}{\partial x} \frac{\partial f}{\partial y}$$

In terms of estimated gradient space (p,q) , this means:

$$\frac{\partial p}{\partial y} = \frac{\partial q}{\partial x}$$

But since p and q were estimated independently at each point as intersection of curves on three reflectance maps, equality is not going to exactly hold



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Horn's Method

["Robot Vision, B.K.P. Horn, 1986]

- Formulate estimation of surface height $z(x,y)$ from gradient field by minimizing cost functional:

$$\iint_{\text{Image}} (z_x - p)^2 + (z_y - q)^2 dx dy$$

where (p,q) are estimated components of the gradient while z_x and z_y are partial derivatives of best fit surface

- Solved using calculus of variations – iterative updating
- $z(x,y)$ can be discrete or represented in terms of basis functions.
- Integrability is naturally satisfied.

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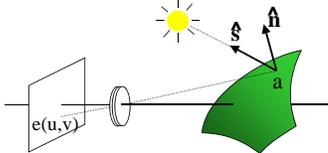
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2. Photometric Stereo: Lambertian Surface, Known Lighting

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Lambertian Surface



At image location (u,v) , the intensity of a pixel $x(u,v)$ is:

$$e(u,v) = [a(u,v) \hat{\mathbf{n}}(u,v)] \cdot [s_0 \hat{\mathbf{s}}] \\ = \mathbf{b}(u,v) \cdot \mathbf{s}$$

where

- $a(u,v)$ is the albedo of the surface projecting to (u,v) .
- $\hat{\mathbf{n}}(u,v)$ is the direction of the surface normal.
- s_0 is the light source intensity.
- $\hat{\mathbf{s}}$ is the direction to the light source.

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Lambertian Photometric stereo

- If the light sources $\mathbf{s}_1, \mathbf{s}_2,$ and \mathbf{s}_3 are known, then we can recover \mathbf{b} from as few as three images. (Photometric Stereo: Silver 80, Woodham81).

$$[e_1 \ e_2 \ e_3] = \mathbf{b}^T [\mathbf{s}_1 \ \mathbf{s}_2 \ \mathbf{s}_3]$$

- i.e., we measure $e_1, e_2,$ and e_3 and we know $\mathbf{s}_1, \mathbf{s}_2,$ and \mathbf{s}_3 . We can then solve for \mathbf{b} by solving a linear system.

$$\mathbf{b}^T = [e_1 \ e_2 \ e_3] [\mathbf{s}_1 \ \mathbf{s}_2 \ \mathbf{s}_3]^{-1}$$

- Normal $\hat{\mathbf{n}} = \mathbf{b}/|\mathbf{b}|$ and albedo $a = |\mathbf{b}|$

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What if we have more than 3 Images? Linear Least Squares

$$[e_1 \ e_2 \ e_3 \dots e_n] = \mathbf{b}^T [\mathbf{s}_1 \ \mathbf{s}_2 \ \mathbf{s}_3 \dots \mathbf{s}_n]$$

Rewrite as

$$\mathbf{e} = \mathbf{S}\mathbf{b}$$

where

- \mathbf{e} is n by 1
- \mathbf{b} is 3 by 1
- \mathbf{S} is n by 3

Solving for \mathbf{b} gives

$$\mathbf{b} = (\mathbf{S}^T \mathbf{S})^{-1} \mathbf{S}^T \mathbf{e}$$

Let the residual be

$$\mathbf{r} = \mathbf{e} - \mathbf{S}\mathbf{b}$$

Squaring this:

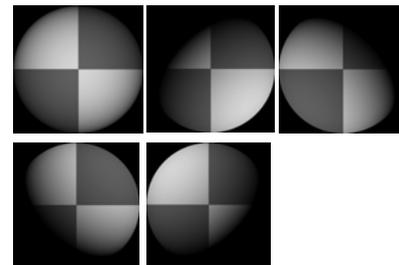
$$r^2 = \mathbf{r}^T \mathbf{r} = (\mathbf{e} - \mathbf{S}\mathbf{b})^T (\mathbf{e} - \mathbf{S}\mathbf{b}) \\ = \mathbf{e}^T \mathbf{e} - 2\mathbf{b}^T \mathbf{S}^T \mathbf{e} + \mathbf{b}^T \mathbf{S}^T \mathbf{S} \mathbf{b}$$

$(r^2)_{\mathbf{b}} = 0$ - zero derivative is a necessary condition for a minimum, or $-2\mathbf{S}^T \mathbf{e} + 2\mathbf{S}^T \mathbf{S} \mathbf{b} = 0$;

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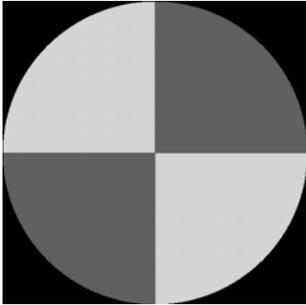
Input Images



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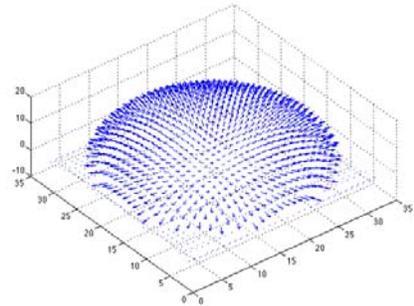
Recovered albedo



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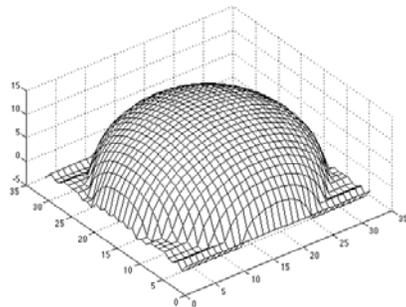
Recovered normal field



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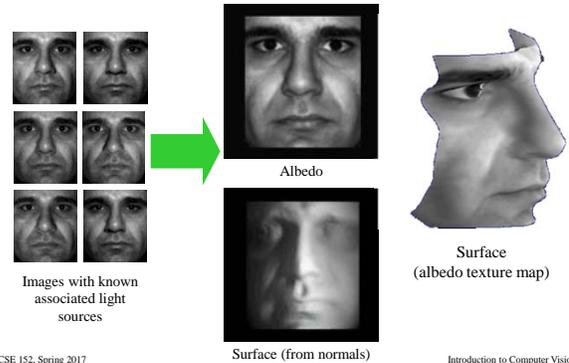
Surface recovered by integration



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An example of photometric stereo



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Next Lecture

- Binary image processing
- Reading:
 - Szeliski, Chapter 3 Image processing, Section 3.3 More neighborhood operators

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