

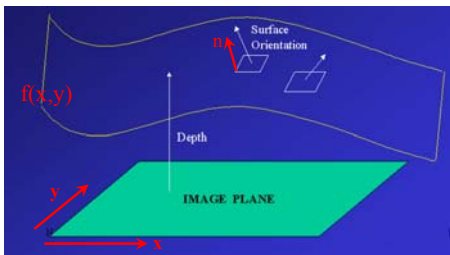
# Photometric Stereo Recap

## Computer Vision I CSE252A Lecture 8a

# Announcements

- HW1 due today

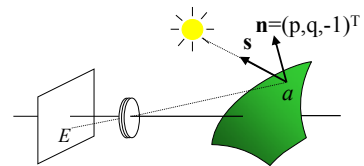
# Coordinate system



Gradient Space:  $(p, q)$   
 $p = \frac{\partial f}{\partial x}, q = \frac{\partial f}{\partial y}$

Normal vector  
 $\mathbf{n} = \frac{\partial s}{\partial x} \times \frac{\partial s}{\partial y} = \left( \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, -1 \right)^T$   
 $\hat{\mathbf{n}} = \frac{1}{\sqrt{p^2 + q^2 + 1}} (p, q, -1)^T$

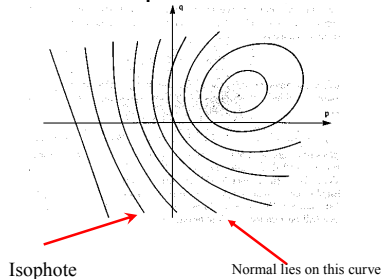
# Reflectance map



For known BRDF, fix light source direction/strength and projection direction

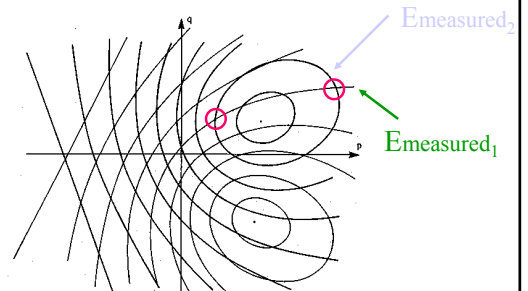
1. Then image irradiance is a function of only the direction of the surface normal.
2. In gradient space, we have  $E(p, q)$  which is known as the reflectance map

# Reflectance Map of Lambertian Surface



What does the value of one pixel in one image tell us?  
 It constrains normal to a curve

# Two Light Sources Two reflectance maps

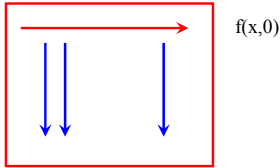


Third image would disambiguate match

## Recovering the surface $f(x,y)$

Many methods: Simplest approach

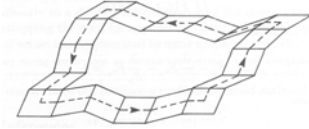
1. From estimate  $\mathbf{n}=(n_x, n_y, n_z)$ ,  $p=n_x/n_z$ ,  $q=n_y/n_z$
2. Integrate  $p=df/dx$  along a row  $(x,0)$  to get  $f(x,0)$
3. Then integrate  $q=df/dy$  along each column starting with value of first row



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## What might go wrong?



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

$$z(x,y) = z(x_0, y_0) + \int_{(x_0, y_0)}^{(x,y)} (p dx + q dy)$$

- 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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## 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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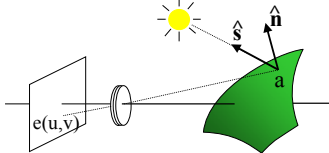
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## II. Photometric Stereo: Lambertian Surface, Known Lighting

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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  $(u,v)$ .
- $\mathbf{n}(u,v)$  is the direction of the surface normal.
- $s_0$  is the light source intensity.
- $\mathbf{s}$  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 is:  $\mathbf{n} = \mathbf{b}/|\mathbf{b}|$ , albedo is:  $|\mathbf{b}|$

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

$$[e_1 \ e_2 \ e_3] = \mathbf{b}^T [s_1 \ s_2 \ s_3]$$

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

Let the residual be

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

Squaring this:

$$\begin{aligned} |\mathbf{r}|^2 &= \mathbf{r}^T \mathbf{r} = (\mathbf{e} - \mathbf{S}\mathbf{b})^T (\mathbf{e} - \mathbf{S}\mathbf{b}) \\ &= \mathbf{e}^T \mathbf{e} - 2\mathbf{b}^T \mathbf{S}^T \mathbf{e} + \mathbf{b}^T \mathbf{S}^T \mathbf{S} \mathbf{b} \end{aligned}$$

$$\frac{\partial |\mathbf{r}|^2}{\partial \mathbf{b}} = 0 \quad \text{- zero derivative is a necessary condition for a minimum, or}$$

$$-2\mathbf{S}^T \mathbf{e} + 2\mathbf{S}^T \mathbf{S} \mathbf{b} = 0;$$

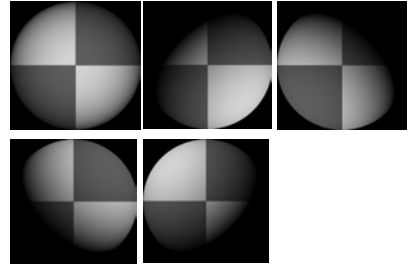
Solving for  $\mathbf{b}$  gives

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

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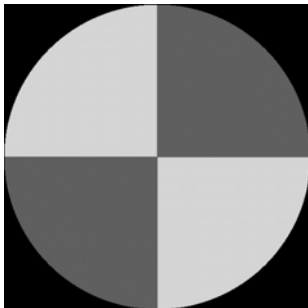
## Input Images



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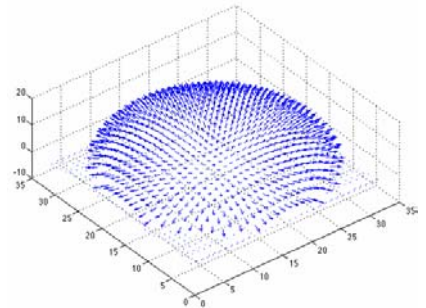
## Recovered albedo



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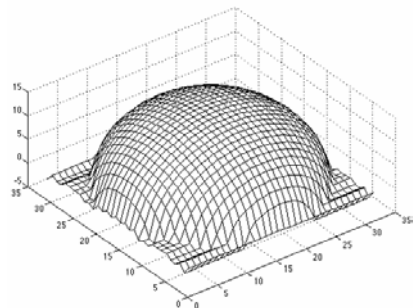
## Recovered normal field



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## Surface recovered by integration



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