

Photometric Stereo

Computer Vision I CSE252A Lecture 7

CS252A, Fall 2014

Computer Vision I

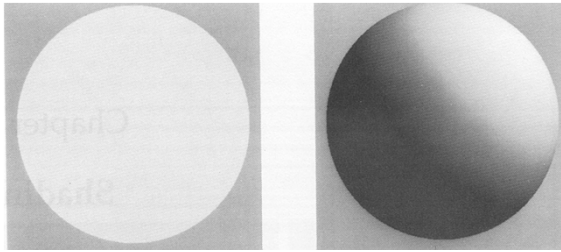
Announcements

- Read Chapter 2 of Forsyth & Ponce
- Instructor office hours
 - Tuesdays 6:30 PM-7:30 PM
 - Library (for now)
- Homework 1 is due today by 11:59 PM

CS252A, Fall 2014

Computer Vision I

Shading reveals 3-D surface geometry



CS252A, Fall 2014

Computer Vision I

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.

CS252A, Fall 2014

Computer Vision I

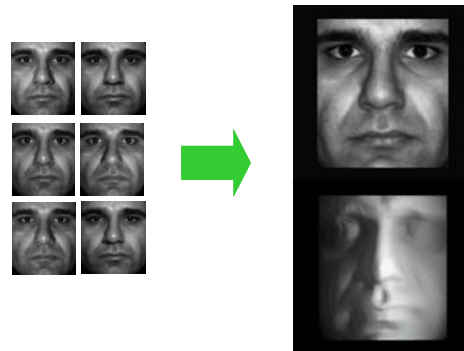
Photometric Stereo Rigs: One viewpoint, changing lighting



CS252A, Fall 2014

Computer Vision I

An example of photometric stereo



CS252A, Fall 2014

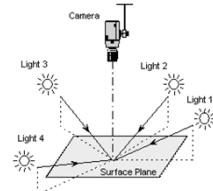
Computer Vision I

Multi-view stereo vs. Photometric Stereo:
Assumptions

- Multi-view Stereo
 - Multiple images
 - Dynamic scene
 - Multiple viewpoints
 - Fixed lighting
- Photometric Stereo
 - Multiple images
 - Static scene
 - Fixed viewpoint
 - Multiple lighting conditions

CS252A, Fall 2014 Computer Vision I

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.

CS252A, Fall 2014 Computer Vision I

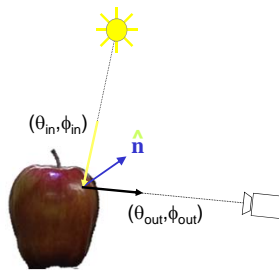
I. Photometric Stereo: General BRDF and Reflectance Map

CS252A, Fall 2014 Computer Vision I

BRDF

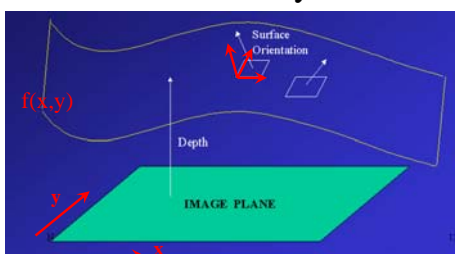
- Bi-directional Reflectance Distribution Function

$$\rho(\theta_{in}, \phi_{in}; \theta_{out}, \phi_{out})$$
- Function of
 - Incoming light direction: θ_{in}, ϕ_{in}
 - Outgoing light direction: θ_{out}, ϕ_{out}
- Ratio of incident irradiance to emitted radiance



CS252A, Fall 2014 Computer Vision I

Coordinate system

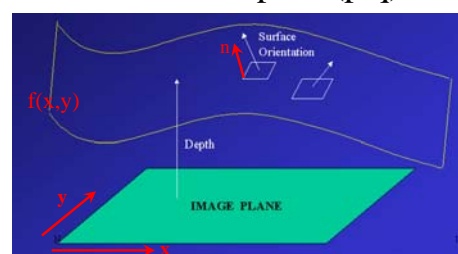


Surface: $s(x,y) = (x, y, f(x,y))$
 Tangent vectors: $\frac{\partial s(x,y)}{\partial x} = \left(1, 0, \frac{\partial f}{\partial x}\right)$
 $\frac{\partial s(x,y)}{\partial y} = \left(0, 1, \frac{\partial f}{\partial y}\right)$

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

CS252A, Fall 2014 Computer Vision I

Gradient Space (p,q)



Gradient Space : (p,q)

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

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

CS252A, Fall 2014 Computer Vision I

Image Formation

For a given point A on the surface, 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

CS252A, Fall 2014 Computer Vision I

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 $E(p,q)$.

CS252A, Fall 2014 Computer Vision I

Example Reflectance Map: Lambertian surface

For lighting from front

CS252A, Fall 2014 Computer Vision I

LAMBERTIAN REFLECTANCE MAP

$$E = L\rho \frac{1 + pp_s + qq_s}{\sqrt{1+p^2+q^2} \sqrt{1+p_s^2+q_s^2}}$$

Light Source Direction,
expressed in gradient space.

CS252A, Fall 2014 Computer Vision I

Reflectance Map of Lambertian Surface

E.g., Normal lies on this curve

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

CS252A, Fall 2014 Computer Vision I

Two Light Sources Two reflectance maps

E.g., Normal lies on this curve

A third image would disambiguate match

CS252A, Fall 2014 Computer Vision I

Three Source Photometric stereo: Step1


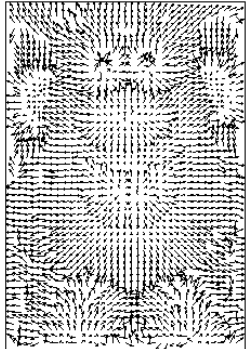
Offline:
Using source directions & BRDF, construct reflectance map for each light source direction. $R_1(p,q)$, $R_2(p,q)$, $R_3(p,q)$

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


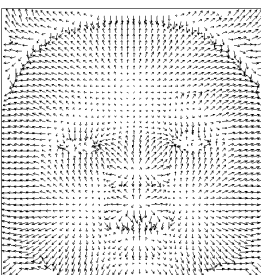
CS252A, Fall 2014 Computer Vision I

Normal Field


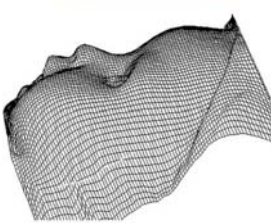
CS252A, Fall 2014 Computer Vision I

Plastic Baby Doll: Normal Field

CS252A, Fall 2014 Computer Vision I

Next step: Go from normal field to surface

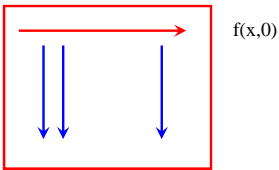



CS252A, Fall 2014 Computer Vision I

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



CS252A, Fall 2014 Computer Vision I

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)

CS252A, Fall 2014 Computer Vision I

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



CS252A, Fall 2014

Computer Vision I

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.

CS252A, Fall 2014

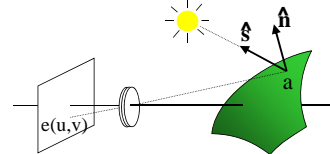
Computer Vision I

II. Photometric Stereo: Lambertian Surface, Known Lighting

CS252A, Fall 2014

Computer Vision I

Lambertian Surface



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

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

where

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

CS252A, Fall 2014

Computer Vision I

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: $|\mathbf{b}|$

CS252A, Fall 2014

Computer Vision I

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

$$\mathbf{e} = \mathbf{Sb}$$

where

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

Let the residual be

$$\mathbf{r} = \mathbf{e} - \mathbf{Sb}$$

Squaring this:

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

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

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

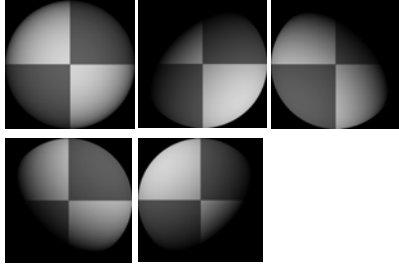
Solving for \mathbf{b} gives

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

CS252A, Fall 2014

Computer Vision I

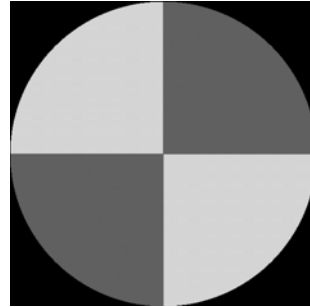
Input Images



CS252A, Fall 2014

Computer Vision I

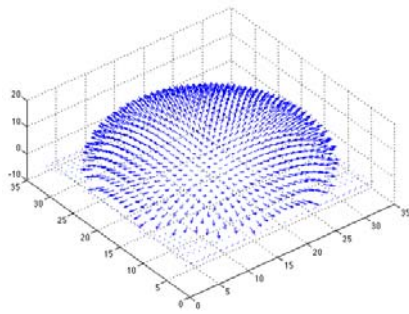
Recovered albedo



CS252A, Fall 2014

Computer Vision I

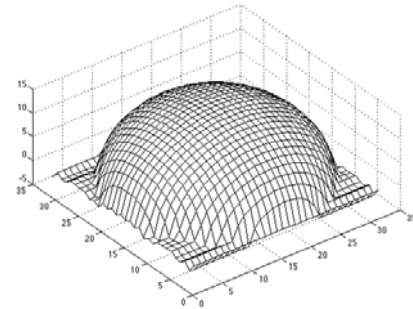
Recovered normal field



CS252A, Fall 2014

Computer Vision I

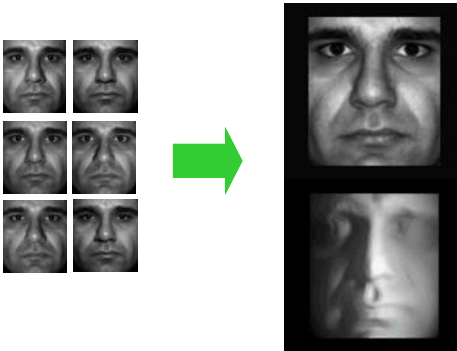
Surface recovered by integration



CS252A, Fall 2014

Computer Vision I

An example of photometric stereo



CS252A, Fall 2014

Computer Vision I

III. Photometric Stereo with unknown lighting and Lambertian surfaces

Covered in Illumination cone slides

CS252A, Fall 2014

Computer Vision I