

# Photometric Stereo

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## 1 Definitions and Notations

Suppose we have  $M$  images that are indexed by  $i$ , and each image has  $N$  pixels that are indexed by  $j$ . The intensity of  $j$ -th pixel in  $i$ -th image is therefore denoted as  $I_{i,j}$ .

At  $j$ -th pixel, denote  $\mathbf{n}_j$  the surface normal,  $\rho_j$  the albedo, and  $\mathbf{b}_j = \rho_j \mathbf{n}_j$  the scaled normal. Note that these quantities are the same across all images and therefore independent of  $i$ .

Each image comes from a different lighting environment, which has a different rendering function  $\mathcal{R}_i(\cdot)$ , written as

$$I_{i,j} = \rho_j \mathcal{R}_i(\mathbf{n}_j), \quad (1)$$

and we consider following rendering models in this note.

1. Directional lighting (distant point light source)

$$\mathcal{R}_i(\mathbf{n}) = \max\{\ell_i^\top \mathbf{n}, 0\}. \quad (2)$$

2. Directional lighting plus an ambient component (first order spherical harmonics<sup>1</sup>)

$$\mathcal{R}_i(\mathbf{n}) = \max\{\ell_i^\top \mathbf{n} + \alpha_i, 0\}. \quad (3)$$

We also define

$$\lambda_i = \|\ell_i\|, \quad \hat{\ell}_i = \frac{\ell_i}{\lambda_i}, \quad (4)$$

where  $\lambda_i$  is the strength of  $i$ -th lighting, and  $\hat{\ell}_i$  is a unit vector for direction of  $i$ -th lighting.

The goal of photometric stereo is to recover the scene property  $\{\rho_j, \mathbf{n}_j\}$  from the intensity measurements  $I_{i,j}$ , given (fully or partially) calibrated lighting environment  $\mathcal{R}_i(\cdot)$ .

## 2 Fully Calibrated Lighting

### 2.1 Directional lighting

For notational simplicity, we first only consider pixels that are not in shadow, and drop the  $\max\{\cdot, 0\}$  part of the rendering function

$$I_{i,j} = \rho_j \ell_i^\top \mathbf{n}_j = \ell_i^\top \mathbf{b}_j. \quad (5)$$

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<sup>1</sup>The first order spherical harmonics model sometimes does not have the  $\max\{\cdot, 0\}$  part.

Define  $\mathbf{I}_j \in \mathbb{R}^{M \times 1}$  the (vertical) concatenation of all  $I_{i,j}$  for  $1 \leq i \leq M$ , and  $\mathbf{L} \in \mathbb{R}^{3 \times M}$  the (horizontal) concatenation of all  $\ell_i$ . Then we have

$$\mathbf{I}_j = \mathbf{L}^\top \mathbf{b}_j, \quad (6)$$

where  $\mathbf{I}_j$  are measured intensities,  $\mathbf{L}^\top$  are calibrated lighting parameters, and  $\mathbf{b}_j$  is the unknown scene property, which can be easily solved in the least squares manner

$$\mathbf{b}_j = (\mathbf{L}^\top)^\dagger \mathbf{I}_j = (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} \mathbf{I}_j. \quad (7)$$

And finally, we can recover  $\rho_j$  and  $\mathbf{n}_j$  as

$$\rho_j = \|\mathbf{b}_j\|, \quad \mathbf{n}_j = \frac{\mathbf{b}_j}{\rho_j}. \quad (8)$$

## 2.2 Directional lighting with an ambient component

The rendering equation in this model can be written as

$$I_{i,j} = \rho_j (\ell_i^\top \mathbf{n}_j + \alpha_i) = \ell_i^\top \mathbf{b}_j + \alpha_i \|\mathbf{b}_j\|. \quad (9)$$

Then we can formulate estimation of scene property as the following optimization problem

$$\min_{\mathbf{b}_j} \sum_{i=1}^M \left( I_{i,j} - \ell_i^\top \mathbf{b}_j - \alpha_i \|\mathbf{b}_j\| \right)^2. \quad (10)$$

Unfortunately, we do not have a fast (non-iterative) algorithm for solving this problem yet.

## 3 Partially Calibrated Lighting

In reality, we can usually calibrate part of the lighting property accurately. For example, using a chrome sphere, we are able to calibrate the lighting directions  $\hat{\ell}_i$ , but not their strengths  $\lambda_i$ . Therefore, we also need to estimate the unknown lighting parameters  $\lambda_i$  from the measurements  $I_{i,j}$ .

Since the number of images  $M$  is much smaller than the number of pixels  $N$ , the number of unknown lighting parameters is also much smaller than number of scene property parameters. We define a cost function on lighting parameters

$$\text{cost}(\{\lambda_i\}) = \min_{\{\rho_j, \mathbf{n}_j\}} \sum_{i=1}^M \sum_{j=1}^N (I_{i,j} - \rho_j \mathcal{R}_i(\mathbf{n}_j))^2, \quad (11)$$

where the minimization can be solved as a fully-calibrated problem described in previous section. We can then perform a optimization on this cost to find the optimal lighting parameters  $\{\lambda_i\}$ .

### 3.1 Directional lighting

We give the specific form of lighting strength estimation under the directional lighting model. The cost function to be minimized is

$$\text{cost}(\{\lambda_i\}) = \min_{\{\rho_j, \mathbf{n}_j\}} \sum_{i=1}^M \sum_{j=1}^N \left( I_{i,j} - \lambda_i \rho_j \hat{\ell}_i^\top \mathbf{n}_j \right)^2 = \sum_{j=1}^M \min_{\mathbf{b}_j} \|\mathbf{I}_j - \mathbf{L}(\boldsymbol{\lambda})^\top \mathbf{b}_j\|^2, \quad (12)$$

where

$$\mathbf{L}(\boldsymbol{\lambda}) = \begin{bmatrix} \lambda_1 \hat{\ell}_1 & \cdots & \lambda_M \hat{\ell}_M \end{bmatrix}. \quad (13)$$

The minimization over  $\mathbf{b}_j$  inside the sum can be analytically solved by a linear least squares, resulting in a cost function

$$\text{cost}(\{\lambda_i\}) = \sum_{j=1}^M \|\mathbf{I}_j - \mathbf{L}(\boldsymbol{\lambda})^\top (\mathbf{L}(\boldsymbol{\lambda})\mathbf{L}(\boldsymbol{\lambda})^\top)^{-1} \mathbf{L}(\boldsymbol{\lambda}) \mathbf{I}_j\|^2. \quad (14)$$

This is a non-linear least squares problem that can be solved with a Levenberg-Marquardt algorithm. For completeness, we provide the gradient (Jacobian) of the cost function.

First, the partial derivative of matrix  $\mathbf{L}(\boldsymbol{\lambda})$  over  $\lambda_i$  is simply

$$\frac{\partial \mathbf{L}}{\partial \lambda_i} = \begin{bmatrix} \mathbf{0} & \dots & \mathbf{0} & \hat{\mathbf{e}}_i & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix}. \quad (15)$$

Now we define

$$\mathbf{f}_j = \mathbf{L}^\top (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} \mathbf{I}_j - \mathbf{I}_j, \quad (16)$$

and take partial derivative of  $\mathbf{f}_j$  with respect to  $\lambda_i$

$$\frac{\partial \mathbf{f}_j}{\partial \lambda_i} = \frac{\partial}{\partial \lambda_i} \left( \mathbf{L}^\top (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} \right) \mathbf{I}_j \quad (17)$$

$$= \left( \frac{\partial \mathbf{L}^\top}{\partial \lambda_i} (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} + \mathbf{L}^\top \frac{\partial (\mathbf{L}\mathbf{L}^\top)^{-1}}{\partial \lambda_i} \mathbf{L} + \mathbf{L}^\top (\mathbf{L}\mathbf{L}^\top)^{-1} \frac{\partial \mathbf{L}}{\partial \lambda_i} \right) \mathbf{I}_j \quad (18)$$

$$= \left( \frac{\partial \mathbf{L}^\top}{\partial \lambda_i} (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} + \mathbf{L}^\top \frac{\partial (\mathbf{L}\mathbf{L}^\top)^{-1}}{\partial \lambda_i} \mathbf{L} + \mathbf{L}^\top (\mathbf{L}\mathbf{L}^\top)^{-1} \frac{\partial \mathbf{L}}{\partial \lambda_i} \right) \mathbf{I}_j \quad (19)$$

$$= \left( \frac{\partial \mathbf{L}^\top}{\partial \lambda_i} (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} - \mathbf{L}^\top (\mathbf{L}\mathbf{L}^\top)^{-1} \frac{\partial (\mathbf{L}\mathbf{L}^\top)}{\partial \lambda_i} (\mathbf{L}\mathbf{L}^\top)^{-1} \mathbf{L} + \mathbf{L}^\top (\mathbf{L}\mathbf{L}^\top)^{-1} \frac{\partial \mathbf{L}}{\partial \lambda_i} \right) \mathbf{I}_j. \quad (20)$$

The last step is based on the fact that for any invertible matrix  $\mathbf{A}$  that depends on a parameter  $t$ , we have [1]

$$\frac{d\mathbf{A}^{-1}}{dt} = -\mathbf{A}^{-1} \frac{d\mathbf{A}}{dt} \mathbf{A}^{-1}. \quad (21)$$

In fact, this calculation can be used to estimate or improve any/all component(s) of the lighting matrix  $\mathbf{L}$ , not restricting to its strength  $\boldsymbol{\lambda}$ .

## References

- [1] Wikipedia, “Plagiarism — Wikipedia, the free encyclopedia,” 2014, [Online; accessed 08-February-2014]. [Online]. Available: [http://en.wikipedia.org/wiki/Invertible\\_matrix](http://en.wikipedia.org/wiki/Invertible_matrix)