

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, ρ_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)

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

2. Directional lighting plus an ambient component (first order spherical harmonics¹)

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

We also define

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

where λ_i is the strength of i -th lighting, and $\hat{\boldsymbol{\ell}}_i$ 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

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

¹The 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 ℓ_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 ρ_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 λ_i . Therefore, we also need to estimate the unknown lighting parameters λ_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

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

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 λ_i is simply

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

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 λ_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]

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

References

- [1] Wikipedia. Plagiarism — Wikipedia, the free encyclopedia, 2014. [Online; accessed 08-February-2014].