Defocus Deblurring and Superresolution for Time-of-Flight Depth Cameras (Supplementary)

Lei Xiao^{2,1} Felix Heide^{2,1} Matthew O'Toole³ Andreas Kolb⁴ Matthias B. Hullin⁵ Kyros Kutulakos³ Wolfgang Heidrich^{1,2} ¹KAUST ²University of British Columbia ³University of Toronto ⁴University of Siegen ⁵University of Bonn

1. Algorithm Details

This section provides implementation details for Algo. 2 (Amplitude update) and Algo. 3 (Depth update) in the main paper. The symbol ∇ defines the derivative operator, T defines the matrix transpose, and I defines the identity matrix.

Algo. 2, Line 2:

$$\mathbf{a} = \underset{\mathbf{a}}{\operatorname{argmin}} \rho ||\mathbf{c} - \mathbf{A}\mathbf{a}||_2^2 + \lambda_1 \rho_a ||\nabla \mathbf{a} - \mathbf{y} - \mathbf{p}_1 + \mathbf{u}_1||_2^2$$
(1)

equals to the solution of the linear equation system:

$$(\rho \mathbf{A}^{\mathsf{T}} \mathbf{A} + \lambda_1 \rho_a \nabla^{\mathsf{T}} \nabla) \mathbf{a} = \rho \mathbf{A}^{\mathsf{T}} \mathbf{c} + \lambda_1 \rho_a \nabla^{\mathsf{T}} (\mathbf{y} + \mathbf{p}_1 - \mathbf{u}_1)$$
(2)

and we solve it by the left division function in Matlab.

Algo. 2, Line 3:

$$\mathbf{y} = \underset{\mathbf{y}}{\operatorname{argmin}} \lambda_1 ||\nabla \mathbf{a} - \mathbf{y} - \mathbf{p}_1 + \mathbf{u}_1||_2^2 + \lambda_2 ||\nabla \mathbf{y} - \mathbf{p}_2 + \mathbf{u}_2||_2^2$$
(3)

equals to the solution of the linear equation system:

$$(\lambda_1 \mathbf{I} + \lambda_2 \nabla^{\mathsf{T}} \nabla) \mathbf{y} = \lambda_1 (\nabla \mathbf{a} - \mathbf{p}_1 + \mathbf{u}_1) + \lambda_2 \nabla^{\mathsf{T}} (\mathbf{p}_2 - \mathbf{u}_2)$$
(4)

and solved by the left division function in Matlab.

Algo. 2, Line 4:

$$\mathbf{p}_{1} = \underset{\mathbf{p}_{1}}{\operatorname{argmin}} ||\mathbf{p}_{1}||_{1} + \rho_{a}||\nabla \mathbf{a} - \mathbf{y} - \mathbf{p}_{1} + \mathbf{u}_{1}||_{2}^{2}$$
(5)

is a soft shrinkage problem and has closed form solution:

$$\mathbf{p}_1 = \text{soft-shrinkage}(\nabla \mathbf{a} - \mathbf{y} + \mathbf{u}_1, \frac{0.5}{\rho_a})$$
(6)

where the soft-shrinkage operator is defined as:

soft-shrinkage
$$(\mathbf{x}, \epsilon) = \begin{cases} \mathbf{x} + \epsilon; \mathbf{x} < -\epsilon \\ \mathbf{0}; -\epsilon \le \mathbf{x} \le \epsilon \\ \mathbf{x} - \epsilon; \mathbf{x} > \epsilon \end{cases}$$
 (7)

Algo. 2, Line 5:

$$\mathbf{p}_2 = \underset{\mathbf{p}_2}{\operatorname{argmin}} ||\mathbf{p}_2||_1 + \rho_a ||\nabla \mathbf{y} - \mathbf{p}_2 + \mathbf{u}_2||_2^2$$
(8)

is a soft shrinkage problem and has closed form solution:

$$\mathbf{p}_2 = \text{soft-shrinkage}(\nabla \mathbf{y} + \mathbf{u}_2, \frac{0.5}{\rho_a})$$
(9)

Algo. 3, Line 2:

$$\mathbf{z} = \underset{\mathbf{z}}{\operatorname{argmin}} \overbrace{\rho || \mathbf{c} - \mathbf{a} \circ \mathbf{g}(\mathbf{z}) ||_{2}^{2}}^{\text{data fitting constraint}} + \overbrace{\tau_{1} \rho_{x} || \nabla \mathbf{z} - \mathbf{x} - \mathbf{q}_{1} + \mathbf{v}_{1} ||_{2}^{2}}^{\text{prior constraint}}$$
(10)

is a nonlinear least squares problem due to the nonlinearity of the modulation function g(z). We solve this problem by the Levenberg-Marquardt method implemented in the lsqnonlin(.) function in Matlab. We provide the analytical Jacobian for acceleration:

$$J(\mathbf{z}) = \begin{bmatrix} J_{data}(\mathbf{z}) \\ J_{prior} \end{bmatrix}$$
(11)

where the matrix $J_{data}(\mathbf{z})$ and J_{prior} define the Jacobian of the 1st (data fitting constraint) and 2nd (prior constraint) least squares in Eq. (10) respectively.

Since the 1st least squares are pixel-wise separable (benefit from our splitting method explained in Sec. 3.1 in the main paper), $J_{data}(\mathbf{z})$ is simply a diagonal matrix composed of:

$$-\mathbf{a}_{k} \cdot \frac{\partial \mathbf{g}(\mathbf{z}_{k})}{\partial \mathbf{z}_{k}} \cdot \sqrt{\rho}$$
(12)

where k is the pixel index. For the ToF cameras based on cosine model modulation (see Eq. (1) in the main paper), the diagonal element in Eq. (12) becomes:

$$-\mathbf{a}_{k} \cdot i \frac{4\pi f}{c} \cdot e^{i(\frac{4\pi f}{c} \cdot \mathbf{z}_{k})} \cdot \sqrt{\rho}$$
(13)

For arbitrary modulation waveforms in the future, the diagonal element in Eq. (12) can be estimated from calibration data. J_{prior} is simply the matrix version of the derivative operator ∇ multiplied by $\sqrt{\tau_1 \rho_x}$, which is independent of z.

Algo. 3, Line 3:

$$\mathbf{x} = \operatorname*{argmin}_{\mathbf{x}} \tau_1 ||\nabla \mathbf{z} - \mathbf{x} - \mathbf{q}_1 + \mathbf{v}_1||_2^2 + \tau_2 ||\nabla \mathbf{x} - \mathbf{q}_2 + \mathbf{v}_2||_2^2$$
(14)

equals to the solution of the linear equation system:

$$(\tau_1 \mathbf{I} + \tau_2 \nabla^{\mathsf{T}} \nabla) \mathbf{x} = \tau_1 (\nabla \mathbf{z} - \mathbf{q}_1 + \mathbf{v}_1) + \tau_2 \nabla^{\mathsf{T}} (\mathbf{q}_2 - \mathbf{v}_2)$$
(15)

and solved by the left division function in Matlab.

Algo. 3, Line 4:

$$\mathbf{q}_1 = \underset{\mathbf{q}_1}{\operatorname{argmin}} ||\mathbf{q}_1||_1 + \rho_x ||\nabla \mathbf{z} - \mathbf{x} - \mathbf{q}_1 + \mathbf{v}_1||_2^2$$
(16)

is a soft shrinkage problem and has closed form solution:

$$\mathbf{q}_1 = \text{soft-shrinkage}(\nabla \mathbf{z} - \mathbf{x} + \mathbf{v}_1, \frac{0.5}{\rho_x})$$
(17)

Algo. 3, Line 5:

$$\mathbf{q}_2 = \operatorname*{argmin}_{\mathbf{q}_2} ||\mathbf{q}_2||_1 + \rho_x ||\nabla \mathbf{x} - \mathbf{q}_2 + \mathbf{v}_2||_2^2$$
(18)

is a soft shrinkage problem and has closed form solution:

$$\mathbf{q}_2 = \text{soft-shrinkage}(\nabla \mathbf{x} + \mathbf{v}_2, \frac{0.5}{\rho_x})$$
(19)