Derivation of Jacobian Matrix in: Simultaneous Localization and Calibration

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Abstract

This supplementary document includes the complete derivation of Jacobian matrix in Section 2.2 of our CVPR 2014 paper "Simultaneous Localization and Calibration: Self-Calibration of Consumer Depth Cameras" [2].

1. Optimization Objective

As stated in the paper, the energy function $E(\mathbf{T}, C)$ is a function of the camera pose trajectory $\mathbf{T} = {\mathbf{T}_i}$ and a calibration function $C(\cdot)$. For every frame *i*, \mathbf{T}_i is a rigid transformation that maps the depth image D_i from its local coordinate frame to the global world frame. *C* is a trilinear interpolation function of a control lattice $\mathbf{V} = {\mathbf{v}_l} \subset \mathbb{P}^3$:

$$C(\mathbf{p}) = \sum_{l} \gamma_l(\mathbf{p}) C(\mathbf{v}_l), \qquad (1)$$

where $\{\gamma_l(\mathbf{p})\}\$ are trilinear interpolation coefficients. They are computed once for all input points and remain constant henceforth.

The energy function is defined as:

$$E(\mathbf{T}, C) = E_a(\mathbf{T}, C) + \lambda E_r(C), \qquad (2)$$

where $E_a(\mathbf{T}, C)$ is the alignment term that measures the point-to-plane distance between corresponding point pairs:

$$E_a(\mathbf{T}, C) = \sum_{i,j} \sum_{(\mathbf{p}, \mathbf{q}) \in \mathcal{K}_{i,j}} \left((\mathbf{p}' - \mathbf{q}') \cdot \mathbf{n}'_{\mathbf{p}} \right)^2.$$
(3)

Here the points \mathbf{p}' and \mathbf{q}' are points \mathbf{p} and \mathbf{q} , transformed from their local coordinate frames to the world frame. We ignore the distortion effect on normals and directly apply the rigid transformation \mathbf{T}_i on \mathbf{n}_p to obtain \mathbf{n}'_p :

$$\mathbf{p}' = \mathbf{T}_i C(\mathbf{p}), \tag{4}$$

$$\mathbf{q}' = \mathbf{T}_j C(\mathbf{q}), \tag{5}$$

$$\mathbf{n}'_{\mathbf{p}} \approx \mathbf{T}_i \mathbf{n}_{\mathbf{p}}.$$
 (6)

For clarity, let $\mathbf{e} = (\mathbf{p}, \mathbf{q})$ denote the corresponding point pair, Equation (3) can be written as:

$$E_a(\mathbf{T}, C) = \sum_{i,j} \sum_{\mathbf{e} \in \mathcal{K}_{i,j}} \left(r_a^{\mathbf{e}} \right)^2, \tag{7}$$

where

$$r_a^{\mathbf{e}} = (\mathbf{p}' - \mathbf{q}') \cdot \mathbf{n}_{\mathbf{p}}' \tag{8}$$

$$= \left(\mathbf{T}_i C(\mathbf{p}) - \mathbf{T}_j C(\mathbf{q})\right)^{\top} \mathbf{T}_i \mathbf{n}_{\mathbf{p}}.$$
 (9)

The regularization energy term $E_r(C)$ is inspired by elasticity theory [1, 3]:

$$E_r(C) = \sum_{\mathbf{v} \in \mathbf{V}} \sum_{\mathbf{u} \in \mathcal{N}_{\mathbf{v}}} \|C(\mathbf{u}) - {}^{\mathbf{v}} \mathbf{R}_{C(\mathbf{v})} \mathbf{u}\|^2, \qquad (10)$$

where $\mathcal{N}(\mathbf{v})$ is the set of neighbors of \mathbf{v} in \mathbf{V} and the transform ${}^{\mathbf{v}}\mathbf{R}_{C(\mathbf{v})} \in SE(3)$ is a local linearization of C at \mathbf{v} . Please refer to Section 3.2 of our ICCV 2013 paper [3] for detailed derivation of the regularization energy term.

2. Gauss-Newton Method

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We minimize $E(\mathbf{T}, C)$ using the Gauss-Newton method. Let \mathbf{x} be the vector of variables that includes all the parameters of \mathbf{T} and C. The calibration function C is parameterized by the calibrated position $C(\mathbf{v})$ of each lattice point \mathbf{v} . The transformations \mathbf{T}_i are parameterized by its local linearization during iteration, as described below.

In iteration 0 the variables are initialized with the vector \mathbf{x}^{0} that includes the camera poses from an initial rigid alignment of the input images $\{\mathcal{D}_i\}$ and a stationary function C that maps all the lattice points to themselves. In each subsequent iteration k + 1, for $k \ge 0$, we locally linearize \mathbf{T}_i around \mathbf{T}_i^k . Specifically, we parameterize \mathbf{T}_i by a 6-vector $\xi_i = (\alpha_i, \beta_i, \gamma_i, a_i, b_i, c_i)$ that represents an incremental transformation relative to \mathbf{T}_i^k . Here (a_i, b_i, c_i) is a translation vector, which we will denote by \mathbf{t}_i , and $(\alpha_i, \beta_i, \gamma_i)$ can be interpreted as angular velocity, denoted by ω_i . \mathbf{T}_i is approximated by a linear function of ξ_i :

$$\mathbf{T}_{i} \approx \begin{pmatrix} 1 & -\gamma_{i} & \beta_{i} & a_{i} \\ \gamma_{i} & 1 & -\alpha_{i} & b_{i} \\ -\beta_{i} & \alpha_{i} & 1 & c_{i} \\ 0 & 0 & 0 & 1 \end{pmatrix} \mathbf{T}_{i}^{k}.$$
 (11)

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The full parameter vector is updated in iteration k + 1 as follows¹:

$$\mathbf{x}^{k+1} = \mathbf{x}^k + \Delta \mathbf{x}.$$
 (12)

Here $\Delta \mathbf{x}$ is a vector that collates $\{\xi_i\}$ and $\{\Delta C(\mathbf{v})\}$. It is computed by solving the following linear system:

$$\mathbf{J}_{\mathbf{r}}^{\top}\mathbf{J}_{\mathbf{r}}\Delta\mathbf{x} = -\mathbf{J}_{\mathbf{r}}^{\top}\mathbf{r}.$$
 (13)

Here $\mathbf{r} = \mathbf{r}(\mathbf{x})$ is the residual vector that collects $\{r_a^{\mathbf{e}}\}$ and $\mathbf{J}_{\mathbf{r}} = \mathbf{J}_{\mathbf{r}}(\mathbf{x})$ is its Jacobian, both evaluated at \mathbf{x}^k . The detailed derivation of the Jacobian matrix will be given in Section 3.

Once the adjustment $\Delta \mathbf{x}$ is computed, $C^k(\mathbf{v})$ is straightforwardly updated by applying the additive increment $\Delta C(\mathbf{v})$:

$$C^{k+1}(\mathbf{v}) = C^k(\mathbf{v}) + \Delta C(\mathbf{v}).$$
(14)

To update the transformations, we apply Equation (11) and then map the transformation matrices back into the SE(3)group, i.e.,

$$\mathbf{T}_{i}^{k+1} = \begin{bmatrix} 1 & 0 & 0 & x_{i} \\ 0 & 1 & 0 & y_{i} \\ 0 & 0 & 1 & z_{i} \\ 0 & 0 & 0 & 1 \end{bmatrix}$$
(15)
$$\cdot \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos \alpha_{i} & -\sin \alpha_{i} & 0 \\ 0 & \sin \alpha_{i} & \cos \alpha_{i} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$
$$\cdot \begin{bmatrix} \cos \beta_{i} & 0 & \sin \beta_{i} & 0 \\ 0 & 1 & 0 & 0 \\ -\sin \beta_{i} & 0 & \cos \beta_{i} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$
$$\cdot \begin{bmatrix} \cos \gamma_{i} & -\sin \gamma_{i} & 0 & 0 \\ \sin \gamma_{i} & \cos \gamma_{i} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

In the next iteration, we re-parameterize T_i around \mathbf{T}_{i}^{k+1} and repeat.

3. Derivation of Jacobian Matrix

The partial derivative of $\{r_a^{\mathbf{e}}\}$ with respect to $C(\mathbf{v}_l)$ is straightforward using Equation (9) and (1):

$$\frac{\partial r_a^{\mathbf{e}}}{\partial C(\mathbf{v}_l)} = \left(\gamma_l(\mathbf{p})\mathbf{T}_i^k - \gamma_l(\mathbf{q})\mathbf{T}_j^k\right)^{\mathsf{T}}\mathbf{T}_i^k\mathbf{n}_{\mathbf{p}}.$$
 (16)

To derive the partial derivative of $\{r_a^{\mathbf{e}}\}$ with respect to ξ_i , we first derive the partial derivative of $f(\xi_i, \mathbf{u}) = \mathbf{T}_i \mathbf{u}$ and $\mathbf{g}(\xi_i, \mathbf{n}) = \mathbf{T}_i \mathbf{n}$, with respect to ξ_i . Here **u** is the homogeneous coordinate of any point and n is the homogeneous coordinate of any unit direction vector (normal). With Equation (11), we have:

$$\mathbf{f}(\xi_i, \mathbf{u}) = \mathbf{T}_i \mathbf{u} \quad \approx \quad \mathbf{T}_i^k \mathbf{u} + \omega_i \times \mathbf{T}_i^k \mathbf{u} + \mathbf{t}_i, \quad (17)$$

$$\mathbf{g}(\xi_i, \mathbf{n}) = \mathbf{T}_i \mathbf{n} \quad \approx \quad \mathbf{T}_i^k \mathbf{n} + \omega_i \times \mathbf{T}_i^k \mathbf{n}. \tag{18}$$

Let $[\mathbf{T}_i^k \mathbf{u}]_{\times}$ and $[\mathbf{T}_i^k \mathbf{n}]_{\times}$ be the skew-symmetric matrices form of the cross product with $\mathbf{T}_{i}^{k}\mathbf{u}$ and $\mathbf{T}_{i}^{k}\mathbf{n}$. The former equations can be written in the matrix multiplication form:

$$\mathbf{f}(\xi_i, \mathbf{u}) \approx \mathbf{T}_i^k \mathbf{u} + \left[-\left[\mathbf{T}_i^k \mathbf{u} \right]_{\times} \big| \mathbf{I} \right] \xi_i, \qquad (19)$$

$$\mathbf{g}(\xi_i, \mathbf{n}) \approx \mathbf{T}_i^k \mathbf{n} + \left[-\left[\mathbf{T}_i^k \mathbf{n}\right]_{\times} |\mathbf{0}| \xi_i, \quad (20)$$

where **I** is the 3×3 identity matrix and **0** is the 3×3 zero matrix. Their Jacobian matrices with respect to ξ_i are:

$$\frac{\partial \mathbf{f}}{\partial \xi_i} \approx \left[- \left[\mathbf{T}_i^k \mathbf{u} \right]_{\times} | \mathbf{I} \right], \qquad (21)$$

$$\frac{\partial \mathbf{g}}{\partial \xi_i} \approx \left[- \left[\mathbf{T}_i^k \mathbf{n} \right]_{\times} \big| \mathbf{0} \right].$$
 (22)

Using this result on Equation (4), (5), and (6), we have:

$$\frac{\partial \mathbf{p}'}{\partial \xi_i} \approx \left[-\left[\mathbf{T}_i^k C^k(\mathbf{p}) \right]_{\times} \left| \mathbf{I} \right], \quad \frac{\partial \mathbf{p}'}{\partial \xi_j} = \mathbf{0}, \qquad (23)$$
$$\frac{\partial \mathbf{q}'}{\partial \xi_i} = \mathbf{0}, \quad \frac{\partial \mathbf{q}'}{\partial \xi_i} \approx \left[-\left[\mathbf{T}_i^k C^k(\mathbf{q}) \right]_{\times} \left| \mathbf{I} \right], \qquad (24)$$

$$\frac{\partial \mathbf{q}'}{\partial \xi_i} = \mathbf{0}, \quad \frac{\partial \mathbf{q}'}{\partial \xi_j} \approx \left[-\left[\mathbf{T}_i^k C^k(\mathbf{q}) \right]_{\times} \left| \mathbf{I} \right], \quad (24)$$

$$\frac{\partial \mathbf{n}'_{\mathbf{p}}}{\partial \xi_i} \approx \left[- \left[\mathbf{T}_i^k \mathbf{n}_{\mathbf{p}} \right]_{\times} \left| \mathbf{0} \right], \quad \frac{\partial \mathbf{n}'_{\mathbf{p}}}{\partial \xi_j} = \mathbf{0}.$$
(25)

Using product rule, we have:

$$\frac{\partial \mathbf{r}_{a}^{\mathbf{e}}}{\partial \xi_{i}} = (\mathbf{p}' - \mathbf{q}')^{\mathsf{T}} \left(\frac{\partial \mathbf{n}'_{\mathbf{p}}}{\partial \xi_{i}} \right) + (\mathbf{n}'_{\mathbf{p}})^{\mathsf{T}} \left(\frac{\partial \mathbf{p}'}{\partial \xi_{i}} - \frac{\partial \mathbf{q}'}{\partial \xi_{i}} \right) \\
\approx \left[\mathbf{T}_{i}^{k} \mathbf{n}_{\mathbf{p}} \times \left(\mathbf{T}_{i}^{k} C^{k}(\mathbf{p}) - \mathbf{T}_{j}^{k} C^{k}(\mathbf{q}) \right) |\mathbf{0}] \\
+ \left[\mathbf{T}_{i}^{k} C^{k}(\mathbf{p}) \times \mathbf{T}_{i}^{k} \mathbf{n}_{\mathbf{p}} | \mathbf{T}_{i}^{k} \mathbf{n}_{\mathbf{p}} \right] \\
= \left[\mathbf{T}_{j}^{k} C^{k}(\mathbf{q}) \times \mathbf{T}_{i}^{k} \mathbf{n}_{\mathbf{p}} | \mathbf{T}_{i}^{k} \mathbf{n}_{\mathbf{p}} \right], \quad (26) \\
\frac{\partial \mathbf{r}_{a}^{\mathbf{e}}}{\partial \xi_{i}} = \left(\mathbf{p}' - \mathbf{q}' \right)^{\mathsf{T}} \left(\frac{\partial \mathbf{n}'_{\mathbf{p}}}{\partial \xi_{i}} \right) + \left(\mathbf{n}'_{\mathbf{p}} \right)^{\mathsf{T}} \left(\frac{\partial \mathbf{p}'}{\partial \xi_{i}} - \frac{\partial \mathbf{q}'}{\partial \xi_{i}} \right)$$

$$\frac{\partial \xi_j}{\partial \xi_j} = (\mathbf{p} - \mathbf{q}) \left(\frac{\partial \xi_j}{\partial \xi_j} \right) + (\mathbf{n}_{\mathbf{p}}) \left(\frac{\partial \xi_j}{\partial \xi_j} - \frac{\partial \xi_j}{\partial \xi_j} \right)$$
$$\approx \left[\mathbf{T}_i^k \mathbf{n}_{\mathbf{p}} \times \mathbf{T}_j^k C^k(\mathbf{q}) \right| - \mathbf{T}_i^k \mathbf{n}_{\mathbf{p}} \right].$$
(27)

References

- [1] R. W. Sumner, J. Schmid, and M. Pauly. Embedded deformation for shape manipulation. ACM Trans. Graph., 26(3), 2007.
- [2] Q.-Y. Zhou and V. Koltun. Simultaneous localization and calibration: Self-calibration of consumer depth cameras. In CVPR, 2014.
- [3] Q.-Y. Zhou, S. Miller, and V. Koltun. Elastic fragments for dense scene reconstruction. In ICCV, 2013.

¹Since $\{\xi_i\}$ are local linearization around \mathbf{T}_i^k , the corresponding part in \mathbf{x}^k is **0**.