Supplementary Material to: Direct Sparse Visual-Inertial Odometry with Stereo Cameras

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Content

Chapter1 Visual-inertial Preliminaries

In our main paper [Ⅳ], The term $\mathrm{J}_r(\boldsymbol{\xi})$ is the right Jacobian of $SE(3)$ can be calculated by (1.1).

$$
\begin{aligned}
&\mathtt{Exp}(\boldsymbol{\xi}^{\wedge}) = \mathbf{T} = \begin{pmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 0 \end{pmatrix}_{4\times4}, \mathtt{Exp}(\delta\boldsymbol{\xi}^{\wedge}) = \begin{pmatrix} \delta\boldsymbol{\phi}^{\wedge} & \delta\boldsymbol{\rho} \\ \mathbf{0}^T & 0 \end{pmatrix}_{4\times4}, \mathbf{p} \in \mathbb{R}^3 \\
&\frac{\partial(\mathbf{Tp})}{\partial\delta\boldsymbol{\xi}} = \lim_{\delta\boldsymbol{\xi}\to\mathbf{0}} \frac{\mathtt{Exp}(\boldsymbol{\xi}^{\wedge})\mathtt{Exp}(\delta\boldsymbol{\xi}^{\wedge})\mathbf{p} - \mathtt{Exp}(\boldsymbol{\xi}^{\wedge})\mathbf{p}}{\delta\boldsymbol{\xi}} \\
&\approx \lim_{\delta\boldsymbol{\xi}\to\mathbf{0}} \frac{\mathtt{Exp}(\boldsymbol{\xi}^{\wedge})(\mathbf{I} - \delta\boldsymbol{\xi}^{\wedge})\mathbf{p} - \mathtt{Exp}(\boldsymbol{\xi}^{\wedge})\mathbf{p}}{\delta\boldsymbol{\xi}} = \lim_{\delta\boldsymbol{\xi}\to\mathbf{0}} - \frac{\mathtt{Exp}(\boldsymbol{\xi}^{\wedge})\delta\boldsymbol{\xi}^{\wedge}\mathbf{p}}{\delta\boldsymbol{\xi}} \\
&= \lim_{\delta\boldsymbol{\xi}\to\mathbf{0}} - \frac{\begin{pmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 0 \end{pmatrix}\begin{pmatrix} \delta\boldsymbol{\phi}^{\wedge}\mathbf{p} + \delta\boldsymbol{\rho} \\ 1 \end{pmatrix}}{\delta\boldsymbol{\xi}} = \lim_{\delta\boldsymbol{\xi}\to\mathbf{0}} - \frac{\begin{pmatrix} \mathbf{R}\delta\boldsymbol{\phi}^{\wedge}\mathbf{p} + \mathbf{R}\delta\boldsymbol{\rho} + \mathbf{t} \\ \mathbf{0}^T \end{pmatrix}}{\delta\boldsymbol{\xi}} \\
&= \lim_{\delta\boldsymbol{\xi}\to\mathbf{0}} - \frac{\begin{pmatrix} -\mathbf{R}\mathbf{p}^{\wedge}\delta\boldsymbol{\phi} + \mathbf{R}\delta\boldsymbol{\rho} + \mathbf{t} \\ \mathbf{0}^T \end{pmatrix}}{\begin{pmatrix} \delta\boldsymbol{\rho} \\ \delta\boldsymbol{\phi} \end{pmatrix}} = \begin{pmatrix} -\mathbf{R} & \mathbf{R}\mathbf{p}^{\wedge} \\ \mathbf{0}^T & \mathbf{0}^T \end{pmatrix}_{4\times6}
\end{aligned} \tag{1.1}
$$

Homogeneous camera calibration matrices are denoted by $\mathbf{K}$ as (1.2.1). and homogeneous 2D image coordinate point $\mathbf{p}$ is represented by its image coordinate and inverse depth as (1.2.3) relative to its host keyframe i^L. Corresponding homogeneous 3D camera coordinate point $\mathbf{p}_{\mathtt{C}}$ is denoted as (1.2.4). $\Pi_{\mathbf{K}}$ are used to denote camera projection functions. The jacobian of $\mathtt{I}_i^L$, $\Pi_{\mathbf{K}}$ is denoted as (1.5)

$$
\begin{aligned}
&\mathbf{K} = \begin{pmatrix} f_x & 0 & c_x & 0 \\ 0 & f_y & c_y & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \mathbf{K}^{-1} = \begin{pmatrix} f_x^{-1} & 0 & -f_x^{-1}c_x & 0 \\ 0 & f_y^{-1} & -f_y^{-1}c_y & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}, \\
&\mathbf{p} = \begin{pmatrix} u^i \\ v^i \\ 1 \\ d_{\mathbf{p}} \end{pmatrix}, \mathbf{p}_{\mathtt{C}} = \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}, d_{\mathbf{p}} = z^{-1}, \mathbf{p} = d_{\mathbf{p}}\mathbf{K}\mathbf{p}_{\mathtt{C}} = \Pi_{\mathbf{K}}(\mathbf{p}_{\mathtt{C}}) \qquad (1.2) \\
&\frac{\partial(\mathtt{I}_i^L(\mathbf{p}))}{\partial\mathbf{p}} = (g_x, g_y, 0, 0), \frac{\partial\mathbf{p}}{\partial\mathbf{p}_{\mathtt{C}}} = \frac{\partial\Pi_{\mathbf{K}}(\mathbf{p}_{\mathtt{C}})}{\partial\mathbf{p}_{\mathtt{C}}} = \begin{pmatrix} f_x z^{-1} & 0 & -x f_x z^{-2} & 0 \\ 0 & f_y z^{-1} & -y f_y z^{-2} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & z^{-2} & 0 \end{pmatrix}
\end{aligned}
$$

Chapter2 IMU Error Factors

1.1 Time-closest measurements selection strategy

Because of asynchronous but same frequency for accelerometer and gyroscope data, there will be different quantity samples of these two sensors between two consecutive keyframes. We select time-closest gyroscope measurement for one accelerometer measurement accordind to (Alg.1)

Algorithm 1 Time-closest measurements selection

Input: $gyro\_list$,$acc\_list[s]$(an element in acc_list)
Output: $gyro\_measure$(time closest element in gyro_list)

function TIME_CLOSEST_SELECT($gyro\_list, i$)
    $t \leftarrow acc\_list[s].timestamp, i \leftarrow s$
    while $true$ **do**
        if $i >= gyro\_list.size$ **then**
            return $gyro\_list.back$
        else
            $t_{now} \leftarrow gyro\_list[i].timestamp$
            $t_{next} \leftarrow gyro\_list[i+1].timestamp$
            if $t_{now} < t$ **then**
                if $t_{next} > t$ **then**
                    $t_{front} \leftarrow abs(t_{now} - t), t_{back} \leftarrow abs(t_{next} - t)$
                    return $t_{front} > t_{back} ? gyro\_list[i+1] : gyro\_list[i]$
                else
                    $i = i + 1$
                end if
            else if $t_{now} > t$ **then**
                $i = i - 1$
            else
                return $gyro\_list[i]$
            end if
        end if
    end while
end function

1.2 Errors and covariance calculation pseudo code

In our main paper [Fig. 2], we can get gyroscope, accelerometer data lists whose size is m, n. We have 8 error items to define:

$\Delta\bar{\mathbf{R}}_{ij}$, $\frac{\partial\Delta\bar{\mathbf{R}}_{ij}}{\partial\mathbf{b}^g}$, $\frac{\partial\Delta\bar{\mathbf{v}}_{ij}}{\partial\mathbf{b}^a}$, $\frac{\partial\Delta\bar{\mathbf{p}}_{ij}}{\partial\mathbf{b}^a}$ aren't related to accelerometer data.

$\Delta\bar{\mathbf{v}}_{ij}$, $\frac{\partial\Delta\bar{\mathbf{v}}_{ij}}{\partial\mathbf{b}^g}$, $\Delta\bar{\mathbf{p}}_{ij}$, $\frac{\partial\Delta\bar{\mathbf{p}}_{ij}}{\partial\mathbf{b}^g}$ are related to both gyroscope and accelerometer data.

1.3 Jacobian derivation

Chapter3 Photo Error Factors

3.1 Construction residual errors

Dynamic multi-view stereo residuals $E_{ij}^{\mathbf{p}}$ are defined as

$$E_{ij}^{\mathbf{p}} = w_{\mathbf{p}} ||(r_{\mathbf{p}}^{d})_{ij}||_{\gamma}, \quad (r_{\mathbf{p}}^{d})_{ij} := I_j^L(\mathbf{p}') - b_j^L - \frac{e^{a_j^L}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L) \tag{2.2}$$

γ is Huber norm. a_i^L, b_i^L is affine brightness parameters to frame iL . $w_{\mathbf{p}}$ is a gradient-dependent weighting parameters, $\mathbf{p}$ in frame I_i^L projected to I_j^L is p' as:

$$w_{\mathbf{p}} := \frac{c^2}{c^2 + ||\nabla I_i(\mathbf{p})||_2^2}, \quad \mathbf{p}' = d_{\mathbf{p}}^{jL}\mathbf{K}(\mathbf{T}_j\mathbf{T}_i^{-1}((d_{\mathbf{p}}^{iL})^{-1}\mathbf{K}^{-1}\mathbf{p})) \tag{2.3}$$

Static one-view stereo residuals $E_{is}^{\mathbf{p}}$ are modified to

$$E_{is}^{\mathbf{p}} = w_{\mathbf{p}} ||r_{\mathbf{p}}^{s}||_{\gamma}, \quad r_{\mathbf{p}}^{s} := I_i^R(\mathbf{p}') - b_i^R - \frac{e^{a_i^R}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L) \tag{2.2}$$

Hostframe of $\mathbf{p}$ is I_i^L. a_i^R, b_i^R is affine brightness parameters to frame iR. $\mathbf{p}$ in frame I_i^L projected to I_i^R is p' as :

$$\mathbf{p}' = d_{\mathbf{p}}^{iR}\mathbf{K}(\mathbf{T}_{RL}((d_{\mathbf{p}}^{iL})^{-1}\mathbf{K}^{-1}\mathbf{p})) \tag{2.2}$$

Total residuals

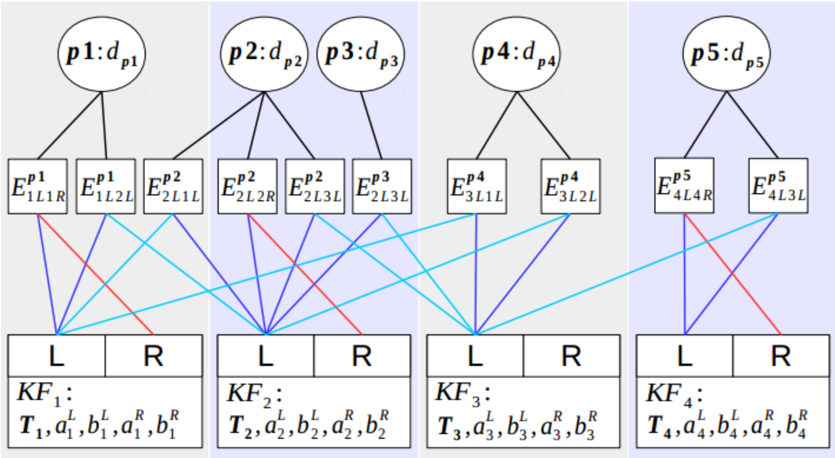
$$E(\delta) = \sum_{i \in \mathcal{F}} \sum_{\mathbf{p} \in \mathcal{P}_i} \Big(\sum_{j \in obs^t(\mathbf{P})} E_{ij}^{\mathbf{p}} + \lambda E_{is}^{\mathbf{p}} \Big) \tag{2.2}$$

$$\boldsymbol{\delta} = \begin{pmatrix} (\boldsymbol{\xi}_1^T, \ldots, \boldsymbol{\xi}_{N_f}^T)^T \\ (d_{\mathbf{p}_1}, \ldots, d_{\mathbf{p}_{N_p}})^T \\ (a_1^L, a_1^R, b_1^L, b_1^R)^T \\ \vdots \\ (a_{N_f}^L, a_{N_f}^R, b_{N_f}^L, b_{N_f}^R)^T \\ (f_x, f_y, c_x, c_y)^T \end{pmatrix} \in \mathbb{R}^{10N_f + N_p + 4}, \boldsymbol{\xi}_i = (ln\mathbf{T}_i)^{\vee} \in \mathbb{R}^6 \tag{2.1}$$

To balance the relative weights of temporal multi-view and static stereo, we introduce a coupling factor λ to weight the constraints from static stereo differently. $\mathcal{P}_i$ is a set of all image point host by frame iL. $obs^t(\mathrm{p})$ are the observations of $\mathbf{p}$ from temporal multi-view stereo. If there are N_p image point and N_f keyframes in $\boldsymbol{\mathcal{F}}$, optimization variable $\boldsymbol{\delta}$ is

In this example, there are 7 dynamic residuals and 3 static residuals, Factor graph of the residuals function is

Total residuals is



Iteration δ^* can be calculated by

$$
\begin{aligned}
E(\delta) &= E^{\mathbf{p}_1}_{1L2L} + E^{\mathbf{p}_2}_{2L1L} + E^{\mathbf{p}_2}_{2L3L} + E^{\mathbf{p}_3}_{2L3L} + E^{\mathbf{p}_4}_{3L1L} + E^{\mathbf{p}_4}_{3L2L} + E^{\mathbf{p}_5}_{4L3L} \\
&\quad + E^{\mathbf{p}_1}_{1L1R} + E^{\mathbf{p}_2}_{2L2R} + E^{\mathbf{p}_5}_{4L4R} \\
&= E_d(\delta) + E_s(\delta)
\end{aligned}
$$

$$
E_s(\delta) = \begin{pmatrix} r^s_{\mathbf{p}_1} \\ r^s_{\mathbf{p}_2} \\ r^s_{\mathbf{p}_5} \end{pmatrix}^T \begin{pmatrix} \lambda w_{\mathbf{p}_1} & 0 & 0 \\ 0 & \lambda w_{\mathbf{p}_2} & 0 \\ 0 & 0 & \lambda w_{\mathbf{p}_5} \end{pmatrix} \begin{pmatrix} r^s_{\mathbf{p}_1} \\ r^s_{\mathbf{p}_2} \\ r^s_{\mathbf{p}_5} \end{pmatrix} = (\mathbf{r}^s)^T \mathbf{W}^s \mathbf{r}^s
$$

$$
\mathbf{J}_s = \begin{pmatrix}
\frac{\partial r^s_{\mathbf{p}1}}{\partial \boldsymbol{\xi}_1} \cdots & \frac{\partial r^s_{\mathbf{p}1}}{\partial \boldsymbol{\xi}_4} & \frac{\partial r^s_{\mathbf{p}1}}{\partial d_{\mathbf{p}1}} \cdots & \frac{\partial r^s_{\mathbf{p}1}}{\partial d_{\mathbf{p}5}} & \frac{\partial r^s_{\mathbf{p}1}}{\partial a^L_1} \cdots & \frac{\partial r^s_{\mathbf{p}1}}{\partial b^R_4} & \frac{\partial r^s_{\mathbf{p}1}}{\partial f_x} \cdots & \frac{\partial r^s_{\mathbf{p}1}}{\partial c_y} \\
\frac{\partial r^s_{\mathbf{p}2}}{\partial \boldsymbol{\xi}_1} \cdots & \frac{\partial r^s_{\mathbf{p}2}}{\partial \boldsymbol{\xi}_4} & \frac{\partial r^s_{\mathbf{p}2}}{\partial d_{\mathbf{p}1}} \cdots & \frac{\partial r^s_{\mathbf{p}2}}{\partial d_{\mathbf{p}5}} & \frac{\partial r^s_{\mathbf{p}2}}{\partial a^L_1} \cdots & \frac{\partial r^s_{\mathbf{p}2}}{\partial b^R_4} & \frac{\partial r^s_{\mathbf{p}2}}{\partial f_x} \cdots & \frac{\partial r^s_{\mathbf{p}2}}{\partial c_y} \\
\frac{\partial r^s_{\mathbf{p}5}}{\partial \boldsymbol{\xi}_1} \cdots & \frac{\partial r^s_{\mathbf{p}5}}{\partial \boldsymbol{\xi}_4} & \frac{\partial r^s_{\mathbf{p}5}}{\partial d_{\mathbf{p}1}} \cdots & \frac{\partial r^s_{\mathbf{p}5}}{\partial d_{\mathbf{p}5}} & \frac{\partial r^s_{\mathbf{p}5}}{\partial a^L_1} \cdots & \frac{\partial r^s_{\mathbf{p}5}}{\partial b^R_4} & \frac{\partial r^s_{\mathbf{p}5}}{\partial f_x} \cdots & \frac{\partial r^s_{\mathbf{p}5}}{\partial c_y}
\end{pmatrix}_{3\times 49} \tag{2.2}
$$

$$
E_d(\delta) = \begin{pmatrix} (r^d_{\mathbf{p}_1})_{12} \\ (r^d_{\mathbf{p}_1})_{21} \\ \vdots \\ (r^d_{\mathbf{p}_5})_{43} \end{pmatrix}^T \begin{pmatrix} w_{\mathbf{p}_1} & 0 & \dots & 0 \\ 0 & w_{\mathbf{p}_1} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & w_{\mathbf{p}_5} \end{pmatrix} \begin{pmatrix} (r^d_{\mathbf{p}_1})_{12} \\ (r^d_{\mathbf{p}_1})_{21} \\ \vdots \\ (r^d_{\mathbf{p}_5})_{43} \end{pmatrix} = (\mathbf{r}^d)^T \mathbf{W}^d \mathbf{r}^d
$$

$$
(\mathbf{J}_s^T \lambda \mathbf{W}^s \mathbf{J}_s + \mathbf{J}_d^T \mathbf{W}^d \mathbf{J}_d)\delta^* = -(\mathbf{J}_s^T \lambda \mathbf{W}^s \mathbf{r}^s + \mathbf{J}_d^T \mathbf{W}^d \mathbf{r}^d) \tag{2.2}
$$

$$
\mathbf{J}_s \in \mathbb{R}^{3\times 49}, \mathbf{W}^s \in \mathbb{R}^{3\times 3}, \mathbf{J}_s \in \mathbb{R}^{7\times 49}, \mathbf{W}^s \in \mathbb{R}^{7\times 7},
$$

$$
\mathbf{J}_d = \begin{pmatrix}
\frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial \boldsymbol{\xi}_1} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial \boldsymbol{\xi}_4} & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial d_{\mathbf{p}1}} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial d_{\mathbf{p}5}} & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial a^L_1} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial b^R_4} & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial f_x} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{12}}{\partial c_y} \\
\frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial \boldsymbol{\xi}_1} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial \boldsymbol{\xi}_4} & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial d_{\mathbf{p}1}} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial d_{\mathbf{p}5}} & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial a^L_1} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial b^R_4} & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial f_x} \cdots & \frac{\partial (r^d_{\mathbf{p}_1})_{21}}{\partial c_y} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
\frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial \boldsymbol{\xi}_1} \cdots & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial \boldsymbol{\xi}_4} & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial d_{\mathbf{p}1}} \cdots & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial d_{\mathbf{p}5}} & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial a^L_1} \cdots & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial b^R_4} & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial f_x} \cdots & \frac{\partial (r^d_{\mathbf{p}_5})_{43}}{\partial c_y}
\end{pmatrix}_{7\times 49} \tag{2.2}
$$

We construct residuals and its formulation.

3.2 Jacobian citation

We know for a Lie algebra $\boldsymbol{\rho} \in \mathbb{R}^3, \boldsymbol{\phi} \in \mathbb{R}^3, \boldsymbol{\xi} = \begin{pmatrix} \boldsymbol{\rho} \\ \boldsymbol{\phi} \end{pmatrix} \in \mathbb{R}^6$ and $\mathbf{p}_w$:

$$
\begin{aligned}
&\boldsymbol{\xi}^{\wedge} = \begin{pmatrix} \boldsymbol{\rho} \\ \boldsymbol{\phi} \end{pmatrix}^{\wedge} = \begin{pmatrix} \boldsymbol{\phi}^{\wedge} & \boldsymbol{\rho} \\ \mathbf{0}^T & \mathbf{0}^T \end{pmatrix} \in \mathbb{R}^{4\times 4} \\
&\boldsymbol{\epsilon} \in \mathbb{R}^3, \begin{pmatrix} \boldsymbol{\epsilon} \\ 1 \end{pmatrix}^{\odot} = \begin{pmatrix} \mathbf{E} & -\boldsymbol{\epsilon}^{\wedge} \\ \mathbf{0}^T & \mathbf{0}^T \end{pmatrix} \in \mathbb{R}^{4\times 6} \\
&\frac{\partial(exp(\xi^{\wedge})\mathbf{p}_w)}{\partial \boldsymbol{\xi}} = \frac{\partial(\mathbf{T}\mathbf{p}_w)}{\partial \boldsymbol{\xi}} = (\mathbf{T}\mathbf{p}_w)^{\odot} \\
&\mathbf{T}\mathbf{p}_w = exp(\xi^{\wedge})\mathbf{p}_w \approx (\mathbf{E} + \xi^{\wedge})\mathbf{p}_w \\
&\frac{\partial(exp(\xi^{\wedge})\mathbf{p}_w)}{\partial \boldsymbol{\xi}} \approx \frac{\partial(\mathbf{E} + \xi^{\wedge})}{\partial \boldsymbol{\xi}} = \mathbf{0} + \frac{\partial(\xi^{\wedge}\mathbf{p}_w)}{\partial \boldsymbol{\xi}} \approx (\mathbf{T}\mathbf{p}_w)^{\odot} \\
&since, \frac{\partial(\mathbf{T}\mathbf{p}_w)}{\partial \boldsymbol{\xi}} = (\mathbf{T}^{-1}\mathbf{p}_w)^{\odot} = \frac{\partial(exp(-\xi^{\wedge})\mathbf{p}_w)}{\partial \boldsymbol{\xi}} \\
&= \frac{\partial(\mathbf{E} - \xi^{\wedge})}{\partial \boldsymbol{\xi}} = -(\mathbf{T}\mathbf{p}_w)^{\odot}
\end{aligned}
\tag{2.2}
$$

1.3 Jacobian derivation

1.3.1 Dynamic Parameter

Firstly, if $\mathbf{p}$ is neither observed by frame mL, mR nor hosted by nL, nR:

$$
\frac{\partial(r^d_{\mathbf{p}})_{ij}}{\partial \boldsymbol{\xi_m}} = \frac{\partial(r^d_{\mathbf{p}})_{ij}}{\partial \boldsymbol{\xi_n}} = \mathbf{0}^T, so \quad \frac{\partial(r^d_{\mathbf{p}_1})_{12}}{\partial \boldsymbol{\xi}_3} = \frac{\partial r^d_{(\mathbf{p}_1})_{12}}{\partial \boldsymbol{\xi}_4} = \ldots = \mathbf{0}^T, \tag{2.2}
$$

$$
\begin{aligned}
&\frac{\partial(r^d_{\mathbf{p}})_{ij}}{\partial \boldsymbol{\xi_i}} = \frac{\partial(I^L_j(\mathbf{p}'))}{\partial \boldsymbol{\xi_i}} = \frac{\partial(I^L_j(\mathbf{p}'))}{\partial \mathbf{p}'}\frac{\partial \mathbf{p}'}{\partial \mathbf{p}'_w}\frac{\partial \mathbf{p}'_w}{\partial \boldsymbol{\xi_i}} \\
&\mathbf{p}'_w = \mathbf{T}_j\mathbf{T}_i^{-1}\mathbf{p}_w = \mathbf{T}_j\mathbf{T}_i^{-1}((d^{iL}_{\mathbf{p}})^{-1}\mathbf{K}^{-1}\mathbf{p})
\end{aligned}
\tag{2.2}
$$

otherwise, we follow

For one frame iL, we have $\mathbf{p}$ and K, then we can get

Secondly, according to

$$\left\{ \mathbf{p}_w = \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix} = \begin{pmatrix} f_x^{-1}(d_{\mathbf{p}}^{iL})^{-1}(u^i - c_x) \\ f_y^{-1}(d_{\mathbf{p}}^{iL})^{-1}(v^i - c_y) \\ (d_{\mathbf{p}}^{iL})^{-1} \\ 1 \end{pmatrix} \right. \tag{2.2}$$

$$\begin{aligned}
&\frac{\partial \mathbf{p}_w^{'}}{\partial \boldsymbol{\xi_i}} = \mathbf{T}_j \frac{\partial(\mathbf{T}_i^{-1}\mathbf{p}_w^{'})}{\partial \boldsymbol{\xi_i}} = -\mathbf{T}_j(\mathbf{T}_i\mathbf{p}_w)^{\odot} \\
&\frac{\partial \mathbf{p}_w^{'}}{\partial \boldsymbol{\xi_j}} = \frac{\partial(\mathbf{T}_j\mathbf{T}_i^{-1}\mathbf{p}_w)}{\partial \boldsymbol{\xi_i}} = (\mathbf{T}_j\mathbf{T}_i^{-1}\mathbf{p}_w)^{\odot} \\
&= \begin{pmatrix} x^{'} \\ y^{'} \\ z^{'} \\ 1 \end{pmatrix}^{\odot} = \begin{pmatrix} 1 & 0 & 0 & 0 & z^{'} & -y^{'} \\ 0 & 1 & 0 & -z^{'} & 0 & x^{'} \\ 0 & 1 & 0 & y^{'} & -x^{'} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \\
&\Rightarrow \frac{\partial (r_{\mathbf{p}}^d)_{ij}}{\partial \boldsymbol{\xi_j}} = \frac{\partial(I_j^L(\mathbf{p}^{'}))}{\partial \mathbf{p}^{'}} \frac{\partial \mathbf{p}^{'}}{\partial \mathbf{p}_w^{'}} \frac{\partial \mathbf{p}_w^{'}}{\partial \boldsymbol{\xi_j}} \\
&= (g_x^{'}, g_y^{'}, 0, 0) \begin{pmatrix} f_x(z^{'})^{-1} & 0 & -x^{'}f_x(z^{'})^{-2} & 0 \\ 0 & f_y(z^{'})^{-1} & -y^{'}f_y(z^{'})^{-2} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & (z^{'})^{-2} & 0 \end{pmatrix} \\
&\begin{pmatrix} 1 & 0 & 0 & 0 & z^{'} & -y^{'} \\ 0 & 1 & 0 & -z^{'} & 0 & x^{'} \\ 0 & 0 & 1 & y^{'} & -x^{'} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} = \begin{pmatrix} g_x^{'}f_x(z^{'})^{-1} \\ g_y^{'}f_y(z^{'})^{-1} \\ -(g_x^{'}x^{'}f_x + g_y^{'}y^{'}f_y)(z^{'})^{-2} \\ -g_y^{'}f_y - (g_x^{'}x^{'}y^{'}f_x + g_y^{'}(y^{'})^2 f_y)(z^{'})^{-2} \\ g_x^{'}f_x + (g_x^{'}(x^{'})^2 f_x + g_y^{'}x^{'}y^{'}f_y)(z^{'})^{-2} \\ -g_x^{'}f_x y^{'}(z^{'})^{-1} + g_y^{'}f_y x^{'}(z^{'})^{-1} \end{pmatrix}^T
\end{aligned} \tag{2.2}$$

$$(r_{\mathbf{p}}^d)_{ij} := I_j^L(\mathbf{p}^{'}) - b_j^L - \frac{e^{a_j^L}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L) \tag{2.2}$$

$$\begin{aligned}
&\frac{\partial (r_{\mathbf{p}}^d)_{ij}}{\partial a_i} = \frac{e^{a_j^L}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L), \frac{\partial (r_{\mathbf{p}}^d)_{ij}}{\partial a_j} = -\frac{e^{a_j^L}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L) \\
&\frac{\partial (r_{\mathbf{p}}^d)_{ij}}{\partial b_i} = \frac{e^{a_j^L}}{e^{a_i^L}}, \qquad \frac{\partial (r_{\mathbf{p}}^d)_{ij}}{\partial b_j} = -1
\end{aligned} \tag{2.2}$$

We have:

add detail Calibration derivation……

$$
\begin{aligned}
&\mathbf{p}^{'} = d_{\mathbf{p}}^{jL}\mathbf{K}(\mathbf{T}_j\mathbf{T}_i^{-1}\mathbf{p}_w) \\
&assume: \mathbf{T}_j\mathbf{T}_i^{-1} = \begin{pmatrix} r_{11}^{ji} & r_{12}^{ji} & r_{13}^{ji} & t_1^{ji} \\ r_{21}^{ji} & r_{22}^{ji} & r_{23}^{ji} & t_2^{ji} \\ r_{31}^{ji} & r_{32}^{ji} & r_{33}^{ji} & t_3^{ji} \\ 0 & 0 & 0 & 1 \end{pmatrix} \\
&\mathbf{p}_w^{'} = \begin{pmatrix} r_{11}^{ji}f_x^{-1}(d_{\mathbf{p}}^{iL})^{-1}(u^i - c_x) + r_{12}^{ji}f_y^{-1}(d_{\mathbf{p}}^{iL})^{-1}(v^i - c_y) + r_{13}^{ji}(d_{\mathbf{p}}^{iL})^{-1} + t_1^{ji} \\ r_{21}^{ji}f_x^{-1}(d_{\mathbf{p}}^{iL})^{-1}(u^i - c_x) + r_{22}^{ji}f_y^{-1}(d_{\mathbf{p}}^{iL})^{-1}(v^i - c_y) + r_{23}^{ji}(d_{\mathbf{p}}^{iL})^{-1} + t_2^{ji} \\ r_{31}^{ji}f_x^{-1}(d_{\mathbf{p}}^{iL})^{-1}(u^i - c_x) + r_{32}^{ji}f_y^{-1}(d_{\mathbf{p}}^{iL})^{-1}(v^i - c_y) + r_{33}^{ji}(d_{\mathbf{p}}^{iL})^{-1} + t_3^{ji} \\ 1 \end{pmatrix} \\
&= \begin{pmatrix} \frac{a}{d_{\mathbf{p}}^{iL}} + t_1^{ji} \\ \frac{b}{d_{\mathbf{p}}^{iL}} + t_2^{ji} \\ \frac{c}{d_{\mathbf{p}}^{iL}} + t_3^{ji} \\ 1 \end{pmatrix} = \begin{pmatrix} x^{'} \\ y^{'} \\ z^{'} \\ 1 \end{pmatrix} \Rightarrow d_{\mathbf{p}}^{jL} = (z^{'})^{-1}, \mathbf{p}^{'} = \begin{pmatrix} f_x x^{'} d_{\mathbf{p}}^{jL} + c_x \\ f_y y^{'} d_{\mathbf{p}}^{jL} + c_y \\ 1 \\ d_{\mathbf{p}}^{jL} \end{pmatrix} \\
&\frac{\partial(I_j^L(\mathbf{p}^{'}))}{\partial \mathbf{p}^{'}} = (g_x^{'}, g_y^{'}, 0, 0) \\
&\frac{\partial \mathbf{p}^{'}}{\partial \mathbf{p}_w^{'}} = \begin{pmatrix} f_x(z^{'})^{-1} & 0 & -x^{'}f_x(z^{'})^{-2} & 0 \\ 0 & f_y(z^{'})^{-1} & -y^{'}f_y(z^{'})^{-2} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & (z^{'})^{-2} & 0 \end{pmatrix}, \frac{\partial \mathbf{p}_w^{'}}{\partial d_{\mathbf{p}}^{iL}} = \begin{pmatrix} -\frac{a}{(d_{\mathbf{p}}^{iL})^2} \\ -\frac{b}{(d_{\mathbf{p}}^{iL})^2} \\ -\frac{c}{(d_{\mathbf{p}}^{iL})^2} \\ 0 \end{pmatrix} \\
&\Rightarrow \frac{\partial(r_{\mathbf{p}}^d)_{ij}}{\partial d_{\mathbf{p}}^{iL}} = \frac{\partial(I_j^L(\mathbf{p}^{'}))}{\partial d_{\mathbf{p}}^{iL}} = \frac{\partial(I_j^L(\mathbf{p}^{'}))}{\partial \mathbf{p}^{'}}\frac{\partial \mathbf{p}^{'}}{\partial \mathbf{p}_w^{'}}\frac{\partial \mathbf{p}_w^{'}}{\partial d_{\mathbf{p}}^{iL}} \\
&= -\frac{g_x^{'}f_x a}{z^{'}(d_{\mathbf{p}}^{iL})^2} - \frac{g_y^{'}f_y b}{z^{'}(d_{\mathbf{p}}^{iL})^2} + \frac{c(g_x^{'}x^{'}f_x + g_y^{'}y^{'}f_y)}{(z^{'}d_{\mathbf{p}}^{iL})^2} \\
&= \frac{c(g_x^{'}x^{'}f_x + g_y^{'}y^{'}f_y) - g_x^{'}f_x a z^{'} - g_y^{'}f_y b z^{'}}{(z^{'}d_{\mathbf{p}}^{iL})^2}
\end{aligned}
\tag{2.2}
$$

1.3.2 Static Parameter

Firstly, For a stereo frame i: inverse depth $d_{\mathbf{p}}^{iL} = d_{\mathbf{p}}^{iR}$, a left frame iL pixel $\mathbf{p}$ is projected to right frame iR with $\mathbf{p}^{'}$:

$$
\begin{aligned}
&\mathbf{p} = \begin{pmatrix} u^i \\ v^i \\ 1 \\ d_{\mathbf{p}}^{iL} \end{pmatrix}, \mathbf{p}_w = \begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}, d_{\mathbf{p}}^{iL} = z^{-1}, \mathbf{p}_w = (d_{\mathbf{p}}^{iL})^{-1}\mathbf{K}^{-1}\mathbf{p} \\
&= \begin{pmatrix} f_x^{-1}(d_{\mathbf{p}}^{iL})^{-1}(u^i - c_x) \\ f_y^{-1}(d_{\mathbf{p}}^{iL})^{-1}(v^i - c_y) \\ (d_{\mathbf{p}}^{iL})^{-1} \\ 1 \end{pmatrix}, \mathbf{T}_{RL} = \begin{pmatrix} 1 & 0 & 0 & t_1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \\
&\mathbf{p}^{'} = d_{\mathbf{p}}^{iR}\mathbf{K}(\mathbf{T}_{RL}\mathbf{p}_w) \\
&= d_{\mathbf{p}}^{iL} \begin{pmatrix} f_x & 0 & c_x & 0 \\ 0 & f_y & c_y & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} f_x^{-1}(d_{\mathbf{p}}^{iL})^{-1}(u^i - c_x) + t_1 \\ f_y^{-1}(d_{\mathbf{p}}^{iL})^{-1}(v^i - c_y) \\ (d_{\mathbf{p}}^{iL})^{-1} \\ 1 \end{pmatrix} = \begin{pmatrix} u^i + t_1 f_x d_{\mathbf{p}}^{iL} \\ v^i \\ 1 \\ d_{\mathbf{p}}^{iL} \end{pmatrix} \\
&\frac{\partial r_{\mathbf{p}}^s}{\partial d_{\mathbf{p}}^{iL}} = \frac{\partial(I_i^R(\mathbf{p}^{'})) - \frac{e^{a_i^R}}{e^{a_i^L}}(I_i^L(\mathbf{p}))}{\partial d_{\mathbf{p}}^{iL}} = (\frac{\partial(I_i^R(\mathbf{p}^{'}))}{\partial \mathbf{p}^{'}} - \frac{e^{a_i^R}}{e^{a_i^L}}\frac{\partial(I_i^L(\mathbf{p}))}{\partial \mathbf{p}^{'}})\frac{\partial \mathbf{p}^{'}}{\partial d_{\mathbf{p}}^{iL}} \\
&= [(g_x^{iR}, g_y^{iR}, 0, 0) - \mathbf{0}^T] \begin{pmatrix} t_1 f_x \\ 0 \\ 0 \\ 1 \end{pmatrix} = g_x^{iR} t_1 f_x
\end{aligned} \tag{1}
$$

Secondly, according to:

$$
r_{\mathbf{p}}^s := I_i^R(\mathbf{p}^{'}) - b_i^R - \frac{e^{a_i^R}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L) \tag{2.2}
$$

We have:

$$
\begin{aligned}
\frac{\partial(r_{\mathbf{p}}^s)_{ij}}{\partial a_i} &= \frac{e^{a_j^L}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L), \frac{\partial(r_{\mathbf{p}}^s)_{ij}}{\partial a_j} = -\frac{e^{a_j^L}}{e^{a_i^L}}(I_i^L(\mathbf{p}) - b_i^L) \\
\frac{\partial(r_{\mathbf{p}}^s)_{ij}}{\partial b_i} &= \frac{e^{a_j^L}}{e^{a_i^L}}, \qquad \frac{\partial(r_{\mathbf{p}}^s)_{ij}}{\partial b_j} = -1
\end{aligned} \tag{2.2}
$$

add detail Calibration derivation……