

$$\begin{aligned}
f_m(\boldsymbol{\delta}) &= I_i(\mathbf{p}_m) - I_j(w(\mathbf{p}_m, D_i(\mathbf{p}_m), \boldsymbol{\delta})), \mathbf{p}_m \in \boldsymbol{\Omega}_{D_i}, 1 \leq m \leq n \\
W_m(\boldsymbol{\delta}) &= \left( 2\sigma_I^2 + \left( \frac{\partial_{r_{\mathbf{p}_m}}(\mathbf{p}_m, \boldsymbol{\delta})}{\partial D_i(\mathbf{p}_m)} \right)^2 V_i(\mathbf{p}_m) \right)^{-1} \\
\mathbf{f} &= \begin{pmatrix} f_1(\boldsymbol{\delta}) \\ f_2(\boldsymbol{\delta}) \\ \vdots \\ f_n(\boldsymbol{\delta}) \end{pmatrix}, \mathbf{W} = \begin{pmatrix} \mathbf{W}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{W}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{W}_n \end{pmatrix} \\
E(\boldsymbol{\delta}) &= \mathbf{f}^T(\boldsymbol{\delta}) \mathbf{W}(\boldsymbol{\delta}) \mathbf{f}(\boldsymbol{\delta}) \\
\mathbf{f}(\boldsymbol{\delta} + \Delta\boldsymbol{\delta}) &\approx l(\Delta\boldsymbol{\delta}) = \mathbf{f}(\boldsymbol{\delta}) + \mathbf{J}(\boldsymbol{\delta}) \Delta\boldsymbol{\delta} \\
\frac{1}{2}E(\boldsymbol{\delta}) &\approx L(\Delta\boldsymbol{\delta}) = \frac{1}{2}l^T(\Delta\boldsymbol{\delta})l(\Delta\boldsymbol{\delta}) \\
&= \frac{1}{2}\mathbf{f}^T \mathbf{W} \mathbf{f} + \Delta\boldsymbol{\delta}^T \mathbf{J}^T \mathbf{W} \mathbf{f} + \frac{1}{2}\Delta\boldsymbol{\delta}^T \mathbf{J}^T \mathbf{W} \mathbf{J} \Delta\boldsymbol{\delta} \\
&= E + \Delta\boldsymbol{\delta}^T \mathbf{J}^T \mathbf{W} \mathbf{f} + \frac{1}{2}\Delta\boldsymbol{\delta}^T \mathbf{J}^T \mathbf{W} \mathbf{J} \Delta\boldsymbol{\delta} \\
L' &= \mathbf{J}^T \mathbf{W} \mathbf{f} + \mathbf{J}^T \mathbf{W} \mathbf{J} \Delta\boldsymbol{\delta} = 0 \\
\Delta\boldsymbol{\delta} &= -(\mathbf{J}^T \mathbf{W} \mathbf{J})^{-1} \mathbf{J}^T \mathbf{W} \mathbf{f}
\end{aligned} \tag{1}$$

$$\left\{ \begin{aligned} \mathbf{p} &:= \begin{pmatrix} p_x \\ p_y \\ d_p \end{pmatrix}, \mathbf{P} = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} p_x/d_p \\ p_y/d_p \\ 1/d_p \end{pmatrix} \\ w(\mathbf{p}, D_i(\mathbf{p}), \boldsymbol{\delta}_{ji}) &:= \begin{pmatrix} x'/z' \\ y'/z' \end{pmatrix}, \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \exp(\boldsymbol{\delta}) \begin{pmatrix} p_x/d_p \\ p_y/d_p \\ 1/d_p \\ 1 \end{pmatrix} \end{aligned} \right. \tag{2.10}$$

$$\begin{aligned}
\mathbf{q} &= \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix}, w_m = (\mathbf{p}_m, D_i(\mathbf{p}_m), \boldsymbol{\delta}) = \begin{pmatrix} x'/z' \\ y'/z' \end{pmatrix} \\
\frac{\partial f_m}{\partial \boldsymbol{\delta}} &= -\frac{\partial I_j(w_m)}{\partial \boldsymbol{\delta}} = -\frac{\partial I_j}{\partial w_m} \frac{\partial w_m}{\partial \mathbf{q}} \frac{\partial \mathbf{q}}{\partial \boldsymbol{\delta}} \\
&= -\begin{pmatrix} g_x & g_y \end{pmatrix} \begin{pmatrix} \frac{1}{z'} & 0 & -\frac{x'}{z'^2} \\ 0 & \frac{1}{z'} & -\frac{y'}{z'^2} \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 & -z' & y' \\ 0 & 1 & 0 & z' & 0 & -x' \\ 0 & 0 & 1 & -y' & x' & 0 \end{pmatrix} \\
&= -\begin{pmatrix} \frac{g_x}{z'} & \frac{g_y}{z'} & -\frac{x'g_x}{z'^2} - \frac{y'g_y}{z'^2} & -\frac{x'y'g_x}{z'^2} - (1 + \frac{y'^2}{z'^2})g_y & (1 + \frac{x'^2}{z'^2})g_x + \frac{x'y'g_y}{z'^2} & -\frac{y'g_x}{z'} + \frac{x'g_y}{z'} \end{pmatrix} \\
\mathbf{J} &= \begin{pmatrix} \frac{\partial f_1}{\partial \boldsymbol{\delta}} & \frac{\partial f_2}{\partial \boldsymbol{\delta}} & \dots & \frac{\partial f_N}{\partial \boldsymbol{\delta}} \end{pmatrix}^T = \begin{pmatrix} \mathbf{J}_1 & \mathbf{J}_2 & \dots & \mathbf{J}_N \end{pmatrix}^T
\end{aligned} \tag{2}$$

$$\begin{aligned}
\begin{pmatrix} x' \\ y' \\ z' \\ 1 \end{pmatrix} &= \exp(\boldsymbol{\delta}) \begin{pmatrix} \mathbf{p}_x/d_p \\ \mathbf{p}_y/d_p \\ 1/d_p \\ 1 \end{pmatrix} = \frac{1}{d_p} \begin{pmatrix} \mathbf{R}_1 & t_1 \\ \mathbf{R}_2 & t_2 \\ \mathbf{R}_3 & t_3 \\ \mathbf{0} & 1 \end{pmatrix}_{4 \times 4} \begin{pmatrix} \mathbf{P} \\ d_p \end{pmatrix}_{4 \times 1} = \frac{1}{d_p} \begin{pmatrix} \mathbf{R}_1 \mathbf{P} + t_1 d_p \\ \mathbf{R}_2 \mathbf{P} + t_2 d_p \\ \mathbf{R}_3 \mathbf{P} + t_3 d_p \\ d_p \end{pmatrix} \\
w_m &= \begin{pmatrix} x'/z' \\ y'/z' \end{pmatrix} = \begin{pmatrix} \frac{\mathbf{R}_1 \mathbf{P} + t_1 d_p}{\mathbf{R}_3 \mathbf{P} + t_3 d_p} \\ \frac{\mathbf{R}_2 \mathbf{P} + t_2 d_p}{\mathbf{R}_3 \mathbf{P} + t_3 d_p} \end{pmatrix} \\
\frac{\partial_{r_{p_m}}(\mathbf{p}_m, \boldsymbol{\delta})}{\partial D_i(\mathbf{p}_m)} &:= \frac{\partial f_m}{\partial d_{p_m}} = -\frac{\partial I_j}{\partial w_m} \frac{\partial w_m}{\partial d_{p_m}} \\
&= -\begin{pmatrix} g_x & g_y \end{pmatrix} \begin{pmatrix} \frac{t_1 z' - x' t_3}{z'^2} \\ \frac{t_2 z' - y' t_3}{z'^2} \end{pmatrix} = -(g_x \frac{t_1 z' - x' t_3}{z'^2} + g_y \frac{t_2 z' - y' t_3}{z'^2}) \\
W_m &:= (2\sigma_I^2 + w_m^2 V_m)^{-1}
\end{aligned} \tag{3}$$

$$\begin{aligned}
\mathbf{J}^T \mathbf{W} \mathbf{J} &= \begin{pmatrix} \mathbf{J}_1^T & \mathbf{J}_2^T & \cdots & \mathbf{J}_N^T \end{pmatrix}_{6 \times N} \begin{pmatrix} \mathbf{W}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{W}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{W}_N \end{pmatrix}_{N \times N} \begin{pmatrix} \mathbf{J}_1 \\ \mathbf{J}_2 \\ \vdots \\ \mathbf{J}_N \end{pmatrix}_{N \times 6} \\
&= \sum_{i=1}^N (\mathbf{J}_i^T \mathbf{W}_i \mathbf{J}_i)_{6 \times 6} = \mathbf{A}_{6 \times 6} \\
\mathbf{J}^T \mathbf{W} &= \sum_{i=1}^N (\mathbf{J}_i^T \mathbf{W}_i)_{6 \times 1} = \mathbf{b}_{6 \times 1} \\
\mathbf{A} \boldsymbol{\delta}^* &= \mathbf{b} \\
\Rightarrow \mathbf{L} \mathbf{D} \mathbf{L}^T \boldsymbol{\delta}^* &= \mathbf{b} \\
\Rightarrow (\mathbf{L} \mathbf{D}^{1/2}) (\mathbf{L} \mathbf{D}^{1/2})^T \boldsymbol{\delta}^* &= \mathbf{b} \\
\Rightarrow \mathbf{G} \mathbf{G}^T \boldsymbol{\delta}^* &= \mathbf{b} \\
\Rightarrow \mathbf{G} \boldsymbol{\delta}^{*'} &= \mathbf{b} \\
\Rightarrow \mathbf{G}^T \boldsymbol{\delta}^* &= \boldsymbol{\delta}^{*'}
\end{aligned} \tag{4}$$

$$cost = \sum_{i=j=1}^5 (A(i, j) - B(i, j))^2 \tag{4.1}$$

$$\begin{aligned}
\vec{s}_1 &= \vec{n}_1 \times \vec{n}_2 = \mathbf{t} \times \vec{n}_1 \times \vec{Op} \\
&= \begin{pmatrix} 0 & -t_3 & t_2 \\ t_3 & 0 & -t_1 \\ -t_2 & t_1 & 0 \end{pmatrix} \begin{pmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} a \\ b \\ 1 \end{pmatrix} \\
&= \begin{pmatrix} -at_3 + t_1 \\ -bt_3 + t_2 \\ 0 \end{pmatrix} = \begin{pmatrix} ep_x \\ ep_y \\ 0 \end{pmatrix}
\end{aligned} \tag{4.2}$$

$$\begin{aligned}
& d_2 \mathbf{p}_{best} = \mathbf{R}(d_1 \mathbf{p}_c) + \mathbf{t} \\
\Rightarrow & 0 = [\mathbf{p}_{best}]_{\times} (d_1 \mathbf{R} \mathbf{p}_c + \mathbf{t}) \\
\Rightarrow & d_1 [\mathbf{p}_{best}]_{\times} \mathbf{R} \mathbf{p}_c = -[\mathbf{p}_{best}]_{\times} \mathbf{t} \\
\Rightarrow & d_1 \begin{pmatrix} 0 & -1 & b_1 \\ 1 & 0 & -a_1 \\ -b_1 & a_1 & 0 \end{pmatrix} \begin{pmatrix} R_{row0} \\ R_{row1} \\ R_{row2} \end{pmatrix} \mathbf{p}_c = \begin{pmatrix} 0 & 1 & -b_1 \\ -1 & 0 & a_1 \\ b_1 & -a_1 & 0 \end{pmatrix} \begin{pmatrix} t_0 \\ t_1 \\ t_2 \end{pmatrix} \\
\Rightarrow & d_1 \begin{pmatrix} b_1 R_{row2} - R_{row1} \\ R_{row0} - a_1 R_{row2} \\ a_1 R_{row1} - b_1 R_{row0} \end{pmatrix} \mathbf{p}_c = \begin{pmatrix} t_1 - b_1 t_2 \\ a_1 t_2 - t_0 \\ b_1 t_0 - a_1 t_1 \end{pmatrix} \\
\Rightarrow & d_1 = \frac{t_1 - b_1 t_2}{(b_1 R_{row2} - R_{row1}) \mathbf{p}_c} \\
\Rightarrow & = \frac{a_1 t_2 - t_0}{(R_{row0} - a_1 R_{row2}) \mathbf{p}_c} \\
\Rightarrow & = \frac{b_1 t_0 - a_1 t_1}{(a_1 R_{row1} - b_1 R_{row0}) \mathbf{p}_c}
\end{aligned} \tag{4.4}$$

$$L := \left\{ \mathbf{x} = \mathbf{p}_{close} + \lambda \begin{pmatrix} l_x \\ l_y \end{pmatrix} \mid \lambda = k|\mathbf{S}|, k \in \mathbf{N}^+ \right\} \tag{4.4}$$

$$\mathcal{N}\left(\frac{\sigma_p^2 d_o + \sigma_o^2 d_p}{\sigma_p^2 + \sigma_o^2}, \frac{\sigma_p^2 \sigma_o^2}{\sigma_p^2 + \sigma_o^2}\right) \tag{2.14}$$

$$\begin{aligned}
d_{new} &= (d_p^{-1} - t_z)^{-1} \\
\sigma_{new}^2 &= \left( \frac{d_{new}}{d_p} \right)^4 \sigma_p^2
\end{aligned} \tag{2.14}$$

$$f := \begin{cases} X_{max} = MAX\{x_1, x_2, \dots, x_m\} \\ X_{min} = MIN\{x_1, x_2, \dots, x_m\} \\ H_{sum} = \frac{X_{max} - X_{min}}{H} \\ Z_{max} = MAX\{z_1, z_2, \dots, z_m\} \\ Z_{min} = MIN\{z_1, z_2, \dots, z_m\} \\ V_{sum} = \frac{Z_{max} - Z_{min}}{V} \\ \mathbf{p}_i = [x_i, z_i]^T \in \mathbf{P}, \mathbf{q}_i = [h_i, v_i]^T \in \mathbf{Q} \\ h_i = \left\lfloor \frac{x_i}{H} \right\rfloor, v_i = \left\lfloor \frac{z_i}{V} \right\rfloor \end{cases} \tag{3.2}$$

---

**Algorithm 1** : Time optimized A\* Algorithm

---

**Require:** *Start, End, Q*

**Ensure:** Father node of *End*

```

1: function ASTARSEARCH(Start, End, Q)
2:   open = binary heap containing Start node
3:   closed = empty set
4:   movecost(x, y) = distance from node x to node y
5:   while End node not in open do
6:     i = node with min f(i) in open
7:     remove i from open
8:     add i to closed
9:     count = 0
10:    for j = neighbor node of i and not in closed and reachable in Q do
11:      count++
12:      cost = g(i) + movecost(i, j)
13:      if j in open and cost < g(j) then
14:        remove j from open
15:      end if
16:      if j not in open and not in closed then
17:        add j into open
18:        f(j) = g(j) + h(j)
19:        set father node of j is i
20:      end if
21:    end for
22:    if count == 0 then
23:      can't find path
24:      break out
25:    end if
26:  end while
27: end function

```

---

$$\ddot{X}_{t-1} \sim \mathcal{N}(0, k_1^2), \ddot{Z}_{t-1} \sim \mathcal{N}(0, k_2^2), \ddot{\theta}_{t-1} \sim \mathcal{N}(0, k_3^2),$$

$$\mathbf{R}_t = \begin{pmatrix} \frac{1}{4}T^4k_1^2 & \frac{1}{2}T^3k_1^2 & 0 & 0 & 0 & 0 \\ \frac{1}{2}T^3k_1^2 & T^2k_1^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{4}T^4k_2^2 & \frac{1}{2}T^3k_2^2 & 0 & 0 \\ 0 & 0 & \frac{1}{2}T^3k_2^2 & T^2k_2^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{4}T^4k_3^2 & \frac{1}{2}T^3k_3^2 \\ 0 & 0 & 0 & 0 & \frac{1}{2}T^3k_3^2 & T^2k_3^2 \end{pmatrix} \quad (3.4)$$

$$\begin{pmatrix} cov(\varepsilon_1, \varepsilon_1) & cov(\varepsilon_1, \varepsilon_2) & \cdots & cov(\varepsilon_1, \varepsilon_6) \\ cov(\varepsilon_2, \varepsilon_1) & cov(\varepsilon_2, \varepsilon_2) & \cdots & cov(\varepsilon_2, \varepsilon_6) \\ \vdots & \ddots & \vdots & \\ cov(\varepsilon_6, \varepsilon_1) & cov(\varepsilon_6, \varepsilon_2) & \cdots & cov(\varepsilon_6, \varepsilon_6) \end{pmatrix} \quad (3.4)$$

---

**Algorithm 2** : Linear Kalman Filter

---

**Require:**  $\mu_{t-1}, \Sigma_{t-1}, z_t$ 
**Ensure:**  $\mu_t, \Sigma_t$ 

```

1: function FILTER( $\mu_{t-1}, \Sigma_{t-1}, z_t$ )
2:   predict  $\bar{\mu}_t = A\mu_{t-1}$ 
3:    $\bar{\Sigma}_t = A\Sigma_{t-1}A^T + R_t$ 
4:   update  $K_t = \bar{\Sigma}_t(\bar{\Sigma}_t + Q_t)^{-1}$ 
5:    $\mu_t = \bar{\mu}_t + K_t(z_t - \bar{\mu}_t)$ 
6:    $\Sigma_t = (E - K_t)\bar{\Sigma}_t$ 
7: end function

```

---

$$\mathcal{F} = \{I_1, I_2, I_3, I_4\} \xi \Pi \frac{\mathbf{P}}{\partial \mathbf{p}_w}, \begin{pmatrix} f_x z^{-1} & 0 & -x f_x z^{-2} & 0 \\ 0 & f_y z^{-1} & -y f_y z^{-2} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & z^{-2} & 0 \end{pmatrix} \quad (3.4)$$

$$\left( \sum_{j \in \text{obs}^t(\mathbf{P})} E_{ij}^{\mathbf{P}} + \lambda E_{is}^{\mathbf{P}} \right)$$

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

$$\begin{aligned} E_s(\delta) &= \begin{pmatrix} r_{\mathbf{p}_1}^s \\ r_{\mathbf{p}_2}^s \\ r_{\mathbf{p}_5}^s \end{pmatrix}^T \begin{pmatrix} \lambda w_{\mathbf{p}_1} & 0 & 0 \\ 0 & \lambda w_{\mathbf{p}_2} & 0 \\ 0 & 0 & \lambda w_{\mathbf{p}_5} \end{pmatrix} \begin{pmatrix} r_{\mathbf{p}_1}^s \\ r_{\mathbf{p}_2}^s \\ r_{\mathbf{p}_5}^s \end{pmatrix} = (\mathbf{r}^s)^T \mathbf{W} \mathbf{r}^s \\ J_s &= \begin{pmatrix} \frac{\partial r_{\mathbf{p}_1}^s}{\partial \xi_1} \dots \frac{\partial r_{\mathbf{p}_1}^s}{\partial \xi_4} & \frac{\partial r_{\mathbf{p}_1}^s}{\partial d_{\mathbf{p}_1}} \dots \frac{\partial r_{\mathbf{p}_1}^s}{\partial d_{\mathbf{p}_5}} & \frac{\partial r_{\mathbf{p}_1}^s}{\partial a_1^L} \dots \frac{\partial r_{\mathbf{p}_1}^s}{\partial b_4^R} & \frac{\partial r_{\mathbf{p}_1}^s}{\partial f_x} \dots \frac{\partial r_{\mathbf{p}_1}^s}{\partial c_y} \\ \frac{\partial r_{\mathbf{p}_2}^s}{\partial \xi_1} \dots \frac{\partial r_{\mathbf{p}_2}^s}{\partial \xi_4} & \frac{\partial r_{\mathbf{p}_2}^s}{\partial d_{\mathbf{p}_1}} \dots \frac{\partial r_{\mathbf{p}_2}^s}{\partial d_{\mathbf{p}_5}} & \frac{\partial r_{\mathbf{p}_2}^s}{\partial a_1^L} \dots \frac{\partial r_{\mathbf{p}_2}^s}{\partial b_4^R} & \frac{\partial r_{\mathbf{p}_2}^s}{\partial f_x} \dots \frac{\partial r_{\mathbf{p}_2}^s}{\partial c_y} \\ \frac{\partial r_{\mathbf{p}_5}^s}{\partial \xi_1} \dots \frac{\partial r_{\mathbf{p}_5}^s}{\partial \xi_4} & \frac{\partial r_{\mathbf{p}_5}^s}{\partial d_{\mathbf{p}_1}} \dots \frac{\partial r_{\mathbf{p}_5}^s}{\partial d_{\mathbf{p}_5}} & \frac{\partial r_{\mathbf{p}_5}^s}{\partial a_1^L} \dots \frac{\partial r_{\mathbf{p}_5}^s}{\partial b_4^R} & \frac{\partial r_{\mathbf{p}_5}^s}{\partial f_x} \dots \frac{\partial r_{\mathbf{p}_5}^s}{\partial c_y} \end{pmatrix} \quad (2.2) \end{aligned}$$

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

$$J_d = \begin{pmatrix} \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial \xi_1} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial \xi_4} & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial d_{\mathbf{p}_1}} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial d_{\mathbf{p}_5}} & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial a_1^L} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial b_4^R} & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial f_x} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{12}}{\partial c_y} \\ \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial \xi_1} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial \xi_4} & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial d_{\mathbf{p}_1}} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial d_{\mathbf{p}_5}} & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial a_1^L} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial b_4^R} & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial f_x} \dots & \frac{\partial(r_{\mathbf{p}_1}^d)_{21}}{\partial c_y} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial \xi_1} \dots & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial \xi_4} & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial d_{\mathbf{p}_1}} \dots & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial d_{\mathbf{p}_5}} & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial a_1^L} \dots & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial b_4^R} & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial f_x} \dots & \frac{\partial(r_{\mathbf{p}_5}^d)_{43}}{\partial c_y} \end{pmatrix} \quad (2.2)$$

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

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

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

$$\frac{\partial \mathbf{p}'}{\partial d_{\mathbf{p}}^{iL}} = 0? \quad (2.2)$$

$$\frac{\partial(r_{\mathbf{p}}^d)}{\partial \xi_i} = \frac{\partial I_j^L(\mathbf{p}')}{\partial \xi_i} = \frac{\partial I_j^L(\mathbf{p}')}{\partial \mathbf{p}'} \frac{\partial \mathbf{p}'}{\partial \mathbf{p}_w'} \frac{\partial \mathbf{p}_w'}{\partial \xi_i} \quad (2.2)$$

$$\mathbf{p}_w' = d_{\mathbf{p}}^{jL} \mathbf{K}(\mathbf{T}_j \mathbf{T}_i^{-1}((d_{\mathbf{p}}^{iL})^{-1} \mathbf{K}^{-1} \mathbf{p}))$$

---

**Algorithm 3** Levenberg-Marquardt方法优化相机位姿

---

**Require:**  $\mathcal{K}_i, \mathcal{I}_j, \delta_{i(i-1)}, k_{max}$  (最大迭代次数)

**Ensure:**  $\delta_{ji}$

```
1: function TRACKFRAME(Array, left, middle, right)
2:    $v \leftarrow 2$ 
3:    $\delta \leftarrow \delta_{i(i-1)}$ 
4:    $\mathbf{f}_i$ 
5:   for  $i = 0 \rightarrow k_{max} - 1$  do
6:      $\mathbf{J}^T \mathbf{W} \mathbf{J}$ 
7:     while true do
8:       solve  $\delta^*$ 
9:       update
10:       $\mathbf{f}_i$ 
11:       $error = \text{cacWeight}$ 
12:      if  $error < lastError$  then
13:         $lastResidual = lastError = error$ 
14:        if  $\lambda \leq 0.2$  then
15:           $\lambda = 0$ 
16:        else
17:           $\lambda = \frac{1}{2} \lambda$ 
18:        end if
19:        break
20:      else
21:        if 增量  $< \varepsilon_1$  then
22:           $i = k_{max} - 1$ 
23:          break
24:        end if
25:        if  $\lambda == 0$  then
26:           $\lambda = 0.2$ 
27:        else
28:           $\lambda = 2 * \text{incry}$ 
29:        end if
30:      end if
31:    end while
32:  end for
33:  return  $\delta$ 
34: end function
```

---