

# VIO from scratch 3-2

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$$\arg \min_{q, p, f} \sum_{i=1}^m \sum_{j=1}^n \| \pi(q_{wc_i}, p_{wc_i}, f_j) - z_{f_j}^{c_i} \| \Sigma_{ij}$$

$q$ : rotation quaternion } camera pose

$p$ : translation

$f$ : feature position in 3D

$C_i$ :  $i$ th camera

$\pi()$ : projection function.

$z_{f_j}^{c_i}$ : observation of  $f_j$  in  $C_i$

$\Sigma_{ij}$ : covariance

Least squares:

find  $x^* \in \mathbb{R}^n$ , to minimize  $F(x)$ :

$$F(x) = \frac{1}{2} \sum_{i=1}^m (f_i(x))^2$$

$m \geq n$ , and local minima means  $\|x - x^*\| < \delta, \Rightarrow F(x^*) \leq F(x)$ .

$$F(x + \Delta x) = F(x) + J \Delta x + \frac{1}{2} \Delta x^T H \Delta x + o(\|\Delta x\|^3)$$

Gradient descent:

We want  $F(x_{k+1}) < F(x_k)$

$F(x + \alpha d) \approx F(x) + \alpha Jd$ ,  $Jd < 0$ , we need to find  $d$  s.t.  $Jd < 0$

line search:  $\alpha^* = \arg \min_{\alpha > 0} \{ F(x + \alpha d) \}$

$\alpha$ : step size,  $d$ : direction.

Steepest GD:  $Jd = \|J\| \cos \theta$ , when  $\theta = \pi$ ,  $d = -J^T$ .

Newton:

$$\frac{\partial}{\partial \Delta x} (F(x) + J \Delta x + \frac{1}{2} \Delta x^T H \Delta x) = J^T + H \Delta x = 0$$

$$\Delta x = -H^{-1} J^T$$

Damp method:

$$F(x + \Delta x) \approx L(\Delta x) \equiv F(x) + J \Delta x + \frac{1}{2} \Delta x^T H \Delta x$$

$$\Delta x \equiv \arg \min \{ L(\Delta x) + \frac{1}{2} \mu \Delta x^T \Delta x \} \quad (*)$$

$\frac{1}{2} \mu \Delta x^T \Delta x = \frac{1}{2} \mu \|\Delta x\|^2$  is regularization on  $\Delta x$ .

derivative of  $(*)$  is  $L'(\Delta x) + \mu \Delta x = 0, \Rightarrow (H + \mu I) \Delta x = -J^T$

$$f(x) = \begin{bmatrix} f_1(x) \\ \vdots \\ f_m(x) \end{bmatrix}, \quad f^T(x) f(x) = \sum_{i=1}^m (f_i(x))^2$$

$$J_i(x) = \frac{\partial f_i(x)}{\partial x}, \quad \frac{\partial f(x)}{\partial x} = J = \begin{bmatrix} J_1(x) \\ \vdots \\ J_m(x) \end{bmatrix}$$

Gauss-Newton:

$$f(x + \Delta x) \approx l(\Delta x) \equiv f(x) + J \Delta x$$

$$F(x + \Delta x) \approx L(\Delta x) \equiv \frac{1}{2} l(\Delta x)^T l(\Delta x)$$

$$= \frac{1}{2} f^T f + \Delta x^T J^T f + \frac{1}{2} \Delta x^T J^T J \Delta x \quad (*)$$

$$= F(x) + \Delta x^T J^T f + \frac{1}{2} \Delta x^T J^T J \Delta x$$

Set derivative of  $(*)$  to zero:  $(J^T J) \Delta x_{gn} = -J^T f$

$\Rightarrow H \Delta x_{gn} = b$ , normal equation.

LM:  $(J^T J + \mu I) \Delta x_{lm} = -J^T f$ ,  $\mu \geq 0$ .

$\mu > 0$ ,  $(J^T J + \mu I)$  is PSD.

$$\mu \text{ large: } \Delta x_{lm} = -\frac{1}{\mu} J^T f = -\frac{1}{\mu} F'(x)^T,$$

$\mu$  small:  $\Delta x_{lm} \approx \Delta x_{gn}$ .

$$J^T J \xrightarrow{\text{SVD}} J^T J = V \Lambda V^T, \quad \Delta x_{lm} = - \sum_{j=1}^n \frac{v_j^T F'^T}{\lambda_j + \mu} v_j$$

$$\mu_0 = \tau \cdot \max \{ (J^T J)_{ii} \}$$

if  $\Delta x \rightarrow F(x) \uparrow$ ,  $\mu \uparrow \rightarrow \Delta x \downarrow$

if  $\Delta x \rightarrow F(x) \downarrow$ ,  $\mu \downarrow \rightarrow \Delta x \uparrow$ .

Outlier rejection:

robust cost function:  $\rho(f^2)$  / M-estimator / IRLS

$$\min_x \frac{1}{2} \sum_k \rho(\|f_k(x)\|^2)$$

let  $s_k = \|f_k(x)\|^2$ ,

$$\frac{1}{2} \rho(s) = \frac{1}{2} (\text{const} + \rho' s + \frac{1}{2} \rho'' s^2)$$