

Suppose we have 3 frames
 we want to optimize $\pi = [\underbrace{\xi_1 \quad \xi_2 \quad \xi_3}_{\text{6DOF pose}} \quad \underbrace{s}_{\text{scale}} \quad \underbrace{z}_{\text{shape code}}] \in \mathbb{R}^{3 \times b + 1}$

\uparrow
 $(19+C) \times 1$
 \downarrow
 code length

we have the π_0 available

now we estimate $\Delta\pi$ by Gauss-Newton



$$\Delta\pi = \begin{pmatrix} J^T J \end{pmatrix}^{-1} (J^T b)$$

$(19+C) \times 1 \quad (19+C) \times (19+C) \quad 19+C \times 1$

so we need to calculate J and b

for each point, either ● ● or ●, we predict its SDF with DeepSDF D_θ
 the result is the residual $b_i = f = D_{\theta}(p, z)$
 the gradient w.r.t p and z are g_p and g_z , can be calculated by pytorch.

Suppose we have N points in total, then $b \in \mathbb{R}^{N \times 1}$

J has the shape $N \times (19+C)$, each point contributes to a row J_i
 $1 \times (19+C)$

$$J_i = \left[\underbrace{\frac{\partial f}{\partial \xi_1}}_{1 \times 6} \quad \underbrace{\frac{\partial f}{\partial \xi_2}}_{1 \times 6} \quad \underbrace{\frac{\partial f}{\partial \xi_3}}_{1 \times 6} \quad \underbrace{\frac{\partial f}{\partial s}}_{1 \times 1} \quad \underbrace{\frac{\partial f}{\partial z}}_{1 \times C} \right]$$

if p_i is ● from frame 1 $\frac{\partial f}{\partial \xi_2}, \frac{\partial f}{\partial \xi_3}$ should be 0

if p_i is ● from frame 2 $\frac{\partial f}{\partial \xi_1}, \frac{\partial f}{\partial \xi_3}$ should be 0

...

$$\frac{\partial f}{\partial \xi_1} = \begin{matrix} 1 \times 3 & 1 \times 3 & 3 \times 3 \\ \left[g_p & g_p P_x \right] \end{matrix} \in \mathbb{R}^{1 \times 6}$$

↓

x means skew

$$[a, b, c]_x = \begin{bmatrix} 0 & a & c \\ -a & 0 & b \\ c & -b & 0 \end{bmatrix}$$

$$\frac{\partial f}{\partial s} = \begin{matrix} 1 \times 3 & 3 \times 1 \\ g_p p \end{matrix} \in \mathbb{R}^{1 \times 1}$$

$$\frac{\partial f}{\partial z} = g_z \in \mathbb{R}^{1 \times c}$$

note, these p
are all under
canonical frame
 $p = T_{c_j} p^i$
 $\hookrightarrow \text{Exp}(\xi_j)$

now we know J_i

we can get $J = \begin{bmatrix} J_1 \\ J_2 \\ \vdots \\ J_N \end{bmatrix}$ similarly

we also already know b .

so we can calculate Δx

$x' = x_0 + \Delta x$, with the new x' , we transform p accordingly.

\hookrightarrow and we do the iteration till convergence