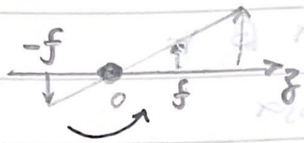
Pose Estimation via Vision

- pinhole model
- triangulation (2D-3D)
- ICP problem (3D-3D)
- optimization

pinhole model



$$\frac{z}{f} = \frac{X}{X'} = \frac{Y}{Y'}$$

$$\therefore \begin{cases} X' = f\dfrac{X}{z} \\ Y' = f\dfrac{Y}{z} \end{cases}$$

from $x'y'$ to u, v
enlarge α, β
translate c_x, c_y

SU

$$\begin{cases} u = \alpha X' + c_x \\ v = \beta Y' + c_y \end{cases}$$

$$\Rightarrow \begin{cases} u = \alpha f \dfrac{X}{z} + c_x \\ v = \beta f \dfrac{Y}{z} + c_y \end{cases}$$

$u - cx$

$\frac{(u-cx)}{\delta x} \cdot s$

$$\Rightarrow \begin{cases} u = f_x \dfrac{X}{z} + c_x \\ v = f_y \dfrac{Y}{z} + c_y \end{cases}$$

$su =$

$\frac{s}{\delta x}$

let $s = z$

$x \begin{cases} \frac{376-635}{630} \cdot 4.3 = -1.76 \\ \frac{432-635}{630} \cdot 5.56 = -1.79 \end{cases}$

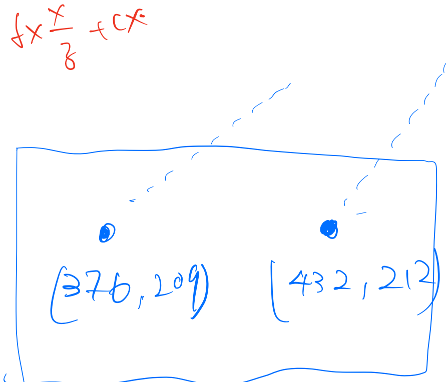
$$\Rightarrow s\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ z \end{bmatrix}$$

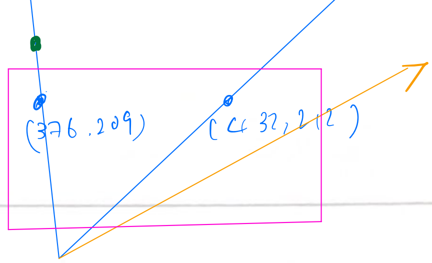
$su = f_x X + c_x z$

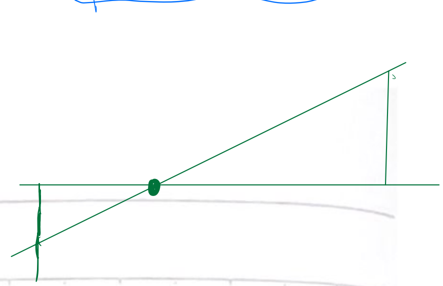
$u = f_x \frac{X}{z} + c_x$

$y \begin{cases} \frac{209-369}{629} \cdot 4.3 = -1.09 \\ \frac{212-369}{629} \cdot 5.56 = -1.38 \end{cases}$

$$\begin{aligned} \Rightarrow su &= K P_c \\ &= K T_{cw} P_w \\ &= K(R_{cw} P_w + t) \end{aligned}$$







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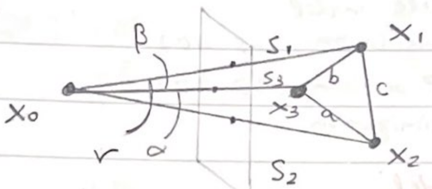
Triangulation (2D-3D)

P3P



known X_1 X_2 X_3 α β γ

$a^2 = S_2^2 + S_3^2 - 2S_2S_3\cos\alpha$

$b^2 = S_1^2 + S_3^2 - 2S_1S_3\cos\beta$

$c^2 = S_1^2 + S_2^2 - 2S_1S_2\cos\gamma$

① $a^2 = S_2^2 + S_3^2 - 2S_2S_3\cos\alpha$

set $u = S_2/S_1$ $\quad v = S_3/S_1$

$a^2 = S_1^2(u^2 + v^2 - 2uv\cos\alpha)$

$\therefore S_1^2 = \dfrac{a^2}{u^2 + v^2 - 2uv\cos\alpha}$

② $b^2 = S_1^2 + S_3^2 - 2S_1S_3\cos\beta$

set $u = S_2/S_1$ $\quad v = S_3/S_1$

$b^2 = S_1^2(1 + v^2 - 2v\cos\beta)$

$\therefore S_1^2 = \dfrac{b^2}{1 + v^2 - 2v\cos\beta}$

③ $c^2 = S_1^2 + S_2^2 - 2S_1S_2\cos\gamma$

set $u = S_2/S_1$ $\quad v = S_3/S_1$

$c^2 = S_1^2(1 + u^2 - 2u\cos\gamma)$

$\therefore S_1^2 = \dfrac{c^2}{1 + u^2 - 2u\cos\gamma}$

$\therefore S_1^2 = \dfrac{a^2}{u^2+v^2-2uv\cos\alpha} = \dfrac{b^2}{1+v^2-2v\cos\beta} = \dfrac{c^2}{1+u^2-2u\cos\gamma}$

parameterize u as v

$\Rightarrow A_4v^4 + A_3v^3 + A_2v^2 + A_1v + A_0 = 0$

get 4 (up to) v solutions

get v $\rightarrow$ solve u

$\rightarrow$ solve S_1 S_2 S_3

now we have two pairs of 3D points

$\rightarrow$ solve 3D-3D problem

EPnP

- we need reference points P to do odometry
- any reference points P can be expressed by control points C_j x4

$\Rightarrow P_i^w = \sum_{j=1}^{4} \alpha_{ij} C_j^w$ w/ $\sum_{j=1}^{4}\alpha_{ij} = 1$

known ↓ unknown known

side note 1:
- how to get C_j^w

side note 2:
- why 4 points, not 3, 2?

now try to get α (intermediate media)

$P_i^c = R_{cw} P_i^w + t$

$= R_{cw}\left(\sum_{j=1}^{4}\alpha_{ij} C_j^w\right) + t$

as $\sum_{j=1}^{4}\alpha_{ij} = 1$

$t = \sum_{j=1}^{4}\alpha_{ij}\, t$

$\therefore P_i^c = R_{cw}\left(\sum_{j=1}^{4}\alpha_{ij} C_j^w\right) + \sum_{j=1}^{4}\alpha_{ij}\, t$

$= \sum_{j=1}^{4}\left[\alpha_{ij}\left(R_{cw} C_j^w + t\right)\right]$

$= \sum_{j=1}^{4}\alpha_{ij} C_j^c$

Both {c} {w} share same α

$P_i^w = \sum_{j=1}^{4}\alpha_{ij} C_j^w$

known ↓ unknown known

get unknown α_{ij} → known

$P_i^c = \sum_{j=1}^{4}\alpha_{ij}(R_{cw} C_j^w + t) = \sum_{j=1}^{4}\alpha_{ij} C_j^c$

unknown unknown known

our objective is to get P_i^c

side note 3:
how to get α_{ij}?

$$P_i^c = \sum_{j=1}^{4} \alpha_{ij}(R_{cw} C_j^w + t) = \sum_{j=1}^{4} \alpha_{ij} C_j^c$$

$$\Rightarrow w_i \begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} = \begin{bmatrix} f_u & 0 & u_c \\ 0 & f_v & v_c \\ 0 & 0 & 1 \end{bmatrix} \sum_{j=1}^{4} \alpha_{ij} \begin{bmatrix} x_j^c \\ y_j^c \\ z_j^c \end{bmatrix}$$

From Last Row:

$$w_i = \sum_{j=1}^{4} \alpha_{ij} z_j^c$$

we get
$$\begin{cases} w_i u_i = f_u \sum_{j=1}^{4} \alpha_{ij} x_j^c + u_c \sum_{j=1}^{4} \alpha_{ij} z_j^c \\ w_i v_i = f_v \sum_{j=1}^{4} \alpha_{ij} y_j^c + v_c \sum_{j=1}^{4} \alpha_{ij} z_j^c \end{cases}$$

$$\Rightarrow \sum_{j=1}^{4} \left[\alpha_{ij} f_u x_j^c + \alpha_{ij} (u_c - u_i) z_j^c \right] = 0$$

$$\sum_{j=1}^{4} \left[\alpha_{ij} f_v y_j^c + \alpha_{ij} (v_c - v_i) z_j^c \right] = 0$$

we hv α, K matrix, u_i v_i

get x_j^c y_j^c z_j^c $\Rightarrow$ 4 control pts
3 dimension
12 unknown

$$Mx = 0$$

$$x \in \mathbb{R}^{12}$$

$$M \in \mathbb{R}^{2n \times 12}$$

no. of points $i = 0, 1 \ldots n$

solve x get c_j^c $(j = 1, 2, 3, 4)$

we then hv c_j^w c_j^c $\rightarrow$ 3D-3D (ICP problem)

we then also hv $P_i^c = \sum_{j=1}^{4} \alpha_{ij} C_j^c \rightarrow \boxed{P_i^w P_i^c \rightarrow \text{ICP}}$

side note 1:

how to get C_j^w?

① as long as c_j^w is invertible

② as per Lepetit et al.: get centre of weight as C_j^w $(j=1)$

$$C_{j=1}^w = \frac{1}{n} \sum_{i=1}^{n} P_i^w$$

let $A = \begin{bmatrix} P_1^{wT} & \cdots & C_1^{wT} \\ \vdots & & \vdots \\ P_n^{wT} & & C_1^{wT} \end{bmatrix}$

$$A^T A \xrightarrow{\text{get}} \lambda_{c,i} \text{ value } i = 1, 2, 3$$
$$V_{c,i} \text{ vector } i = 1, 2, 3$$

$$C_j^w = C_{j=1}^w + \lambda_{c,j-1}^{\frac{1}{2}} V_{c,j-1} \quad j = 2, 3, 4$$

side note 2:

why 4, not others?

$$P_i^w = \begin{bmatrix} x_i^w \\ y_i^w \\ z_i^w \end{bmatrix} = \begin{bmatrix} C_1^w & C_2^w & C_3^w \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \end{bmatrix}$$

$$\sum_{i=1}^{3} \alpha_{ij} = 1$$

4 equations w/ 3 unknown

overdefined.

$\therefore j = 4$

side note 3:

how to get α_{ij}?

4 equations 4 unknowns

$P_i^w = \sum_{j=1}^{4} \alpha_{ij} C_j^w$ w/ $\sum_{j=1}^{4} \alpha_{ij} = 1$

solve linear system

remark 3D-2D $4\alpha_{ij}$ $\rightarrow$ varies.
$4C_{jc}$ $\rightarrow$ const

ICP Problem

known data association

$$Y = \{y_1, \ldots y_I\}$$
$$X = \{X_1, \ldots X_J\}$$
$\}$ w $C = \{i, j\}$

$$\sum_{(i,j) \in C} \| y_i - R x_j - t \|^2 \rightarrow \min$$

matched points pairs:

X_n Y_n

$$\bar{X}_n = R X_n + t$$

$$\sum \| Y_n - \bar{X}_n \|^2 p_n \rightarrow \min$$

exist & let's derive direct solution

$$y_0 = \frac{\sum y_n p_n}{\sum p_n} \quad X_0 = \frac{\sum X_n p_n}{\sum p_n}$$

$$H = \sum (y_n - y_0)(X_n - X_0)^T p_n$$

$$\text{svd}(H) = U D V^T$$

$$R = V U^T$$

$$t = y_0 - R X_0$$

why is this a good solution? $\rightarrow$

No.

Date

$$\bar{X}_n = RX_n + t$$
$$\bar{X}_n - y_0 = RX_n + t - y_0$$
$$\bar{X}_n - y_0 = R(X_n + \underbrace{R^T t - R^T y_0}_{})$$
$$\bar{X}_n - y_0 = R(X_n - X_0)$$ set as unknown varible X_0

ICP (SVD) (cont'd)

$$\sum \| y_n - \bar{X}_n \|^2 p_n \rightarrow \min$$

$$\Rightarrow \sum \| \underbrace{y_n - y_0}_{} - \underbrace{RX_n - t}_{\bar{X}_n} + \underbrace{y_0}_{} \|^2 p_n \rightarrow \min$$

$$\Rightarrow \sum \| y_n - y_0 - (\bar{X}_n - y_0) \|^2 p_n \rightarrow \min$$

$$\Rightarrow \sum \| y_n - y_0 - R(X_n - X_0) \|^2 p_n \rightarrow \min$$

$$\therefore R^* X_0^* = \underset{R, X_0}{\operatorname{argmin}} \sum \| y_n - y_0 - R(X_n - X_0) \|^2 p_n$$

$$\Phi(X_0, R) = \sum [(y_n - y_0) - R(X_n - X_0)]^T [(y_n - y_0) - R(X_n - X_0)] p_n$$

$$\Phi(X_0, R) = \sum (y_n - y_0)^T (y_n - y_0) p_n$$ no X_0, R
$$+ \sum (X_n - X_0)^T (X_n - X_0) p_n$$ no R
$$- 2 \sum (y_n - y_0)^T R (X_n - X_0) p_n$$

① w.r.t X_0

$$\frac{\partial \Phi(X_0, R)}{\partial X_0} = -2 \sum (X_n - X_0) p_n + 2 \sum R^T (y_n - y_0) p_n$$

set $\frac{\partial \Phi(X_0, R)}{\partial X_0} = 0$

$$\therefore 0 = -2 \sum (X_n - X_0) p_n + 2 \sum R^T (y_n - y_0) p_n$$
$$\Rightarrow \sum (X_n - X_0) p_n = 0$$
$$\sum X_n p_n - \sum X_0 p_n = 0$$
$$\Rightarrow X_0 = \frac{\sum X_n p_n}{\sum p_n}$$

optimal value for X_0 is the weighted mean of points X_n

② w.r.t R

$$R^* = \underset{R}{\operatorname{argmin}} - 2 \sum (y_n - y_0)^T R (X_n - X_0) p_n$$
$$= \underset{R}{\operatorname{argmax}}\ 2 \sum (y_n - y_0)^T R (X_n - X_0) p_n$$

let $b_n = y_n - y_0$

$a_n = X_n - X_0$

$$R^* = \underset{R}{\operatorname{argmax}} \sum b_n^T R a_n p_n$$

$$R^* = \underset{R}{\operatorname{argmax}}\ tr(RH)$$

$$H = \sum (a_n b_n^T) p_n$$

find R max $tr(RH)$

$$SVD(H) = UDV^T$$

$U^T U = I$

$V^T V = I$

$D = diag(d_i)$

$R = VU^T$

$H = UDV^T$

$$tr(RH) = tr(VU^T UDV^T)$$
$$= tr(VDV^T)$$
$$= tr(VD^{\frac{1}{2}} D^{\frac{1}{2}} V^T)$$ set $A = VD^{\frac{1}{2}}$
$$= tr(AA^T)$$

$$\therefore tr(RH) = tr(AA^T)$$

$$tr(AA^T) \geq tr(R' AA^T)$$

Schwarz inequality

$$tr(RH) = tr(AA^T) \geq tr(R'AA^T)$$
$$\parallel$$
$$tr(R'RH)$$

any other rotation matrix

$\therefore$ choice $R = VU^T$

optimal to maxize the trace

$R'R$ is also another $SO(3)$

let $R'R = R''$

$tr(R''H)$ will always $<$ $tr(RH)$

if $R = VU^T$

i.e, if RH can be written as AA^T

$tr(RH)$ will be max.

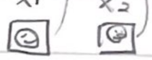
What's SVD

- for data deduction
- data-driven generalization of Fourier Transform (FFT)
- "tailored" to specific problem
- solve $Ax = b$ for non-square A
- regression
- PCA
- correlation

$$\bar{X} = \begin{bmatrix} | & | & | & & | \\ x_1 & x_2 & x_3 & \cdots & x_m \\ | & | & | & & | \end{bmatrix}_{\mathbb{R}^{n\times m}}$$

$x_k \in \mathbb{R}^n$

x_1 x_2 ....



$$\bar{X} = \begin{bmatrix} | & | & | & & | \\ x_1 & x_2 & x_3 & \cdots & x_m \\ | & | & | & & | \end{bmatrix}_{\mathbb{R}^{n\times m}} = U\Sigma V^T,$$

eigen — importances — mixtures of U's to make X's

$$U\Sigma V^T = \begin{bmatrix} | & | & & | \\ u_1 & u_2 & \cdots & u_n \\ | & | & & | \end{bmatrix} \begin{bmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & \ddots \ \sigma_m \\ & 0 & \end{bmatrix} \begin{bmatrix} v_1 & v_2 & \cdots & v_m \end{bmatrix}^T$$

eigen faces — order by importance — eigen time series, eigen mixtures

left singular vectors — singular values — right singular vectors

- u, v unitary — normal length orthogonal

$UU^T = U^TU = I_{n\times n}$

$VV^T = V^TV = I_{m\times m}$

Σ diagonal $\sigma_1 \geq \sigma_2 \geq \cdots \sigma_m \geq 0$

$$\bar{X} = \begin{bmatrix} | & | & & | \\ x_1 & x_2 & \cdots & x_m \\ | & | & & | \end{bmatrix} = U\Sigma V^T = \begin{bmatrix} | & | & & | \\ u_1 & u_2 & \cdots & u_n \\ | & | & & | \end{bmatrix} \underbrace{\begin{bmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & \ddots \ \sigma_m \\ & 0 & \end{bmatrix}}_{m\times m} \begin{bmatrix} — v_1^T — \\ — v_2^T — \\ \vdots \end{bmatrix}$$

$n \gg m$, usually — gauranteed to exist, unique

$= u_1\sigma_1 v_1^T + u_2\sigma_2 v_2^T \cdots + u_m\sigma_m v_m^T + 0$

$= \hat{U}\hat{\Sigma}V^T$ (economy SVD)

$n\times m$ $m\times m$

[U, S, V] = svd(X, 'econ')

$= \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \cdots + \sigma_m u_m v_m^T + 0$

$= \sigma_1 \, u_1 v_1^T + \sigma_2 \, u_2 v_2^T + \cdots + \sigma_m \, u_m v_m^T$

rest negligible

truncate at rank r

$\tilde{U}^T\tilde{U} = I_{r\times r}$

$\tilde{U}\tilde{U}^T \neq I_{r\times r}$

$= \tilde{U}\tilde{\Sigma}\tilde{V}^T$ (Eckard-Yang [1936] Theory)

$$\underset{\tilde{X} \text{ s.t. } \operatorname{rank}(\tilde{X}) = r}{\operatorname{argmin}} \|\bar{X} - \tilde{X}\|_F = \tilde{U}\tilde{\Sigma}\tilde{V}^T$$

SVD + correlation

$$\bar{X}^T\bar{X} = {}_m \begin{bmatrix} — x_1^T — \\ — x_2^T — \\ \vdots \end{bmatrix}^{n} \; {}_n\begin{bmatrix} | & | & \\ x_1 & x_2 & \cdots \\ | & | & \end{bmatrix}_m$$

correlation matrix

$$= \begin{bmatrix} x_1^Tx_1 & x_1^Tx_2 & & x_1^Tx_m \\ x_2^Tx_1 & x_2^Tx_2 & \cdots & x_2^Tx_m \\ \vdots & \vdots & & \vdots \\ x_m^Tx_1 & x_m^Tx_2 & & x_m^Tx_m \end{bmatrix}$$

$x_i^Tx_j = \langle x_i, x_j \rangle$

$\bar{X} = \hat{U}\hat{\Sigma}V^T$

$\bar{X}^T = V\hat{\Sigma}\hat{U}^T$

$\bar{X}^T\bar{X} = V\hat{\Sigma}\hat{U}^T\hat{U}\hat{\Sigma}V^T$

$= V\hat{\Sigma}^2V^T$ (eigen decomposition)

$\bar{X}^T\bar{X}V = V\hat{\Sigma}^2$ → eigenvalues

eigenvectors

$\bar{X}\bar{X}^T = \hat{U}\hat{\Sigma}V^TV\hat{\Sigma}\hat{U}^T = \hat{U}\hat{\Sigma}^2\hat{U}^T$

$\bar{X}\bar{X}^T\hat{U} = \hat{U}\hat{\Sigma}^2$ → eigenvales.

eigenvectors

ICP

unknown data association

corresponding points y_n, x_n $n = 1, \ldots, N$

weights p_n $n = 1, \ldots, N$

find R, t s.t.

$\bar{x}_n = R x_n + t$ $n = 1, \ldots, N$

so that

$\sum \|y_n - \bar{x}_n\|^2 p_n \longrightarrow \min$

correspondencies unknown

guess ⟶ point locations or point correspondences

↓

iteration

ICP (Vanilla)

```
x̄n = xn
e = ∞
while e > thres
    c = correspondencies ({yn, x̄n})
    (t, R) = compute T (c)
    x̄n = R(xn - x0) + y0
    e = E(t, R) = Φ(Rᵀy0 - Rᵀt, R)
return {x̄n}
```

No.

Date

if easy → analytical form
→ through $\frac{dF}{dx} = 0$
→ else

Non-linear Least-Square Problom

$$\min_{x} F(x) = \frac{1}{2}\|f(x)\|_2^2 \qquad f(x): \mathbb{R}^n \to \mathbb{R}$$

objective: get X s.t. $F(x)$ has min

optimization algo

```
while true
    at i = k
    search ΔX_k
    get ||f(X_k + ΔX_k)||_2^2
    if ΔX_k < b
        return
    else
        continue
    X_{k+1} = X_k + ΔX_k
```

How to get ΔX_k?

A: different tricks

Here introduce

Gauss-Newton Method

$$f(x) = \frac{1}{2}\sum_{j=1}^{m} r_j(x)^2 = \frac{1}{2}\sum_{j=1}^{m}\|r(x)\|_2^2$$

$$\begin{cases} r_j(x) = \phi(x;t_j) - y_j \\ j = 1, 2, 3 \dots m \\ r(x) = [r_1(x), r_2(x) \dots r_m(x)]^T \end{cases}$$

x is the objective parameter (e.g. pose) $X \in \mathbb{R}^n$

r is the residual result calculated from X (e.g. reprojection u, v) $m = 1, 2$

math preliminaries

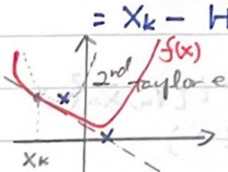
$$\nabla f(x_1, x_2) = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}\right) \qquad J(x) = \left[\frac{\partial r_j}{\partial x_i}\right]_{\substack{j=1\dots m \\ i=1\dots n}} = \begin{bmatrix} \nabla r_1(x)^T \\ \nabla r_2(x)^T \\ \vdots \\ \nabla r_m(x)^T \end{bmatrix}$$

$$H(f(x_1, x_2)) = \begin{pmatrix} \frac{\partial f}{\partial x_1^2} & \frac{\partial f}{\partial x_1 \partial x_2} \\ \frac{\partial f}{\partial x_2 \partial x_1} & \frac{\partial f}{\partial x_2^2} \end{pmatrix}$$

recall Newton's Method

$$X_{k+1} = X_k + \Delta X_k$$

$$\Rightarrow X_{k+1} = X_k - [\nabla^2 f(x_k)]^{-1} \nabla f(x_k) = X_k - H^{-1} J_r(x_k)^T r(x_k)$$



2nd taylor expension $f(x) = f(x_k) + f'(x_k)(x - x_k) + \frac{1}{2} f''(x_k)(x - x_k)^2$

1st taylor expension $f(x) = f(x_k) + f'(x_k)(x - x_k)$

not a good value for ΔX_k, as it could over-shoot exagerattingly

much better. at least we hv a minimum value (quadratic)

1st order: $f(x_k) + f'(x_k)(x - x_k) = 0$

2nd order: $\underbrace{f(x_k) + f'(x_k)(x - x_k) + \frac{1}{2} f''(x_k)(x - x_k)^2}_{g(x)} = 0$

solve X value, and set it as next X_k.

Newton's method opt the second 2nd order.

$$\frac{d}{dx} g(x) = f'(x_k) + f''(x_k)(x - x_k)$$

$$x^* = \arg\min_{x} g(x)$$

$$\therefore 0 = \frac{d}{dx} g(x) = f'(x_k) + f''(x_k)\underbrace{(x - x_k)}_{\Delta x}$$

$$\Delta x = \frac{-f'(x_k)}{f''(x_k)}$$

$$\therefore X_{k+1} = X_k - [\nabla^2 f(x_k)]^{-1} \nabla f(x_k) = X_k - H^{-1} J_r(x_k)^T r(x_k)$$

yet: still greedy

Hessian matrix not easy to solve

∴ Gauss-Newton Method

w/ $\nabla f = J_r^T r$

$$\nabla^2 f = J_r^T J_r + \sum_{j=1}^{m} r_i \nabla^2 r_i = J_r^T J_r + Q$$

$$\nabla^2 f \approx J_r^T J_r$$

substitute H as $J^T J$

$$\therefore X_{k+1} = X_k - [J_r(x_k)^T J_r(x_k)]^{-1} \cdot \underbrace{J_r(x_k)^T r(x_k)}_{\Delta x}$$

$$\therefore \boxed{\Delta x = -[J_r(x_k)^T J_r(x_k)]^{-1} J_r(x_k)^T r(x_k)}$$

$f = \frac{1}{2}\sum_{j=1}^{m} r_j(x)^2$

$\frac{\partial f}{\partial x_i} = \sum_{j=1}^{m} \frac{\partial r_j}{\partial x_i} r_j$

1st order

$$\nabla f(x) = \nabla \frac{1}{2} \sum_{j=1}^{m} (r_j(x))^2 = \sum_{j=1}^{m} r_j(x) \nabla r_j(x) = J(x)^T r(x)$$

2nd order

$$\nabla^2 f(x) = \nabla \sum_{j=1}^{m} r_j(x) \nabla r_j(x) = \sum_{j=1}^{m} \nabla r_j(x) \nabla r_j(x) + \sum_{j=1}^{m} r_j(x) \nabla^2 r_j(x) = J(x)^T J(x) + \sum_{j=1}^{m} r_j(x) \nabla^2 r_j(x) = J(x)^T J(x) + Q(x)$$