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CS-512 - Assignment-4

Ans-1

a) Projection equation $p = MP$,

Problem of :

forward projection -

\Rightarrow one is radial lens distortion,
It gives huge shrink away from the center
once parameters are determined, the image
can be corrected

$$P^{(i)} = \begin{bmatrix} \lambda & \\ & \lambda \end{bmatrix} K^* [R^* T^*] P^{(w)}$$

$$\lambda = 1 + k_1 d + k_2 d^2$$

d = distance from center

k_1 = linear distortion coefficient

k_2 = quadratic distortion coefficient

\Rightarrow second is weak perspective camera.

It is correct when depth variation in the scene is small compared with distance from camera.

$$C = |M_o p - M_p| = \frac{\text{depth variation}}{d_o} \frac{(M_p - P_o)}{\text{distance from center}}$$

distance from camera

calibration -

camera uses 3×4 projection Matrix,
 $M = K^* [R^* | T^*]$. which includes internal and external parameters.

Here we need to find 12 unknown parameters of M . It requires minimum 6 points. Every point gives us two equations. So, finally we will get 12 equations.

Parameters $\rightarrow K^*, R^*, T^*$

$\rightarrow R, T, f, k_u, k_v, u_0, v_0, s,$

reconstruction -

one-to-one correspondence is not possible

- object points not visible in both views (occlusion)

- ambiguous points (multiple candidates)

- uniform regions (inside points cannot be distinguished)

forward projection problem is the easiest.
reconstruction problem is the most difficult

- b) In camera calibration we need to find values of projection matrix M which is 3×4 .
we need to find 12 values of M .

we required points $\{P_i\}_{i=1}^m \leftrightarrow \{\underline{P}_i\}_{i=1}^m$

Here, P_i is 2D image coordinates and \underline{P}_i is 3D world coordinates.

To find 12 unknowns, we need 12 equations. But each point gives us 2 equations. So, we need at least 6 points

using these 12 equations?

- find projection matrix M

- find parameters from M .

$$M \rightarrow K^*, R^*, T^*$$

$$\rightarrow f, K_u, K_v, u_0, v_0, \text{ and } \theta$$

c) In non-coplanar calibration,

Given: $\{\underline{P}_i\}_{i=1}^m \leftrightarrow \{\underline{p}_i\}_{i=1}^m$

2D FL

image

points

3D FL

world

points

Steps: - find projection matrix M

Here, projection matrix M is 3×4 .
we need to find 12 values.

$$M = \begin{bmatrix} -m_1^T & - \\ -m_2^T & - \\ -m_3^T & - \end{bmatrix}$$

- using m_1, m_2, m_3 find parameters

$$M \rightarrow K^*, R^*, T^* \rightarrow f, K_u, K_v, u_0, v_0, s, R, T$$

M_1, M_2, M_3 have 12 unknowns, it requires 12 equations, so we need minimum 6 points. each point gives 2 equations.

$$d) \quad M = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 0 & 3 & 4 \\ 1 & 1 & 1 & 1 \end{bmatrix}, \quad P_i^w = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix}$$

3D 3DH

$$P_i^i = MP_i^w = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 0 & 3 & 4 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 18 \\ 14 \\ 7 \end{bmatrix}$$

2D 2DH

$$2D \text{ image coordinates} = \left(\frac{18}{7}, \frac{14}{7} \right)$$

$$e) \quad \begin{matrix} (1, 2, 3) \\ 3D \end{matrix} \leftrightarrow \begin{matrix} (100, 200) \\ 2D \end{matrix}$$

$$\begin{matrix} (1, 2, 3, 1) \\ 3DH \end{matrix} \leftrightarrow \begin{matrix} (100, 200, 1) \\ 2DH \end{matrix}$$

Ans \hat{o}

$$\begin{bmatrix} 1 & 2 & 3 & 1 & 0 & 0 & 0 & 0 & -100 & -200 & -300 & -100 \\ 0 & 0 & 0 & 0 & 1 & 2 & 3 & 1 & -200 & -400 & -600 & -200 \end{bmatrix}$$

f) M is a 3×4 matrix which has 12 unknown values

To find 12 unknown values, we need 12 equations.

every point gives us 2 equations,
so, we need at least 6 points.

$$\begin{aligned} M_1^T \underline{P_i} - x_i M_3^T \underline{P_i} = 0 \\ M_2^T \underline{P_i} - j_i M_3^T \underline{P_i} = 0 \end{aligned} \quad \left. \begin{array}{l} x_i = \frac{x_i}{w_i} = \frac{M_1^T \underline{P_i}}{M_3^T \underline{P_i}} \\ j_i = \frac{j_i}{w_i} = \frac{M_2^T \underline{P_i}}{M_3^T \underline{P_i}} \end{array} \right\}$$

for single point :

$$\begin{bmatrix} \underline{P_i}^T & 0 & -x_i \underline{P_i}^T \\ 0 & \underline{P_i}^T & -j_i \underline{P_i}^T \end{bmatrix}_{2 \times 12} \begin{bmatrix} M_1 \\ M_2 \\ M_3 \end{bmatrix}_{12 \times 1} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}_{3 \times 1}$$

for m points :

$$\begin{bmatrix} \underline{P_1}^T & 0 & -x_1 \underline{P_1}^T \\ 0 & \underline{P_1}^T & -j_1 \underline{P_1}^T \\ \vdots & \vdots & \vdots \\ \underline{P_n}^T & 0 & -x_n \underline{P_n}^T \\ 0 & \underline{P_n}^T & -j_n \underline{P_n}^T \end{bmatrix}_{2m \times 12} \begin{bmatrix} M_1 \\ M_2 \\ M_3 \end{bmatrix}_{12 \times 1} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}_{3m \times 1}$$

$$AX=0$$

To solve $Ax=0$ use SVD

$$A = UDV^T$$

Solution: column of V belonging to zero singular value

$$\hat{x} = \begin{bmatrix} \hat{m}_1 \\ \hat{m}_2 \\ \hat{m}_3 \end{bmatrix} \Rightarrow \hat{M} = \begin{bmatrix} -\hat{m}_1^T \\ -\hat{m}_2^T \\ -\hat{m}_3^T \end{bmatrix}$$

The solution is not unique if $A\hat{x}=0$
we also have $A(\hat{s}\hat{x})=0 \Rightarrow \hat{s}\hat{x}$ is a solution.

2) finding parameters from M_s

$$M = S\hat{M} = K^* [R^* | T^*]$$

$$[K^* R^* | K^* T^*] = S\hat{M}$$

$$S\hat{M} = \left[\begin{array}{c|c} -a_1^T & b \\ -a_2^T & \\ -a_3^T & \end{array} \right] = \left[\begin{array}{c|c} \alpha_1 \sigma_1^T + s \sigma_2^T + u_0 \sigma_3^T & \\ \alpha_1 \sigma_2^T + v_0 \sigma_3^T & \\ \sigma_3^T & \end{array} \right] K^* T^*$$

Unknown Known Unknown.

$$\rightarrow \alpha_1 \sigma_1^T + s \sigma_2^T + u_0 \sigma_3^T = S a_1^T \quad \text{Known}$$

$$\rightarrow \alpha_1 \sigma_2^T + v_0 \sigma_3^T = S a_2^T \quad a_1, a_2, a_3, b$$

$$\rightarrow \sigma_3^T = S a_3^T$$

$$\rightarrow K^* T^* = S b$$

Unknown
 $\sigma_1, \sigma_2, \sigma_3, T^*, (K^*)$
 $s, \alpha_1, \alpha_2, u_0, v_0, S$

$$|\mathcal{S}| = 1/103)$$

$$v_0 = |\mathcal{S}|^2 a_1 \cdot c_3$$

$$v_0 = |\mathcal{S}|^2 a_2 \cdot c_3$$

$$\alpha_v = C (|\mathcal{S}|^2 a_2 \cdot c_2 - v_0^2)^{1/2}$$

$$s = |\mathcal{S}|^2 / \alpha_v (c_1 \times c_3) \cdot (c_2 \times c_3)$$

$$\alpha_u = (|\mathcal{S}|^2 a_1 \cdot c_1 - s^2 - v_0^2)^{1/2}$$

$$K^* = \begin{bmatrix} \alpha_u & s & v_0 \\ 0 & \alpha_v & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

E : Sym(3)

$$T^* = E |\mathcal{S}| (K^*)^{-1} b$$

$$\tau_3 = E |\mathcal{S}| c_3$$

$$\tau_1 = |\mathcal{S}|^2 / \alpha_v c_2 \times c_3$$

$$\tau_2 = \tau_3 \times \tau_1$$

$$R^* = [\tau_1^T \ \tau_2^T \ \tau_3^T]^T$$

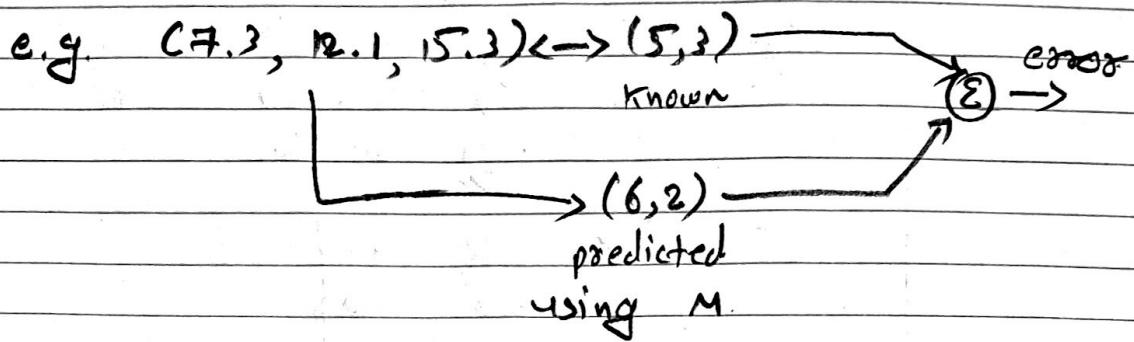
h) Given $\{\underline{P}_i\}_{i=1}^m \leftrightarrow \{\underline{p}_i\}_{i=1}^m$ and
image point world point

estimated $M = \begin{bmatrix} -n_1^T \\ -n_2^T \\ -n_3^T \end{bmatrix}$

assess the quality of fit using:

$$E = \frac{1}{m} \sum_i \left(\left| \left| \underline{x} - \frac{m_1^T \underline{p}_i}{m_3^T \underline{p}_i} \right| \right|^2 + \left| \left| \underline{z}_i - \frac{m_2^T \underline{p}_i}{m_3^T \underline{p}_i} \right| \right|^2 \right)$$

distance between known and predicted positions.



i) To recover M we need to solve,

$$\begin{bmatrix} p_1^T & 0 & -x_1 p_1^T \\ 0 & p_1^T & -y_1 p_1^T \\ \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \end{bmatrix}$$

- when p_i are all on the same plane π , we have $\pi^T p_i = 0 \forall p_i$

$$\underbrace{(a, b, c, -d)}_{\text{normal}} \quad (x, y, z, 1)$$

- there are many possible solutions

$$\begin{bmatrix} m_1 \\ m_2 \\ m_3 \end{bmatrix} = \alpha \begin{bmatrix} \pi \\ 0 \\ 0 \end{bmatrix} + \beta \begin{bmatrix} 0 \\ \pi \\ 0 \end{bmatrix} + \gamma \begin{bmatrix} 0 \\ 0 \\ \pi \end{bmatrix}$$

e.g., $\alpha=1, \beta=0, \gamma=0$

$$\begin{bmatrix} \underline{P}_1^T & 0 & -\underline{x}_1 \underline{P}_1^T \\ 0 & \underline{P}_1^T & -\underline{j}_1 \underline{P}_1^T \\ 1 & 1 & ; \\ 1 & 1 & ; \end{bmatrix} \begin{bmatrix} \underline{\Pi} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ ; \\ ; \end{bmatrix}$$

any combination of α, β, γ could be a solution.

Additional degenerate configurations are points on a quadratic surface.

here, infinite number of solutions are possible. so we cannot get unique solution of projection matrix M . but we can get unique solution in non-coplanar one.

i) difference between the homography H (2D projective map) and the projection matrix M .

$$\underline{P}_i = \overset{3 \times 4}{M} \underline{P}_i = \overset{3D H}{S} \overset{3D M}{A} \underline{P}_i \Rightarrow \overset{3 \times 4}{M} = \begin{bmatrix} -\overset{3}{M}_1^T & - \\ -\overset{3}{M}_2^T & - \\ -\overset{3}{M}_3^T & - \end{bmatrix}$$

$$\underline{P}_i = \overset{3 \times 3}{H} \underline{P}_i \Rightarrow \underline{P}_i = \overset{2D H}{K^*} [\overset{3 \times 4}{R^*} | \overset{3 \times 3}{T^*}] \overset{3 \times 4}{P_i}$$

$$= K^* [x_1, x_2, x_3, T^*] \begin{bmatrix} x_i \\ j_i \\ 0 \end{bmatrix}$$

$$= K^* [x_i x_1 + j_i x_2 + T^*]$$

$$= k^* \begin{bmatrix} x_1 & x_2 & T^* \end{bmatrix} \begin{bmatrix} x_i \\ \ddots \\ 1 \end{bmatrix}$$

2D projection

To get a 2D projective map we assume:
 (a) Z coordinate is 0.

$$\{P_i\}_2 = 0 \iff P_i^o = (x_i, y_i, 0)$$

$$\begin{bmatrix} y_i \\ v_i \\ w_i \end{bmatrix} = \frac{H P_i^*}{2DH} = \begin{bmatrix} -h_1^T \\ -h_2^T \\ -h_3^T \end{bmatrix} \begin{bmatrix} x_i^o \\ y_i^o \end{bmatrix}$$

$$\begin{matrix} 5 & 8 & 0 & 1 & 1 & 3 & x & 3 \\ 0 & 1 & 0 & 1 & 1 & 1 & 1 & 1 \end{matrix} \quad \begin{matrix} 3 & x & 3 \\ 1 & 1 & 1 \end{matrix} \quad \begin{matrix} 8 & 0 & 1 & 1 & 3 & 0 \end{matrix}$$

Projection matrix M is 3×4 , and 2D projection map is 3×3

$$\text{Given } \left\{ p_i \right\}_{i=1}^m \longleftrightarrow \left\{ p_i \right\}_{i=1}^m \quad p_i = \begin{bmatrix} x_i \\ y_i \end{bmatrix}$$

Define $\mathbf{P}_i^* = \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$

$$\begin{bmatrix} u_i \\ v_i \\ w_i \end{bmatrix} = K^* \underbrace{\begin{bmatrix} x_1 & x_2 & T^* \end{bmatrix}}_{3 \times 3} \begin{bmatrix} p_i \\ e_{DH} \end{bmatrix}$$

$$x_i = \frac{u_i}{w_i} = \frac{h_1^T p_i^*}{h_3^T p_i^*} \Rightarrow h_1^T p_i^* - x_i h_3^T p_i^* = 0$$

$$j_i = \frac{v_i}{w_i} = \frac{h_2^T p_i^*}{h_3^T p_i^*} \Rightarrow h_2^T p_i^* - j_i h_3^T p_i^* = 0$$

for projection matrix \hat{M} 12 unknowns
 (M) require 12 eqⁿ to solve
 require 6 points minimum

for 2D-projection map \hat{M} 9 unknowns
 (H) (8 independent)
 require 8 eqⁿ to solve
 require 4 points minimum

each point gives two eq^h's.

$$H = K^* \begin{bmatrix} x_1 & x_2 & T^* \end{bmatrix} = \alpha \hat{H}$$

$$\hat{H} = \begin{bmatrix} \hat{h}_1 & \hat{h}_2 & \hat{h}_3 \end{bmatrix} \quad \text{columns of } H$$

$$\hat{M} = \begin{bmatrix} M_1^T \\ M_2^T \\ M_3^T \end{bmatrix} \quad \text{rows of } M$$

Ans-25

$$\text{a) } \begin{aligned} P_{im} &= (1, 2) \\ P_w &= (3, 4, 5) \end{aligned} \Rightarrow \begin{aligned} P_i &= (1, 2, 1)^T \\ P_i^0 &= (3, 4, 5, 1)^T \end{aligned} \Rightarrow \begin{aligned} x_i &= 1 \\ y_i &= 2 \end{aligned}$$

Ans: $\begin{bmatrix} 3 & 4 & 5 & 1 & 0 & 0 & 0 & 0 & -3 & -4 & -5 & -1 \\ 0 & 0 & 0 & 0 & 3 & 4 & 5 & 1 & -6 & -8 & -10 & -2 \end{bmatrix}$

$$= \begin{bmatrix} P_i^T & 0 & -x_i P_i^T \\ 0 & P_i^T & -y_i P_i^T \end{bmatrix}$$

b) $\hat{M} = \left[\begin{array}{ccc|c} 1 & 2 & 3 & 4 \\ 2 & 3 & 4 & 5 \\ 3 & 4 & 5 & 6 \end{array} \right]$ $y_0 = ?$
 $v_0 = ?$

$$a_1 = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} \quad a_2 = \begin{bmatrix} 2 \\ 3 \\ 4 \end{bmatrix} \quad a_3 = \begin{bmatrix} 3 \\ 4 \\ 5 \end{bmatrix}$$

$$|S| = 1 / |a_3| = 1 / \sqrt{50} = 1 / \sqrt{50}$$

$$y_0 = |S|^2 a_1 \cdot a_3 = \frac{1}{50} \cdot 26 = \frac{13}{25} = 0.52$$

$$v_0 = |S|^2 a_2 \cdot a_3 = \frac{1}{50} \cdot 38 = \frac{19}{25} = 0.76$$

c) $P_{im} = (1, 2)$, $M = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 2 & 3 & 4 & 5 \\ 3 & 4 & 5 & 6 \end{bmatrix}$
 $P_w = (3, 4, 5)$

$$\begin{aligned}
 m_1^T &= (1 \ 2 \ 3 \ 4) \\
 m_2^T &= (2 \ 3 \ 4 \ 5) \\
 m_3^T &= (3 \ 4 \ 5 \ 6) \\
 p_i^o &= (3, 4, 5, 1)^T
 \end{aligned}$$

$$E = \frac{1}{m} \sum_i \left(\left\| x_i - \frac{m_1^T p_i^o}{m_3^T p_i^o} \right\|^2 + \left\| y_i - \frac{m_2^T p_i^o}{m_3^T p_i^o} \right\|^2 \right)$$

$$= \frac{1}{4} \left[\left\| 1 - \frac{30}{56} \right\|^2 + \left\| 2 - \frac{43}{56} \right\|^2 \right]$$

$$\begin{aligned}
 &= \| 0.464 \|^2 + \| -1.232 \|^2 \\
 &= 0.215 + 1.518 \\
 &= \underline{\underline{1.733}}
 \end{aligned}$$

$$\begin{aligned}
 d) \quad I + Q &= \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 5 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 6 & 0 & 0 & 0 \end{bmatrix} \\
 R^* &= \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix} \\
 &\quad \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix} \\
 &\quad \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}
 \end{aligned}$$

$$T^* = \begin{bmatrix} 1 \\ 7 \\ 2 \\ 3 \\ 1 \end{bmatrix}, \quad Q = ?, \quad T = ?$$

$$\begin{aligned}
 R^* &= R^T \Rightarrow Q = (R^*)^T \\
 T^* &= -R^T T \Rightarrow T = -(R^*)^T T^*
 \end{aligned}$$

$$R = \begin{bmatrix} 6 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$T = - \begin{bmatrix} 6 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 3 \\ 1 \end{bmatrix} = - \begin{bmatrix} 6 \\ 2 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} -6 \\ -2 \\ -3 \\ -1 \end{bmatrix} = \begin{bmatrix} 6 \\ 2 \\ 3 \\ 30 \end{bmatrix}$$

c) $P_{im} = (1, 2)$
 $P_w = (3, 4, 0) \Rightarrow P_w^* = (3, 4)$

$$x_i = 1, \quad y_i = 2, \quad P_i^{*T} = (3, 4, 1)$$

Ans: $\begin{bmatrix} P_i^{*T} & 0 & -x_i P_i^{*T} \\ 0 & P_i^{*T} & -y_i P_i^{*T} \end{bmatrix}_{2 \times 9}$

$$\therefore \begin{bmatrix} 3 & 4 & 1 & 0 & 0 & 0 & -3 & -4 & -1 \\ 0 & 0 & 0 & 3 & 4 & 1 & -6 & -8 & -2 \end{bmatrix}_{2 \times 9}$$

Ans-3

- u) In sparse approach we detect feature points and then match. These feature points are not everywhere. So, it is sparse. It is at some locations only.

In dense approach we match every point of one image with every point in another image. There are lot of match everywhere. So, it is dense. We use correlation or sum of square distances. It produce more points.

advantages :-

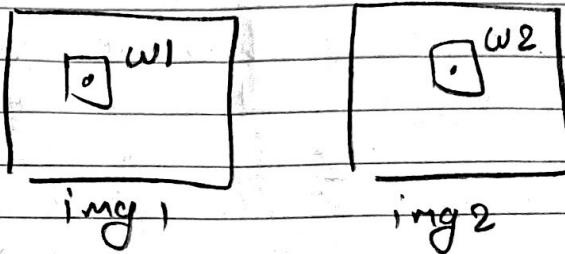
- > sparse → It handle large disparities
- > more robust
- > if big change in scene then it can handle it

dense → it limited to very small change of the view

disadvantages :-

- > sparse → ambiguous points (multiple candidates)
- > dense → object points not visible in both views (occlusion)
- > uniform regions (inside points cannot be distinguished)

- b) - Instead of feature points compose all patches
 - Instead of distance b/w feature vectors
 measure correlation or SSD
 - Apply regularization to reduce errors and
 find correspondence in difficult areas.
 (e.g uniform)



match all patches of img_1 with all patches of img_2

$$\text{Correlation} : \Psi(w_1, w_2) = \sum_i w_1(x_i, y_i) \cdot w_2(x_i, y_i)$$

High means good similarity and vice versa

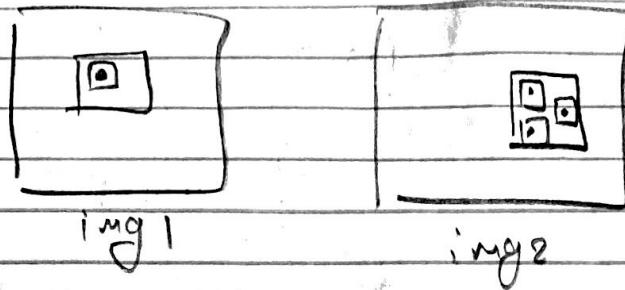
$$\text{SSD} : \Psi(w_1, w_2) = \sum_i (w_1(x_i, y_i) - w_2(x_i, y_i))^2$$

We take Euclidean distance. Large distance bad similarity and vice versa.
 High value = good correspondence

$$\text{ZNCC} : \Psi(w_1, w_2) = \sum_i \frac{(w_1(x_i, y_i) - \bar{w}_1)(w_2(x_i, y_i) - \bar{w}_2)}{\sqrt{w_1} \sqrt{w_2}}$$

$$\text{ZNSSD} : \Psi(w_1, w_2) = \sum_i \left(\frac{w_1(x_i, y_i) - \bar{w}_1}{\sqrt{w_1}} - \frac{w_2(x_i, y_i) - \bar{w}_2}{\sqrt{w_2}} \right)^2$$

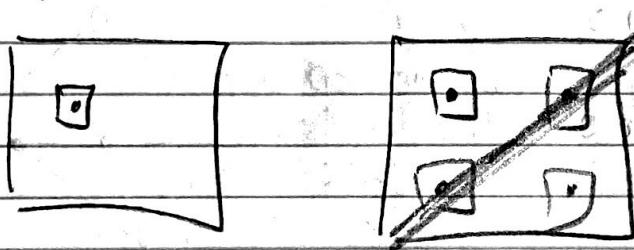
→ The risk in allowing the search space to be the entire image is difficult areas like uniform regions



because of uniform regions many solutions are possible.

so, apply regularization to reduce error

→ To reduce search space to a line, define constraints for reducing # of candidates.



during search for corresponding points, only search for points along the line, it will reduce # of candidates

$$c) P_L = (100, 200) = (X_L, Y_L)$$

$$P_R = (103, 200) = (X_R, Y_R)$$

$$f = 10$$

$$T = 100$$

$$Z = ?$$

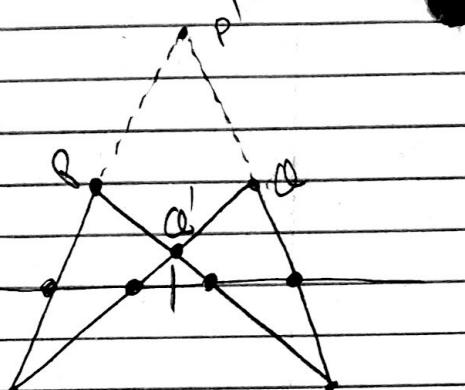
$$\text{depth, } Z = f \cdot \frac{T}{d} = \frac{10 \times 100}{3} = 1000/3 \\ = 333.33$$

$$d = X_R - X_L = 103 - 100 = 3$$

d) In stereo matching, there is an ambiguity in correspondence between points matching.

Correct: P, Q
incorrect: P', Q'

Scene has two 3D Points
project both points on
both image



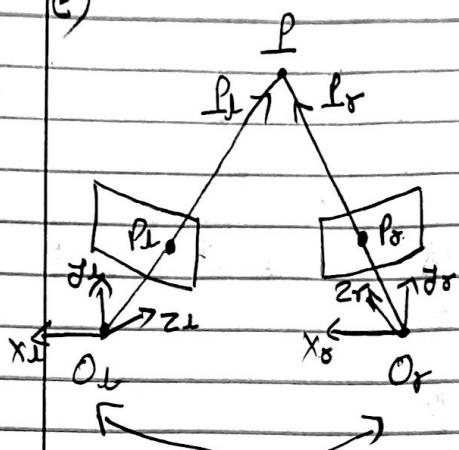
P, Q correct correspondence or
 P', Q' incorrect correspondence

because of the triangulation we get points P', Q'
on intersection.

in incorrect matching $P' = Q, Q' = P$
here P', Q' are far from P, Q .

In simple correspondence mistake we get big outliers.

c)



P = 3D point in world coordinate

P_L = 3D point in left coordinate

P_R = 3D point in right coordinate

p_L = image point (2D) in left coordinates

p_R = image point (2D) in right coordinates

R, T external

calibration $\Rightarrow \begin{cases} R_L, T_L & \text{rotation / translation} \\ R_R, T_R & \text{of left / right camera} \\ & \text{w.r.t. world.} \end{cases}$

$$M_{L \leftarrow \sigma} = M_{L \leftarrow w} M_{w \leftarrow \sigma}$$

$$R_L^T T_L^{-1} (R_R^T T_R^{-1})^{-1} = TR$$

$$= R_L^T T_L^T T_R R_R = TR$$

$$= [R_L^T \ 0] [I - T_L] [I \ T_R] [R_R \ 0]$$

$$= \begin{bmatrix} R_L^T & -R_L^T T_L \\ 0 & 1 \end{bmatrix} \begin{bmatrix} R_R & T_R \\ 0 & 1 \end{bmatrix}$$

rotation $\underbrace{\begin{bmatrix} R_L^T R_R & R_L^T (T_R - T_L) \\ 0 & 1 \end{bmatrix}}_{\text{translation}}$

$$\Rightarrow R = R_L^T R_R, \quad T = R_L^T (T_R - T_L)$$

Ans-4

a) $f = 10 \text{ mm}$
 $\bar{T} = 20 \text{ mm}$
 $d = 30 \text{ mm}$
 $z = ?$

$$z = f \cdot \frac{\bar{T}}{d} = \frac{10 \cdot 20}{30} = \frac{20}{3} = 6.667$$

b) $A = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, B = \begin{bmatrix} 2 \\ 3 \\ 4 \end{bmatrix}$

$$A \times B = \begin{bmatrix} x & y & z \\ 1 & 2 & 3 \\ 2 & 3 & 4 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ -1 \end{bmatrix}$$

$$A \times B = [A] \times B = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \\ 4 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & -3 & 2 \\ 3 & 0 & -1 \\ -2 & 1 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ 3 \\ 4 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ -1 \end{bmatrix}$$

$$[A]_x = \begin{bmatrix} 0 & -3 & 2 \\ 3 & 0 & -1 \\ -2 & 1 & 0 \end{bmatrix}$$

c) $F = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix}$ $P_1 = (1, 2) = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$
 $P_2 = (2, 3) = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$

$$P_8^T F P_L = ?$$

$$= \begin{bmatrix} 2 & 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 3 & 4 & 5 \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix}$$

$$= [11 \ 17 \ 23] \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} = \underline{\underline{68}}$$

d) $P' = (x', y') = (1, 2)$
 $P = (x, y) = (2, 3)$

$$\text{Ans} = [xx' \ xy' \ x \ yx' \ yy' \ y \ x' \ y' \ 1]$$

$$= [2 \ 4 \ 2 \ 3 \ 6 \ 3 \ 1 \ 2 \ 1]$$