· Perspective pose Estimation

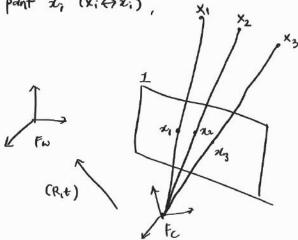
Given 30 points X; and corresponding image point x; (X; +> z;),

find cameron pose (R,t)

Xi in Fw, di in Fc

As rays intersect at C, it is called

Perspecitive - n-paint (Pnp) problem



· Uncalibrated camera case

P=K[RIT] where KIRIT are all unknown

PER3X4 W/ 12 unknowns

{x; ↔ x; \ ∀i , Viz; = Px;

$$\int_{0}^{\infty} (\partial_{i} x_{i}) \times (p x_{i}) = x_{i} \times (p x_{i}) = 0 \quad \Rightarrow \quad \left[\begin{array}{c} A \\ p^{2} \\ p^{3} \end{array} \right] = 0$$

For n 30-20 correspondences

I Ignore last now: linearly dependent => AER2x12

Ap = 0 where A = R 2hx12

Since rank(A) = 11 (12 - scale(1)), at least 6 20-30 correspondences required

SUD(A) = UEUT

p = last column of v

If collected data has noise (which is most cores), required n>6 correspondences

(i) Minimize algebraic error

Naive method: min 1/Ap11 -> p=6

La Add normalization constraint / 1/11 =1 (same as homography/fundamental case)

L ||p3||=1 where p3 is first entires of last row

(only applicable in Ap=0 case)

(ii) Minimize geometric error

Petine P after (1) using representation error

min I d(xi, pxi)2 where xi is newwed image point & pxi is projected 30 point

Solved using non-linear optimization method e.g. Gauss-Newton, Levenberg-Margnardt

- · Data normalization
 - · 20 points (21) : origin = central of points RMS distance from centroid = 52

$$\Rightarrow T = \begin{bmatrix} S & O & -SC_X \\ O & S & -SC_Y \\ O & O & I \end{bmatrix}$$
where
$$\begin{array}{c} C : \text{ centraid} \\ \hline d : \text{ mean distance from certaid} \\ \hline G : \underline{J2} \\ \hline d$$

· 30 points (xi): origin = central of points RMS distance from centroid = 53

- · Overall algorithm
 - 1) Normalize zi,Xi
 - 2) DUT: Solve Ap= 6 S.t min 1/11/11, 1/191=1
 - 3) Reprojection error: Refine p using min \(\(\mathbb{Z} \) d(\(\pi_i, \pi_i)^2 \)
 - 4) Denormalize P = Tab PT 3D
- · Decomposition of P

M=KR: KIR obtained by Ra decomposition of M

Py = -MC -> ~= -M'Py : C solved by M and last column of p

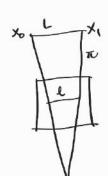
t = -Rc: translation is up-to-scale

6 solve Lepth 1 using 3D point X

Then $t \leftarrow \frac{t}{\|t\|} \cdot \lambda$ gives absolute scale of t

· Line correspondences

20-30 (previously)



L47 l correspondence:

Line L tepresented by 2 Points: Xo, K,

Line 1 back-projected to plane $\pi = p^T l$

Since $X_{0,X_{1}}$ on π $\begin{bmatrix} (L^{T}p)X_{0}=0 \\ (L^{T}p)X_{1}=0 \end{bmatrix}$

. Each 30-20 correspondence gives 2 linear equations

Ap= 0 where AER2hx12, PER12X1

Solve argmin ||Ap| 1 s.t. ||p||=1 or ||p3||=1

 (\Rightarrow) $SVD(A) = UZV^T \rightarrow argmin(p) = last column of v$

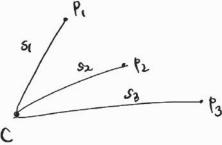
then, minimize geometric error:

 $\frac{\min_{i} \sum_{i} e(\ell_{i}, PX_{io}, PX_{ii})}{\widehat{x}_{io}} \quad \text{where} \quad e = \frac{dotd_{1}}{2(||\widehat{x}_{io} - \widehat{x}_{ii}||)}, \quad d_{j} = \frac{(|\widehat{x}_{ij}|^{2}L_{i})}{\int \widehat{L}_{ix}^{2} + \ell_{iy}^{2}}$

Normalize " inherit bias on longer line

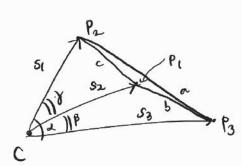


In general, 2-stage approach | Compute depths Si of three 30 points Pi Losolve Rit using absolute orientation algo.



Each correspondence Pi +> Pi gives 2 constraints

.. Minimum 3 correspondences required to solve R(3 dof), t(3 dof) " The Grunet (1841) Solution - P3P (Minimal 3 points)



Let P: are inhomogenous 30 points i.e. $p_i = \begin{pmatrix} x_i \\ Y_i \\ z_i \end{pmatrix}$

Then, length blw points are colculated as: $a = 11p_2 - p_311$, $b = 11p_1 - p_311$, $c = 11p_1 - p_211$

Let q_i are perspective projective points of p_i i.e. $q_i = \binom{u_i}{v_i}$ Since k is known, if $c_{x=c_y=0}$, $c_{y=0} = c_{y=0}$, $c_{y=0} = c_{y=0}$, $c_{y=0} = c_{y=0}$ Then, unit vectors pointing from $c_{y=0} = c_{y=0} = c_{y=0}$ Derive $c_{y=0} = c_{y=0} = c_{y=0}$ Derive $c_{y=0} = c_{y=0} = c_{y=0} = c_{y=0}$

Derive pargle blu i vectors: Cosch=j2:j3, cosp=j1:j3, cost=j1:j2

distance of P from C: Pi = Si;

Using law of cosines,

$$S_{1}^{2} + S_{3}^{2} - 25_{2}S_{3} \cos \alpha = \alpha^{2}$$

 $S_{1}^{2} + S_{3}^{2} - 2S_{1}S_{3} \cos \beta = \beta^{2}$
 $S_{1}^{2} + S_{2}^{2} - 2S_{1}S_{2} \cos \beta = \zeta^{2}$

three unknowns
$$: S_{1}, S_{2}, S_{3}$$

Let 52 = US1, S3 = US2 -> three unknowns: S1, u, V

After organizing equations, 4-degree uninbriate polynomial is obtained:

Aqu4+A3v3+A2v2+A1v+A6=0 W/ known coefficients A;

I use companion notifix

Eigen-value of
$$\begin{bmatrix} 0 & 0 & 0 & -A4/A_0 \\ 1 & 0 & 0 & -A_3/A_0 \\ 0 & 1 & 0 & -A_2/A_0 \end{bmatrix}$$
 are roofs of equation $\begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -A_1/A_0 \end{bmatrix}$

.. U.V (alculated, thus 51,152,53 can be obtained

· Absolute orientation

Since $P_1' = S_{iji}$, 30 points in camera frame P_i' can be obtained objective: Find Rit sit. $(P_1' P_1' P_3') \xrightarrow{R_i t} (P_1 P_2 P_3')$ camera frame world frame

· Steps

1) Remove translation

 $r_i = p_i - \overline{p}$, $r'_i = p'_i - \overline{p}'$ where $\overline{p}_i \overline{p}'$ are central rit. world/canen frame

2) Compute rotation matrix

Let
$$M = \sum_{i=1}^{n} r_i' r_i^T$$
 i.e. sum of outer product

Then,
$$R = M(M^TM)^{-\frac{1}{2}} = MQ^{-\frac{1}{2}}$$

Ly can be easily computed using eigendecomposition 2f Q=UZUT where Z = dig(d1, d2, d3)

Q-12 = V diag (1/ 1/ 1/ 1/ 1/3) VT

3) Compute translation vector

· Degenerate Solution

To solve for (1,52,53:

$$S_{1}^{2} + S_{3}^{2} - 25_{1}S_{3} \cos \alpha = \alpha^{2}$$

 $S_{1}^{2} + S_{3}^{2} - 2S_{1}S_{3} \cos \beta = \beta^{2}$
 $S_{1}^{2} + S_{2}^{2} - 2S_{1}S_{2} \cos \beta = C^{2}$

Estimating center can derive s;

$$S_{1}^{2} + S_{3}^{2} - 2S_{1}S_{3} \cos \alpha = \alpha^{2}$$

$$S_{1}^{2} + S_{3}^{2} - 2S_{1}S_{3} \cos \beta = \beta^{2}$$

$$f_{1}(x,y,t) = 0$$

$$f_{2}(x,y,t) = 0 \quad \text{where } (x,y,t)^{T} \text{ is the } f_{3}(x,y,t) = 0$$

$$f_{3}(x,y,t) = 0 \quad \text{camera center}$$

who, for n unknowns and equations,

For non-degenerate / Stable solution, small first-order change of unknown $\left(\frac{\partial f_i}{\partial x_i}\right)$

Shouldn't affect the solution $(dx_j = 0)$

$$J \begin{pmatrix} dx_1 \\ dx_2 \\ \vdots \\ dx_n \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \qquad \frac{\partial f_i}{\partial x_1} = \frac{\partial f_i}{\partial x_1} \frac{\partial x_1}{\partial x_1} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \vdots \\ 0 \end{pmatrix} \qquad \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_1}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \vdots \\ 0 \end{pmatrix} \qquad \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_1}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \vdots \\ 0 \end{pmatrix} \qquad \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_1}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \vdots \\ 0 \end{pmatrix} \qquad \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_1}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \vdots \\ 0 \end{pmatrix} \qquad \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_1}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_1}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} \\ \frac{\partial f_i}{\partial x_n} = \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{\partial x_n}{\partial x_n} + \dots + \frac{\partial f_i}{\partial x_n} \frac{$$

Is must have no non-trivial solution

For P3P algorithm, the form is:

$$\int dx = 0$$

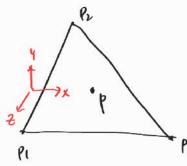
$$M_{3K3} dx = \frac{1}{S_{1}S_{2}S_{3}} AB \begin{pmatrix} Jx \\ dy \\ dz \end{pmatrix} = \begin{pmatrix} Jf_{1} \\ Jf_{3} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \Rightarrow \text{ form of homogeness linear equation}$$

$$M_{K} = 0$$

when M is rank-deficient, dx \$0, which is degenerate condition

... A is rank-deficient -> M is rank deficient -> dx has non-trivial solution

Camera center and (P1,P2,183) plane are coplanar



$$A = \begin{pmatrix} x - x_1 & y - y_1 & z - z_1 \\ x - x_2 & y - y_2 & z - z_2 \\ x - x_3 & y - y_3 & z - z_3 \end{pmatrix}$$
This column is 0 °: $z = z_1 - z_2 - z_2$

.. A is rook-deficient -> M is none deficient - dx has non-trivial solution

· Problem of P3P

4th degree polynomial -> 4 possible solutions

: 64th paint is required to get a unique Solution

i.e. preject Py using 4 possible cases, select w/ smallest reprojection distance

· Linear 4-point algorithm

Recall for 3 point correspondences:

$$S_{1}^{2} + S_{3}^{2} - 25_{2}S_{3} \cos \alpha = \alpha^{2}$$

$$S_{1}^{2} + S_{3}^{2} - 2S_{1}S_{3} \cos \beta = \beta^{2}$$

$$f_{12}(S_{1}, S_{2}) = 0$$

$$f_{13}(S_{1}, S_{3}) = 0$$

$$f_{13}(S_{1}, S_{3}) = 0$$

$$f_{23}(S_{2}, S_{3}) = 0$$

$$f_{23}(S_{2}, S_{3}) = 0$$

$$f_{23}(S_{2}, S_{3}) = 0$$

$$f_{23}(S_{2}, S_{3}) = 0$$

$$S_{12}(S_{1},S_{2}) = 0$$
 | $S_{13}(S_{1},S_{3}) = 0$ | $S_{14}(S_{1},S_{4}) = 0$
 $S_{23}(S_{2},S_{3}) = 0$ | $S_{24}(S_{2},S_{4}) = 0$ | $S_{34}(S_{3},S_{4}) = 0$
Overconstrained system of 6 equations (4(2))

Naive approach: Take subset of 3 equations \rightarrow 6(3 # of $J \rightarrow$ find common solution La problem: T computational cost, X common solution ble of noise, x profit from data redundricy Better approach proposed by Quan and Lan [TPAMI'99]

take three 4th-order polynomial: g(x), g(x), g'(x) where x=5,2

$$\begin{pmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \\ a'_1 & a'_2 & a'_3 & a'_4 & a'_5 \end{pmatrix} \begin{pmatrix} x^4 \\ x^3 \\ x^2 \\ x \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \qquad \text{At = 0 matrix form}$$

$$\Rightarrow \text{ solve for t}$$

Since $A \in \mathbb{R}^{3\times5}$, max tank(A) = 3 : $t \in \mathbb{R}^5$ cannot be directly at A's 3d-span space 6 Solution: Take SVD(A) = U3x5 dag(01, 02,03,0,0) V3x5

then, null-space of A is spanned by V4, US

is t(1,1) = lug + (15 where lifer Equi)

Non-linear constraints of t = (x4, x3, x2, x1, x0) T

Substituting Egsi) into Egsz):

where bib2,63 are coefficients defined by 14,145 (i.i. 4,2)

office there are 1 possible combinations for (injuly):

$$\begin{pmatrix}
b_1 & b_2 & b_3 \\
b'_1 & b'_2 & b'_3
\end{pmatrix}
\begin{pmatrix}
\lambda^2 \\
\lambda \ell \\
\ell^2
\end{pmatrix} = By = 0$$

$$\Rightarrow Solve for y : Overdetermined system$$

$$SVO(B) = UZV^T, then y = right column vector$$
of V

Also,
$$t = (1, x_1 x^2, x^3, x^4)^T$$

$$= \lambda (v_{\psi_1}^* v_{\psi_1}^* v_{\psi_2}^* + v_{\psi_3}^*)^T + ((v_{\xi_1}^* v_{\xi_2}^* v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^*)^T$$

$$= \lambda (v_{\psi_1}^* v_{\psi_1}^* v_{\psi_2}^* + v_{\psi_3}^*)^T + ((v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^*)^T$$

$$= \lambda (v_{\psi_1}^* v_{\psi_1}^* v_{\psi_2}^* + v_{\psi_3}^* + v_{\psi_3}^*)^T + ((v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^* v_{\xi_3}^*)^T$$

Can solve hel using Equal and Equal

$$t + con use = \frac{1}{\ell} = \frac{1}{2} \left(\frac{y_0}{y_1} + \frac{y_1}{y_2} \right)$$
 i.e. average

Since x = tilto or telti or telte or telte, take average of four volutions (": Hey are usually similar values)

52,53,54 can be derived using fix (5,152) =0 etc.

Apply absolute orientation to solve Rit Li uniquely determined if not degenerate (i) Pr-Py collinear (ii) PI-P4 & P coplanar

· Linear n-point Algorithm

e.g. 5-points :
$$502 = \text{ten } f_{ij}(s_i, s_j) = 0$$

Jix 4th-degree polynomials:

$$\begin{pmatrix} a_1 & a_2 & a_3 & a_4 & a_5 \\ a'_1 & a'_2 & a'_3 & a'_4 & a'_5 \\ \vdots & & & & & \\ a_1^{(5)} & a_2^{(5)} & a_3^{(5)} & a_3^{(5)} & a_5^{(5)} \end{pmatrix} \begin{pmatrix} x^4 \\ x^3 \\ x^2 \\ x \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \quad \text{where } x = S_1^2$$

$$A \text{ then } x = S_1^2$$

$$A \text{ then } x = S_1^2$$

$$\rightarrow$$
 Sufficiently many equations to solve $At=0$
 $SVD(A6x5) = U6x6 Z_{6x5}V_{5x5}$

Since max
$$rank(A) = 4$$
, find min ||At|| s.t. ||H||=|

80 t = right singular vector us $(t_5 = \lambda v_5)$

Since first element of t is 1,
$$\lambda v_6^{(0)} = 1$$
 - 7 find λ Calculate $x = t_1/t_0$ or ... t_4/t_3 , then $\sigma_1 = J_{24}$

I For a points,

Size of
$$A = \frac{(n-1)(n-2)}{2} \times 5$$
 \rightarrow Take $SUD(A)$ to find t

Problem: Expensive time complexity o(n3)

- · Epap: Accurate o(n) solution
 - · Linear time complexity -> tractable for large # of paints
 - · Express n point sets w) 4 control points
 - ... problem to solve: depth values of n points $(s_i) \rightarrow$ camera coordinates of control paints (c_i)
 - · 4 non-planar control points

known: 30 world points
$$p_i^{\omega}$$
 ($i=1,2,\cdots,n$)

known: 3D world points P_i^{ω} (i=1,2,...,n) — Each referenced points expressed as heighted sum of control points

$$p_{i}^{\omega} = \sum_{j=1}^{4} \angle i_{j} C_{i}^{\omega} \quad \text{where} \quad \sum_{j=1}^{4} \angle i_{j} = 1 \quad / p_{i}^{c} = \sum_{j=1}^{4} \angle i_{j} C_{i}^{c}$$

$$1 \quad \text{fixed whee} \qquad \qquad \text{(Converse force)}$$

I fixed value point of pifferent by reference point of shared by world & cornera frome

- · Computing Ci
 - 1) Select centroid as first control point Co = 1 2 pi
 - 2) select principal exes of world points for other three control points (distribution Calculated by SUD of Covariance matrix

$$SVV(V) = U\Sigma U^T$$

• Computing
$$d_{ij}$$

$$P_{i}^{\omega} = \sum_{j=1}^{4} d_{ij} c_{j}^{\omega} \implies \begin{pmatrix} P_{ix} \\ P_{iy} \\ P_{iz} \\ 1 \end{pmatrix} = d_{i1} \begin{pmatrix} C_{ix} \\ C_{iy} \\ C_{iz} \\ 1 \end{pmatrix} + d_{iz} \begin{pmatrix} C_{2x} \\ C_{2y} \\ C_{2z} \\ 1 \end{pmatrix} + d_{i3} \begin{pmatrix} C_{3x} \\ C_{3y} \\ C_{3z} \\ 1 \end{pmatrix} + d_{i4} \begin{pmatrix} C_{4x} \\ C_{4y} \\ C_{4y} \\ C_{4z} \\ 1 \end{pmatrix}$$

4 equations, 4 unknowns -> can solve dil, diz, diz, diy for all points i

$$P_i^c = \underbrace{\xi}_{j=1}^t d_{ij} c_j^c$$
, $\forall i \ \omega_i \begin{bmatrix} u_i \\ 1 \end{bmatrix} = k P_i^c = k \underbrace{\xi}_{j=1}^t d_{ij} c_j^c$ Camera-to-image projection formula

Scalar Projective Intrinsic Unknown

Porometers (known)

Vi,
$$\omega_i \begin{bmatrix} u_i \\ v_i \end{bmatrix} = \begin{bmatrix} fu & o & u_c \\ o & fv & v_c \\ o & o & 1 \end{bmatrix} \underbrace{\begin{cases} x_i^c \\ y_i^c \\ z_i^c \end{cases}} \underbrace{\begin{cases} x_i^c \\ y_i^c \\ z_i^c \end{bmatrix}} \underbrace{\begin{cases} x_i^c \\ y_i^c \end{bmatrix}} \underbrace{\begin{cases} x_i^c \end{bmatrix}} \underbrace{\begin{cases} x_i^c \\ y_i^c \end{bmatrix}} \underbrace{\begin{cases} x_i^c \end{bmatrix}} \underbrace{\begin{cases} x_i^c \end{bmatrix}} \underbrace{\begin{cases} x_i^c \\ y_i^c$$

$$MX = 0 \rightarrow X$$
 lies on hull space of M

 $X = \sum_{i=1}^{N} \beta_i v_i$ where v_i are right singular vectors of M

("" noise, right singular values are unlikely be 0)

Since SVD(M) = SVD(MTM) where $MTM \in R^{12X12}$ (constant size) Calculate $SVD(MTM) = U \Sigma U T$ which is most time consuming step O(n)

(i)
$$N = 1$$

$$X = \beta V$$
. Since $rank(M) = 11$, requires at least 6 point correspondences $\int solve \beta$

Since
$$\forall i,j$$
, $\|c_{i}^{\omega} - c_{i}^{\omega}\|^{2} = \|c_{i}^{\varepsilon} - c_{i}^{\varepsilon}\|^{2}$ (distance maintained atthough frame changes)
$$= \|\rho v^{\varepsilon_{i}} - \beta v^{\varepsilon_{i}}\|^{2} \quad \text{where} \quad V = \left[v^{\varepsilon_{i}}, v^{\varepsilon_{i}}, v^{\varepsilon_{i}}, v^{\varepsilon_{i}}\right]^{T}$$

Can compute B w/ six pairs of (VCi), VCi)

(ii) N = 2

 $x = \beta_1 v_1 + \beta_2 v_2$. Since rank(M) = 12 - 2 = 10, requires $n \ge 5$ point correspondences Calculate $\|c_i^{\omega} - c_i^{\omega}\|^2 = \|c_i^{\varepsilon} - c_i^{\varepsilon}\|^2 = \|(\beta_1 v_1^{\varepsilon_1} + \beta_2 v_2^{\varepsilon_1}) - (\beta_1 v_1^{\varepsilon_1} - \beta_2 v_2^{\varepsilon_1})\|^2$ Can be rewritten as

Overdetermined System LB=P where $\beta = [\beta_1^2, \beta_1\beta_2, \beta_2^2]^T$.. $\beta = L^{\dagger}p$

X= B1U1+ B2U2+ B3U3 . rank(A) =9 , n ≥ 5

 $L\beta = \ell$ where $\beta = L\beta_1^2, \beta_1\beta_2, \beta_1\beta_3, \beta_2^2, \beta_2\beta_3, \beta_3^2]^T$ $\beta_1\beta_2\beta_3, \beta_3\beta_3$

· 3 coplanar control points

= Any control point is dependent to other 3 points

.. only select 3 control points -> size of M = 2nxq

 $||c_i^{\omega} - c_j^{\omega}||^2 = ||c_i^{\varepsilon} - c_j^{\varepsilon}||^2$ 3C2 = 3 constraints \Rightarrow only solvable when N=1,2

• Calculate p_i^c $p_i^c = \sum_{j=1}^{4} \angle j_j C_j^c$ Then (Rit) calculated using absolute orientation $b/w p_i^c \leftrightarrow p_i^w$