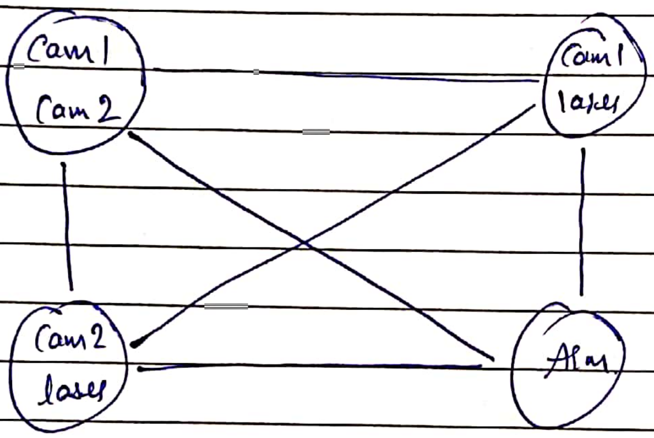
Joint Calibration of Multiple Sensors

Joint Calibration: The Groups are formed using a unifying principle.
Each group is created the output 3D data.
Made use of a fact that a sensor can appear in different groups to have redundancy.
Then calibrate the entire system in one optimization.



- ✓ Although intrinsic and extrinsic calibration done seperately.
- ✓ In this approach intrinsic & extrinsic calibration combined & performed simultaneously by posing a single calibration optimization objective, that is minimized through numerical optimization.

Extrinsic Parameters :

The extrinsic parameters of two Co-ord. s/m. Consists of a rotational matrix and a translation Vector between the frames

Assume the co-ord of a point P is $[x, y, z]^T$ in frame A, its co-ord in frame B is:

$$R[x, y, z]^T + t \quad \text{--- (1)}$$

rotation matrix also satisfies the orthogonal constraint :

$$R^T \cdot R = I \quad \text{--- (2)}$$

Intrinsic Parameters

We define a 3D System as a sensor or a group of sensors that gives us 3D data with known depth scales.

A single camera is not a 3D s/m because it does not produce depth data. A 3D range finder or a stereo camera are 3D s/ms.

$$I(d, u) \in R^3 \quad \text{--- (3)}$$

u = Calibration datum

d = intrinsic model parameters eg: focal lengths, distorsions, rotation & translation between diff. members of a group

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Extrinsic Calibration of 3D systems

$p^{(A)} = I_A(d_A, u^{(A)})$ → a point in frame A

$p^{(B)} = I_B(d_B, u^{(B)})$ → same " " frame B.

Now, the coord. of $p^{(A)}$ in frame B under co-ord. transformation is:

$$p^{(B)} = Rp^{(A)} + t$$

As data may be noisy, we can model dist. as a normal random variable.

$$d = \| Rp^{(A)} + t - p^{(B)} \|$$

Objective funct for calibrating multiple sensors.

$$Ext(R,t) = \sum_i \| R\, I(d_A, u_i^A) + t - I(d_B, u_i^B) \|^2 \quad (4)$$

Intrinsic Calibration of 3D systems

The set of constraints we can use for intrinsic calibration of 3D s/m are distance preservation, collinearity, coplanarity.

In our framework, these constraints are enforced by likelihood estimations.

each pixel has (u, v) coord.
in our case $\boxed{u = u_i \\ v = u_j}$

a. Distance preservation constraints.

$u_i, u_j \rightarrow$ collected calibration data.
$d_{ij} \rightarrow$ Known dist in 3D slm (ground truth).
$P_i, P_j \rightarrow$ 2 points in 3D, given by intrinsic models of a 3D slm.

$d_{ij} \rightarrow$ dist betn P_i & P_j i.e points & it is represented by random normal variable

i.e $$p(d_{ij}) = \frac{1}{Z} \exp\left(-\frac{\|d_{ij} - \bar{d}_{ij}\|^2}{\sigma^2}\right) \quad \text{—— (5)}$$

$u_i = \{u_i^{(1)}, u_i^{(2)}\} \rightarrow$ corresponding pixels of 2 cameras images.

using u_i, slm can construct point in 3D i.e P_i

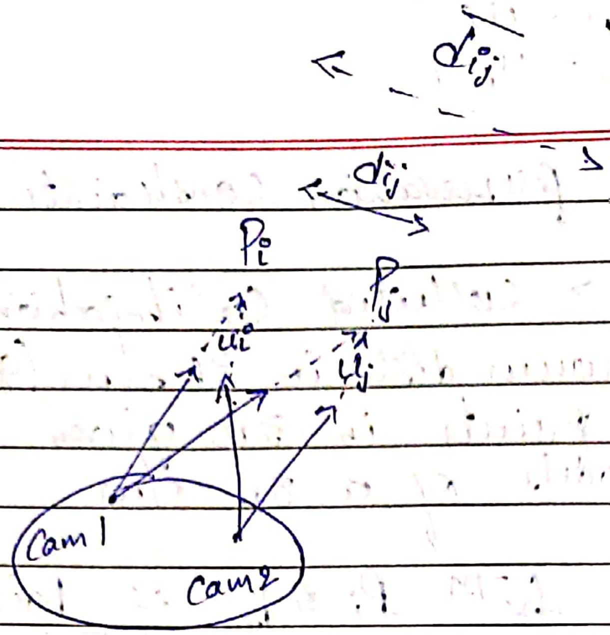
similarly u_j gives P_j

b. Collinearity and Coplanarity constraints.

Distance 'd' from the points to the line/plane represented by random normal variable

i.e $$p(d) = \frac{1}{Z} \exp\left(-\frac{\|d\|^2}{\sigma^2}\right) \quad \text{—— (6)}$$

distance can be obtained by fitting a line or plane to a set of points via SVD - singular value decomposition.



$\overline{d_{ij}} \rightarrow$ Ground truth dist. (size of checkerboard square) betn. P_i & P_j

$d_{ij} \rightarrow$ hypothetical dist. given by calibration parameters.

By forcing d_{ij} to be close to $\overline{d_{ij}}$, we get good estimation of calibration parameters.

d. Combining all constraints.

" likelihood of the constraints in (6) & (6)

ie $E_{ints}(\alpha) = \sum_i \left(\| I(\alpha, u_i) - I(\alpha, u_j) \| - \overline{d_{ij}} \right)^2$

$+ \sigma_1^2 \sum_L \sum_{k \in L} d(I(\alpha, u_k), L)^2$

$+ \sigma_2^2 \sum_p \sum_{l \in P} d(I(\alpha; u_l), p)^2$ (7)

where, $d(x, L) \rightarrow$ dist. from point 'x' to line 'L'

$d.(x, P) \rightarrow$ " " " " " plane 'P'

Joint Intrinsic and Extrinsic Calibration of 3D Systems

We first calibrate the intrinsics of each s/m, & then calibrate the extrinsics between them.

$$ExtsInts(R, t, \alpha_A, \alpha_B) = Ints(\alpha_A) + Ints(\alpha_B) + \gamma\, Exts(R, t, \alpha_A, \alpha_B) \quad (8)$$

3D - Systems

a. Stereo Systems:

It contains 2 or more cameras, with depth is found by triangulation.

Stereo function for stereo systems with two cameras.

$$Stereo(\{R, t, \alpha_{cam}^{(1)}, \alpha_{cam}^{(2)}\}, \{u^{(1)}, u^{(2)}\}) = [x, y, z]^T \quad (9)$$

$\alpha_{cam}^{(1)}, \alpha_{cam}^{(2)} \rightarrow$ parameters of 2 cameras

$\alpha_s = \{R, t, \alpha_{cam}^{(1)}, \alpha_{cam}^{(2)}\}$
$\hookrightarrow$ intrinsic parameters of stereo s/m.

$u^{(1)}, u^{(2)} \rightarrow$ pixel coord's in 2 images of 2 cameras.

b. Active triangulation s/m's:

→ System contains laser scanner & camera

→ A motor on the laser scanner records offset angles (β).

→ This system finds 3D location of image pixel

$$\text{ActiveTriangulation}(\{R, t, d_{cam}\}, \{\beta, u\}) = [x, y, z]^T \quad (10)$$

β, u → Calibration data.

u → pixel coord.

d_{cam} → Camera intrinsic.

R, t → rotation & translation parameter.

$$d_{\text{ActiveTriangulation}} = \{R, t, d_{cam}\}$$

→ Intrinsic parameters.

c. Range finder:

→ Calibrated internally by the manufacturer & hence they do not have intrinsic parameters. & do not need further calibration

$$\text{RangeFinder}(u) = [x, y, z]^T$$

u → calibration data, can be 'pixel' location in the depth map image.

Scanned by CamScanner