

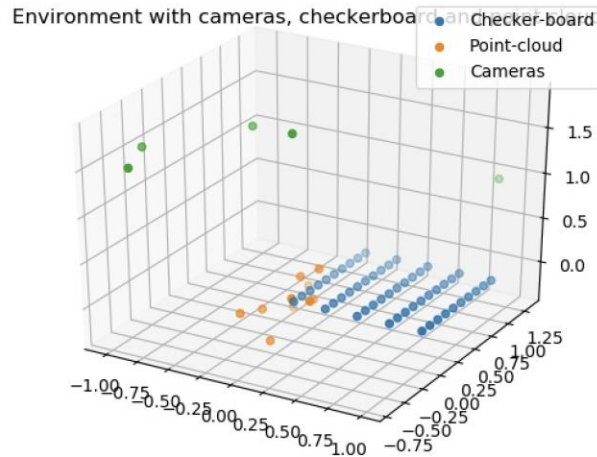
# Classical Algorithm Engineer Assignment Report



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# Problem statement

## Given configuration of environment



- **Camera Specifications:**

- Focal length: 200
- Principle point: (0,0)
- No distortion

- **Checkerboard Details:**

- Size: 1m x 1m
- Features: 50 identifiable corners

- **Point Cloud:**

- Location: Fixed within the environment

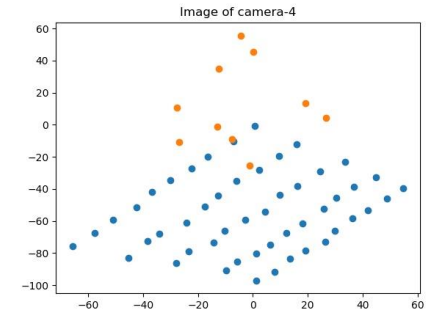
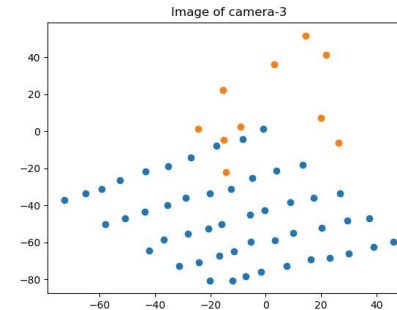
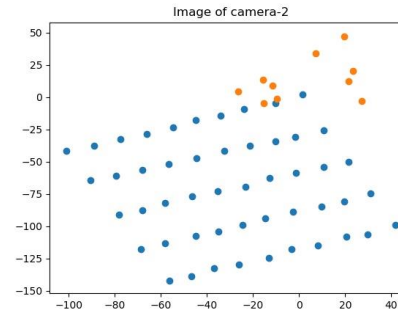
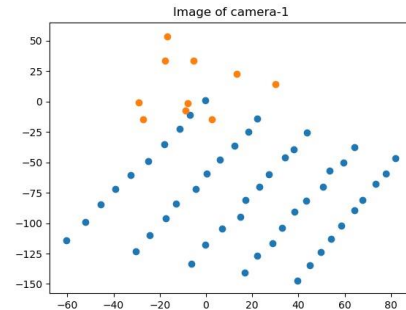
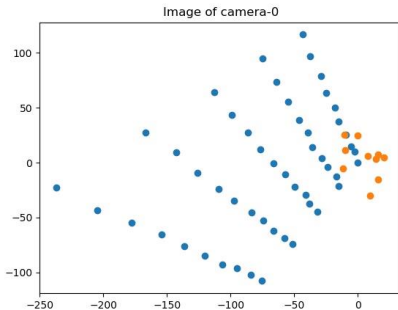
- **Imaging Process:**

- The camera captures the checkerboard and point cloud from five different angles.

- **Objective:**

- Determine the most accurate 3D positions for the points in the point cloud using multi-view geometry.

## Projection of points in each camera

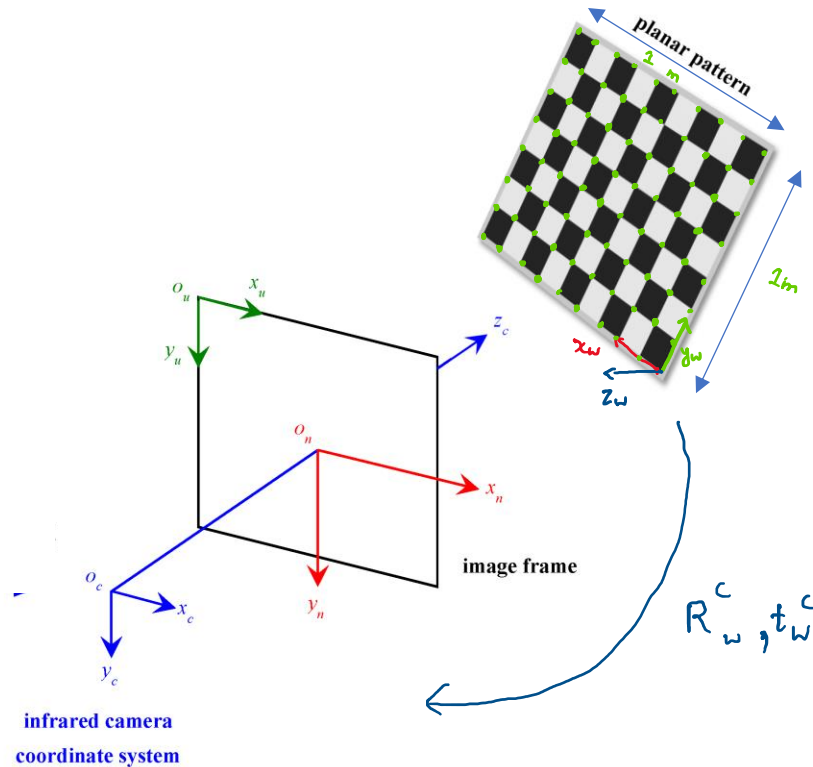


# Homography

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# Homography Matrix



$$(x, y, 1)^T \sim x \cdot PX = K[r_1 \ r_2 \ t] \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = H \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

$$H = \lambda K[r_1 \ r_2 \ t]$$

$$K^{-1}H = \lambda[r_1 \ r_2 \ t]$$

$$P = K[r_1 \ r_2 \ (r_1 \times r_2) \ t]$$

- Ensures that the rotation matrix columns have a unit norm
- The cross product  $r_1 \times r_2$  yields a vector orthogonal to both  $r_1$  and  $r_2$ ,
- Aligns the scale of the translation with the scale of the rotation column

$$R|t = K^{-1}H = [r_1 \ r_2 \ t]$$

$$r_1 = \frac{r_1}{\|r_1\|}$$

$$r_2 = \frac{r_2}{\|r_2\|}$$

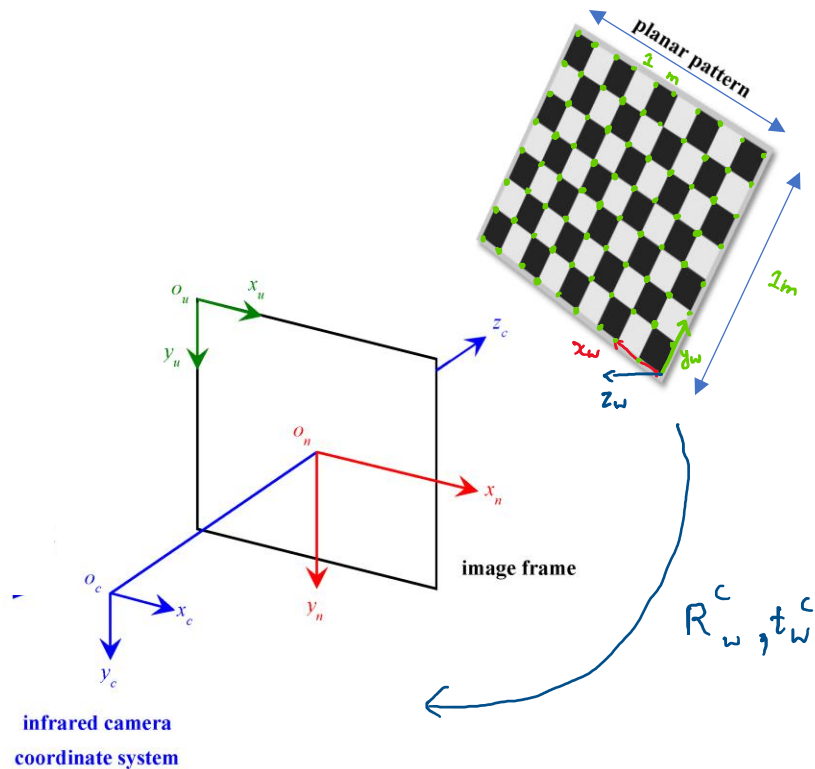
$$r_3 = r_1 \times r_2$$

$$t = \frac{t}{\|r_1\|}$$

## Reference:-

1. [https://docs.opencv.org/4.x/d9/dab/tutorial\\_homography.html](https://docs.opencv.org/4.x/d9/dab/tutorial_homography.html)
2. [https://web.archive.org/web/20171226115739/https://ags.cs.uni-kl.de/fileadmin/inf\\_ags/3dcv-ws11-12/3DCV\\_WS11-12\\_lec04.pdf](https://web.archive.org/web/20171226115739/https://ags.cs.uni-kl.de/fileadmin/inf_ags/3dcv-ws11-12/3DCV_WS11-12_lec04.pdf)

# Compute the optimal rotation matrix



$$\hat{R} = U\Sigma V^T$$

where  $U$  and  $V$  are orthogonal matrices from the SVD of  $\hat{R}$ , and  $\Sigma$  is a diagonal matrix. To ensure that  $\Sigma$  is also orthogonal and thus  $R$  is a proper rotation matrix with  $\det(R) = 1$ , we modify  $\Sigma$  as follows:

$$d = \text{sign}(\det(VU^T))$$

$$\Sigma' = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & d \end{bmatrix}$$

$$R = V\Sigma'U^T$$

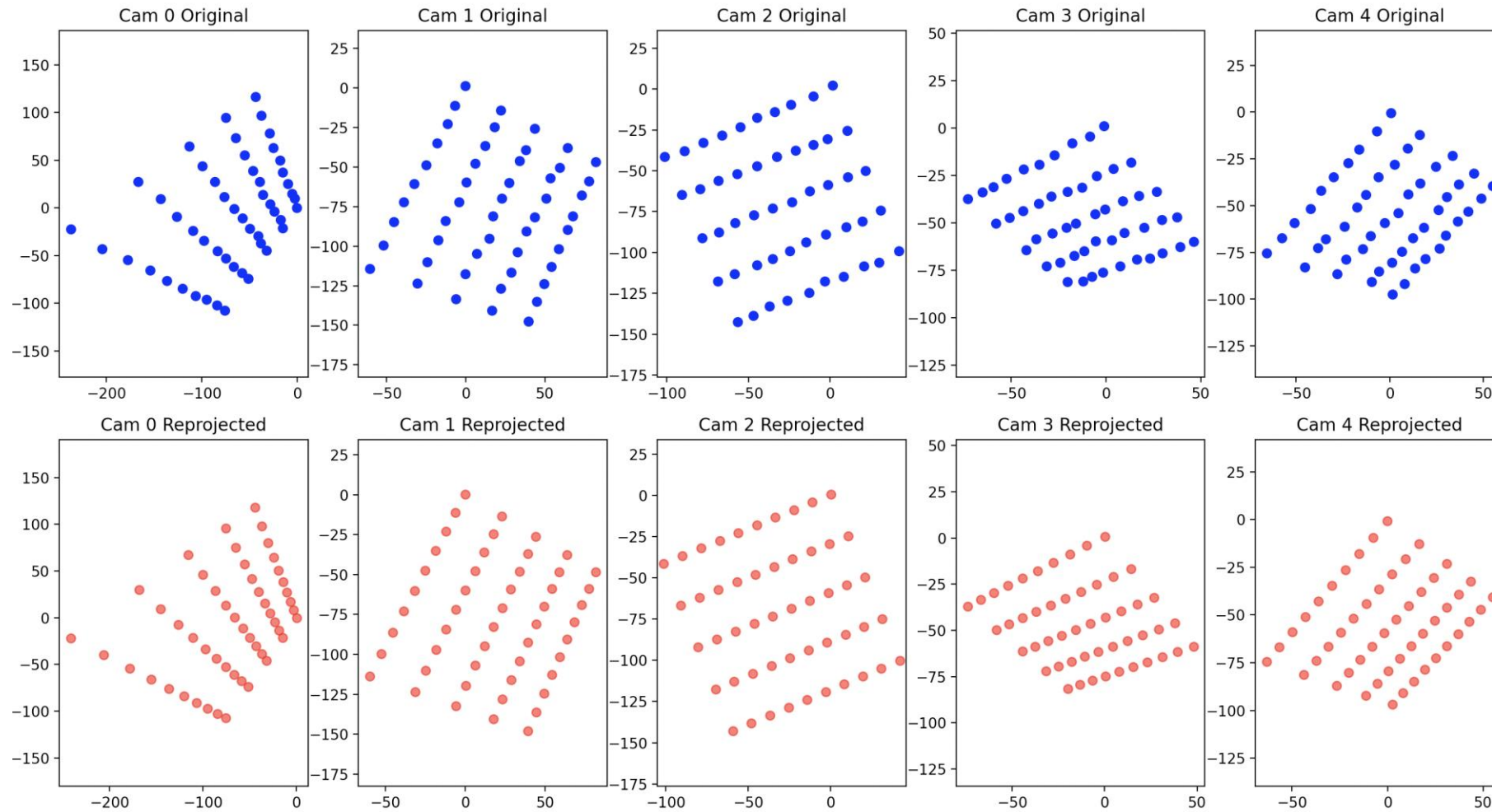
This adjustment guarantees that  $R$  is orthogonal since  $V$  and  $U$  are orthogonal and  $\Sigma'$  is chosen such that  $R$  has a determinant of  $+1$ , which is a necessary condition for a rotation matrix.

## Reference:-

1. [https://en.wikipedia.org/wiki/Kabsch\\_algorithm#Computation\\_of\\_the\\_optimal\\_rotation\\_matrix](https://en.wikipedia.org/wiki/Kabsch_algorithm#Computation_of_the_optimal_rotation_matrix)

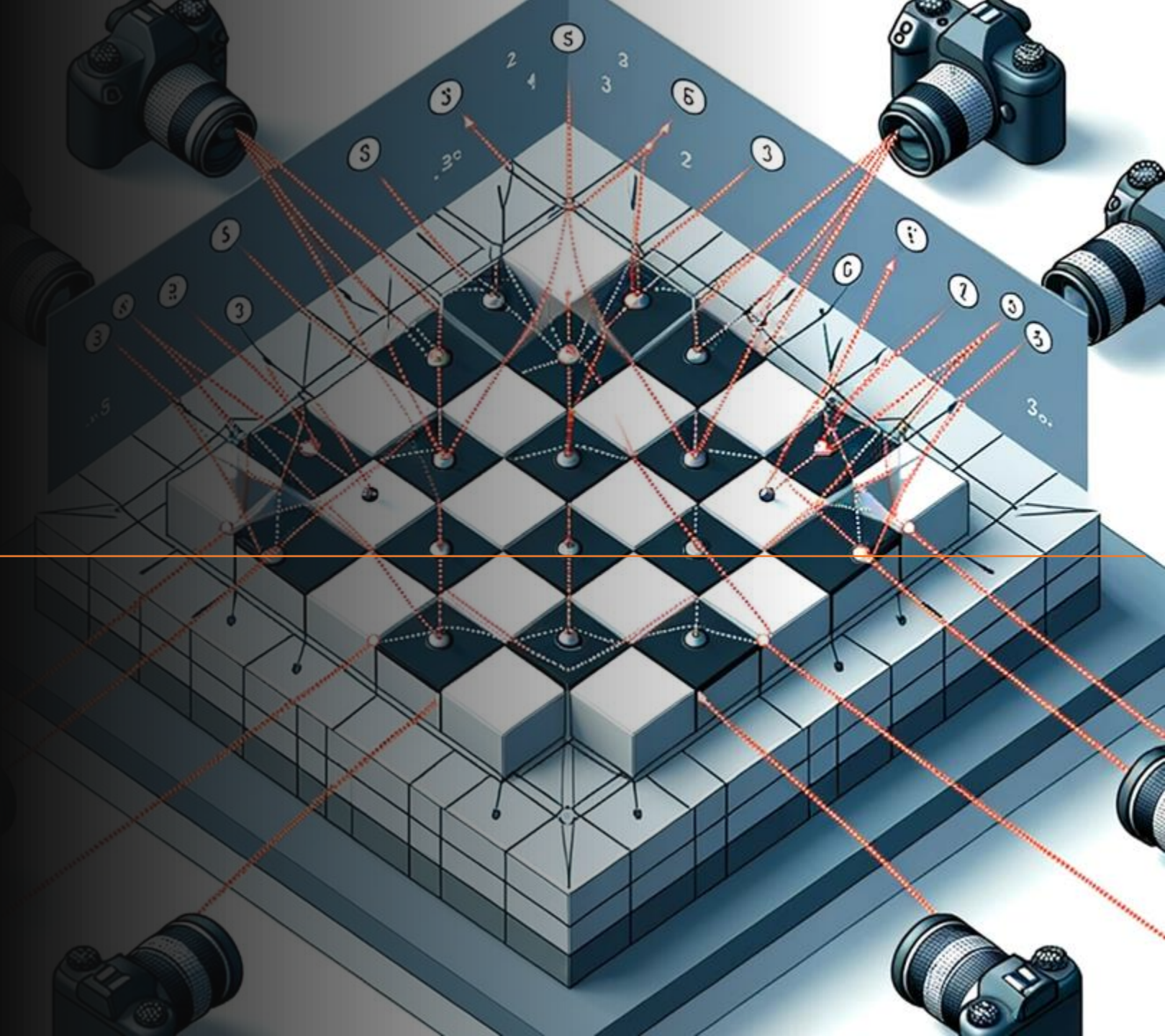


# Reprojection based on $[R | t]$ (Homography)

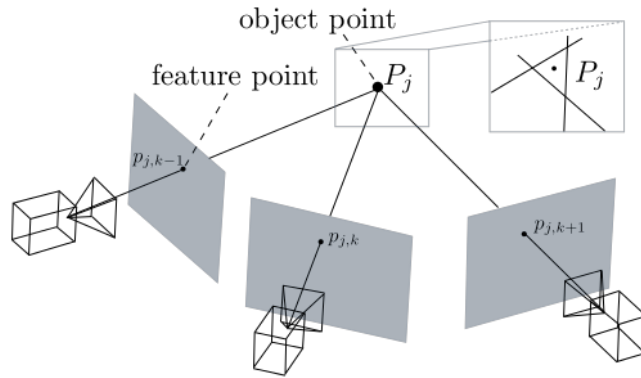


# Multi-View Triangulation

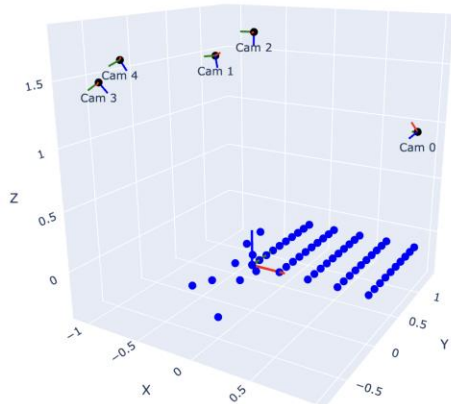
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# Multi-View Stereo Triangulation



## Resulting configuration after triangulation



3D Visualization of World Frame, Camera Frames, and Checkerboard Points

## Reference:-

1. <https://3d.bk.tudelft.nl/nail/stereo/>

### 1. Representation of Rays:

- $P_i = C_i + \lambda_i d_i$
- $P_i$ : Point on the ray from the  $i^{th}$  camera
- $C_i$ : Camera center in world coordinates
- $\lambda_i$ : Scalar representing distance along the ray
- $d_i$ : Direction vector of the ray from the  $i^{th}$  camera

### 2. Ideal Case (No Noise):

- $\lambda_i d_i \approx X - C_i$
- Assumes the 3D point  $X$  lies exactly on the ray from  $C_i$  in the absence of noise

### 3. Ray Equation and Residual:

- $r = X - C_i - d_i d_i^T (X - C_i)$
- $r$ : Residual vector, component perpendicular to  $d_i$
- $d_i^T (X - C_i)$ : Projection of  $X - C_i$  onto  $d_i$

### 4. Loss Function:

- $L = \sum_{i=1}^N ((I - d_i d_i^T)(X - C_i))^2$
- $L$ : Sum of squares of residuals for all cameras
- $I$ : Identity matrix

### 5. Minimization and Derivative:

- $\frac{\partial L}{\partial X} = 2 \sum_{i=1}^N (I - d_i d_i^T)(X - C_i) = 0$
- Derivative of  $L$  with respect to  $X$  set to zero

### 6. Matrix Formulation and Solution:

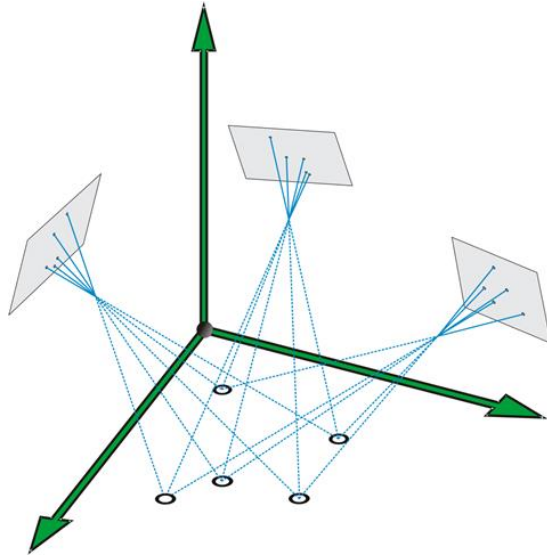
- $A_i = (I - d_i d_i^T)$
- $X = (\sum_{i=1}^N A_i^T A_i)^{-1} \sum_{i=1}^N A_i^T C_i$
- $A_i$ : Matrix to find orthogonal component of  $X - C_i$  to  $d_i$





# Bundle Adjustment

# Bundle Adjustment



## Note -

- Used both Axis – Angle and quaternion for Rotation representation
- Fixed the checkboard 3d point to fix the structure
- Used sparse Jacobian method to speed up the bundle adjustment

The reprojection error equation in bundle adjustment is formulated as:

$$e_{ij} = x_{ij}^{\text{obs}} - \pi(K_i, P_i, X_j) \quad \min_{X, P, K} \sum_{i=1}^n \sum_{j=1}^m \|e_{ij}\|^2$$

where:

- $e_{ij}$  is the reprojection error for the  $j$ th point in the  $i$ th image.
- $x_{ij}^{\text{obs}}$  is the observed image point.
- $\pi$  represents the projection function that maps 3D points  $X_j$  into 2D image points using the camera intrinsic parameters  $K_i$  and the extrinsic parameters  $P_i = (R_i, t_i)$ .
- $K_i$  are the intrinsic parameters of the  $i$ th camera.
- $P_i = (R_i, t_i)$  represents the pose (rotation  $R_i$  and translation  $t_i$ ) of the  $i$ th camera.
- $X_j$  is the  $j$ th 3D point in the world coordinate system.

The goal is to find the parameters  $\theta = \{X_j, P_i, K_i\}$  that minimize the sum of squared reprojection errors for all observations. The LM optimization problem can be formulated as:

$$\min_{\theta} \sum_{i=1}^n \sum_{j=1}^m \|e_{ij}(\theta)\|^2$$

The update rule in the LM method is given by:

$$\Delta\theta = -(J^T J + \lambda \cdot \text{diag}(J^T J))^{-1} J^T e$$

where:

- $J$  is the Jacobian matrix of partial derivatives of the error terms with respect to the parameters,
- $e$  is the vector of all reprojection errors,
- $\lambda$  is the damping factor controlling the step size and the mix between the gradient descent and Gauss-Newton method,
- $\text{diag}(J^T J)$  represents the diagonal matrix of  $J^T J$ .

The parameters are updated iteratively:

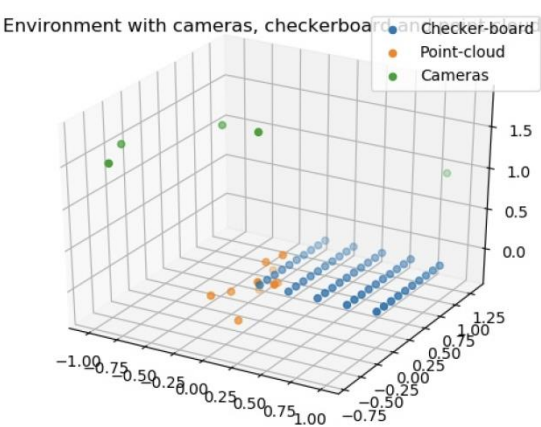
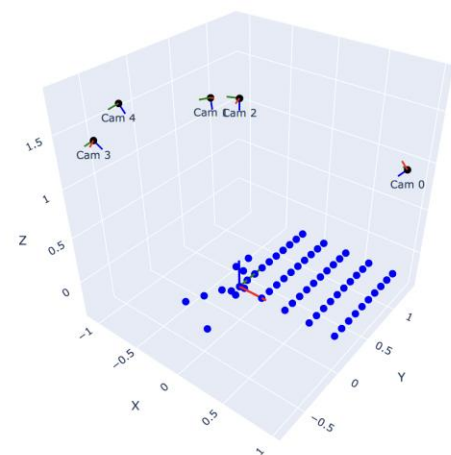
$$\theta^{(k+1)} = \theta^{(k)} + \Delta\theta^{(k)}$$

## Reference:-

1. <https://www.telesens.co/2016/10/25/bundle-adjustment-part-3/>

# Bundle Adjustment

Resulting configuration after Bundle Adjustment      Given configuration



Resulting point cloud location

Point #	X Coordinate	Y Coordinate	Z Coordinate
1	0.13	-0.21	0.12
2	-0.13	0.21	-0.02
3	-0.34	-0.36	-0.11
4	-0.02	0.10	-0.10
5	-0.02	-0.21	0.10
6	-0.26	-0.19	-0.11
7	-0.11	-0.33	-0.34
8	-0.00	0.14	0.24
9	-0.18	0.10	-0.22
10	-0.09	0.07	0.14