# **Camera Lidar Calibration**

Team NERF-TM

Mitansh Kayathwal (2021101026) Vineeth Bhat (2021101103) P Gnana Prakash (2021111026)

### **Camera Intrinsic Calibration**

- Started off with camera calibration without lidar owing to simplicity
- Used available datasets initially
- Also tested it on our own data
- Used Zhang's method

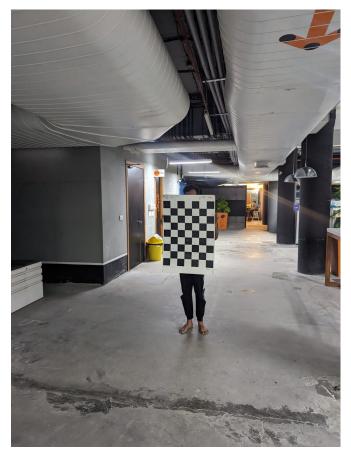


Fig: GP holding the checkerboard

### **Zhang's method**

- Target based calibration (Checkerboard target)
- Set world coordinate system to a corner of the checkerboard. All points lie in the X/Y plane.
- We can delete the 3rd column of the extrinsics matrix
- We estimate a 3x3 homography instead of a 3x4 projection matrix
- Solving a system of linear equation leads to an estimate of H.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \end{bmatrix} \begin{bmatrix} x \\ y \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} x \\ y \\ r_{31} & r_{32} & r_{33} & r_{33} \end{bmatrix}$$

$$\begin{array}{rcl} \boldsymbol{h} & = & (h_k) = \mathrm{vec}(\mathsf{H}^{\mathsf{T}}) \\ \boldsymbol{a}_{x_i}^{\mathsf{T}} & = & (-X_i, \, -Y_i, \, -\cancel{\mathsf{X}}_i, \, -1, 0, \, 0, \, \cancel{\mathsf{N}}, \, 0, x_i X_i, \, x_i Y_i, \, x_i \cancel{\mathsf{X}}_i, \, x_i) \\ \boldsymbol{a}_{y_i}^{\mathsf{T}} & = & (0, \, 0, \, \cancel{\mathsf{N}}, \, 0, -X_i, \, -Y_i, \, -\cancel{\mathsf{X}}_i, \, -1, y_i X_i, \, y_i Y_i, \, y_i \cancel{\mathsf{X}}_i, \, y_i) \end{array}$$

\_

## **Zhang's method (Continued...)**

- Get the "**b**" vector from SVD using the last equation
- Then, when obtain the intrinsics from the Cholesky decomposition
- The extrinsics can be directly obtained from equations and the data we have till now (Homography matrix **H** and also the intrinsics **K** we have calculated
- These values serve as initial estimates for the LM algorithm from which we obtain better values for calibration

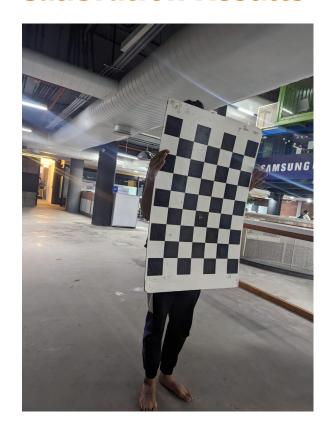
$$B = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix} \quad \text{chol}(B) = AA^{T}$$

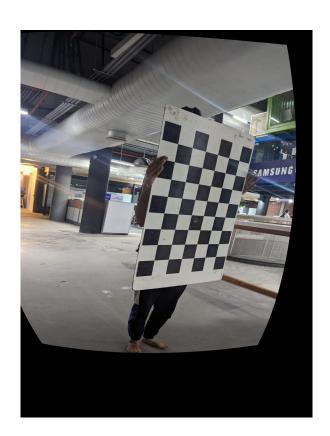
$$A = K^{-T}$$

$$V = \begin{pmatrix} v_{12}^T \\ v_{11}^T - v_{22}^T \end{pmatrix} \quad \text{with} \quad v_{ij} \quad = \quad \begin{bmatrix} h_{1i}h_{1j} \\ h_{1i}h_{2j} + h_{2i}h_{1j} \\ h_{3i}h_{1j} + h_{1i}h_{3j} \\ h_{2i}h_{2j} \\ h_{3i}h_{2j} + h_{2i}h_{3j} \\ h_{3i}h_{3j} \end{bmatrix}$$

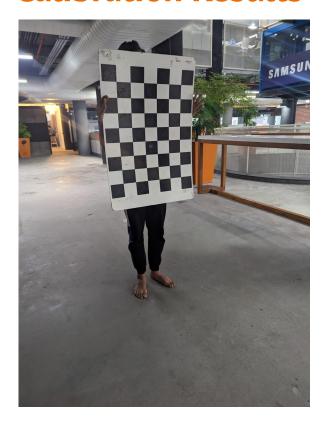
$$b^* = rg \min_{oldsymbol{b}} \| oldsymbol{V} oldsymbol{b} \| ext{ with } \| oldsymbol{b} \| = 1$$

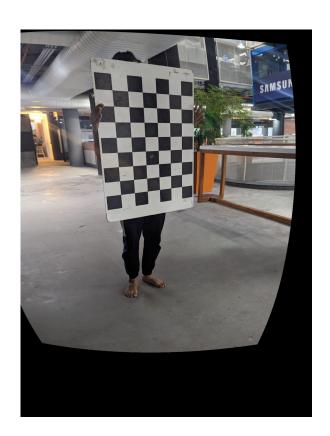
## **Calibration Results**





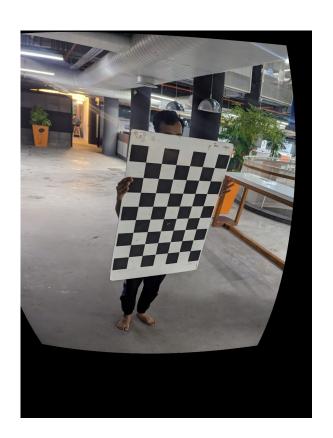
### **Calibration Results**





### **Calibration Results**





#### **Extrinsic Calibration**

- Used ROS simulations
- Added normal camera, Intel RealSense Camera, 2D and 3D "sic" lidar
- Manually annotated point clouds
- Assumption: Checkerboard pattern ends correspond to board's ends (can be corrected later if needed)

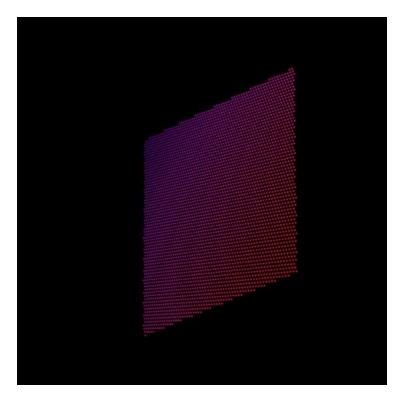


Fig: Point cloud of checkerboard

### **ROS Simulations**

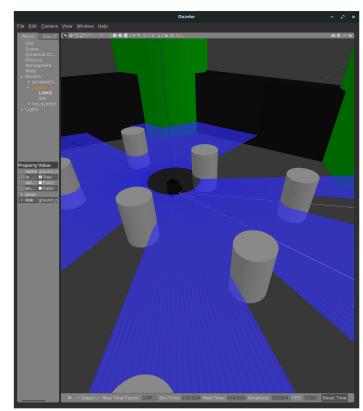


Fig: 2D Lidar Scan

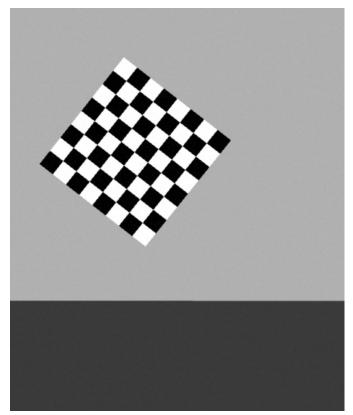


Fig: Image taken during 3D data collection

#### **Data Collection**

- Collected data through self-written subscribers
  - Camera Data (raw image)
  - 3D Lidar (PointCloud2)
  - 2D Lidar (LaserScan)
- Manually annotated data later on to extract point cloud edges
- Code is well documented through RFADMFs

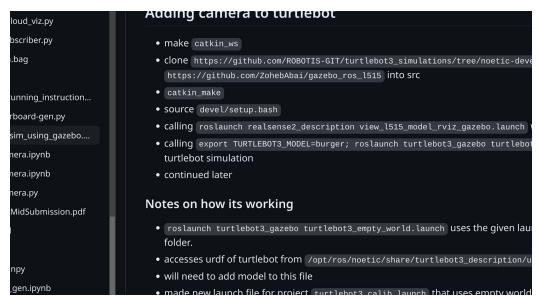


Fig: Screenshot of documentation

#### **3D** calibration

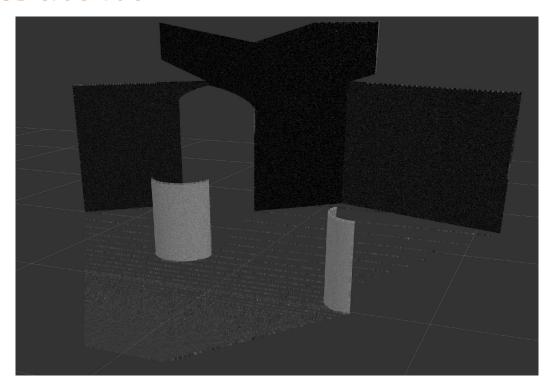


Fig: Some background data in point cloud

- Did extensive Literature
   Review nothing was sweet
   and simple
- Finally, wrote from scratch code that
  - Takes in Image
  - Gets checkerboard endpoints
  - Takes in point cloud (.bag data)
  - Manually annotate the endpoints of checkerboard
  - Run PnP
- Why? Next slide

#### **PnP**

- Given 3D world coordinates and 2D image points, returns the extrinsic calibration matrix
- If we assume lidar to be the world frame, the 3D coordinates are in world frame
- So, running PNP gives the camera extrinsics which is the transformation between camera and lidar

#### EPnP: An Accurate O(n) Solution to the PnP Problem

Vincent Lepetit · Francesc Moreno-Noguer · Pascal Fua

Received: date / Accepted: date

**Abstract** We propose a non-iterative solution to the PnP problem—the estimation of the pose of a calibrated camera from n 3D-to-2D point correspondences whose computational complexity grows linearly with n. This is in contrast to state-of-the-art methods that are  $O(n^5)$  or even  $O(n^8)$ , without being more accurate. Our method is applicable for all  $n \geq 4$  and handles properly both planar and non-planar configurations. Our central idea is to express the n 3D points as a weighted sum of four virtual control points. The problem then reduces to estimating the coordinates of these control points in the camera referential, which can be done in O(n)time by expressing these coordinates as weighted sum of the eigenvectors of a  $12 \times 12$  matrix and solving a small constant number of quadratic equations to pick the right weights. Furthermore, if maximal precision is required, the output of the closed-form solution can be

proves accuracy with negligible amount of additional time. The advantages of our method are demonstrated by thorough testing on both synthetic and real-data. <sup>1</sup>

**Keywords** Pose estimation  $\cdot$  Perspective-n-Point  $\cdot$  Absolute orientation

#### 1 Introduction

The aim of the Perspective-n-Point problem—PnP in short—is to determine the position and orientation of a camera given its intrinsic parameters and a set of n correspondences between 3D points and their 2D projections. It has many applications in Computer Vision, Robotics, Augmented Reality and has received much attention in both the Photogrammetry [21] and Com-

#### 2D Calibration

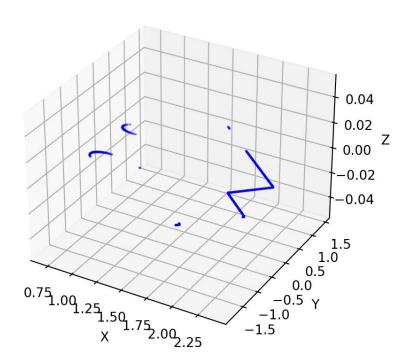


Fig: 2D Lidar Scan from ROS

- Made assumptions
  - Rotation between camera and lidar is only through one axis
     This means that we assume that we know that the lidar scan line is horizontal to image's horizontal axis
- If we don't make such assumptions then then calibration becomes very hard
- Did not find existing literature that tackled this in a simple way
- Here's what we did

### **2D Calibration**

- Data collection
  - Take an image
  - Take the laser scan reading
  - Manually annotate correspondences
- Wrote math and tried figuring it out
- Made extra assumption that points won't be collinear
- Got a few equations
- Realised that it's the same as Grunert's P3P
- Used PnP to solve this as well

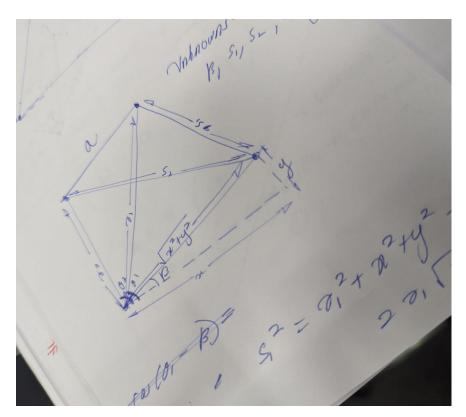


Fig: Some math we tried

#### **Conclusions**

- Our code works
- Real world demonstration of intrinsic calibration
- Simulated data for extrinsic calibration
- We spent close to 25-30 hours per person
  - ROS simulations alone took up about 15 hours to figure out and another 5 for data collection
  - Zhang implementation from scratch took up around 15 hours to code and test
  - Writing code for extrinsic calibration took up 20 hours to debug first tried on external datasets and then made our own basic rudimentary data
  - Debugging took around 5 hours

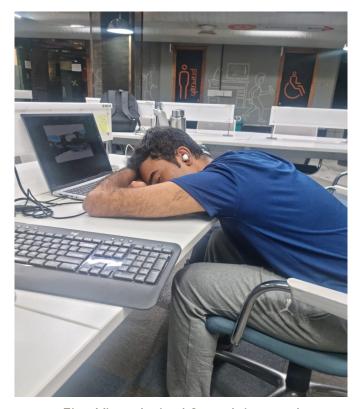


Fig: Vineeth tired from doing math

### Thank you