Lidar-Camera Calibration for Self Driving Cars

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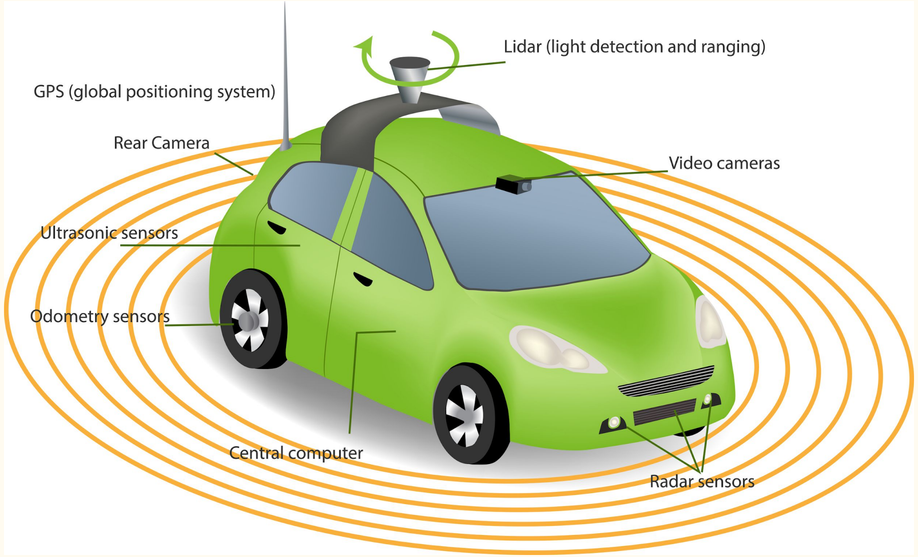
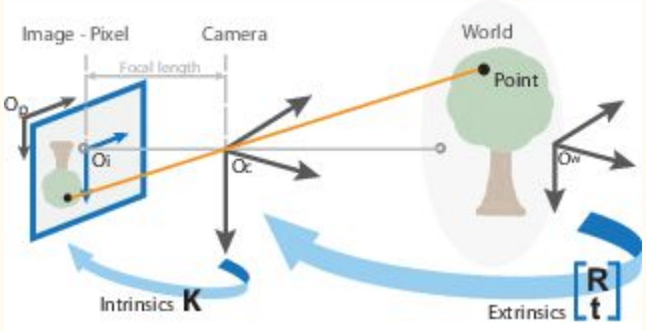
Introduction

1. Multiple Sensors used in Autonomous Systems
    a. LiDAR
    b. Camera
    c. Radar
2. 3D structure reconstruction requirements
3. Camera Calibration to interpret the world
4. Cross Calibration for coordination between multiple sensors

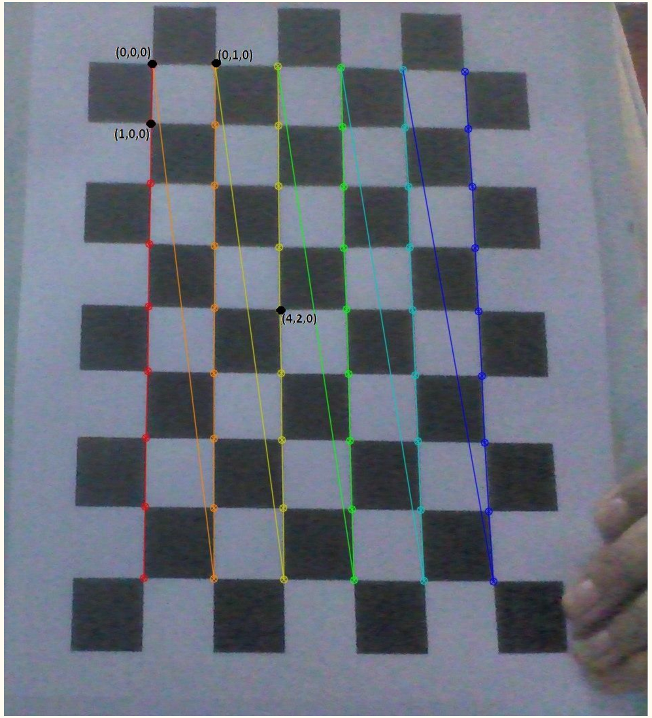


Geometric Camera Calibration

1. Linking world coordinate frame to image plane
2. Types of calibration
   a. <u>Extrinsic Calibration</u> - World coordinate frame to camera's 3D coordinate frame
      i. Rotation vector ($R_W{}^C$)
      ii. Translation vector ($T_W{}^C$)
   b. <u>Intrinsic Calibration</u> - Camera's 3D coordinate frame to 2D Image plane
      i. Internal properties like focal length , coordinates of optical centre



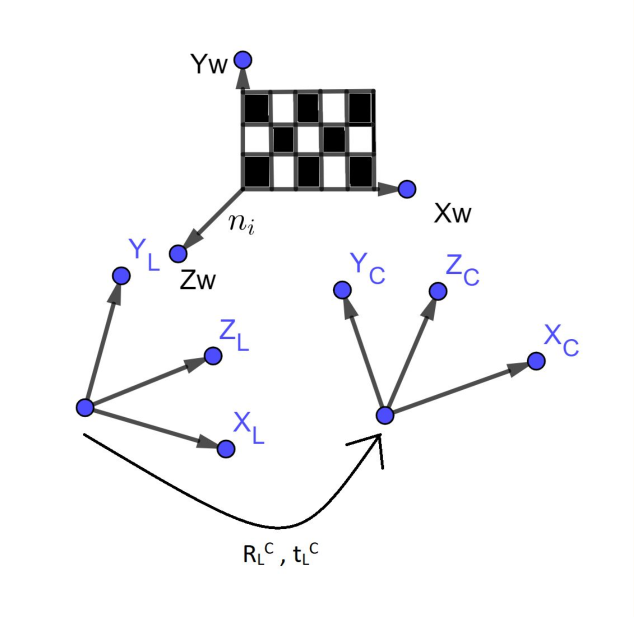
Zhang’s method of Calibration



1. Used the famous checkerboard plane as a calibration pattern.
2. World coordinates defined
    a. (0,0,0) , (0,1,0), (0,2,0) .... etc.
3. Z-coordinate is 0.
4. Equations solved to get translation and rotation matrices. (From world coordinate to 2D Image plane)

Cross Calibration between LiDAR and Camera

1. AV Systems need to identify agents on road (roads, cars, pedestrians etc).
2. Data from multiple sensors should be combined.
3. Bring the coordinate frames of LiDAR and camera into a common frame.
4. Calculate the Transformation Matrix
   a. Rotation Vector (R_L^C)
   b. Translation Vector (T_L^C)



Estimating Transformation Vectors

1. Challenge - No direct mapping between LiDAR and Camera data
2. Solution - Use normals in both the frames to find the correspondence

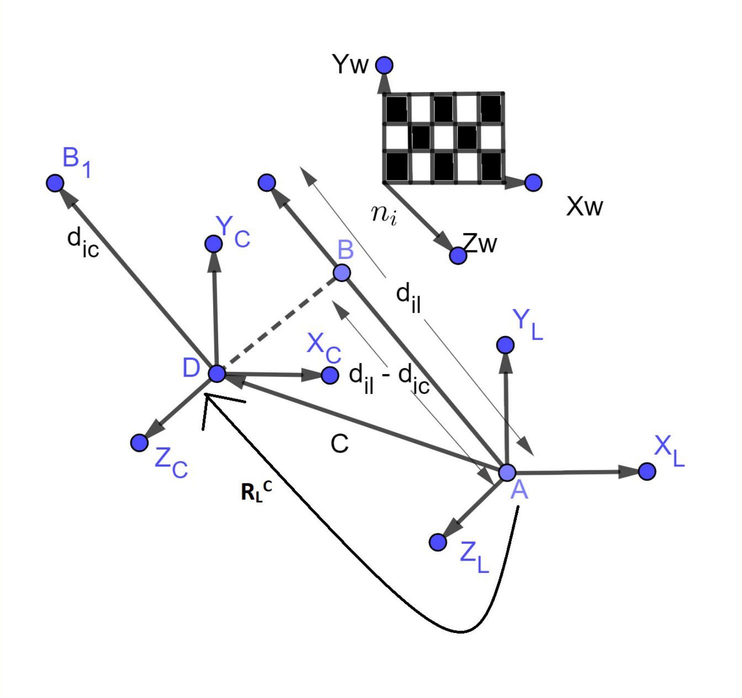
Estimating Rotation Vector

$$R_L^C A = B$$

$$A = [n_1^L, n_2^L, n_3^L \ldots ..n_m^L]$$

$$B = [n_1^C, n_2^C, n_3^C \ldots ..n_m^C]$$

Estimating Transformation Vectors



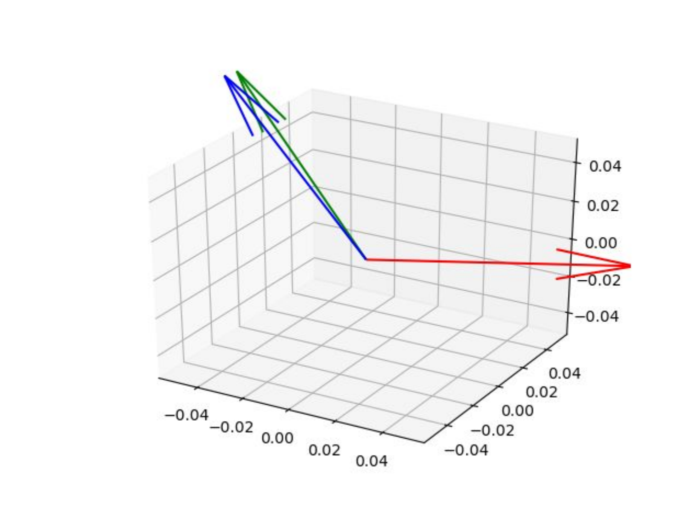
<u>Estimating Translation Vector</u>

1. We know the distance of plane to the LiDAR along the normal. (Equation of Plane)

2. Can calculate the distance of coordinate plane from Camera through euclidean distance.

Verification of Results

1. Evaluation of Rotation Vector
    a. Rotation Matrix - Orthogonal Matrix
        i. $R \times R^T = 0.9999999999999998$
    b. Visualization
        i. Red - Normal in LiDAR frame
        ii. Blue - Normal in Camera frame
        iii. Green - Rotated vector from LiDAR to camera frame
    c. Cosine Distance
        i. $1 - \cos\Theta \cong 0$



2. Evaluation of Translation Vector
    a. Randomly sampled few images (15 out of 29) and performed the experiment 1000 times.
    b. Result - all of the vectors lie within the range $[\mu + \boldsymbol{\sigma}, \mu + \boldsymbol{\sigma}]$

State of the Art

1. Sensor Fusion
    a. RGB cameras perceive color and texture,
    b. LiDAR provide distance information (Range Sensors)
    c. RADARs provide velocity and distance

<u>Fusion Strategies</u>

a. LLF(Low level fusion) - combines low level data from different sensor types and performs fusion.
b. HLF(High level fusion) - detects objects with each sensor separately and combines the results.

<u>One Such Strategy</u>

a. project the LiDAR point cloud onto RGB image , upsample it and extract features.
b. Faster RCNN is modified for improved object detection and classification

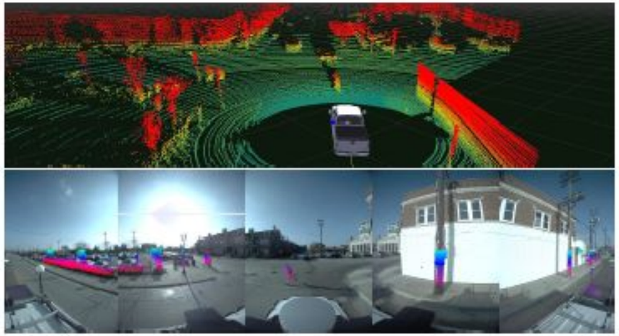


Figure 1: The top panel is a perspective view of the 3D lidar range data, color-coded by height above the ground plane. The bottom panel depicts the 3D lidar points projected onto the time-corresponding omnidirectional image. Several recognizable objects are present in the scene (people, stop signs, lamp posts, trees). (Only nearby objects are projected for visual clarity.)

State of the Art

2. Cross Calibration

a. Drift can affect sensor's position
   i. Performs online calibration
   ii. Uses edges to perform cross calibration
   iii. Able to perform recalibration after jerks
      1. Assumes the timestamp of each point recorded by the LiDAR

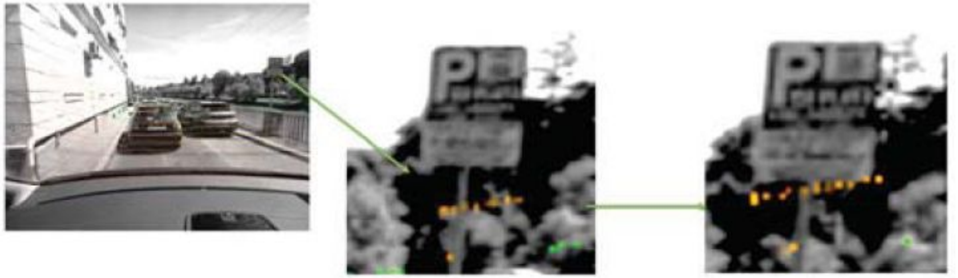


Figure 1. An example of miss-calibration detection and correction

State of the Art

3. Automatic Calibration

a. No manual intervention
b. Targetless extrinsic calibration of LiDAR and Camera
c. Mutual Information based algorithm
    i. Assumes correlation between LiDAR reflectivity and Camera Intensity
    ii. Statistical dependence between random Variables X and Y
        1. X - laser reflectivity of a 3D point
        2. Y - grayscale value of image pixel
d. MI should be at maxima after rigid body transformation
e. Able to fine tune itself

Conclusion

1. Gained an in-depth understanding of Camera Calibration.
2. Performed Cross Calibration between LiDAR and Camera.
3. Were able to validate our results.
4. Literature Study helped us to discover existing methodologies and future prospects.

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THANK YOU!