A GENERIC METHOD TO ESTIMATE CAMERA EXTRINSIC PARAMETERS

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ABSTRACT

In this paper, an approach to self-calibrate an outward-looking camera from camera images is presented. Ego lane boundaries are detected in the image frame. A straight line is fitted to each detected boundary. Vanishing point in image space is computed as the intersection of the fitted straight lines. A closed-form solution is obtained for camera pitch and yaw angles using vanishing points coordinates. A particle filter is initialized using pitch and yaw angles from closed-form solution and the rest of the camera extrinsic parameters (viz., roll, and translation parameters) obtained from approximate measurements.

Index Terms— Autonomous vehicles, Front-camera module, Multi-camera systems, Self-Calibration, Particle Filter

1. INTRODUCTION

Camera systems are being deployed in automotive for applications like Autonomous Driving Systems. Accurate camera calibration parameters are an ineludible ingredient to establish a consistent representation of vehicle environment. In general, camera calibration applications include experimental setups, end-of-line calibration, and recalibration during long-term operation. These approaches for camera calibration are time-consuming. And, the accuracy of calibration result is evaluated against the experimental setup, but not in the actual use case scenario.

Pin-hole camera calibration is used in the current study. Self-calibration is the process of determining extrinsic camera parameters, directly from camera images and map (reference). Self-calibration avoids the onerous task of calibrating cameras using special calibration objects and/or setup. In this work, we propose an approach to estimate camera external parameters. We assume that camera intrinsic parameters are pre-calibrated and known. When vehicle is traveling on a straight road, lane boundaries are detected in the captured image frame. Lane boundary detection is limited to Ego lane boundaries only. A straight line is fitted to each detected lane boundary. Vanishing point is computed as the intersection of straight lines fitted to Ego lane boundaries. Camera pitch and yaw angles are computed using vanishing points which are used as initial values in the iterative step.

Initial values for camera extrinsic shall be obtained using simple manual measurements or by referring to camera mounting position in vehicle Computer-Aided Design diagrams. Around this inital values, a search region is defined. This search region volume is based on the inaccuracies in the manual measurements or manufacturing limitations. Similarly, for angles, the search range is defined. A particle filter is used to search for optimal camera extrinsic parameters. The goal of this particle filter is to find the camera extrinsics which minimizes the error between camera detected lanes and lanes obtained from map.

2. RELATED WORK

2.1. Offline Calibration Methods

Offline calibration methods involve the use of a special calibration object whose geometry is known. [1] Zhang proposed technique required the camera to observe a planar pattern shown at a few different orientations. Either the camera or the calibration target can be moved to obtain a different position and orientation. The motion need not be known. [1] the proposed method consists of a closed-form solution, followed by a nonlinear refinement based on the maximum likelihood criterion.

Camera extrinsic parameters obtained using offline calibration methods map points from world to camera coordinates. The rigid transformation from vehicle to calibration target coordinate frame is needed to map from sensor to vehicle coordinate frame. This exercise is time-consuming and suffers from manual errors.

2.2. Self-Calibration Methods

[2] Self-calibration is the process of determining internal camera parameters directly from multiple uncalibrated images. [3] the proposed method, which uses simple properties of vanishing points, is divided into two steps. In the first step, the intrinsic parameters of the camera are recovered from a single image of a cube. In the second step, the extrinsic parameters of a pair of cameras are estimated from an image stereo pair of a suitable planar pattern. [4] Pollefeys et al propose a self-calibration method that efficiently deals with all kinds of constraints on the intrinsic camera parameters. [5] Hartley proposes the self-calibration method, at least three

images are taken from the same point in space with different orientations of the camera, and calibration is computed from an analysis of point matches between the images. The method requires no knowledge of the orientations of the camera.

3. CAMERA EXTRINSIC PARAMETERS ESTIMATION

This section provides details on how to effectively solve the camera extrinsic calibration problem in vehicle coordinates. A forward-looking camera setup is used for the current study. An analytical solution for camera pitch and roll is obtained using a vanishing point. This is followed by a particle filter approach to search for accurate camera extrinsic parameter estimation.

3.1. Pin-hole Camera Model

The purpose of the camera calibration is to establish the projection from the 3D world coordinates to the 2D image coordinates. Once this projection is known, 3D information can be inferred from 2D information, and vice versa. Thus camera calibration is a prerequisite for any application where the relation between image and world is needed [6].The anatomy of the central projection camera model is examined using the tools of projective geometry.

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_c \\ 0 & \beta & v_c \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \tag{1}$$

$$x = K(R|t)X \tag{2}$$

Where K captures the intrinsic properties of the camera, (R,t) are the extrinsic parameters, X is a point in the world coordinate frame and x is a point in the image coordinate frame [7].

3.2. Proposed Solution

Fig. 1 depicts the self-calibration algorithm pipeline for a forward-looking camera. The algorithm is designed to perform self-calibration when traveling on a straight road with lane markers. The pipeline is composed of a closed-form solution to compute camera pitch and yaw angles and an iterative approach to obtain the best camera extrinsic parameters. These processing steps are explained in detail below.

3.3. Closed-form Solution

Sensor extrinsic parameters are used to mathematically define its position and orientation in vehicle coordinate system. Fig. 2 explains the 6 DoF of sensor extrinsic parameters.

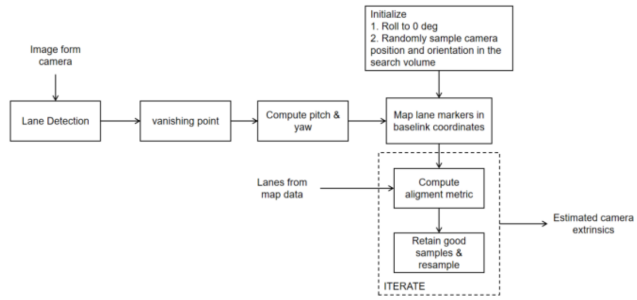

Fig. 1. Camera extrinsic parameter estimation algorithm.

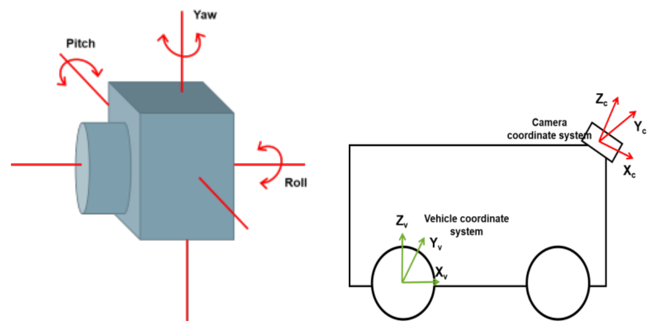

Fig. 2. 6DoF of camera extrinsic parameters. (left)Camera extrinsic angles, (right) Camera and vehicle coordinate system. Extrinsic translation parameters in vehicle coordinate system.

Of the 6 extrinsic parameters, two are estimated using a closed-form solution. Lane boundaries are detected in the images captured from the forward-looking camera. A plethora of approaches is discussed in detail in [8] and [9]. Detected lane boundaries are shown in green colors (Fig. 3).

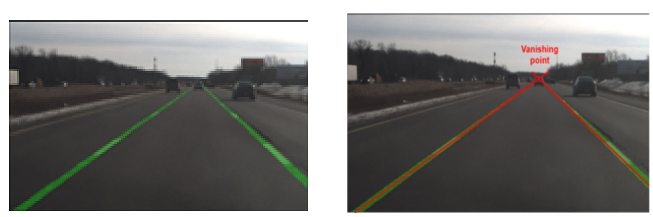

Fig. 3. (left) Lane detection output (right) Vanishing point computation.

Ego lane boundaries are preferred as their detection accuracy is better than adjacent lane boundaries. Otherwise, adjacent lane boundaries shall also be used for vanishing point computation. Say, ego-left and ego-right lane boundaries are fitted with straight line as a_Lx + b_Ly + c_L = 0 and a_Rx + b_Ry + c_R = 0, respectively. Vanishing point (say, vp_x, vp_y) in images coordinates are computed using the below equations (Eq 3, 4):

$$vp_x = \frac{b_L C_R - b_R C_L}{a_L b_R - a_R b_L} \quad (3)$$

$$vp_y = \frac{a_R C_L - a_L C_R}{a_L b_R - a_R b_L} \quad (4)$$

The vanishing point is normalized using the camera intrinsic matrix (K).

$$nvp = K^{-1} \begin{bmatrix} vp_x \\ vp_y \\ 1 \end{bmatrix} \quad (5)$$

Where nvp (normalized vanishing point) is a 3x1 vector. Camera pitch and yaw angles in-vehicle coordinate system are computed using below equations:

$$Camera\,Pitch\,Angle = sin^{-1}(nvp[2]) \quad (6)$$

$$Camera\,Yaw\,Angle = tan^{-1}(\frac{nvp[1]}{nvp[2]}) \quad (7)$$

3.4. Particle Filter For Accurate Extrinsic Parameter Estimation

3.4.1. Initialization

In this step, several particles are generated for camera extrinsic. Each particle is considered a potential solution. Each particle is generated by randomly sampling each parameter in extrinsic in the predefined search ranges (for angles) and search volume (for translation). A forward-looking camera is mounted so that the roll angle is zero degrees. Roll angle in the particles is generated by randomly sampling around zero degrees. A closed-form solution is used to compute the camera pitch and yaw angles. Pitch and yaw angles shall be sampled around the computed angles.

A search volume is defined for the camera extrinsic translation parameter. Approximate camera position in vehicle coordinates shall be obtained from camera mounting in the vehicle Computer-Aided Design diagram. Or, approximate camera position in vehicle coordinates shall be measured using any off-the-shelf devices. The position of search volume is defined around the approximate camera position. And, the search volume is defined based on manufacturing limitations and/or position measurement accuracy.

3.4.2. Cost Functions

For each particle, project lane boundaries detected in images to vehicle coordinates. Using offline map data, fetch the lane boundary for the current vehicle position. Alignment of detected lane boundary with the map generated boundary is found to be a reasonable metric to assess the accuracy of camera calibration parameters. Smaller the misalignment, the better chance of the current particle being right camera extrinsic parameters. The cost function is regularized to improve the robustness of the algorithm. Regularization is achieved by adding the absolute difference in lane model parameters from map and lane detection to the cost function.

$$\begin{aligned} Cost\ Function = Average\ lateral\ offset \\ along\ y\ direction \end{aligned} \quad (8)$$

$$\begin{aligned} Regularized\ Cost\ Function = Avg.\ lateral\ offset \\ along\ y\ direction \\ + (k_1 * |a_{map} - a_{LD}|) \\ + (k_2 * |b_{map} - b_{LD}|) \\ + (k_3 * |c_{map} - c_{LD}|) \end{aligned} \quad (9)$$

Where, k_1, k_2, and k_3 are regularization parameters, $(a_{map}, b_{map}, c_{map})$ and (a_{LD}, b_{LD}, c_{LD}) are lane model parameters obtained from map and lane detection algorithm, respectively.

3.4.3. Iterative Process

For each iteration, all particles are arranged in order of increasing cost. A fraction of particles with minimal cost is selected. New samples are re-generated around the retained fraction of particles. The iterations continue until desired camera extrinsic accuracy is achieved or pre-defined maximum iterations are executed. At the end of algorithm, a particle with minimal cost function is selected as possible camera extrinsic. However, a more comprehensive approach for the best possible candidates shall be employed. Say, a median of solutions obtained from multiple frames outcome.

4. EXPERIMENTAL RESULTS

4.1. Test vehicle Set-up and Test Track

For evaluating this algorithm, we are considering two cameras from different vendors. These cameras are mounted on the same vehicle (Lincoln MKZ) at different positions. Fig. 4 shows the specification of these cameras.

Camera Manufacturer	Horizontal Field of View	Mounting Position	Image Resolution
PointGrey	25 degrees	[Internal] behind the windshield inside the vehicle (refer to Fig xyz)	1280*720
Leopold Imaging AR0233	60 degrees	[External] roof of the vehicle	1920*1080

Fig. 4. Camera Specifications.

The proposed extrinsic estimation approach is used to calibrate extrinsic of both cameras. Fig. 5 shows the stretch of freeway over which the test vehicle was driven to estimate camera extrinsic parameters.

Fig. 5. Test track followed to estimate camera extrinsic parameters.

4.2. Cost function

Fig. 6 compares the performance of proposed self-calibration algorithm against an offline calibration algorithm. Alignment of detected lane boundaries in the camera with lane boundaries obtained from the map is used to assess the quality of camera calibration parameters. From the graph, it is evident that the self-calibration algorithm estimated extrinsic are more accurate than those obtained using the offline calibration method.

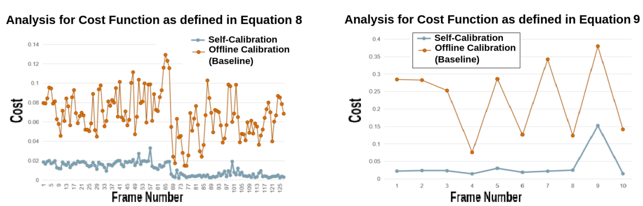

Fig. 6. Extrinsic calibration algorithm performance compared against offline calibration algorithm. (left) using cost function 1, (right) using regularized cost function.

4.3. Number of Particles

Proposed algorithm performance is evaluated by varying the number of particles by keeping other parameters constant,see Fig. 7. The search volume is set to 1000cm^3 and maximum iteration count is set to 50. For point grey camera, best possible performance is achieved for the number of particles is greater than 50. However, for the AR0233 camera, best possible performance is achieved for 100 or more particle counts.

4.4. Search Volume

Proposed algorithm performance is evaluated by increasing the search volume. Fig. 8 shows the quality of estimated camera extrinsic parameters with different search volumes.

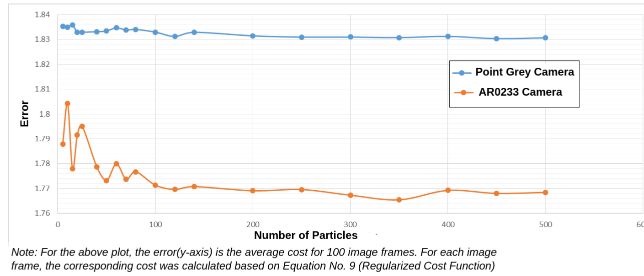

Fig. 7. Extrinsic calibration algorithm performance for the different number of particles.

The number of particles and the maximum number of iterations is set to 50. For the proposed approach performance is consistent with an increase in search volume.

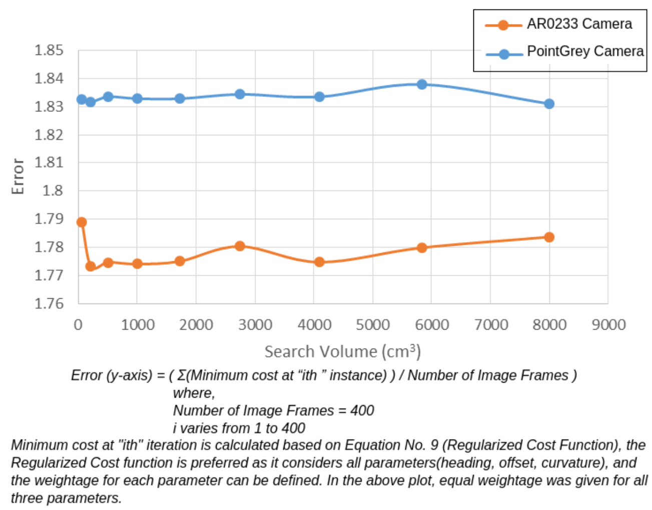

Fig. 8. Extrinsic calibration algorithm performance with different search volumes.

5. CONCLUSION

In this paper, we studied the problem of estimating the extrinsic parameters of a camera. An algorithm was proposed to calculate all the extrinsic using Closed-Form Solution and Particle Filter. The results were compared against the Offline Calibration which is considered as baseline. The performance of the algorithm was compared by varying different parameters (Cost Function, Number of Particles, Search Volume). It was concluded that the results using the proposed method perform better than the Offline Calibration (Baseline). The results are consistent on both the cameras. Future work will aim at extending this algorithm for Lidar sensors.

6. REFERENCES

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