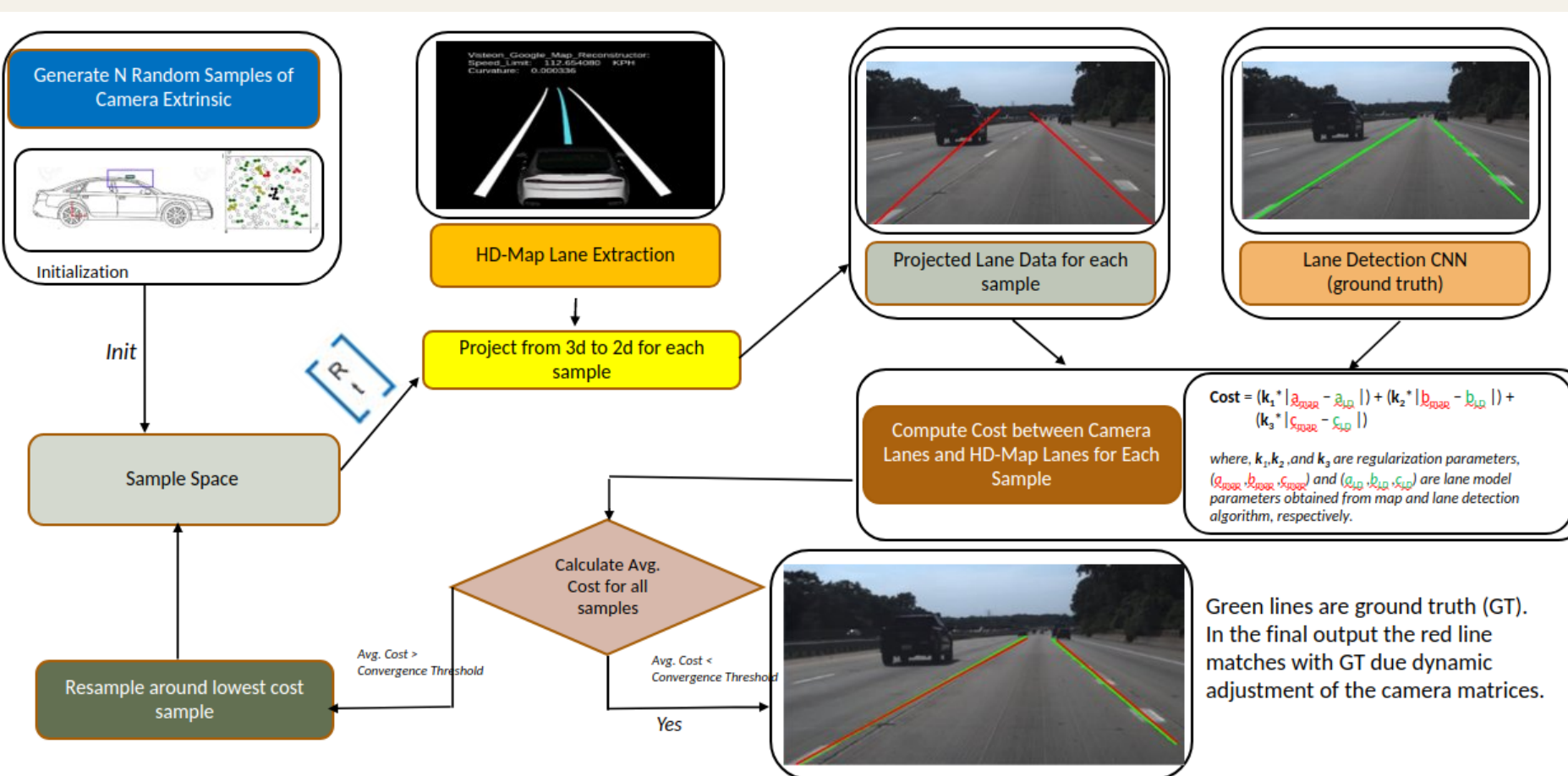


Introduction

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.

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 initial 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 extrinsic which minimizes the error between camera detected lanes and lanes obtained from map.

Proposed Self-Calibration Method

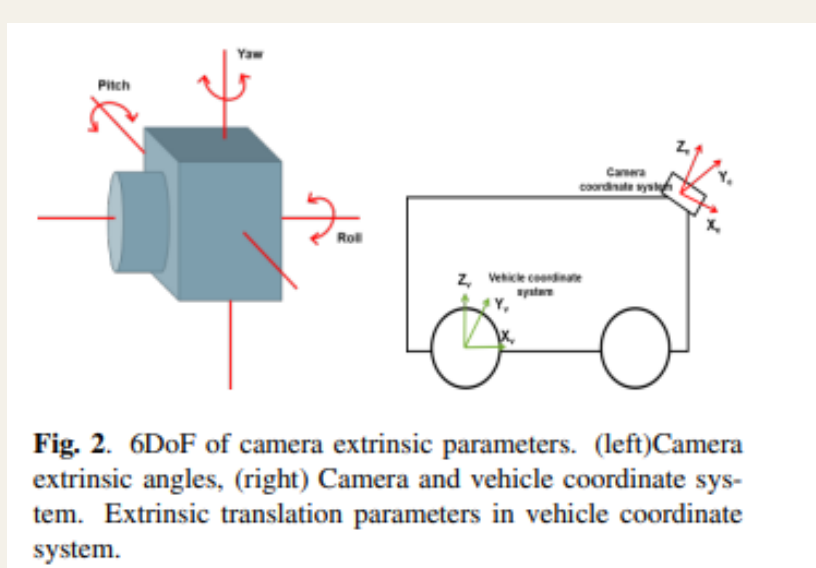


Initialization

A sample space of random particles is generated. In this sample space, Each sample consists of Rotation and Translation matrix. This matrix are nothing but the extrinsic parameters of the camera that are to be estimated.

Iteration

For each sample, the 3d lanes from HD-Map are projected in the image space. The cost between this projected lanes and the lanes from Camera Lane Detection CNN (ground-truth) is calculated. This cost is calculated for each sample.



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

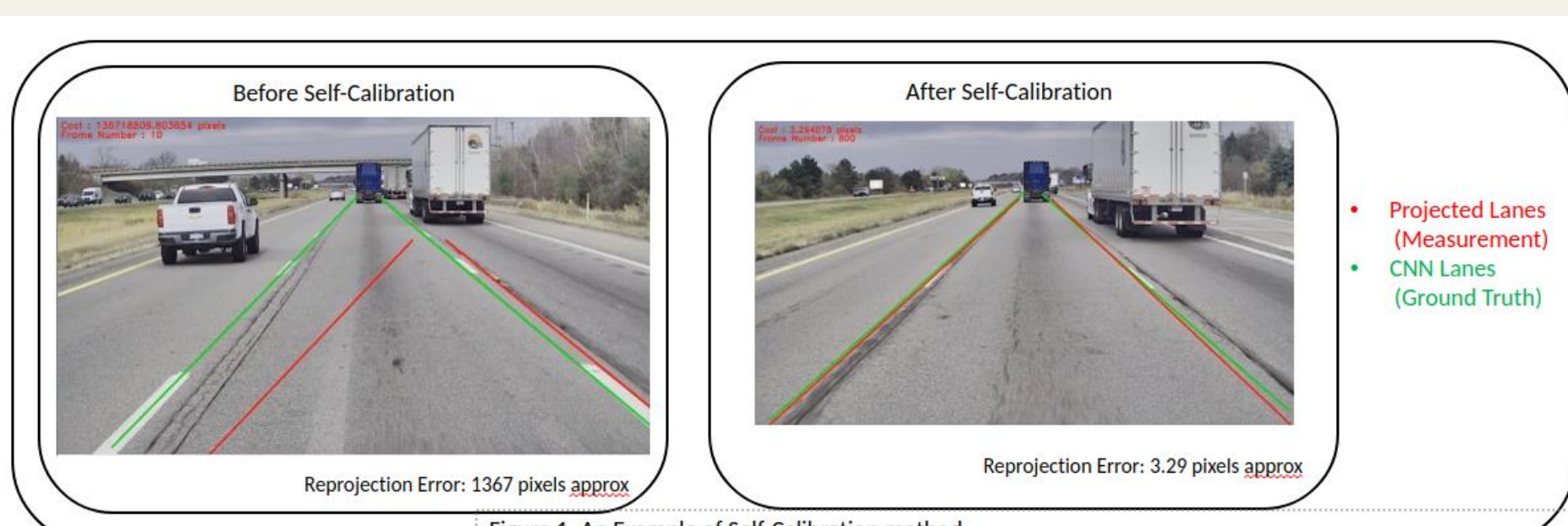
$$\text{Regularized Cost Function} = \text{Avg. lateral offset along y direction} + (k_1 * |r_{avg} - a_{L,D}|) + (k_2 * |r_{avg} - b_{L,D}|) + (k_3 * |r_{avg} - c_{L,D}|) \quad (9)$$

Where, $k_1, k_2,$ and k_3 are regularization parameters. ($r_{avg}, r_{max}, r_{min}$) and ($a_{L,D}, b_{L,D}, c_{L,D}$) are lane model parameters obtained from map and lane detection algorithm, respectively.

After this, the average cost is calculated for all samples. If this Average Cost is greater than the Convergence Threshold, the sample with minimum cost is selected, and new samples are generated around that minimum cost samples.

After resampling, the process of cost calculation is repeated. The iteration is terminated once the Convergence Criteria is met. For this, the average cost should be less than the Convergence Threshold.

The final output is the cost with lowest sample. Usually, the average reprojection error is around 2 pixels.



Test Setup for the Proposed Self-Calibration

The proposed Self-Calibration Algorithm has been tested for 2 cameras having different configurations.

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

Fig1 : Camera Configuration

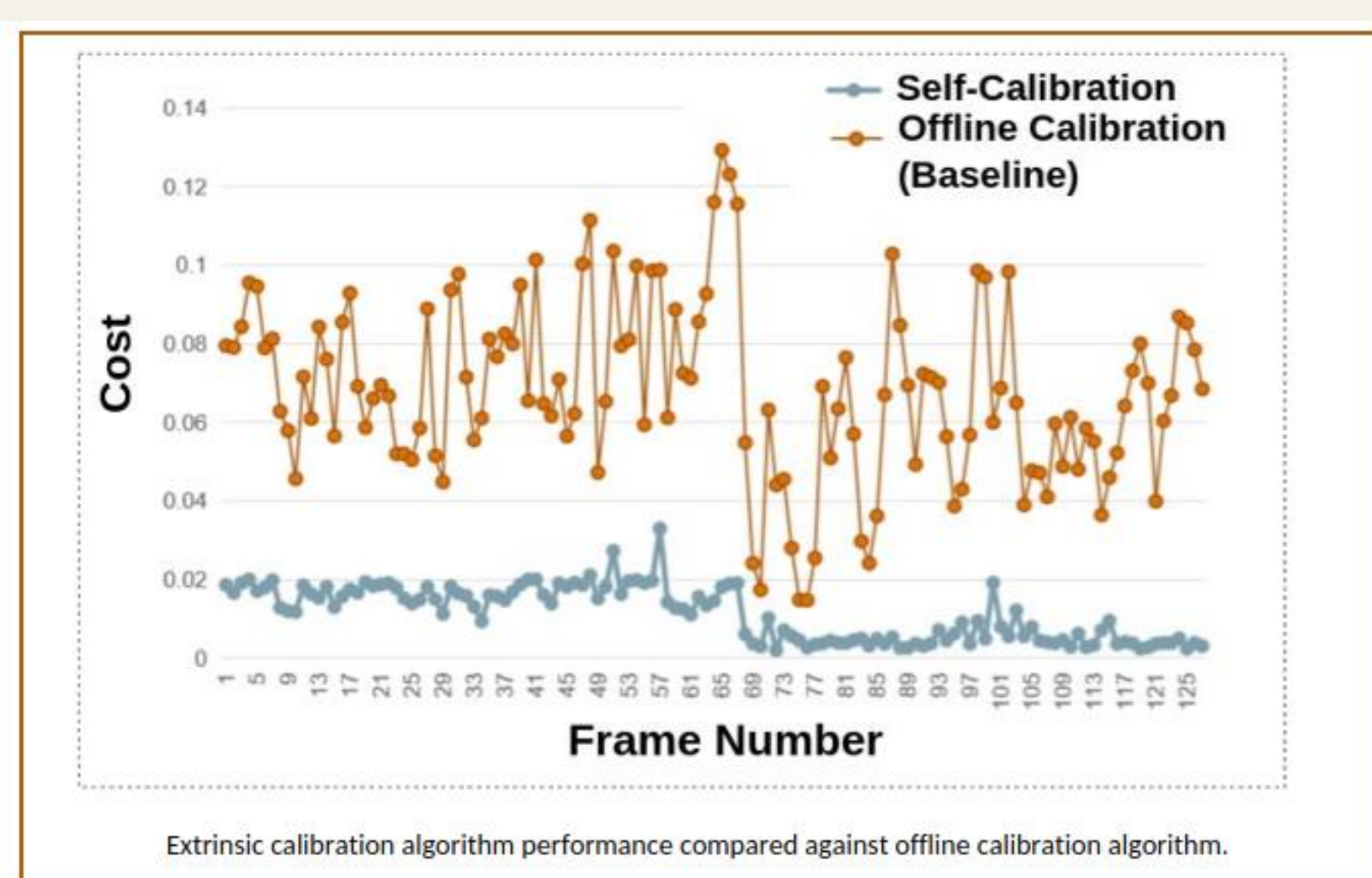
The testing was conducted for 2 cameras with different mounting positions on same vehicle (Vehicle Model : Lincoln MKZ



This testing was conducted on an Interstate highway. The algorithm converged for a 4 miles drive.



Accuracy of the Proposed Method



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.

Adaptability of the proposed Algorithm

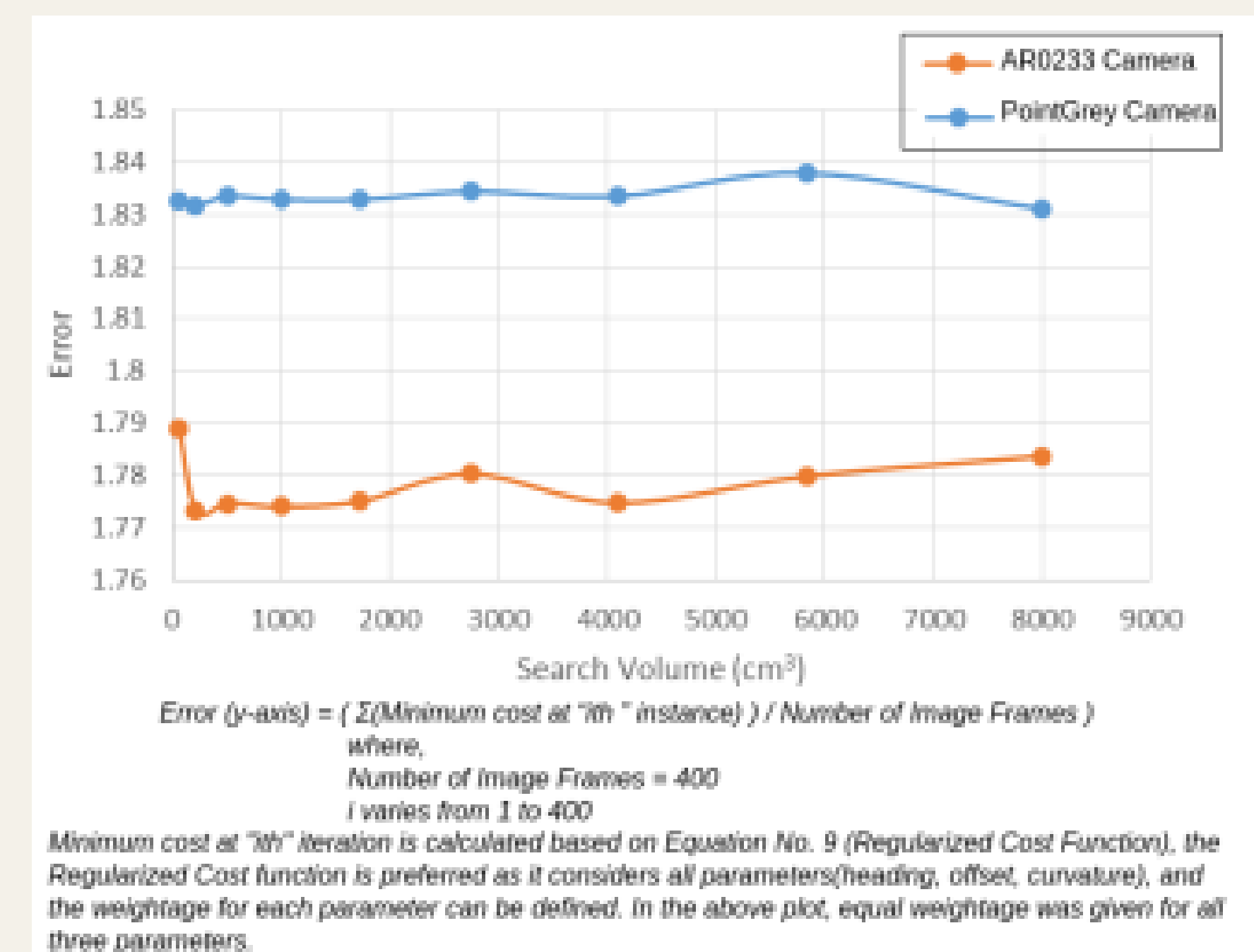
Automotive OEM's :

Most of the Autonomous Driving Software Stack (Level 2.5+) have HD-Maps and CNN Lane Detection Modules in them.

This software can easily be adapted as it only requires the HD-Map lanes and the CNN- Camera Lane Data. Both modules are already present in most of the Autonomous Driving S/W stack.

In the proposed method, the HD-Maps are considered as a reference as they provide accurate Lane data. This algorithm also has a strong requirement on the Vehicle Localization. The Localization module is also a part of the Autonomous driving S/W stack.

Experimental Results



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

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.

References

- [1] Zhengyou Zhang, "A flexible new technique for camera calibration," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 22, no. 11, pp. 1330–1334, 2000.
- [2] Alex M Andrew, "Multiple view geometry in computer vision, by richard hartley and andrew zisserman, cambridge university press, cambridge, 2000, xvi+ 607 pp., isbn 0-521-62304-9 (hardback, £ 60.00)," *Robotica*, vol. 19, no. 2, pp. 233–236, 2001.
- [3] Bruno Caprile and Vincent Torre, "Using vanishing points for camera calibration," *International journal of computer vision*, vol. 4, no. 2, pp. 127–139, 1990.
- [4] Marc Pollefeys, Reinhard Koch, and Luc Van Gool, "Self-calibration and metric reconstruction inspite of varying and unknown intrinsic camera parameters," *International Journal of Computer Vision*, vol. 32, no. 1, pp. 7–25, 1999.
- [5] Richard I Hartley, "Self-calibration from multiple views with a rotating camera," in *European Conference on Computer Vision*. Springer, 1994, pp. 471–478.
- [6] Olivier D Faugeras, Q-T Luong, and Stephen J Maybank, "Camera self-calibration: Theory and experiments," in *European conference on computer vision*. Springer, 1992, pp. 321–334.
- [7] Wilhelm Burger, "Zhangs camera calibration algorithm: in-depth tutorial and implementation," *HGB16-05*, pp. 1–6, 2016.
- [8] Yang Xing, Chen Lv, Long Chen, Huaji Wang, Hong Wang, Dongpu Cao, Efstathios Velenis, and Fei-Yue Wang, "Advances in vision-based lane detection: algorithms, integration, assessment, and perspectives on acp-based parallel vision," *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 3, pp. 645–661, 2018.
- [9] Dun Liang, Yuan-Chen Guo, Shao-Kui Zhang, Tai-Jiang Mu, and Xiaolei Huang, "Lane detection: a survey with new results," *Journal of Computer Science and Technology*, vol. 35, pp. 493–505, 2020.

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