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An automatic online camera calibration system for vehicular applications

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***Abstract*— Nowadays, the camera online calibration module has been a fundamental and often requested component in an Advanced Driver Assistance System (ADAS). The proposed system provides an efficient and practical solution to such request, and also shows technical advances compared to earlier systems. It utilizes the lane markings for camera orientation calibration. At each image frame, multiple vanishing points of the lane markings are estimated using the weighted least squares method, followed by a tracking process with Kalman Filter for better consistency and robustness. With the filtered vanishing point the camera extrinsic tilt and pan angles can be estimated. Even though the proposed system relies on the lane markings for calibration, unlike other similar systems, the number of the lane markings in the system is not restricted, and the shape of the lane markings is also not restricted to straight lines or any other pre-defined models. A Monte Carlo evaluation scheme is devised for that purpose using real world driving sequences. The final result has shown that given an initial calibration error, in ± 4 degree interval w.r.t. ground truth for both tilt and pan angles, the proposed system is capable of converging to accurate angles and providing consistent results.**

I. Introduction

Camera calibration is one of the fundamental components for various driver assistance applications. An accurate projection between the 3D world and the 2D image depends on the accurate camera calibration and it is crucial in object detection and tracking applications.

Camera calibration consists of intrinsic and extrinsic calibration. The camera intrinsic parameters can be calibrated once and are constant in the camera system for vehicular applications. On the contrary, the extrinsic camera parameters, which define the position and orientation of the camera in the vehicle coordinate system, can be variable. It is still a challenging topic. For example, the tilt angle of the camera mounted in the driving cabin of a truck can vary by a great amount, depending on many factors like loading. In this work, we propose a system for the extrinsic camera calibration, more specifically the tilt and pan angels calibration based on a zero roll angle assumption. The camera height calibration is not part of this work and is also not relevant for the calculation of other parameters. Based on the optical system used in the vehicle, an ideal pinhole camera model is sufficient and therefore has been chosen.

As reviewed by Lepetit et al. in [1] the camera parameters can be extracted based on the detection of correspondence points or features in multiple images. Various number of correspondences are needed, depending on the geometry of these points. Such methods have high computational costs, and for the application on an embedded system these methods are normally not feasible without sacrificing much computing resources, let alone constantly online running. A vanishing point based method is proposed in [2] for camera calibration, in which the intrinsic and extrinsic parameters are both estimated from the vanishing points. For vehicular applications this type of methods is convenient, because the lane markings are appropriate for vanishing point calculation, and the lane detection and tracking module is already a standard component in ADAS. In [3] Nedevschi et al. proposed a system for online calibration of stereo cameras using lane markings. In their work the lane markings need to be parallel to the vehicle longitudinal axis, and most importantly they need to be straight without curvatures. Such prerequisites are not necessary in our system.

In the proposed system the short line segments detected on the lane marking boundaries are directly used as system input. They are the intermediate result of a lane detection and tracking system, such as the systems in [4]. No extra computation for feature detection is needed if similar systems run concurrently. Comparing with other methods [5] [6], which need to fit the detected lane marking features to a pre-defined model (linear, curve, spline etc.) for lane marking representation, the proposed system is more concise. Theoretically, the vanishing point is defined as the intersection of lines in the image, which are the projection of parallel lines from the vehicle coordinate system. In rather complicated driving scenarios it is clear parallel lane markings can not always be ensured. So for better robustness the system is designed as an iterative procedure consisting of two steps, vanishing point estimation in each frame and filtering across multiple frames.

II. Method

Each image frame is vertically divided into multiple ROIs (Region of Interest). The line detection results with their parameter variances in each ROI are provided as calibration system input, and the vanishing point is estimated together with its covariance.

A. Problem Formulation

There are multiple lines detected in each ROI, direct calculation of vanishing point using its definition is not feasible. In our proposed system, the vanishing point is formulated as a point which has the minimal average distance to all the

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detected line segments in its ROI. Then the vanishing point estimation can be formulated as an optimization problem and solved efficiently by the least squares method.

With parameters θ and b a line is defined as

$$x - b = \tan(\theta) \cdot (y - y_0^i), \tag{1}$$

in which y_0^i is a pre-defined y-coordinate for the ROI with index i in one image. It is assumed that these two parameters have independent zero mean errors, with variance σ_θ^2 and σ_b^2 respectively. Because the estimation process is same for each ROI, in the following section the superscript of y_0^i is dropped off for brevity without causing confusion.

Let $\hat{p}_v$=$(\hat{x}, \hat{y})$ denote the estimated vanishing point, and d denote the distance from $\hat{p}_v$ to a line segment, which has unit normal vector $(n_x, n_y)^T$ and a point (b, y_0) on it,

$$\begin{pmatrix} n_x & n_y \end{pmatrix} \cdot \begin{pmatrix} b - \hat{x} \\ y_0 - \hat{y} \end{pmatrix} = d. \tag{2}$$

Minimizing distance $d \to 0$, Equation 2 becomes

$$\begin{pmatrix} n_x & n_y \end{pmatrix} \cdot \begin{pmatrix} \hat{x} \\ \hat{y} \end{pmatrix} = z. \tag{3}$$

z is a scalar value, which is referred to as measurement in the least squares method,

$$z = n_x b + n_y y_0. \tag{4}$$

This is a linear problem about point $(\hat{x}, \hat{y})$, and the weighted least squares estimation can be applied.

B. Vanishing Point Estimation

A linear estimation problem can be written in matrix form as a linear Equation [1]

$$\mathbf{A}\mathbf{x} = \mathbf{z}. \tag{5}$$

$\mathbf{x}$ is the estimated parameter vector, $\mathbf{z}$ is the measurement vector and matrix $\mathbf{A}$ describes the linear relation between them. By assigning each measurement a weight coefficient the weighted least squares estimation treats them differently. The estimation is an iterative process. At each iteration a weight coefficient is assigned to each measurement according to its residual. By introducing a weight coefficient matrix $\mathbf{W}$, $\mathbf{x}$ can be calculated using the pseudo inverse as

$$\mathbf{x} = \mathbf{F}\mathbf{z}, \tag{6}$$

$$\mathbf{F} = (\mathbf{A^T W A})^{\mathbf{-1}} \mathbf{A^T W}. \tag{7}$$

After each iteration the matrix $\mathbf{W}$ is updated based on the latest estimated $\mathbf{x}$. Equation 6 can be executed iteratively until this estimation process converges. Let $\mathbf{Q_z}$ denote the covariance of the measurement vector in Equation 6, because of the linear relation the covariance $\mathbf{Q_x}$ of parameter vector $\mathbf{x}$ is

$$\mathbf{Q_X} = \mathbf{F Q_z F^T}. \tag{8}$$

The weight coefficients in $\mathbf{W}$ are defined using the Tukey estimator [1] as a diagonal matrix, with each of the diagonal element corresponds to the weight coefficient of one measurement z. An initial point is needed to initialize the weight coefficient matrix. For this purpose the Random Sample Consensus (RANSAC) [7] is deployed here as a fast and simple initialization method.

The detection variances, i.e. variances of the position and slope parameters of the line segments in the image coordinate, are propagated during the weighted least squares process. Furthermore, this propagated variance is directly incorporated into the Kalman filtering process as the measurement noise. Assume the parameters b and θ of a line have independent, zero-mean variances σ_θ^2 and σ_b^2 respectively. These two variances are pre-defined, and their value can be evaluated offline by labeling ground truth. For the later filtering process, the covariance of the estimated vanishing point, $\mathbf{Q_x}$ in Equation 8 needs to be determined. A simple and efficient way for this conversion is by linearization of the trigonometric functions [8] [9].

According to Equation 3 the unit normal vector $\vec{n} = (n_x, n_y) = (\cos(\theta), -\sin(\theta))$ of a line segment can be linearized at a given measurement $z = (\theta_m, b_m)$, and the variances of its elements are [8] [10]

$$\sigma_{nx}^2(\theta_m) \approx \sin^2(\theta_m)\sigma_\theta^2, \tag{9}$$

$$\sigma_{ny}^2(\theta_m) \approx \cos^2(\theta_m)\sigma_\theta^2. \tag{10}$$

Let σ_z^2 denote the variance of measurement z in Equation 4, it can be calculated as

$$\sigma_z^2 = Var(n_x b) + Var(n_y y_0) + 2Cov(n_x b, n_y y_0), \tag{11}$$

in which Var and Cov denote the variance and covariance respectively. Since the line parameters θ and b are assumed independent, n_x and b are independent, together with the first order Taylor expansion the variance at the measurement $z = (\theta_m, b_m)$ is approximately calculated as

$$\begin{aligned}\sigma_z^2 \approx{} & \cos^2(\theta_m)\sigma_b^2 + b_m^2 \sin^2(\theta_m)\sigma_\theta^2 \\ & + y_0^2 \cos^2(\theta_m)\sigma_\theta^2 + 2y_0 b_m \sin(\theta_m)\cos(\theta_m)\sigma_\theta^2.\end{aligned} \tag{12}$$

The covariance $\mathbf{Q_z}$ of measurement set is formulated as a diagonal matrix, with each of the diagonal element corresponds to the variance of one measurement defined in Equation 12. After the weighted least squares process has converged, the covariance of the estimated vanishing point $\mathbf{Q_x}$ can be calculated according to Equation 8.

C. Tilt and Pan Calculation

An image is vertically divided into N ROIs, and in each ROI the line detection algorithm is applied. If there are enough line segments detected in each ROI, the vanishing points from each of them can be estimated separately. To have a robust and stable results, these estimation results are filtered using the Kalman filter. Because the camera system runs at related high frequency, the vanishing points between two consequent frames can be assumed constant. This assumption greatly simplifies the system model of the filter. The system state is directly modeled as the position of the vanishing point, and the measurement is the estimated vanishing point. Then the measurement model becomes an identity matrix, and the filter becomes very simple and efficient. More details related to Kalman filter can be found in [8], [10].

In the Kalman filter, following criteria are defined to determine the convergence or confidence of the tracked vanishing point. First, thresholds are defined for the state covariance as one criterion. Since the tilt and pan angles are calculated based on the x- and y-component of the vanishing point independently, these thresholds also indicates indirectly thresholds for the tilt and pan angle variances. Second, a minimal threshold is defined for the percentage of valid measurements in a given time interval. If the tracker satisfies the above criteria, the tilt and pan angles are calculated based on the pinhole camera model with zero skew coefficient and a zero roll angle assumption can be calculated as

$$\alpha = \arctan\left(\frac{(p_y - \hat{y}) \times pl_x}{f}\right) \tag{13}$$

$$\beta = \arctan\left(\frac{(p_x - \hat{x}) \times pl_y}{f}\right) \tag{14}$$

in which α and β are the tilt and pan angles. $\hat{p}_v$=$(\hat{x}, \hat{y})$ is the estimated vanishing point, and the rest are the intrinsic camera parameters. f is the focal length of the camera. p_x and p_y are the coordinates of the principal point, which is the intersection of the optical axis with the image sensor plane pl_x and pl_y are the pixel size in x and y coordinates respectively.

III. Evaluation

For the evaluation, A Monte Carlo scheme for evaluation is devised, and applied on real world highway driving sequences, which include straight and curved roads, solid and dashed markings, worn out or temporally covered lane markings by other traffic participants.

Assume the ground truth of the tilt and pan angles of the camera system is given, the camera system is started using biased angles. The biases for both angles are uniformly and randomly generated in a given interval respectively, and added to the ground truth angels. The criteria discussed in subsection II-C are used as conditions for convergence determination, and the estimated angles are checked after convergence. This process is repeated enormously, and each time new biases are generated. Finally the statistics about the system convergence and estimated angles are collected. The advantages of this Monte Carlo evaluation scheme is the system consistency is statistically evaluated with its accuracy at the same time.

During the evaluation 800 trials were carried out. The biases for the artificial added tilt and pan are randomly generated in ± 4 degree interval w.r.t. the ground truth. If a satisfying evaluation result can be obtained, later this ± 4 interval can also be used as a reference for the camera mounting angle tolerance. Thus the proposed system can also be used for vehicle factory or server calibration. This is an additional by-product of this evaluation scheme. As the ground truth of the evaluation video set the tilt, pan and roll angles of the camera extrinsic angles are -0.12, 1.11 and 0.60 degree respectively. This small roll angle violates the zero roll angle assumption in the proposed system, certain estimation error could be expected. The mean values in Table I show that a satisfying accuracy has been achieved.

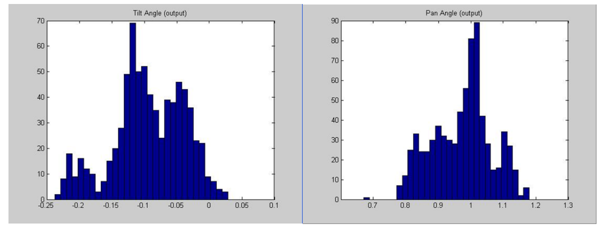

Fig. 1: The estimated tilt and pan angles of 800 Monte Carlo trials shown in histogram

	Ground Truth	Estimation	
		Mean	Standard Deviation
Tilt	-0.12	-0.09	0.05
Pan	1.11	0.97	0.09

TABLE I: Statistics of the evaluation results. The mean values of the tilt and pan angles are shown in degree.

IV. Conclusions

An online camera extrinsic calibration system is proposed in this work, which uses existing detections from a lane detection and tracking module to estimate the vanishing points with robustness. The weighted least squares method is chosen for vanishing point estimation in each image frame with the RANSAC technique, and followed by a tracking process using the Kalman filter. Using a Monte Carlo evaluation scheme on the real world highway driving sequences the evaluation results have shown good calibration accuracy and consistency. We have shown in the evaluation, given a ± 4 degree angle error, the proposed system provide satisfying results. One possible future working direction could be improving the overall system robustness so this angle tolerance can be further expanded.

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