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Self-Calibration of Fish-Eye Camera for Advanced Driver Assistance Systems

Atef Alaaeddine Sarraj, Brendan Jackman, Frank Walsh

***Abstract*—**Tomorrow's car will be more automated and increasingly connected. Innovative and intuitive interfaces are essential to accompany this functional enrichment. For that, today the automotive companies are competing to offer an advanced driver assistance system (ADAS) which will be able to provide enhanced navigation, collision avoidance, intersection support and lane keeping. These vision-based functions require an accurately calibrated camera. To achieve such differentiation in ADAS requires sophisticated sensors and efficient algorithms.

This paper explores the different calibration methods applicable to vehicle-mounted fish-eye cameras with arbitrary fields of view and defines the first steps towards a self-calibration method that adequately addresses ADAS requirements. In particular, we present a self-calibration method after comparing different camera calibration algorithms in context of ADAS requirements. Our method gathers data from unknown scenes while the car is moving, estimates the camera intrinsic and extrinsic parameters and corrects the wide-angle distortion. Our solution enables continuous and real-time detection of objects, pedestrians, road markings and other cars. In contrast other camera calibration algorithms for ADAS need pre-calibration, while the presented method calibrates the camera without prior knowledge of the scene and in real-time.

***Keywords*—**ADAS, Fish-Eye, Real-Time, Self-Calibration.

I. Introduction

Tomorrow's car will be more automated and increasingly connected to assure a high level of safety, as it's being an important factor for the automotive industry. So as to reduce the number of accidents or mitigate its consequences, automotive manufacturers are competing to offer an advanced driver assistance system (ADAS). Advanced Driver Assistance Systems (ADAS) also known as Active safety systems, enhance vehicle safety and driver experience by utilizing a variety of connected sensors and electronic control units (ECUs). Their global purpose is to reduce road accidents and facilitate the driving experience and make it more comfortable. ADAS support the driver at different four levels. At the first level, ADAS provide drivers with basic information which help them to have safer driving, for example information not visible to the driver during parking. At the next level, ADAS can give the driver warnings of an imminent and possibly hazardous situation to provide them enough time to take a safe decision.

At the last level of intervention involves the system to take decision. Independently of level of intervention, manufacturers who implement these systems hope to assist the driver before a critical situation arises or, at least, to reduce the consequences of driver error. An important family of these sensors is video cameras of different classes.

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Today these are used for recognition of pedestrians, traffic signs, and other vehicles, as well as localization of arbitrary obstacles, e.g. with the help of stereo vision. To make use of these results it is imperative to accurately map positions in the camera's image frame to the direction of the respective object with respect to the vehicle coordinate system. Determining this mapping is known as calibration.

II. Camera Calibration Techniques

Camera calibration is to determine the relation between the camera's units (pixels) and the real world units (millimeters). It estimates the parameters of an image sensor that can be used also to correct lens distortion, determine the location of the camera in world scene and measure the size of an object in world units.

A. Camera Model

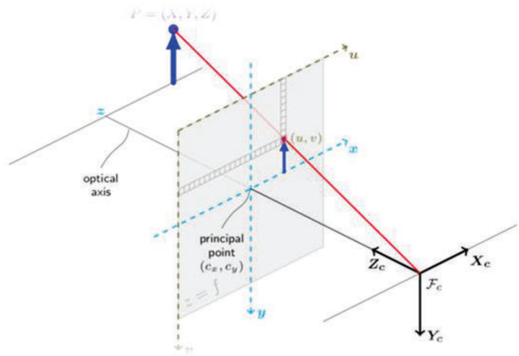

Fig. 1 Pinhole model

The pinhole model is the basis for most graphics and vision. It's derived from physical construction of early cameras. In this model, the camera parameters are presented in a 4-by-3 matrix, called the camera matrix and also know by P, which maps 3-D world scene into the image plane. To calibrate the camera it must calculate the camera matrix using intrinsic and extrinsic parameters. The extrinsic parameters represent the spatial orientation of the camera in the 3-D scene. . The intrinsic parameters allow a mapping between camera coordinates and pixels coordinates in the image frame. The intrinsic parameters are: the optical center, also known as the principal point, and the skew coefficient.

The extrinsic parameters are used to transforme the world points to camera coordinates. The intrinsic parameters are used to map the camera coordinates into the image plane.

$$W[x\ y\ 1] = [X\ Y\ Z\ 1]P \quad (1)$$

$$P = \begin{bmatrix} R \\ T \end{bmatrix} K \quad (2)$$

Where $[\, x\ y\ 1]$ is image point, $[X\ Y\ Z\ 1]$ is the world points and P is the camera matrix. The intrinsic parameters are presented by the matrix K and the extrinsic parameters represented by extrinsic rotation and translation $\begin{bmatrix} R \\ T \end{bmatrix}$.

The intrinsic parameters encompass the focal length, the principal point, also known as optical center, and a skew parameter. Thus defines camera intrinsic matrix K:

$$K = \begin{bmatrix} f_x & 0 & 0 \\ s & f_y & 0 \\ c_x & c_y & 1 \end{bmatrix} \tag{3}$$

Where $[c_x \quad c_y]$ is the optical center in pixels, (f_x, f_y) is the focal length in pixels and s the skew coefficient, which is non-zero if the image axes are not perpendicular.

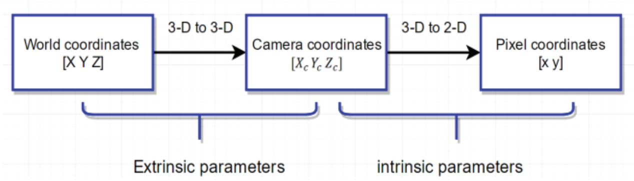

Fig. 2 Extrinsic and intrinsic parameters

The extrinsic parameters represent the rotation and translation which relates the world coordinate system to the camera coordinate system. The intrinsic parameters represent a transformation from the camera's coordinates into image coordinates.

B. Related work/ Currents approaches

There are several camera calibration methods, some of which use a line based calibration like Geyer and Daniilidis [1] which they present a method of calibration from the images of only three lines. Barreto and Araujo [2] presented geometric properties of line images study and they conclude by giving a calibration method suitable for any kind of central catadioptric system. But those approaches required a pattern, so they need to have pre-calibration phase.

Some others are performed by observing a calibration object whose geometry in 3-D space is known with very good precision. Puig et al. [3] present an approach based on the Direct Linear Transformation (DLT) using lifted coordinates to calibrate any central catadioptric camera. It computes a generic projection matrix valid for any central catadioptric system. From this matrix the intrinsic and extrinsic parameters are extracted in a closed form and refined by nonlinear optimization afterwards. This approach requires a single omnidirectional image containing points spread in at least three different planes [4].

Also some techniques use a 2D calibration pattern with control points which can be corners, dots or any characteristic that can be easily extracted from the image. Scaramuzza et al. [5] propose a technique to calibrate single viewpoint omnidirectional cameras. They assume that the image projection function can be described by a Taylor series expansion whose coefficients are estimated bysolving a two-step least squares linear minimization problem [4].

The self-calibration uses only point correspondences in multiple views without needing to know the camera position or knowledge of the scene. The literature on self-calibration can be divided into two main approaches: calibration under arbitrary and calibration under restricted motion [6]. Civera et al. [7] showed that the intrinsic parameters of a radially distorted camera can be estimated along with the 3D-position and camera location (SLAM) in a combined filtering method, although they rely on a sophisticated Sum-Of-Gaussians filter to handle the nonlinearities. Likewise, Micusık et al. [8] present a method for estimating the fundamental matrix with the help of a linearized version of the radial distortion function based on the work of Fitzgibbon [9]. If the camera motion is controlled or known within a certain accuracy one can arrive at algorithms which usually tend to be numerically more stable. For example, we cite the work by Kelly et al. [10] for fusing a visual and an inertial sensor and refer to Ramalingam et al. [11] for a perspective on calibration under purely translational and rotational motion [6].

Those approaches for self-calibration weren't designated for an automotive field. Nowadays, Vehicles are not information islands any more. Moreover they are connected systems with the ability to interact with a broad spectrum of external services via vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communications.]. A report published by the U.S. Department of Transportation (USDOT) showed that vehicle-to-vehicle (V2V) communication would be able to reduce about 80% of potential vehicle crashes [12]. So vehicles will be able to know its own position, the position of other vehicles, location and dimensions of physical road infrastructure and more. All this automotive specification can enhance those different self-calibration techniques to be suitable for vision-based ADAS.

III. ADAS CAMERA SELF-CALIBRATION CHALLENGES

The vision system for driver assistance is an important part of ADAS. Existing calibration and self-calibration procedures are often general and not a tailor-made for specific applications. In object-based calibration the pre-calibration is mandatory. Self-calibration method is the only choice when pre-calibration is impossible. In case of accident, car maintenance or calibration problems, it's waste of money and time to change and re-calibrate the camera. Self-calibration doesn't require any pre-calibration, just an efficient algorithm to determine the intrinsic and extrinsic parameters. Today's cars are connected and tomorrow will be more automated and increasingly interacting with environment. Environment data used with vehicle odometry present a key opportunity for the next generation of self-calibration methods.

IV. METHODOLOGY

A. Self-Calibration for ADAS

Assuming that intrinsic parameters are all that's needed to describe the mapping between a world point (with the respect of the camera position) and an image point. This includes focal length, pixel sizes and lens or mirror distortion parameters. This paper focuses on intrinsic calibration and assumes that the extrinsic calibration is known to certain accuracy. This is reasonable since the vehicle chassis defines the position and alignment of the camera [6]. In practice, the calibration procedure implies using GPS for vehicle position and for environment data.

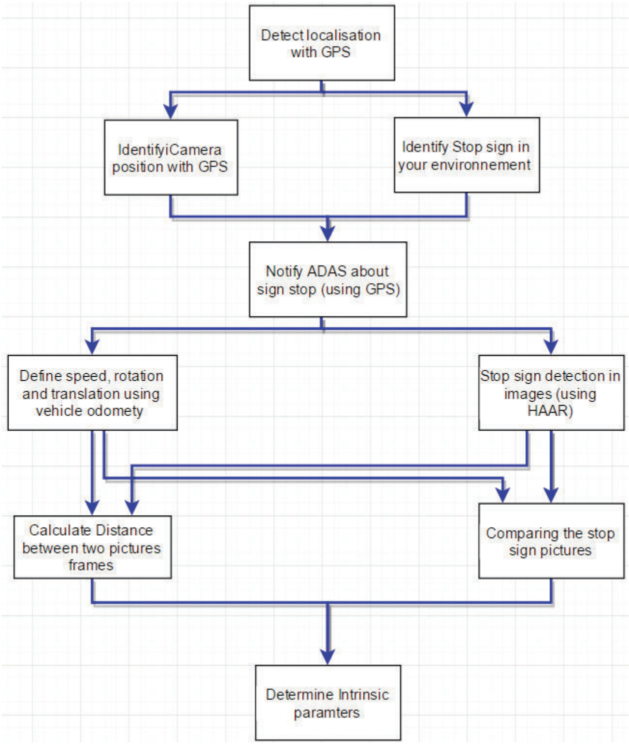

Fig. 3 Intrinsic parameters determination

This paper presents a self-calibration method that estimates the intrinsic parameters without knowledge of the scene. It addresses the method under the context of vehicle-mounted cameras, so we will have access to all sensor data from the ADAS Unit (Speed, Acceleration, I/O…) and data from the environment through GPS. The idea is to combine vehicle odometry and environment data to have a time synchronized data. It calculates the distance driven between successive frames of video using GPS data and car's speed. It's also using a known random object in the road such as the stop sign, which will have a known, regulated size.

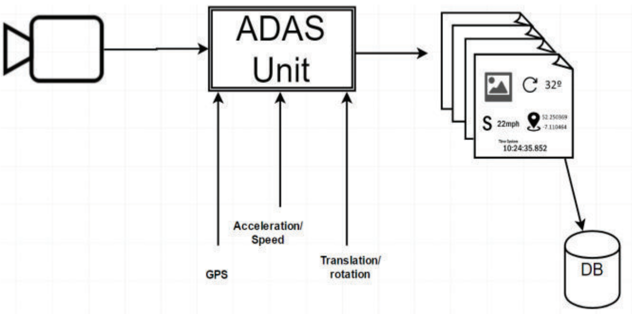

Fig. 4 Data Synchronized

This environment data allows the intrinsic parameters to be calculated to calibrate the camera. Vehicle odometry data are also used to recognize when a translation or rotation is performed and to localize the camera position over time. The presence of these odometry readings is very common in modern cars and is readily available on in-vehicle networks.

B. Test bench: CANape

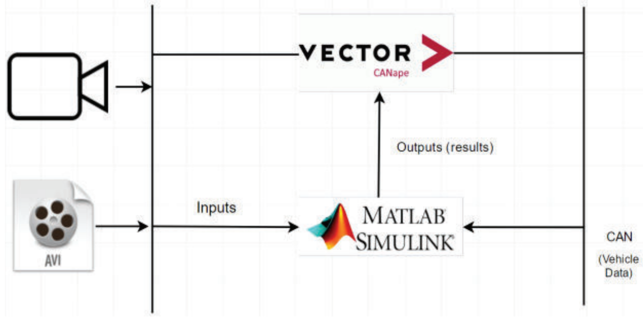

Fig. 5 CANape for test bench

The lack of test environment pushes researchers to look for a test bench which can test different algorithms in real time with an interactive interface. Our test environment is based on Vector CANape[13], which collects media resources (AVI video, Streaming Camera) and Vehicle odometry data through the CAN Bus. Combining this data with the camera calibration algorithm on Matlab/Simulink, the CANape performs a real time simulation and presents a visual interface.

CANape connected to both vehicle data and video provides an ideal real-time and data-synchronous test bench. It can test and check the feasibility of different calibration approaches by uploading the algorithm from Matlab/Simulink. It can interact in real time with signals thanks to the visual interface. The advantage of the use of CANape is that the time synchronized between media data and vehicle odometry data.

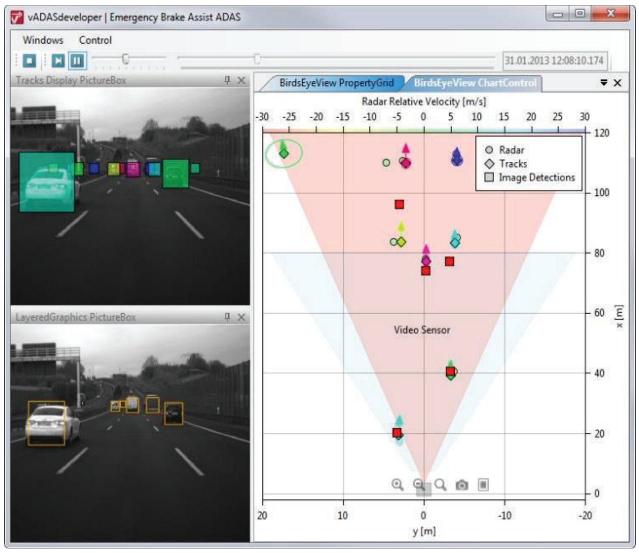

Fig. 6 CANape Visual interface

V. Conclusion

This work presents a self-calibration method which integrates with ADAS and uses environment data with vehicle odometry to calibrate a vehicle-mounted camera. In future work we want to look more deeply at different self-calibration methods and check its suitability for ADAS.

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