

# Line Processes for Highly Accurate Geometric Camera Calibration

Manfred Klopschitz, Niko Benjamin Huber, Gerald Lodron and Gerhard Paar

**Abstract**—The availability of highly accurate geometric camera calibration is an implicit assumption for many 3D computer vision algorithms. Single-camera applications like structure from motion or rigid multi-camera systems that use stereo matching algorithms depend on calibration accuracy. We present an approach that has proven to deliver accurate geometric information in a reliable, repeatable manner for many industrial applications. The major limitation in typical camera calibration methods is the printing accuracy of the used target. We address this problem by modeling the calibration target uncertainty as a line process and incorporate a lifted cost function into a bundle adjustment formulation. The regularized target deformation is incorporated directly into the non-linear least-squares estimation and is solved in a non-iterative, principled framework.

## I. INTRODUCTION

Geometric camera calibration defines the mapping between points in world coordinates and their corresponding image locations. These parameters model imperfections of the camera optics, i.e. lens distortion, intrinsic parameters of the idealized pinhole camera and extrinsic parameters like absolute camera orientation and relative orientation for multi-camera setups. Most calibration methods assume known 3D world points and minimize a reprojection error of the known 3D structure into detected image correspondences. The resulting error is a result of model imperfections, target imperfections and feature point localization inaccuracies.

Impressive reprojection errors have been shown in [5] by estimating feature points and 3D structure in an iterative procedure. We argue, like [2], [4], that the most important aspect for many applications is printing accuracy, but present a non-iterative calibration formulation that estimates and corrects for target uncertainty within a single bundle adjustment minimization.

The geometric camera calibration process estimates the mapping between points in world coordinates and their corresponding image locations. We define the image projection using standard notation, for the pinhole model

$$\mathbf{x}_p = KR[I | -\tilde{\mathbf{C}}]\mathbf{X} = P\mathbf{X} \quad \left| \quad K = \begin{bmatrix} f & & c_x \\ & f & c_y \\ & & 1 \end{bmatrix}$$

$R$  and  $\tilde{\mathbf{C}}$  model the location of the camera in space and  $K$  defines the intrinsics. Lens distortion is added to the pinhole

Joanneum Research Forschungsgesellschaft mbH, Steyrergasse 17, 8010 Graz, Austria `firstname.lastname@joanneum.at`

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projection, for example using this popular model:

$$\mathbf{x}_d = \mathbf{x}_p + \mathcal{F}_D(\mathbf{x}_p, \delta)$$

$$\mathcal{F}_D(\mathbf{x}_p, \delta) = \begin{bmatrix} x_{1p}(k_1 r_p^2 + k_2 r_p^4) + 2p_1 x_{1p} x_{2p} + p_2 (r_p^2 + 2x_{1p}^2) \\ x_{2p}(k_1 r_p^2 + k_2 r_p^4) + p_1 (r_p^2 + 2x_{2p}^2) + 2p_2 x_{1p} x_{2p} \end{bmatrix}$$

with  $\mathbf{x}_p = (x_{1p}, x_{2p})^T$ ,  $r_p = \sqrt{x_{1p}^2 + x_{2p}^2}$  and  $\delta = (k_1, k_2, p_1, p_2)^T$ .  $k_1, k_2$  are the radial distortion coefficients and  $p_1, p_2$  the tangential distortion coefficients.

## II. A LIFTED STRUCTURE ADJUSTMENT FORMULATION

Bundle adjustment (BA) minimizes the sum of the geometric distances of all image measurements  $\mathbf{x}_j$  and their corresponding projected 3D points  $P_i \mathbf{X}_j$  in image space:

$$\min_{P_i, \delta, \mathbf{X}_j} \sum C(\mathbf{x}_{ij}, \mathcal{F}_D(P_i \mathbf{X}_j, \delta))$$

where  $P_i$  is the pinhole camera model,  $\delta$  the distortion parameters and  $C$  is the reprojection error, for example with a quadratic error  $C_s(\mathbf{x}, \mathbf{x}_p) = \|\mathbf{x} - \mathbf{x}_p\|^2$  for classical BA. Optimizing all BA parameters with all pinhole terms, distortion terms and the structure  $\mathbf{X}_j$  simultaneously is ill-conditioned. Therefore, related work that also adjusts the calibration target updates the structure  $\mathbf{X}_j$  in an iterative way by using heuristics of multiple BA runs [2] or use minimal structure constraints [4] and suffer from convergence issues and limitations in possible distortion models.

We want to limit the adjustment of the calibration target as far as possible and only adjust the structure if the observed error cannot be explained by other parameters of our model. Suppose we have a scalar error  $e$  and rewrite the error as a robust kernel  $\psi(e)$  by introducing an additional variable  $w$ , i.e. a line process [3]

$$\psi(e) = \min_w (2w^2 e^2 + (1 - w^2)^2) \quad | w \in [0, 1].$$

For small errors  $w \rightarrow 1$  and for large errors  $w$  vanishes and  $\psi(e)$  becomes constant, see [7] for an intuitive explanation in the context of outlier estimation (the same kernel is used here for simplicity) and [6] for a recent application to robust BA. We apply this concept to camera calibration and introduce variables to represent the correctness of the calibration target and therefore 3D structure. Adding the lifted cost function to represent structure imperfections leads to this extended calibration formulation:

$$\min_{P_i, \delta, \mathbf{X}_j, w_j} \left\{ \sum C(\mathbf{x}_{ij}, \mathcal{F}_D(P_i \mathbf{X}_j, \delta)) + \alpha \sum_j \psi(\|\mathbf{X}_j - \mathbf{X}_{jc}\|) \right\}$$

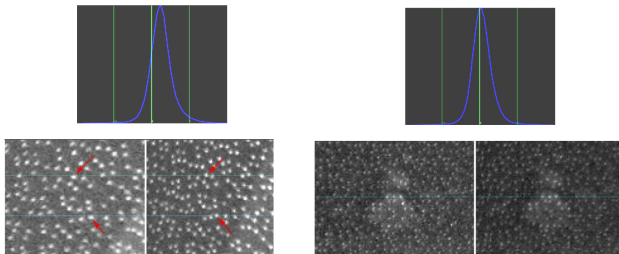
$$= \min_{P_i, \delta, \mathbf{X}_j, w_j} \left\{ \sum_{ij} C(\mathbf{x}_{ij}, \mathcal{F}_D(P_i \mathbf{X}_j, \delta)) \right.$$

$$\left. + 2\alpha \sum_j w_j^2 \|\mathbf{X}_j - \mathbf{X}_{jc}\| + \alpha \sum_j (1 - w_j^2)^2 \right\}$$

where  $\mathbf{X}_{jc}$  is the original reference 3D point and  $\|\mathbf{X}_j - \mathbf{X}_{jc}\|$  corresponds to the deviation from this reference during calibration and  $\alpha$  is a free parameter. Note that here each structure point has its own lifting variable  $w_j$ , it is also possible to represent the target accuracy with just one global scalar  $w$ . The system is solved using a standard non-linear least squares solver [1].

### III. INDUSTRIAL APPLICATIONS

The presented calibration formulation has been used in different industrial applications for single- and multi-camera calibration and long term calibration maintenance using commercially printed (low cost) targets that are affected by printing inaccuracies. A handheld stereo system calibration has been kept by non-expert users under 0.06 pixel RMS reprojection error for over a year. Because non-expert users are involved, strong and robust convergence properties are essential. Figure 1 shows rectified images of this device with and without the proposed structure adjustment. The whole system performs volumetric simultaneous localization and mapping (SLAM) without opportunities for loop closing. A 3D model of the volumetric fusion can be seen in Figure 2. For the accuracy evaluation ground truth data of the floor plan of the scene is available. Rectification errors are accumulated through the volumetric fusion, leading to a detectable influence of slight rectification errors. A rectification error like in Figure 1a leads to drift in height of about 5cm, the shown scene is 4 meters long.



(a) Weak calibration, 0.15px rectification deviation from zero mean. (b) Rectification with proposed method, nearly perfectly centered optical flow check.

Fig. 1: The top row shows a histogram of rectification deviations. They are obtained by computing a histogram of the vertical component of unconstrained optical flow initialized with the stereo result. The histogram range is  $\pm 2$  pixel. The bottom row shows the image pairs with example epipolar lines.

Figure 3 shows a stereo based inspection application for corrosion monitoring in hot steel components, ladles and process chambers that can cope with up to 1.600°C. The main goal of the system is the detection of thinning of material i.e. volumetric changes in registered consecutively measured models. The typical distance to the target lies between 60 and 200cm. To cope with the varying distance range focusable liquid lenses were used (Varioptic Caspian). The lenses are focusable from 7cm to infinity and are newly calibrated

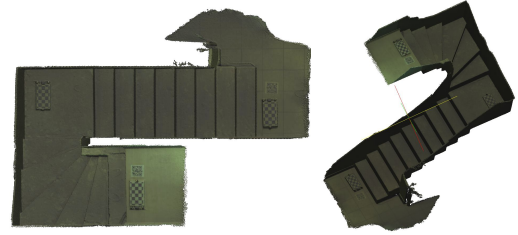


Fig. 2: A resulting 3D model obtained with a SLAM system calibrated by the presented method. Rectification errors of 0.2px are clearly noticeable in this application and lead to insufficient model accuracy.



Fig. 3: Stereo system with active speckle projection for the inspection of red hot steel components, ladles and chambers with up to 1.600°C. ©Materials Processing Institute supported by Dr BG Crutchley of i3D robotics Ltd.

after focus change and prior to each measurement campaign. The calibration of the liquid lenses together with the high temperature environment poses the greatest challenge in this application.

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