Refined Geometric Camera Calibration using Linear Simplex Method

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Abstract. A camera is considered calibrated if the focal distance, principal point and lens distortion parameters are known. The level of accuracy of the measurement of these parameters has always been a fundamental factor in stereo metrology. In this work we present a calibration algorithm for microscopic images where optical aberrations degrade the accuracy of traditional methods. A linear refinement steep is added to a state of art algorithm to improve the accuracy of the current methods. Experimental results show the quantitative improvement of the proposed method in a volume of inspection of 60x60x126 μm using both, synthetic and real images.

Keywords: camera calibration, simplex method, linear optimization.

1 Introduction

Geometric camera calibration is a necessary prerequisite for recovering the 3D position of a scene point when only its projection in two images captured from different viewpoint location is known, in this case, each projection defines a ray in space and the intersection of both rays is precisely the 3D point location.

The key idea behind calibration is to write the projection equations linking the known coordinates of a set of 3D points and their image projections, and solve for the camera parameters. This mean the determination of the projection matrix P which encompass both, intrinsic and external pose parameters (camera's position and rotation in the world coordinate frame) modeling the image formation process. Usually, radial and pincushion distortions are also modeled using additional parameters. In this stage, the estimated parameters relate the 3D coordinates of a point of the scene, and the 2D coordinates of the projected point of the image. However, when microscopic images are captured, lens optical aberrations introduce additional image distortions which must be considered.

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Numerous methods for camera calibration have been developed, each one having its pros and cons. Pioneer methods use 11 parameters to define the camera projection matrix P and optimize a cost criterion to compute those parameters. Linear methods use linear algebra tools to find and initial solution [1,2], Non-linear methods refine the solutions to improve the estimate [3]. A recent linear method [4] based on the Gintic camera model originally proposed in [2] models the image formation process using 16 parameters has shown its superiority when considering microscopic images.

2 The Gintic Camera Model

The mapping between 3D space coordinates $W = (x_n, y_n, z_n)$, and 2D image locations $w = (p_x, q_x, s)$ in homogeneous coordinates are expressed using the Haralick Reduced model proposed in [2] by

$$\begin{matrix} p_x \\ q_y \\ s \end{matrix} = R(\omega, \phi, \kappa) \begin{pmatrix} x_n \\ y_n \\ z_n \end{pmatrix} \quad (1)$$

where ω, ϕ and κ are the rotation angles for the x, y and z axes respectively, then after some algebraic substitutions by using a perspective camera model with a_u and a_v the focal length in x and y axes respectively; k_1 and k_2 representing radial geometric distortion of lens, and (u_p, v_p), principal point in the image coordinates the following expression can be derived:

$$(1 + k_1 r_n^2 + k_2 r_n^4 + k_3 r_n^6) \begin{pmatrix} u_n - u_p \\ v_n - v_p \end{pmatrix} = \frac{1}{s_n} \begin{pmatrix} a_u p_n \\ a_v q_n \end{pmatrix}, \quad (2)$$

where r_n^2 is the distance of the pixel at (u_n,v_n) to the principal point in the image plane given by:

$$r_n^2 = (u_u - u_p)^2 + (v_u - v_p)^2 \quad (3)$$

Finally the two linear equations of the Gintic calibration model are:

$$\begin{matrix} a_1 x_n + b_1 y_n + c_1 z_n + d_1 u_n + e_1 u_n x + f_1 u_n y_n + g_1 u_n z_n + 1 = 0 \\ a_2 x_n + b_2 y_n + c_2 z_n + d_2 v_n + e_2 v_n x + f_2 v_n y_n + g_2 v_n z_n + 1 = 0 \end{matrix} \quad (4)$$

Since each point imaged from the calibration pattern contributes in two linear equations, by stacking 2n linear equations a linear system can be constructed and solved to bring an estimate of the camera projection parameters involved in the image formation process.

Thus, from (3) and (4) it can be observed that 16 parameters are considered to model the projective mapping of a single camera. Then, using linear algebra tools a solution can be estimated when an over determined set of equations is known, see [1] for details. However, due to image noise and image quantization, the initial estimate is prone to limited accuracy we propose to add a second stage to improve the solution using the Simplex method.

3 Gintic Camera Calibration Refinement

Given the initial linear solution we compute a refinement over the Gintic camera parameters.

An error function is defined based on the measurement of the geometric distance in the image plane.

3.1 Proposed Optimization Error Function

The error function called the reprojection error, considers the difference between the measured image coordinates w_i and the estimated image coordinates $\widehat{w_i} = PW_i$ computed using the W_i 3D coordinates and the parameters of the Gintic camera model P.

We use the notation $d = \|w_i - \widehat{w_i}\|$ to denote the Euclidean distance between the points represented by w_i and $\widehat{w_i}$. Then, the total error for the set of points used in the calibration process is:

$$\sum_{i=1}^{n} \|w_i - \widehat{w_i}\| \tag{6}$$

We use the simplex method introduced in [5] to minimize the error function (6). The simplex method has the advantage that neither requires the derivative of the error function nor the orthogonal condition needed by non linear optimization methods like least squares [3].

The algorithm starts with an initial basic feasible solution (bfs) and tests its optimality. If some optimality condition is verified, then the algorithm terminates. Otherwise, the algorithm identifies an adjacent bfs, with a better objective value. The optimality of this new solution is tested again, and the entire scheme is repeated, until an optimal bfs is found. Since every time a new bfs is identified the objective value is improved, and the set of bfs's is finite, it follows that the algorithm will terminate in a finite number of iterations.

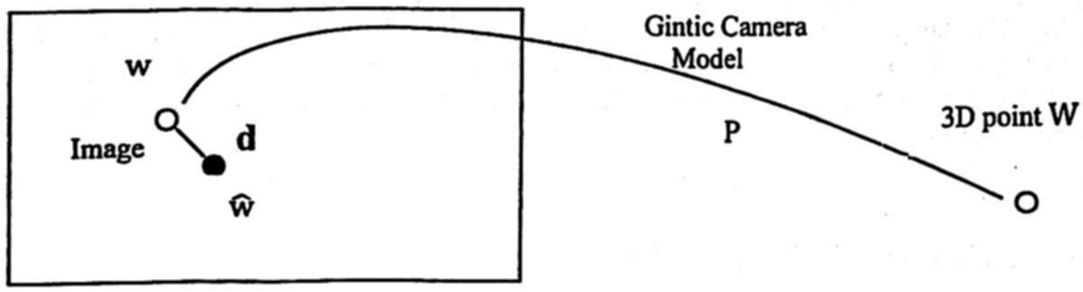

Fig. 1. The graphic representation of the reprojection error.

4. Experiments

Synthetic and real images were used to evaluate the accuracy of the calibration method proposed in this work (see figure 2). In the real setup we have captured four images of a check board calibration pattern using a stereo imaging setup in a volume of inspection of 60x60x120 μm. Then, using only the closest and farther images, the imaging system is calibrated. Ten additional images taken inside the volume of inspection where used to evaluate the real accuracy of the proposed algorithm, detecting and matching corner points and measuring the estimated 3D coordinates by triangulation [4].

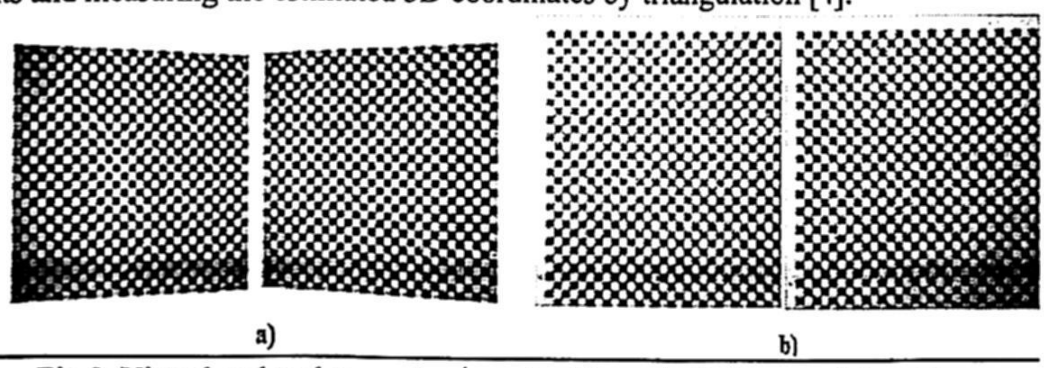

Fig.2. Virtual and real stereo image pair: (a) synthetic images, (b) real images.

The accuracy of the improved Gintic camera model is illustrated by figure 3. In 3-(a) the accuracy of calibration method using synthetic images. Figure 3-(b) shows the accuracy of the proposed method using real images. Note that the method allows accurate measurements. Table 1 summarize the absolute difference in the calibration accuracy using synthetic and real images (The standard deviation absolute difference is about 0.25*μm*, 0.37 *μm*, and 0.6 *μm* for *x*, *y* and z axis respectively).

Table1. The absolute difference of statistical variation for synthetic and real data

Comparative Results (All units in μm)						
	X Mean	**Y mean**	**Z mean**	**X std**	**Y std**	**Z std**
Synthetic	-1.87e-12	5.77e-14	3.44e-13	0.064	0.056	0.096
Microscope	-0.02	-0.008	0.142	0.31	0.425	0.711
Absolute Difference	**0.02**	**0.008**	**0.142**	**0.24**	**0.369**	**0.614**

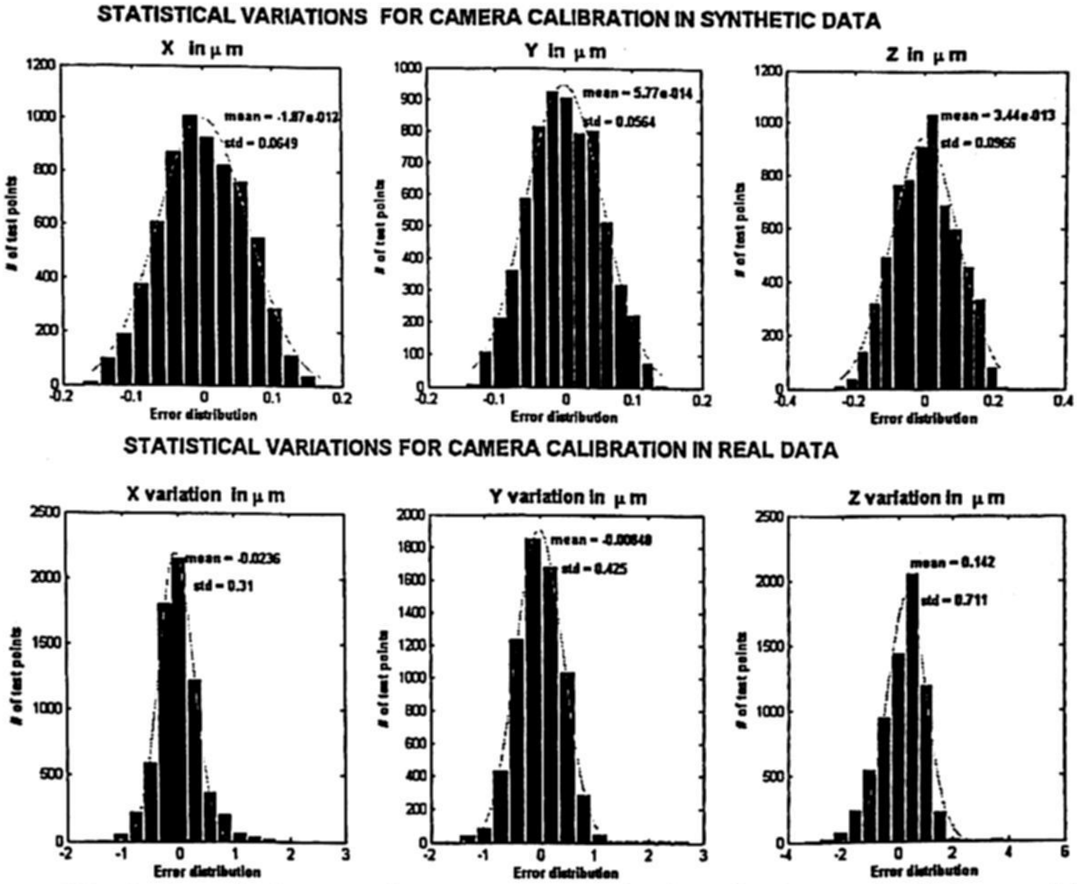

Fig. 3. Quantitative metrology accuracy evaluation. a) using synthetic images, b) evaluation using real images.

5. Conclusions

An improved calibration algorithm was presented; an initial estimate of the camera parameters that model the image formation process using a linear method was first presented. Then, a linear refinement using the Simplex method was derived to improve the estimation of the Gintic camera parameters. The new method was evaluated using synthetic and real images where an improvement of an order of magnitude was obtained. In future work we plan to integrate a preprocessing stage to overcome some of the limitations of the algorithm to take into account higher order optical aberrations in microscopic images.

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