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A ROBUST MULTISTAGE ALGORITHM FOR CAMERA SELF-CALIBRATION DEALING WITH VARYING INTRINSIC PARAMETERS

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ABSTRACT

We present a practical algorithm for camera self-calibration dealing with varying parameters. Given a projective reconstruction, we retrieve the calibration matrices for each frame by minimizing a non-linear least square. We firstly start the minimization procedure by a stage of initialization to get a first estimation of the focal lengths, then, we start the estimation of the camera intrinsic parameters in a multistage algorithm, in each stage a parameter is estimated assuming some constraints on the other parameters. In the final stage a refinement of all parameters is done at once to allow them to vary freely. The robustness and accuracy of the algorithm are shown in the experiments on both synthetic and real data.

Keywords: *Camera Self-Calibration, Multistage Algorithm, Varying Intrinsic Parameters, Least Square Minimization*

1. INTRODUCTION:

During last few years, digital cameras became omnipresent because of their low costs giving an easy access to video sequences to everybody. Nowadays, the areas of application of cameras are more and more large: Medical imaging, Virtual visiting, Cinema, Robotics, Artificial vision … for many applications based on a 3d reconstruction of the scene, as a matter of fact, camera self-calibration is an essential step for this kind of reconstructions.

More generally, we can talk about the Structure-From-Motion (SFM) problem, which consists on computing a metric reconstruction of a camera from a projective one; it is a fundamental problem in computer vision. The numerous studies done in recent decades have led to a good established formulations and a lots of solution algorithms. A key finding is that a projective reconstruction can be calculated from two (or more) uncalibrated images, provided that neither the camera nor the points lie on a critical surface. The desired metric reconstruction is obtained by applying a homography to rectify the projective reconstruction. Calculate the homography from constraints on the camera parameters is a self-calibration problem and is equivalent to find the unknown intrinsic parameters of the camera.

In the literature, three main approaches are distinguished : (i) those based on Kruppa's equations [13, 3], historically, this are considered as the first self-calibration method, they require the epipolar geometry of each pair of views and consist of two independent equations in the elements of the image of the absolute conic (ii) those using a stratified approach, based on the affine rectification of a projective reconstruction, and finds linearly a transformation "*affine-metric*" , The first step for this kind of algorithms is solved using the

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modulus constraint [7] or by an exhaustive search for the plane at infinity [9], the subsequent determination of the calibration matrix is then relatively simple because there exist a linear solution (iii) those making a direct calculation of the homography to rectify the reconstruction from "*projective-to-metric*" [2,10,11,15,27].Triggs [11] introduced a practical algorithm using the absolute dual quadric where embedded the plane at infinity and the intrinsic parameters of the camera in a compact way. This model has been used in [10] to introduce non-linear and linear algorithms to deal with the case of varying intrinsic parameters.

Concerning algorithms trying to resolve the problem of camera self-calibration with varying parameters, based on the absolute dual quadric [8, 27], most of them try to minimize a non-linear cost function at once using only one initialization stage. This is a real drawback because the minimization procedure critically depends on the quality of the initialization step, if isn't considered to be optimal, the algorithm may converge to a local minimum.

In this paper, we study the problem of self-calibration for a camera with varying intrinsic parameters using the absolute dual quadric introduced in computer vision by Triggs [11]. Specifically, this work is an extension of the great work done by Pollefeys in [10].

After the formulation of a cost function to be minimized. We start the minimization procedure by an initialization step; this is done by setting the camera projection matrix for the first frame to unit to get an initial solution. Once done, we propose our main contribution which consists on using the initial solution, computed in the initialization stage, in a multistage algorithm to retrieve the intrinsic parameters one by one and finally refine all of them at once. The refinement procedure continues till getting an optimal solution for the camera calibration matrix.

This paper is organized as follows: section 2 presents the background and definitions of the necessary parameters for camera self-calibration and how the projective reconstruction is obtained. Then, in section 3 we formulate the self-calibration equations to be minimized in section 4 where we present the multistage algorithm, a test of the proposed algorithm is shown in the experiments in section 5 and finally, conclusion is in section 6.

2. BACKGROUND:

2.1 Notations

In this paper we will use the following notations: an entity L in the Euclidean frame will be note with a subscript E: L_E, a 3D world points X will be denoted by a homogeneous 4-vector $(X, Y, Z, 1)$ and a2D image points x by homogeneous 3-vector $(x, y, 1)$. Suppose a camera observing a scene composed of 3Dpoints X_j, the perspective projection of the scene points into the image plane is given by (figure 1).

Mathematically, we express this projection as follow:

$$x_{ij} \cong P_{Ei}X_{Ej};\ i = 1,\dots,m,\ j = 1,\dots,n, \quad (1)$$

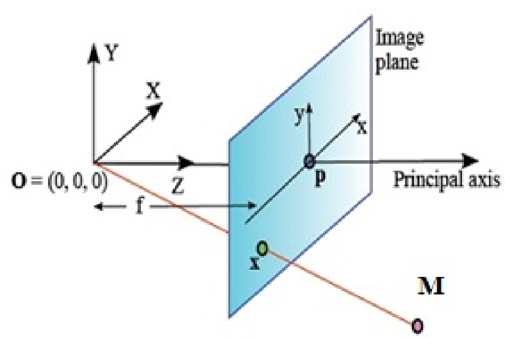

Figure 1: the perspective projection of the scene into the image plane

Where: P_{Ei}, $i = 1,\dots,m$, are the Euclidean cameras parameterized as 3×4 matrices:

$$P_{Ei} = K_i(R_i|\ t_i), \text{ where}$$

$$K_i = \begin{pmatrix} f_x & s & u_0 \\ 0 & f_y & v_o \\ 0 & 0 & 1 \end{pmatrix}$$ is the camera calibration matrix with: f_x and f_y are the focal lengths, $r = \frac{f_x}{f_y}$ is the aspect ratio, s is the image

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skew and (u_0, v_0) are the image coordinates of the principal point

$R_i$is the 3×3 rotation matrix and t_i is the3×1 translation matrix. The above equality (1) holds up to a scale factor. Then, a projective reconstruction can be computed as a set of cameras $P_i, i = 1, \dots, m$ and a set of points X_j, $j = 1, \dots, n$ satisfying the following equalities:

$$\lambda_{ij} xij = P_i X_j;\ i = 1, \dots, m,\ j = 1, \dots, n. \quad (2)$$

Where λ_{ij} is the projective depth, to be computed during the projective reconstruction step.

From (1) and (2), one can see that the projective reconstruction is related to the Euclidean one by an arbitrary 4×4 homography:

$$P_i = P_{Ei} H^{-1}, i = 1, \dots, m, \quad X_j = H X_{Ej}, j = 1, \dots, n. \quad (3)$$

2.2 Projective reconstruction

Step 1: Feature detection and matching: We used the following Harriscorners detector [17] to detect corners in each frame of the video sequence:

$$G = \begin{pmatrix} \left(\frac{\partial I}{\partial u}\right)^2 & \left(\frac{\partial I}{\partial u}\right)\left(\frac{\partial I}{\partial v}\right) \\ \left(\frac{\partial I}{\partial u}\right)\left(\frac{\partial I}{\partial v}\right) & \left(\frac{\partial I}{\partial v}\right)^2 \end{pmatrix}$$

(4)

Where I is the pixel intensity, $\left(\frac{\partial I}{\partial u}\right)$ and $\left(\frac{\partial I}{\partial v}\right)$ are its respective derivative in the u and v directions

To detect corners in a frame from the video sequence, Harris uses a variable r for which the value is superior to zero in the case of a corner; its value is given by:

$$r = \det(G) - \gamma\,(\mathrm{trace}(G)) (5)$$

With $\gamma = 0.04$ (fixed by Harris based on the experiments)

Step 2: Matching features: The above detected features (corners in this case) have been matched with the other features from the video sequence using the Zero mean Normalized Cross Correlation ZNCC [20][23]:

$$ZNCC(m_i, m_j) = \frac{\sum_n x_n y_n}{\sqrt{\sum_n x_n^2 \sum_n y_n^2}} (6)$$

Where m_i and m_j are two points detected by Harris Corner Detector in the previous step from two images i and j of the video sequence.

$$x_n = I(mi + n) - \bar{I}(mi)$$
$$y_n = I'(mj + n) - \bar{I}'(mj) \quad (7)$$

$\bar{I}(mi)$and$\bar{I}'(mj)$ are means of pixel luminance on a 11×11 (experimentally, this choice gives the best results) window centered respectively in m_i and m_j.

Step 3: Fundamental matrix: The fundamental matrix has been used to reject the outliers features detected in the previous step; we used the 8-point algorithm [3] in a RANSAC framework. A good matching couple must satisfy:

$$m_j^T \times F \times m_i = 0 (8)$$

Step 4: Iterative projective factorization: the selected matched features from the previous steps had been used as an input data for an iterative algorithm to get a projective reconstruction. We used the robust algorithm CIESTA [16] to retrieve the projective depths, the camera projection matricesP_i and the projective structure X_j.

3. CAMERA SELF-CALIBRATION EQUATIONS:

3.1 problem formulation

Giventhe projective reconstruction (P_i, X_j), computed in the previous section, the purpose of self-calibration is to estimate the best homographyH that upgrades the projective reconstruction to a metric one. This is done through the search of the camera intrinsic parameters, once they are retrieved, the homography H can be computed linearly.

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The absolute conic:

It's well known in multiple view geometry that two entities stays invariant in Euclidean space when the camera undergoes a rigid transformation, the first one is the plane at infinity π_∞ (used to compute the affine calibration when using a stratified self-calibration algorithm [9]) and the second one is the absolute conicω which is embedded in π_∞. Metric measurements are possible if both of those entities had been localized.

If the camera undergoes a rigid transformation and looking at a static scene, only one conic will be enough for camera self-calibration, because its relative position towards the cameras stays invariant [3]

The Absolute Dual Quadric:

The Absolute Dual Quadric Q* is a degenerate dual quadric represented mathematically by a 4×4 rank 3 homogenous matrix, its importance for camera self-calibration comes from the fact that it encodes both the plane et infinityπ_∞ and the absolute conicω:

$$\omega_i^* = K_i K_i^T \cong P_i Q_\infty^* P_i^T \quad (9)$$

$Q_\infty^*$is the Absolute Quadric and ω_i^* is the Dual Image Absolute Conic (DIAC)

It follows that Q_∞^*projects to the dual image absolute conic:

$\omega_i^* = K_i K_i^T$(10)Given (9), constraints on $\omega_i^* = K_i K_i^T$ can be translated into constraints on Q_∞^* using the projection matrices computed previously, thus Q_∞^* can be computed in the projective reconstruction using constraints onK_i.We recommend the reference [3] (section 19.3 p-462) for a thorough treatment of this operation.

If we have enough constraints, we need only one quadric to satisfy all of them: it's the absolute quadric; in this case metric measurements are possible and Q_∞^* will be brought to its canonical form:

$$Q_{E\infty}^* = \begin{pmatrix} I_{3\times3} & 0 \\ 0 & 0 \end{pmatrix} \quad (11)$$

Equation (9) can be used to retrieve metric measurements from a given projective reconstruction, however Q_∞^*should be parameterized in a manner to enforce the constraints on K_i, an easy way to do this is by using a minimum parameterization of Q_∞^*, i.e. we put $(Q_\infty^*)_{33} = 1$ and compute $(Q_\infty^*)_{44}$using the rank 3 constraint.

$$Q_\infty^* = \begin{pmatrix} KK^T & -KK^T p \\ -p^T KK^T & p^T KK^T p \end{pmatrix} \quad (12)$$

Where p defines the position of the plane at infinity $\pi_\infty = (p' \; 1)'$

Using the above formulation ofQ_∞^*, camera intrinsic parameters can be extracted by minimizing the following criterion:

$$\min_{K_i} \sum_{i=1}^{n} \left\| \frac{K_i K_i^T}{\|K_i K_i^T\|_F} - \frac{P_i Q_\infty^* P_i^T}{\|P_i Q_\infty^* P_i^T\|_F} \right\|_F^2 \quad (13)$$

Both elements in (13) should be normalized to eliminate the scale factor in equation (9)

Equation (13) is a nonlinear least square that requires an important stage of initialization, to do this, we will choose the first image center to be centered with the world coordinate frame, in this case we have: $P_1 = (I\,|0)$. Using this formulation the equation for the first view will be perfectly satisfied, unfortunately, the noise has to be spread over all frames of the sequence, for this reason we propose to use this parameterization as an initial guess for a multistage algorithm to estimate the intrinsic parameters one by one:

4. THE MULTISTAGE ALGORITHM:

Iteration one: Initial estimation of the focal length

We will start our self-calibration algorithm by an initial estimation of the focal length, to do this, equation (13) will be minimized using the following approximations: assuming a camera with zero skew and the principal point in the image center:

$s = 0$ and $(u_0, v_0) = (u_c, v_c)$.

We will also assume a unit aspect ratio, thus we still have only one unknown parameter, i.e. the focal length.

Iteration 2: Estimation of the aspect ratio

The solution obtained in the first iteration will be used as an initial input to calibrate the aspect ratio, Further on; we will assume a camera with

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zero skew and a principal point at the image center. So we still have two unknown parameters, namely the two focal lengths. Equation (13) will be minimized using those constraints to calibrate the aspect ratio $r = \frac{f_x}{f_y}$.

Iteration 3: Estimation of the principal point

In this iteration we will estimate the coordinate of the principal point. Till now, the principal point corresponds to the image center, to refine it, we will use the output K_2 from the previous iteration as an initial guess to minimize (13) assuming only zero skew, consequently, three parameters are allowed to vary, i.e. the two focal lengths and the principal point.

Iteration 4: Re-estimation of the focal lengths

It's well known in computer vision, mainly in camera self-calibration and 3D reconstruction, that the focal lengths had the major impact on the reconstruction procedure. We will use a similar procedure to iteration 1 for a new refinement of the focal lengths. The output K_3 from the previous step will be used as an initial guess for the minimization of (13).

Iteration 5: Refinement of all camera intrinsic parameters.

In this final step, we will use the output from iteration 4 to refine all parameters at once assuming only zero skew (we can enforce the skew to be different from zero, but this has no impact on the calibration procedure because almost actual cameras had no skew and it has been shown in [3]that it doesn't create serious error, beside this, it's easy to minimize our cost function in a four dimensional space than in a five dimensional one).

Iteration	**Intrinsic parameters to be estimated**	**Assumptions**	**Output Calibration Matrix**
1	The focal length	$s = 0$, $(u_0, v_0) = (u_c, v_c)$. $r = \frac{f_x}{f_y} = 1$	$K_1 = \begin{pmatrix} \tilde{f}_x^{(0)} & 0 & u_c \\ 0 & \tilde{f}_x^{(0)} & v_c \\ 0 & 0 & 1 \end{pmatrix}$
2	The aspect ratio	$s = 0$, $(u_0, v_0) = (u_c, v_c)$. Use K_1 as initial guess	$K_2 = \begin{pmatrix} \tilde{f}_x^{(1)} & 0 & u_c \\ 0 & \tilde{f}_y^{(1)} & v_c \\ 0 & 0 & 1 \end{pmatrix}$
3	The principal point	$s = 0$ Use K_2 as initial guess	$K_3 = \begin{pmatrix} \tilde{f}_x^{(2)} & 0 & \tilde{u}_0^{(0)} \\ 0 & \tilde{f}_y^{(2)} & \tilde{v}_0^{(0)} \\ 0 & 0 & 1 \end{pmatrix}$
4	The focal lengths f_x and f_y	$s = 0$ Use K_3 as initial guess	$K_4 = \begin{pmatrix} \tilde{f}_x^{(3)} & 0 & \tilde{u}_0^{(1)} \\ 0 & \tilde{f}_y^{(3)} & \tilde{v}_0^{(1)} \\ 0 & 0 & 1 \end{pmatrix}$
5	Refinement of all parameters	$s = 0$ Use K_4 as initial guess	$K_5 = \begin{pmatrix} \tilde{f}_x^{(4)} & 0 & \tilde{u}_0^{(2)} \\ 0 & \tilde{f}_y^{(4)} & \tilde{v}_0^{(2)} \\ 0 & 0 & 1 \end{pmatrix}$

Table 4.1 Algorithm outline

5. EXPERIMENTATIONS

The proposed method was tested on a number of synthetic and real scenes and has given similar results; we will present here the results obtained from 2 images sequences. First we used a set of images of a checkerboard pattern [25] which we considered as a synthetic data for the test of the algorithm. Seconde we used a set of images of a real fixed scene [24] to confirm the good results obtained using the checkerboard pattern and to demonstrate the performances of the proposed algorithm.

5.1 Synthetic Data

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We used a set of images of a checkerboard pattern [25] to test the algorithm. 4 images of the sequence are represented here (figure 5.1) with the corresponding calibration matrices in each iteration of the algorithm (Table 5.1).

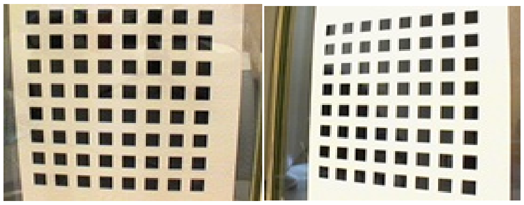

Image 1 Image 2

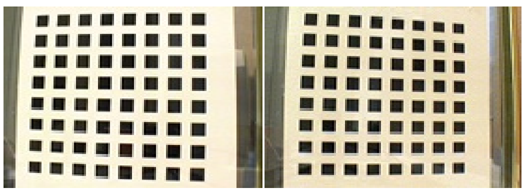

Image 3 Image 4

Figure 5.1: the 1st four checkerboard pattern images used for the test of the algorithm

5.2 Real Data:

The algorithm was tested on many real images. We will report the results obtained from a set of images of a fixed rigid scene, 4 of them are represented in fugure 5.2 and the resulting calibration matrix in each iteration of the algorithm in Table 5.2.

Firstly, a projective reconstruction has been performed using the image correspondences obtained from the detected corners. As mentioned before (section 2.2) we used the robust algorithm CIESTA to retrieve the projective structure (Camera matrices and 3D scene points in the projective space).

Then, we used our algorithm to retrieve the Calibration matrices for each camera. We will present here (table 5.2) the result obtained in each iteration of the algorithm for the 1st 4 images.

Image 1 Image 2

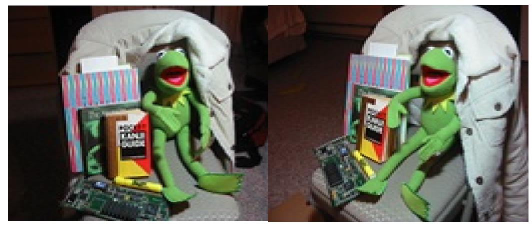

Image 3 Image 4

Figure 5.2: the 1st four real images used for the test of the algorithm

The final obtained value of the focal lengths and the principal point coordinates using the real sequence are represented in table 5.3

	f_x	f_y	u_0	v_0
Frame 1	862	683	33.42	87.30
Frame 2	817	691	82.46	64.52
Frame 3	796	599	61.33	9.5
Frame 4	787	644	4.83	-5.9
Frame 5	825	732	25.4	5.2
Frame 6	780	650	5.6	-12.5
Frame 7	805	690	32.6	25.0
Frame 8	886	750	42.8	20.6

Table 5.3: the recovered focal lengths and principal point coordinates for 8 images from the sequence

Focal length relative error:

We used the following equation to compute the focal length relative error:

$$f_{x\,error} = (f_x - f_{xgt})/f_{xgt}$$

Where f_x is the computed focal length value and f_{xgt} is the ground truth focal length value. Figure 5.3 shows the obtained results for a set of 8 images.

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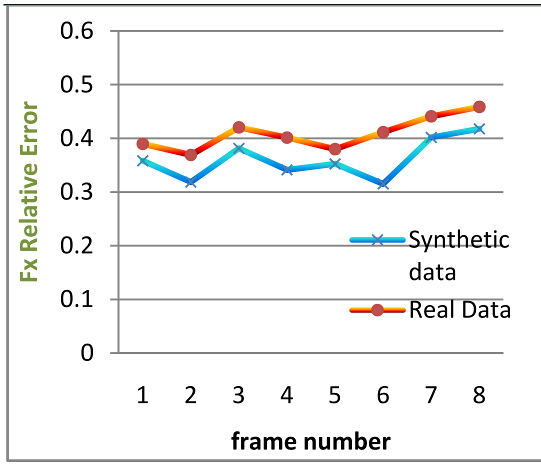

Figure 5.3: Focal length f_x relative error for 8 images from the sequence

As shown on figure 5.3, the relative error is very small and approximately the same for both synthetic and real data, thing that demonstrate the accuracy and robustness of the proposed method compared to other standard algorithms.

6. CONCLUSION AND PERSPECTIVES

In this paper we presented a new algorithm for camera self-calibration dealing with the case of varying parameters. Our algorithm allow each parameter to vary freely, it consist on minimizing a nonlinear least square defined by the projection of the absolute quadric. The obtained projcetion is the Dual Image of the Absolute Conic DIAC which is directly related to the camera intrinsique parameters. The proposed algorithm starts with a initialization stage to get a first estimate of the focal length. Then, all the other intrinsic parameters are estimated and refined in a multistage iterative scheme. The experiments on both synthetic and real scenes show the robustness and accuracy of the proposed method. New ways have to be explored to improve the quality of our algorithm. First, in the projective reconstruction step, we used the first two frames to initialize the projective structure in the CIESTA algorithm; this maybe inaccurate for some special motions(small inter-view motion for example). To get more reliable results we need to choose two images with large motion (translation and rotation) between them, to do this, a criterion to choose the images has to be adopted. Second, it's also very important in near future to add different noise to image point to test the robustness and accuracy of the algorithm in different imaging conditions. Such test will allow us to test the effect of noise on each intrinsic parameter and try to use more optimal procedure to best estimate it.

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	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Image 1	K1_1 = 666.42 0 0 0 666.42 0 0 0 1.00	K1_2 = 836.5472 0 0 0 722.17 0 0 0 1.00	K1_3 = 884.17 0 5.23 0 741.03 -4.15 0 0 1.00	K1_4= 1100.9 0 15.3 0 736.9 - 20.3 0 0 1.0	K1_5 = 1211.7 0 37.3 0 728.9 - 10.1 0 0 1.0
Image 2	K2_1 = 763.65 0 0 0 763.65 0 0 0 1.00	K2_2 = 838.77 0 0 0 903.21 0 0 0 1.00	K2_3 = 923.5 0 4.30 0 960.8 2.0 0 0 1.00	K2_4 = 962.40 0 - 8.46 0 845.81 - 32.54 0 0 1.00	K2_5 = 1067.2 0 - 19.5 0 882.3 - 57.0 0 0 1.0
Image 3	K3_1 = 660.34 0 0 0 660.34 0 0 0 1.00	K3_2= 710.34 0 0 0 667.35 0 0 0 1.00	K3_3 = 760.34 0 - 0.00 0 661.35 0.00 0 0 1.00	K3_4 = 859.82 0 -0.38 0 651.46 -0.18 0 0 1.00	K3_5 = 967.16 0 - 0.46 0 658.28 - 0.46 0 0 1.00
Image 4	K4_1 = 666.40 0 0 0 666.40 0 0 0 1.00	K4_2 = 686.39 0 0 0 666.38 0 0 0 1.00	K4_3 = 716.38 0 0.08 0 666.36 0.02 0 0 1.00	K4_4= 844.96 0 0.63 0 665.28 0.80 0 0 1.00	K4_5 = 864.62 0 0.92 0 665.01 1.07 0 0 1.00

Table 5.1: Output Calibration matrices, in each iteration of the algorithm, for the first images of the checkerboard pattern

	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Image 1	K1_1 = 666.42 0 0 0 666.42 0	K1_2 = 672.63 0 0 0 661.15 0	K1_3 = 716.8 0 2.2 0 665.3 1.1	K1_4 = 776.17 0 27.44 0 627.71 81.10	K1_5 = 862.17 0 33.42 0 683.71 87.30
Image 2	K2_1 = 665.16 0 0 0 665.16 0 0 0 1.00	K2_2 = 684.94 0 0 0 609.70 0 0 0 1.00	K2_3 = 626.11 0 13.18 0 510.65 5.72 0 0 1.00	K2_4 = 709.71 0 85.91 0 540.12 71.50 0 0 1.00	K2_5 = 817.93 0 82.46 0 691.23 64.52 0 0 1.00
Image 3	K3_1 = 660.75 0 0 0 660.75 0 0 0 1.00	K3_2 = 680.3834 0 0 0 539.12 0 0 0 1.00	K3_3 = 647.8789 0 12.11 0 500.37 18.84 0 0 1.00	K3_4 = 696.40 0 54.82 0 518.40 73.40 0 0 1.00	K3_5 = 796.51 0 61.33 0 599.77 9.50 0 0 1.00
Image 4	K4_1 = 666.70 0 0 0 666.70 0 0 0 1.00	K4_2 = 683.12 0 0 0 665.97 0 0 0 1.00	K4_3 = 700.8586 0 21.02 0 608.08 25.22 0 0 1.00	K4_4 = 748.15 0 67.53 0 677.02 89.60 0 0 1.00	K4_5 = 787.33 0 4.83 0 644.82 - 3.59 0 0 1.00

Table 5.2: Output Calibration matrices, in each iteration of the algorithm, for the first 4 real images