An Automatic Method for Adjustment of a Camera Calibration Room

Ehsan Khoramshahi, Eija Honkavaara, and Tomi Rosnell, Finland

Key words: Close-Range Photogrammetry, Block -Adjustment, Camera Calibration

SUMMARY

Recent advancement in newly developed camera technologies such as multi-spectral sensors, multi-projective cameras, and surveying systems that contain the advanced camera technologies highlights the essence of developing new geometric and radiometric calibration methods.

A valuable part of a calibration process is to access a rigid body with a priori known geometry, such as a calibration room. In this work the main focus will be on conceptual development of a calibration room, which consists of coded-target design, algorithm design for automatic CT detection, 3D network formation and bundle block adjustment.

The final goal of this design is to make sure that the proposed approach is able to find robust estimation of the calibration room within a few minutes after a data measurement. In the first part of this article we demonstrate design phase of the coded-targets with criterions such as good visibility in a range of (10cm-4m), precise integrated scale, and ease of automatic detection, then a computer vision algorithm is proposed to detect the coded-targets. Next, 3D network formation by stereo pair analysis with normalized 8-point algorithm is discussed. Finally, camera calibration and geometric reconstruction of the new camera calibration room of the Finnish Geospatial Research Institute is demonstrated.

An Automatic Method for Adjustment of a Camera Calibration Room

Ehsan Khoramshahi, Eija Honkavaara, and Tomi Rosnell, Finland

1. INTRODUCTION

Machine vision is becoming a part of our everyday lives. Measurements by cameras are a fundamental part of this automation process. During past few years revolution has taken place in the development of the camera technologies. High resolution multi-spectral sensors with highly accurate lenses are more accessible than any time. Such technologies also exist in many everyday use devices such as smart phones, DSLRs and tablets. In order to position the measurements by cameras, the geo-referencing is required. The basis of geo-referencing is the accurate calibration of internal parameters of a camera which involved focal length, principal point and lens distortions estimation. The determination of geometric characteristics of systems is becoming essential because different sensors have very different operating principles. Finnish Geospatial Research Institute (FGI) is investigating new aspects of camera calibration by developing a new calibration room and calibrating novel cameras. The essence of accessing a camera calibration room to facilitate estimating a camera's internal-parameters suggests developing a fast and reliable approach for automatic calibration-room adjustment. Such a room could be employed to calibrate planar, multi-planar, fish-eye or multi fish-eye cameras. By the context of "automatic target adjustment" we mean estimating fixed targets with good spatial coverage in the local coordinate system of a calibration room with the possibility of automatic reading of their image observations in a short time (10-30 min). In this work we demonstrate such development for a calibration room by employing fixed-location coded-targets designed for good visibility in short range (30cm-4m). Our easy-to-read coded-targets ensure automatic and robust measurements of ties. A minimum-constraint bundle block-adjustment is employed to optimize the cost function and propagate errors from observations to unknowns. Our results demonstrate that the locations of targets are estimated with high precision (0.1-0.4 mm std.) in a distance of 30cm-4m. All object points are re-projected for residual investigation; sub-pixel image residuals are consequently observed for all coded-targets which ensure the quality of adjustment. Finally, repeated measurements (6 data sets) confirm the correctness of the proposed (95%) positional confidence intervals of the object points.

2. BACKGROUND

Geometric camera calibration has a long history in photogrammetric system design. Many diverse systems that contain one or more cameras need a calibration process to be able to associate image coordinates to the object reality.

In recent literatures the focus is mainly on self calibration through a bundle block -adjustment where the calibration parameters considered free in the calibration model.

Developing an automatic approach to precisely estimate a calibration room comes handy when there is an immediate need to calibrate for example a single-frame (SF) or a multi-projective camera system (MPCS). By assuming the calibration room a priori known, the degree of freedom (DOF) of the BBA model will decrease which stabilize the calibration process of the MPCS camera.

Standard BBA proved as an efficient tool for single/stereo camera calibration (see for example Granshaw, 1980, Fraser 1997, Grune and Huang 2001, Fraser, 2013). It is not far that Photogrammetric BBA is used to calibrate non-metric cameras in a very cost-effective manner, e.g. Triggs (98) proposed an automatic calibration approach coupled with planar coded-targets (CTs) for projective cameras. His method was able to run the calibration with at-least 5 shots. His only assumption was that the IOPs and the structure remain fixed during a measurement. Zhang (2000) introduced a planar chessboard CT to calibrate a projective camera. He employed a corner detector to automatically find CT in an image set. A few shots from different angles was usually enough to run the BBA. Bouguet later modified Zhang's tool box to accept SCs (see Bouguet calibration toolbox). Svoboda et. al (2002) used an easily-detectable moving object (a laser track pointer) to calibrate a set of cameras that were fixed on an indoor environment (1st class $\mathrm{MPCS_n}$, where n is the number of cameras in the system). Their goal was to find IOPs and EOPs of a set of cameras that was specifically designed for indoor localization of moving objects. In Svoboda et. al (2002)'s $\mathrm{MPCS_n}$, distances between cameras were relatively large, and $\mathrm{MPCS_n}$ was supposed to geometrically stay fixed during the operational period of the localization system (Svoboda et. al 2011 toolbox). Li et. al (2013) proposed an algorithm that was able to detect partially visible chessboard CT. Consequently, their method was usable even for cases that neighboring cameras were non-overlapping. They mainly focused on projective and catadioptric cameras ($\mathrm{MPCS_n}$), and used a geometrically known CT to glue neighboring cameras under the condition that no overlap exists. In their paper, a $\mathrm{MPCS_4}$ of vertically located projective cameras was calibrated. Urban et. al (2017) presented a BBA approach to calibrate a multi-omnidirectional camera system ($\mathrm{MOCS_n}$, where n is the number of cameras) (MultiCol). They simulated a $\mathrm{MOCS_{15}}$ with few randomly placed cameras to show the usefulness of their method and implementation.

In order to lay down the foundation of MPCS calibration, we here propose a automatic approach that estimates 3D points and their corresponding error ellipsoids. To enable this goal, we present a coded target that could be automatically detected in images, and then employ the standard BBA to find robust estimation of the calibration room.

3. MATERIAL AND METHOD

3.1 The Calibration room

For the calibration, a room of size [356 (cm) × 519 (cm) × 189 (cm)] was considered as the rigid structure. The number of 215 CT was printed and stitched on the ceiling, floor, walls, and a staircase's fence. Since the stitched CTs were not strictly rigid, beside each CT, a laminated dot was printed and fixed to ensure the rigidness of CTs.

3.2 SF cameras and datasets

In order to determine the geometry of the calibration room, a single frame camera (SFC) (Canon EOS-6D, sensor 20MPix =5472x3648 pix^2, Lens=Canon EF 24mm f/2.8 IS USM, focal length:

FL=20.65mm $\pm$ 2 micron) was employed. A second SFC (Samsung NX300, sensor=20MPix 5472x3648 pix^2, Lens: Samsung ultra wide angle lens f/2.4, FL=16.34mm$\pm$3.3 micron) was employed for cross-checking of the calibration-room's CT locations (Fig. 4). Naïve initial estimations of IO's were used to initiate BBA.

Seven datasets each containing 50-90 images were captured by the EOS-6D camera. Two cross-check data sets of 50 and 80 images were taken by NX300 camera.

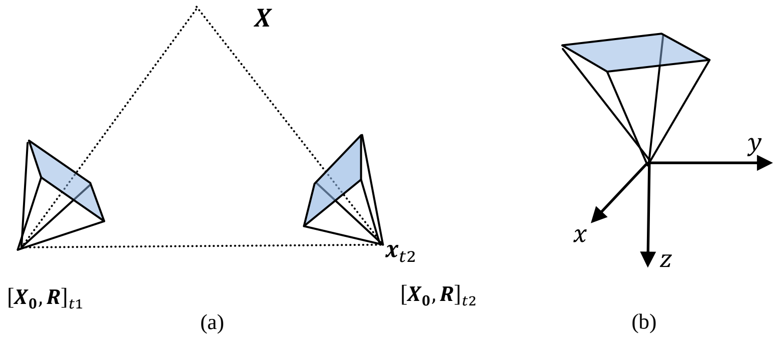


Fig. (1): Co-planarity, collinearity and camera local coordinate system: (a) two pinhole cameras looking inward an object point. Co-planarity equation is defined according to the intersection geometry; (b) local coordinate system of the ideal pinhole camera.

Fig. (2) Single frame cameras, from left to right: Samsung NX300, Canon EOS 6D

3.3 Coded Target

A coded-target (CT) was designed for this work by considering the following criterions:

1- Good-visibility in a distance range of (30cm-4cm)
2- Relative ease of automatic detection
3- Containing an Embedded ID
4- Embedding a scale

With the above criterions, a set of black circles were printed on a A4 paper with a binary ID part that was printed below the CT's structure part. The radius of ID part's ellipses considered to be different. The maximally-stable extreme region (MSER) algorithm was used to initially detect elliptical features of an image. Then, the k-mean clustering was used to find elliptical regions with sub-pixel accuracy. Finally, least-square is employed to fit an ellipse to the sets of accurately located ellipses were then filtered to remove regions which were far from near perfect ellipses. Next, collinear elliptical sets with suitable affine intervals were detected.

Finally, the complete topology was employed as a projective model of intersecting sets of ellipses to extract CTs.
extracted boundaries.

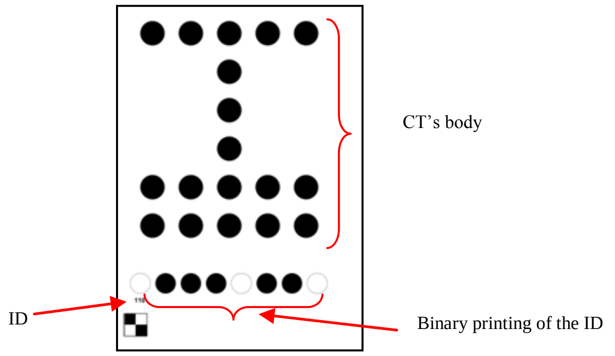


Fig. (3) The proposed coded target (CT)'s strucure.

3.4 The standard BBA

If we consider R to be an Euler rotation matrix of a camera at time (t), an Essential matrix is defined as the following:

$$E = [(X_0)_t]_x . R_t \quad (1)$$

For constructing a network of images with unknown location/orientation, co-planarity equations comes helpful in the situations that collinearity equations could easily get stuck in local optimums, if the initial values are not close enough to global optimums (>5°). However, the collinearity plays an essential rule after having close-enough approximations of location/orientation variables. Collinearity consequently removes all the unnecessary constraints and connects all cameras throughout a uniform model.
The essential matrix is consequently decomposed into relative location/orientation of a pair of cameras.

We can remove the unknown scale in collinearity equation by dividing local coordinates in a pinhole camera system by the third axis value; then two observational equations are generated that will be employed in the body of BBA:

$$x_t = -\frac{M_{t_{(1,:)}}.(X-(X_0)_t)}{M_{t_{(3,:)}}.(X-(X_0)_t)}, \; y_t = -\frac{M_{t_{(2,:)}}.(X-(X_0)_t)}{M_{t_{(3,:)}}.(X-(X_0)_t)}, \quad (2)$$

where $M = R^{-1}$.

In equation (1-2) pinhole coordinates (Fig. 1 b) are used. The distortion and scale caused by an optical system are considered as a non-linear function that connects pixel coordinates to normal coordinates (Fraser 1982, Grune and Huang 2001):

$$x_1 = \frac{(x)_{t_1} - PP_x}{f},\ y_1 = \frac{(y)_{t_1} - PP_y}{f},\ r^2 = \sqrt{x_1^2 + y_1^2},\ Rad = (1 + K_1.r^2 + K_2.r^4 + K_3.r^6)$$

$$(x_n)_{t_1} = x_1.Rad + 2.P_1.x_1.y_1 + P_2.(r^2 + 2(x_1)^2) - \delta.x_1 + \lambda.y_1 \quad (3)$$

$$(y_n)_{t_1} = y_1.Rad + 2.P_2.x_1.y_1 + P_1.(r^2 + 2(y_1)^2) \qquad + \lambda.x_1$$

In equation (3) $((x_n)_{t_1},(y_n)_{t_1})$ are the undistorted pinhole coordinates corresponding to the distorted image coordinates $((x)_{t_1},(y)_{t_1})$, Rad is the radial term, (K_i, P_i) are tangential and radial distortion coefficients, (PP_x, PP_y) is the location of principal point in pixel unit, and (δ, λ) are scale and shear factor respectively. Equation (3) boils down to a non-linear function of the form:

$$F\left((f, \mathbf{PP}, \mathbf{K}, \mathbf{P}, \sigma, \lambda), R_{(\omega,\phi,\kappa)_{(t_1:t_m)}}, X_{0_{(t_1:t_m)}}\right) = 0 \quad (4)$$

In equation (4), f is focal length, **PP** is the location of principal point in pixel unit, **K** is 3x1 vector of radial distortion, ***P*** is 2x1vector of radial distortions, and σ, λ are scale and shear factor respectively.

Fig. (4) Side view of the calibration room at FGI. Coded targets (CT) are installed on all surfaces.

4. RESULTS AND DISCUSSION

The proposed automatic CT algorithm was observed as a robust CT detector. After processing over 10000 images, no outlier was detected.

The standard BBA was used to determine the geometry of the calibration room by employing two cameras: Canon EOS-6D and Samsung NX300, as well as to calibrate the two cameras.

The self-calibrating BBA was performed by employing 10 parameters (principal distance, principal point in x and y directions, radial distortions, tangential distortions, scale, and shear for the SFCs.

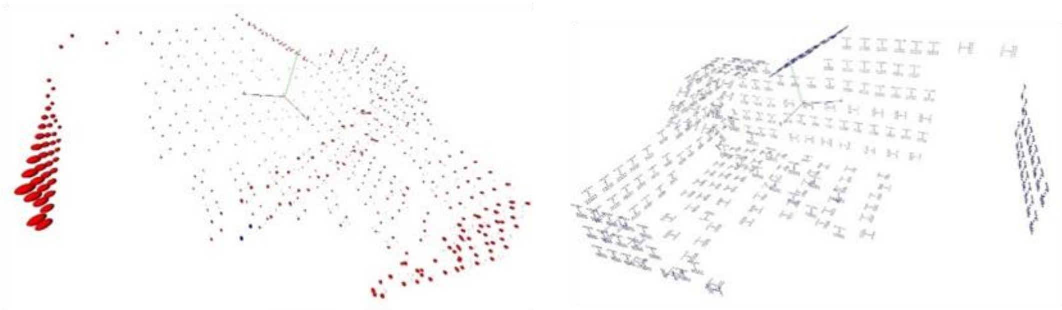
The estimated sensorial information including a posteriori variances regarding Canon EOS-6D and NX300 are listed in Table I. Most of estimated distortion values could be considered as significant when comparing the parameter value to its standard deviation.

The Scale factor in the standard BBA didn't exhibit significant effect on image residuals, which was also confirmed by close estimated std. value to the estimated values in Table I; therefore the SFCs didn't noticeably affected by the conformality induced by this parameter. The order of the corresponding std. values for scale and shear still suggested that the estimated values were meaningful. The results showed fairly lower std. values of IOPs for EOS 6D than of NX300.

Depending on the quality captured images, approximately 30 min time is required for automatic CT detection and BBA; therefore we successfully achieved our primary goal in a quick and high precision estimation of the calibration room.

The new calibration room will be used to calibrate and investigate various novel cameras, such as multi projective camera systems intended for 360-degree environment reconstruction.In the future work.

we will improve the distribution of CTs stitched on the calibration room; moreover, MSER will be examined with some other hole detection algorithms. This work successfully laid the foundation for a general SFC and MPCS calibration.



(a) (b)

Fig. (5) Structure of the calibration room from bundle block adjustment: (a) 300X larger 3D Error ellipsoids of points; (b) location of points

Table I. The calibrated parameters for Canon EOS 6D and Samsung NX300.

No	*Param. Name*	*value*	*Std.*	*value*	*Std.*
		Canon EOS-6D		*Samsung NX300*	
1	Focal Length (px.)	3157.65	1.22E-01	3806.53	2.76E-01
2	Focal Length (mm)	20.65	7.96E-04	16.34	1.18E-03
3	Principal Point x dir.(px.)	2754.72	1.57E-01	2685.69	3.86E-01
4	Principal Point y dir.(px.)	1516.57	1.60E-01	1833.81	3.56E-01
5	K1	8.34E-02	1.35E-04	1.57E-02	2.30E-04
6	K2	-7.41E-02	3.57E-04	-2.53E-02	7.86E-04
7	K3	1.06E-02	2.80E-04	1.26E-02	8.19E-04
8	P1	3.66E-04	1.30E-05	-6.72E-04	2.50E-05
9	P2	9.30E-05	1.50E-05	1.60E-03	2.80E-05
10	Scale factor	1.60E-05	1.10E-05	9.90E-05	1.80E-05
11	Shear factor	-1.06E-04	5.00E-06	-1.20E-05	8.00E-06

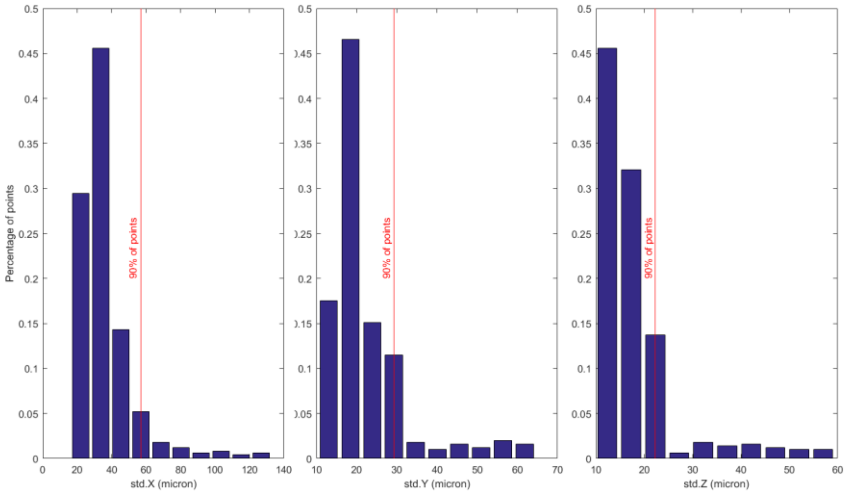


Fig. (6) Histograms of the targets std. values. (dataset 7, Canon EOS-6D)

REFERENCES

Fraser, C. S. 1982. On the use of non-metric cameras in analytical non-metric photogrammetry. International Archives of Photogrammetry and Remote Sensing, 24(5), 156–166.

Fraser, C. S., 1997. Digital camera self-calibration. ISPRS Journal of Photogrammetry and Remote Sensing, 52(4): 149–159.

Fraser, C. S., 2013. Automatic camera calibration in close range photogrammetry. Photogrammetric Engineering & Remote Sensing, 79(4): 381–388.

Granshaw, S. I., 1980. Bundle adjustment methods in engineering photogrammetry. Photogrammetric Record, 10(56): 181–207.

Grune A., Huang T.S., 2001, Calibration and Orientation of Cameras in Computer Vision, Springer Series in Information Sciences (34), ISBN: 978-3-642-08463-8.

Hartley R. I.,1997. In defense of the eight-point algorithm, IEEE Transactions on Pattern Analysis and Machine Intelligence, 19(6): 580-593.
doi: 10.1109/34.601246

Hartley, R.I. and Zisserman, A., 2004. Multiple View Geometry in Computer Vision, second edition, Cambridge University Press, ISBN: 0521540518.

BIOGRAPHICAL NOTES:

Ehsan Khoramshahi**:** He has been a research staff in photogrammetry and remote-sensing department at Finnish Geospatial Reseach Institute (FGI) since 2014. His primary interests are multiple-view geometry computer vision, and machine learning. Currently, He is a PhD student in department of Computer Science at University of Helsinki.

Eija Honkavaara**:** Functions as Research Manager and research group leader at the FGI. Her research interests include automation in photogrammetry, with the special emphasis to drone photogrammetry and hyper spectral remote sensing.

Tomi Rosnell**:** Tomi Rosnell is a Research Scientist at the FGI. His current research interests include indoor and outdoor close-range photogrammetry, three-dimensional modeling, and unmanned aerial vehicles.

CONTACTS

Mr.Ehsan Khoramahshi
Department of Photogrammetry and Remote sensing,
Finnish Geospatial Research Institute (FGI),
Geodeetinrinne 2
FI-02430 Masala
FINLAND
Tel. +3584044444135
Email:Ehsan.khoramshahi@nls.fi
Website: http://www.mv.helsinki.fi/home/khoramsh/