 ISSN : 2229-4333(Print) | ISSN : 0976-8491(Online)

Planar Self-Calibration with Less Constraint

[1]A. El Abderrahmani, [2]A. Saaidi, [3]K. Satori
LIIAN, Dept. of Mathematics and Informatics, Faculty of Sciences Dhar-Mahraz Atlas-Fez, Morocco

Abstract
In this article, we are presenting a robust method of camera self-calibration (characterized by constant intrinsic parameters), by an unknown planar scene. The originality of our method is the use of only two matches detected in the images taken by the camera that can simplify the equations of self-calibration and to estimate the camera intrinsic parameters. The strong point of our new method is the camera self-calibration with less constraint. Three images and two points of an unknown 2D scene are sufficient for camera self-calibration. The simulations and the experimental results show the performance of our algorithms in terms of precision, convergence and stability.

Keywords
Self-Calibration, Segment, Homography, non-linear optimization.

I. Introduction
Computer vision is the base of any system of artificial vision that takes as input one or more images taken by digital cameras, and performs processing on these images to extract information about the scene. The fundamental problem in computer vision is to estimate the camera parameters (intrinsic and extrinsic).
The numbers studies in recent decades have give to formulations well prepared and many new methods of resolution. On one part, methods based on a scene known [4, 18, 19, 21, 22] called calibration, and second part, the methods based on a scene unknown [1, 3, 5, 6, 7, 12, 13, 14, 15, 17, 20] called self-calibration.
In this work, we are interested in the camera self-calibration by using the primitive segment of a unknown scene 2D and the cameras free movement. Our technique is to estimate the camera intrinsic parameters with the detection of some matches for every couple of images. The homography between images is estimated from matches detected by using the RANSAC technique [16]. Next, this matrix will be used with two matchings (the projections of the two extremities of the segment) to estimate the projection matrix and determined the equations system.
Finally, three images are sufficient to determine the camera intrinsic parameters by the resolution of a non linear equation system that requires a phase of initialization and optimization of a costly function associated with the parameters searched through the algorithm of Levenberg-Marquardt [8].
The paper is organized as follows: The model of camera and scene are explained in the second section. The projection of the scene is described in the third section. The camera self-calibration is presented in the fourth section. The experimentations are presented in the fifth section and the conclusion in the sixth section.

II. Scene and camera

A. Scene
Consider two points P_1 and P_2 in the 2D scene used, which are the extremities of a segment $[P_1P_2]$. We define an euclidien reference (O, X, Y, Z) with O in the middle of the segment $[P_1P_2]$ and Z is perpendicular on the plan of the scene. We note that:

$$P_1 = (d\cos\alpha, d\sin\alpha, 1)$$
$$P_2 = (-d\cos\alpha, -d\sin\alpha, 1) \qquad (1)$$

are respectively the coordinates of the point P_1 and P_2 in the reference (O, X, Y, Z) as α is the angle between the segment $[P_1P_2]$ and the axe X (Fig.1), with $\alpha \in [0\ 2\Pi]$ and $d = P_1P_2/2$.

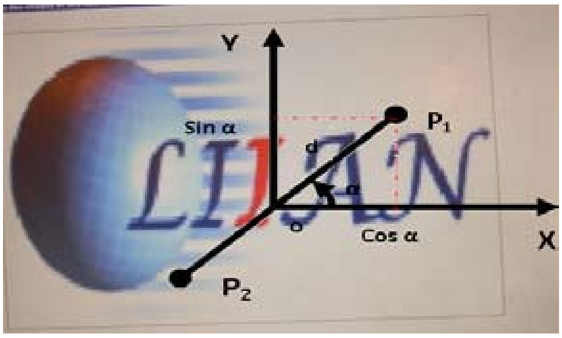

Fig. 1: The reference (O, X, Y, Z) as its origin is on the middle of the segment $[P_1P_2]$

B. Camera
To transform a point in the scene in this image, we use the pinhole model camera defined by the perspective projection 3×4 matrix represented by the following formula: $P = A(R\ \ t)$
With:

$$A = \begin{pmatrix} f & \tau = 0 & u_0 \\ 0 & \varepsilon f & v_0 \\ 0 & 0 & 1 \end{pmatrix} \qquad (2)$$

$(R\ \ t)$ is the matrix of the extrinsic parameters of camera as R is the rotation matrix representing the orientation of camera and t is the translation's vector representing the position of camera. $(f, \varepsilon, \tau, u_0, v_0)$ are the intrinsic camera parameters such as f is the focal length, τ is the image skew, ε is the scale factor and (u_0, v_0) are the image coordinates of the principal point.

III. Projection of the scene

A. Interest points
Detector Harris: To extract the local maxima from the images of the scene, Harris [9] uses a matrix N defined by:

$$N = \begin{pmatrix} \left(\frac{\partial I}{\partial u}\right)^2 & \left(\frac{\partial I}{\partial u}\right)\left(\frac{\partial I}{\partial v}\right) \\ \left(\frac{\partial I}{\partial u}\right)\left(\frac{\partial I}{\partial v}\right) & \left(\frac{\partial I}{\partial v}\right)^2 \end{pmatrix} \qquad (3)$$

To detect the corners in the images, Harris uses a variable that is superior to zero in the corner case. His value is given by:

$$r = \det(N) - \lambda.(\text{trace } N)^2 \quad \text{with } \lambda = 0.04 \qquad (4)$$

Correlation measure: To match the points of Harris previously detected we use the measure of ZNCC correlation [2, 10] (Zero mean Normalized Cross Correlation) that is invariant to the local linear changes of luminance and defined by the following formula:

$$\mathrm{ZNCC}(p_i, p_j) = \frac{\sum_n a_n b_n}{\sqrt{\sum_n a_n^2 \sum_n b_n^2}} \quad (5)$$

As :

$a_n = I(p_i + n) - \bar{I}(p_i)$ and $b_n = I'(p_j + n) - \bar{I'}(p_j)$ With p_i and p_j two detected points Harris's in the two images i and j. $\bar{I}(p_i)$ and $\bar{I'}(p_j)$ are the averages of the luminance of pixels on a 11 x 11 window centered respectively in p_i and p_j.

B. Homographies between images

RANSAC: Algorithm to estimate the geometric entities in a robust method to matching, with error compared to the entity found is inferior to a threshold.

Homographies image-image: For every couple of images (i, j), there is a 3×3 matrix H_{ij} as:

$$p_j \sim H_{ij}\, p_i \quad (6)$$

With p_i and p_j are, respectively projections of one even point of the scene in the image i and j. The H_{ij} matrix is called the homography between the two images, that can be calculated, up to a scale factor, by the knowledge at least of four matching between the two images by applying the RANSAC function.

C. Absolute conic and its image

Absolute conic: On the plane at infinity is a special conic, named the absolute conic (AC) and noted Ω. The **AC** is composed only of imaginary points, which come in pairs of conjugal points on π_∞, its canonical matrix is noted $\Omega \sim I_3$.

Image of the absolute conic: The projection of **AC** in the image, which we named the image of the AC (**IAC**), is noted ω is also composed of conic imaginary points. The **IAC** is very primitive, but also interesting because it is directly connected to internal parameters of the camera with the following decomposition:

$$\omega = (AA^T)^{-1} \quad (7)$$

If the intrinsic parameters are constant, then ω is the same in all views and its knowledge is equivalent to the intrinsic parameters $(f, \varepsilon, \tau, u_0, v_0)$ and therefore to the camera self-calibration [11].

D. Projection matrix

There are two homographies that permit to project the scene 2D in the two images i and j (Fig. 2) noted H_i and H_j.

According to article [7] was:

$$Hq \sim ARq \begin{pmatrix} 1 & 0 & \\ 0 & 1 & Rq^T tq_i \\ 0 & 0 & \end{pmatrix}, q = i, j \quad (8)$$

According to Fig. 2, the projection of the points of the scene p_1 and p_2 on the image i and j is given by the following formulas:

$$p_1^q \sim H_q P_1 \text{ and } p_2^q \sim H_q P_2 \text{ with } q = i, j \quad (9)$$

According to formula (1):

$P_1 = CU$ and $P_2 = CV$

With: U and V two vectors as: $U = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ and $V = \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix}$ (10)

And $C = \begin{pmatrix} d\cos\alpha & 0 & 0 \\ 0 & d\sin\alpha & 0 \\ 0 & 0 & 1 \end{pmatrix}$

Therefore the formula (9) is written in the form:

$$p_1^q \sim H_q CU \text{ and } p_2^q \sim H_q CV \text{ with } q = i, j \quad (11)$$

We pose the following:

$$K_i = H_i C \text{ and } K_j = H_j C \quad (12)$$

K_i and K_j are two 3×3 matrixes that permit to project the two vectors U and V respectively, in the two images i and j. Therefore in the image i, the relation (11) becomes:

$$p_1^i \sim K_i U \text{ and } p_2^i \sim K_i V \quad (13)$$

From formula (13) we can deduce four linear equations.

From formula (12) we can deduce: $C \sim H_i^{-1} K_i$ and $K_j \sim H_j C$, we replace C by its formula to get:

$$K_j \sim H_{ij} K_i \text{ with } H_{ij} \sim H_j H_i^{-1} \quad (14)$$

In the image j, the relation (11) becomes:

$$p_1^j \sim K_j U \text{ and } p_2^j \sim K_j V \quad (15)$$

We replace K_j by its formula (14), so the formula (15) becomes:

$$p_1^j \sim H_{ij} K_i U \text{ and } p_2^j \sim H_{ij} K_i V \quad (16)$$

From formula (16) we can deduce four linear equations by the K_i matrix. Therefore the total that we can have is eight linear equations for the K_i matrix permits to estimate this matrix.

The K_j matrix is estimated and from the equation (14).

ISSN : 2229-4333(Print) | ISSN : 0976-8491(Online)

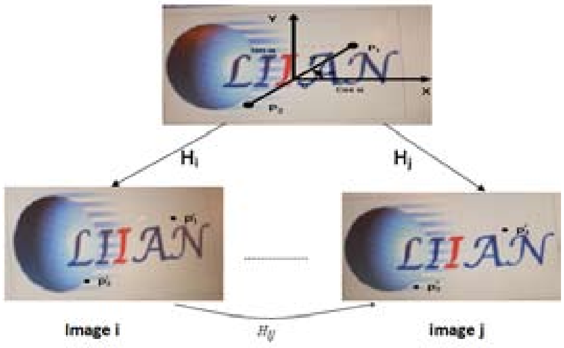

Fig. 2: Projection of the segment $\left[P_1 P_2\right]$ in the two images i and j by the two matrix H_i and H_j

IV. Camera self-calibration

A. Self-calibration Equations

From the equation (6) we find that:

$$A^{-1}K_i = R_i \begin{pmatrix} 1 & 0 & \\ 0 & 1 & R_i^T t_i \\ 0 & 0 & \end{pmatrix} C$$

, that gives:

$$K_i^T \omega \, \mathrm{K}_i \sim \begin{pmatrix} C'^T C' & C'^T R_i^T t_i \\ t_i^T R_i C' & t_i^T t_i \end{pmatrix} \quad (17)$$

With $C' = \begin{pmatrix} d\cos\alpha & 0 \\ 0 & d\sin\alpha \\ 0 & 0 \end{pmatrix}$

We notes by $M_i = \begin{pmatrix} m_{1i} & m_{3i} \\ m_{3i} & m_{2i} \end{pmatrix}$ the matrix that contains the two first lines and columns of the matrix $K_i^T \omega \, \mathrm{K}_i$, and from equation (17) we can write:

$$M_i = C'^T C' \quad (18)$$

The formula (18) expresses the relation between the camera intrinsic parameters and those of a Segment. In the same way, for the matrix from equation (17 and 18), we find

$$K_j^T \omega \, \mathrm{K}_j \sim \begin{pmatrix} C'^T C' & C'^T R_j^T t_j \\ t_j^T R_j C' & t_j^T t_j \end{pmatrix} \text{ and } M_j = C'^T C'$$

This gives:

$$M_i = M_j \quad (19)$$

From the formula (19) between two images. Therefore we get the following system of equations:

$$\frac{m_{1i}}{m_{2i}} = \frac{m_{1j}}{m_{2j}}, \quad \frac{m_{3i}}{m_{1i}} = \frac{m_{3j}}{m_{1j}}, \quad \frac{m_{3i}}{m_{2i}} = \frac{m_{3j}}{m_{2j}} \quad (20)$$

Finally:

$$\begin{cases} m_{1i}m_{2j} - m_{2i}m_{1j} = 0 \\ m_{3i}m_{1j} - m_{1i}m_{3j} = 0 \\ m_{3i}m_{2j} - m_{2i}m_{3j} = 0 \end{cases} \quad (21)$$

These three previous equations are non linear between every couple of images i and j.

B. Minimization

To solve the equations (21). We minimize the following cost function:

$$\min_{\omega} \sum_{j=i+1}^{n} \sum_{i=1}^{n-1} \left(\lambda_{ij}^2 + \mu_{ij}^2 + \beta_{ij}^2\right) \quad (22)$$

With:

$$\lambda_{ij} = m_{1i}m_{2j} - m_{2i}m_{1j}$$
$$\mu_{ij} = m_{3i}m_{1j} - m_{1i}m_{3j}$$
$$\beta_{ij} = m_{3i}m_{2j} - m_{2i}m_{3j} \quad (23)$$

n represent the number of images used. Function (22) is optimized by the Levenberg-Marquardt [8], which must an initialization phase.

C. Initialization

To initialize the cost function (22), we suppose that some conditions on the model of vision are verified:

- The principal point is in the center of the image, therefore u_0 and v_0 are known.

- The pixels are squared therefore $\varepsilon = 1$

While replacing these parameters in the equations system (21),

We find a linear equation system between the image i and j according to f^2, which will be easily resolved in accordance with article [17] to determine the value of f.

V. Experimentations

A. Simulations

We simulate a sequence of 512×512 images of known 2D scene. Our model of camera moves freely to take the images. The points of the scene are projected in the images and a classic method of calibration is applied to find the intrinsic parameters of camera that are: $f = 1125$, $\varepsilon = 0{,}93$, $u_0 = 260$, $v_0 = 262$. A noise Gaussian with varying deviation σ is added on the coordinates of the image points. The interesting points detected by Harris [9] and matched by the ZNCC correlation function [2, 10], then the homography matrixes between the images and the projections matrixes of the vector are calculated. Finally the resolution of a non linear equation system permits to estimate the elements of the images of the absolute conic and to calculate the camera intrinsic parameters.

The presented test concentrated on the comparison of the focal length estimated by our method with the technique of calibration.

The experiences show that the relative error of the focal length:

- Decreases linearly if the number of the images is superior to three (Fig. 3).

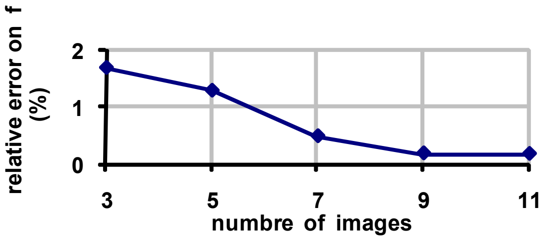

Fig. 3: The relative error on f according to number of images.

- Increases if the noise applied on the points of the images increases (Fig. 4).

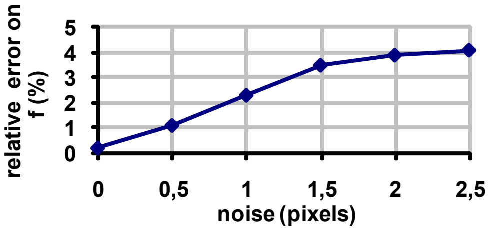

Fig. 4: The relative error on f according to noise.

B. Real data

To show the robustness of our method, three 512×512 images of an unknown planar scene are taken by a digital camera (Samsung ES55) of which the intrinsic also based on a programming language, object oriented, robust and reliable in the domain of advanced programming such as Java.

- Graphical interfaces are created by the use of the Swing API
- Loading images on our application and using some classes defined in Java as ImageIO class and another class.
- Implementation of our algorithms such as the algorithm of Harris [9], ZNCC [2, 10] and the calculated matrix and solving systems of equations are based on the Java language and other APIs are available freely on the JAMA API and other API.

The images are load by couples in our interface (Fig. 6). The interest points are detected and displayed in our interface (Fig. 7), and matching interest points are calculated and displayed (Fig. 8). Then the matrices of homographies and projection matrices and vectors are calculated. Finally the system of nonlinear equations (22) is solved to determine the camera intrinsic parameters.

Fig. 5: the three images used for the camera self-calibration

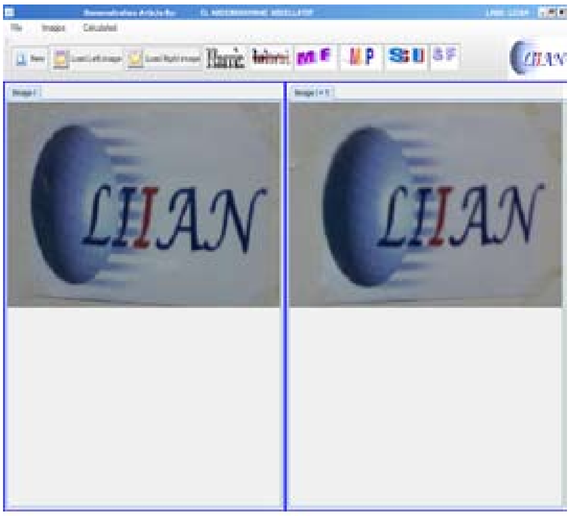

Fig. 6: loading of the two left and right images in our java application

Fig. 7: display the interests points in red the two images on the bottom half of the interface

ISSN : 2229-4333(Print) | ISSN : 0976-8491(Online)

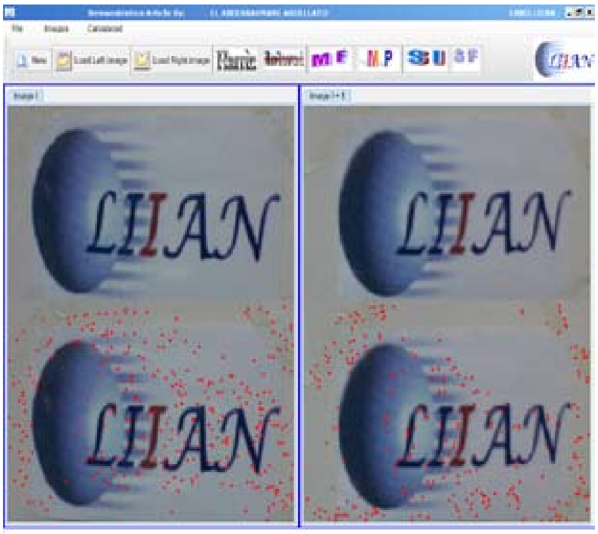

Fig. 8: display the matchings between the couple of image in red on the bottom half of the interface

The following table indicates the initial and optimal result of the intrinsic camera parameters by our method

Table 1: Initial and optimal solution of the intrinsic camera parameters.

	f	ε	u_0	v_0
Initial solution	1139	1	256	256
Optimal solution	1173	0.93	260	264

VI. Conclusion

In this article, we treated the problem of camera planar self-calibration, by using, witch only, two interest points, are the projection of extremities of the segment on every image. These points will be used to estimate the homography matrix between the images and the projection matrix of U and V vectors for each couple image, to deduce finally a non-linear equations system that permits to determine the camera intrinsic parameters. Our approach allows the camera self- calibrating with an unknown 2D scene, by a simple, reliable and robust method relative to other methods

References

[1] A.Elabderrahmani, A.Saaidi, K.Satori. "Camera Self-Calibration Using Planar Scenes On Software", Knowledge, Information Management And Applications. Fez, Marrocco, Octobrer2009.

[2] A.Saaidi, H.Tairi , K.Satori. "Fast Stereo Matching Using Rectification And Correlation Techniques". Isccsp, Second International Symposium On Communications, Control And Signal Processing, Marrakech, Morrocco, March2006.

[3] P.Sturm, "A case against Kruppa's equations for camera self-calibration", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, Issue 10, pp. 1199-1204, October 2000.

[4] A.Elabderrahmani, A.Saaidi, K.Satori. "Camera Calibration Using An Unknown Parallelogram On Doctoral Days", Information Technology and Communication. Fez, Marrocco, Jul 2010.

[5] P.Gurdjos, P.Sturm., "Methods and Geometry for Plane-Based Self-Calibration". CVPR, pp. 491-496, 2003.

[6] B.Triggs., "Autocalibration from planar sequences", In Proceedings of 5th European Conference on Computer Vision, Freiburg, Allemagne, Juin 1998.

[7] A. Saaidi, A. Halli, H. Tairi , K. Satori., "Self-Calibration Using a Planar Scene and Parallelogram". ICGST-GVIP, ISSN 1687 398X, February 2009

[8] J.More., "The levenberg-marquardt algorithm, implementation and theory". In G.A.Watson, editor, Numerical Analysis, Lecture Notes in Mathematics 630. Springer-Verlag, 1977.

[9] C.Harris, M.Stephens., "A combined corner and edge detector". In Alvey Vision Conference, 1988

[10] M.Lhuillier, L.Quan., "Quasi-dense reconstruction from image sequence". ECCV, 2002

[11] P.F.Sturm, S.J.Maybank., "On Plane-Based Camera Calibration: A General Algorithm, Singularities, Applications". CVPR-IEEE Conference on Computer Vision and Pattern Recognition, Colorado, USA, 1999.

[12] A.Saaidi, A.Halli, H.Tairi, K.Satori., "Self Calibration Using A Particular Motion Of Camera". Transaction on Computer Research. Issue 5, Vol. 3, May 2008.

[13] Wei Zhang., "A simple Method for 3D Reconstruction from Two Views". GVIP 05 Conference, CICC, Cairo, Egypt, December 2005.

[14] Elsayed E.Hemayed., "A Survey of Camera Self-Calibration". In Proceedings of the IEEE Conference on AVSS, 2003.

[15] Peijun Liu, Jiaoying Shi, Ji Zhou, Longchao Jiang., "Camera Self-Calibration Using The Geometric Structure In Real Scenes". In Proceedings Of The Computer Graphics International, 2003.

[16] P.H.S.Torr, D.W.Murray., "The Development And Comparison Of Robust Methods For Estimating", The Fundamental Matrix. IJCV, 1997.

[17] A.El abderrahmani, A.Saaidi, K. Satori., "Robust Technique for Self-Calibration of Cameras based on a Circle". ICGST-GVIP, Volume 10, Issue 5, December 2010

[18] Xiaoqiao Meng, Hua Li, Zhanyi Hu., "A New Easy Camera Calibration Technique Based on Circular Points", BMVC2000.

[19] Liangfu Li, Zuren Feng, Yuanjing Feng., "Accurate Calibration of Stereo Cameras for Machine Vision". JCS&T Vol. 4 No. 3 October 2004.

[20] Xiaochun Cao, Jiangjian Xiao, Hassan Foroosh, Mubarak Shah., "Self-calibration from turn-table sequences in presence of zoom and focus". Computer Vision and Image Understanding 102, 2006

[21] Jin Sun, Hongbin Gu., "Research of Linear Camera Calibration Based on Planar Pattern". World Academy of Science, Engineering and Technology 60, 2009.

[22] Tarek A. Al-Saeed, Nahed H. Solouma, Said M. El-Sherbiny., "Retinal Motion Detection and 3D Structure Recovery From Two Perspective Views". GVIP Special Issue on Medical Image Processing, March, 2006.

Abdellatif El abderrahmani received the bachelor's and master's degrees from USMBA-Fez University in 2002 and 2007 respectively. He is currently working toward the PhD degree in the LIIAN Laboratory (Laboratoire d'Informatique, Imagerie et Analyse Numérique) at USMBA-Fez University. His current research interests include camera self calibration, 3D reconstruction and real-time rendering.

Abderrahim Saaidi received the PhD from USMBA-Fez University in 2010. He is currently a professor of computer science at USMBA-Taza University. He is member of the LIIAN Laboratory (Laboratoire d'Informatique, Imagerie et Analyse Numérique) at USMBA-Fez University. His research interests include camera self clibration, 3D reconstruction and real-time rendering.

Khalid Satori received the PhD degree from the National Institute for the Applied Sciences INSA at Lyon in 1993. He is currently a professor of computer science at USMBA-Fez University. He is the director of the LIIAN Laboratory. His research interests include real-time rendering, Image-based rendering, virtual reality, biomedical signal, camera self calibration and 3D reconstruction.