Novel Planar Self-calibration Approach of a Camera having Variable Intrinsic Parameters

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Abstract: -The self-calibration of a camera is an important computer vision problem it allows us to estimate the camera intrinsic parameters without any knowledge of the used scene. In this work we proposed a novel method of camera self-calibration with varying intrinsic parameters from an unknown planar scene. The principle of the present approach consists of using some projection points of the scene in only two image planes to obtain a system of equations according to the intrinsic camera parameters and the image of absolute conic in the both views. From this system of equations we formulated a non-linear cost function whose minimization permits us to estimate the intrinsic camera parameters in the both images. The experimental results on synthetic and real data justify the effectiveness of our method.

Key-Words: - Self-calibration, Computer vision, Varying intrinsic parameters, Image of the absolute conic, nonlinear cost function, Unknown planar scene.

1 Introduction

The camera self-calibration is a primary computer vision field it was introduced by [1, 2] to find camera intrinsic parameters without any knowledge of the observed scene. This research of intrinsic parameters is based on the matching points between the images [3,4,5,6,7,8,9,10,11,12,13,14,15,16,17] by using imaginary primitives that describe the metric structure of the scene [18]. The self-calibration problem is often accompanied by three types of constraints, constraints about camera intrinsic parameters, constraints about the scene viewed and constraints about the camera motion. Recently the dimension of the self-calibration problem has been extended to address variable intrinsic parameters such as the zoom and the focus of the camera.

This article presents a new method of camera self- calibration by surmounting the above constraints. In fact we used an unknown planar scene to self-calibrate a camera having variable intrinsic parameters and performing a free motion. This approach is based on the use of only three points of the scene whose projection into the planes of the both images allow us to obtain two equations according to the intrinsic camera parameters and the image of absolute conic. The two equations obtained are insufficient to self-calibrate our camera because we used two images of the scene and for each image we have five intrinsic parameters where the idea of applying to the above three points which are the vertices of an unknown parallelogram a sequence of random transformations to obtain other unknown parallelograms in the scene. All these points are then projected into the image planes to obtain more equations according to the camera intrinsic parameters. These equations are used to formulate a non-linear cost function whose minimization permits to estimate all the camera intrinsic parameters in the both images. The figure 1 presents the self-calibration steps of our method.

This work is structured as follows: in the second section we reviewed some of the related works, the third section presents the vision system used to project the points of the scene in the image planes, the fourth section presents our method of self-calibration addressed in this paper, in this part we demonstrate how we formulated the self-calibration equations based on intrinsic camera parameters from the projection of the scene points. The fifth section tests the performance of our new approach by performing an evaluation on synthetic and real data and the last section contains a conclusion of our paper.

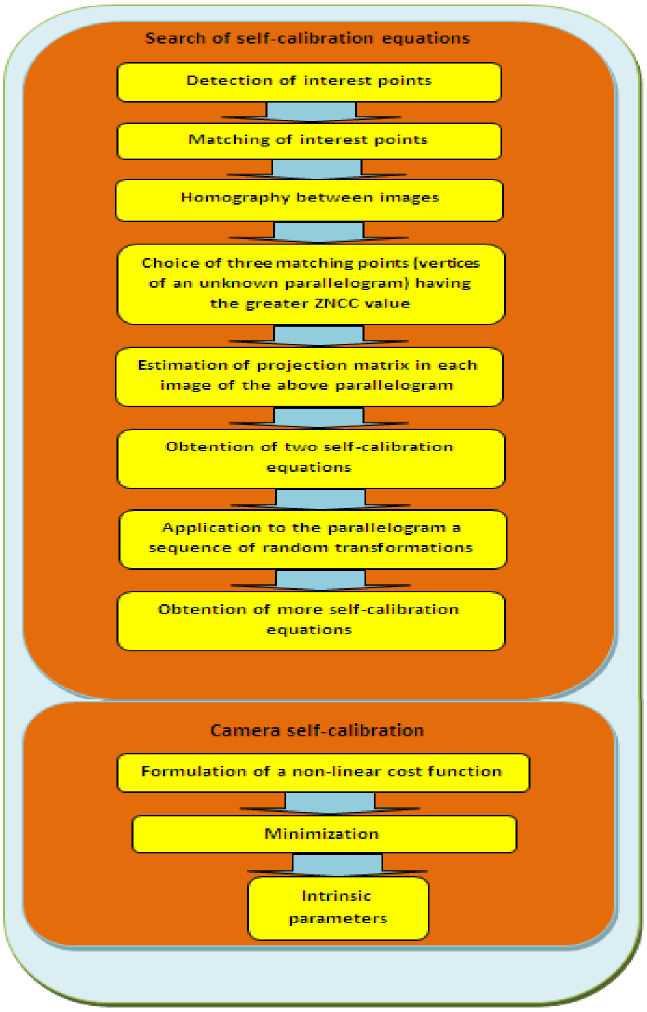


Fig. 1. Our procedure of camera self-calibration

2 Previous works

In computer vision the camera self- calibration is a fundamental step; it forms an important domain of research that attracts many researchers around the world. In [19], the author proposed a self-calibration method with variable intrinsic parameters from a sequence of images of a 3D unknown object. The projection of two points of the 3D scene in the image planes is used with the fundamental matrix to determine the matrices of the projection of the object in images. These projection matrices are used to formulate a non-linear cost function [20] which resolution is used to estimate the intrinsic parameters of the camera in different images. In [21], a self-calibration method of cameras with varying intrinsic parameters is presented. It is based on quasi-affine reconstruction, after reconstruction , the homography of the plane at infinity is determined, and used with constraints on the image of the absolute conic for estimating the intrinsic camera parameters . In [22] , a new self - calibration algorithm is presented, the author has followed a phased approach with low complexity to obtain a polynomial optimization function based on the singular values of the fundamental matrix according to the intrinsic camera parameters . The weak point of this method is that the number of images used is relatively high. The problem addressed in [23] is that of self- calibration of the cameras with varying intrinsic parameters, this method is based on a so-called quasi - affine reconstruction in other words by locating the plane at infinity of the scene which allows to obtain a system of equations based on the intrinsic parameters of the camera. The disadvantage of this algorithm is the difficulty, in some particular cases of the scene used to define the coordinates of the plane at infinity. In [24] the authors presented a new self-calibration method with the possibility of varying the focal length and the principal point. In this approach the camera intrinsic parameters are extracted from a non- linear fitting algorithm, however in this work the authors have assumed that the scale factor is known and equal to one with the absence of distortion which makes the method inapplicable in real conditions. A new self-calibration method of cameras is processed in [25], this method is based on the relative distance of the scene and the homography matrix that converts the projective reconstruction in the metric and whose elements are dependent on the intrinsic parameters of the camera . These parameters and 3D structure are obtained by minimizing a cost function that is related to the relative distance of the scene used .A new method is treated in [26], in this paper the authors assumed that the camera intrinsic parameters are known except for the focal length which varies from one view to another. The basic point of this work is the use of the homography induced by the plane at infinity, transforming the image of the absolute conic between frames, to estimate the intrinsic parameters of the camera. The method presented in this article is limited due to the nature of the movement, pure rotation, applied to the camera. The problem addressed in [27] is the self-calibration of the cameras with varying intrinsic parameters, in effect M.Pollefeys and all presented a self-calibration method for a metric reconstruction of a scene from a sequence of images, The main contribution in this work is the proposition of an effective technique which addresses the self-calibration problem with all types of constraints on the camera intrinsic parameters. The weak point of this approach is that the number of images used to give good results must be greater than or equal to eight which makes the method greedy in terms of computation time. In [28] the authors are proposed a self-calibration method of camera characterized by the variation of the focal length and principal point. This method is an extension of the technique presented by Hartley based on the use of the properties of the essential matrix. The three singular values of the essential matrix must meet two conditions: one of them must be zero and the other two must be identical. The essential matrix is obtained from the fundamental matrix by transformation with the intrinsic camera parameters in two views. Thus, the constraints on the essential matrix can be brought to those of constraints on the intrinsic parameters of the camera in two positions this allows a search in the space of intrinsic parameters of the camera to minimize a nonlinear function to obtain the intrinsic camera parameters.

3 Vision system used

The projection of the scene into the image planes is performed by a homogeneous linear transformation called homography. This homography is characterized by a non-singular 3x3 matrix given by:

$$H \sim KR\begin{pmatrix} 1 & 0 & \\ 0 & 1 & R^T t \\ 0 & 0 & \end{pmatrix} \qquad (1)$$

With *(R , t)* represents the extrinsic parameters of the camera and K is the intrinsic parameters matrix defined by:

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

With:

g : Focal length

ε : Scale factor

τ: Skew factor

u_0 and v_0: Coordinates of the principal point.

For each three points A_q , B_q and C_q of a set of n points of an unknown planar scene it exists one and only one point such as the four points form a parallelogram with q varying from *1* to n . Associate for each three points A_q , B_q and C_q a reference $(O_q\ X_q\ Y_q\ Z_q)$ with Z_q axis is perpendicular to the plane containing the points A_q , B_q , C_q (figure 2).

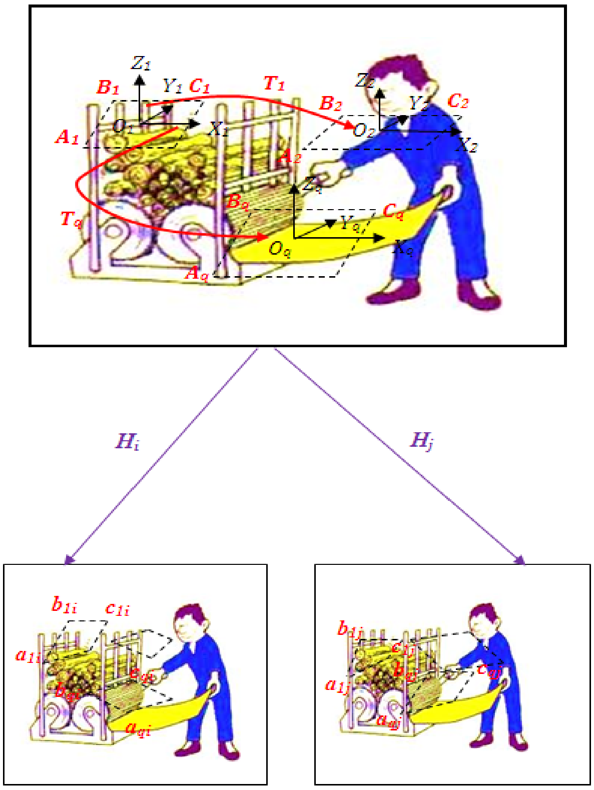


Image *i* Image *j*

Fig. 2. Projection of the planar scene

We consider $(O_1\ X_1\ Y_1)$ a fixed reference in the scene associated of the points A_1 , B_1 and C_1 and $(O_q\ X_q\ Y_q)$, with q varying from *2* to n , are the mobile references according to $(O_1\ X_1\ Y_1)$ associated of the points A_q , B_q and C_q .The references $(O_q\ X_q\ Y_q)$ are obtained by applying to $(O_1\ X_1\ Y_1)$ a transformation which consists of a rotation R^q and a translation t^q (see figure 2). The homogeneous coordinates of the points A_q , B_q and C_q for q varying from *2* to n in mobile references are respectively:

$$\left(-c_{2q}\ \ -c_{3q}\ \ 1\right)^T, \left(-c_{1q}\ \ c_{3q}\ \ 1\right)^T, \left(c_{2q}\ \ c_{3q}\ \ 1\right)^T$$

With:

$$c_{1q} = l_q - l'_q \cos(\alpha_q)$$

$$c_{2q} = l_q + l'_q \cos(\alpha_q).$$

$$c_{3q} = l'_q \sin(\alpha_q)$$

And:

$$l_q = \left\| A_q B_q \right\|$$

$$l'_q = \left\| B_q C_q \right\|$$

These coordinates can be rewritten as: $W_q U_1, W_q U_2, W_q U_3$ with:

$$W_q = \begin{pmatrix} l_q & l'_q \cos(\alpha_q) & 0 \\ 0 & l'_q \sin(\alpha_q) & 0 \\ 0 & 0 & 1 \end{pmatrix}, U_1 = \begin{pmatrix} -1 \\ -1 \\ 1 \end{pmatrix}, U_2 = \begin{pmatrix} -1 \\ 1 \\ 1 \end{pmatrix}$$

and $U_3 = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$.

The expression of homogeneous coordinates of points A_q, B_q and C_q in the fixed reference, with q varying from 1 to n, are respectively:

$R^q A_q + t^q, R^q B_q + t^q$ and $R^q C_q + t^q$ or:

$$\begin{cases} R^q W_q U_1 + t^q \\ R^q W_q U_2 + t^q \\ R^q W_q U_3 + t^q \end{cases} \quad (3)$$

4 Proposed method

In this section we presented how to estimate the intrinsic parameters of the camera in the two images of a planar unknown scene by using our new method proposed in this paper. We begin by estimating the projection matrices of each three points A_q, B_q and C_q for q varying from *1* to *n*. These projection matrices permit us to build a system of self-calibration equations according to the intrinsic camera parameters.

Let :

$$a_{iq} = (x_{iq}^a \ y_{iq}^a \ 1)^T, a_{jq} = (x_{jq}^a \ y_{jq}^a \ 1)^T$$
$$b_{iq} = (x_{iq}^b \ y_{iq}^b \ 1)^T, b_{jq} = (x_{jq}^b \ y_{jq}^b \ 1)^T$$
$$c_{iq} = (x_{iq}^c \ y_{iq}^c \ 1)^T, c_{jq} = (x_{jq}^c \ y_{jq}^c \ 1)^T$$

the projections of vertices A_q, B_q and C_q in the two images i and j for q go from *1* to n . By referring to the fixed reference, we can write:

$$\begin{cases} (x_{iq}^a \ y_{iq}^a \ 1)^T \sim H_i(R^q W_q U_1 + t^q) \\ (x_{jq}^a \ y_{jq}^a \ 1)^T \sim H_j(R^q W_q U_1 + t^q) \\ (x_{iq}^b \ y_{iq}^b \ 1)^T \sim H_i(R^q W_q U_2 + t^q) \\ (x_{jq}^b \ y_{jq}^b \ 1)^T \sim H_j(R^q W_q U_2 + t^q) \\ (x_{iq}^c \ y_{iq}^c \ 1)^T \sim H_i(R^q W_q U_3 + t^q) \\ (x_{jq}^c \ y_{jq}^c \ 1)^T \sim H_j(R^q W_q U_3 + t^q) \end{cases} \quad (4)$$

With H_i and H_j are respectively the homography matrices scene to image *i* and scene to image *j*. by developing the equations of system (4) we obtain:

$$\begin{cases} (x_{iq}^a \ y_{iq}^a \ 1)^T \sim H_i R^q W_q U_1 + H_i t^q \\ (x_{jq}^a \ y_{jq}^a \ 1)^T \sim H_j R^q W_q U_1 + H_j t^q \\ (x_{iq}^b \ y_{iq}^b \ 1)^T \sim H_i R^q W_q U_2 + H_i t^q \\ (x_{jq}^b \ y_{jq}^b \ 1)^T \sim H_j R^q W_q U_2 + H_j t^q \\ (x_{iq}^c \ y_{iq}^c \ 1)^T \sim H_i R^q W_q U_3 + H_i t^q \\ (x_{jq}^c \ y_{jq}^c \ 1)^T \sim H_j R^q W_q U_3 + H_j t^q \end{cases} \quad (5)$$

Let:

$$\lambda_{iq} = H_i R^q W_q, \lambda_{jq} = H_j R^q W_q \quad (6)$$

$$\delta_{iq} = H_i t^q, \delta_{jq} = H_j t^q \quad (7)$$

So the system (5) can be written as follows:

$$\begin{cases} (x_{iq}^a \ y_{iq}^a \ 1)^T \sim \lambda_{iq} U_1 + \delta_{iq} \\ (x_{jq}^a \ y_{jq}^a \ 1)^T \sim \lambda_{jq} U_1 + \delta_{jq} \\ (x_{iq}^b \ y_{iq}^b \ 1)^T \sim \lambda_{iq} U_2 + \delta_{iq} \\ (x_{jq}^b \ y_{jq}^b \ 1)^T \sim \lambda_{jq} U_2 + \delta_{jq} \\ (x_{iq}^c \ y_{iq}^c \ 1)^T \sim \lambda_{iq} U_3 + \delta_{iq} \\ (x_{jq}^c \ y_{jq}^c \ 1)^T \sim \lambda_{jq} U_3 + \delta_{jq} \end{cases} \quad (8)$$

On the other hand from (6) and (7) we can deduce:

$$\lambda_{jq} = H_{ij}\lambda_{iq}\,,\ \delta_{jq} = H_{ij}\delta_{iq} \tag{9}$$

With $H_j\, H_i^{-1}$ is the homography matrix transforming the points from image i to image j.
By replacing in (8) λ_{jq} and δ_{jq} by their expressions given by (9), we obtain:

$$\begin{cases} (x_{iq}^a\ \ y_{iq}^a\ \ 1)^T \sim \lambda_{iq}U_1 + \delta_{iq} \\ (x_{jq}^a\ \ y_{jq}^a\ \ 1)^T \sim H_{ij}\lambda_{iq}U_1 + H_{ij}\delta_{iq} \\ (x_{iq}^b\ \ y_{iq}^b\ \ 1)^T \sim \lambda_{iq}U_2 + \delta_{iq} \\ (x_{jq}^b\ \ y_{jq}^b\ \ 1)^T \sim H_{ij}\lambda_{iq}U_2 + H_{ij}\delta_{iq} \\ (x_{iq}^c\ \ y_{iq}^c\ \ 1)^T \sim \lambda_{iq}U_3 + \delta_{iq} \\ (x_{jq}^c\ \ y_{jq}^c\ \ 1)^T \sim H_{ij}\lambda_{iq}U_3 + H_{ij}\delta_{iq} \end{cases} \tag{10}$$

The system (10) contains twelve equations with eleven unknowns (eight unknowns for λ_{iq} and three unknowns for δ_{iq}) where the possibility of estimating λ_{iq} and δ_{iq} . The matrix λ_{jq} and the vector δ_{jq} are estimated by using the relationship (9).

Formulation of self-calibration equations. From the equations (1) and (6) we can write for the image i:

$$\lambda_{iq} \sim K_i R_i \phi_i R^q W_q \tag{11}$$

With $\phi_i = \begin{pmatrix} 1 & 0 & \\ 0 & 1 & R_i^T t_i \\ 0 & 0 & \end{pmatrix}$ by multiplying the two terms of the previous equation by K_i^{-1} we obtain:

$$K_i^{-1}\lambda_{iq} \sim R_i \phi_i R^q W_q \tag{12}$$

Or:

$$\lambda_{iq}^T K_i^{-T} \sim W_q^T R^{qT} \phi_i^T R_i^T \tag{13}$$

By multiplying (12) and (13) we have:

$$\lambda_{iq}^T K_i^{-T} K_i^{-1} \lambda_{iq} \sim W_q^T R^{qT} \phi_i^T R_i^T R_i \phi_i R^q W_q \tag{14}$$

Or:

$$\lambda_{iq}^T \omega_i \lambda_{iq} \sim W_q^T R^{qT} \phi_i^T R_i^T R_i \phi_i R^q W_q \tag{15}$$

By developing the above equation we obtain:

$$\lambda_{iq}^T \omega_i \lambda_{iq} \sim \begin{pmatrix} V_q^T V_q & V_q^T R_i^T t_i \\ t_i^T R_i V_q & t_i^T t_i \end{pmatrix} \tag{16}$$

With ù$_i$ is the matrix of image of absolute conic given by:

$$\omega_i = K_i^{-T} K_i^{-1} \text{ and } V_q = \begin{pmatrix} l_q & l_q^{'}\cos(\alpha_q) \\ 0 & l_q^{'}\sin(\alpha_q) \\ 0 & 0 \end{pmatrix}$$

For the image j we have:

$$\lambda_{jq}^T \omega_j \lambda_{jq} \sim \begin{pmatrix} V_q^T V_q & V_q^T R_j^T t_j \\ t_j^T R_j V_q & t_j^T t_j \end{pmatrix} \tag{17}$$

The first two rows and columns of the equations (16) and (17) are identical, let:

$$(\lambda_{iq})^T \omega_i (\lambda_{iq}) = \begin{pmatrix} f_{qi11} & f_{qi12} & f_{qi13} \\ f_{qi12} & f_{qi22} & f_{qi23} \\ f_{qi13} & f_{qi23} & f_{qi33} \end{pmatrix} \tag{18}$$

$$(\lambda_{jq})^T \omega_j (\lambda_{jq}) = \begin{pmatrix} f_{qj11} & f_{qj12} & f_{qj13} \\ f_{qj12} & f_{qj22} & f_{qj23} \\ f_{qj13} & f_{qj23} & f_{qj33} \end{pmatrix} \tag{19}$$

From (18) and (19) we can deduce the following equations:

$$\begin{cases} f_{q11i} f_{q12j} - f_{q11j} f_{q12i} = 0 \\ f_{q11i} f_{q22j} - f_{q11j} f_{q22i} = 0 \end{cases} \tag{20}$$

With q varying from *1* to n.
For each parallelogram, including the basic parallelogram, we obtain two equations where the total number of intrinsic parameters is ten: five parameters for image i and five parameters for image j we need at least five parallelograms to estimate the intrinsic parameters of our camera in its two positions see fifteen points between the two

images used. In the present work we can determine several points matching between the two images which allow us to have more self-calibration equations.

The system (20) contains non- linear equations to solve it we minimize the following cost function:

$$\min_{\psi_{ij}} \sum_{i=1}^{r-1} \sum_{j=i+1}^{r} \sum_{h=1}^{d} (\rho_{ijh}^2 + \sigma_{ijh}^2) \qquad (21)$$

The minimization of the cost function (21) is performed by using the algorithm of Levenberg-Marquardt [29].
With r is the number of images used, d is the number of matching points between the two images used and :

- Ψ_{ij} is the vector of the intrinsic parameters of the camera in both views .
- $\rho_{ij\,h}$ and $\sigma_{ij\,h}$ are given by:

$$\rho_{ijh} = f_{h11i} f_{h12j} - f_{h11j} f_{h12i}$$
$$\sigma_{ijh} = f_{h11i} f_{h12j} - f_{h11j} f_{h12i}$$

The algorithm of Levenberg-Marquardt requires an initialization step . Assume for this purpose that the following conditions are satisfied:

- The principal point is in the center of the image so u_{0i}, v_{0i} , u_{0j} and v_{0j} are known.
- The pixels are squares so $\varepsilon_i = \varepsilon_j = 1$ and $\tau_i = \tau_j = 0$.
- By replacing the above parameters by their values in the system (20) we can estimate g_i and g_j .

5 Experimental evaluations

To evaluate the robustness of our approach two types of data are used: synthetic and real.

5.1 Computer simulations

In this simulation two 512x512 images of a planar scene is considered. After the detection of the interest points by using the Harris detector [30] and determining the matching points between the two images by using the correlation measure ZNCC [31,32,33,34,35], the inter-images homographies are estimated. The projection points of the scene in the image planes permit to formulate linear equations whose solutions are used with image of absolute conic in both views (see equations (18) and (19)) to obtain a system of non-linear equations from which we obtain a non-linear cost function, the resolution of the latter is given by performing a minimization using algorithm of Levenberg-Marquardt. The estimation of the elements of the matrix of the image of the absolute conic leads to the obtaining of the intrinsic camera parameters in each image. The different algorithms (Harris, ZNCC, Levenberg-Marrquardt, estimation of homography between images) used in this article are implemented by the object oriented programming language that is java.

To test the effectiveness of our algorithm we compared it with two methods. A reliable classical calibration [12] presented by Z. Zhang and another self-calibration method of camera characterized by variable intrinsic parameters [21] developed by Z. Jiang. The choice of the method of Z. Zhang is that it is a calibration method (uses a scene known so it gives very accurate results) which may be considered us a reference to self-calibration methods to test their strength while the choice of the approach of the Z. Jiang can be justified by the fact that this method contains common points with ours whose the main one is the variable intrinsic parameters. The methods are compared in the study of the relative errors in the focal length, the principal point, the scaling factor, the skew factor and the time of calculation, and this according to the number of matching points between the two images.

In this first computer simulation, we begin by studying the influence of the number of matching points between the two images on the calculation time covered by the three methods. To measure the execution time we implemented in our application java a class based on the method currentTimeMillis() of de class System. The following table shows the calculation time taken in seconds (by the three methods).

Table 1. Calculation time in seconds in function of the number of matching points

Number of matching points	Execution time in seconds		
	Our method	**Z.Zhang**	**Z.Jiang**
15	0.6	1.8	3.93
18	1.2	2	4.54
21	2.34	3.76	5.65

24	3.82	4.22	7.86
27	5.2	5.8	8
30	6	7.53	10.30
33	8.15	8.9	12.40
36	10.33	12.68	15
39	12.75	13.80	16.55

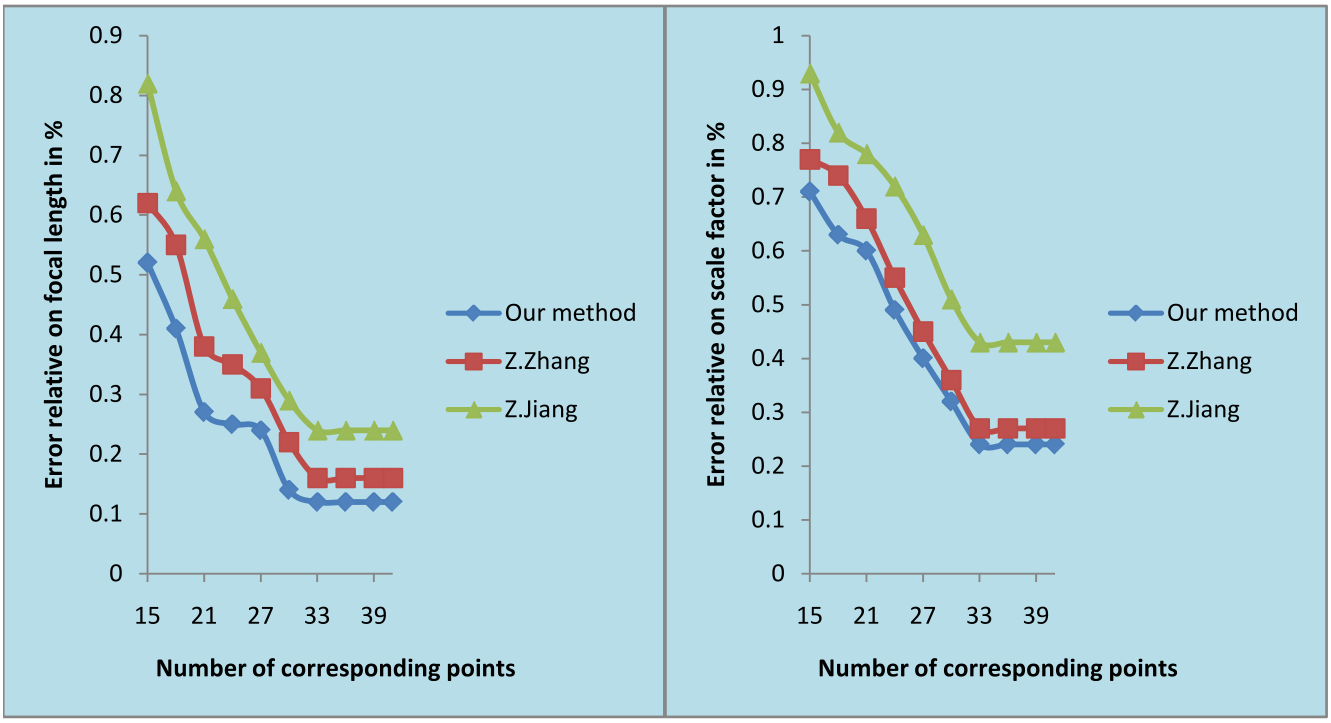
The values showed by the above table show that our method gives the satisfactory results. The growth in the number of matching points between the two images used causes an increase in the number of self-calibration equations on the one hand and the number of iterations performed to estimate the intrinsic parameters of the camera on the other hand; which explains the growth of the execution time for the three method; nevertheless, our method appears faster compared to others and this can be explained by the fact that the method presented by Z.Zhang performs two minimizations: the first to estimate the homography matrix scene to image and the second to determine the intrinsic parameters of the camera. While the approach given by Z.Jiang involves a determination of the coordinates of the plane at infinity and the estimation of the homography matrix of this plane which requires more calculation than our method.

The second half of our simulation tests the influence of the number of the matching points between the two images on the focal length , the principal point , the scale factor and the skew factor by performing a comparison with the methods [12] and [21] (figure 3).

The figure 3 shows that the estimation of the intrinsic parameters of the camera by our method is more accurate than the methods of Z.Jiang and Z.Zhang.This can be explained by the fact that this method uses directly the interest points in the images without finding out the geometric structure of the scene. These interest points are numerous and easy to detect. The above figures show that the relative errors of different intrinsic parameters decrease for a number of matching points between 15 and 33 this can be explained by the fact that the optimal solution of the cost function is not yet reached once the latter is reached the relative errors become constant and this for a number of matching points greater than 33.

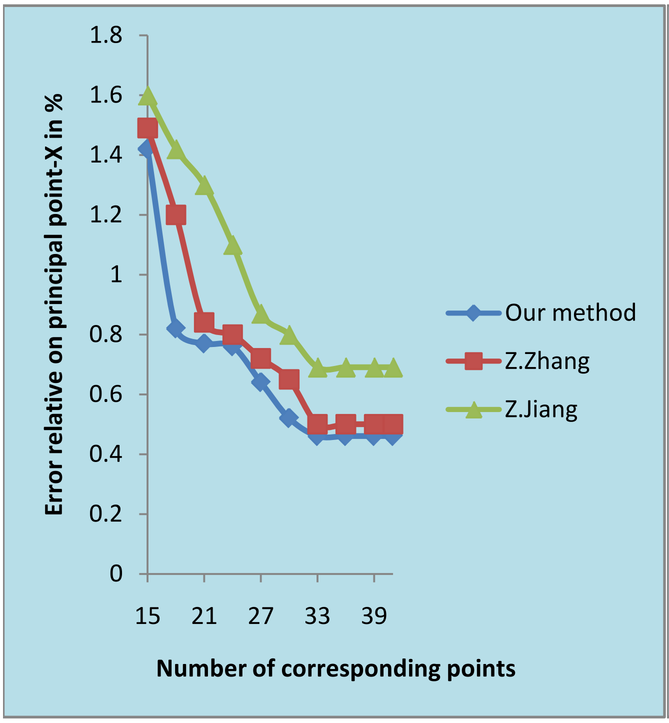
5.2 Real images

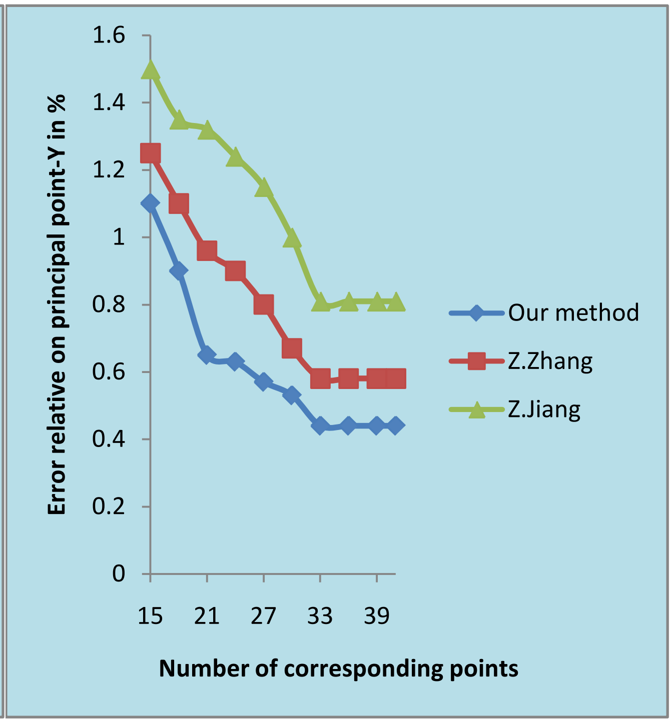
In this real evaluation two images of size 512 × 512 of a real planar scene (to construct the scene used, we placed a cartoonish image on a planar surface see figure 4) are acquired from two different views with a CCD camera having varying intrinsic parameters. The interest points are determined by the Harris detector and



a. Simulation results on focal length

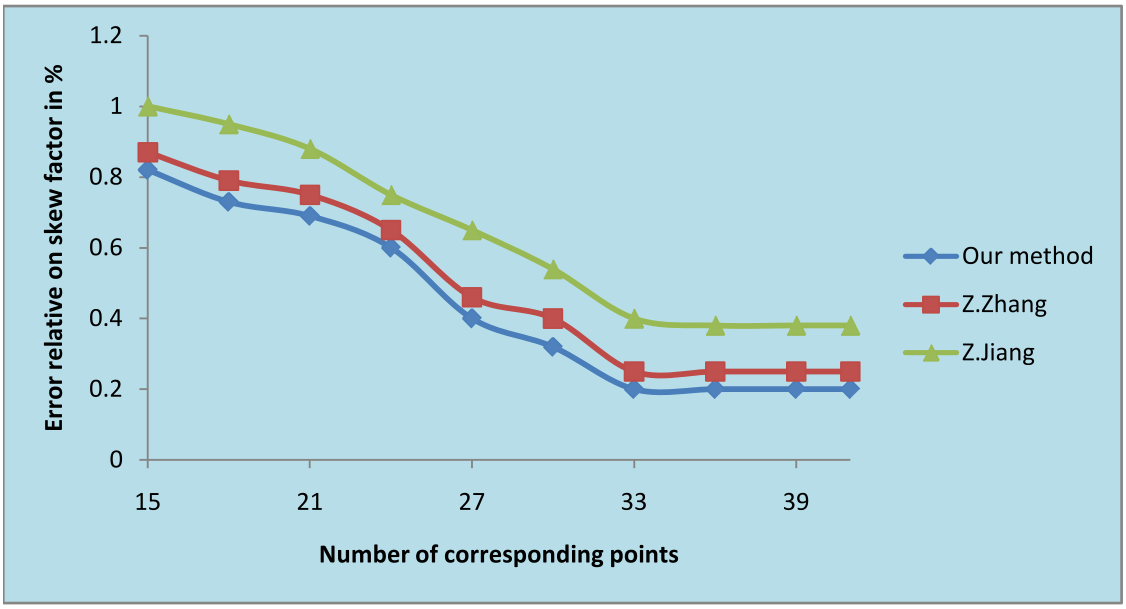
b. Simulation results on scale factor





c. Simulation results on principal point- X

d. Simulation results on principal point – Y



e. Simulation results on skew factor

Fig. 3. Simulation results on the g, ε, τ, u_0 and v_0 according to the number of matching points between the both images

their matching is given by the ZNCC correlation measure then the intrinsic camera parameters are estimated by applying our method proposed in this present article. The interest points in the two images, as reported previously, are detected by using the Harris detector and then are matched by using the ZNCC algorithm (Figure 5).

Estimation of intrinsic camera parameters. This step consists of estimating the intrinsic parameters of the camera in its two positions by applying our

new self-calibration method. The table 2 shows the solution obtained by using our method and those presented by Z.Jiang and Z.Zhang. For clarity we have displayed in table 2 only the results for fifteen and eighteen matching points between the two images *i* and *j*.

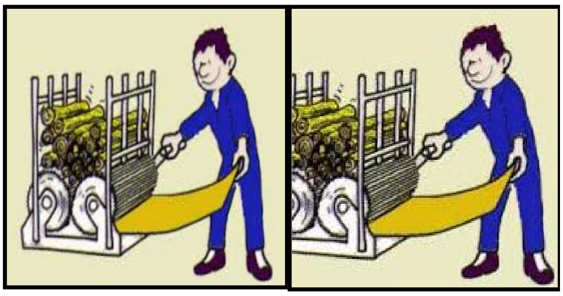
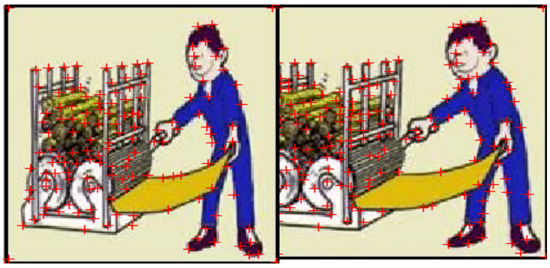
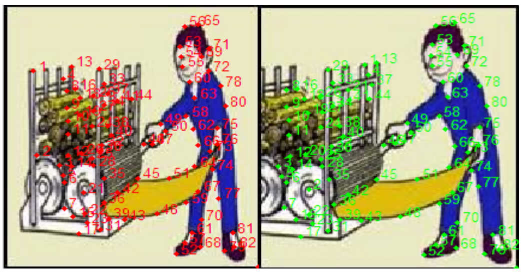


Fig. 4. The two real images used



a. Interest points detected by Harris detector



b. Matching points by ZNCC measure

Fig. 5. Detection and matching of interest points.

As showed in the table 2, the results obtained by our approach are similar to those given by the method of Z.Zhang which justifies the performance of our method (because the calibration methods are reliable) and better than those estimated by the method of Z. Jiang and this by considering the following advantages: our method is capable of self-calibrating a camera which moves freely, with variable intrinsic parameters and by using only two images of a unknown planar scene.

Table 2. Results of the experiment on real data given by the three methods

		Matching points	g	u_0	v_0	τ	ε
Our method	Image i	15	1650	261	258	0 ,08	0,87
		18	1654	262	260	0 ,05	0,90
	Image *j*	15	1652	261	255	0 ,07	0,93
		18	1656	260	259	0 ,04	0,94
Z.Zhang	Image *i*	15	1657	263	259	0,07	0,85
		18	1655	262	260	0,06	0,91
	Image *j*	15	1654	260	261	0,09	0,89
		18	1653	263	261	0,06	0,93
Z.Jiang	Image *i*	15	1636	252	261	0,21	0,65
		18	1635	261	260	0,16	0,74
	Image *j*	15	1637	253	262	0,23	0,68
		18	1638	260	261	0,18	0,76

6 Conclusion

This article proposes a novel algorithm for camera self-calibration in the case of the varying intrinsic parameters. The main point of this work is the possibility of surmounting the constraints of the self-calibration problem, constraints about camera intrinsic parameters, constraints about the scene viewed and constraints about the camera motion. In fact, our present method is capable of self-calibrating a camera having variable intrinsic parameters, from an unknown planar scene and by applying to the camera a free motion. The principle of this new approach treated in this paper, is based on the use of three non-collinear points of the scene that represent the vertices of an unknown parallelogram and its projections into only two images *i* and *j*. The projection of the three non-collinear points of the scene permits us to obtain two equations according to the intrinsic camera parameters and the image of the absolute conic in both images. Since for two images the number of variables representing the intrinsic parameters of the camera is ten so we will need at least ten equations. To solve this problem we have applied to the basic parallelogram a sequence of random transformations consists of translations and rotations to find new parallelograms to obtain more equations. In our future research we will try to improve our approach by reducing the number of matching points used between the two images, in other words by using a single unknown parallelogram of an unknown planar scene. The robustness of our method is proved by experimental results on synthetic and real data.

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