Camera Calibration with Varying Parameters Based On Improved Genetic Algorithm

MOSTAFA MERRAS[1], NABIL EL AKKAD[1], ABDERRAHIM SAAIDI[1,2] , ABDERRAZAK GADHI NAZIH[1], KHALID SATORI[1]

[1]LIIAN, Department of Mathematics and computer science
Faculty of Sciences, Dhar-Mahraz
Sidi Mohamed Ben Abdellah University
B.P 1796 Atlas- Fez
MOROCCO.

[2]LIMAO, Department of Mathematics, physics and computer science
polydisciplinary Faculty of Taza
Sidi Mohamed Ben Abdellah University
B.P 1223 Taza
MOROCCO

Email: merras.mostafa@gmail.com, ngadhi@hotmail.com, {nabil_abdo80, saaidi.abde, khalidsatorim3i}@yahoo.fr

Abstract: - In this paper, we propose an approach based on improved genetic algorithms for the camera calibration having the varying parameters. The present method is based on the formulation of a nonlinear cost function from the determination of the relationship between points of the image planes and all parameters of the cameras. The minimization of this function by a genetic approach enables us to simultaneously estimate the intrinsic and extrinsic parameters of different cameras. Comparing to traditional optimization methods, the camera calibration based on improved genetic algorithms can avoid being trapped in a local minimum and does not need the initial value. The proposed technique to find the near optimal solution without the need for initial estimates of the cameras parameters. Tested on several cases, the proposed method proved to be an effective tool to determine the camera parameters necessary for various applications, such as the images rectification, the analytical photogrammetry and 3D reconstruction from 2D images.

Key-words: - Camera calibration, computer vision, improved genetic algorithms, varying parameters, non-linear optimization.

1 Introduction

The camera calibration is a crucial step in the vision stereo and the 3D reconstruction [1], it consists of estimating the intrinsic and extrinsic parameters of the cameras. Different techniques of the calibration exist in [2, 3, 4 and 5] they are generally based on the pinhole model and use of images of an object reference with of known dimensions (Calibration pattern).

The mathematical optimization methods used may have some problems (stability of the method, the initial point of optimization), and this has prompted researchers to test approaches based on genetic algorithms [6, 7]. These approaches can be classified as methods of nonlinear stochastic optimization.

The optimization algorithms, and specifically those based on the evolutionary approach are widely used in the field of computer vision for various applications [8, 9, 10] their success in the field of the camera calibration and the stereoscopic vision is that they are capable to minimize the non-linear function for the calculating the cameras parameters. The minimization of nonlinear cost functions is not an easy task to achieve, as this function is not convex and contains of many the local minima complex.

The genetic algorithms have a significant contribution for the camera calibration relative to conventional methods, because they have no constraints vis-a-vis the model and can explore all the solutions of search space in order to optimize the result. Compared to conventional methods, the genetic algorithms offer the following advantages:

- Simple: the GA are simple in nature, they use a stochastic method to be closer the optimal solution.
- Effective: the GA is particularly effective in areas where the calculation of the optimal solution is linearly very difficult if not impossible.
- Flexible: the GA can adapt to of configurations and different models, and do not require the initial parameters accurate to find an optimal solution.
- Robustness: the GA explore a great population of solutions, they can explore parally the different sub-populations and avoid falling in a local minimum.

The GA showed that they were promising in various applications of the computer vision, and recently in the calibration and self-calibration of the cameras. We describe below the various applications of evolutionary algorithms used for calibration and self-calibration of camera. In the literature, two genetic algorithms methods used to estimate the camera parameters, one lets find the intrinsic and extrinsic parameters of the camera directly by genetic algorithms [11, 12, 13, 14, 15, 16, 17, and 18] the authors which have developed of genetic algorithms for estimating the camera parameters per minimizing a non-linear cost function. They use 2D grid and objects geometrically known (cube) to calibrate the camera with very reliable results. The other serves to find the camera parameters by compounds algorithms between the genetic algorithm and other non-linear optimization algorithms namely Levenberg-Marquardt, Particle Swarm optimization, Nelder-Mead simplex, In several papers [19, 20] the authors have proposed a procedure of camera calibration into two stages, first, a GA is used for finding a good approximation of the solution. Then a non-linear minimization algorithm (Nelder-Mead simplex, Levenberg-Marquardt) is applied to refine the results. At the end of the execution of the GA, the best individual will make office as input to the non-linear minimization algorithm, a refined solution is obtained. If the error obtained after the latter execution is acceptable, the results will be final if not the calibration process will restart from the GA which will include the last best individual for initialization of the new population. In both approaches, the authors use the cameras characterized by constant parameters.

In the paper [21] we deal the camera calibration having by varying parameters based on hybrid optimization algorithm, in this approach the formulation and optimization of the cost function performed in 3D.

In the present work, we use the coordinates of 3D points for the formulation a non-linear cost function from matching points in the images couple. Our approach solves the problem of camera calibration in three steps: First, the detecting and matching of interest points in the pair of images (left and right) is performed. Secondly, formulating the non-linear cost function, and finally the minimal value of the optimized cost function is calculated by the algorithm IGA.

The proposed approach is distinguished from other genetic approaches by the following points:

- We used a three-dimensional grid for calibration, this will provide more learning points in a shooting and can avoid the photographic capture of various orientations of a planar grid the chessboard type, and the calibration process is thus simplified and faster.
- The cameras used are characterized by varying parameters which render the calibration procedure most robust with any constraint on the cameras used.

The rest of what paper is organized as follows: In section 2, we will present the background. Section 3 describes the camera calibration procedure. The experiments results and analysis are explained in section 4 and the conclusion is presented in section 5.

2 Background

To better understand the operating principle, we are proposing below a brief introduction to GA and of projective geometry used for the camera calibration.

2.1 Perspective geometry

To get the Pinhole model of the camera, the coordinate system must be specified. All coordinate systems are Cartesians [19]. The image plane is before the center to optical C (Figure 1), which is the origin of the Camera Coordinate System (CCS). In fact, the image plane is behind the optical center located at the objective optical, this change a for intended to simplify the understanding of this system, no geometric calculation is influenced by this change. The origin of the Image Coordinate System (ICS) is the point representing the center of the surface of the optical sensor (CCD), in some algorithms we assume that it is left at the top end.

In the image plane, the coordinates are expressed in pixels, whereas in other systems the main unit is the millimeter.

Given a point P_w, its coordinates in the Coordinate System of the Scene (CSS) are written as: $P_w = [X_w \ Y_w \ Z_w]^T$. This corresponds to the point:

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$P_C = [X_C \ Y_C \ Z_C]^T$ in the Camera Coordinate System (CCS), and it is projected as much as $P_1 = [X_1 \ Y_1]^T$ in the Image Coordinate System (ICS) (Figure 1).
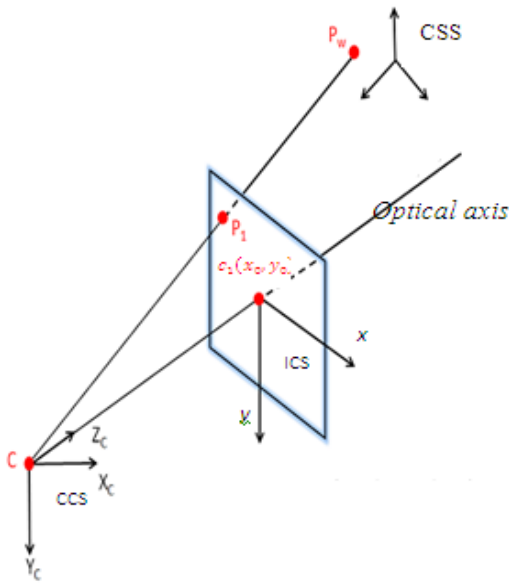

Fig. 1 Perspective projection geometry

The transformation matrix between the CSS and the CCS can be defined as follows:

$$H_C^W = \begin{bmatrix} R_C^W & T_C^W \\ 0 & 1 \end{bmatrix} \qquad (1)$$

Where:

$T_C^W = [t_x \ t_y \ t_z]^T$ is the translation vector, R_C^W is the 3x3 rotation matrix determine the three rotation angles $(\omega, \emptyset, \theta)$ of Euler, on three respective axes (x, y, z).

$$R_c^w = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \qquad (2)$$

$$\begin{cases} r_{11} = \cos \emptyset \cos \theta \\ r_{12} = \sin \omega \sin \phi \cos \theta + \sin \omega \sin \theta \\ r_{13} = -\cos \omega \sin \phi \cos \theta + \sin \omega \sin \theta \\ r_{21} = -\cos \emptyset \sin \theta \\ r_{22} = -\sin \omega \sin \phi \sin \theta + \cos \omega \cos \theta \\ r_{23} = \cos \omega \sin \phi \sin \theta + \cos \theta \sin \omega \\ r_{31} = \sin \phi \\ r_{32} = -\sin \omega \cos \emptyset \\ r_{33} = \cos \emptyset \cos \omega \end{cases} \qquad (3)$$

The point on the image plane is obtained by a perspective projection of 3D point in the CSS to a 2D point using the combined transformation matrix:

$$H_F^C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \frac{1}{f} & 1 \end{bmatrix} \qquad (4)$$

Where f is the focal length (distance between the optical center and the image plane).

The coordinates in the image plane are obtained by:

$$H_I^F = \begin{bmatrix} dx & 0 & x_0 \\ 0 & dy & y_0 \\ 0 & 0 & 1 \end{bmatrix} \qquad (5)$$

Where: $dx = k_x . f$ and $dy = k_y . f$, (k_x, k_y) are the scale factors vertical and horizontal, x_0 and y_0 are the coordinates of the image center.

- The intrinsic parameters are: f, k_x, k_y, x_0, y_0
- The extrinsic parameters are: $\omega, \emptyset, \theta, t_x, t_y, t_z$

Offering a total of 11 parameters for this model of the each camera which will be determined by the calibration procedure. The camera calibration requires a mathematical equation linking the coordinates of the scene with that of the image. For a given point P_W, the relation can be written as follows

$$P_1 = H_I^F . H_F^C . H_C^W . P_W \qquad (6)$$

2.2 Genetic algorithms

The Genetic Algorithms are stochastic exploration algorithms based on the mechanism of natural selection and evolution [6]. They were designed to explore efficiently the large space of the non-linear solutions, where the problem to be solved can be formulated in an accurate, putting in difficulty the traditional optimization methods. The GA performs a multidirectional search in a population of potential solutions. A population of potential solutions is modified by the application of genetic operators from one generation to another. The main "genetic operators" are: generating the initial population, the evaluation of each individual, the selection and the recombination (crossover / mutation). The evaluation of an individual has for goal is to give a note to each according to its relevance (fitness) to the problem processed order to evolve the population in direction with the acceptable solutions [22].

The execution of a genetic algorithm of generally speaking can be place as follows:

1. Random generation of a population of "N" individuals (chromosomes).
2. Evaluation of each individual in the population.
3. Selection two parents individuals according on their fitness score.

4. According on the probability of crossover, cross the two parent individuals and generates two children.
5. Depending on the mutation probability, mutate the two children previously generated.
6. Place the new individuals in the population.
7. Use the new population for a new execution of the algorithm until a satisfactory approximate solution is found.

2.3 Vision system

To determine the intrinsic and extrinsic parameters of the cameras, we propose the following vision system.

The projection the a three-dimensional grid provided with its global reference (O, X', Y', Z'), in the image plane left and right by two different cameras (Figure 2) is given by the projection matrices associated to each left and right cameras respectively according to the following expression:

$$\begin{cases} D_1 = H_{I1}^F . H_{F1}^C . H_{C1}^W \\ D_2 = H_{I2}^F . H_{F2}^C . H_{C2}^W \end{cases} \tag{7}$$

With $H_{I1}^F . H_{F1}^C$ and $H_{I2}^F . H_{F2}^C$ respectively matrices of intrinsic parameters of left and right cameras, and H_{C1}^W and H_{C2}^W are the matrices of the extrinsic parameters of left and right cameras.
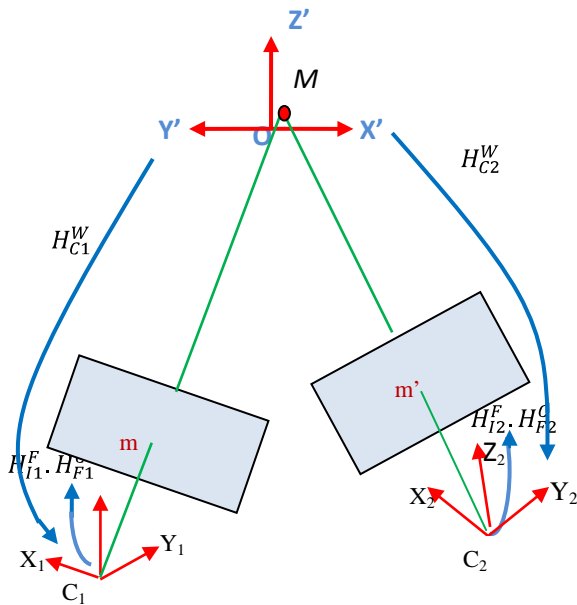

Fig. 2 Our vision system used for calibration

3 Camera calibration procedure

The cameras calibration having the varying parameters by improved genetic algorithms consists to find the intrinsic and extrinsic parameters of the cameras with a 3D grid known geometrically. To optimize the IGA, we opted for a favored generation of initial population, for a desired initial population for example, a number N of individuals is randomly generated according to the initial bounds of the parameters.

Each individual represents a potential solution of the calibration problem, and each individual is composed of genes representing the intrinsic and extrinsic parameters to estimate. These genes are encoded by real values in a vector to 22 parameters (parameters of two cameras).

3.1 Input data

The input data of our method is a set of coordinates of 3D points beforehand determined in the 3D grid. And the coordinates of 2D points detected and matched on each pair of images. These points are detected by the Harris detector and matched by a correlation measure ZNCC (Zero mean Normalized Cross-Correlation) the main idea of this correlation is to measure the pixels similarity between pair of images by calculating the correlation score between two windows, see more details in [23, 24].

We also provide to algorithm the initial bounds to the parameters to be estimate which limiting the search space for the optimal solution. Parameters to be estimated are:

- For left camera
  The intrinsic parameters of the left camera are: $f_g, k_{xg}, k_{yg}, x_{0g}, y_{0g}$ (f_g: focal length, (k_{xg}, k_{yg}): scale factors horizontal and vertical, (x_{0g}, y_{0g}): the coordinates of image center).
  The extrinsic parameters of the left camera are: $\omega_g, \emptyset_g, \theta_g, t_{xg}, t_{yg}, t_{zg}$ (($\omega_g, \emptyset_g, \theta_g$): rotation angles, (t_{xg}, t_{yg}, t_{zg}) translation vector).
- For right camera
  The intrinsic parameters of the right camera are: $f_d, k_{xd}, k_{yd}, x_{0d}, y_{0d}$ (f_d: focal length, (k_{xd}, k_{yd}): scale factors horizontal and vertical, (x_{0d}, y_{0d}): the coordinates of image center.
  The extrinsic parameters of the right camera are: $\omega_d, \emptyset_d, \theta_d, t_{xd}, t_{yd}, t_{zd}$ (($\omega_d, \emptyset_d, \theta_d$): rotation angles, (t_{xd}, t_{yd}, t_{zd}) translation vector).
  Offering into total, 22 parameters for the two cameras.

3.2 Objective function

We denote by v the vector formed by the intrinsic and extrinsic parameters to estimate:

$$v = [f_g, k_{xg}, k_{yg}, x_{0g}, y_{0g}, \omega_g, \emptyset_g, \theta_g, t_{xg}, t_{yg}, t_{zg},$$

$$f_d, k_{xd}, k_{yd}, x_{0d}, y_{0d}, \omega_d, \emptyset_d, \theta_d, t_{xd}, t_{yd}, t_{zd}]^{\mathrm{T}}$$

$$(8)$$

For reasons of notation, the vector v is denoted by: $v = (v_1, v_2, \dots, v_{22})^{\mathrm{T}}$ where v_i are the predefined parameters previously. This vector corresponds to a possible solution to the calibration problem and is part of the set of potential solutions V.

$$V = \{v : v_i \in [v_i^-, v_i^+]; i = 1, 2, \dots, n\} \quad (9)$$

Where v_i^- and v_i^+ are the bounds of the variation interval given for each parameter obtained. These bounds are transmitted into input to IGA and are initially obtained by the knowledge we have of the camera (large bounds can be set for the unknown parameters). The parameters do not necessarily have the same bounds. For example $\omega_g, \emptyset_g, \theta_g \in [-\pi, \pi]$, $f_g \in [20,70]$(the variation interval of f_g) and so on. An optimal solution of v with M control points can be obtained by minimizing the next non-linear cost function:

$$\begin{cases} F(v) = \sum_{i=1}^{M} \begin{bmatrix} \left(q^g(v, X_i) - x_i^g\right)^2 + \left(w^g(v, X_i) - y_i^g\right)^2 + \\ \left(q^d(v, X_i) - x_i^d\right)^2 + \left(w^d(v, X_i) - y_i^d\right)^2 \end{bmatrix} \\ v \in V \end{cases} \quad (10)$$

Where:
- $X_i = (x_i, y_i, z_i)^T$: are the coordinates of point X_i in the scene.
- (x_i^g, y_i^g) and (x_i^d, y_i^d) Matching Couple between the left and right images.
- $q^g(v, X_i)$, $w^g(v, X_i)$ and $q^d(v, X_i)$, $w^d(v, X_i)$ are the functions to find the coordinates of the projection of a point X_i of the scene on the left and right images respectively, such as:

$$\begin{cases} q^d(v, X_i) = f_d k_{xd} \dfrac{r_{11d}x_i + r_{12d}y_i + r_{13d}z_i + t_{xd}}{r_{31d}x_i + r_{32d}y_i + r_{33d}z_i + t_{zd}} + x_{0d} \\ w^d(v, X_i) = f_d k_{yd} \dfrac{r_{21d}x_i + r_{22d}y_i + r_{23d}z_i + t_{yd}}{r_{31d}x_i + r_{32d}y_i + r_{33d}z_i + t_{zd}} + y_{0d} \end{cases}$$

$$\begin{cases} q^g(v, X_i) = f_g k_{xg} \dfrac{r_{11g}x_i + r_{12g}y_i + r_{13g}z_i + t_{xg}}{r_{31g}x_i + r_{32g}y_i + r_{33g}z_i + t_{zg}} + x_{0g} \\ w^g(v, X_i) = f_g k_{yg} \dfrac{r_{21h}x_i + r_{22h}y_i + r_{23h}z_i + t_{yh}}{r_{31h}x_i + r_{32h}y_i + r_{33h}z_i + t_{zh}} + y_{0h} \end{cases} \quad (11)$$

The improved genetic algorithm performs optimization by the repeating of the genetic operations until the stopping criterion be pleased. The stopping criterion is that the minimum evaluation function F_{min} remains the same for a given time. The best individual is be defined as optimal solution to the problem.

3.3 Minimization the cost function by an improved genetic algorithm
The genetic operators necessary to form an IGA are:

3.3.1 Non linear selection
To select the best individuals we adopt in this approach a non-linear selection, is the card of individuals following: $pop = \{v^1, v^2, \dots v^i \dots, v^N\}$ with N the size of the population, we distribute the probability of each individual from best to worst by a non-linear function, so that the probability of selection of the individual v^i is:

$$p(v^i) = \frac{\beta(1-\beta)^{i-1}}{1-(1-\beta)^N} \quad (12)$$

Where β the selection probability of the best individual, i is the serial number of the individual.

Once the probability of each individual in the population is determined, the roulette selection is used to select individuals excellent.

3.3.2 Mutation
Different from the uniform mutation of simple genetic algorithm, the mutation operation with adaptive change of scaling of mutation is used in this paper. With a uniform probability, based on the concept that the mutation scaling ψ is decreasing gradually during the process, a monotonically decreasing function of the mutation scaling ψ is built:

$$\psi(\xi) = 1 - \Upsilon^{\left(1 - \frac{\xi}{\aleph}\right)^2} \quad (13)$$

Where $\aleph$ is the number of generation or iteration, ξ the current iteration, and the weight $\Upsilon \in [0, 1]$.

Knowing that $\psi \in [0\ 1]$ the scaling of the mutation (13). The element $v_k(v_k \in [v_k^-, v_k^+])$ selected in the individual $(v_1, v_2, \dots, v_k, \dots, v_{22})$ is to be mutated with a mutation probability P_m, the original value of v_k must be replaced by the new value mutated v_k^{new} chosen in the interval defined by the following formula:

$$v_k^{new} \in \left\{ max\left(v_k - \psi \frac{v_k^+ - v_k^-}{2}, v_k^-\right), min\left(v_k + \psi \frac{v_k^+ - v_k^-}{2}, v_k^+\right) \right\} \quad (14)$$

The importance of this type of mutation is to use a largest interval to maintain a diverse population in the first generation for performing a global search and avoid rapid convergence of the algorithm. This mutation interval gradually decreased during the iterations for to focus on local search of the solution.

3.3.3 Crossover

The crossover of our approach is the follows: Suppose v_i and v_j two potential solutions to a generation $l(i \# j)$. A generation $l + 1$ two son individuals v_{1a}, v_{2a} can be generated by crossover by next formulas:

$$\begin{cases} v_{1a} = v^+(1 - \eta) + max(v_i, v_j)\,\eta \\ v_{2a} = v^-(1 - \eta) + min(v_i, v_j)\,\eta \end{cases} \quad (14)$$

Where $\eta \in [0\ 1]$ is a weight, $max(v_i, v_j)$ is the vector of each element obtained by taking the maximum between the corresponding elements of v_i and v_j. The same $min(v_i, v_j)$ denotes the vector obtained by taking the minimum values.

We executed the IGA under the following parameters (Table 1).

Table 1   Parameters of IGA

Population size	Crossover probability P_c	Mutation probability P_m	Number of iterations T
200	0.80	0.1	120

4 Experimental results

4.1 Synthetic data

In this section, a sequence of 512×512 images of a 3D grid is simulated to test the performance and robustness of the present approach. After the detection of control points by the Harris detector [24, 25], the matches between each pair of images are determined by the correlation function ZNCC [23, 24]. The 3D grid is projected in images plan taken from different views with Gaussian noise of standard deviation σ. The determination of a relationship between the points of the 3D grid and their projections in the images plan can define a non linear cost function. This cost function is minimized by our IGA, finally the intrinsic and extrinsic parameters are obtained.

The table 2 show the relative error of the focal length (for example) of the left camera used depending on Gaussian noise of our approach compared with other methods Tsai's two step

calibrations technique [2] to be implemented and executed on our test images.

Table 2 the relative error (%) of the f_g according the noise

Noise (σ)	0	0,5	1	1,5	2	2,5	3
Our approche	0,01	0,07	0,09	0,098	0,13	0,16	0,23
Tsai's	0,09	0,2	0,3	0,52	0,67	0,93	1,1

The figure 3 shows the graphical representation of the relative error on the focal length of the left camera.
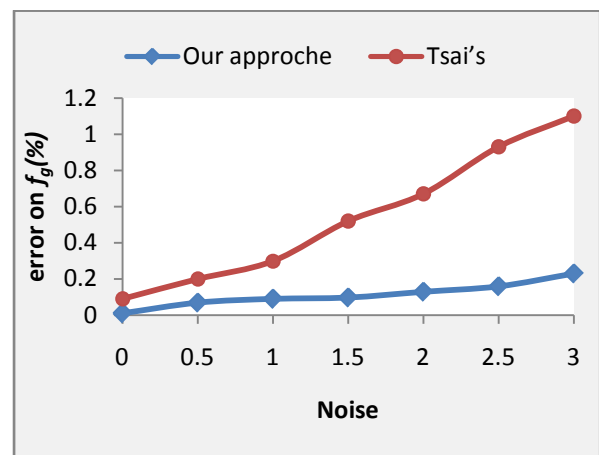

Fig. 3 Relative error of f_g according the Gaussian noise

A Gaussian noise with a standard deviation (so that $\sigma \leq 3$ pixels) is added to all image pixels to show the performance and robustness of the present method. A simple reading of Fig. 3 and Table 2, we ignored the results of the Tsai's method, because from $\sigma \geq 1$, the errors of the cameras parameters enlarge , we can conclude that the Tsai's method gives results accurate when the images are not noisy or slightly noisy. Unlike, in our approach the error of the camera parameters is approximately constant for various noise values up to $\sigma = 2.5$, but these errors increase slowly if σ exceeds 2,5 pixels. This shows that the presented approach is more accurate and robust to noise.

4.2 Real data

This section deals with the experiment results of the different algorithms implemented by the Java object oriented programming language. We use the 512x512 images (Fig. 4), in which we know the locations of interest points on the image pair and their corresponding 3D object coordinates. Based on

CCD camera which is characterized by varying parameters. Two images are show in Fig 4. The interest points and matches between these two images are shown respectively in Figs. 5 and 6, the intrinsic and extrinsic parameters estimated by two methods (the present method and Tsai's [2]) shown in table 3.

Figure 5 shows the interest points obtained by the Harris detector in the two images. 46 interest points were detected in the first image, and 46 interest points were detected in the second image.

The interest points detected by the Harris algorithm are matched between two images by the correlation function ZNCC. Figure 6 shows the 32 matches obtained by this correlation.
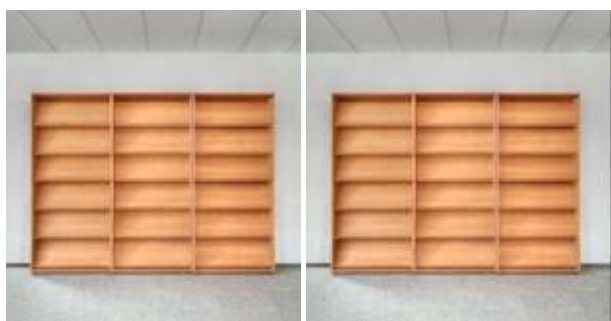
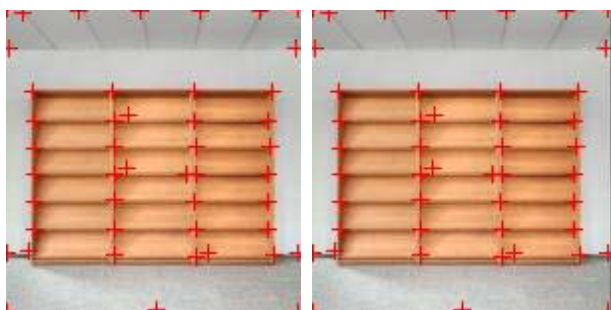

Fig. 4 two Images of 3D scene

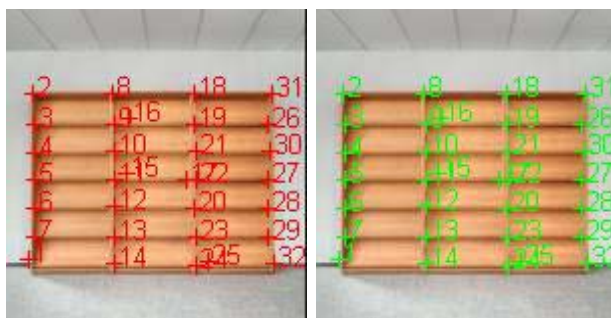Fig. 5 the interest points are shown in red in the two images

Fig. 6 The matches are shown in the two images

In order to obtain the good values of the intrinsic and extrinsic parameters of two cameras, we gives to the algorithm the initial bounds for the parameters to be estimated which limiting the search space for the optimal solution. The large bounds (table 3) can be defined for the unknown parameters to obtain a good accuracy. Table 3 shows the optimal solution of the parameters of cameras used obtained by our method and Tsai's [2].

Table 3 The results of the cameras parameters estimated by the two methods

Parameters of two cameras		Our method		Tsai's (single camera)
		Large Bounds $[v^-, v^+]$	optimal value by IGA	
Left camera	f_g	[10,100]	64.00	63,94
	k_{xg}	[50,90]	69.00	67,32
	k_{yg}	[50,90]	70.25	63,01
	x_{0g}	[200,280]	252.00	257,00
	y_{0g}	[190,220]	210.00	206,00
	t_{xg}	[-400,400]	-93.00	-102,00
	t_{yg}	[-400,400]	-88.00	-94,10
	t_{zg}	[700,2000]	1802.00	1793,00
	ω_g	[-π, π]	0.500234	0,41003
	ϕ_g	[-π, π]	0.020134	0,02965
	θ_g	[-π, π]	0.043671	0,01784
Right camera	f_d	[10,100]	61.50	
	k_{xd}	[50,90]	68.20	
	k_{yd}	[50,90]	70.00	
	x_{0d}	[200,280]	250.00	
	y_{0d}	[190,220]	201.00	
	t_{xd}	[-400,400]	-96.50	
	t_{yd}	[-400,400]	-80.00	
	t_{zd}	[700,2000]	1841.46	
	ω_d	[-π, π]	0.512679	
	ϕ_d	[-π, π]	0.024671	
	θ_d	[-π, π]	0.046237	

After comparing the results on the synthetic data, the results of the present approach on real data (the two images shown in Fig. 4) are compared to those obtained by Tsai's [2]. The reading and the analysis of the camera parameters presented in Table 3 show that the results of the present approach are a little different from those obtained by Tsai's [2], this is logical because the impoved genetic algorithm has less chance to generate values far removed from the optimum and helps avoid the local minima of the cost function. Therefore, this approach provides a robust performance and accuracy. In addition, this method has several advantages: the use of free cameras with varying parameters this which make the calibration process more robust without no constraints on the cameras used, the use an IGA to optimize the cost function, this algorithm converges to an optimal

solution without initial estimates of the parameters and helps avoid the local minima of the cost function.

5 Conclusion

In this article, a robust method of camera calibration with varying parameters based on improved genetic algorithms is presented. This new approach is based on determination of a relationship between points in 3D scenes and their projection in planes of images, this relationship give a non linear cost function and the minimisation of this function provides the intrinsic and extrinsic of the cameras used. The importance of our approach of calibration manifested in two points, the first is the use of free cameras with varying parameters this which make the calibration process more robust without no constraints on the cameras used. The second point is the use an IGA to optimize the cost function, this algorithm converges to an optimal solution without initial estimates of the parameters and helps avoid the local minima of the cost function. The robustness of this method in terms of simplicity, accuracy, stability, and convergence is shown by the results of the experiments and the simulations conducted.

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