Erciyes Üniversitesi Fen Bilimleri Enstitüsü Dergisi 26 (4) 340-350 (2010)

Erciyes University Journal of the Institute of Science and Technology
Erciyes Üniversitesi Fen Bilimleri Enstitüsü Dergisi
http://fbe.erciyes.edu.tr
ISSN 1012-2354
Cilt (Volume) 26, Sayı (Issue) 4, Aralık/December-2010

The effectiveness of intelligent optimization techniques in camera calibration

Coşkun Özkan[1], Emre Bendeş[2]
[1] *Erciyes University, Engineering Faculty, Computer Engineering, Kayseri*
[2] *Erciyes University, Engineering Faculty, Geomatics Engineering, Kayseri*

Keywords
Luca Lucchese
Camera Calibration
Artificial Bee Colony
(ABC)

ABSTRACT
In this paper, it is aimed to examine the effectiveness of the intelligent optimization algorithms to optimize the camera parameters with respect to the calibration method introduced by Luca Lucchese (LL). The motivation of the intelligent optimization algorithms is that they are so effective, flexible and easy adaptable for the real complex problems. The selected optimization algorithms are Artificial Bee Colony (ABC), Differential Evolution (DE), Genetic Algorithm (GA) and Particle Swarm (PSO). These algorithms except ABC have been used effectively for many complex problems. ABC has recently developed and its effectiveness has not been tested for a type of the camera calibration problem. But it is highly capable of generating good solutions for many benchmark functions such as Rosenbrock and Rastrigin with both low and very high dimensions. The other artificial intelligent optimization algorithms are also the first time being used in this camera calibration problem. In order to show the effectiveness of these intelligent optimization algorithms, their results have been compared with the conventional derivative-based Levenberg-Marquardt (LM).

Kamera kalibrasyonunda zeki optimizasyon yöntemlerinin etkinliği

Anahtar Kelimeler
Luca Lucchese Kamera Kalibrasyonu
Yapay Arı Kolonisi (ABC)

ÖZET
Bu çalışmanın amacı, literatürde Luca Lucchese'ın önerdiği kamera kalibrasyon metoduna ait model parametrelerinin optimizasyonunda zeki optimizasyon yöntemlerinin etkinliklerinin incelenmesidir. Bu algoritmalar, gerçek karmaşık dünya problemlerinin çözümünde oldukça etkili, esnek ve kolay adapte edilebilir oldukları için tercih edilmişlerdir. Seçilen algoritmalar, Yapay Arı Kolonisi (ABC), Diferansiyel Gelişim (DE), Genetik Algoritma (GA) ve Parçacık Sürü Optimizasyonu (PSO) algoritmalarıdır. Bu algoritmalardan ABC hariç diğerleri birçok gerçek dünya probleminin çözümünde kullanılmıştır. ABC algoritması yeni geliştirilmiş olduğu için literatürde Rosenbrock ve Rastrigin gibi az ve çok boyutlu bir çok temel fonksiyon üzerinde test edilmiş fakat henüz etkinliği bu tip bir kamera kalibrasyon probleminde araştırılmamıştır. Diğer zeki optimizasyon yöntemleri de bu tip bir kamera kalibrasyon problemi için ilk defa kullanılmaktadır. Algoritmaların etkinlikleri, sonuçlar Levenberg-Marguardt yöntemiyle karşılaştırılarak ortaya konulmuştur.

* *Sorumlu yazar (Corresponding author) e-posta:* cozkan@erciyes.edu.tr

Erciyes Üniversitesi Fen Bilimleri Enstitüsü Dergisi 26 (4) 340-350 (2010)

1. INTRODUCTION

Camera calibration is an important step in many fields such as computer vision and image processing. The main idea in the camera calibration is to determine the camera transformation parameters from 2D image points to the corresponding 3D space points. Thus, camera calibration is especially used to extract metric information from 2D images [1]. The number of camera parameters can change depending to the type of camera calibration approach.

Basically there are two types of camera parameters: (i) internal parameters that create mathematically the inner geometry of a camera when the image exposed, they are principal point coordinates, effective focal length and distortions, (ii) external parameters that define the angular attitudes in terms of roll, pitch and yaw angles and the positional displacements with respect to an object coordinate system. Although these two types of parameters can be computed through the redundant measurements during the calibration, it is the main purpose to determine the internal parameters for a calibration process. In the close range and the industrial photogrammetric computer vision applications, depending on the widely usage of the digital cameras, internal and external parameters are generally determined together in a multi-view geometry in a kind of self calibration.

The calibration mathematical models can be assembled as linear or nonlinear models [2]. Although the linear calibration algorithms such as Direct Linear Transformation [3] are easy to apply to the problem, the mathematical model does not represent the real physical model because of ignoring some parameters like lens distortions. Thus, the solution becomes lack of stability and accuracy. So, these models can be only approximate solutions. The parameters of the linear models can be easily estimated by a least squares method. In addition to the parameters of linear models, nonlinear calibration models take into account the lens distortions as radial and tangential, aspect ratio as well. Although the nonlinear solutions are more realistic and robust physical models with additional parameters, they require iterative optimization algorithms for parameter estimation. So, the computational complexity of nonlinear models is higher than the linear systems. The most widely used method for solution of these systems is the Levenberg-Marquardt (LM) algorithm. In order to converge a solution, very good initial values of parameters are required in LM.

Many calibration methods have been developed so far [1, 3-6]. They differ from each other based on which parameters are taken into account. Although there are different approaches to the calibration problem, the underlying mathematical model generally used is the colinearity principle, i.e. the colinearity equation is the basic equation on which the most of the calibration methods depend. It can be defined the object point, projection center and the corresponding image point must be collinear. The colinearity equation sets the physical model of a light ray from the object space coordinates to the corresponding image coordinates in terms of the camera lens system.

Another calibration method (LL) considered in this study was introduced by Luca Lucchese [5]. In this method, the way of homography is from the image frame to reference image frame whereas it is usually from space to image coordinates at many methods. Another difference comes up with using calibration board. 3D object coordinates are not used in LL. The coordinates of the virtual reference image are derived from 3D coordinates of calibration board with the constant distance.

In this study, Artificial Bee Colony (ABC), Differential Evolution (DE), Genetic Algorithm (GA) and Particle Swarm (PSO) Algorithms are used to calibrate LL model in comparison with Levenberg-Marquardt method. Besides ABC algorithm is the first time being used in a camera calibration problem DE, GA and PSO that have been used for other calibration models such as Tsai [7-9] are the first time being used for LL model. ABC and PSO are the member of population based swarm intelligence algorithms [10, 11] while DE and GA are population based evolutionary algorithms [12, 13]. All of them are heuristic and iterative algorithms [11, 14-16].

Artificial bee colony algorithm

ABC algorithm is inspired by the behavior of the bee colonies to find out food sources. All of the bees are represented with their positions and by changing parameters of positions they try to find optimal solution. ABC works iteratively and iterations continue until minimum objective value equal or smaller then the goal. There are three types of bee in ABC: (i) employed bee that is going to the food source visited by itself previously, (ii) onlooker bee that waits on the dance area for making decision to choose a food source and (iii) scout bee that carries out random search [14]. Half of the colony consists of employed bees and the other part of the colony consists of onlooker bees. In each food source there is only one employed bee. During the iterations positions of food sources are changed by bees. At the beginning of the algorithm employed bees go to their starting positions randomly and measure fitness of positions. After that onlooker bee chooses its starting point by fitness of food source of employed bee. The food source of the most convenient fitness value has a higher probability of choosing by onlooker. Bees start search from this initial point for iteration.

Although in a food source there is only one employed bee number of onlooker bees can change because onlooker bees don't have ownership of food source. In other words, the number of employed bees is equal to the number of food sources around the hive. In search process, randomly chosen parameters of the position of randomly chosen food source is subtracting from own parameters. Results are multiplied by a number produced in [-1,1] interval and the products are added to the parameters. If fitness value of new position produced with this way is more convenient than previous food source is chanced. At each iteration searching new position of a food source is executed by bees at this food source. The employed bee whose food source is exhausted by the employed and onlooker bees becomes a scout. Limit and colony size values are the parameters of ABC to be tuned. The main steps of the algorithm can be given like this:

(i) Initialize.

(ii) REPEAT.

- (a) Place the employed bees on the food sources in the memory;
- (b) Place the onlooker bees on the food sources in the memory;
- (c) Send the scouts to the search area for discovering new food sources.

(iii) UNTIL (requirements are met).

In standard ABC for a food source just one position parameter is changed. But it is seen that this approach is not sufficient for the calibration problem. Therefore additionally a perturbation rate parameter is employed [17]. This parameter determines the change probability for each parameter.

2. METHODOLOGY

a. Images

Bouguet's images available on the internet were employed [4]. Images contain black-and-white checkerboard of high contrast with a size of 3cm. Thanks to this feature control points can be determined on the images by using Harris Corner Detector [18-20].

b. Camera Parameters

Internal parameters define where a light ray that came into the camera falls onto the image plane. The contact point of the optical axis of lens to the image plane are called principal point and quantized with x_p and y_p image coordinate pairs. Because of the imperfection of the optical system of a real digital camera, principal point very seldom coincides with actual physical center of its image plane [5, 21]. According to the perspective projection, a 3D point is mapped into 2D image point as Eq 1.

$$x = f_x \frac{X}{Z} \qquad y = f_y \frac{Y}{Z} \tag{1}$$

In perspective projection f_x and f_y are also internal parameters. Effective focal length f is the distance between image plane and the optical center of lens and described as $f=f_x w$ and $f=f_y h$ where w and h is width and height of a pixel respectively. Also f_x/f_y ratio defines aspect ratio[5, 21-23].

The lens distortions are separated into two types as radial and tangential distortions. The former one arises because of the deficient curvature of the lens surface and the latter one is caused by misalignment of lens center. So, tangential distortion has two components along the directions of x and y. However the radial distortion is mainly affected by the radial distance from the principal point. Because of the distortions, pixel coordinates of the control points do not coincide with the correct places. Therefore a straight line can be seen as a bending line. Radial and tangential distortions are expressed Eq. 2 and Eq. 3, respectively.

$$\delta_r = k_1 r^2 + k_2 r^4 + k_3 r^6 + \ldots \qquad (2)$$

$$\begin{aligned} \Delta x_s &= q\left[p_1(r^2 + 2(x_d - x_p)^2) + 2p_2(x_d - x_p)(y_d - y_p)\right] \\ \Delta y_s &= q\left[p_2(r^2 + 2(y_d - y_p)^2) + 2p_1(x_d - x_p)(y_d - y_p)\right] \end{aligned} \qquad (3)$$

In the above equations, k_1, k_2 and k_3 are the radial distortion coefficients, p_1, p_2 and p_3 are the tangential distortion parameters and x_d and y_d define image coordinate have distortions. r and q parameters are

$$\begin{aligned} r^2 &= (x_d - x_p)^2 + (y_d - y_p)^2 \\ q &= 1 + p_3 r^2 \end{aligned} \qquad (4)$$

External parameters determine the position and the orientation of a camera according to a specific coordinate system. Roll, pitch and yaw angles are three of external parameters with that rotation matrix R

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} = \begin{bmatrix} \cos\theta\cos\varphi & \sin\theta\cos\varphi & -\sin\varphi \\ -\sin\theta\cos\omega + \cos\theta\sin\varphi\sin\omega & \cos\theta\cos\omega + \sin\theta\sin\varphi\sin\omega & \cos\varphi\sin\omega \\ \sin\theta\sin\omega + \cos\theta\sin\varphi\cos\omega & -\cos\theta\sin\omega + \sin\theta\sin\varphi\cos\omega & \cos\varphi\cos\omega \end{bmatrix} \qquad (5)$$

Translation elements along x, y, and z directions are other external parameters showed as a vector

$$T = [T_x, T_y, T_z] \qquad (6)$$

c. Luca Lucchese Method

Calibration method introduced by Lucchese looks like Tsai or Zhang methods. The main difference comes from the calibration pallet used. This model uses an imaginer reference image as a calibration pallet rather than a real pallet. It is assumed that the reference image is generated by an ideal pinhole camera (C_r) having parallel CCD axes to pallet and having orthogonal optical axis to pallet intersected at center [5]. This ideal camera located at a distance L+f from the pallet. The L distance is chosen arbitrary with a condition of comprising whole imaginary pallet. This ideal camera does not have any distortions and its focal length is the same as the real camera.

As seen in Figure 1, image I_r acquired by ideal camera C_r placed with L distance from pallet P and in O\`X\`Y\`Z\` object coordinates. On the other hand image I_d is generated by C_d camera at different place from C_r. in OXYZ coordinate system. In LL method, images are generated from different positions and orientations. In Figure 1, o´x´y´ is the coordinate system of reference image and $\tilde{o}\tilde{x}\tilde{y}$ is the coordinate system of real images. Because of imperfection of lens, real image center of oxy coordinate system is not coincide with center of $\tilde{o}\tilde{x}\tilde{y}$ coordinate system.

Camera parameters are obtained via perspective projection of all images to reference image. Transformation between O\`X\`Y\`Z\` and OXYZ is considered as a two stages process (Figure 2). Image I_d obtained by C_d has warp and distortions. At the first stage, lens distortions are corrected and I_u image is generated by radial and tangential distortion equations.

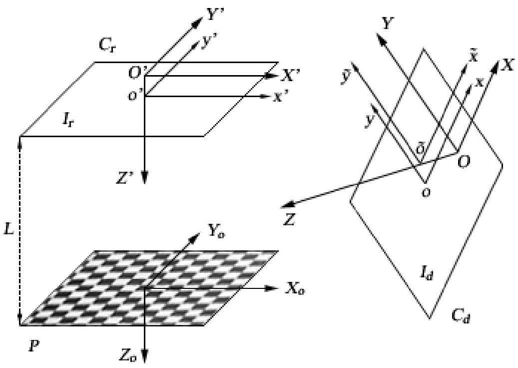

Figure 1. Camera calibration geometry of LL [5].

$$\begin{aligned} x_u &= x_d + (x_d - x_p)\delta_r + \Delta x_s \\ y_u &= y_d + (y_d - y_p)\delta_r + \Delta y_s \end{aligned} \tag{7}$$

Afterwards, I_u is related to the reference image I_r through perspective projection as Eq. 1.

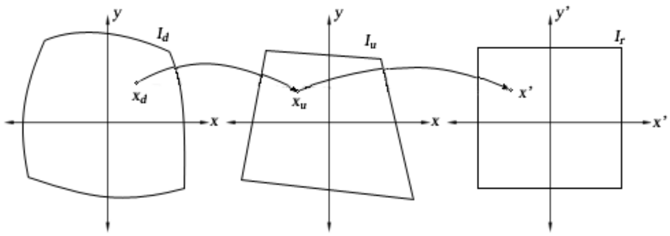

Figure 2. Geometric Transformation [5].

In Eq. 8, coefficients of (a_{11},a_{12},a_{21},a_{22},b_1,b_2,c_1,c_2) are the forward homography coefficients, which depends on the camera parameters.

$$\begin{aligned} x' &= \frac{a_{11}(x_u - x_p) + a_{12}(y_u - y_p) + b_1}{c_1(x_u - x_p) + c_2(y_u - y_p) + 1} \\ y' &= \frac{a_{21}(x_u - x_p) + a_{22}(y_u - y_p) + b_2}{c_1(x_u - x_p) + c_2(y_u - y_p) + 1} \end{aligned} \tag{8}$$

In matrix form forward homography coefficients are inverse of the backward homography coefficients. They are obtained through

$$\begin{bmatrix} a_{11} & a_{12} & b_1 \\ a_{21} & a_{22} & b_2 \\ c_1 & c_2 & 1 \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \beta_1 \\ \alpha_{21} & \alpha_{22} & \beta_2 \\ \gamma_1 & \gamma_2 & 1 \end{bmatrix}^{-1} \tag{9}$$

$$\begin{cases} \alpha_{11} = \dfrac{r_{11}}{D}, \quad \alpha_{12} = \dfrac{f_x r_{12}}{f_y D}, \quad \alpha_{21} = \dfrac{f_y r_{21}}{f_x D}, \quad \alpha_{22} = \dfrac{r_{22}}{D} \\ \beta_1 = f_x \dfrac{r_{13} + \tau_x}{D}, \quad \beta_2 = f_y \dfrac{r_{23} + \tau_y}{D}, \quad \gamma_1 = \dfrac{r_{31}}{f_x D}, \quad \gamma_2 = \dfrac{r_{32}}{f_y D} \\ D = r_{33} + \tau_z, \quad \tau_n = \dfrac{T_n}{L + f}, \quad n \in \{X, Y, Z\} \end{cases} \tag{10}$$

The calibration with LL method has 10 internal parameters that are the same for all images and have 6 external parameters that are different for all images. Therefore numbers of parameters to calculate can be obtained with

$$p = m * 6 + 10 \qquad (11)$$

where m is the number of image.

3. APPLICATION

Objective function that is necessary for optimization algorithms contains calibration method. This function gets parameters produced by optimization algorithm and compute perspective projection of image coordinates. As a result of calibration method candidate pallet coordinates are produced. The flowchart of the application in this paper was illustrated in Figure(3).

Since the ultimate usage of the calibration parameters is to compute the object space coordinates of image points, we have two types of computed data of x and y coordinates. The performance measure of the problem is the root mean squares error (RMSE) of x and y directions

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - x_i')^2 + \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2} \qquad (12)$$

Where n is the number of control points, x and y are the image coordinates of the control points, x` and y` are the computed virtual reference image coordinates. Whole system error is computed with RMSE value. Parameters with the minimum value of RMSE measure are considered as the solution of the problem.

In this study, all images are included to calibration procedure in a multi-view geometry. In that case, since all images were sensed by the same camera, the internal parameters must be the same for all images. So, the optimization algorithms try to estimate 10 internal parameters for whole images and 6 external parameters for each image. Thus, for 25 images there are totally 160 unknowns. This interdepency among images through internal parameters makes problem quite complex to handle.

Since the calibration problem handling in this paper is a nonlinear functional optimization problem, Levenberg-Marquardt optimization method is employed. LM is a derivative based functional optimization method between Gauss-Newton and Steepest Decent [24]. Because of the linearization of the observation equations, solution is obtained in a manner of iteration. So, the initial values of the unknown parameters are required to be able to start the iteration. The closer the initial values to the real values are, the less iteration is processed and the more stable the solution is. The initial values required for LM are determined by the same way given in [5].

The external parameters adjusted by LM are not given in a tabular format as in other optimization methods because of the huge table size. The internal parameters adjusted by LM are given in Table 2 in purpose of comparison. The LM results for homography are visualized in Figure4 for image 2. “x” markers represent the corner points on the real image, i.e. forward homography from real image to reference image and the “+” markers represent the corner points of the reference image. The quality of the homography can also be easily seen from the graphics

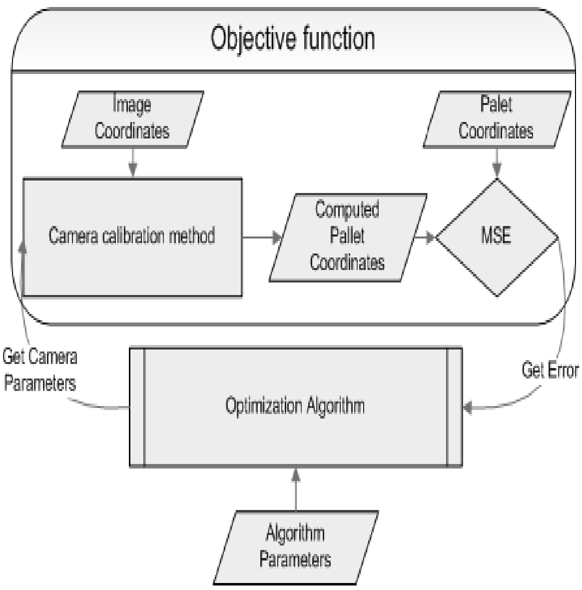

Figure 3. Structure of the used calibration system

.

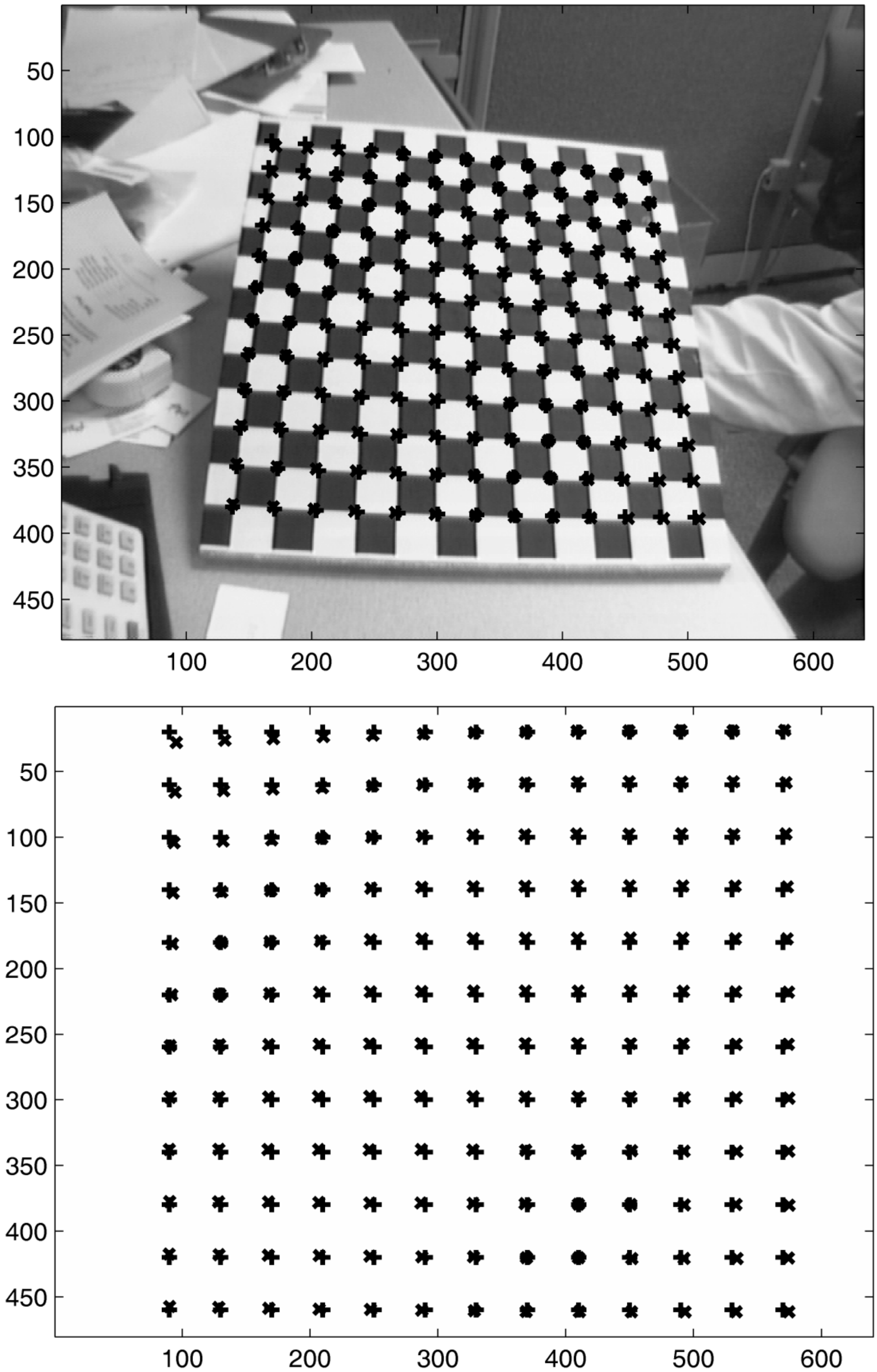

Figure 4. LM homographies of image 2.

The specific algorithm parameters of ABC, DE, PSO and GA algorithms were determined after many trial and error processes. The detailed explanations about these algorithm parameters can be found in many references. The values of some of them are given in Table 1. Population or colony size (N) for all algorithms was set 50 and all the algorithms were run for 2000 iterations. These model values should be tuned as precisely as possible for guarantying them to run effectively.

Unlike LM which needs the initial values for the unknowns, ABC, DE, GA and PSO need only specific working intervals for the unknowns. These intervals must cover for all unknown values in order that search space would be too large to find a solution. But if they are too large, it makes the algorithm converge an acceptable solution very difficult. In order to obtain the optimal interval values, firstly each image is separately optimized. For the internal parameters, optimal intervals are obtained taking the minimum and maximum values coming from single frame solutions. For the external parameters, the optimal intervals are computed by adding and subtracting an adequate little value to the external parameters from single frame solutions. Consequently, the search space including the real values is made narrower. Thus, it is supposed to obtain more stable solutions. After more realistic interval values are computed from these individual operations, the main optimization process is done with these intervals for 160 unknowns for 15 parallel runs and the results with smallest RMSE values were chosen. Table 2 shows the optimized internal parameters comparing to LM with RMSE values.

According to the RMSE values, none of the intelligent algorithms gave an comparable solution to LM. Among them, ABC and DE have the higher performances respectively. Homographies of image 2 for ABC were computed and visualized in Figure 5

Table 1. Parameters of ABC, DE, PSO and GA algorithms.

ABC		DE		PSO		GA	
Pertubation Rate	0.9	Crossover Rate	0.9	Ineteria Weights	(0.9-0.6)	CrosoverFunction	Scattered
Scale Factor	0.6	Scale Factor	0.6	Accelerator Weights	(2.1-2.1)	Selection Function	StochasticUniform
Limit	(Nxp)/2					Mutation Function	Gaussian
						Crossover Rate	0.9

Table 2. The optimized internal parameters from ABC, DE, GA, PSO.

	ABC	DE	GA	PSO	LM
x_p	0.198	3.490	0.028	1.530	-16.517
Y_p	2.725	-5.550	14.700	2.740	-2.889
k_1	$9.76x10^{-07}$	$-7.89x10^{-06}$	$1.15x10^{-06}$	$7.26x10^{-07}$	$2.97x10^{-07}$
k_2	$3.45x10^{-11}$	$1.55x10^{-10}$	$-1.34x10^{-10}$	$5.89x10^{-11}$	$6.05x10^{-13}$
k_3	$-5.11x10^{-16}$	$-4.55x10^{-16}$	$1.31x10^{-15}$	$-8.97x10^{-16}$	$-8.66x10^{-19}$
p_1	$-5.14x10^{-06}$	$-2.77x10^{-04}$	$1.48x10^{-05}$	$-2.73x10^{-05}$	$4.79x10^{-05}$
p_2	$-2.41x10^{-05}$	$2.98x10^{-04}$	$5.75x10^{-05}$	$-4.46x10^{-05}$	$-3.87x10^{-05}$
p_3	$4.64x10^{-05}$	$-6.69x10^{-06}$	$-4.00x10^{-05}$	$3.40x10^{-05}$	$-5.31x10^{-06}$
f_x	633.89	261.41	596.59	602.00	656.64
f_y	654.35	278.19	833.49	615.66	657.85
RMSE	15018	17166	27425	141987	249

.

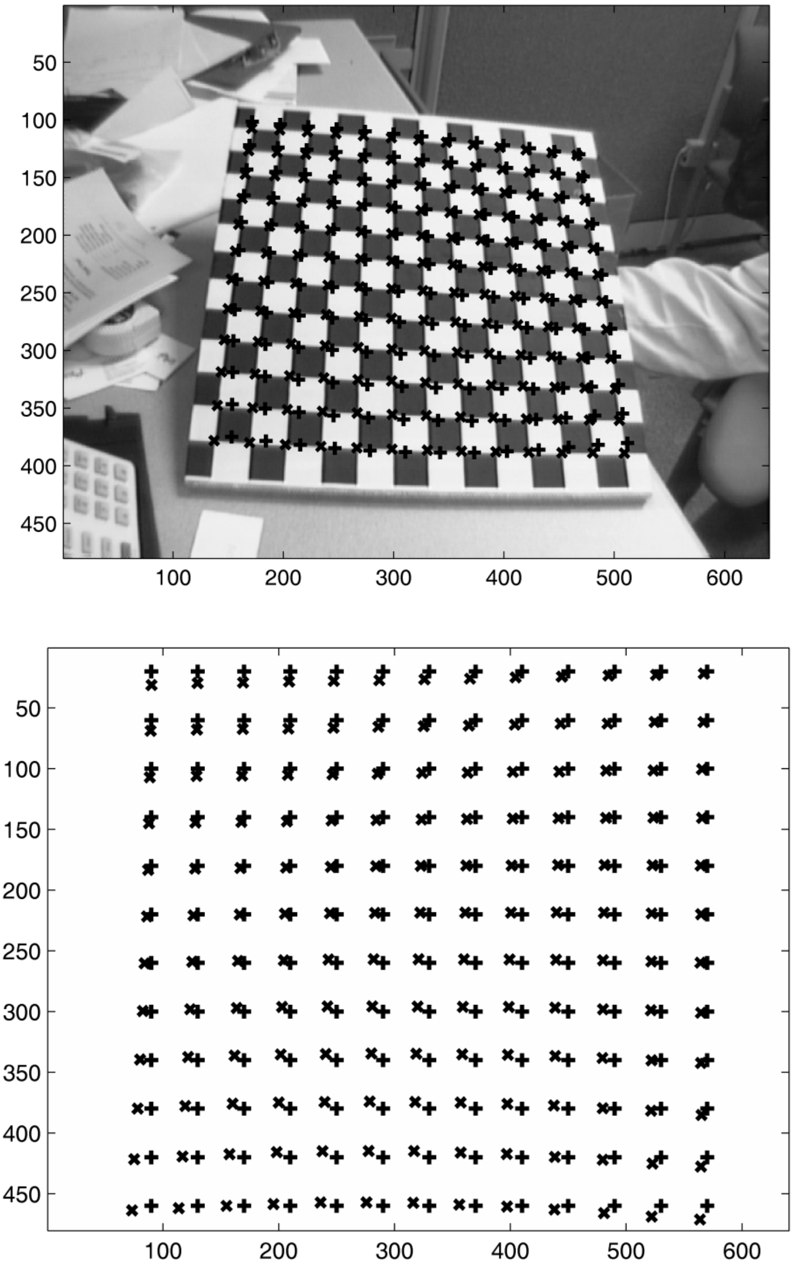

Figure 5. ABC homographies of image 2.

4. CONCLUSIONS

In this paper the usage possibilities of intelligent optimization algorithms, ABC, DE, GA and PSO have been examined with respect to the recently proposed camera calibration approach of LL. Especially as a novel method ABC has not been used in any calibration problem yet. Both the error values and the graphical homographies show that intelligent optimization methods do not give satisfactory results. For especially high dimensional problems, this situation is not surprising for DE, GA and PSO. But in recent literatures ABC has showed very good performances for different benchmark problems. Although there are some algorithm parameter combinations to be tuned for these algorithms it can be accurately concluded these algorithms are not as stable and robust as Levenberg-Marquardt. In spite of the fact that it is very hard to explain these deficiencies because of the heuristic natures of these algorithms, the redundancies and scale differences among the internal parameter may cause the failure of these algorithms. The distortion parameters have relatively too small values and consequently very sensitive to little changes, as well. So, this situation may cause instabilities and increasing search time, i.e. finding global minimum is either impossible or very difficult. Another reason may be because of the fact that the physical reality of the digital imagery can be modeled mathematically well enough by nonlinear colinearity equations with distortions.

Despite the numerical effectiveness of LM, since the camera calibration problem is nonlinear, LM needs very good initial values for convergent stable solutions. So, it can be concluded that ABC can be employed as an initializing tool for LM in the camera calibration problem in terms of LL model.

Acknowledgments

We gratefully acknowledge the research project grant (EUBAP FBY-08-357) from Erciyes University Foundation of Scientific Research Projects.

REFERENCES

1. Zhang, Z., A Flexible New Technique for Camera Calibration, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 22(11) , 1330-1334, 2000.
2. Zhang, Y. and Ji, Q., Camera Calibration with Genetic Algorithms, *IEEE Transactions on Systems, Man and Cybernetics*, 31(2), 120-130, 2001.
3. Abdel-Aziz, Y.I. and Karara, H.M., Direct Linear Transformation into Object Space Coordinates in Close-Range Photogrammetry, *Proceedings of Symposium on Close-Range Photogrammetry*, Urbana-Champaign, IL, 1–18, 1971.
4. Bouguet, J.Y., Camera Calibration Toolbox for Matlab, 2001. http://www.vision.caltech.edu/bouguetj/calib_doc/index.html.
5. Lucchese, L., Geometric calibration of digital cameras through multi-view rectification, *Image and Vision Computing*, 23, 517-539, 2005.
6. Tsai, R.Y.A., Versatile Camera Calibration Technique for High Accuracy 3D Machine Vision Metrology using off The Shelf TV Cameras and Lenses, *IEEE Transactions on Robotics and Automation*, 3(4), 323-344, 1987.
7. Abellard, A., Bouchouicha, M., Khelifa, M.M.B., A Genetic Algorithm Application to Stereo Calibration, *Proceedings of IEEE International Symposium on Computational Intelligence in Robotics and Automation*, 285-290, 2005.
8. Fraga, L.G., Silva, I.V., Direct 3D Metric Reconstruction from Multiple Views using Differential Evolution, *LNCS Applications of Evolutionary Computing, Springer-Verlag*, 4974, 341-346, 2008.
9. Wang, D., Tu, Y., Zhang, T., Research on The Application of PSO Algorithm in Non-Linear Camera Calibration, *Proceedings of Intelligent Control and Automation WCICA,* 4495-4500, 2008.
10. Karaboga, D. Basturk, B., On The Performance of Artificial Bee Colony (ABC) Algorithm, *Applied Soft Computing*, 8(1), 687-697, 2008.
11. Kennedy, J., Eberhart, R. C., Particle Swarm Optimization, *Proceedings of IEEE Conference on Neural Networks*, Piscataway, NJ, 1942–1948, 1995.
12. Holland, J.H., Adaptation in Natural and Artificial System, University of Michigan Press, MI, 1975.
13. Storn, R., Price, K. Differential Evolution: A Simple and Efficient Adaptive Scheme for Global Optimization over Continuous Spaces, International Computer Science Institute, Berkeley, 1995 (ftp://ftp.icsi.berkeley.edu/pub/techreports/1995/tr-95-012.pdf)
14. Karaboga, D., Basturk, B., A Powerful and Efficient Algorithm for Numerical Function Optimization: Artificial Bee Colony (ABC) algorithm, *Journal of Global Optimization*, 39(3), 459-171, 2006.
15. Pham, D.T., Karaboga, D., Intelligent Optimization Techniques, New York: Springer-Verlag, 1998.
16. R. Storn, "Differential Evolution", 2001 (http://www.icsi.berkeley.edu/~storn/code.html.)
17. Karaboğa, D., Basturk, B., Artificial Bee Colony (ABC) Optimization Algorithm for Solving Constrained Optimization Problems, *LNCS Advances in Soft Computing: Foundations of Fuzzy Logic and Soft Computing*, 4529, 789-798, 2007.
18. Derpanis, K.G., The Harris Corner Detector, 2004. (http://www.cse.yorku.ca/~kosta/CompVis_Notes/harris_detector.pdf)
19. Nixon, M., Aguado, A., Computer Vision Demonstration, 2005. (http://users.ecs.soton.ac.uk/msn/book/new_demo/corners/)

Erciyes Üniversitesi Fen Bilimleri Enstitüsü Dergisi 26 (4) 340-350 (2010

20. Schmid, C., Morn, R., Bauckhage, C., Evaluation of Interest Point Detectors, *International Journal of Computer Vision*, 37(2), 151-172, 2000.
21. Lucchese, L., Closed-Form Pose Estimation from Metric Rectification of Coplanar Points, *Proceedings of IEE Vision, Image and Signal Processing*, 153(3), 364-378, 2006.
22. Lucchese, L., Estimating The Pose and Focal Length of a Camera From The Perspective Projection of a Planar Calibration Plate, *Proceedings of Signal and Image Processing,* Honolulu, USA, 2003.
23. Lucchese, L., Geometric Calibration of Digital Cameras. Part I: Camera Model, Subpixel Feature Extraction and Algorithm Initialization, *Proceedings of Visualization, Imaging, and Image*, Benalmádena, Spain, 2003.
24. Nocedal, J., Wright, S.J., Numerical Optimization, Springer-Verlag New York, 262-266, 1999.