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on

"Embedded Mutation Strategies in Particle Swarm Optimization for Solving Camera Calibration Problem"

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B.Sc. (H) Mathematics

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CERTIFICATE

This is to Certify that **Aarti Singh, Sagar Joshi and Sanskar Sharma** has carried out their project work entitled:
“Embedded mutation strategies in Particle swarm Optimization for solving Camera Calibration problem” under the supervision of **Dr. Vanita Garg**. This work is fit for submission for the award of Bachelor Degree in Mathematics.

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CANDIDATE DECLARATION

We, hereby declare that the dissertation entitled "**Embedded Mutation Strategies in Particle Swarm Optimization for Solving Camera Calibration Problem**". Submitted by us in partial fulfilment for the degree of B.Sc. in Mathematics to the Division of Mathematics, School of Basic and Applied Science, Galgotia's University, Greater Noida, Uttar Pradesh, India, is our original work. It has not been submitted in part or full to this University or any other Universities for the award of Diploma or Degree.

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"Embedded Mutation Strategies in Particle Swarm Optimization for Solving Camera Calibration Problem"

I would like to acknowledge that this project was completed entirely by our group and not by someone else. Finally, I would want to convey our sincere thanks to my friends and supporters; without them, the task would not have been accomplished in such a timely manner.

Thanking you!

Title of the Proposed Thesis

"Embedded Mutation Strategies in Particle Swarm Optimization for Solving Camera Calibration Problem"

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ABSTRACT

Particle Swarm Optimization is a very effective Nature influenced innovation that relic widely used in solving many real-world problems over the years. This paper is an attempt to embed different mutation schemes in PSO and testing the different versions of PSO on camera calibration problem. One of the more challenging real-world issues in the realm of image processing is the calibration of cameras. The ideal parameter value for achieving the shortest pixel length is investigated in this research using the enlarged Particle Swarm Optimization approach. The results obtained in the empirical section of the paper suggest that PSO has proved to be a better version while embedding different mutation strategies for this problem.

Keywords: Particle Swarm Optimization, Camera calibration problem

CONTENT

1. Introduction

Optimization is the process of selecting the best option among the available options. It provides us with a set of instruments, mostly drawn from computer science and mathematics, that may be applied to practically any field, including business, industry, biology, physics, medical data mining, engineering, and even the fine arts.

Advanced matrix computation techniques and methods, graph theory, and optimization are being used more and more in the data mining industry. These techniques define data mining tasks as optimization problems with matrix variables and describe the data using a matrix representation (the graphs are represented by their adjacency matrix). With these, the effort of data mining is reduced to the process of minimising or maximising the anticipated objective function of the matrix's variables.

The topic of optimization has attracted a lot of interest recently, largely as a result of the quick development of user-friendly software and its usefulness, as well as the emergence of fast parallel processors and artificial neural networks, among other improvements in computer technology.

The two basic classifications for optimization issues are local and global optimization. Local optimization aims to find the highest or lowest value in a constrained region of the function value space. Global optimization is the process of determining the highest or lowest value across the entire region of the function value space.

A single-objective optimization issue is formulated in the following way without losing generality

$$minx\epsilon sf(x), x = Li \leq xi \leq Ui$$
$$s.t. g_i(x) \leq 0, j = 1,2, \dots, j$$
$$h_k(x) = 0, k = 1,2 \dots., K$$

Where $f(x)$ is objective function
x is D-dimensional decision vector
j shows the number of inequality constraints
k indicates the number of equality constraints, L_i, U_i are the lower and upper bound of the i^{th} variables, respectively.

The aim and constraint functions can be linear or non-linear, explicit or implicit. A good algorithm will never transgress any of the side constraints. An unconstrained optimization problem may have side constraints but does not have equality or inequality constraints. One or more equality and/or inequality constraints are present in constrained optimization problems.

Finding the design variable values that fulfil all equality, inequality, and side constraints while producing the optimal objective function value is the method's key step. It is important to keep in mind that many problems might have numerous optimums, often known as local or relative optimum.
The following is how the paper is set up: PSO and its several suggested iterations are briefly introduced in Section 2. The introduction of the camera model for image formulation is provided in Section 3. The mathematics for the camera calibration problem are provided in Section 4 to help formulate the optimization problem. The Camera Calibration Problem is solved in Section 5 utilising Blended BBO and all six proposed PSO versions. The numerical analysis of the solution is presented in Section 6. The conclusion and some potential future directions are then suggested.

2. Proposed Versions of Particle Swarm Optimization

Academics from many different professions have drawn inspiration and curiosity from nature, which has evolved over a billion years, to create a wide range of nature-inspired optimization algorithms. The bulk of optimization problems with several non-linear constraints are used in real-world applications.

Some of the earlier developed conventional optimization techniques, like gradient-based techniques, are ineffective. The heat and trail method is used to tackle those real-world problems as well as the bulk of them. Therefore, nature-inspired optimization methods are used to address the highly nonlinear problems.

The success rate of these nature-inspired algorithms is mostly due to their adaptability and ability to address NP-hard tasks. Numerous algorithms have been developed by taking design cues from creatures like lions, fish, ants, and birds.

Two basic categories of nature-inspired algorithms include (1) evolutionary algorithms and (2) swarm-based algorithms. Among these, PSO (Particle Swarm Optimization) is thought to be the most well-liked. The algorithm's specifics are provided as follows:

2.1 Swarm Optimization for Particles

A widely used optimization technology is called particle swarm optimization (PSO). Kennedy and Eberhart introduce PSO in 1995. Fishes or birds collect their food using the social and individual skills. This phenomenon gives rise to a stochastic optimization algorithm which is popularly known as PSO. The natural tendency to find the best solution among the given choices is formulated mathematically using two update equations, which are given as follows:

Velocity updates equation

In a multidimensional search space, a swarm of particles moves in quest of the ideal. Each particle in a swarm is influenced by its immediate surroundings and personal perception. The velocity by which the particle moves from one place to another is given in the following equation:

$$v_{t+1} = v_t + C1 * rand(Pbest - x_t) + C2 * rand * (Gbest - x_t)$$

$$\mathrm{Where} v_t = velocity of x particle at t^{th} iteration.$$
$$C1 = the individual factor$$
$$C2 = social factor$$
$$Pbest = the individual best particle$$
$$Gbest = the global best particle$$
$$Rand\ is\ the\ uniform\ random\ number\ between\ 0 \wedge 1$$

Particle updates equation

The direction a particle is travelling in quest of an optimal path is determined by its velocity. The following is the particle update equation for PSO

$$x_{t+1} = x_t + v_{t+1}$$

These two equations will update the solution, and they will be repeated until a predefined termination threshold is reached. PSO is a population-based approach that optimises the answer utilising a number of potential solutions. Each solution is built on the local and global best results from the entire search space. This results in the perfect harmony between exploitation and exploration for a strong algorithm. The following are some of the crucial PSO characteristics:

1. PSO is a very simple algorithm to understand and thus, its simplicity makes it more convenient to apply to real life problems. Its foundation is swarm intelligence.
2. Hence useful to both engineering and science.
3. It does not use mutation calculations or overlaps like GA.

2.2 Version of PSO using Mutation Strategies

Genetic Algorithm is one of the basic and prelim Nature inspired optimization technique. Mutation operator is considered as the main operator in genetic algorithm to enhance the exploring characteristic of the algorithm. In this paper we have investigated the aspect of incorporating mutation operator of GA in PSO. Garg and Deep (2016) successfully have used real coded mutation operators. Taking into consideration the better performance of mutation operators in the previous work. We are investing the embedding of mutation operators-Cauchy, Gaussian, Polynomial, Random, Power mutation to Particle swarm optimization algorithm. The five different mutation operators are given as follows;

2.2.1 PSO with Power Mutation (PM -PSO)

Power mutation is a new form of SCA that incorporates the power mutation report-ed in (Garg&Deep,2016). It is recommended that the mutation operator be based on the distribution of power. It is referred to as Power Mutation. Its distribution function is given by

$$f(x) = px^{p-1}, 0 \leq x \leq 1 \ldots (6)$$

and the density function is presented by

$$F(x) = x^{p}, 0 \leq x \leq 1 \ldots\ldots (7)$$

The index of the distribution is denoted by p. The PM is used to generate a solution y near a parent solution z that follows the previously mentioned distribution. The mutated solution is then created using this formula below.

$$y = \begin{cases} x - z(x - x_l) if r < t \\ x - z(x_u - x) if r \geq t \end{cases} \ldots\ldots (8)$$

Where t=$\frac{x-x_l}{x_{u-x_l}}$ and x_i and x_u are lower bound value and upper bound value of the decision variable respectively and r is a random number uniformly distributed between zero and one. The power distribution function p = 0.25 & p = 0.50. Probability of mutation used in PM-PSO is 0.5. Algorithm 2 provide the pseudo code for Power Mutation.

Algorithm2. Pseudo Code for the Power Mutation in PSO Algorithm

Power Mutation in PSO
For each solution
For each dimension
Choose each position based on the probability of mutation
If $X(i,j)$ is chosen then find a new generated position based on r and t

$$y = \begin{cases} x - z(x - x_i) if r < t \\ x - z(x_u - x) if r \geq t \end{cases} \ldots \ldots (9)$$

Replace $X(i,j)$ with a new generated position based on power mutation;
End if
End for
End for

2.2.2 PSO with Polynomial Mutation (Poly -PSO)

A new version of PSO proposed name Poly-PSO that incorporates in PSO displayed in (Garg & Deep,2016). Using power mutation on the provided solution $[x_l, x_u]$, Mutated solution x is constructed.

$$x' = \begin{cases} x + \delta_i(x - x_l) if u \leq 0.5 \\ x + \delta_i(x_u - x) if u > 0.5 \end{cases}$$

Where $u \epsilon [0,1]$ is a random number The values δ_l and δ_r are computed as given by the formula.

Where $\rho_m \in [20,100]$ is user defined parameter. Algorithm 3 provide the Pseudo code for Polynomial Mutation.

Algorithm 3. Pseudo Code For Polynomial Mutation In Sine-Cosine Optimization Algorithm

Polynomial Mutation in PSO
For each solution
For each dimension
Choose each position based on the probability of mutation
If X(i,j) is chosen then find a new generated position

$$x' = \begin{cases} x + \delta_i(x - x_l) if u \leq 0.5 \\ x + \delta_i(x_u - x) if u > 0.5 \end{cases}$$

Replace $X(i,j)$ with a new generated position based on power mutation
End if
End for
End for

2.2.3 PSO with Random Mutation (Rand-PSO)

A new version is suggested called Rand SCA is proposed by integrated Rand mutation in SCA. Suppose x is any given solution than a rand mutation operator is used as $x \in [x_l, x_u]$ and a random solution h is created using a neighbourhood of the replaced solution.

$$h = x_l + (x_u - x_l) \times rand$$

Where rand∈ [0,1] represents a uniform distribution. Algorithm 4 provide the pseudo code for Random Mutation.

Algorithm 4. Pseudo for the Random Mutation in Sin-Cosine Based Optimization

Random Mutation in PSO:
For each solution
For each dimension
Choose each position based on the probability of mutation
If$X(i,j)$ is chosen then find a new generated position

$$z = x_l + (x_u - x_l) * rand$$

Replace $X(i,j)$ with a new generated position based on power mutation;
End if
End for
End for

2.2.4 PSO with Gaussian Mutation (G-PSO)

Gaussian Mutation causes a small random change in the population. A random number from Gaussian distribution N (0,1) with parameter 0 as a mean and 1 as std dev. is generated. Algorithm 5 provides the pseudo code for the Gaussian Mutation.

Algorithm 5. Pseudo Code for Gaussian Mutation in Sin -Cosine based Optimization

Gaussian Mutation in PSO
For each solution
For each dimension
Choose each position based on the probability of mutation
If$X(i,j)$ is chosen then find a new generated position

$$z = X(i,j) + N_i(0,1)$$

Replace $X(i,j)$ with a new generated position based on power mutation;
End if
End for
End for

2.2.5 PSO with Cauchy Mutation(C-PSO)

Cauchy Mutation is defined in SCA as the same way as G- SCA. Suppose a random number is generated from Cauchy distribution and defined by $\delta_i(t)$,The scale parameter represented by t, where t>0. Consider the value t=1 as used in LX C-BBO in this paper. Algorithm 6 provide the pseudo code for Cauchy Mutation.

Algorithm 6. Pseudo Code for the Cauchy Mutation in Sin -Cosine based Optimization

Cauchy Mutation in PSO
For each solution
For each dimension
Choose each position based on the probability of mutation
If$X(i,j)$ is chosen then find a new generated position

$$z = X(i,j) + \delta_i(1)$$

Replace $X(i,j)$ with a new generated position based on power mutation;
End if
End for
End for

3. Formulation of the Camera Calibration Problem Mathematically

Two steps make up the mathematical description of the camera calibration problem. First, the camera model used to create images is defined. Second, the camera calibration problem is referred to as a non-linear optimization problem.

3.1 Model of Camera for Image Creation

The pinhole camera model used in this study to define the geometry of the image is intended for binocular vision systems. It consists of five co-ordinate frames: World reference frame (X, Y, Z), camera frame (X_i, Y_i, Z_i) and image frame (u_i,v_i) for i=1,2. The origins O_1 and O_2 of the cameras coordinate systems coincide with their corresponding optical canters and their Z coordinate axes are collinear with corresponding optical axes which are perpendicular to corresponding image planes and intersect them in their respective principal points. The image plane and optical centre of each camera is at a distance f_i (its focal length) i=1, 2 apart. (See Figure 5.1)

If an object point P has coordinates in the 3D world reference frame of (X,Y,Z) Its world coordinates must be transformed into picture coordinates using the following steps:

1. First, the camera coordinates are converted from the 3D world coordinates using the relation:

$$\begin{pmatrix} X_c \\ Y_c \\ Z_c \end{pmatrix} = R \begin{pmatrix} X \\ Y \\ Z \end{pmatrix} + T \qquad (1)$$

Where T is the translation vector that depicts the camera's position in relation to the world coordinate system and R is a 3 x 3 rotation matrix that depicts the camera's orientation in relation to the world coordinate system Another way to express R and T is as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} T = \begin{pmatrix} T_x \\ T_y \\ T_z \end{pmatrix} \qquad (2)$$

The elements r_{ij} of the matrix R can further be expressed in terms of swing, tilt and pan angle (α,β,γ) as

$$R = \begin{bmatrix} cos\alpha cos\beta & sin\alpha cos\gamma + cos\alpha sin\beta sin\gamma & sin\alpha sin\gamma - cos\alpha sin\beta cos\gamma \\ -sin\alpha cos\beta & cos\alpha cos\gamma - cos\alpha sin\beta sin\gamma & cos\alpha sin\gamma + sin\alpha sin\beta cos\gamma \\ sin\beta & -cos\beta sin\gamma & cos\beta cos\gamma \end{bmatrix} (3)$$

2. Using prospective projection equations, the 3D camera coordinates (Xc, Yc, Zc) are then converted into the ideal retinal coordinates (Xu, Yu) of the camera

$$X_u = f\frac{X_c}{Z_c}, \quad Y_u = f\frac{Y_c}{Z_c} \qquad (4)$$

3. The ideal retinal coordinates (X_u, Y_u) are then transformed into actual retinal coordinates (X_d, Y_d) by considering lens radial distortion coefficient k:

$$X_d = X_u(1+kr^2)^{-1} \text{ and} Y_d = Y_u(1+kr^2)^{-1} \qquad (5)$$

4. Finally, the following relation is used to convert the real retinal coordinates into pixel coordinates (u, v):

$$u = X_d N_x + u_0 v = Y_d N_x + v_0 \qquad (6)$$

Here, (u_0,v_0) denotes the pixel coordinates of the image's centre, while N_x and N_y express the number of pixels that are contained in the unit distance of the image plane along the X and Y axes, respectively. The total of the previous four phases can be used to represent the mathematical process of creating an image of a 3D point P(X,Y,Z):

$$u = \frac{fN_x}{(1+kr^2)}\left(\frac{r_{11}X + r_{12}Y + r_{13}Z + T_x}{r_{31}X + r_{32}Y + r_{33}Z + T_z}\right) + u_0 \dots\dots \quad (7)$$

$$v = \frac{fN_y}{(1+kr^2)}\left(\frac{r_{21}X + r_{22}Y + r_{23}Z + T_y}{r_{31}X + r_{32}Y + r_{33}Z + T_z}\right) + v_0 \dots\dots \quad (8)$$

Equations (5.7) and (5.7) represent the transformation of the 3D world coordinates P(X,Y,Z) into the pixel coordinates (u,v) for a single camera (5.8). Since this process is irreversible, it is impossible to uniquely derive the 3D position of point P from its pixel coordinates (u, v). The stereo images pl(ul,vl) and pr(ur,vr) of a point

P(X,Y,Z) taken by two cameras (left and right) or by a single camera in two distinct locations can, however, be used to uniquely identify a point in the 3D environment.

3.2. The issue of camera calibration as an optimization problem

The camera calibration problem is mathematically formulated using the image formation model described above as a nonlinear unconstrained optimization problem with the goal of minimising the root mean square distance between the observed pixel positions and their corresponding calculated pixel positions of the control points.

Given sufficient number of control points N whose world coordinates and corresponding observed pixel position $p_{li}(u_{li}, v_{li})$&$p_{ri}(u_{ri}, v_{ri})$,(i =1,2,3….,N) in left and right cameras respectively , are known with a high precision , the problem is to estimate the optimal values of the 24 camera parameters(12 parameters (f, N_x, $N_y, u_0, v_0, k, T_x, T_y, \alpha, \beta, \gamma$ for each camera) so that the objective function given by following equation is minimized :

$$F = \sqrt{\frac{1}{N}\sum_{i}^{N}\left[\left(u_{il} - u_{il}^{'}\right)^2 + \left(u_{ir} - u_{ir}^{'}\right)^2 + \left(v_{il} - v_{il}^{'}\right)^2 + \left(v_{ir} - v_{ir}^{'}\right)^2\right]} \quad (9)$$

Where $p_{lj}^{'}(u_{lj}^{'}, v_{lj}^{'})$and $p_{rj}^{'}(u_{rj}^{'}, v_{rj}^{'})$are
the associated pixel coordinates determined by the predicted parameters. On the basis of the camera's inform ation, any relevant search area for a variable can be selected. Finding the global minimum of the goal functio n while all 24 factors are changing will be tricky because it will be considerably more difficult.

4. Optimization Problem Solution

A vector S is created to represent the unknown intrinsic and extrinsic properties of the left and right cameras, respectively, in order to solve the camera calibration problem.

$$\boldsymbol{S = \left(u_{0l}, v_{0l}, N_{xl}, N_{yl}, f_l, k_l, \alpha_l, \beta_l, \gamma_l, T_{xl}, T_{yl}, T_{zl}, u_{0r}, v_{0r}, N_{xr}, N_{yr}, f_r, k_r, \alpha_r, \beta_r, \gamma_r, T_{xr}, T_{yr}, T_{zr}\right)} \quad (10)$$

Where T_x, T_y, T_z, α, β and γ are the extrinsic parameters which denote the location and direction of the camera in World Co-ordinate system (WCS).(u_0, v_0)Image centre, (f) focal length, (k) radial lens distortion and ($N_x$and N_y) off- axis lens distortion are intrinsic parameters which represents camera optical and geometry features. Extrinsic parameters give the relationship between World Co-ordinate system (WCS) and Camera Co-ordinate System (CCS). Then internal parameters can be used to set the relationship between the co-ordinate systems i.e. Camera Co-ordinate System (CCS) and Ideal Co-ordinate system. Camera calibration is an unconstrained, non-linear optimization problem, where objective function is given by eq. (9) and decision variables or independent variables are given by eq. (10).

Camera calibration problem is solved by all the variants of Laplacian Biogeography Based Optimization (LX-BBO) proposed in chapter 2 and 3 with varying number of control points.
Through camera faults, calibration accuracy is evaluated. The Euclidean distance between the estimated value of a parameter and its ground truth is known as camera error in that parameter. Ground truth values are the intrinsic left and right camera parameter values that are utilised to generate data, i.e., the values used to calculate the 2D picture coordinates from the 3D grid points. The ground truth value and the parameter bounds are provided in Table 1.

4.1 Generation of Synthetic Data

The fabricated data was produced by a calibration chart with 8 × 8 grids in the X and Y dimensions. 64 grid points are created as a result. This chart is shifted along Z direction on eight different positions to get a total of 512 points Pi (X_i ,Y_i ,Z_i) in 3D space.

4.2 Setting Parameters

All algorithms' parameters have been set in accordance with Chapters 2 and 3 recommendations. But there are two conditions that must be met for this problem to be terminated. First, the maximum number of iterations (5000) must be reached. Additionally, the absolute error value is below 10-6. Absolute value in this context refers to the pixel error, which is taken to be the objective function in and of itself. Whichever of these two outcomes occurs first becomes the necessary termination criterion.

5. Experimental Results

On the camera calibration problem, the performance of Blended BBO and PSO is compared to that of all six PSO versions. The outcomes of 50 independently conducted minimal camera mistakes for varied numbers of control points are presented in Tables 2 and 3.

Here, many simulations employ control points at 10, 50, 100, 200, and 500. PSO offers values for 6 camera parameters that are closer to their true values when there are 10 control points. LX-L PSO creates 4 camera parameters that are closer to the ground truth value for 50 control points and offers better camera error values for 6 camera parameters than the other LX-PSO versions.

LX-Rand BBO outperforms the other versions in terms of camera error in 3 parameters when there are 100 control points. when there are 100 control points Five camera settings that use LX-G PSO and 200 control points show more camera inaccuracy. LX-L PSO outperforms all other varieties of LX PSO when there are 500 control parameters; however, for 6 camera parameters, LX-L PSO offers the lowest camera error.
Table 4 provides the analysis based on the data produced by all LX-PSO variations. It lists the number of parameters that each LX-PSO variant's optimal value for.

According to Table 4, Blended BBO outperformed all other LX-PSO variants in terms of performance. For all control points, blended PSO offers the lowest camera error among all LX-PSO variants. For camera calibration problems, LX-L PSO has proven to be a superior algorithm to the other version of LX-PSO. The best algorithm, LX-PSO with random mutation, which was demonstrated in Chapter 3 is unable to give satisfactory results for this issue.

The results of the camera calibration show that even while Rand PSO and C PSO, which were tested against all other PSO versions, delivered the best results, the other PSO variants are still significant. Every version can be proven to be beneficial for an optimization work based on how difficult it is.

For the camera calibration problem, convergence graphs for all PSO and Blended BBO versions are provided in Figure 5.2. The number of generations is on the horizontal axis, and the value of the objective function is on the vertical axis. The pixel error acquired as indicated in equation serves as the objective function value in this situation (5.8). For a fair comparison, all algorithms are run with the same initial population. It can be shown that, when compared to other PSO versions, Blended BBO has the worst convergence. L PSO converges more quickly than any other PSO variation.

6. Conclusion and Future Scope

The six PSO versions can all be used to solve any unconstrained optimization problem, according to the analysis above. Camera calibration problem is considered as a complex problem in computer vision study.

Evolutionary Algorithms have not been quite successful in solving camera calibration problem. However, due to their wide applicability on optimization problems, present study is an attempt to solve such kind of problems using PSO. The problem has been solved using Rand PSO, Poly PSO, PM PSO, C PSO, G PSO and L PSO. L PSO is proved to be a better version among all the other variants considered. In future, other unconstrained optimization problems can also be solved by using the variants of PSO.

Table 1: Value of the left and right cameras' ground truth

Parameter	a left camera		Right camera	
	Ground truth value	Bounds	Ground truth value	Bounds
f	10	[5,15]	25	[20,40]
N_x	200	[170,230]	144	[100,200]
N_y	200	[170,230]	144	[100,200]
u_0	20	[15,25]	256	[200,300]
v_0	19	[15,25]	192	[150,250]
k	0.15152	[0,0.5]	0.15152	[0,0.5]
T_X	60	[20,80]	-38	[-100,80]
T_Y	35	[25,45]	35	[25,45]
T_Z	1210	[1000,1400]	1210	[1000,1400]
α	0	[-π/2,π/2]	-1.90146	[-π,π]
β	0	[-π/2,π/2]	0.20916	[-π/2,π/2]
γ	0	[-π/2,π/2]	0.15152	[-π/2,π/2]

Table 2: For different numbers of control points, there are left camera mistakes						
parameter	Algorithm	10	50	100	200	500
f	Rand PSO	0.076868	0.024334	0.157513	0.124538	0.024437
	PM PSO	0.0344981	0.434759	0.121133	0.046615	0.047882
	Poly PSO	0.04324238	0.008042	0.028207	0.01648	0.07599
	G PSO	0.048427	0.103863	0.144257	0.069504	0.006694
	C PSO	0.0030938	0.092509	0.007664	0.187033	0.139281
	L-PSO	0.0279277	0.04823	0.069935	0.022762	0.052066
	Blended BBO	0.0322	0.02618	0.00495	0.00671	0.02101
N_x	Rand PSO	1.67	0.385597	0.382618	0.548318	0.730356
	PM PSO	0.29898	1.159758	0.059637	0.998098	0.31041
	Poly PSO	0.08727	1.39171	0.071564	1.197718	0.372492
	G PSO	0.87745	1.670052	0.085877	1.437261	0.44699
	C PSO	0.5623	2.004062	0.103053	1.724713	0.536388
	L-PSO	0.07651	2.404874	0.123663	2.069656	0.643666
	Blended BBO	0.3934	2.885849	0.148396	2.483587	0.772399
N_y	Rand PSO	2.3093973	11.82527	1.319943	1.9135	0.369863
	PM PSO	0.387762	30.39693	8.714069	19.66042	22.65397
	Poly PSO	4.893	0.975087	18.41438	1.575908	38.95181
	G PSO	1.838734	0.683595	2.605886	1.110187	2.891485
	C PSO	10.3938	8.050961	28.01932	6.066603	0.534862
	L-PSO	0.873	0.490529	6.037532	5.533563	4.518829
	Blended BBO	0.40837	0.17199	0.23465	0.16406	0.16835
u_0	LX-Rand BBO	0.0292	0.031997	0.256192	0.18951	0.073873
	LX-PM BBO	0.04847	0.2431	0.061802	0.177463	0.337853
	LX-Poly BBO	0.1983	0.21491	0.404932	0.479892	0.068281
	LX-G BBO	0.09837	0.128807	0.052503	0.354757	0.940733
	LX-C BBO	0.112938	0.024072	0.040034	0.05118	0.582759
	LX-1 BBO	0.0178398	0.000705	0.014607	0.429354	0.280561
	Blended BBO	0.08989	0.06981	0.00988	0.02119	0.00104
v_0	Rand PSO	1.34265	0.741057	0.682209	1.015719	4.175725
	PM PSO	0.3357	4.119933	1.733164	0.481672	0.086142
	Poly PSO	0.4598	0.805775	0.251563	2.922266	3.639468
	G PSO	0.30877	0.065042	0.004492	0.007795	0.040118
	C PSO	0.6988	0.392656	1.841579	0.570943	0.191385
	L-PSO	0.9766	0.017161	0.03813	0.64016	0.021408
	Blended BBO	0.018927	0.13884	0.02613	0.17277	0.07241
k	Rand PSO	0.0012892	0.007537	0.005751	0.022836	0.003475
	PM PSO	0.00824	0.001756	0.002176	0.007588	0.012832
	Poly PSO	0.002872	0.00354	0.001167	0.001895	0.008437
	G PSO	0.002988	0.001249	0.022905	0.005643	0.000103
	C PSO	0.00092761	0.005876	0.004667	0.03083	0.033955
	L-PSO	0.00792	0.006664	1.17E-05	0.029757	0.003078
	Blended BBO	0.004982	0.01027	0.01677	0.01729	0.00156
T_x	Rand PSO	0.11972	0.026052	0.297564	0.864591	0.066409
	PM PSO	0.59272	0.065632	0.63135	0.598079	0.020628
	Poly PSO	0.735091	1.010329	0.371582	0.435924	0.032583
	G PSO	0.073639	1.21052	0.646933	0.530257	0.029168

	C PSO	0.1938	0.221803	0.260677	0.222334	0.104469
	L-PSO	0.31838	1.00999	0.167359	0.351686	0.112323
	Blended BBO	0.6583	0.66404	1.00126	0.89232	0.23205
T_y	Rand PSO	1.23983	5.142888	0.790665	0.912582	2.035849
	PM PSO	7.40292	9.213382	2.426164	2.357414	0.510078
	Poly PSO	1.89202	8.029741	1.62026	4.407579	0.419929
	G PSO	0.076939	0.72936	0.941844	1.703283	0.935087
	C PSO	6.9802	5.560166	7.603574	4.731641	0.104048
	L-PSO	0.2639839	0.394265	0.576217	0.488848	0.505852
	Blended BBO	0.1527	1.312987	0.217567	0.457192	0.14602
T_z	Rand PSO	0.67292	0.863252	1.301638	1.160016	0.301665
	PM PSO	1.40292	6.685754	1.027865	1.186357	2.646604
	Poly PSO	0.0919187	11.9774	3.154013	3.064638	0.663101
	G PSO	3.9282	10.43866	2.106338	5.729853	0.545908
	C PSO	6.3938	0.948168	1.224397	2.214268	1.215613
	L-PSO	0.18484	7.228216	9.884646	6.151133	0.135262
	Blended BBO	0.093983	0.512545	0.749082	0.635502	0.657608
alpha	Rand PSO	0.01383	1.706883	0.282837	0.594349	0.189826
	PM PSO	0.012928	1.122228	1.692129	1.508021	0.392165
	Poly PSO	0.00008474 9	8.691481	1.336224	1.542264	3.440585
	G PSO	0.000017	15.57062	4.100217	3.98403	0.862032
	C PSO	0.030038	13.57026	2.738239	7.448809	0.70968
	L-PSO	0.024849	1.232618	1.591716	2.878548	1.580297
	Blended BBO	0.000298	9.396681	12.85004	7.996473	0.175841
beta	Rand PSO	0.073332	0.666308	0.973807	0.826153	0.85489
	PM PSO	0.047565	2.218948	0.367688	0.772654	0.246774
	Poly PSO	0.007292	1.458896	2.199768	1.960427	0.509814
	G PSO	0.045428	11.29892	1.737091	2.004943	4.47276
	C PSO	0.0375675	20.2418	5.330282	5.179239	1.120641
	L-PSO	0.01284575	1.458896	2.199768	1.960427	0.509814
	Blended BBO	0.0059	11.29892	1.737091	2.004943	4.47276
gamma	Rand PSO	0.245493	20.2418	5.330282	5.179239	1.120641
	PM PSO	0.0158373	17.64134	3.559711	9.683451	0.922584
	Poly PSO	0.0013847	1.602404	2.069231	3.742113	2.054386
	G PSO	0.00001987	12.21568	16.70505	10.39542	0.228593
	C PSO	0.008387	0.8662	1.265949	1.073999	1.111357
	L-PSO	0.03629874	2.884632	0.477994	1.00445	0.320806
	Blended BBO	0.00598	1.896565	2.859699	2.548555	0.662758

Table 3: Camera mistakes using the appropriate camera for various numbers of control points

parameter	Algorithm	10	50	100	200	500	Average
F	Rand PSO	0.044406	0.18	0.11172	0.052761	0.043144	0.0864062
	PM PSO	0.074132	0.079752	0.080253	0.106694	0.014889	0.071144
	Poly PSO	0.066342	0.159004	0.007878	0.149157	0.101876	0.0968514
	G PSO	0.05697	0.056588	0.025016	0.100576	0.022319	0.0522938
	C PSO	0.034158	0.139876	0.077253	0.18627	0.059315	0.0993744
	L-PSO	0.478059	0.045168	0.015363	0.001168	0.162348	0.1404212
	Blended BBO	0.31616	0.33453	0.133498	0.000769	0.271253	0.211242
N_x	Rand PSO	1.373803	0.044301	0.197815	0.164958	0.129119	0.3819992
	PM PSO	0.004764	0.084025	0.976119	0.815793	1.198443	0.6158288
	Poly PSO	0.477428	0.100776	0.172758	0.487176	0.06959	0.2615456
	G PSO	0.312556	0.41266	0.231014	0.113208	0.299791	0.2738458
	C PSO	0.262216	0.036426	0.088562	0.241455	1.205115	0.3667548
	L-PSO	2.27699	0.219725	1.106474	0.240857	0.25447	0.8197032
	Blended BBO	0.26576	0.00432	0.424428	0.518146	0.122522	0.2670352
N_y	Rand PSO	0.193095	1.06913	0.317453	1.553951	0.387519	0.7042296
	PM PSO	0.42701	0.883951	0.844218	1.545705	0.079553	0.7560874
	Poly PSO	0.520066	1.239188	1.031169	0.595897	0.628988	0.8030616
	G PSO	0.020741	0.352441	0.316507	0.672235	0.914089	0.4552026
	C PSO	0.188418	0.128667	1.190323	0.398805	0.923642	0.565971
	L-PSO	1.417966	0.475952	0.121807	0.99797	1.566333	0.9160056
	Blended BBO	0.19728	0.18135	0.416902	0.346858	0.05602	0.239682
u_0	LX-Rand BBO	0.967718	0.477842	0.065884	2.642091	3.782402	1.5871874
	LX-PM BBO	0.020769	0.066174	0.429793	0.173863	1.01068	0.3402558
	LX-Poly BBO	0.382444	0.56381	0.460645	2.242422	0.881862	0.9062366
	LX-G BBO	0.151233	1.192916	0.674603	1.118233	0.143079	0.6560128
	LX-C BBO	0.353092	1.189723	0.197002	0.611511	0.321765	0.5346186
	LX-l BBO	1.684685	0.113715	1.654228	0.499089	1.230732	1.0364898
	Blended BBO	0.26704	0.32139	0.213977	0.30217	0.494239	0.3197632
v_0	Rand PSO	0.189348	0.243143	0.283194	0.667557	0.206054	0.3178592
	PM PSO	0.711386	0.960224	0.126378	0.057336	0.228718	0.4168084
	Poly PSO	0.311976	0.07163	0.354237	1.536039	0.121138	0.479004
	G PSO	1.030991	0.158625	143.2231	0.861066	0.315927	29.117942
	C PSO	0.306065	0.619149	0.774449	0.278219	1.236844	0.6429452
	L-PSO	0.535554	0.719699	0.148611	0.021479	0.34391	0.3538506
	Blended BBO	0.15408	0.15939	0.044477	0.524075	0.821402	0.3406848
k	Rand PSO	0.001876	0.000481	0.000738	0.006913	0.001189	0.0022394
	PM PSO	0.004312	0.001092	0.005227	0.012322	0.000652	0.004721
	Poly PSO	0.002155	0.006408	0.001389	0.000578	0.005187	0.0031434
	G PSO	0.000886	0.00783	0.00995	0.000677	0.003373	0.0045432
	C PSO	0.010874	0.000252	0.007142	0.00085	0.002382	0.0043
	L-PSO	0.004796	0.013398	0.001453	0.008632	0.002341	0.006124
	Blended BBO	0.01096	0.00108	0.003254	0.019105	0.000546	0.006989
T_x	Rand PSO	0.655016	0.921915	0.385354	0.776072	0.484104	0.6444922
	PM PSO	0.502832	0.023805	0.159177	0.440791	0.136339	0.2525888

	Poly PSO	0.220064	0.033263	0.162125	0.06153	0.207657	0.1369278
	G PSO	0.486602	0.186402	0.200331	0.075301	0.443852	0.2784976
	C PSO	0.376899	0.403617	0.282945	0.57978	0.195036	0.3676554
	L-PSO	0.009539	0.163548	0.223046	0.270093	0.089128	0.1510708
	Blended BBO	0.72184	0.03222	0.113701	0.067198	0.237947	0.2345812
T_y	Rand PSO	0.348973	0.112831	0.121461	0.464107	0.214681	0.2524106
	PM PSO	0.058383	0.602893	0.101501	0.016955	0.094817	0.1749098
	Poly PSO	0.404024	0.052901	0.133641	0.708794	0.410576	0.3419872
	G PSO	0.032359	0.123519	0.154569	0.276816	0.138895	0.1452316
	C PSO	0.077124	0.042046	0.062864	0.63851	0.120051	0.188119
	L-PSO	0.027562	0.058642	0.096728	0.240211	0.165829	0.1177944
	Blended BBO	0.00296	0.00702	0.035731	0.013615	0.010156	0.0138964
T_z	Rand PSO	4.558761	1.423436	4.806374	3.697145	0.909133	3.0789698
	PM PSO	1.558562	0.160899	0.263311	6.910535	3.17732	2.4141254
	Poly PSO	0.906546	7.254022	1.185153	3.026315	2.322818	2.9389708
	G PSO	0.637114	3.056054	6.319311	4.290712	3.641515	3.5889412
	C PSO	2.812785	8.606612	0.132218	1.825775	5.913478	3.8581736
	L-PSO	0.519471	1.312794	3.318024	0.965552	2.608121	1.7447924
	Blended BBO	0.14104	0.29457	1.555332	1.102941	0.027628	0.6243022
alpha	Rand PSO	0.264531	0.297598	0.226021	0.366034	0.361085	0.3030538
	PM PSO	0.264531	0.297598	0.226021	0.363069	0.361085	0.3024608
	Poly PSO	0.264531	0.297598	0.226021	0.366034	0.361085	0.3030538
	G PSO	0.264531	0.297598	0.226021	0.366034	0.361085	0.3030538
	C PSO	0.264531	0.297598	0.226021	0.366034	0.364033	0.3036434
	L-PSO	0.264531	0.297598	0.226021	0.366034	0.361085	0.3030538
	Blended BBO	0.1748	0.03852	0.018035	0.021191	0.00819	0.0521472
Beta	Rand PSO	0.217726	0.253488	0.115886	0.1006	0.483546	0.2342492
	PM PSO	0.213613	0.511743	0.194694	0.775676	0.23811	0.3867672
	Poly PSO	0.24171	0.380763	0.170667	0.347232	0.147447	0.2575638
	G PSO	0.246247	0.527518	0.474766	0.747659	0.780586	0.5553552
	C PSO	0.238898	0.648911	0.268385	0.104427	0.219637	0.2960516
	L-PSO	0.225727	0.640835	0.48925	0.867623	0.822768	0.6092406
	Blended BBO	0.01392	0.00072	0.004543	0.024705	0.008408	0.0104592
Gamma	Rand PSO	0.000946	0.00022	0.000057	0.000121	0.010253	0.0023194
	PM PSO	0.010277	0.001793	0.000175	0.00033	0.012286	0.0049722
	Poly PSO	0.002064	0.001163	5.76E-05	0.000182	0.011406	0.0029745
	G PSO	0.009871	0.013056	0.000168	0.000272	0.010915	0.0068564
	C PSO	0.002473	0.000184	4.14E-05	0.000386	0.011693	0.0029555
	L-PSO	0.006225	0.013733	1.42E-05	0.000586	0.010614	0.0062344
	Blended BBO	0.00176	0.00288	0.00061	0.004502	0.005023	0.002955

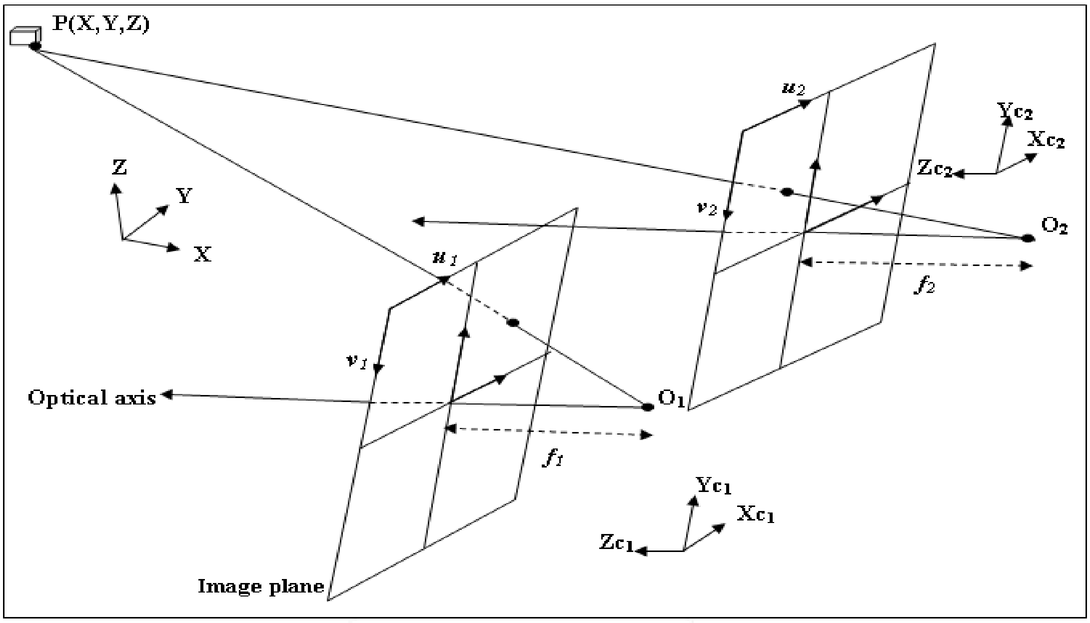

Figure 1: Pinhole Model Image Formation by Two Cameras (Adapted from Kumar et al., 2008)

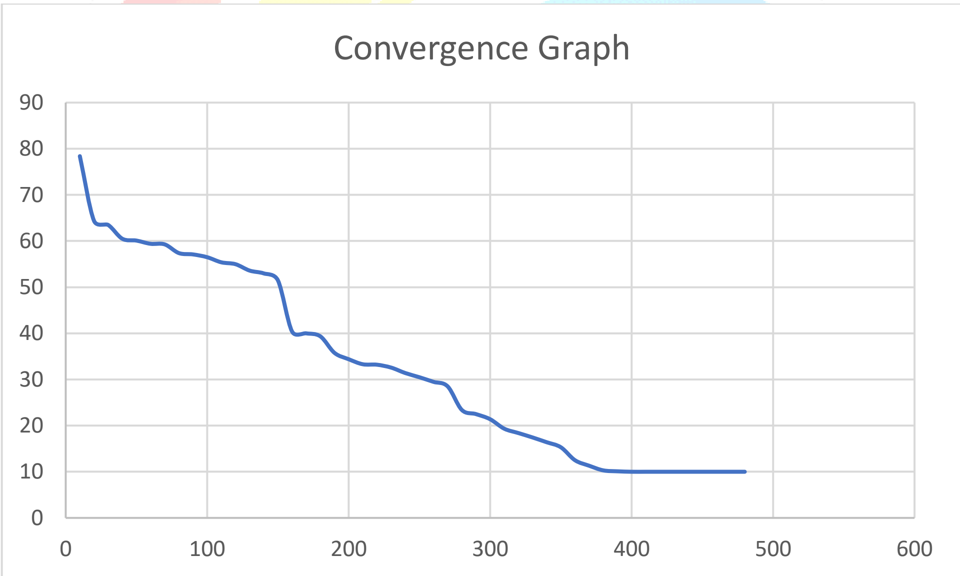

Figure 2: Convergence Behavior for Stereo Camera Calibration Problem solved by PSO

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