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# Optimum Design For Close Range Photogrammetry Network Using Particle Swarm Optimization Technique

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***Abstract:*** *With the rapid development in close range photogrammetry and low cost of this technique, it is important to improve the accuracy of the result of this technique. For that, the main aim of that paper is using the Particle Swarm Optimization. The mathematical model of Particle Swarm Optimization for the close range photogrammetry network is developed. The experimental tests have been carried out to develop a Particle Swarm algorithm to determine the optimum camera station and evaluate the accuracy of the developed.*

***Keywords:*** *Close range photogrammetry network design, artificial intelligence and Particle Swarm Optimization.*

## I. Introduction

Close-range stereo photogrammetry is an accurate method of recording 3-D information about an object that results as well in an archival, high-resolution photographic base record of the object. We obtain highly accurate measurements through one of these networks. Close range photogrammetry network design has been divided into four design stages from which only the first three are used in close range photogrammetry[1].

- Zero Order Design (ZOD): The datum problem – involves the choice of an optimal reference system for parameters and their variance-covariance matrix.
- First Order Design (FOD): The configuration problem – involves the optimal positioning of points and the design of an optimal observation plan.
- Second Order Design (SOD): The weight problem – involves the identification of optimal precision and distribution of observation.
- Third Order Design (TOD): The densification problem – involves the optimal improvement of an existing network via the addition of observation or points.

The order presented above is not fixed, although it is accepted by most geodesist and photogrammetrists as the chronological order for assisting network design problems. In practice the design problems are interrelated and solution of the various design problems may occur in different sequence. For example, addition of object points may be carried out in the FOD phase to strengthen the image configuration, however this process is essentially a TOD (densification) problem. It should be noted that the datum problem is not independent of the configuration problem. A change in the datum will influence the object point precision and the magnitude of such changes is dependent upon the imaging geometry. Hence, perior to evaluation of the datum definition, a good estimate of imaging geometry should be available. If, after the ZOD analysis, then the effect of such changes upon the datum definition should be determined, i.e. repeat the datum definition.

In the design of close range photogrammetric network, the accuracy of the various solutions, with respect to the datum definition and imaging geometry, etc., is assessed on the assumption that only random errors are present on observations. In other words, the effect of the network, and only the network, upon estimates of the parameters is assessed. In such a case, where observations do not include systematic and gross errors, precision rather than accuracy estimates are required. [2] The close range photogrammetric network design is the process of optimizing a network configuration in terms of the accuracy of object-points. This design stage must provide an optimal imaging geometry and convergence angle for each set of points placed over a complex object. [3]

## II. Heuristic Optimization Algorithms

Optimization has been an active area of research for several decades. As many real world optimization problems become increasingly complex, better optimization algorithms are always needed. Recently, meta-heuristic global optimization algorithms have become a popular choice for solving complex and intricate problems, which are otherwise difficult to solve by traditional methods [4]. The objective of optimization is to seek values for a set of parameters that maximize or minimize objective functions subject to certain constraints. [5]

Choices of values for the set of Parameters that satisfy all constraints are called a feasible solution. Feasible solutions with objective function value(s) as good as the values of any other feasible solutions are called optimal solutions [5]. In order to use optimization successfully, we must first determine an objective through which we can measure the performance of the system under study. The objective relies on certain characteristics of the system, called variable or unknowns. The goal is to find a set of values of the variable that result in the best possible solution to an optimization problem within a reasonable time limit. The optimization algorithms come from different areas and are inspired by different techniques. But they all share some common characteristics. They are iterative; they all begin with an initial guess of the optimal values of the variables and generate a sequence of improved estimates until they converge to a solution. The strategy used to move from one potential solution to the next is what distinguishes one algorithm from another [4].

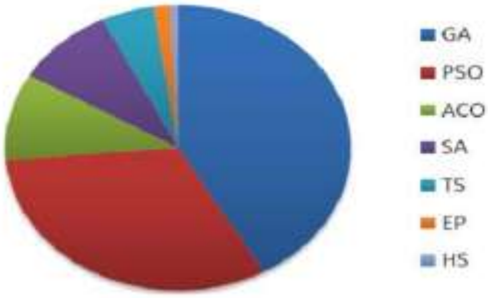


**Figure1: pie chart of the publication distribution of meta-heuristic algorithms**

Broadly speaking, optimization algorithms can be placed in two categories: the conventional or deterministic methods and the modern heuristics or stochastic methods. Conventional methods adopt the deterministic approach. During the optimization process, any solutions found are assumed to be exact and the computation for the next set of solutions completely depends on the previous solutions found. That's why conventional methods are also known as deterministic optimization methods. In addition, these methods involve certain assumptions about the formulation of the objective functions and constraint functions. Conventional methods include algorithms such as linear programming, nonlinear programming, dynamic programming, Newton's method and others. In the past few decades, several global optimization algorithms have been developed that are based on the nature inspired analogy. These are mostly populated based meta-heuristics also called general purpose algorithms because of their applicability to a wide range of problems. Some popular global optimization algorithms include Evolution Strategies (ES), Evolutionary Programming (EP), Genetic Algorithms (GA), Artificial Immune System (AIS), Tabu Search (TS), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Harmony Search (HS) algorithm, Bee Colony Optimization (BCO), Gravitational Search Algorithm (GSA), etc. [4].

Figure 1 shows the distribution of publications which applied the meta-heuristics methods to solve the optimization problem. This survey is based on ISI Web of Knowledge databases and included most of the papers that have been published during the past decade. Figure 1 shows that the PSO is one of the most popular algorithms.

## III. Particle Swarm Optimization (PSO)

Particle swarm optimization is a heuristic global optimization method put forward originally by Doctor Kennedy and E Beirut in 1995 (Kennedy J, Eberhart, R, 1995; Eberhart, R, Kennedy J, 1995) It is developed from swarm intelligence and is based on the research of bird and fish flock movement behavior. [6] While searching for food, the birds are either scattered or go together before they locate the place where they can find the food. While the birds are searching for food from one place to another, there is always a bird that can smell the food very well, that is, the bird is perceptible of the place where the food can be found, having the best food resource information. Because they are transmitting the information, especially the good information at any time while searching the food from one place to another, conduced by the good information, the birds will eventually flock to the place where food can be found. As far as particle swarm optimization algorithm is concerned, solution swamis compared to the bird swam, the birds' moving from one place to another is equal to the development of the solution swarm, good information is equal to the most optimist solution, and the food resource is equal to the most optimist solution during the whole course. The most optimist solution can be worked out in particle swarm optimization algorithm by the cooperation of each individual. The particle without quality and volume serves as each individual, and the simple behavioral pattern is regulated for each particle to show the complexity of the whole particle swarm. This algorithm can be used to work out the complex optimist problems.

Due to its many advantages including its simplicity and easy implementation, the algorithm can be used widely in the fields such as function optimization, the model classification, machine study, neural network training, the signal procession, vague system control, automatic adaptation control and etc.

## IV. Basic Particle Swarm Optimization Algorithm

In the basic particle swarm optimization algorithm, particle swarm consists of "n" particles, and the position of each particle stands for the potential solution in D-dimensional space. The particles change its condition according to the following three principles:

(1) To keep its inertia.
(2) To change the condition according to its most optimist position.
(3) To change the condition according to the swarm's most optimist position.

The position of each particle in the swarm is affected both by the most optimist position during its movement (individual experience) and the position of the most optimist particle in its surroundings (near experience). When the whole particle swarm is surrounding the particle, the most optimist position of the surrounding is equal to the one of the whole most optimist particle; this algorithm is called the whole PSO. If the narrow surrounding is used in the algorithm, this algorithm is called the partial PSO. Each particle can be shown by its current speed and position, the most optimist position of each individual and the most optimist position of the surrounding. In the partial PSO, the speed and position of each particle change according the following equations:

$$x_i^{k+1} = x_1^k + v_i^{k+1} \quad (1)$$

$$v_i^{k+1} = v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (p_g^k - x_i^k) \quad (2)$$

Where, $x_i^k$ represent Particle position

$v_i^k$ represent Particle velocity

$p_i^k$ represent personal best position

$p_g^k$ represent global best position

$C_1$, $C_2$ represents Particle position

$r_1$, $r_2$ represents Particle position

In these equations, $v_i^k$ and $x_i^k$ stand for separately the speed of the particle "i" at its "k" times and the d-dimension quantity of its position; $p_i^k$ represents the d-dimension quantity of the individual "i" at its most optimist position at its "k" times. $p_g^k$ is the d-dimension quantity of the swarm at its most optimist position. In order to avoid particle being far away from the searching space, the speed of the particle created at its each direction is confined between $-v_{dmax}$, and $v_{dmax}$. If the number of $v_{dmax}$ is too big, the solution is far from the best, if the number of $v_{dmax}$ is too small, the solution will be the local optimism; $c_1$ and $c_2$ represent the speeding figure, regulating the length when flying to the most particle of the whole swarm and to the most optimist individual particle. If the figure is too small, the particle is probably far away from the target field, if the figure is too big, the particle will maybe fly to the target field suddenly or fly beyond the target field. The proper figures for $c_1$ and $c_2$ can control the speed of the particle's flying and the solution will not be the partial optimism. Usually, $c_1$ is equal to $c_2$ and they are equal to 2; $r_1$ and $r_2$ represent random fiction, and 0-1 is a random number.

In local PSO, instead of persuading the optimist particle of the swarm, each particle will pursuit the optimist particle in its surrounding to regulate its speed and position. Formally, the formula for the speed and the position of the particle is completely identical to the one in the whole PSO. [7]

Steps in PSO algorithm can be briefed as below:

1) Initialize the swarm by assigning a random position in the problem space to each particle.
2) Evaluate the fitness function for each particle.
3) For each individual particle, compare the particle's fitness value with its $p_{best}$. If the current value is better than the $p_{best}$ value, then set this value as the $p_{best}$ and the current particle's position, $x_i$, as $p_i$.
4) Identify the particle that has the best fitness value. The value of its fitness function is identified as a guest and its position as $p_g$.
5) Update the velocities and positions of all the particles using (1) and (2).

6) Repeat steps 2–5 until a stopping criterion is met (e.g., maximum number of iterations or a sufficiently good fitness value). [6]

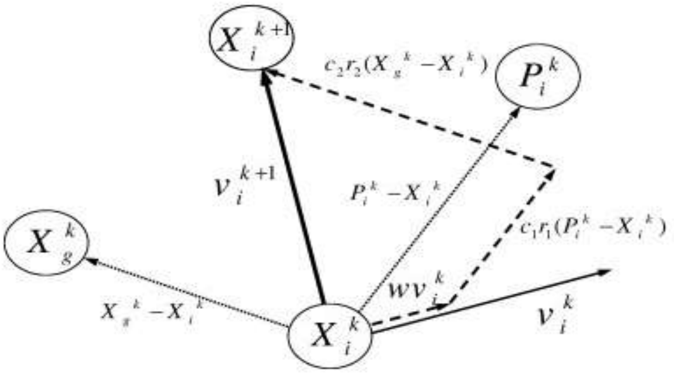


**Figure 2: A graphical representation of PSO particle updating position**

**Mathematical model for close range photogrammetry network design**

The object point, its image on photographs and perspective center all lies on the same straight line. This case is expressed by the collinearity equations, which are the basis for the computation of object space coordinates of points in photogrammetry. These condition equations are as follows:

$$x + \Delta x = f \, \frac{(X - X_0)m_{11} + (Y - Y_0)m_{12} + (Z - Z\ )m_{13}}{(X - X_0)m_{31} + (Y - Y_0)m_{32} + (Z - Z\ )m_{33}} \qquad (3)$$

$$y + \Delta y = f \, \frac{(X - X_0)m_{21} + (Y - Y_0)m_{22} + (Z - Z\ )m_{23}}{(X - X_0)m_{31} + (Y - Y_0)m_{32} + (Z - Z\ )m_{33}}$$

Where:

The index I refer to any ground points, which are imaged on two overlapped photographs, j refers to any exposure station.

x, y: refined photo coordinates of a point ;

f : camera focal length

M,s : elements of the orthogonal transformation matrix in which the rotations omega, phi, kappa of the photographs are implicit.[8]

X, Y, Z object space coordinates of any point.

$X_o$, $Y_o$, $Z_o$ object space coordinates of the camera perspective center.

$\Delta x$, $\Delta x$ : systematic errors

Where:

$$\Delta x = x^{-}(k_1 r^2 + k_2 r^4 + k_3 r^6) + p_1(r^2 + 2x^{-2}) + 2p_2 x^{-} y^{-}$$

$$\Delta y = y^{-}(k_1 r^2 + k_2 r^4 + k_3 r^6) + 2p_1 x^{-} y^{-} + 2p_2 (r^2 + 2y^{-})$$

$$\bar{x} = x - x_o \qquad \bar{y} = y - y_o \qquad r^2 = (x - x_o)^2 + (y - y_o)^2 \qquad (4)$$

x, y are image coordinates

$p_1$ and $p_2$ are two asymmetric parameters for decentring distortion

$k_1$ ,$k_2$ and $k_3$ are three symmetric parameters for radial distortion

r is the radial distance from the principal point [9], [10]

**Assessment of Accuracy**

There are two different methods can be used to evaluate accuracy: one can evaluate accuracy by using check measurements and determining from these check measurements the value of appropriate accuracy criteria; and one can use accuracy predictors. In this study, check measurements will be used to evaluate accuracy [11].
In this study, we consider n (i = 1,2...n) check points in the studied object that is points whose true coordinates are known but not used in the photogrammetric computations. Then, if $X_{it}$,$Y_{it}$ and $Z_{it}$ are the true coordinates of the check points, and $X_{iph}$,$Y_{iph}$ and $Z_{iph}$ its photogrammetric coordinates, an estimation of the MRXYZ spatial residual is

$$MRXYZ = \sqrt{\frac{1}{n}\sum_{1}^{n}(X_{iph}-X_{it})^2+(Y_{iph}-X_{it})^2+(Z_{iph}-Z_{it})^2} \quad (5)$$

Analogous quantities can be estimated for three axes:

The X- direction:
$$MRX = \sqrt{\frac{1}{n}\sum_{1}^{n}(X_{iph}-X_{it})^2}$$

The Y-direction:
$$MRY = \sqrt{\frac{1}{n}\sum_{1}^{n}(Y_{iph}-X_{it})^2}$$

The Z-direction:
$$MRZ = \sqrt{\frac{1}{n}\sum_{1}^{n}(Z_{iph}-Z_{it})^2}$$

**The Test Field and Discussion**

The photogrammetric test field shown in figure 3 was used. The three dimensional coordinates of 48 well distributed ground control points (18 points) and checkpoint (30 points) with varying heights were measured using Sokkia Reflector less Total Station (SET330RK) as shown in figure 3. The average precision values of the ground control points and check points are ±0.2, ±0.4 and ±0.2 mm for X, Y and Z axes, respectively [12]. A program was carried out using Matlab programs to design the close range photogrammetry network, using particle swarm optimization. The Program has been designed for computation of the optimal outer orientation for three camera station. The test field was photographed from optimal camera stations outing of the particle swarm optimization. All photographs were taken using a high resolution CCD camera (Nikon D 3100) as shown in figure 4. The camera settings such as zoom factor, focus, white balance, etc. were kept constant during the test procedure.

**Figure 3: The 3D Test Field**


**Figure 4: The Nikon D 3100 digital camera**

Another Matlab program has been designed for computation of the spatial coordinates (X, Y, Z) of the n checkpoints, the maximum and minimum residual in the X, Y and Z-direction, the maximum and minimum spatial differences among the checkpoints and the variance-covariance matrix of the parameters. It is to be mentioned that the determinations of the residuals have been carried out from optimal camera stations outing of the particle swarm optimization using collinearity condition equations. The estimated accuracy and standard deviations (SD) for the space coordinates will also be presented in tabular form.

**Table (4): Statistics for the obtained 3D coordinate differences associated with different camera stations at the used checkpoints (in mm)**

| | δX | | δY | | δZ | | POS. | |
|---|---|---|---|---|---|---|---|---|
| | Max | Min | Max | Min | Max | Min | Max | Min |
| Case (1) | 14.320145 | 1.983215 | 11.048265 | 2.132586 | 6.732521 | 1.056816 | 17.521364 | 2.315624 |
| Case (2) | 7.532487 | 1.078624 | 10.326512 | 1.564362 | 5.329873 | 0.896545 | 11.327564 | 1.632768 |

Where:

Case–1: using collinearity mathematical model without optimization
Case–2 using collinearity mathematical model using optimal camera stations outing by particle swarm optimization.

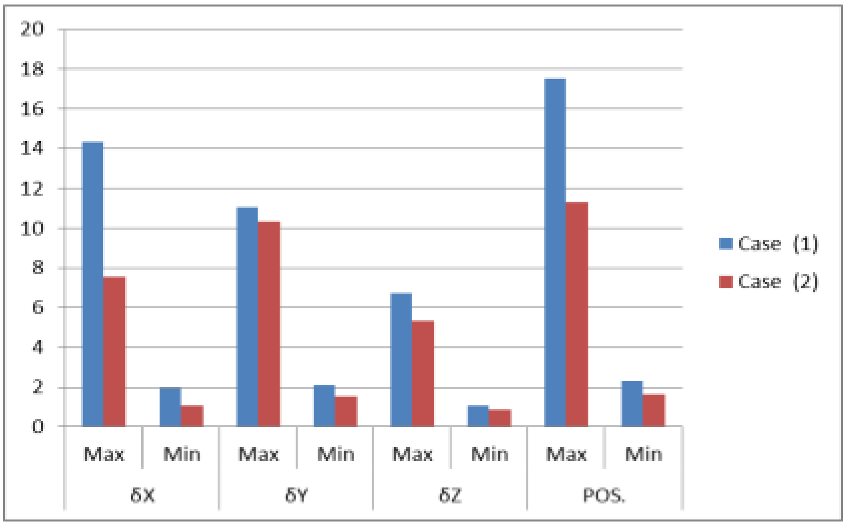


**Figure 5: the obtained 3D coordinate differences associated with different camera stations at the used checkpoints (in mm)**

**Table (5): Statistics for the evaluated standard deviations of the 3D coordinates, as extracted from the evaluated variance-covariance matrix, associated with different cameras.**

| | Std (δX)mm | | Std (δY)mm | | Std (δZ)mm | |
|---|---|---|---|---|---|---|
| | Max | Min | Max | Min | Max | Min |
| Case (1) | 6.356247 | 0.865423 | 7.892653 | 1.833625 | 4.215628 | 0.875462 |
| Case (2) | 3.564283 | 0.536284 | 6.326585 | 1.605492 | 3.596872 | 0.546325 |

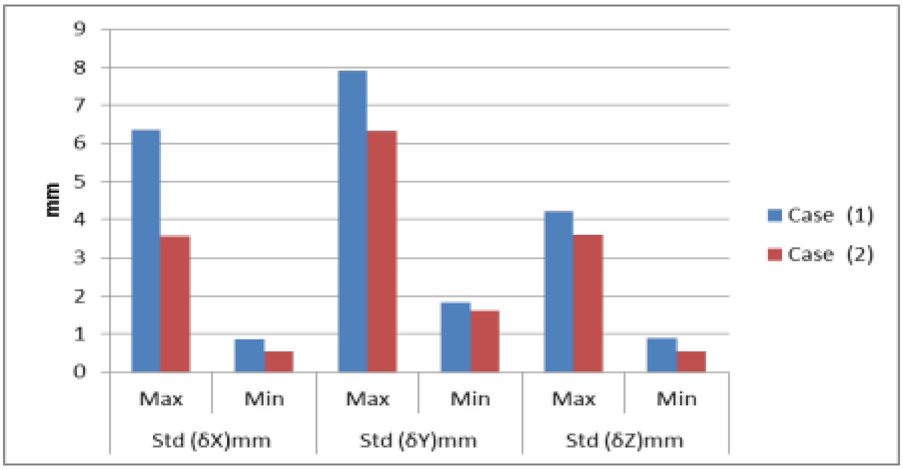


**Figure 6: the evaluated standard deviations of the 3D coordinates, as extracted from the evaluated variance-covariance matrix, associated with different cameras.**

Using insight into Tables 4, 5 and figures 5, 6 some interesting points are noted:
- In the X, Y and Z direction, the best accuracy has been obtained, when the particle swarm optimization is used.
- According to the obtained results, the minimum position error is provided by using the particle swarm optimization.

## V. Conclusions

The particle swarm optimization has been used to design the close range photogrammetry network and the obtained accuracy is discussed and presented. Based on the experimental results, it can be seen that the particle swarm optimization provides good results for the X, Y and Z coordinates. From all of the above discussions, the following Advantages for particle swarm optimization can be drawn:

- Particle swarm optimization is easier to implement and there are fewer parameters to adjust.

- Particle swarm optimization has an effective memory capability.
- Particle swarm optimization is more efficient in maintaining the diversity of the swarm, since all the particles use the information related to the most successful particle in order to improve themselves.

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