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Performance of Heuristic Algorithms in Designing Deformation Monitoring Networks

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ABSTRACT

Deformation monitoring is a kind of continuous recording positions (horizontal and vertical coordinates) precisely regardless the deformation pattern and instrument used. In general, a deformation monitoring network can be designed using the trial and error method or analytical methods such as linear programming and nonlinear programming. Recently, a deformation monitoring network may also be designed by heuristic optimization algorithms such as Evolutionary Algorithms (EAs), Particle Swarm Optimization (PSO) and Simulated Annealing (SA).

In this paper, heuristic optimization algorithms such as SA and PSO are investigated to design the deformation monitoring networks. The results proved that both SA and PSO are able to determine an optimal design of deformation monitoring and these can used as alternative methods in place of the traditional optimization techniques with high efficiency.

تعتبر قياس تشوهات المنشآت ذو فائدة عظيمة للمهندس الإنشائي إذ تسمح له بتقدير مدى الخطورة التي يمكن ان تهدد المنشأة مع مرور الزمن , لذا يجب اخذ احتياطات كبيرة جدا أثناء إجراء القياسات لان مقدار التشوه صغير نسبياً وعلى المهندس الذي يقوم بإجراء القياسات أن يكون ذو خبرة واسعة في هذا المجال. ولقد ثبت أن الطرق الجيوديسية المصحوبة بأرصاد وتحليلات دقيقة "الشبكات الجيوديسية" من أفضل الطرق المستخدمة لدراسة ومتابعة مثل هذه التشوهات. ويعتبر تصميم الشبكات الجيوديسية من أهم الأعمال التي تشغل بال القائمين بالأعمال المساحية ومع تطور الطرق الرياضية ودخول الطرق الإستكشافية لحساب المتغيرات المطلوبة عند التصميم أصبح من الضروري إستخدام هذه الطرق كبديل للطرق التقليدية. وفي هذا البحث استخدمت طريقة محاكاة الصلب وطريقة تحسين سرب الجزيئات في تصميم الشبكات الجيوديسية وقد تم عمل مقارنة بين هاتين الطريقتين والطريقة التقليدية للتصميم في تصميم إحدي الشبكات الجيوديسية والتي تم تصميمها بطريقة تقليدية مسبقا .

Keywords: Sediment transport, Steady, Unsteady

1. INTRODUCTION

Whenever any stress is applied to an object or a surface, this object or surface might be prone to changes in its shape and form, also known as deformations (e.g. elongation, compression or distortion). Any object, natural or man-made, undergoes changes in space and time. Being sure is very important that the movement of an engineering structure, which serves the human life of today's modern world, are exhibiting safe behaviors. So, a lot of deformation studies for determining and analyzing kinds of engineering structures are implemented. Since the results of deformation surveys are directly relevant to the safety of human life and engineering surveying, recently deformation analysis has become more important.

There are several techniques for measuring the deformations. These can be grouped mainly into two as: geodetic survey, which include conventional (terrestrial such as precise leveling measurements, angle and distance measurements etc.), photogrammetric (terrestrial, aerial and digital photogrammetry), satellite (such as Global Positioning System-GPS, InSAR), and non-geodetic techniques using lasers, tiltmcters, strainmeters, extensometers, joint-meters, plumb lines, micrometers etc. The major motivation of this study is geodetic methods.

One of the main aims of geodesy is detection of the deformations imposed on an object or an area which is characterized with points of a geodetic network. Since it is essential to detect deformations for many purposes (monitoring plate tectonics, determination of global datum, taking precautions for a construction which may be under damage, etc.), many considerable efforts and investigations have been performed on deformation analysis (Kavouras, 1982; Chen 1983; Chrzanowski et al. 1983).

Before any deformation measurement campaign is started, the geodesists should know about the result of their work according to the set objectives. This leads to the need for the optimization and design of deformation monitoring schemes.

Essentially, the purpose for the optimization and design of monitoring schemes is to prevent the deformation measurement campaigns from failing. It enables us to make decisions on which instruments should be selected from the hundreds of available models and where they should be located in order to estimate the unknown parameters and achieve the desired criteria derived from and determined by the purpose of the monitoring scheme (Kuang, 1996).

There are, however, significant differences in the design problems in positioning networks versus monitoring networks (Kuang, 1991). The classification of the optimization problems (design orders):

a) **Zero Order Design (ZOD):** It is the search for an optimal datum. But here in the deformation monitoring network there is **no ZOD problem**.

b) **First Order Design (FOD)**: It involves the geometric shape of the network including the optimum number and location of the geodetic stations.

c) **Second Order Design (SOD):** It deals with the determination of the weights of network measurements.

d) **Third Order Design (THOD) Problem:** Improvement of existing networks might be very useful for monitoring networks.

Traditional techniques have been applied to geodetic problems in the past. Cross and Thapa (1979) invistigated the design of leveling networks using linear programming. Linear programming was also used for the design of monitoring network by Benzao and Shaorong (1995). On the other hand, some optimization techniques based upon heuristic have been started to be used recently in geodetic science such as Evolutionary algorithms (EAs), Simulated annealing (SA) and Particle swarm optimization (PSO) algorithms.

The major motivation of this study as the subject of this paper is to solve the SOD problem using heuristic algorithms and make a comparison between the results of using these algorithms and the previous results of using the traditional method for the same deformation network in Kuang, 1991.

2. Observing Campaigns

If the geodetic observables involved in a campaign can be considered in a network without a configuration defect, then the vector of observations, can be related to the unknown coordinates, x, of the points or stations involved by:

$$L = Ax + v \qquad \text{....................... (1)}$$

Where:

$\underline{L}$ is an n-vector of observations; $\underline{x}$ is a u-vector of unknown parameters,

$\underline{v}$ is an error vector and $\underline{A}$ is the design matrix.

The least squares estimates of the coordinates are obtained by (Vanicek and Krakiwsky, 1986; Amiri-Simkooei et al. 2012)

$$\mathbf{x} = \left(\mathbf{A}^T \mathbf{P}\, \mathbf{A}\right)^{-1} \mathbf{A}^T \mathbf{P}\, \mathbf{L} \qquad \text{............. (2)}$$

in which **P** is the weight matrix of the observables, the inverse of their covariance, **C.** The variance-covariance matrix, $\mathbf{C_x} = \sigma_o^2 \left(\mathbf{A}^T \mathbf{P}\, \mathbf{A}\right)^{-1}$, provides the knowledge of the accuracy of the coordinates corresponding to the combination of the choice of instrumentation and observation techniques, through the matrix **P,** and of the configuration of the network, through **A.** In most instances, σ_o^2 is taken as unity. In an actual adjustment, ***L*** in Equation (2) is the misclosure vector **w = Ax -** ***L*** since the normal equations are non-linear but this is not of consequence in the design or pre-analysis.

The design for deformation monitoring assumes that the same configuration and observables will be involved in the repetition of a campaign. Consequently, the process can be extended to consider a pair of campaigns. The deformation can be described, in a displacement field, dx, as the difference in coordinates between the two campaigns, i.e., $dx = x_2 - x_1$, with $C_{dx} = C_{x1} + C_{x2}$, so $P_{dx} = \mathbf{C}_{dx}^{-1}$, and campaign 2 following campaign 1. This displacement field would be the "observed" displacement field since it results from measurements and its displacement components are located only at points involved in the network of observables. The observed displacement field is related to the deformation model parameters, *c*, through (Secord, 1995):

$$dx + v = Bc \qquad \text{......................... (3)}$$

where:

B : is a deformation matrix with its elements being some selected base functions,

c : is the vector of unknown deformation parameters.

By the modeling design matrix, ***B***. The least squares estimates of the deformation parameters are then obtained from (Kuang, 1991; Secord, 1995):

$$c = \left(B^T P_{dx} B\right)^{-1} B^T P_{dx} dx \qquad \text{...............(4)}$$

With the covariance matrix of the parameters, $c_c = \left(B^T P_{dx} B\right)^{-1}$.

For design purposes, the covariance of the deformation parameters can be related directly to the covariance of the observables by combining the above to yield:

$$\mathbf{c_c = 2.\left(B^T A^T C^{-1} A B\right)^{-1}} \quad \text{....................(5)}$$

By specifying the type of instrumentation and the observation techniques, the elements of C^{-1} are defined ($C^{-1} = P$ in Equation (2)). A appendix (A), a MATLAB implementation of the model in Eq. (5) "computation of an initial covariance of the deformation parameters".

Criterion matrices are very adequate tools to set up objective function. Let us consider the case in which a criterion matrix C_c^c for deformation parameters has been chosen as the precision criterion, the design problem then seeks an optimal weights such that it can be best approximated by C_c, i.e., (Kuang, 1991; Kuang 1996; Yetki et al. 2008 and 2011; Baselga, 2011)

$$\mathbf{SQRT\sum_i\sum_j\left((C_c^c)_{ij} - (C_c)_{ij}\right)^2 = min} \quad \text{......(6)}$$

This approach to design can guide in selecting the instrumentation, the techniques of observation, the location of the points, and the deformation model. In the present study, some constraints can be put on the weights to be obtained using intelligent optimization techniques.

3. Heuristic Optimization Algorithms

The word “heuristic” was initially coined by the Greeks; its original form was heuriskein, which meant “to discover”. Today, the term is used to describe algorithms that are effective at solving complex problems quickly. In such problems the objective is to find the optimal of all possible solutions, that is one that minimizes or maximizes an objective function. The objective function is a function used to evaluate a quality of the generated solution (Eq. 6). The successful performance of these optimization techniques have made it applicable to many other problems in geodesy and geodynamics.

Recently, optimization problems for deformation monitoring networks may be solved by heuristic optimization techniques such as Evolutionary algorithms (EAs), particle swarm optimization (PSO) and simulated annealing (SA).

A basic strategy for an heuristic as applied to design the monitoring networks could be as follows:

a) Choose an initial parameters,
b) Swap two of the objective functions to make the objective of a lower value
c) Repeat step 2 until no improvements can be made.

The major goal of this study is solving the mathematical model in Equation (6) for a pre-solved example in Kuang, 1991 which has been solved using traditional technique, using SA and PSO, then compare the obtained results from SA and PSO with the results of Kuang, 1991.

3.1 Simulated Annealing (SA) Method

Originally, the concepts of simulated annealing were heavily inspired by an analogy between the physical annealing process of solids and the problem of solving large combinatorial optimization problems.

The method SA is one of the most suitable for large-scale optimization problems, especially when there is a global extremum which is to be determined among many other poorer local extrema. The method is based on the work by Metropolis et al. , 1953, although many essential contributions (e.g. Kirkpatrick et al. 1983; Černỳ (1985) have given form to the present algorithm.

The basis of the SA method is an analogy with thermodynamics. At high temperature the particles of a body move freely in a relatively wide range. As it is cooled, mobility decreases: the particles are still able to move, but within smaller boundaries. When temperature decreases, so does mobility and, provided the cooling is slow enough, the particles are able to arrange themselves in states of increasingly lower energy, leading eventually to the state of lowest energy, i.e., crystalline pattern (i.e. the global optimum state) (Baselga, 2011 ; Ranjbar and Mosavi, 2012).

Following this ability of nature to find the minimum energy state of the system, it is possible to derive an algorithm that implements the basic features of the process and is adapted to the particular optimization problem.

The SA method was independently described by Scott Kirkpatrick, C. Daniel Gelatt and Mario P. Vecchi in 1983 (Kirkpatrick et al., 1983), and by (Černý.V, 1985). The method is an adaptation of the Metropolis-Hastings algorithm, a Monte Carlo method to generate sample states of a thermodynamic system, invented by M.N. Rosenbluth and published in a paper by (N. Metropolis et al., 1953).

3.1.1 Simulated Annealing Process:

The annealing process can start from any initial state in the domain of interest. According to the selected objective function (Equation 6), the energy of the current state E_0, is calculated. Then a constraint-based new state is generated from the current one, with energy of E_1. Let ΔE be the energy change state, $\Delta E= E_1- E_0$. The next state is decided according to the Metropolis criterion (Kirkpatrick et al., 1983). If the new state is better then the current one ($\Delta E \leq 0$), it is accepted unconditionally and becomes the next current state. otherwise ($\Delta E > 0$), the new state is not rejected outright but accepted with a certain probability (Ranjbar et al. 2012).

For more detailed information on the simulated annealing method, refer to more specific sources in the literature (e.g., Van Laaarhoven, 1987; Paradalos and Romeijn, 2002; Berne´ and Baselga, 2004). A MATLAB SA code was developed to optimize the SOD problem by Baselga 2011

3.2 Particle Swarm Optimization (PSO)

PSO deals with problems in which a best solution can be represented as a point or surface in an n-dimensional space. The main advantage of swarm intelligence techniques is that they are impressively resistant to the local optima problem. PSO was originally designed and introduced by Eberhart and Kennedy in 1995 based on social intelligence of a group of birds or fishes (Kennedy and Eberhart, 1995; Shi and Eberhart, 1998; Kennedy and Eberhart, 2001). Compared with other optimization algorithms, the PSO is more objective and easily to perform well, it is applied in many fields such as the function optimization, the neural network training, the fuzzy system control, etc.

In PSO algorithm, each individual is called “particle”, which represents a potential solution. The algorithm achieves the best solution by the variability of some particles in the tracing space. The particles search in the solution space following the best particle by changing their positions and the fitness frequently, the flying direction and velocity are determined by the objective function.

In binary PSO, a population (swarm) of birds (possible solutions or individuals or particles) is initialized randomly with values of {0,1}. It means each particle is a combination of one and zero which indicate the presence or absence of corresponding coefficient in the cost function respectively (similar to the chromosome). These particles are represented as the current positions (p). Then the fitness values of these particles are calculated using the cost function (Equation "6"). Based on these fitness scores, the best positions of each particle ***(PBest)*** and the global best position of all particles ***(GBest)*** are determined. In an iterative process, the velocity of each particle (v) is updated as below (Yavari et al. 2012):

$$v_{ij}(t+1) = w(t).\ v_{ij}(t)+C1\ r\ .[GBest_i\ (t)-P_{ij}(t)]+C_2.r_2.[PBest_i\ (t)-P_{ij}(t)] \quad \ldots\ldots\ldots(8)$$

where:

- i is the index of particle in the population;
- j: is the index of bits in the binary string of each particle;
- t is the iteration number;
- r_1 and r_2 are two uniform random values in [0,1];
- C1 and C_2 are two constant acceleration coefficients and
- w(t) is time varying inertia weight.

A nonlinear inertia weight (w) is used to adjust the effect of the current velocities in computation of the new velocity values as:

$$w(t) = w_{min} + (w_{max} - w_{min}).\ \frac{t_{max} - t}{t} \quad \ldots\ldots(9)$$

where:

- w_{max} *and* w_{min} are two constant experimental parameters, and
- t_{max}: is the maximum number of iterations.

Once the velocity for each particle is calculated, each particle’s position is updated by applying the new velocity to the particle’s previous position:

$$x_i\ (t + 1) = x_i\ (t) + v_{ij}\ (t + 1) \quad \ldots\ldots\ldots\ldots\ldots(10)$$

The three steps of velocity update, position update, and fitness calculations are repeated until a desired convergence criterion is met.

Currently, several researchers are being carried out in the area of particle swarm optimization and hence the application area also increases tremendously (Sivanandam and Deepa, 2008; Doma and Sedeek, 2012; Doma, 2013). Sedeek 2012 wrote PSO MATLAB code for SOD of deformation geodetic networks as Appendix A in his Thesis.

4. Applied Case Study:

As shown in Fig. (3), the network consists of 6 points (according to Kuang, 1991). The simulated approximate coordinates of all the network points are given in Table (1).

Assume that the deformation model to be detected includes a homogeneous strain field over the whole area plus single point movements of points # 3, # 4 and # 5. That is, the vector of deformation parameters to be detected can be expressed as:

$$e = (d_{x_3}\ \ d_{y_3}\ \ d_{x_4}\ \ d_{y_4}\ \ d_{x_5}\ \ d_{y_5}\ \ \varepsilon_x\ \ \varepsilon_{xy}\ \ \varepsilon_y)^T \quad ..(11)$$

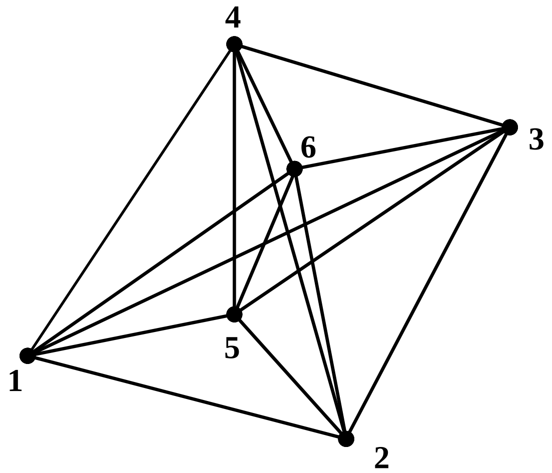

Figure (3): *The two-dimensional free trilateration monitoring network*

Where dx_i, dy_i (i= 3, 4,5) represent the displacements of points # 3, # 4 and # 5 in x-and y-directions respectively, and ε_x , ε_y and ε_{xy} the normal strain and shear strain parameters respectively. The deformation model can be expressed as:

$$\left.\begin{aligned} u_i &= \varepsilon_x x_i + \varepsilon_{xy} y_i \\ v_i &= \varepsilon_{xy} x_i + \varepsilon_y y_i \end{aligned}\right\} \quad \text{for } i = 1, 2, 6 \text{ and} \qquad (12)$$

$$\left.\begin{aligned} u_j &= dx_j + \varepsilon_x x_j + \varepsilon_{xy} y_j \\ v_j &= dy_j + \varepsilon_{xy} x_j + \varepsilon_y y_j \end{aligned}\right\} \quad \text{for } j = 3, 4, 5 \qquad (13)$$

One can compute the deformation matrix with its elements being some selected base functions (B) from Equations (12 and 13), where:

$$\begin{pmatrix} u(x,y,z;t-t_o) \\ v(x,y,z;t-t_o) \end{pmatrix} = \begin{pmatrix} B_u(x,y,z;t-t_o)\, c_u \\ B_v(x,y,z;t-t_o)\, c_v \end{pmatrix} \qquad (14)$$

We assume that the displacements have to be determined with a standard deviation of 0.71 mm. while the strains with a standard deviation of 0.14 ppm. The following diagonal matrix will be used as the precision criterion matrix, i.e.,

$$C_e = 2 \,.\, \text{Diag}\,[(0.5\text{ mm})^2 \; ..... \; (0.5\text{ mm})^2 \; ..... \; (0.1\text{ ppm})^2]$$

Table 1*. The simulated approximate coordinates of network points*

Point	Approximate coordinates	
	X(m)	Y(m)
1	1125	1625
2	4625	375
3	6250	4625
4	3250	5875
5	3375	1500
6	4375	4625

The PSO parameters used in this research are shown in Table (2). These parameters are selected based on Yavari et al. 2012 and also experimentally to balance the global and local search of PSO. However, it should be noticed that PSO is rather stable to the mild changes of these parameters.

Table (2): *PSO parameters*

Parameter	Value
No. of particles	30
Iteration	300
(C1)	1.75
(C2)	1.1

The target function for precision is then used to best approximate the above criterion matrix is Eq. (6). After the optimization solution process is done by using heuristic algorithms (both PSO and SA), the optimization results obtained from optimization model are listed in Tables (3 and 4) and Fig. 2.

At first, Table (3) lists the optimal weights using the traditional method (Kuang 1991) and both PSO and SA techniques. From this table one can see that, the numerical summation of the squares of the weights using traditional method equal 436.803, , but, the summation of the squares of the weights which had been obtained from intelligent techniques (both PSO and SA) = 377.109 and 337.653 respectively. This means that the heuristic techniques can be used an alternative method to design a deformation network with high efficiency. Figure (2) shows the performance of three algorithms. From Table (3), we can see the chosen parameters for PSO Algorithm.

Finally, At Table (4) we can see the Goodness of fitting of the precision criteria for traditional technique (from Kuang, 1991), PSO technique and SA technique, the precision criteria are less than and close to the required value for all used techniques.

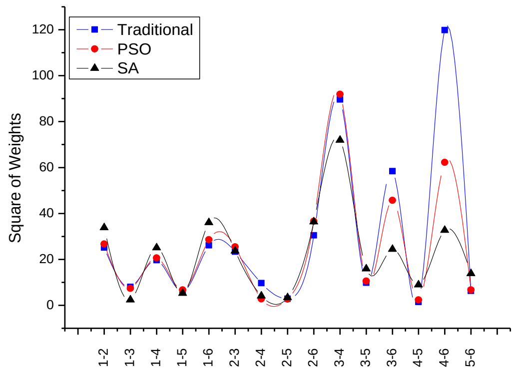

Figure (2)*: The performance of traditional, PSO and SA techniques in designing deformation network*

Table 3. *The desired weights of the observations obtained by traditional method (from Kuang, 1991) and the heuristic techniques (both PSO and SA).*

Obser.		**Optimal weights**					
from	to	Traditional method (Kuang, 1991)		Heuristic techniques: PSO technique		Heuristic techniques: SA technique	
from	to	P	P^2	P	P^2	P	P^2
1	2	5.02	25.16	5.17	26.68	5.82	33.81
1	3	2.84	8.0407	2.72	7.381	1.54	2.384
1	4	4.43	19.617	4.54	20.633	5.00	25.043
1	5	2.46	6.072	2.59	6.7398	2.29	5.238
1	6	5.11	26.131	5.35	28.605	6.00	36.01
2	3	4.83	23.331	5.05	25.463	4.87	23.692
2	4	3.11	9.680	1.67	2.794	2.03	4.129
2	5	1.70	2.8975	1.63	2.668	1.84	3.379
2	6	5.52	30.44	6.05	36.62	6.03	36.988
3	4	9.47	89.63	9.59	91.876	8.48	71.945
3	5	3.13	9.8178	3.25	10.571	3.98	15.857
3	6	7.64	58.364	6.75	45.745	4.94	24.393
4	5	1.21	1.4719	1.55	2.386	2.99	8.911
4	6	10.9	119.86	7.89	62.272	5.71	32.651
5	6	2.51	6.2813	2.58	6.674	3.72	13.82
Sumations		**69.93**	**436**	**66.3**	**377.1**	**65.24**	**337.6**

Where:

P: the optimal weights and

Table (4): *Goodness of fitting of the precision criteria for both linear programming (L.P.) method and the proposed PSO method.*

Parameters	Required precision	Obtained Precision: Precision from traditional technique	Obtained Precision: Precision from the heuristic techniques: **PSO**	Obtained Precision: Precision from the heuristic techniques: **SA**
dx_3	2.83 mm	0.52 mm	0.53 mm	0.57
dy_3	2.83 mm	0.71 mm	0.71 mm	0.71
dx_4	2.83 mm	0.66 mm	0.68 mm	0.71
dy_4	2.83 mm	0.59 mm	0.60 mm	0.58
dx_5	2.83 mm	0.68 mm	0.67 mm	0.67
dy_5	2.83 mm	0.65 mm	0.63 mm	0.54
ε_x	5.66 ppm	0.14 ppm	0.14 ppm	0.14 ppm
ε_{xy}	5.66 ppm	0.10 ppm	0.11 ppm	0.10 ppm
ε_y	5.66 ppm	0.11 ppm	0.11 ppm	0.11 ppm

5. Conclusions

Deformation measurements are of major importance in the board spectrum of activities covered by surveying engineering. Essentially, there are both practical and scientific reasons for the study of deformations. Practical reasons include checking the stability of a structure and detection of the precursors of earthquakes or failure signals of structures. Scientific reasons include a need for a better understanding of the deformation mechanism and to establish prediction methods. Through the study of deformation measurements our knowledge about behavior of deformable bodies will be greatly improved.

This paper presents an investigation on the efficacy of particle swarm optimization (PSO) and simulated annealing (SA) to solve complex optimization problems, for the SOD problem, make decisions on which instruments should be selected from the hundreds of available models a process, in a deformation network while satisfying the desired precision criteria at minimal cost. The algorithms are tested on a deformation network which was solved using traditional method by Kuang 1991. The results have shown that the heuristic optimization algorithms have yielded better results than the classical method in solving the SOD problem.

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