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Comparison Result of Inversion of Gravity Data of a Fault by Particle Swarm Optimization and Cuckoo Optimization Methods.

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ABSTRACT

The purpose of this study was to compare the performance of two methods for gravity inversion of a fault. First method [Particle swarm optimization (PSO)]is a heuristic global optimization method and also an optimization algorithm, which is based on swarm intelligence. It comes from the research on the bird and fish flock movement behavior. Second method [The Cuckoo Optimization(COA)] is new evolutionary optimization algorithm which is inspired by lifestyle of a bird family called cuckoo. In this paper first we discussed the gravity field of a fault ,then describes the algorithms of PSO and COA And presents application of Cuckoo Optimization algorithm, and a particle swarm algorithm in solving inverse problem of a fault. Most importantly the parameters for the algorithms are given for the individual tests. Inverse solution reveals that fault model parameters are agree quite well with the known results. A more agreement has been found between the predicted model anomaly and the observed gravity anomaly in COA Method rather than PSO method.

Keywords: Particle swarm optimization, Cuckoo Optimization method, inversion, gravity data, fault

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INTRODUCTION

Optimization has been an active area of research for several decades. As many real-world optimization problems become more complex, better optimization algorithms were needed. In all optimization problems the goal is to find the minimum or maximum of the objective function. Thus, unconstrained optimization problems can be formulated as minimization or maximization of D dimensional function:

$$Min\ (or\ max)\ f(x), x = (x_1, x_2, x_3, \dots, x_D) \qquad (1)$$

where D is the number of parameters to be optimized. Many population based algorithms were proposed for solving unconstrained optimization problems. Genetic algorithms (GA), particle swarm optimization (PSO), are most popular optimization algorithms which employ a population of individuals to solve the problem on hand. The success or failure of a population based algorithms depends on its ability to establish proper trade-off between exploration and exploitation. A poor balance between exploration and exploitation may result in a weak optimization method which may suffer from premature convergence, trapping in a local optima and stagnation. PSO algorithm is another example of population based algorithms [Ardito, C. et al., 2005.]. PSO is a stochastic optimization technique which is well adapted to the optimization of nonlinear functions in multidimensional space and it has been applied to several real-world problems [Boehner, K., DePaula, R., Dourish, P. & Sengers, P., 2007.]. [K Khan, A Sahai,2012][Toushmalani ,2013b]

Another algorithm which is inspired by cuckoo lifestyle is “Cuckoo Optimization Algorithm (COA)” developed by Rajabioun. Through using a benchmarking study, he demonstrated the efficiency of this algorithm which can be considered as the most appropriate algorithm for discrete issues, proving its accelerated confluence and global optima accomplishment. [Rajabioun,2011]

The gravity method was the first geophysical technique to be used in oil and gas exploration. Despite being eclipsed by seismology, it has continued to be an important and sometimes crucial constraint in a number of exploration areas. In oil exploration the gravity method is particularly applicable in salt provinces, over thrust and foothills belts, underexplored basins, and targets of interest that underlie high-velocity zones. The gravity method is used frequently in mining applications to map subsurface geology and to directly calculate ore reserves for some massive sulfide ore-bodies. There is also a modest increase in the use of gravity techniques in specialized investigations for shallow targets. Also it has application in agriculture and archeology .Data reduction, filtering, and visualization, together with low-cost, powerful personal computers and color graphics, have transformed the interpretation of gravity data. Also in gravity methods, Euler and Werner deconvolution depth and edge - estimation techniques can help define the lateral location and depth of isolated faults and boundaries from gravity data. Complex geology with overlapping anomalies arising from different depths can, however, limit the effectiveness of deconvolution fault-detection results.(M. N. Nabighian et al.(2005);Toushmalani Reza,(2010a);Toushmalani Reza,(2010b)

Toushmalani Reza,(2010c); Toushmalani Reza,(2010d);;Toushmalani Reza,(2011) Toushmalani(2013a) Toushmalani(2013b) Toushmalani, R., & Esmaeili(2013)).

The outline of this paper is as follows. In first section we discussed the gravity field of a fault, Section II describes the algorithms of PSO and COA. Section III presents application of **Cuckoo Optimization** algorithm, and a particle swarm algorithm in solving inverse problem of a fault. Most importantly the parameters for the algorithms are given for the individual tests. Section IV presents conclusions and final comments.

APPPLICATION TO THE GRAVITY FIELD OF A FAULT

A fault structure can be approximated by two Semi-infinite horizontal sheets, one displaced vertically from the other. The general situation of a fault is presented in Figure 1, together with the shape of the Expected anomaly which is described by the formula 2 [Telford, et al 1976]:

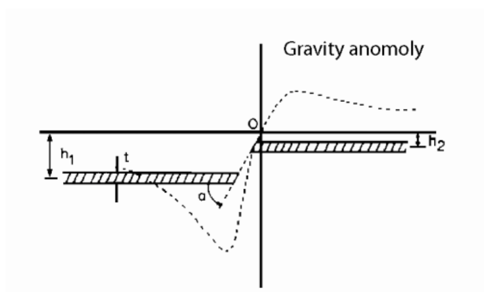

Figure 1. Fault model illustrating various parameters used in work, and shape of expected gravity anomaly.

g=2kбt[π+tan-1{(x/h1+cot (a)}- tan-1{(x/h2+cot (a)}]

K=6.672e-3

б =density contrast

t=thickness of sheet

h1,2=depth of each side to the middle of the sheet

a =fault angle.[Thanassoulas, C.; Tselentis, G.A.; Dimitriadis, K. 1987.Telford, et al 1976,Toushmalani, R. 2010.Toushmalani 2013a].

Methodology Approach of Cuckoo Optimization Algorithm (COA)

One of the most commonly used type of these optimization algorithms are meta heuristic algorithms which are inspired from nature. A most recent, yet powerful, kind of these evolutionary meta heuristic algorithms inspired by the cuckoos' lifestyle is the cuckoo optimization algorithm (COA), one of which is known as "cuckoo search", which was evolved by Yang and Deb[Yang X S & Deb S,2009;Yang X S,2011]. Proposed by these two researchers, the cuckoo search algorithm is mainly based on the behavior of obligate brood parasitic of certain cuckoo species accompanied with the Lévy flight behavior of some kind of birds and fruit flies.

The cuckoo search algorithm has been compared to other metaheuristics algorithms in several studies.

Another algorithm which is inspired by cuckoo lifestyle is“Cuckoo Optimization Algorithm (COA)” developed by Rajabioun. Through using a benchmarking study, he demonstrated the efficiency of this algorithm which can be considered as the most appropriate algorithm for discrete issues, proving its accelerated confluence and global optima accomplishment. In the current study, this algorithms developed by Rajabioun[2011] is mostly applied, creating a random population of potential solutions (candidate elements) each indicating the nests in COA. Here, the parameters of the candidate elements are assessed in the fitness function, considering a violation term as a limitation. In the following, the steps through which one can achieve the optimum solution are outlined. First, considering an initial population of cuckoos which lay some eggs in some host bird’s nest, the algorithm starts. Among these eggs those which are alike the host bird’s own eggs have a great chance to grow up and attain maturity, others, however, are caught by the host birds and are destroyed. The suitability of the nests in the area can be figured out from the hatched eggs. The more hatched eggs in the area, the more profits are achieved in that area. Hence, the term based on which COA is going to optimize is the place where more eggs survive with each cuckoo having a *“cuckoo’s distance”* to the goal point (best habitat).

Solving a problem with COA requires considering the valued of the issue as an array known as “habitat”. When an issue is N_{var} dimensional problem, then a habitat is an array of 1x N_{var} that indicates the position in which a cuckoo is currently lives. This can be summarized as follows:

$$\text{Habitat}= [x_1, x_2, \ldots, x_{Nvar}] \qquad \ldots(3)$$

The profit of a habitat can be calculated through profit function f_b at a habitat of ($x_1, x_2, \ldots, x_{Nvar}$)

$$\text{Profit}= f_b\,(\text{habitat})= f_b(x_1, x_2, \ldots, x_{Nvar}) \qquad \ldots(4)$$

By creating a candidate habitat matrix of size N_{pop}x N_{var} the optimization algorithm initiates. For each of these initial nests, random produced number of eggs is considered. This range is known as “Egg Laying Radius (ELR), since the cuckoos lay their eggs within the maximum distance from their habitat. This ELR can be demonstrated as follows:

$$ELR= \alpha \times \frac{\textit{Number of current cuckoos egges}}{\textit{total number of eggs}} \times (var_{hi}- var_{low}) \qquad \ldots(5)$$

Here, α is an integer which manage the maximum value of ELR, var_{hi} and var_{low} are the variables’ upper and lower limit respectively. After the process of laying eggs, P% of all eggs (frequently 10%) with lesser profit values will be destroyed, having no chance to hatch. Others’ have the opportunity of hatch and grow up and the host birds feed them as their own chickens.

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Another matter at issue is that the groups of cuckoos are formed in various areas and to immigrate it is nearly impossible to figure out which cuckoo belongs to which group. To solve the mentioned issue, the author here employed an algorithm work with K-means clustering method. When immigrating, cuckoos do not fly to the destination habitat; however, they just fly a part of the way back to destination and have a deviation as well. Considering that each cuckoo fly λ% of the overall distance of the considered habitat and has a deviation of ϕ radians. λ and ϕ are two parameters through which cuckoos can search many more places in various areas. These two parameters are defined for each cuckoo as follows:

$$\lambda \sim U(0,1), \qquad (6)$$
$$\lambda \sim U(-\omega, \omega)$$

$\lambda \sim U(0,1)$ means that λ is a random number uniformly distributed between 0 and 1. ω is a parameter, bounding the deviation from targeted habitat. For good confluence, an ω of Л/6 (radian) is enough, the author suggests.

Based on what already noted, a brief summary of the cuckoo optimization algorithm (COA) is outlined in the following:

1. Starting cuckoo habitants with considering some random points on the profit function;
2. Apportioning a number of eggs to each cuckoo;
3. Illustrating ELR for each cuckoo;
4. Laying eggs inside corresponding ELR by each cuckoo;
5. Devastating the identified eggs by host birds
6. Other eggs which are not recognized hatch and attain maturity;
7. Assessing the habitant of each newly grown cuckoo;
8. Regarding cuckoo's maximum number in environment, destroying those belong to worse habitat;
9. Clustering cuckoos and figuring out a best, targeted habitat for each;
10. Letting them immigrate to that targeted habitat;
11. If the condition is satisfied, stop otherwise go to 2.

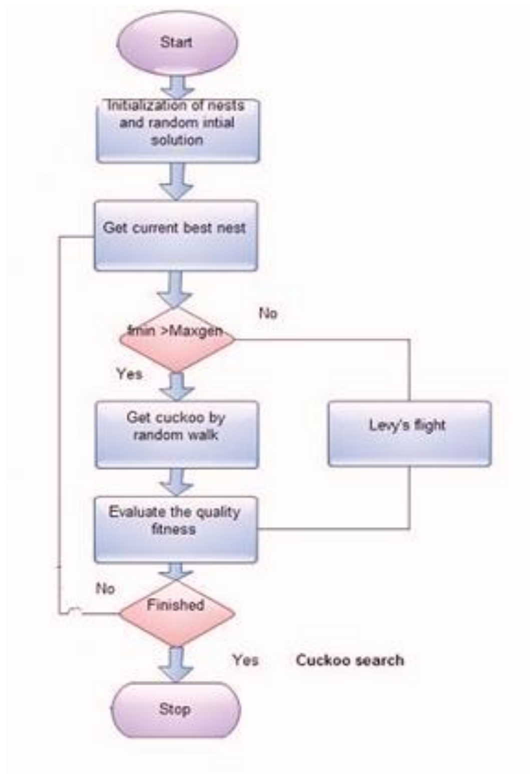

Figure 2: Scheduling flow chart

Particle Swarm Optimization (PSO) The PSO algorithm was first introduced by Eberhart and Kennedy [[Council of Ministers of Education. UNESCO World Conference on Higher Education, Report, 1998. ,ISO 9241., 1998. ,Chiu, C., et al., 2005. Hannula, M., 2006.]. Instead of using evolutionary operators to manipulate the individuals, like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companion s' flying experience. Each individual is treated as a volume-less particle (a point) in the D-dimensional search space (cf. Figure 4). [K Khan, A Sahai,2012]

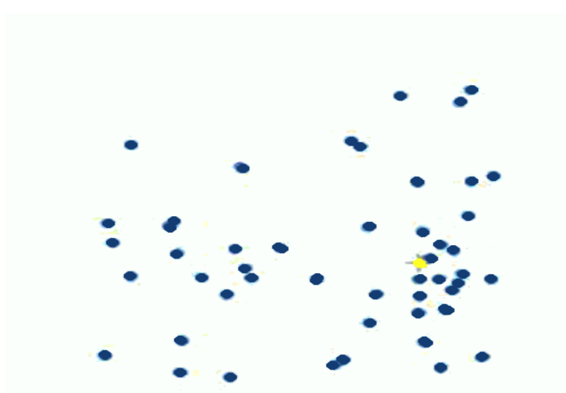

Figure 3: Particles movement in PSO

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The ith particle is represented as $X_i = (x\ i1, x\ i2\ \ ,\ldots, x_{iD})$. The best previous position (the position giving the best fitness value) of the ith particle is recorded and represented as $P_i = (p\ i1, p\ i2\ \ ,\ldots, p_{iD})$. The index of best particle among all the particles in the population is represented by the symbol gb representing global best. The index of the best position for each particle in the population is represented by the symbol ib representing the individual's best. The rate of the position change (velocity) for particle i is represented as V_i to the following equation: $(v_{i1}, v_{i2}\ \ ,\ldots, v_{iD})$. The particles are manipulated according to the following equations:

$$v_{id} = v_{id} + c_1 * rand(\ \ ) * (p_{ib} - x_{id}) + c_2 * rand(\ \ ) * (p_{gb} - x_{id}) \quad (7)$$

$$x_{id} = x_{id} + v_{id} \quad (8)$$

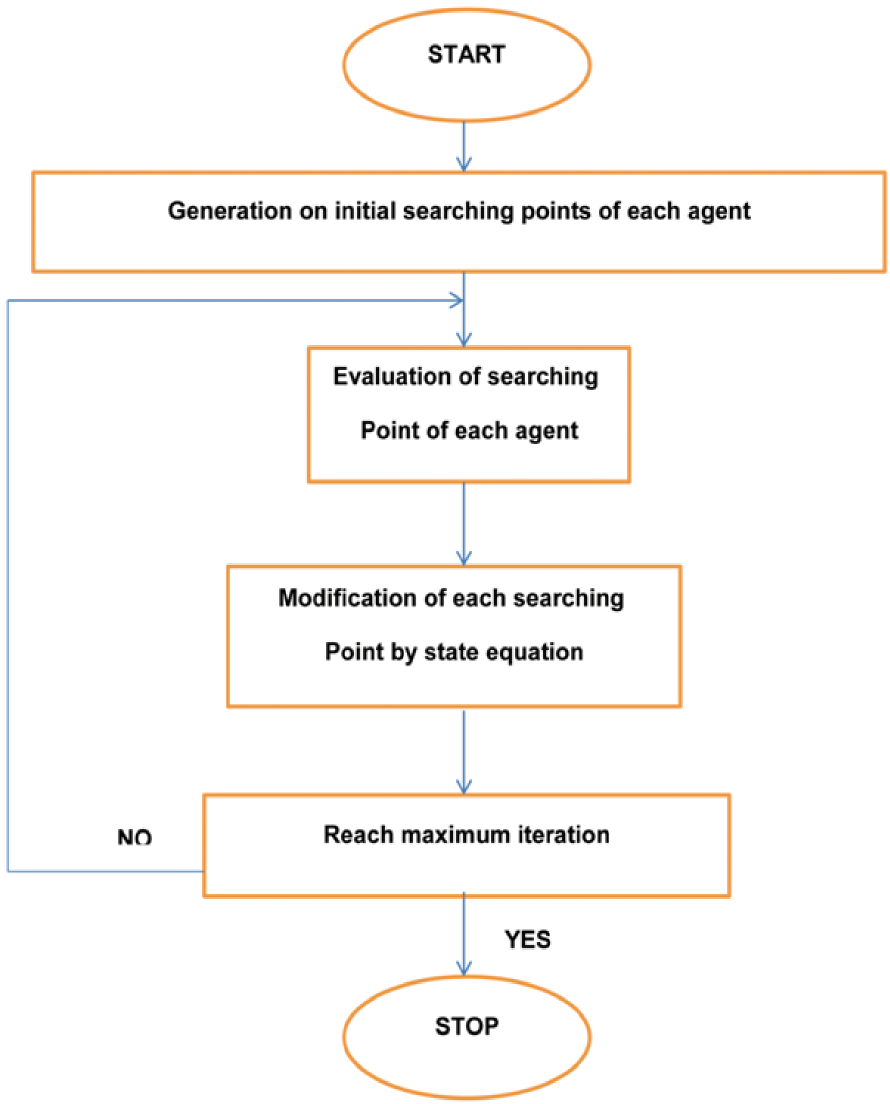

Figure 4. PSO Flowchart

The algorithm can be summarized as follows:

Step1 Initialize position and velocity of all the particles randomly in the *N* dimension space.
Step2 Evaluate the fitness value of each particle, and update the global optimum position.
Step3 According to changing of the gathering degree and the steady degree of particle swarm, determine whether all the particles are re-initialized or not.
Step4 Determine the individual best fitness value. Compare the p_i of every individual with its current fitness value. If the current fitness value is better, assign the current fitness value to p_i.
Step5 Determine the current best fitness value in the entire population. If the current best fitness value is better than the p_g, assign the current best fitness value to p_g.
Step6 For each particle, update particle velocity,
Step7 Update particle position.
Step8 Repeat **Step**2 - 7 until a stop criterion is satisfied or a predefined number of iterations are completed. [K Khan, A Sahai,2012] [Toushmalani 2013a, Toushmalani 2013b].The particle swarm flowchart is shown on Figure 5.

Application of PSO and LM optimization in inverse problem solving

Using Equation (1), the theoretical anomaly which corresponds to a fault with t = 500m, h_1 = 6000m (left), h 2 = 2000 m, a = 30 °, and б = 1, is presented as a continuous line in Figure 2. To test the program, the theoretical anomaly of Figure 2 is digitized every 5000m (Table 1), and a "bad" initial model with parameters h1 = 3000m, h2 = 1600 m, t = 700 m, and a = 30 ° is entered. [Thanassoulas, C.; Tselentis, G.A.; Dimitriadis, K. 1987]. Table 1shows Gravity anomaly for inversion .

Table 1: Gravity anomaly for inversion

x-coordinate (m)	Gravity anomaly(mgal)
-15000	- 2.24
-10000	- 3.47
-5000	- 5.60
0	0
5000	2.02
10000	1.61
15000	1.27
20000	1.04

During the iterations the density contrast is kept as a fixed parameter, assuming that its value has been estimated previously. The parameters which are optimized are:
(a) the thickness of the sheet,
(b) the left distance to the middle of the sheet,
(c) the right distance to the middle of the sheet, and

(d) the angle of the fault.

Table 2. Parameters of obtained solution with COA:

Thickness of fault: 501.4m
Fault angle (a): 18 °
Depth to bottom of the fault (h1): 6003m
Depth to top of the fault (h2): 2001m
-. Parameters of obtained solution with PSO :
Thickness of fault: 501.44 849 m;
Fault angle (a): 1.0 5*p- p =189-180 = 9°,
Depth to bottom of the fault (h1): 6000 m;
Depth to top of the fault (h2): 2001 .6431 m; [Toushmalani 2013]. Table 2 shows Parameters of obtained solution

Table 2: Parameters of obtained solution

Observed gravity	Calculated gravity with PSO	Calculated gravity with COA
- 2.24	-2.23	2.23-
- 3.47	- 3.47	-3.47
- 5.60	- 5.60	-5.60
0	0	0
2.02	2	2.01
1.61	1.63	1.63
1.27	1.29	1.28
1.04	1.05	1.04

CONCLUSION

The parameters which are optimized with these methods are: (a) the thickness of the sheet,(b) the left distance to the middle of the sheet,(c) the right distance to the middle of the sheet, and(d) the angle of the fault. Inverse solution reveals that fault model parameters are agree quite well with the known results. A more agreement has been found between the predicted model anomaly and the observed gravity anomaly in COA Method rather than PSO method.

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