Inversion of Gravity Data based Artificial Bee Colony Optimization (BCO) Algorithm: Application to Synthetic and Real Data

Ahmad Alvandi¹*, Rasoul Hoseini Asil²

¹Young Researchers Club and Elites, Toyserkan Branch, Islamic Azad University, Toyserkan, Iran
²Young Researchers Club and Elites, Sahneh Branch, Islamic Azad University, Sahneh, Iran

*Corresponding author: a.alvandi@iau.ac.ir

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In this paper we applied a new method in solving inverse problems in geophysics based on meta-heuristic algorithms relevant to artificial intelligence. Artificial bee colony optimization (BCO) algorithm works based on probability, test and trial and it stems from honey bees in the nature. Such behavior in bees is closely similar to the inverse problems in geophysics for finding the best parameters. Therefore, this idea is applied to solve an inverse problem. Firstly, using synthetic model with and without random noise, the efficiency of this method is evaluated and after a theoretical verification, the procedure is applied to the field data from Qom salt dome, Iran. The agreement between the results obtained by the artificial bee colony optimization (BCO) algorithm and other procedures is good.

Key-Words: Artificial Bee Colony Optimization Algorithm, Gravity Data Inversion, Synthetic and Real Data, Qom Salt Dome, Iran

1. Introduction

Gravity method has been used in investigations of wide range of scales such as tectonic studies, geotechnical and archaeological studies; regional geological mapping; engineering studies; coal, petroleum and mineral explorations; groundwater finding, environmental studies; volcanology and geothermal studies (Paterson and Reeves, 1985; Hinz 1990). Gravity data inverse modeling refers to a numerical procedure that constructs a model of subsurface geology from measured data on the earth surface (Qiu et al., 2009). Modeling is one of the most critical and sensitive stages of interpretation of Gravity Anomalies (Shadmehri et al., 2014). In the inverse modeling, whether the relationship between model parameters and data is linear or not, gravity data apply two different types of operator (Figure 1). In the first case if the distribution of density is going to be specified, the geometry is assumed constant and a linear operator used (Mottl and Mottlova, 1972; Oldenburg 1974; Last and Kubik, 1983; Shadmehri et al., 2014). In the second case, if the geometric parameters of the source are going to be determined, the density contrast must be assumed constant and a non-linear operator used (Barbosa et al., 1997; Farquharson and Oldenburg, 1998; Montesinos et al., 2005). Most practical geophysical inversion problems are non-linear (Yang 1997; Wang 2002), so non-linear inversion methods may be the best choices to solve these problems (Sanyi et al., 2009; Greenhalgh et al., 2006). Since in most of the inverse modeling problems, the number of the model parameters is more than the observations, the application of the numerical method is more effective (Rama et al., 1999). In addition, as the problem has great dimensions, meta-heuristic algorithms are appropriate method to solve these problems (Sanyi et al., 2009; She Yang 2011). Metaheuristic algorithms have many advantages over conventional algorithms due to their global search capability (Yang 2008, 2009, 2010). Meta-heuristic algorithms are becoming increasingly popular and powerful and they have the potential to provide better solution strategies (She Yang 2011).

Accordingly, in order to the inversion of gravity data through Simulated Annealing (She Yang 2011), Genetic Algorithm (GA) (Montesinos et al., 2005; Tiampo et al., 2004), Particle Swarm Optimization (PSO) (Sanyi et al., 2009; Roy 2009), Ant Colony Optimization (ACO) (Sanyi et al., 2009; She Yang 2011; Sanyi et al., 2008; Shadmehri et al., 2014), Simulated Annealing (SA) (Sanyi et al., 2009; She Yang 2011), Firefly Algorithm (Yang 2008, Yang and Deb, 2009, She Yang 2011) etc. are used. The present paper has used artificial bee colony optimization (BCO) as a new and effective procedure for the inversion of gravity data. In this paper, to depict the efficiency of this procedure, theoretical data with and without random noise are investigated. Artificial bee
colony optimization (BCO) algorithm is discussed in section II. In section III, the produced theoretical data and ground survey data set from Qom salt dome, Iran is analyzed.

![Figure 1: operators of gravity data inversion (Sanyi et al., 2009)](image)

2. Artificial Bee Colony Optimization (BCO) Algorithm

There was a great interest between researchers to generate search algorithms that find near-optimal solutions in reasonable running time (Sousa et al., 2003; Salem et al., 2009). The swarm-based algorithms (For example, ant colony optimization (ACO) algorithm; particle swarm optimization (PSO) algorithm; artificial bee colony optimization (BCO) Algorithm; Imperialist Competitive Algorithm (ICA)) are a search algorithm capable of locating good solutions efficiently (Sousa et al., 2003; Salem et al., 2009). The artificial bee colony optimization (BCO) represents the new meta-heuristic capable to solve optimization problems (Lucic et al., 2006). The artificial bee colony optimization (BCO) behaves partially alike, and partially differently from bee colonies in nature (Lucic et al., 2006). The BCO is applied to solve the optimization problems and finding the optimal degree of a function or a combination of multi-variable numerical functions (Karaboga et al., 2008; Marinakis et al., 2011; Pham et al., 2006). In the BCO algorithm, the food foraging process of a bee colony is started by onlooker bees that are sent to forage randomly for food sources in promising lands. A bee colony is able to forage food sources for a long distance and in different feasible directions. As the food foraging behavior process starts, some colony bees are selected continuously as onlookers. If food from a direction reaches a standard level, the onlooker bees store it in hive and proclaim a relative direction through waggle dance. The waggle dance is a significant relational instrument for colony which includes all information outside hive. BCO begins with presenting an initial random population of search space, i.e. the initial population phase:

\[ s_{mi} = s_{min} + rand \ast (s_{max} - s_{min}) \]  

which in equation (1) \( s_{mi} \) is a solution to the optimization problem and each \( s_j \) is an n-dimensional vector. Then fitness function of each solution is calculated (Marinakis et al., 2011). The next step of the algorithm is employed bees' phase in which a new solution \( Y_{mi} \) in the neighborhood of \( s \) is generated for each \( s_i \).

\[ Y_{mi} = s_{mi} + \rho_{mi}(s_{mi} - s_{kj}) \]  

\[ k = int(rand \ast SN) \]  

In equation (2), \( \rho_{mi} \) is a uniform distribution of the real random numbers on the interval \([-1, 1]\). \( s_{kj} \) suggests \( i^{th} \) from \( k^{th} \) solution of population in which \( k \) is randomly chosen among \( \{1, 2, 3..., SN, SN\} \). If the new solution is a better fitting, it is replaced with previous solution. In the phase of onlooker bees, each bee choosing a solution based on the probability calculated with equation (4), with a selective approach. Then onlooker bee chooses a new solution for chosen solution, the previous one is replaced by new solution, provided the latter is better than the former.

\[ \bar{p}_m = \frac{fit_m(s_m)}{\sum_{m=1}^{SN}fit_m(s_m)} \]  

which in the equation (4), \( fit_m(s_m) \) is fitting function \( s_m \). If the number of the cycles which are not improved by the solution is higher than a pre-determined degree, the solution is discarded and a new solution is randomly generated (Karaboga 2005). These phases are repeated until some stopping criteria are satisfied (Pham et al., 2006; Pham et al., 2007; Lucic et al., 2006; Hadidi et al., 2010; Zhang and Wu, 2011). Pseudo code of the BCO algorithm in its simplest form is shown in figure 2.
3. Modeling of Gravity Data

The model used here is one of the most popular ones described by Last and Kubik (1983) in order to model gravity anomalies. The gravity effect at the observation point \( i \) is given by:

\[
g_i^{calculated} = \sum_{j=1}^{M} a_{ij} \rho_j + p_i \quad i = 1, 2, ... N
\]

where \( g \) is the gravity anomaly, \( M \) is the number of blocks, \( a_{ij} \) is the kernel matrix, \( p_i \) is the noise of the \( i^{th} \) data, \( \rho_j \) is the density contrast of the \( j^{th} \) block. Here, density contrast is solved by BCO algorithm. A MATLAB Code for the BCO algorithm was implemented and was tested on theoretical and real gravity data.

3.1. The Synthetic Modeling

In this section, one simple model is applied to test the abilities of the BCO algorithm for inversion of gravity data. The bottom and top depths of causative body were selected as 40 and 20 m, the widths of body in the \( x \) and \( y \) coordinates were selected as 20 and 20 m, respectively. The density contrast is set to 1000 kg/m\(^3\) for the causative body. The 3D causative body model and its gravity anomaly are shown in Figure 3. The map of inverse modeling without random noise is shown in figures 4. Then, 15% random noise was added to the synthetic model. The picture of inverse modeling with random noise is shown in figures 5. Root mean square (RMS) values and the iteration number for synthetic model are shown in figure 6.

Figure 3: A) The three-dimension subsurface synthetic model; B) The gravity anomaly map of the causative body
Figure 4: The result of the inverse modeling for the theoretical model

Figure 5: The result of the inverse modeling for the theoretical model (with 15% random noise)

Figure 6: RMS values against the iteration number for synthetic model (Iteration Number= 100; Convergence Value= 40)
3.2. The Real Modeling
In this section, the real data inversion is considered. The case study for performing gravity method was a salt dome in Qom province. The area investigated is located in the center Iran (Motasharreie et al., 2010). The map of geographic location of Qom area is shown in figures 7. This research aimed to investigate the depth of salt dome of Qom (Motasharreie et al., 2010). The gravity measurement was done by Institute of Geophysics University of Tehran. Based on a priori information density contrast of 0.6 g/cm³ is chosen for the inversion (Salimi and Teymoorian, 2014). Residual gravity anomalies measured over salt dome of Qom is shown in Figure 8. The result from the inversion of bee colony optimization algorithm is presented in Figure 9. RMS values and the iteration number for real model are shown in figure 10. The depth obtained in this case is found to be in very good agreement with wavelet transform, least squares approach, Oldenburg-Parker inversion and Euler deconvolution methods (Table 1).

Table 1: Depth Estimation from Gravity Data of Qom Salt Dome

<table>
<thead>
<tr>
<th>Method</th>
<th>Depth (km)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet</td>
<td>1.06</td>
<td>Motasharreie et al., 2010</td>
</tr>
<tr>
<td>Least Squares</td>
<td>1.05</td>
<td>Motasharreie et al., 2010</td>
</tr>
<tr>
<td>Oldenburg - Parker</td>
<td>1.2</td>
<td>Salimi and Teymoorian, 2014</td>
</tr>
<tr>
<td>Euler Deconvolution</td>
<td>1.1</td>
<td></td>
</tr>
</tbody>
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Figure 7: Geographic location of Qom area in the map of Iran.
Figure 8: The gravity anomaly map of the study area

Figure 9: The result of the inverse modeling for the salt dome of Qom

Figure 10: RMS values against the iteration number for real model (Iteration Number = 100; Convergence Value = 50)
Conclusion
By using a proposed inverse modeling method of gravity anomaly, i.e. honey bee colony optimization algorithm, it is possible to optimize models with simple geometries. However, note that having basic knowledge of model helps significantly solving the problem of non-uniqueness of the answer in inverse modeling. This approach was tested on one theoretical and real data, and the very good results achieved in determining the depth.

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