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Model parameter estimations from residual gravity anomalies due to simple-shaped sources using Differential Evolution Algorithm☆

Yunus Levent Ekinci [a,b,*], Çağlayan Balkaya [c], Gökhan Göktürkler [d], Seçil Turan [d]

[a] Bitlis Eren University, Faculty of Arts and Sciences, Department of Archaeology, TR-13000 Bitlis, Turkey
[b] Bitlis Eren University, Career Research and Application Center, TR-13000 Bitlis, Turkey
[c] Süleyman Demirel University, Engineering Faculty, Department of Geophysical Engineering, TR-32260 Isparta, Turkey
[d] Dokuz Eylül University, Engineering Faculty, Department of Geophysical Engineering, TR-35160 İzmir, Turkey

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ABSTRACT

An efficient approach to estimate model parameters from residual gravity data based on differential evolution (DE), a stochastic vector-based metaheuristic algorithm, has been presented. We have showed the applicability and effectiveness of this algorithm on both synthetic and field anomalies. According to our knowledge, this is a first attempt of applying DE for the parameter estimations of residual gravity anomalies due to isolated causative sources embedded in the subsurface. The model parameters dealt with here are the amplitude coefficient (A), the depth and exact origin of causative source (zo and xo, respectively) and the shape factors (q and η). The error energy maps generated for some parameter pairs have successfully revealed the nature of the parameter estimation problem under consideration. Noise-free and noisy synthetic single gravity anomalies have been evaluated with success via DE/best/1/bin, which is a widely used strategy in DE. Additionally some complicated gravity anomalies caused by multiple source bodies have been considered, and the results obtained have showed the efficiency of the algorithm. Then using the strategy applied in synthetic examples some field anomalies observed for various mineral explorations such as a chromite deposit (Camaguey district, Cuba), a manganese deposit (Nagpur, India) and a base metal sulphide deposit (Quebec, Canada) have been considered to estimate the model parameters of the ore bodies. Applications have exhibited that the obtained results such as the depths and shapes of the ore bodies are quite consistent with those published in the literature. Uncertainty in the solutions obtained from DE algorithm has been also investigated by Metropolis–Hastings (M–H) sampling algorithm based on simulated annealing without cooling schedule. Based on the resulting histogram reconstructions of both synthetic and field data examples the algorithm has provided reliable parameter estimations being within the sampling limits of M–H sampler. Although it is not a common inversion technique in geophysics, it can be stated that DE algorithm is worth to get more interest for parameter estimations from potential field data in geophysics considering its good accuracy, less computational cost (in the present problem) and the fact that a well-constructed initial guess is not required to reach the global minimum.

1. Introduction

Based on measuring the variations in the Earth's gravitational field due to the effects of anomalous density differences between the subsurface rocks, both large and small scale geological problems can be investigated by means of gravity surveys (e.g., Paterson and Reeves, 1985; Oruç, 2010; Al-Garni, 2013; Ekinci et al., 2013; Pallero et al., 2015; Ekinci and Yiğitbaş, 2015). Numerous surveys on the use of gravity method have been reported in the literature so far such as regional geological studies, basin researches, explorations for mineral deposits, geodesic and seismological studies, isostatic compensation determinations, detection of subsurface cavities and archaeo-geophysical studies (particularly microgravity), determinations of glacier thicknesses, subsurface modelling studies, hydrogeological and environmental studies, and engineering applications (see Reynolds, 1997, Kearey et al., 2002; Jacoby and Smilde, 2009; Hinze et al., 2013 and the references therein). Among those investigations mentioned above, mineral (ore bodies) explorations take an important place because of the economic reasons. The isolated gravity anomaly due to single ore body is commonly interpreted in terms of some model parameters such as location, source geometry and depth (Roy et al., 2000). Incorporating a prior

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* Corresponding author at: Bitlis Eren University, Faculty of Arts and Sciences, Department of Archaeology, TR-13000 Bitlis, Turkey.
E-mail addresses: ylekinci@beu.edu.tr (Y.L. Ekinci), caglayanbalkaya@sdu.edu.tr (Ç. Balkaya), gokhan.gokturkler@deu.edu.tr (G. Göktürkler), secil.turan@deu.edu.tr (S. Turan).

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information by assigning a simple-shaped geometry (e.g., sphere, infinitely long horizontal and semi-infinite vertical cylinders) to the causative body clearly facilitates the interpretation. Since the gravity anomalies are not particularly sensitive to slight variations in the shape of the anomalous mass, the use of simple-shaped model bodies often yields solutions that are close enough to be useful (Telford et al., 1990). Assuming a fixed simple geometry, various methods have been developed for determining some model parameters of the gravity sources. These methods are, for example, depth rules (Smith, 1959), characteristic and windows curves methods, graphical and characteristic points methods (e.g., Siegel et al., 1957; Nettleton, 1962, 1976; Rao and Murthy, 1978; Reynolds, 1997), spectral analysis (e.g., Odegard and Berg, 1965), ratio methods (e.g., Bowin et al., 1986; Abdelrahman et al., 1989), numerical horizontal derivatives methods (Abdelrahman and Sharafeldin, 1995a; Abdelrahman et al., 2001a), some moving average methods (Abdelrahman et al., 2006), successive least-squares minimization methods (Abdelrahman and Sharafeldin, 1995b; Abdelrahman et al., 2001b; Essa, 2011, 2012, 2014), application of some transforms (Mohan et al., 1986; Shaw and Agarwal, 1990) and inverse modelling techniques (e.g., Tlas et al., 2005; Asfahani and Tlas, 2012; Mehanee, 2014). Among those interpretation techniques, only inverse modelling procedures aim to estimate the model parameters whose responses are similar to the measured data. By this way, the fit between the observed and calculated anomalies can be analysed. However, the well-known non-unique, non-linear (in the present problem) and ill-posed nature of the gravity data inversion makes the processing and interpretation difficult. In other words, if the potential field is known only on a bounding surface, there are infinitely equivalent source distributions inside the boundary that can produce the same field (Li and Oldenburg, 1996). Thus, the inverse modelling problem of gravity anomalies intensely requires some constraints in order to recover interpretable and realistic model solutions (e.g., Last and Kubik, 1983; Li and Oldenburg, 1998; Camacho et al., 2000; Zhdanov et al., 2004; Ekinci, 2008; Zhdanov, 2009; Feng et al., 2014).

Local and global optimization techniques are frequently used for inversion of geophysical data sets. Local optimization algorithms compared to the global ones are usually capable to achieve a fast convergence to the solution. However, these algorithms as optimizers typically attempt to find a local minimum in the vicinity of the initial model (Sen and Stoffa, 1995). Thus, a well-constructed initial model involving the model parameters is essential to avoid getting trapped in a local minimum. On the other hand, global optimization methods as sampler are better suited to achieve sampling while optimizing. Thus, these algorithms have a capability to escape local minima by performing a stochastic search within the model space and do not require well-constructed initial model providing a robust and versatile search processes. In addition, considering the noise content being always an unavoidable matter for real world optimization problems, they can take into consideration an enlarged search space for the model parameters, and this is the only a priori information required (Fernández-Martínez et al., 2010). However, the main disadvantage of these algorithms is their high computational cost due to the large number of objective function evaluations especially in the presence of dense data sets and the forward problems having formidable anomaly equations. Despite this drawback, they may be preferred instead of former local approaches in the noisy data and in the absence of a priori information when a solution greatly sensitive to initial model (Fernández-Martínez et al., 2010).

Considering the high technological development of the fast and powerful computers in the recent years, the use of global optimization algorithms for inversion of geophysical data sets is also becoming more popular. The most commonly used naturally inspired global optimization algorithms in geophysics are the genetic algorithm (GA) (e.g., Başokur et al., 2007; Fernández Alvarez et al., 2008; Balkaya et al., 2012), simulated annealing (SA) (e.g., Göktürkler, 2011; Asfahani and Tlas, 2012; Göktürkler and Balkaya, 2012) and particle swarm optimization (PSO) (e.g., Shaw and Srivastava, 2007; Fernández-Martínez et al., 2010; Pekşen et al., 2011; Toushmalani, 2013; Pallero et al., 2015). Interestingly, although differential evolution (DE) algorithm (Price et al., 2005; Storn, 2008; Storn and Price, 1995) is one of the powerful population-based global optimization algorithm and is widely used to solve real-valued numerical optimization problems, only a few applications of geophysical data inversion have been reported so far (Růžek and Kvasnička, 2001; Goswami et al., 2004; Saraswat et al., 2010; Li and Yin, 2012; Balkaya, 2013; Balkaya et al., 2014; Song et al., 2014; Balkaya et al., 2015a, 2015b, 2015c). Additionally, to the best knowledge of the authors, there is no study on the parameter estimations from gravity data sets using DE algorithm except for a conference abstract (Balkaya et al., 2015c). Thus to fill that gap, an attempt was made to show the efficiency of DE algorithm on residual gravity data sets. Applications were performed using both theoretically produced data, and the field data sets including three known anomalies observed for various mineral explorations such as a chromite deposit (Camaguey district, Cuba), a manganese deposit (Nagpur, India) and a base metal sulphide deposit (Quebec, Canada).

2. DE algorithm

Unlike conventional least-squares approaches mainly used for potential field inverse problems, metaheuristic algorithms do not require good initial estimates to reach the global minimum. Since DE algorithm (Price et al., 2005; Storn, 2008; Storn and Price, 1995) is one of the powerful population-based evolutionary metaheuristics, it is widely used to solve real-valued numerical optimization problems as reported by Qing (2009, pp. 41-51) in detail. In DE, a scaled difference between two individuals randomly chosen from the population is added to third one to generate new individuals at each generation (Storn and Price, 1997). It iteratively modifies randomly generated individual solutions via some genetic operations including mutation, crossover and selection similar to those in genetic algorithm until a predefined termination criterion is satisfied. Thus, the population evolves toward an optimal solution (Lin et al., 2011). As clearly seen from the simplified flowchart of DE algorithm (Fig. 1), it requires to set only three user-defined control parameters including number of population (Np), weighting factor (mutation constant, F) and crossover probability (Cr), and it has two stages including initialization and evolution that includes several vector transforms (i.e., operations).

In the initialization stage, the initial individuals of the population (i.e., parameter vectors) which is located within a predefined search space are randomly created as follows.

$$x^j_{i,G} = x^j_l + rand(0,1).\left(x^j_u - x^j_l\right), \quad j = 1, 2, ..., D \tag{1}$$

where x represents target vectors, $x_{i,G} = (x^1_{i,G}, x^2_{i,G} ..., x^D_{i,G}), i = (1, \ldots, Np)$, i is the index for individuals, G is the current generation, j denotes parameters, $rand()$ indicates uniformly distributed random number in the range between 0 and 1, l and u are the lower and upper bounds, respectively for each parameter, and D represents the number of the parameters. Evolution cycle that is second stage in DE is achieved by mutation, crossover and selection operations, respectively as seen in the flowchart. Mutation, the first operation in the evolution cycle, is performed to create a mutant (donor) vector,$v_{i,G} = (v^1_{i,G}, v^2_{i,G} ..., v^D_{i,G}), i = (1, \ldots, Np)$, for each target vector, and the procedures are carried out by perturbing the base vector by a difference vector scaled by a weighting factor F. In multi-strategy DE, DE/best/1/bin yields better results with a good accuracy and less computational cost for the inversion of low-dimensional