Journal of Applied Geophysics 148 (2018) 189–200

Contents lists available at ScienceDirect

Journal of Applied Geophysics

journal homepage: www.elsevier.com/locate/jappgeo

Black hole algorithm for determining model parameter in self-potential data

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ARTICLE INFO

Article history:
Received 14 June 2017
Received in revised form 3 October 2017
Accepted 25 November 2017
Available online 28 November 2017

Keywords:
Black hole algorithm
Estimation model
Model uncertainty
Self-potential data

ABSTRACT

Analysis of self-potential (SP) data is increasingly popular in geophysical method due to its relevance in many cases. However, the inversion of SP data is often highly nonlinear. Consequently, local search algorithms commonly based on gradient approaches have often failed to find the global optimum solution in nonlinear problems. Black hole algorithm (BHA) was proposed as a solution to such problems. As the name suggests, the algorithm was constructed based on the black hole phenomena. This paper investigates the application of BHA to solve inversions of field and synthetic self-potential (SP) data. The inversion results show that BHA accurately determines model parameters and model uncertainty. This indicates that BHA is highly potential as an innovative approach for SP data inversion.

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1. Introduction

The self-potential (SP) method is a process of calculating natural potentials derived from three different sources, namely: electrokinetic, electrochemical, and thermoelectric sources. Consequently, this method is favored in the following applications: embankment leakage detention (Al-Saigh et al., 1994; Moore et al., 2011; Rozycki et al., 2006), cavity identification (Jardani et al., 2006), uranium, sulfide and graphite localizations (Biswas and Sharma, 2014a), landslide study (Lapenna et al., 2003), geothermal exploration (Byrdina et al., 2012), landfill leachate identification (Arora et al., 2007), and groundwater investigations (Bolève et al., 2012; Rizzo et al., 2004; Sill, 1983; Titov et al., 2015). The SP method is often successfully used due to its relatively easy application and simplicity in producing qualitative interpretations of the measured data.

Recently, tomography processes involving SP anomalies uses various methods for imaging subsurface anomalies such as the finite element method (Soueid Ahmed et al., 2013, 2014), continuous wavelet transform (Saracco et al., 2004), and change occurrence probability (Patella, 1997). On the other hand, SP anomalies can also be calculated upon assumption that the anomalies are in the form of simple geometries such as sphere, horizontal or vertical cylinder, or inclined sheet. Several numerical methods have been proposed for interpreting SP data, such as the least square approaches (Candra et al., 2014; Mehanee, 2014; Srigutomo et al., 2006), signal analysis not only using the Fourier analysis but also wavelet transform (Mauri et al., 2011; Srivastava and Agarwal, 2009), moving average (Hafez, 2005), and global optimization approaches, namely: simulated annealing (SA) (Biswas and Sharma, 2014b), genetic algorithm (GA) (Di Maio et al., 2016), particle swarm optimization (PSO) (Monteiro Santos, 2010), and differential evolution (DE) (Li and Yin, 2012). However, not all global optimization algorithms are sufficiently robust in solving optimization problems. Some algorithms, including GA, SA, DE, and PSO, often encounter premature convergence problems, depending on the parameters for each algorithm.

This work investigates the application of black hole algorithm (BHA) (Hatamlou, 2013) to invert single and multiple SP anomalies caused by spherical, cylindrical or inclined sheet sources. BHA is a relatively recent global optimization method with very few applications in geophysical problems so far. However, BHA has been successfully used in several field studies (Bouchekara, 2014; Hatamlou, 2013), with three known advantage: having a simple structure, ease of application, and free from tuning parameter issues.

2. Self-potential

The self-potential (SP) anomaly for shape body at a point x_i can be expressed as follows:

$$v(x_i) = K\frac{(x_i - D)\ \cos(\theta) + h\ \sin(\theta)}{\left((x_i - D)^2 + h^2\right)^q} \qquad (1)$$

where K denotes the polarization magnitude (or electrical dipole moment), x_i describes a measurement point coordinate at the surface along the profile, θ denotes the polarization angle, and h is the depth

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https://doi.org/10.1016/j.jappgeo.2017.11.015
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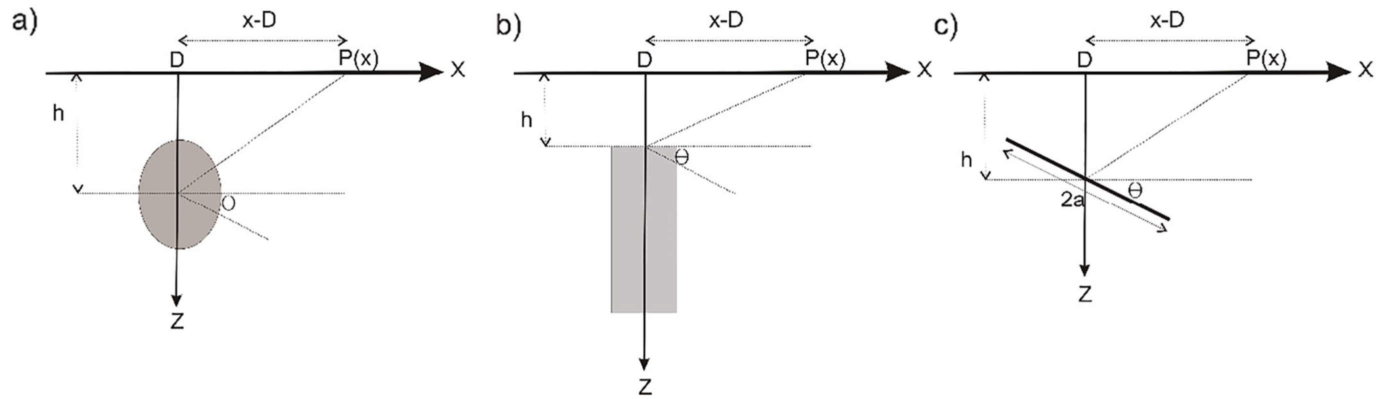

Fig. 1. Notation parameters for sphere and horizontal cylinder (a), vertical cylinder (b), and inclined sheet (c) in subsurface.

of the anomaly body's center source. D is the anomaly located at the center from the origin of measurement point, while q denotes the shape factor. The shape factors are 1.5, 1.0, and 0.5 for sphere, horizontal cylinder, and semi-infinite vertical cylinder, respectively.

The SP anomaly is located at a point on the surface, on a line perpendicular to the strike of an inclined sheet of infinite horizontal extent (perpendicularly to the measuring profile, Fig. 1), as given by follows (Biswas and Sharma, 2014c):

$$v(x_i) = K \ \ln\left(\frac{[x_D - x_a]^2 + [z - x_b]^2}{[x_D + x_a]^2 + [z + x_b]^2}\right) \tag{2}$$

where $x_D = x_i - D$, $x_a = a \cos \alpha$, and $x_b = a \sin \alpha$. α denotes the inclination angle and a is the half-width of the sheet-like body. For multiple SP anomalies sources, the equation for SP can be written as:

$$V(x_i) = \sum_{j=1}^{NM} v_j(x_i) \tag{3}$$

where $v_j(x_i)$ denotes the SP anomaly at x_i measured location for j-th body and NM is the number of bodies.

3. Black hole algorithm

Black hole algorithm (BHA) is a global optimization method initially descripted by Hatamlou (2013)). BHA is successful in solving unimodal and multimodal problems (Farahmandian and Hatamlou, 2015). BHA's algorithmic performance indicates that the algorithm is more powerful when compared to other optimization methods, such as GA, PSO, gravitational search algorithm, and big bang-big crunch algorithm (Farahmandian and Hatamlou, 2015; Hatamlou, 2013).

BHA is a population-based algorithm, where each population represents a number of stars. These starts generate a random population of candidate solutions. The population is placed in the search space of the model parameters. After initialization, the objective function values within each population are evaluated and the lowest value is set to be the black hole while the others are normal stars. The black hole absorbs the stars surrounding it and all the stars moving towards the black hole.

Absorption of the stars by the black hole is described in the following equation:

$$x_i(t+1) = x_i(t) + \ rand \times (x_{BH} - x_i(t)) \tag{4}$$

where $x_i(t)$ and $x_i(t+1)$ denote the locations of the i-th star at iterations t and $t+1$, respectively. x_{BH} represents the location of the black hole in the search space. $rand$ is a random number in the interval [0, 1]. In the BHA, the number of star M is used in the iteration process. After determining the movement of the stars using Eq. (4), if the objective function value of a star is better than the value of black hole, the star is then selected as the black hole. Further, the BH algorithm will continue with the new black hole and the other stars start moving towards this new black hole.

In addition, there exists the probability of crossing the event horizon (a star's distance to the black hole) during the movement of stars towards the black hole. This start will be swallowed by the black hole. Thus, it dies. In order to keep the number of stars constant, every time a star dies, another star is born by being generated randomly in the search space. The next iteration takes place after all the stars have been moved.

The radius of the event horizon in the BHA is formulated as the follows:

$$R = \frac{f_{BH}}{\sum_{i=1}^{M} f_i} \tag{5}$$

where f_{BH} and f_i represents the fitness values for the black hole and the i-th star, respectively. If the difference of objective functions between a candidate solution and the black hole is less than R, that candidate is considered dead and a new star is formed through random generation in the search space. Further understanding of this phenomena can be observed in the following papers (Farahmandian and Hatamlou, 2015; Hatamlou, 2013; Kumar et al., 2015).

Table 1
Synthetic model parameters, parameter ranges in BHA, and their results for a horizontal cylinder model.

Parameter	K	D	h	θ	q
True model	−10,000	40	10	60	1.5
Ranges of model	−100000–100,000	1–100	0–100	−20–180	0.7–1.8
BHA results	−10332.40 ± 3561.78	40.05 ± 1.53	10.73 ± 6.88	60.85 ± 6.94	1.50 ± 0.03

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