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Ant colony optimisation inversion of surface and borehole magnetic data under lithological constraints

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ABSTRACT

The ant colony optimisation algorithm has successfully been used to invert for surface magnetic data. However, the resolution of the distributions of the recovered physical property for deeply buried magnetic sources is not generally very high because of geophysical ambiguities. We use three approaches to deal with this problem. First, the observed surface magnetic data are taken together with the three-component borehole magnetic anomalies to recover the distributions of the physical properties. This cooperative inversion strategy improves the resolution of the inversion results in the vertical direction. Additionally, as the ant colony tours the discrete nodes, we force it to visit the nodes with physical properties that agree with the drilled lithologies. These lithological constraints reduce the non-uniqueness of the inversion problem. Finally, we also implement a K-means cluster analysis for the distributions of the magnetic cells after each iteration, in order to separate the distributions of magnetisation intensity instead of concentrating the distribution in a single area. We tested our method using synthetic data and found that all tests returned favourable results. In the case study of the Mengku iron-ore deposit in northwest China, the recovered distributions of magnetisation are in good agreement with the locations and shapes of the magnetite orebodies as inferred by drillholes. Uncertainty analysis shows that the ant colony algorithm is robust in the presence of noise and that the proposed approaches significantly improve the quality of the inversion results.

1. Introduction

Inspired by the social behaviour of individuals in nature (swarms), particle swarm optimisation (PSO) and ant colony optimisation (ACO) are two kinds of important swarm intelligence algorithms, both of which have been successfully applied in the inversion of geophysical data. For example, Tronicke et al. (2012) applied PSO-based optimisation strategies to reconstruct 2D P-wave velocity fields from crosshole traveltime data sets. Shaw and Srivastava (2007) used a PSO algorithm to invert for direct current (DC), induced polarisation (IP) and magnetotelluric (MT) data sets over a multilayered 1D earth model. Fernández Martínez et al. (2008, 2010) also used PSO to invert for vertical electric sounding (VES) and 1D DC data. ACO has primarily been used to invert for seismic records, e.g., Chen et al. (2005a, 2005b), Yan et al. (2009), and Xu and Song (2012), who inverted the impedances of the horizontal layer model and the Rayleigh wave dispersion curves. Using ACO and PSO, Yuan et al. (2009) inverted the parameters of the fixed shape model according to gravity and magnetic anomalies. Liu et al. (2014) introduced the node partition strategy ACO (NP-ACO) algorithm to recover the density and magnetisation distributions of potential field data and showed that ACO can be use to obtain distributions of physical properties that are sharper than those obtained by traditional linear inversion methods. For their test cases, ACO showed good optimisation capability, robustness, parallel implementation and portability.

Despite the foregoing examples, deep-buried magnetic bodies cannot be accurately recovered using current ACO methods, however. For example, in the synthetic test cases of Liu et al. (2014), the two parallel prisms, the core of the syncline, the deeper magnetic body of cut prisms and the reproduced prisms could not be clearly differentiated, due to the inherent geophysical non-uniqueness and to the low resolution of the surface magnetic data. The recovery of the distributions of physical properties is therefore problematic. Additionally, because of the rapid attenuation of magnetic anomalies with the increase in distance between sources and observers, the resolution of deeper magnetic sources of surface magnetic anomalies is relatively low, especially where the magnetic anomalies are concealed by significant interference.

We present three strategies to deal with this problem, making full use of borehole information obtained from magnetic three-component anomalies and lithological logs. First, we simultaneously invert for surface and borehole magnetic data as per Li and Oldenburg (2000). Borehole magnetic data have a higher vertical resolution and help to improve the ability of the method to identify deeply buried magnetic sources. Second, we use drillhole lithologies as a priori information in order to introduce an additional constraint to the iterative optimisation

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process, thereby reducing geophysical non-uniqueness. It is more convenient to add such drillhole constraint information to stochastic inversion methods than to linear inversion methods. As pointed out by Yao et al. (2007), nonlinear global optimisation algorithms do not need to compute the derivatives of the high-dimensional objective function and therefore have a decreased technical threshold for combining different kinds of constraint conditions. The nonlinear inversion methods simplify the mathematical description of geological constraints and make the combination of complex geological and geophysical constraints more convenient. To implement the additional constraint, we interfere with the movements of the ant colony and constrain the physical properties of the drilled mesh cells according to the drilled lithologies. Third, we analyse the distributions of the magnetic cells and divide them into K clusters based on their spatial distributions. Here, cluster analysis is the task of grouping a set of objects such that the objects in the same group are more similar to each other than to those in other groups. Cluster analysis is the main task of the exploratory data mining and a common technique for statistical data analysis; it is used in many fields, including machine learning, pattern recognition, image analysis, information retrieval and bioinformatics. K-means clustering, as a classic clustering method based on distance similarity, has been widely applied to near-surface geophysics and exploration geophysics. For example, Eppstein and Dougherty (1998) implemented a 3D traveltime tomography in which the dimensionality and geometry of the parameterisation are dynamically determined using cluster analysis, together with region merging using random field union. Paasche and Tronicke (2007) proposed a novel 2D approach based on fuzzy c-mean cluster analysis (i.e., K-means analysis) for the cooperative inversion of disparate data sets. Paasche et al. (2010) evaluated the regularised missing-value fuzzy c-means cluster algorithm and applied it to a database comprising of partially collocated crosshole tomographic P- and S-wave-velocity models. Paasche and Eberle (2009) employed fuzzy c-means (FCM) cluster analysis for the rapid and largely automated integration of complementary geophysical data sets comprising airborne radiometric and magnetic as well as ground-based gravity data. Paasche et al. (2006) demonstrated the potential of the fuzzy c-means (FCM) clustering technique to combine the information contained in the physical-property models that result from inverting the individual data sets and to estimate the spatial distribution of the petrophysical parameters in the regions where these are known at only a few locations. Ugalde and Morris (2010) applied clustering and kernel density distribution techniques to a Euler-generated data set. Sun and Li (2011, 2012) used this technique for geophysical inversion with petrophysical constraints by introducing an additional term that measures the misfit between the recovered cluster centres and those estimated a priori from the rock sample measurements. Teranishi et al. (2013) advanced a 3D joint inversion method to estimate two physical parameters, namely the density and the magnetisation of subsurface materials; this they achieved using field intensity measurements and by introducing the fuzzy c-means (FCM) clustering technique to relate gravity to the magnetic data. Li and Sun (2014) used fuzzy c-means clustering to implement the magnetisation vector inversion to limit the magnetisation directions into a small number of possible directions. The K-means cluster analysis separates the magnetisation distributions and improves the inversion quality.

The present paper is organised as follows. We begin with a description of the ant colony optimisation methodology. We then discuss the details of the inversion of the surface and borehole magnetic data and of the K-means cluster technique. The method is then tested using synthetic and real data. Finally, we conclude with a brief discussion.

2. Methodology

2.1. Ant colony optimization algorithm

Ant colony optimisation (ACO) is primarily used to solve discrete combinatorial optimisation problems (COPs), including the travelling salesman problem (TSP) and the quadratic assignment problem (QAP). The inversion of magnetic data minimises the multi-dimensional and continuous objective function

$$\phi(\mathbf{m}) = \phi_d(\mathbf{m}) + \lambda\phi_m(\mathbf{m}), \tag{1}$$

where ϕ is the objective function; $\mathbf{m}$ is the model parameter; ϕ_d and ϕ_m are the data misfits and regularisation terms, respectively and λ is the regularisation factor.

We implement the node partition strategy ACO (NP-ACO) (Liu et al., 2014) to invert for the surface and borehole magnetic data. This method minimises the continuous objective function of Eq. (1) by discretising the continuous model parameters. Therefore, the ranges (i.e., the minimum and maximum values) for all model parameters must be specified prior to dividing the model parameters into the discrete nodes (see Fig. 1). The model parameter ranges are usually divided equally into discrete nodes, but they also can be divided unequally. For example, it is reasonable to divide the ranges with a higher probability into a greater number of nodes. While a smaller node spacing may lead to a higher accuracy of the inverted parameters, it also increases the computational cost (Liu et al., 2014). The optimal node spacing is therefore determined by a trade-off between the inversion accuracy and the computational cost. After the discretisation of the model parameters, the ant colony visits the nodes layer by layer, touring from node $(i-1,j)$ to node (i,k) with the transition probability

$$P_{(i-1,j)}^{(i,k)}(t) = \frac{\left[\tau_{(i,k)}(t)\right]^{\alpha}\left[\eta_{(i,k)}(t)\right]^{1-\alpha}}{\sum_{l=1}^{N}\left[\tau_{(i,l)}(t)\right]^{\alpha}\left[\eta_{(i,l)}(t)\right]^{1-\alpha}}, \tag{2}$$

where $i = 1, 2, \cdots, n-1, j, k = 1, 2, \cdots, N, \tau_{(i,k)}$ is the number of pheromone trails at node (i,k), $\eta_{(i,k)}$ is the heuristic function related to some a priori information, α and $1-\alpha$ are the coefficients specifying the relative weights of the pheromone trails and the heuristic function, and n and N are the number of layers and the number of partitions for each layer, respectively (see Fig. 1). When all the ants have completed their tour, the number of pheromone trails at node (i,j) is updated using

$$\tau_{(i,j)}(t+1) = (1-\rho)\tau_{(i,j)}(t) + \nabla\tau_{(i,j)}(t), \tag{3}$$

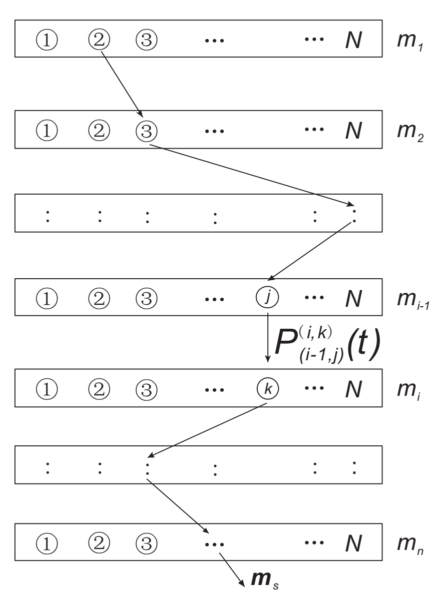

Fig. 1. Diagram of the ant colony optimisation algorithm minimising the continuous and multi-dimensional function.