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Inversion of Residual Gravity Anomalies using Tuned-PSO Technique

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Abstract

Many kinds of particle swarm optimization (PSO) technique are now available and various efforts have been made to solve linear and non linear problems as well as one dimensional and multidimensional problem of geophysical data. Particle swarm optimization is a Meta heuristic optimization method that requires the intelligent guess and suitable selection of controlling parameters (i.e. Inertia weight and acceleration coefficient) for better convergence at global minima. The proposed technique Tuned–PSO is an improved technique of PSO, in which effort has been made for choosing the controlling parameters and these parameters have selected after analysing the response of various possible exercises using synthetic gravity anomalies over various geological sources. The applicability and efficacy of the proposed method is tested and also validated using synthetic gravity anomalies over various source geometries. Finally Tuned-PSO is applied over field residual gravity anomalies of two different geological terrains to find out the model parameters namely amplitude coefficient factor (A), shape factor (q) and depth (z). The analysed results have been compared with published results obtained by different methods that show a significantly excellent agreement with real model parameters. The results also show that the proposed approach is not only superior to the other methods but also shows that the strategy has enhanced the exploration capability of proposed method. Thus Tuned-PSO is an efficient and more robust technique to achieve optimal solution with minimal error.

Keywords: Tuned–PSO, gravity anomalies, inversion.

1. Introduction

Gravity method is based on the measurement of gravity anomalies caused by the density variation due to source anomalies. Gravity method has been used in a wide range of application as a reconnaissance method for oil exploration and as a secondary method for mineral exploration, to find out the approximate geometry of the source anomalies, bedrock depths, and shapes of the earth. Interpretation of geophysical data that involves solving an inverse problem; many techniques have been developed to invert the geophysical data to estimate the model parameters. These methods can be broadly categorised into two groups: (1) local search technique (e.g. Steepest descent method; conjugate gradient method, ridge regression, Levenberg- Marquardt method etc.) and (2) global search techniques (e.g., simulated annealing, genetic algorithms, particle swarm optimization, Ant colony optimization etc.) Local search technique is simple and requires a very good initial presumption – close to true model for a successful convergence. In other hand global search method may provide an acceptable solution but computationally time intensive. There are several local and global inversion technique has been developed to interpret gravity anomalies (Thanassoulas *et al.*, 1987; Shamsipour *et al.*, 2012; Montesinos *et al*., 2005; Qiu, 2009; Toushmalani, 2013). However, PSO has been successfully applied in many fields, such as model construction, biomedical images, electromagnetic optimization, hydrological problem etc. (Cedeno and Agrafiotis, 2003; Wachowiak *et al*., 2004; Boeringer and Werner, 2004; Kumar and Reddy, 2007; Eberhart and Shi, 2001; El-Kaliouby and Al-Garni, 2009) but in the geophysical field PSO has limited number of applications (Alvarez et al., 2006; Shaw and Srivastava, 2007).

In this paper improved Particle Swarm Optimization known as Tuned-PSO with fine tuning of learning parameters have been tested using synthetic gravity anomalies over kinds of geometrical bodies and compared their efficacy. On the basis of performance, finally Tuned PSO has been used to invert gravity anomalies to find out the essential model parameters such as shape factor (q), depth (z), amplitude coefficient factor (A) and horizontal location of the source geometry.

2. Forward modelling for generating the synthetic gravity anomalies

A general expression of gravity anomaly caused by a sphere, an infinite long horizontal cylinder and a semi-infinite vertical cylinder have been used for generating the gravity anomalies in forward problem that is given in equation 1 (Abdelrahman *et al*., 1989) as follows:

$$g(x_{i}, z, q) = A\frac{z^{m}}{(x_i^2+z^2)^{q}} \qquad (1)$$

Where

$$A = \begin{cases} \frac{4}{3}\pi G\sigma R^3 & \text{for a sphere ,} \\ 2\pi G\sigma R^2 & \text{for a horizontal cylinder,} \\ \pi G\sigma R^2 & \text{for a vertical cylinder,} \end{cases} \qquad m = \begin{cases} 1, \\ 1, \\ 0, \end{cases}$$

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$$q = \begin{cases} \frac{3}{2} & \text{for sphere,} \\ 1 & \text{for horizontal cylinder,} \\ \frac{1}{2} & \text{for a vertical cylinder ; } R<<Z. \end{cases}$$

Where A, q and z represent amplitude coefficient factor, shape factor and depth respectively; and x_i, σ, G and R are the position coordinate, density contrast, universal gravitational constant and radius of geometrical bodies respectively. For semi-infinite vertical cylinder the gravity response is only applicable when the radius of the cylinder is much smaller than the distance from observation position to the top of the cylinder. In the forward modelling for generating the synthetic gravity anomalies, the amplitude coefficient factor of 600 mGal*km^2 and 200 mGal for sphere and vertical cylinder respectively, correspond to the shape factor as 1.5 and 0.5, and the depth of 5.0 km and 3.0 km are used. The shape factor approaches to zero as the structure becomes a nearly horizontal bed and approaches 1.5 as the structure becomes a perfect sphere (point mass). As in the formulae x_i is the position coordinate; at the origin $x_i = 0$ then equation 1 becomes,

$$g(0) = \frac{A}{z^{2q-m}} \tag{2}$$

The equation 3 is taken for addition of 10% white Gaussian noise.

$$g_{noisy}(x) = awgn(g(x), 0.1) \tag{3}$$

3. Tuned- Particle Swarm Optimization (Tuned-PSO)

Tuned-Particle Swarm Optimization (Tuned-PSO) is an improved Particle swarm optimization (PSO) method after the fine tuning of its learning parameters. The concept of PSO is described as follows (Eberhart and Kennedy, 1995): (a) each potential solution called as particles and knows its best values so far (P_{best}) and its position more over each particle knows the best value in the group (G_{best}) among the P_{best}. All of the best values are based on objective function *(Q)* for each problem to be solved. Each particle tries to modify its position through the current velocity and its positions. The velocity of each particle can be updated using the following equations (Santos, 2010):

$$v_i^{k+1} = \omega^k v_i^k + c_1 rand() * \left(P_{best-i}^k - x_i^{k+1}\right) + c_2 rand() * \left(G_{best}^k - x_i^{k+1}\right)$$
$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{4}$$

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Geoscientific Instrumentation Methods and Data Systems Discussions
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Where v_i^k is the velocity of i_{th} particle at k_{th} iteration, x_i^k represents current position of i_{th} particle at k_{th} iteration, $rand()$ is a random number in the range of 0 and 1. c_1 & c_2 are constants known as cognitive coefficient and social coefficient respectively. The coefficient c_1 has contribution towards the self exploration of a particle and the coefficient c_2 has a contribution towards the motion of the particles in global direction, and ω is an inertia weight in the range [0, 1]. The objective function has calculated by following equation (Santos, 2010).

$$Q = \frac{2\sum_i^N |V_i^o - V_i^c|}{\sum_i^N |V_i^o - V_i^c| + \sum_i^N |V_i^o + V_i^c|} \qquad (5)$$

Where N is the number of iteration, v_i^o and v_i^c are observed and calculated gravity anomaly measured at point $p(x_i)$ respectively.

4 Discussion and Results

4.1 *Selection of learning parameter for Tuned-PSO Modelling*

In this paper, a judicious selection of the parameters (i.e. ω, c_1, and c_2,) has been discussed for controlling the convergence behaviours of Tuned-PSO based algorithm. The settings of these parameters determine how it optimizes the search-space. These algorithms with suitable selection of parameter become more powerful global search algorithm for their practical applications.

4.1.1 *Inertia weight*

Inertia weight ω controls the momentum of the particle (Eberhart and Shi, 2001; Eberhart and Kennedy, 1995). Here two kinds of source geometry are adopted to evaluate more suitable ranges of parameters in the Tuned-PSO. For tuning of inertia weight, 0, 0.4, 0.7, 0.9, has been taken for two different acceleration coefficients at 1.4 and 2.0 respectively. From Figure 1, it is clear that the best convergence has performed by algorithm at inertia weight 0.7.This value of inertia weight produces high convergence rate at less number of iteration than the other values.

4.1.2 The maximum velocity v_{max}

The maximum velocity v_{max} determines the maximum change one particle can undergo in its positional coordinates during iteration and used to avoid explosion and divergence. Usually, the full search ranges of the particle's positions as the vmax are fixed. For example, in case, a particle has position vector $x = (x_1, x_2, x_3)$ and if $-15 <= x_i <= 15$ for i=1, 2 and 3, then $v_{max} = 30$ is fixed.

4.1.3 *The swarm size*

It is quite a common practice in the PSO literature to limit the range of number of particles. Van den Bergh and Engelbrecht have shown that though there is a slight improvement of the optimal value with increasing swarm size, a larger swarm increases the number of function evaluations to converge to an error limit. However, Eberhart and Shi Illustrated that the population size has hardly any effect on the performance of the PSO method. So, in this paper population size has taken 100.

4.1.4 *The acceleration coefficients c_1 and c_2*

To find the best tuning of learning parameters, various values of c_1, c_2 (i.e. $c_1 = c_2 = 1.0$, 1.2, 1.4, 1.6, 1.8, and 2.0) and inertia weights (i.e. 0.4, 0.7 and 0.9) are taken, and various exercises have been made using the two different geometrical bodies by fixing the each of the inertia weight (Table 1). The results was analysed and found that more suitable values of c_1 and c_2 (i.e. $c_1 = c_2 = 1.4$) are the best tuned acceleration coefficients for our case. These values of acceleration coefficients have been used to invert the gravity anomalies, which provide significant improvement and produce optimal solutions of the geological bodies.

4.2 *Application to Synthetic gravity anomalies*

Initially two geometrical models i.e. sphere and vertical cylinder has been considered for testing the applicability and efficacy of Tuned-PSO. The efficacy of proposed algorithm in terms of RMS error versus iterations is as shown in Figure 1. The gravity anomalies over these models are computed from equation (1) for the model parameters as shown in Table 1(a, b) and 2(a, b). In each case, the length of gravity profile of 51 km has 51data points at one km equal interval. The gravity anomaly for every source model is corrupted with 10% of white gaussian noise and Tuned-PSO based inversion algorithms applied on them. The optimized results obtained by Tuned-PSO algorithms for synthetic noise free and with 10% noisy data. The Figure 1 shows that tuned-PSO has best results at values 1.4, 1.4 and 0.7 for c_1, c_2 and inertia weight (w) respectively. This also shows that Tuned-PSO curve is having less number of local minima than other values. It means that the Tuned-PSO technique minimise the number of local minima for solving the geophysical nonlinear inverse problems. The simulated gravity anomaly by Tuned-PSO and computed gravity anomaly are shown in Figure 2(a) and 3(a) respectively and correspond to synthetic gravity anomaly and computed anomaly corrupted with 10% of white gaussian noise as shown in Figure 2(b) and 3(b).

Figure 2 and Figure 3 show the well matching between the synthetic curves and Tuned-PSO calculated gravity anomalies curves over spherical model and vertical cylindrical model respectively. Figure 4 shows the behaviour of p_{best} and g_{best} variation inside the algorithm and suggests that g_{best} decreases more rapidly toward the minimal error with high convergence. We observed from Table 2 and 3 that the RMS error increases with increasing the noise in gravity anomaly however, the horizontal location (x_0) is a substantially stable parameter and varies in a small scale.

4.3 *Application to Field gravity anomalies*

4.3.1. *Mobrun Sulphide Body, Near Rouyn- Noranda, Canada*

Mobrun polymetallic deposit near Rouyn- Noranda comprises two complexes of massive lenses within mainly felsic volcanic rocks of the Archean Blake River Group (Barrett. *et al*., 1992). The main lens contents mainly massive sulphide, approximately 3.37 Million Ton with some other elements in least amount in comparison to sulphide are 0.95 Million Ton at 0.81% Cu, 2.44% Zn, 30.3 g/t Ag, and 2.2 g/t Au estimated in 1989. The 1100 complex is located at 250 m to southeast of the Main complex. Host volcanic rocks of main complex are mostly massive, breciated, and tuffaceous rhyolites. Mobrun ore body is located at shallow depth; top of the body approximately 30 m depth and extended to 175 m.

Tuned-PSO in MATLAB environment has been applied to field residual gravity anomaly. This anomaly profile of length 268 m has been taken from the Mobrun sulphide body, Noranda, Canada (Nettleton, 1976; Essa, 2012). It is seen from Figure 5 that both curves analysed from Tuned-PSO and observed gravity anomalies are extremely well correlated with optimal RMS error of 0.0271%. The results in terms of model parameters (amplitude coefficient factor, shape factor and depth) over the Mobrun ore body analysed from Tuned-PSO method can seen in Table 4(a). This table provides the optimum results obtained from Tuned-PSO with 0.0271% error agrees well with the results obtained from other methods. The calculated value of shape factor, q is 0.77 (Table 4a). This value over Mobrun sulphide ore body reflects the shape of a semi-infinite vertical cylindrical geological body is present at depth of 30 m. It can be seen from Table (b), the values of amplitude coefficient factor, shape factor and depth correspond to 60.0, 0.77 and 30 are more stable and consistent with results analysed from various authors.

4.3.2. *Louga Anomaly West coast of Senegal, West Africa*

The study area Louga anomaly of west coast of Senegal is taken for another case study for interpretation of gravity data using Tuned –PSO. The Senegal basin is part of the north-west African coastal basin- a typical passive margin basin opening west to the Atlantic. The complexities of the rift tectonics of the Atlantic opening gave rise to a series of sub-basins aligned north-south. The pre-rift (Upper Proterozoic to Palaeozoic), syn-rift (Permian to Lower Jurassic) and post-rift are divided into a number of sub-basins, controlled by east west transform related lineaments (Nettleton, 1962). In this paper Tuned-PSO in MATLAB environment has been also applied to another field case study. Gravity anomaly of Louga area, West coast of Senegal, West Africa (Essa, 2014) has taken for Tuned- PSO analysis as shown in Figure 6 has Profile length 32 km. The results in terms of model parameters (amplitude coefficient factor, shape factor and depth) over the Louga anomaly analysed from Tuned-PSO method can seen in Table 5(a). It is seen from Figure 6 that both curves analysed from Tuned-PSO and observed gravity anomalies are extremely well correlated with optimal RMS error of 0.0271%. The optimum obtained results of model parameters amplitude coefficient factor (A), shape factor (q) and depth (z) are 545.30 mGal, 0.53 and 4.92 km respectively that shows significantly good agreement with the results obtained by various authors as shown in Table 5(b). The Tuned PSO analysed value of shape factor confirms that the shape of the causative body is semi-infinite vertical cylindrical body present at depth about 4.92 km.

5. Conclusions

In this paper, various synthetic gravity anomalies and field gravity anomalies have been adopted for evaluating the applicability and efficacy of Tuned-PSO algorithms and also determining the suitable ranges of learning parameters setting (i.e. inertia weight and acceleration coefficients). On the basis of the performance, a novel algorithm PSO with suitable learning parameters has been implemented to gravity anomalies assuming models with gravity source geometry such as sphere and vertical cylinder. This technique has been tested and demonstrated on synthetic gravity anomalies with and without gaussian noise and finally applied to field residual gravity anomalies over Mobrun sulphide ore body, Noranda, QC, Canada and Louga Anomaly of West coast of Senegal, West Africa. This technique provides robust and plausible results even in the presence of noise that are consistent with the results obtained from other classical methods. Thus this technique is powerful tool that improves the results of classical PSO and other technique significantly with less time and optimal error.

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Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
Manuscript under review for journal Geosci. Instrum. Method. Data Syst.
Published: 25 August 2016

Geoscientific Instrumentation Methods and Data Systems
Discussions
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Figure and Table Captions

Figure 1. Iteration versus RMS error plot at different acceleration coefficients and inertia weights.

Figure 2. (a) Synthetic gravity anomaly versus Tuned-PSO calculated gravity anomaly over spherical model and (b) Synthetic gravity anomaly versus Tuned-PSO calculated gravity anomaly over same model with 10% white gaussian noise.

Figure 3. (a) Synthetic gravity anomaly versus Tuned-PSO calculated gravity anomaly over vertical cylindrical model, (b) Synthetic gravity anomaly versus Tuned-PSO calculated gravity anomaly over same model with 10% white gaussian noise.

Figure 4. Iteration versus RMS error of Tuned-PSO showing p_{best} and g_{best} over synthetic gravity anomaly.

Figure 5. Observed field gravity anomaly versus Tuned-PSO calculated gravity anomaly over Mobrun sulphide ore body, Canada.

Figure 6. Observed field gravity anomaly versus Tuned-PSO calculated gravity anomaly over West Senegal anomaly, Louga area, South Africa.

Table 1. Performance of the acceleration coefficients c_1 and c_2 using the synthetic gravity anomalies over spherical and vertical cylindrical geometrical bodies.

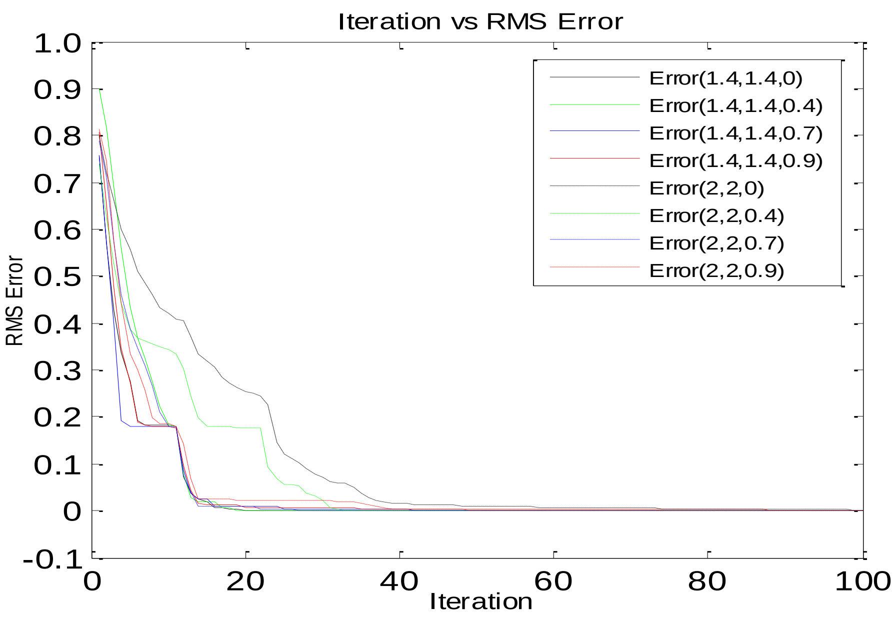
Table 2. (a) Optimized model parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly over a spherical source model and (b) optimized parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly with 10% white gaussian noise over a same source model from Tuned-PSO.

Table 3. (a) Optimized model parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly over a vertical cylindrical source model and (b) optimized parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly with 10% white gaussian noise over a same source model from Tuned-PSO.

Table 4. (a) Analysed results and parameters (A, z and q) used to invert the gravity anomaly over Mobrun sulphide ore body and (b) comparative results over Mobrun field, Canada from various methods and Tuned- PSO.

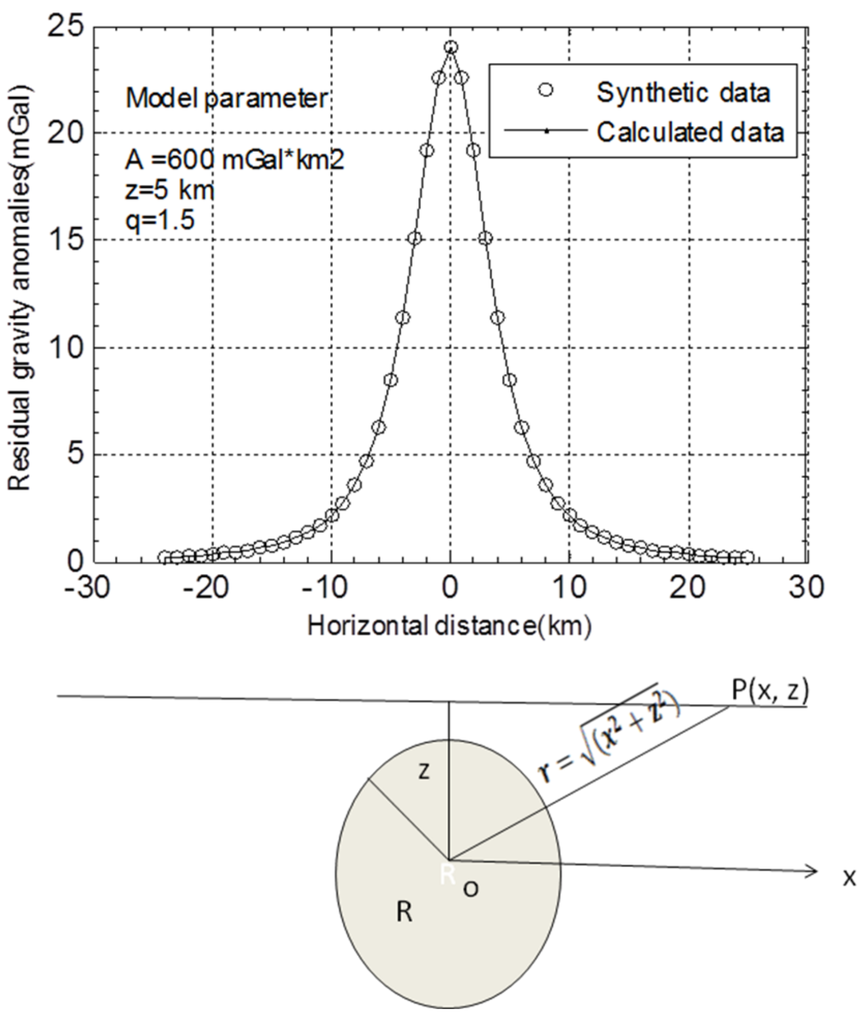
Table 5. (a) Analysed results and parameters (A, z and q) used to invert the gravity anomaly over West Senegal anomaly, Louga area, South Africa and (b) comparative results over same area from various methods and Tuned- PSO.

Figure 1


Iteration vs RMS Error
RMS Error
Iteration
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
0
20
40
60
80
100
Error(1.4,1.4,0)
Error(1.4,1.4,0.4)
Error(1.4,1.4,0.7)
Error(1.4,1.4,0.9)
Error(2,2,0)
Error(2,2,0.4)
Error(2,2,0.7)
Error(2,2,0.9)

Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
Manuscript under review for journal Geosci. Instrum. Method. Data Syst.
Published: 25 August 2016

Figure 2(a)



Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
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Figure 2(b)

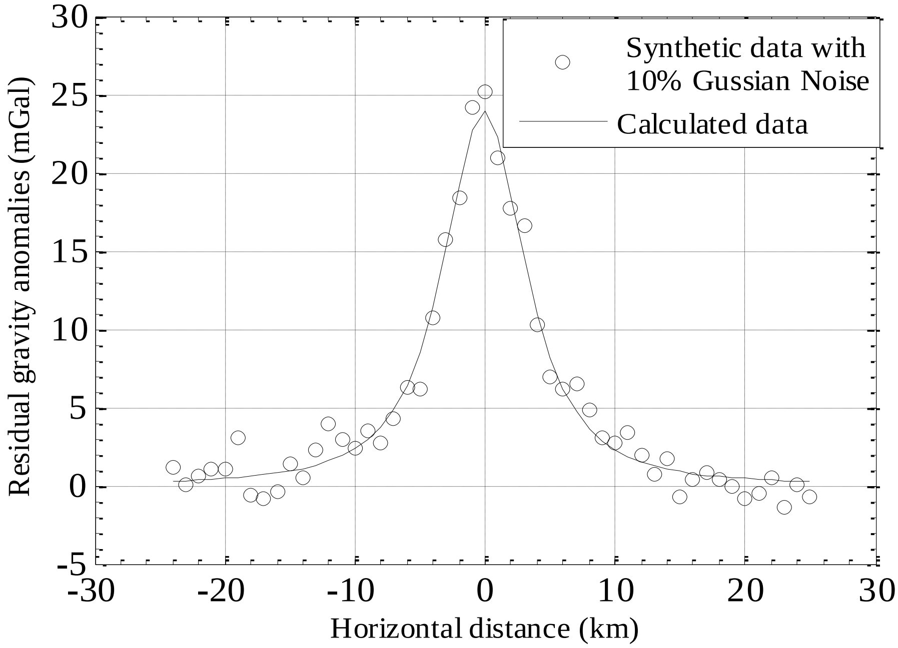
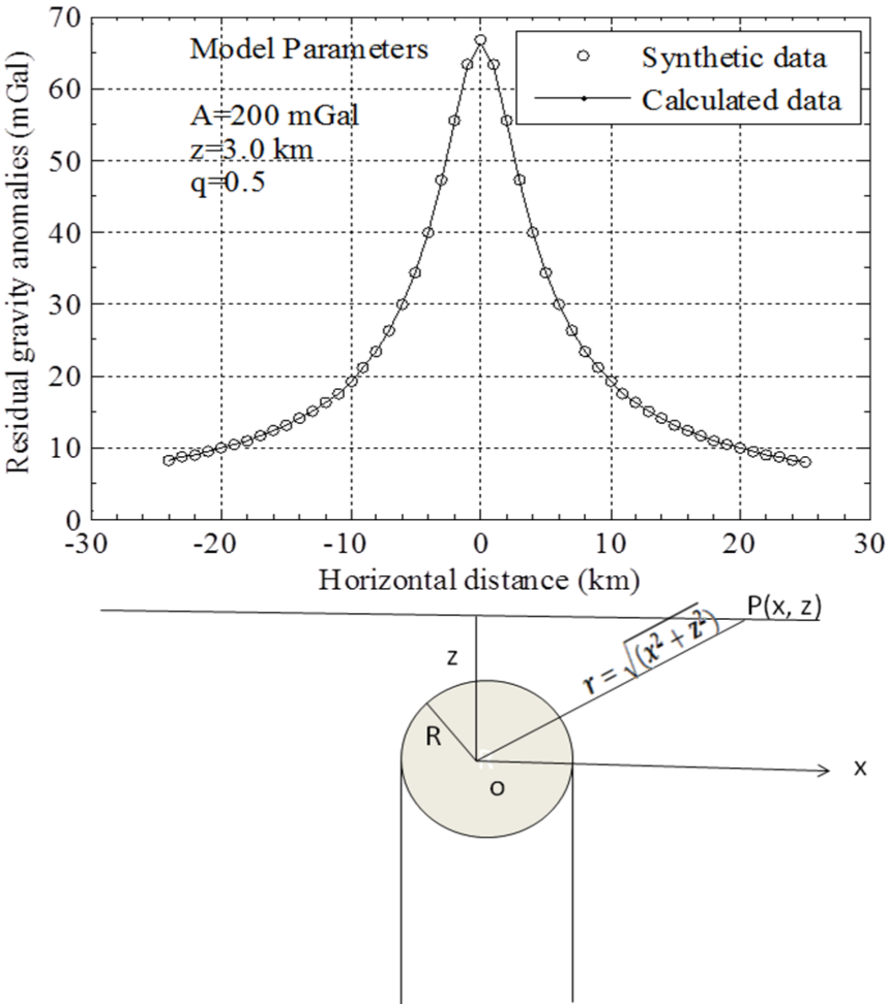


Figure 3(a)


Model Parameters
A=200 mGal
z=3.0 km
q=0.5
Synthetic data
Calculated data
Residual gravity anomalies (mGal)
Horizontal distance (km)
P(x, z)
$r = \sqrt{(x^2 + z^2)}$
z
R
O
X

Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
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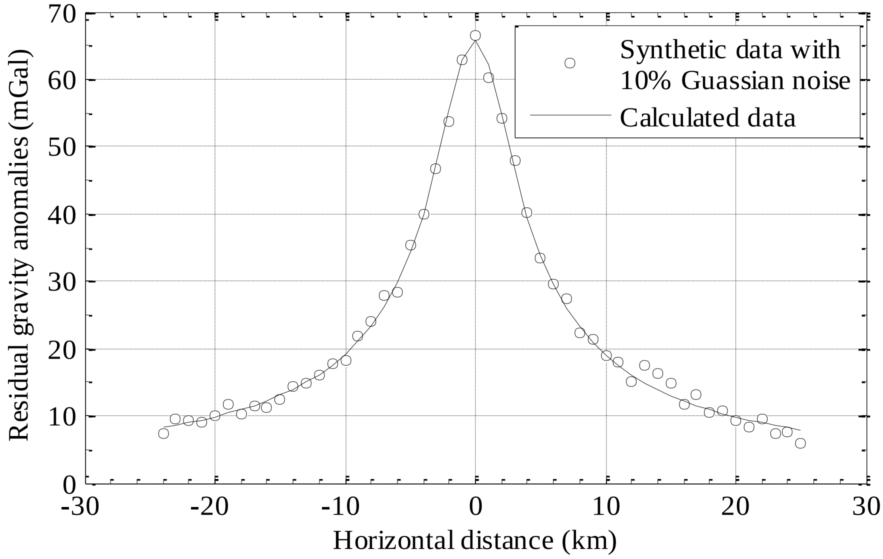
Figure 3(b)



Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
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Published: 25 August 2016

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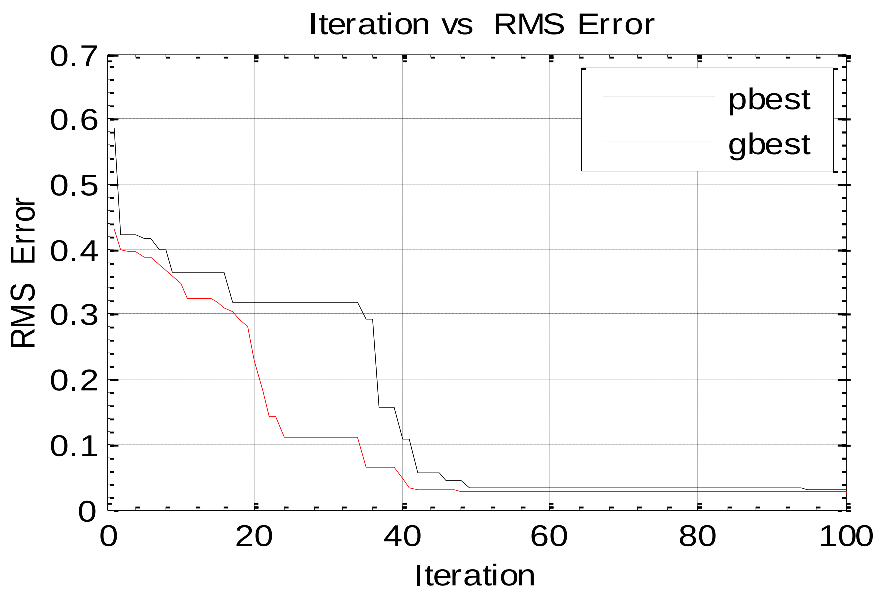
Open Access
Discussions

Figure 4



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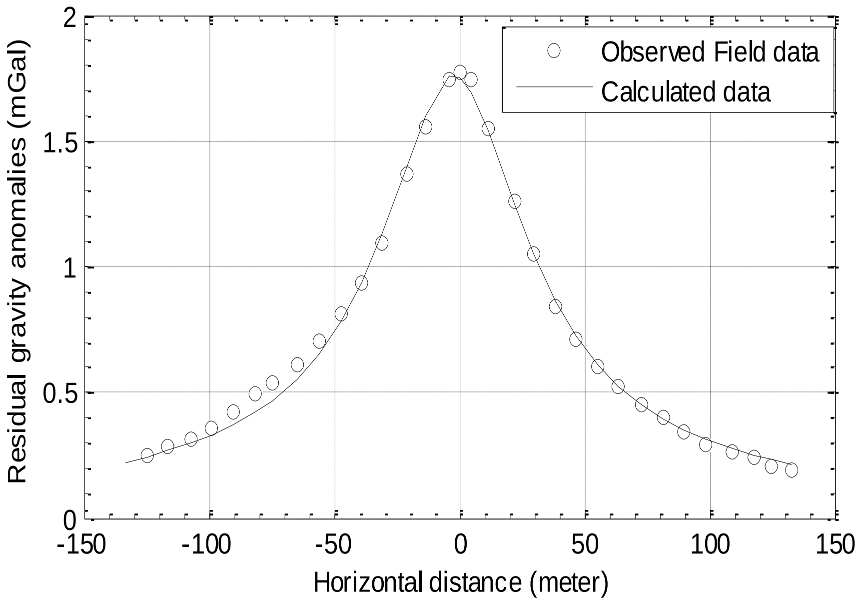
Geoscientific Instrumentation Methods and Data Systems
Discussions

Figure 5



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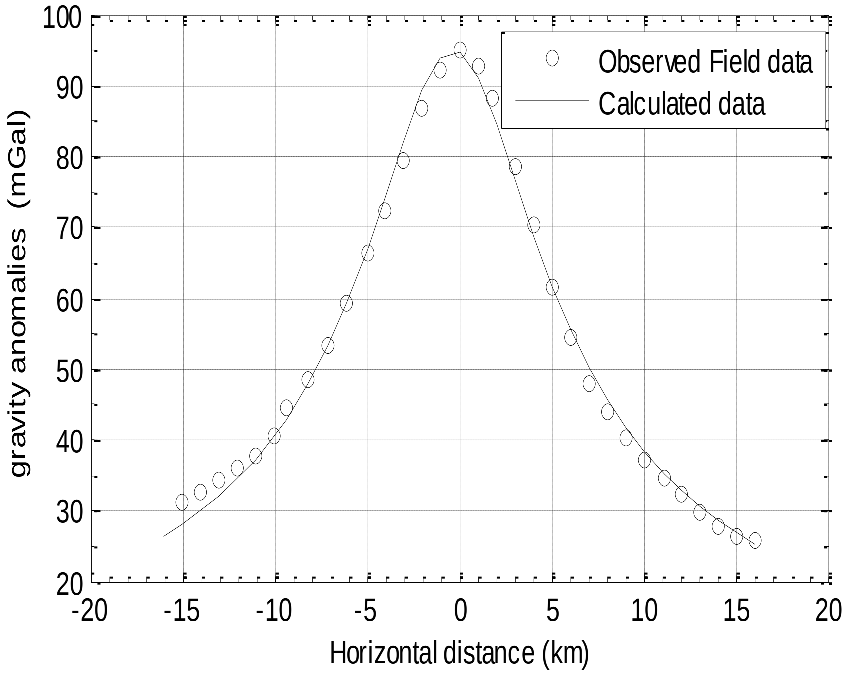
Geoscientific Instrumentation Methods and Data Systems Discussions

Figure 6



Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
Manuscript under review for journal Geosci. Instrum. Method. Data Syst.
Published: 25 August 2016

Geoscientific Instrumentation Methods and Data Systems Discussions

Table 1

Gravity data description	Weighting factor	$c_1 = 1.0$, $c_2 = 1.0$	$c_1 = 1.2$, $c_2 = 1.2$	$c_1 = 1.4$, $c_2 = 1.4$	$c_1 = 1.6$, $c_2 = 1.6$	$c_1 = 1.8$, $c_2 = 1.8$	$c_1 = 2.0$, $c_2 = 2.0$
		RMS Error					
Synthetic spherical body	w = 0.4	0.004899	0.002899	0.00014	0.000907	0.000853	0.000861
	w = 0.7	0.002532	0.000118	0.000013	0.000087	0.000187	0.000247
	w = 0.9	0.005215	0.000118	0.000063	0.000379	0.000167	0.002695
Synthetic vertical Cylindrical body	w = 0.4	0.004892	0.003231	0.000327	0.000835	0.000704	0.000932
	w = 0.7	0.001913	0.000318	0.000011	0.000065	0.000207	0.000511
	w = 0.9	0.003259	0.000551	0.000189	0.000183	0.001265	0.002747

Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
Manuscript under review for journal Geosci. Instrum. Method. Data Syst.
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Table 2

(a) Optimized Parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly over a spherical source model.

Z (km)	A (mGal*km^2)	q	g_0 (mGal)	x_0 (km)	Iteration	RMS Error (%)
4.99883	550	1.5	24.0	-1.89×10^{-3}	100	0.000405
4.9999	660.31	1.5	24.0	2.39×10^{-5}	200	0.000015
5.00	610.15	1.5	24.0	-1.44×10^{-6}	300	0.00
5.00	604.36	1.5	24.0	3.3×10^{-13}	400	0.00
5.00	604.10	1.5	24.0	8.17×10^{-16}	500	0.00

(b) Optimized Parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly with 10% white guassian noise over a spherical source model.

z (km)	A (mGal*km^2)	q	g_0 (mGal)	x_0 (km)	Iteration	RMS Error (%)
4.5	605.49	1.5	24	$-6.95\text{X}10^{-2}$	100	0.174890
4.5	603.99	1.5	24	$-6.81\text{X}10^{-2}$	200	0.174885
4.5	550.32	1.5	24	$-6.86\text{X}10^{-2}$	300	0.174883
4.5	601.42	1.5	24	$-6.86\text{X}10^{-2}$	400	0.174883
4.5	680.0	1.5	24	$-6.85\text{X}10^{-2}$	500	0.174883

Geosci. Instrum. Method. Data Syst. Discuss., doi:10.5194/gi-2016-26, 2016
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Table 3

(a) Optimized Parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly over a vertical cylindrical source model.						
Z (km)	A (mGal*km^2)	q	g_0 (mGal)	x_0 (km)	Iteration	RMS Error (%)
3.015	182.31	0.5	66.33	-4.4×10^{-3}	100	0.001743
3.016	185.92	0.5	66.33	-3.7×10^{-4}	200	0.001635
3.016	192.59	0.5	66.33	-2.74×10^{-10}	300	0.001633
3.015	162.15	0.5	66.33	-7.98×10^{-11}	400	0.001633
3.016	169.00	0.5	66.33	-6.58×10^{-11}	500	0.001633
(b) Optimized Parameters, converged iteration and RMS error in the inversion of synthetic gravity anomaly with 10% white guassian noise over a vertical cylindrical source model.						
z (km)	A (mGal*km^2)	q	g_0 (mGal)	x_0 (km)	Iteration	RMS Error (%)
3.02	167.33	0.5	65.81	-3.95×10^{-2}	100	0.036732
2.99	160.38	0.5	66.33	1.36×10^{-2}	200	0.036968
3.02	161.74	0.5	65.88	-4.52×10^{-2}	300	0.036672
30.2	160.35	0.5	65.88	-4.50×10^{-2}	400	0.036672
3.02	198.67	0.5	65.88	-4.50×10^{-2}	500	0.036672

Table 4

(a) Optimized Parameters, converged iteration and RMS error in the inversion of field gravity anomaly over Mobrun sulphide ore body.

z (km)	A (mGal*km^2)	q	g_0 (mGal)	x_0 (km)	Iteration	RMS Error (%)
31	58.08	0.77	1.7781	-2.99078	100	0.027149
31	59.55	0.76	1.1156	-3.02429	200	0.027163
31	58.00	0.76	1.7826	-2.13091	300	0.027125
31	59.03	0.77	1.7826	-2.15033	400	0.027124
30	59.99	0.77	1.7992	-2.15013	500	0.027124

(b) Comparative results over Mobrun field example from various methods and GPSO.

Parameter	Grant and West (1965)	Euler deconvoltuion (Roy et al., 2000)	Fast interpretation Method	Tuned- PSO Method
Z(m)	30	29.44	33.3	30.0
q	-	0.77	0.78	0.77
A(mGal)	-	-	59.1	60.0

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Table 5

(a) Optimized Parameters, converged iteration and RMS error in the inversion of field gravity anomaly over West Senegal (Louga area) anomaly.

z (km)	A (mGal*km^2)	q	g_0 (mGal)	x_0 (km)	Iteration	RMS Error (%)
4.90	549.44	0.52	94.83	-2.60x10^{-1}	100	0.027065
4.90	550.0	0.53	94.80	-2.56x10^{-1}	200	0.026552
4.91	549.57	0.53	94.79	-2.45x10^{-1}	300	0.026552
4.91	547.66	0.53	94.79	-2.42x10^{-1}	400	0.026551
4.91	545.30	0.53	94.79	-2.39x10^{-1}	500	0.025551

(b) Comparative results of various methods over West Senegal (Louga area) anomaly.

Parameter	New fast least square method (Essa, 2014)	Tuned-PSO method
z (km)	4.94	4.92
q	0.53	0.53
A (mGal)	545.68	545.30