Introduction

Fast and accurate 3D density distribution imaging of large-scale gravity data has always been one of the most concerned problems for geophysicists. The most widely used quantitative interpretation method is regularized inversion (Tikhonov, 1977). Millions of line kilometres of gravity data are collected every year, but 3D inversion for mega-regions is rarely performed resulting from its complexity and time consuming. Zhdanov et al. (2011) proposed an alternative fast approach called potential field migration which is based on a direct integral transformation of the observed gravity data into a subsequent density distribution. It can provide real time imaging, but the imaging results are divergent. Later, this method was extended to combined iterative migration with drilling data, contributing to an improvement in imaging accuracy to some extent. However, the introduction of iterative process causes a certain loss of computational efficiency. Compared with CPU computing technology, GPU has obvious advantages in processing capacity and memory bandwidth. With the characteristics of low cost, high performance and fast speed, GPU has certain applications in large-scale potential field inversion where the modelling domain is discretized into billions of cells. A number of publications have discussed GPU parallel technology to implement potential field forward modelling and inversion (Cuma and Zhdanov, 2014).

We propose a regularized focusing migration method based on the conjugate migration direction utilizing GPU parallel architecture. When solving the model parameters, the iterative direction is chosen along the conjugate migration direction, and the iterative step size is selected based on the Wolfe-Powell conditions. The parallel computing program of forward modelling and regularized migration on multi-GPU control with Openmpi is optimized by reducing data transfer, access restrictions and instruction restrictions as well as latency hiding. By comparing the computing speed of traditional single thread CPU method and CUDA-based GPU parallel technology, the excellent acceleration performance of GPU parallel computing is verified. We then demonstrate how the regularized focusing migration method can be applied for rapid imaging of synthetic model and practical data showing a higher spatial resolution and better noise resistance.

Methodology

Given that the gravity field $d^{obs}$ is collected on the observation surface, our question is how to determine the subsurface density distribution $m$. In the framework of the regularization theory, the solution of the inverse problem is simplified to solve the minimum of the Tikhonov parameter functional.

$$m = k_\alpha (W_m W_m)^{-1} A d^{obs} = k_\alpha \omega_\alpha^2 A d^{obs}$$

(1)

where $A^*$is the adjoint operator:

$$A^* = \gamma \int_{|r-z|^2} (z' - z) ds$$

(2)

We can consider $k_\alpha$ in equation (1) as the step size and $\omega_\alpha^2 A^* A$ as the migration direction. In this case the migration is essential to an iteration of a general regularized inversion problem. Although single migration has great advantages in efficiency, it does not yield a reasonable convergent result. So we provide the regularized focusing migration whose principle is shown below. The parameter functional is weighted by weighting matrices of $W_e, W_d, W_m$:

$$P_\alpha (m^{\omega_0}, d^{\omega_0}) = \| (W_d A W_m^{-1} W_e^{-1}) (W_e W_m m) - (W_d d) \|^2 + \lambda \| W_e W_m m \|^2$$

(3)

When solving the model parameters, different from the conjugate gradient method used in the general inversion problem, we provide the conjugate migration direction method where the search direction of each iteration is along the conjugate migration direction. Therefore, according to equation (1) we define the migration direction for the $n$th iteration $(n = 0, 1, ...)$ as

$$I_n = A^{\omega_0}^* (A^{\omega_0} m^{\omega_0} - d^{\omega_0}) + \lambda_n (m^{\omega_n})$$

(4)

and the conjugate migration direction for the current model parameter $m^{\omega_n}$ is:

$$\overline{r}^{\omega_n}_n = \overline{r}^{\omega_n} + \beta_n \overline{r}^{\omega_n-1}$$

(5)

The successive line search in the conjugate gradient direction can be written as:
Here, $k_n$ is the iteration step size, and we take the Wolfe-Powell inexact line search criterion to obtain the step size. The actual model parameters can be converted as:

$$m_{n+1}^m = m_n^m - k_n l_n$$  \tag{6}

Then $m_{n+1}^m$ is reweighted to obtain $m_{n+1}^{\text{reweighted}}$. After reweighting, we estimate the regularization parameter based on the method from Portniaguine and Zhdanov (1999) to ensure that the misfit functional is focused to the smallest in the whole region. Iteration process terminates when the misfit reaches a given range and then output $m_N$.

The general GPU programming language based on Nvidia-CUDA and the Openmpi standard for multi-GPU control are used to realize regularized migration of massive gravity data. We optimize the parallel computing program by reducing data transfer, access restrictions and instruction restrictions as well as latency hiding.

**Examples**

Figure 1 shows the computational time of the regularized focusing migration method for varying model scales on the CPU and GPUs. We ran 100 iterations. It can be seen that the CPU-based computation time increases at a near-linear trend with model scale. For models less than 4x4x4 cells, the GPU-based computation is more time-consuming due to the domination by initialization work and memory transfers. For models less than 8x8x8 cells, the GPU-based computation time almost keeps the same because the model is relatively small that does not utilize much parallelism of the GPU as finer model discretization does. The transition from constant computation time to linear increase for the GPUs occurs at a model scale of 16x16x16 cells, after which the computing performance has reached a plateau. Within the linear domain, 300x speedup for the Tesla P100 are achieved compared to a single thread CPU.

![Figure 1](image)

**Figure 1** Computing time of regularized migration for models with different scale. We ran 100 iterations.

Then we consider a synthetic model formed by dike complex and a rectangle. Figure 2(b) shows the gravity anomaly generated by the model as Figure 2(a). The data is inverted in the subsurface region divided into 100x50x50 cells. Figure 2(c) and (d) show the results from the regularized focusing migration, which delineate the approximate position and divide the trend of the dikes. Figure (e) and (f) show the conventional iterative migration imaging results, which barely distinguish abnormal bodies. We also added 5% random Gaussian noise to the observed gravity data and its imaging results are shown in Figure 2 (g) and (h) respectively. It can be seen that the result of direct migration of the noise-containing data hardly changes compared with that of noiseless data. It’s demonstrated that the regularized focusing migration method has good noise resistance. It should be noted that for our novel method the 50 iterations using 4xTesla P100 take only 40s with a model scale of 100x100x50 cells, which reduces the runtime by a further 99% compared to the CPU. It is indeed an encouraging speed.
Figure 2 (a) and (b) show the prospective view of the synthetic model and its gravity anomalies respectively; (c) and (d) show the cross sections obtained from 3D regularized focusing migration of $y=250m$ and $z=150m$ respectively; (e) and (f) show the cross sections obtained from conventional iterative migration of $y=250m$ and $z=150m$ respectively; (g) and (h) show the cross sections obtained from 3D regularized focusing migration of the noise-corrupted data of $y=250m$ and $z=150m$ respectively.

Case Study

We applied our novel method to the interpretation of local gravity anomalies in the skarn-type iron deposit, Shandong Province, China. The gravity data shown in Figure 3(a) is inverted in the subsurface region of $21.5km \times 39km \times 20km$, divided into $100 \times 50 \times 50$ cells. The 3D perspective of imaging results is shown in Figure 3(b), and the horizontal slices at different heights are shown in Figure 3(c) - (j). The spatial distribution relationship of high-density bodies indicating iron mine can be seen from the above drawings.

Conclusions

The proposed novel regularized focusing migration method improves the horizontal and vertical resolution, and has good noise resistance. The GPU parallel computing program optimized has good acceleration ability and lays the foundation to invert regional to continental size data with up to billion cells for interpretation of large airborne surveys. This method is well suited for evaluating mining targets because our efficient algorithms allow for fast imaging without being constrained by millions of data sets in a large mining area. Focusing stabilizers can distinguish the boundaries of each geological body aggregating at relatively high densities. The case study shows how this advanced method can be effectively applied to explain the whole gravity anomaly in the iron mining area, Shandong Province, China, indicating the spatial distribution of minerals.
Figure 3 (a) shows the local gravity anomalies; (b) shows a 3D perspective of the imaging results with a density greater than 0.6 g/cm$^3$; (c)-(j) show the horizontal cross sections at different heights.

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References


