Two-stage deep learning for 3D joint inversion of gravity and magnetic
Yinshuo Li*, Wenkai Lu, Zhuo Jia, Cao Song, Tsinghua University;

Summary

The joint inversion of gravity and magnetic method is non-destructive and widely applied in geophysics. Deep learning methods are widely applied in the physical property inversion recently. However, most of these methods highly rely on high-quality training data, which is not available in geophysics. Researchers have proposed to train the method on the synthetic data and then apply it to the field data. Since the synthetic data and the field data are not independently identically distributed, these methods do not perform better. This abstract proposes a two-stage deep learning (DL) network for 3D joint inversion of gravity and magnetic (GMNet). In the first stage, GMNet is trained on the synthesized data, which can take advantage of the generalization ability of DL. In the second stage, GMNet is fine-tuned on the target field data by closed loops of inversion and forward models. Besides, the constraint information of physical property and structure has been added in GMNet to obtain a reasonable result. The experimental results demonstrate that the proposed GMNet has obtained outstanding performance in the 3D joint inversion of gravity and magnetic.

Introduction

3D physical property inversion is one of the most mainstream methods of quantitative interpretation, which can be used to describe the structures of abnormal bodies more intuitively and accurately (Chasseriau, 2003). Inversion of gravity and magnetic anomalies is widely used to obtain subsurface density and susceptibility structure (Parker, 1974; Last, 1983). The inversion results of gravity and magnetic anomalies are widely applicable in the exploration of crustal structure (Woollard, 1959), mining (Zhang, 2020), and hydrocarbon (Li, 2016).

However, both gravity inversion and magnetic inversion are ill-posed problems, and the solution space is not unique (Ellis, 2012). Researchers utilize 3D joint inversion of gravity and magnetic to reduce the uncertainty of gravity and magnetic inversion and obtain more reliable results (Frey, 2021). General 3D joint inversion methods obtain the morphology and physical properties of the subsurface abnormal body by human interaction (Lü, 2013) or automatic calculation according to specific rules (Kim, 2014). Whereas, the inversion results of these methods are limited since they are judged only by data fitting. Thus, more human intervention is required to get a better result in general 3D joint inversion. Thus, Li and Oldenburg (1996, 1998) have introduced regularization in optimization theory to reduce the multiple solutions of inversion results and process instability. Besides, reasonable results of 3D inversion can be calculated by adding the constraint information of physical property and structure (Pilkington, 1959).

With the development of computer hardware and big data, deep learning (DL) has provided outstanding performances in various computer vision problems. DL-based methods are trained on plenty of high-quality data and obtain excellent generalization ability in various estimation tasks. Since inversion and other geophysics tasks can be regarded as estimation tasks, DL has also been widely applied in the geophysical field recently (Li, 2020). DL-based methods have provided robust and efficient results in improving the inversion results of seismic velocity (Li, 2021) and electrical models (Jia, 2022). Besides, DL-based methods also have been used in inversion of gravity (Zhang, 2020) and magnetic (Guo, 2021) by regarding inversion as an estimation task from 2D images to 3D data. Nevertheless, the biggest obstacle to DL-based inversion methods is the lack of high-quality training data. A viable solution is synthesizing training data based on expert knowledge (Li, 2020), but its effectiveness is limited since the synthesized data is not independently identically distributed with the field data. Li et al. (2022) proposed learning a gravity inversion model on the target field data directly by a self-supervised DL method, this is a feasible solution notwithstanding it does not take advantage of the generalization ability of DL.

In this abstract, we proposed a two-stage deep learning method for 3D joint inversion of gravity and magnetic, which is named as GMNet. In the first stage, the proposed GMNet is trained on the synthesized data, which can take advantage of the generalization ability of DL. In the second stage, GMNet is fine-tuned on the target field data by a closed loop of inversion and forward model. Then the limitation of the synthesized data is overcome.

Method

This abstract proposed a DL-based inversion method for 3D joint inversion of gravity and magnetic, which is named as GMNet. GMNet is trained on the synthesized data and further applied to field data. Considering that the synthesized data is not independently identically distributed with the field data, we proposed to fine-tune GMNet on the target field data. Given that the subsurface density and susceptibility are unavailable, there is no ground truth for joint inversion in the field task. Since the forward models of gravity and magnetic are presupposed, the accuracy of the
Two-stage deep learning for 3D joint inversion of gravity and magnetic

Inversion results can be indirectly verified by the closed loops between inversion and forward models. Besides, the constraint information of physical property and structure has been added in GMNet to obtain a reasonable result. As shown in Figure 1, four closed loops with mean absolute error (MSE) and a cross-gradient loss are utilized to optimize the inversion model in GMNet.

**Structure of inversion model.** The structure of the inversion model in GMNet is shown in Figure 2. The inversion model of GMNet estimates 3D density and susceptibility matrices from the observed 2D gravity and magnetic anomalies. Besides, inspired by SSGI (Li, 2022), guidelines are utilized in the inversion model to constrain the uncertainty of inversion. The expression of the proposed inversion model is as follows:

\[
Di, S' = \mathcal{I}(G, L_g, L_m; \theta),
\]

where \( \theta \) represents parameters of the inversion model \( \mathcal{I} \), while \( D' \) and \( S' \) denote the obtained 3D density and susceptibility matrices. Besides, \( G \) and \( M \) stand for the observed 2D gravity and magnetic anomalies. Meanwhile, \( L_g \) and \( L_m \) denote 1D guide lines of gravity and magnetic inversion, which is average of the two matrices in the depth direction. As shown in Figure 2, the inversion model consists of two encoders, one expander, one decoder, and two 3D refiners. Specifically, gravity inversion and magnetic inversion share decoder and own propriety encoder and 3D refiner.

**Loss function of inversion model on synthetic data.** The synthetic training data contains paired gravity anomaly, magnetic anomaly, density matrix, and susceptibility matrix. Thus, supervised learning is utilized to optimize parameters of the inversion model.

The loss function of inversion model on synthetic data can be expressed as follows:

\[
\mathcal{L}_f = \lambda_1 \ell_1(D', D) + \lambda_1 \ell_1(S, S') + \lambda_3 \ell_1(L_g, L_g') + \lambda_4 \ell_1(L_m, L_m') + \lambda_5 \tau(D', S'),
\]

where \( G' \) and \( M' \) stand for the reconstructed 2D gravity and magnetic anomalies, while \( L_g' \) and \( L_m' \) denote the guide lines extracted from \( D' \) and \( S' \). Besides, \( \ell_1 \), \( \tau \), and \( \mathcal{F}_g \) represent L1-norm, cross gradient function, and forward model, respectively. Meanwhile, \( \lambda , i \in [1, 5] \) stand for trade-off parameter for these parts of loss function. MSE between the original and estimated density and MSE between the original and estimated susceptibility are employed as the loss function of inversion model. Besides, cross gradient loss between the estimated density and susceptibility matrices is utilized to couple structures of the two physical properties.
Two-stage deep learning for 3D joint inversion of gravity and magnetic

Figure 3: The structure of inversion model.

Closed loops in self-supervised fine-tune. Giving that the synthesized data not independently identically distributed with the target field data, we proposed to fine-tune GMNet on the target field data. However, the ground truth is inaccessible. Li et al. (2022) have proposed SSGI for self-supervision gravity inversion, which builds two neural networks to realize a closed loop between inversion and forward. Specifically, the parameters of forward model in SSGI is fixed and the parameters in the inversion model can be optimized by the closed loop. Inspired by SSGI, we proposed to build two closed loops for gravity inversion and magnetic inversion respectively. Besides, two 1D guide lines are provided to the GMNet to build another two closed loops which contain constraint information of physical property. The two guide lines furnish depth information to GMNet.

Loss function of GMNet for fine-tuning on the field data. The loss function of inversion model on field data can be expressed as follows

$$L_f = \lambda_1 \ell_1(G, G') + \lambda_2 \ell_2(M, M') + \lambda_3 \ell_3(l_M, l_{M'}) + \lambda_4 \ell_4(l_{m'}, l_{m}) + \lambda_5 \ell_5(D', S') + \lambda_6 \|D'\|_1 + \lambda_7 \|S'\|_1 + \lambda_8 TV(D') + \lambda_9 TV(S'),$$

where $G'$ and $M'$ stand for the reconstructed 2D gravity and magnetic anomalies, while $l_{m'}$ and $l_{m}$ denote the guide lines extracted from $D'$ and $S'$. Besides, $\ell_1$, $\ell_2$, $TV$, and $\ell_5$ represent L1-norm, cross gradient function, total variation function, and forward model, respectively. Meanwhile, $\lambda_i$, $i \in [1,9]$ stand for trade-off parameter for these parts of loss function.

Examples

In this section, the proposed GMNet is evaluated on the synthetic data and field data. Specifically, supervised training result in step one is evaluated on the synthetic data, and the pre-trained model is fine-tuned on the field data by self-supervision.

Example on synthetic data. A wildly used data synthesis model (Li, 2014) is employed to generate synthetic data for training (8k), verification (2k), and testing (4k). To evaluate the proposed joint inversion method, two single inversion methods are utilized for contrast. The contrast methods are named as GraNet and MagNet, which are the gravity inversion method and magnetic inversion method, respectively. Specifically, both are made up of an encoder, an expander, a decoder, and a 3D refiner. Besides, GMNet-w, a variant of the proposed method, is utilized to evaluate the cross-gradient function. The quantitative comparison of the performance of GraNet, MagNet, GMNet-w, and GMNet in Table 1 has demonstrated that the proposed GMNet has obtained the best results in both magnetic inversion and gravity inversion. Besides, Figure 4 shows the visual comparison of the proposed joint inversion method and separate inversion on the synthetic data. Visual comparison in Figure 4 demonstrates that the proposed method has obtained outstanding performance which is most similar to the ground truth.

Example on field data. GMNet is further evaluated on field data, which is from the Jinchuan deposit. The reconstructed gravity and magnetic anomalies obtained by the closed loops fit well with the original surface anomalies. Besides, the matrixes of the density and susceptibility are constrained by the guidelines, which can overcome the downside problem and reduce uncertainty. Figure 5 shows the estimation results on field gravity and magnetic anomalies from the Jinchuan deposit.

<table>
<thead>
<tr>
<th>Method</th>
<th>Gra3D MSE</th>
<th>Mag3D MSE</th>
<th>Cross Grad Loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>GraNet</td>
<td>0.074197</td>
<td>-</td>
<td>0.002124</td>
</tr>
<tr>
<td>MagNet</td>
<td>-</td>
<td>0.068021</td>
<td>0.002117</td>
</tr>
<tr>
<td>GMNet-w</td>
<td>0.070180</td>
<td>0.066497</td>
<td>0.000125</td>
</tr>
<tr>
<td>GMNet</td>
<td>0.066445</td>
<td>0.062722</td>
<td>0.000064</td>
</tr>
<tr>
<td>ground truth</td>
<td>-</td>
<td>-</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 1: Quantitative evaluation on synthetic data.
Two-stage deep learning for 3D joint inversion of gravity and magnetic deposit, Northwest China. Though the resolution of the gravity and magnetic anomalies are different, the proposed method can obtain satisfactory inversion results. Meanwhile, the resolution of the reconstructed gravity anomaly is higher than that of the observed gravity anomaly.

Conclusions

This abstract proposes a two-stage deep learning (DL) network for 3D joint inversion of gravity and magnetic (GMNet). First, GMNet is trained on the synthesized data, which can take advantage of the generalization ability of DL. Then, GMNet is fine-tuned on the target field data by closed loops of inversion and forward models, to overcome the drawback of DL in geophysics. Experiments show that two-stage training can obtain better joint inversion results, and every state is necessary. The constraint information of physical property and structure has been added in GMNet to obtain reasonable results.

Acknowledgments

This work was supported by the National Key Research & Development Program of China (Grant No. 2018YFA0702501), the National Natural Science Foundation of China (Grant No. 41974126).