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Neural network joint implicit geophysical inversion

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Summary

In this study, we introduce a neural network framework for multi-physics joint inversion of geophysical data. Typically, multi-physics models, such as seismic data, and gravity data in separate domains and vary significantly in scale, making it challenging to represent them as a unified entity. To address this issue, we employ neural networks to generate features for these geophysical models. These features are unitless, typically ranging from -1 to 1. We then use prior information to scale these features, mapping them to their respective physical domains, enabling forward modeling. The forward modeling for each type of geophysical model produces corresponding synthetic data, allowing for the evaluation of loss values specific to each data type. The total loss for the joint inversion is calculated by summing these individual losses, and the neural network is updated to minimize this total loss. By using this inversion strategy, we use the neural network to represent the geophysical model of a particular area as an entity, and the joint inversion of the multi-physics model can be evaluated. In this paper, we examine the joint inversion of gravity and seismic data. The results indicate that incorporating gravity data improves the convergence rate of the density model inversion compared to using seismic data alone.

Theory

In recent years, significant advances have been achieved in joint inversion, particularly in high-resolution imaging for oil and gas exploration, geothermal studies, and mineral prospecting. The joint inversion of seismic and EM data, for example, has seen substantial progress (Hu et al., 2009; Colombo and De Stefano, 2007; Abubakar et al., 2012). Researchers have successfully applied constraints from seismic information to refine EM inversion, improving structural imaging in challenging areas such as salt and volcanic regions, where seismic or EM methods alone often struggle to provide reliable models (Chen et al., 2023). Additionally, advances in the joint inversion of magnetotelluric (MT) and controlled-source electromagnetic (CSEM) data have demonstrated the feasibility of using a unified objective function or sequential constraints for high-precision subsurface characterization. Full waveform inversion (FWI), a method that employs the complete waveform, of seismic data for high-resolution imaging, has been a focal point in recent joint inversion studies (Lailly and Bednar, 1983; Tarantola, 1984). FWI allows for accurate velocity, and density model reconstruction. However, integration of multi-parameter data—such as the gravity data, or the EM data into FWI algorithms remains challenging. Mainly due to that these physics models are living in different physical domains.

To address this issue, we employ neural networks to generate features for these geophysical models. These features are unitless, typically ranging from -1 to 1. We then use prior information to scale these features, mapping them to their respective physical domains, enabling forward modeling. The forward modeling for each type of geophysical model produces corresponding synthetic data, allowing for the evaluation of loss values specific to each data type. The total loss for the joint inversion is calculated by summing these individual losses, and the neural network is updated to minimize this total loss. By using this inversion strategy, we use the neural network to represent the geophysical model of a particular area as an entity, and the joint inversion of the multi-physics model can be evaluated.

We demonstrate how we use a neural network to perform joint implicit inversion for seismic and gravity data, which is a variation of the implicit FWI (IFWI) work given by (Zhang, et. al, 2023). Figure1 presents the inversion diagram. The input to the neural network is the coordinate information of the model. The spatial grid of the input coordinates is relatively dense, with a small grid size (e.g., dx = dz = 10 meters in a model with dimensions of 200 vertical points and 400 horizontal points). The coordinate information is fed into the MLP network to generate features for both the elastic models, Vp and Vs, as well as the density model ρ. Two resampling methods are defined in the diagram, denoted as RS1 and RS2. These RS functions are used to resample the features of the models to a desired grid length, enabling stable forward modeling.

As shown in the Figure1, RS1 rescales the density feature ρ1 to a model dimension of 50 ×100, with a spatial grid of 40 meters. This feature model is then scaled to the gravity density anomaly domain, allowing us to calculate the synthetic gravity data. Using RS2, we rescale the features generated by the neural network to a model dimension of 100 × 200, with a spatial grid of 20 meters, for Vp, Vs, and ρ2. The Vp, Vs, and ρ2 models are also scaled so that we can use the finite difference method (formulated as a recurrent neural network in this study) to calculate the synthetic data. The total data loss will consist of two parts. The first part is about the gravity data loss part, and the second part will be the seismic data error part. The weights in the neural network will be trained to generate models to decrease the total data misfit, resulting in the joint inversion scheme for both the seismic data, and also the gravity data. We also refer to this inversion as the IFWI regularized with gravity data.

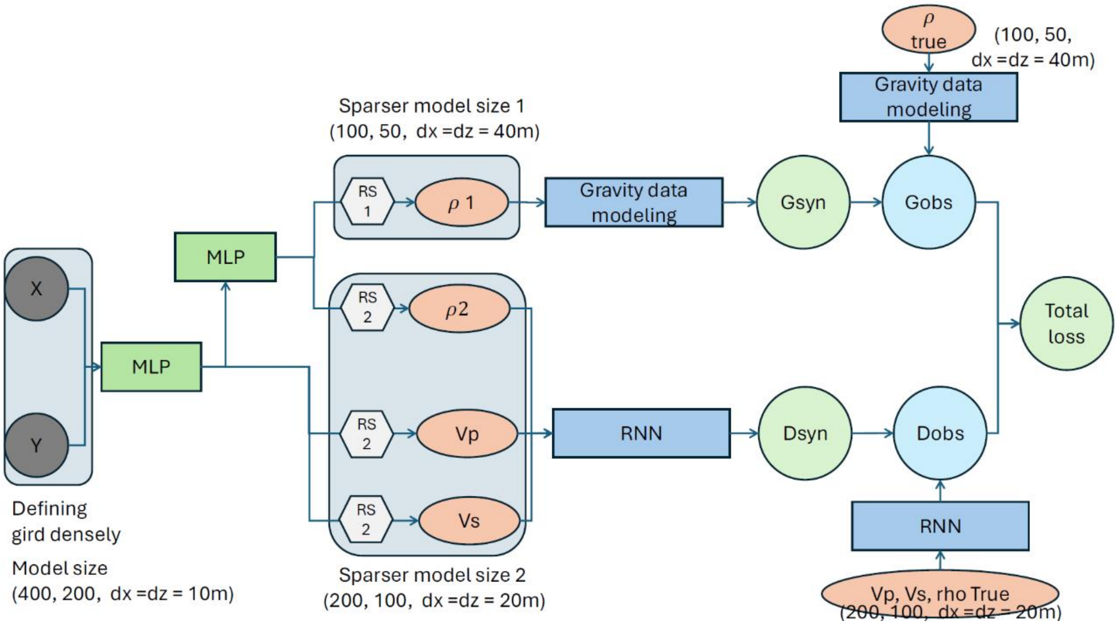

FIG. 1. The diagram for using the neural network joint implicit geophysical inversion.

Results

In Figure 2 and 3, we present the density model inversion results. Figure 2(a), and 3(a) show the true density model. Figure 2 (b) presents the IFWI density result using only the seismic data. Figure 3 (b) presents the IFWI density result using the combination of seismic data, and gravity data. Compared Fig 2(b), and Fig 3(b), we can see that the gravity-data-informed joint density anomaly inversion result demonstrates fewer spatial inversion artifacts, with the location of the low-density anomaly more clearly resolved.

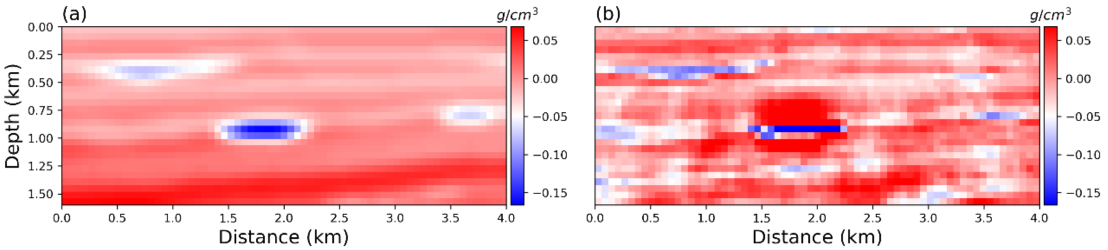

FIG. 2. (a) The true density anomaly used to calculate the gravity data. (b) No gravity data regularized density anomaly prediction result.

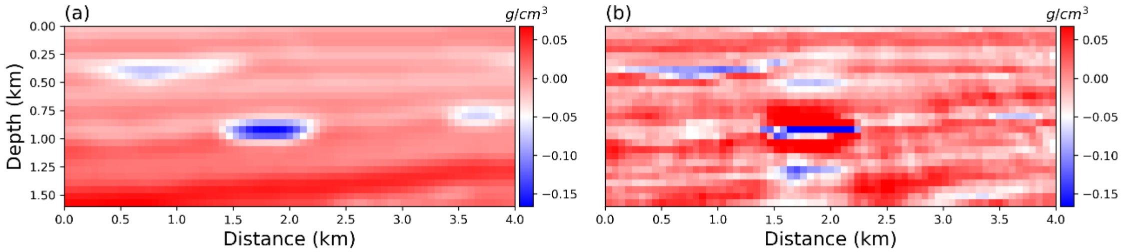

FIG. 3. (a) The true density anomaly used to calculate the gravity data. (b) Gravity data regularized density anomaly prediction result.

In Figure 4, we show how the density model error changes with the increase in iteration number. The density model error variation with the incorporation of gravity data in IFWI is plotted as a dashed black line, while the error variation without gravity data is shown as a solid black line. The results indicate that the inversion scheme with gravity data achieves better convergence compared to the inversion without gravity data, underscoring the value of incorporating gravity data into seismic parameter inversion. This figure highlights the benefits of joint multi-physics inversion for improving the accuracy of geo physical parameter estimation.

Conclusions

In this study, we utilize neural networks to derive features for the multi-physics geophysical models. These features are dimensionless and generally range between -1 and 1. Using prior knowledge, we rescale these features, aligning them to their specific physical domains to facilitate forward modeling for joint multi-physics inversion. The forward modeling of each geophysical model generates corresponding simulated data, enabling the calculation of loss values unique to each data set. The combined loss for the joint inversion is determined by adding these individual losses, with the neural network adjusted to reduce this total loss. This inversion approach allows the neural network to represent the geophysical model of a given region as a cohesive entity, enabling the evaluation of multi-physics joint inversion. In this study, we focus on the joint inversion of gravity and seismic data. The findings show that integrating gravity data enhances the convergence rate for density model inversion compared to relying solely on seismic data.

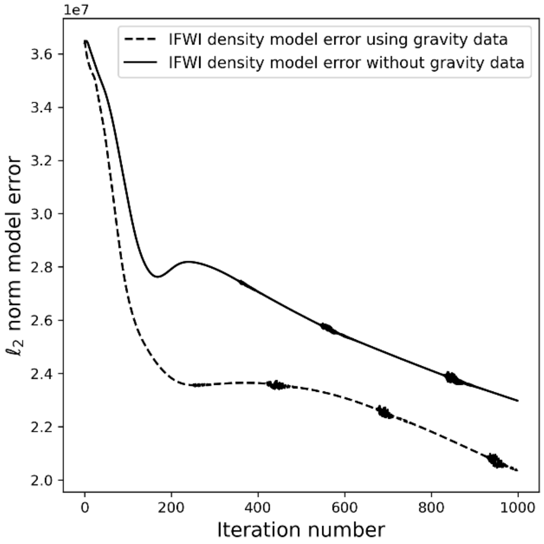

FIG. 4. Density model error as a function with respect to iterations.

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