Deep Learning Enhanced Joint Geophysical Inversion for Crosswell Monitoring

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***Abstract*—A deep learning enhanced framework is proposed to jointly invert the crosswell DC resistivity and seismic travel time data. With the strong capability to extract the implicit patterns of the input data, our deep neural network is trained to fuse and extract the connections between separately inverted resistivity and velocity models by the conventional methods, while the structural similarity is imposed by letting the outputs of network approach the true resistivity and velocity models with the same structures. In the joint inversion framework, the well-trained network is adopted in an iterative way to generate the enhanced resistivity and velocity models to perform as the inputs for next round of inversion. Moreover, under our framework, multiple geophysical data can be used simultaneously to jointly invert the corresponding multiple properties. Numerical simulation demonstrates an improved accuracy of our method.**

I. Introduction

A geological formation can be sensed by multiple measuring methods with different sensitivities to the geophysical properties. These methods have different resolutions and their own advantages in dealing with specific formations. For example, electromagnetic (EM) data are better at describing the boundary between hydrocarbons and water, while seismic data prevail when distinguishing gas-bearing from oil-bearing layers [1]. Jointly inverting two or multiple complementary data can further facilitate each of the separate inversion, providing the potential to achieve a higher accuracy. Currently, two technology categories are available for joint inversion: petrophysical relationship [2] and structural similarity [3]. Taking integrating electromagnetic and seismic data to invert the resistivity and seismic velocity as an example, methods based on petrophysical relationship suffers from the complicated and non-unique relationships between resistivity/velocity and the petrophysical properties, e.g., porosity and fluid saturation. Methods based on structural similarity of the velocity and resistivity profiles are attractive because it is a generalized quantitative criterion, but there are still a lot of other information such as amplitude that are not taken into consideration. In recent years, deep learning techniques have been applied to solve inverse problems for single type of data and have achieved considerable results [4]. In this paper, we propose a flexible deep learning enhanced framework to improve the accuracy of joint inversion for DC resistivity and seismic data.

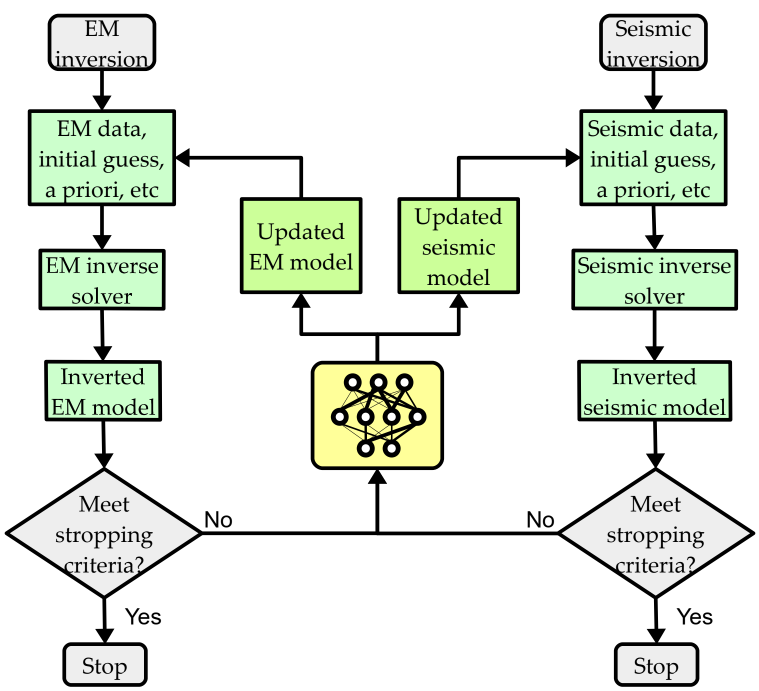

Fig. 1. The flowchart of the deep learning enhanced joint inversion framework.

II. Deep learning enhanced joint inversion

The basic idea of our deep learning enhanced joint inversion framework is to utilize the network to extract the implicit connections between different geophysical data instead of deterministic formulation. After the network is well-trained, it will be combined with the traditional inversion workflow to achieve a higher accuracy.

A. Training process

Different from the conventional end-to-end network, we adopt the separately inverted resistivity and velocity models instead of the data as the inputs and let the outputs approach the true resistivity and velocity respectively. This endows the network the ability to extract not only the amplitude relationship between the resistivity and velocity, but also the complementary structure information, as well as other geophysical patterns that can not be described in rigorous forms. This is a more direct way to capture the connection of the insights into different physics by combining the network with the traditional separate inversions (by taking the inversion results as the inputs of the network) during the training process. Please be noted that this architecture can be extended to jointly invert multiple geophysical data. Accordingly, in the training process, the multiple inverted properties will make up a multi-channel data cube performing as the input of the network.

B. Joint inversion framework

The joint inversion flowchart embedded with the well-trained network is shown in Fig. 1. The left and right parts are separated conventional inversions with respect to EM data and seismic data. Each inversion starts with the corresponding observed data, the initial guess, and other prior information. In each iteration, if the conditions for stopping the loop are not met, the individually inverted EM model and seismic model will be inputted into the network and get improved into the updated models. Then the updated models will perform as the inputs for the next iteration. Please be noted that the "iteration" here can be a complete traditional inversion or an actual iteration inside an inversion.

III. Experiments

Here we use the joint inversion of the crosswell DC resistivity data and seismic travel time as the example to demonstrate the effectiveness of our proposed framework and the results are shown in Fig. 2. two boreholes separated by a distance of $20\mathrm{m}$, with depth ranging from $0 \sim -40\mathrm{m}$, is considered. For the DC resistivity survey, we adopt a bipole-bipole AM-BN array, i.e., the current electrodes A and B are distributed inside one of the boreholes and the potential electrodes M and N are insider the other borehole. In each borehole, the electrodes have a take-out of 4 m and the spacing is also 4 m, so there are totally 81 measurements. Similarly, for the seismic survey, the sources and receivers with distance of $2\mathrm{m}$ respectively are in different boreholes and the number of measurements is 400. The inversion domain is divided into $1\mathrm{m} \times 1\mathrm{m}$ cells. Our preliminary results are given in Fig. 2. Fig. 2(a) and Fig. 2(d) are the true models to generates the observed data. Fig. 2(b) and Fig. 2(e) are the separate inversion results. Fig. 2(c) and Fig. 2(f) are the joint inversion results. In this experiment, the initial model is the uniform background and each "iteration" is an entire inversion. A significant improvement of both the reconstructed resistivity and velocity is achieved with our deep learning enhanced framework.

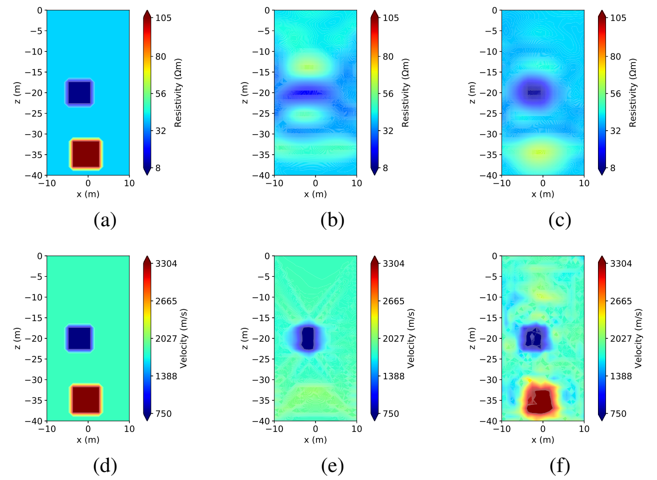

Fig. 2. Demonstration of the joint inversion results. (a) and (d) are the true models. (b) and (e) are the separately inverted models, (c) and (f) are the jointly inverted models.

IV. Conclusion

In this work, we proposed a deep learning enhanced framework for joint inversion of crosswell DC resistivity and seismic data. This framework uses a deep neural network to fuse and extract the amplitude and structure information from different physics, building up the inherent connections that are difficult to describe in rigorous forms. Moreover, this framework is flexible to jointly invert multiple geophysical data. Preliminary results show a promising performance of the proposed framework. Further exploration is underway.

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