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Prestack Seismic Inversion Based on Deep Learning and Seismic Attributes

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Abstract

Objectives/Scope: Prestack seismic inversion is a pivotal technology in reservoir characterization, facilitating the extraction of elastic parameters from seismic data. However, seismic inversion is inherently nonlinear and often plagued by multiple solutions, posing significant challenges. Deep learning excels at mapping complex nonlinear relationships. By leveraging deep learning, we aim to enhance the reliability of elastic parameters obtained through prestack seismic inversion, effectively addressing the issues of nonlinearity and ambiguity that typically arise during this process.

Methods, Procedures, Process: The proposed method employs multi-task deep convolutional neural networks to establish nonlinear relationships between prestack seismic data and elastic parameters, including P-wave velocity, S-wave velocity, and density. To improve interpretability and generalization, seismic forward modeling is seamlessly integrated with neural networks during training, enabling semi-supervised learning. Furthermore, the neural network incorporates seismic coherence attribute as input, reflecting geological sedimentary information and providing geological constraints. The overall framework is illustrated in Fig. 1. Once trained, the network can accurately predict elastic parameters.

Results, Observations, Conclusions: To validate the proposed approach, we chose the 3D Stanford VI model, characterized by fluvial sedimentary features. The model encompasses P-wave velocity, S-wave velocity, and density. Synthetic prestack seismic data was generated using a 35Hz Ricker wavelet, with incident angles ranging from 1° to 35°. Eight CDPs were randomly selected as wells, with one designated as a validation well, excluded from training. As the Fig. 2 shows. Compared to physics-constrained deep learning-based inversion, our method's inversion results align more closely with the model's true values. Notably, our approach more accurately depicts river boundaries. This validates that seismic coherence attribute effectively provides geological priors, constraining inversion and guiding the neural network to yield more reliable, geologically consistent predictions. Thus, our method not only implements physics-constrained deep learning for prestack seismic inversion, but also integrates additional geological information to obtain more reliable inversion results, effectively bridging geoscience knowledge with deep learning techniques.

Novel/Additive Information: Deep learning has gained widespread application in seismic inversion, yet its reliance on labeled data remains a challenge. Our method seamlessly integrates seismic forward modeling with neural networks, leveraging semi-supervised learning to effectively utilize unlabeled seismic data in the training process. This approach reduces dependence on labeled data and enhances generalization capabilities. Furthermore, we introduce seismic coherence attribute as input, which offers geological priors to constrain inversion, resulting in more reliable inversion outcomes.

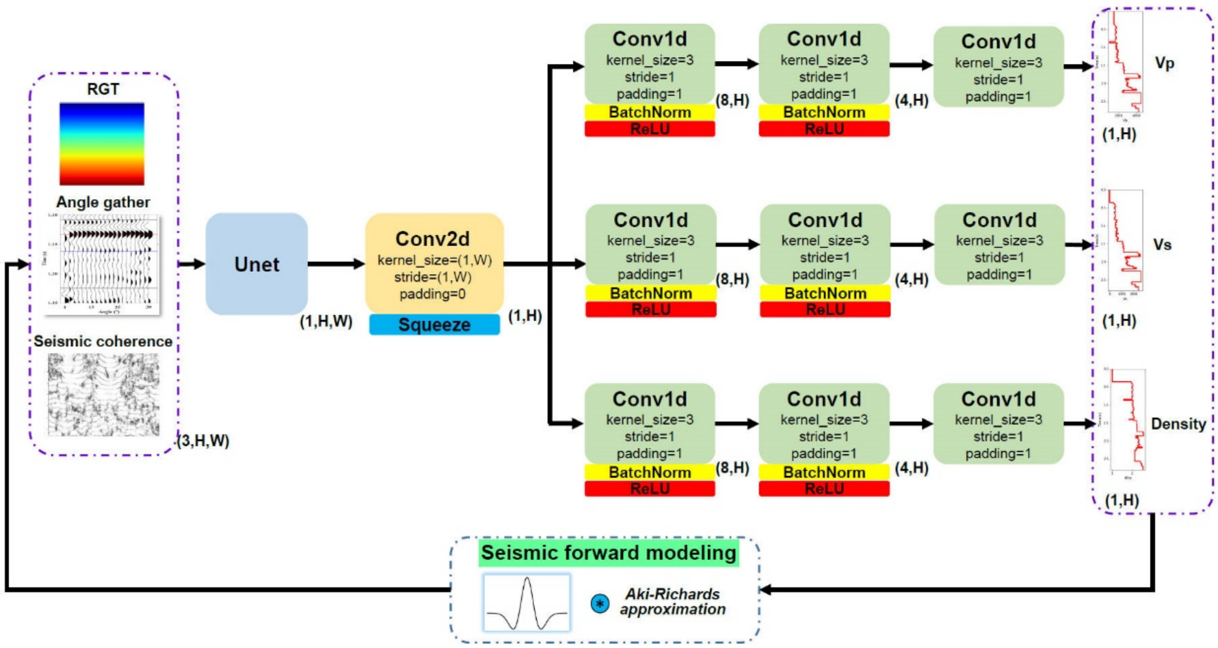

Fig. 1—Framework of the proposed multi-task deep convolutional neural network.

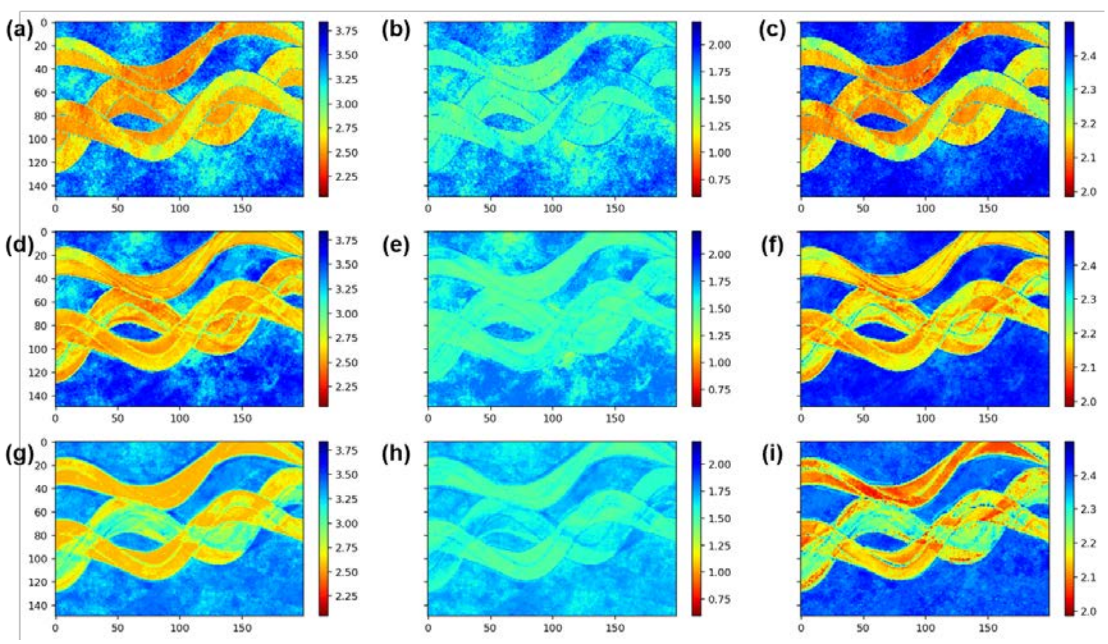

Fig. 2—Comparisons between inverted results from different methods and the true values. (a)-(c) is the true values of P-wave velocity, S-wave velocity and density, respectively; (d)-(f) is the inverted results of P-wave velocity, S-wave velocity and density based on the proposed method, respectively; (g)-(i) is the inverted results of P-wave velocity, S-wave velocity and density based on the physics-constrained deep learning- based inversion method, respectively.