Deep-pre-trained-FWI: where supervised learning meets the physics-informed neural networks

Ana Paula O. Muller [1,2], Clecio R. Bom [2,5] *, Jessé C. Costa [3,4] , Matheus Klatt [2], Elisangela L. Faria [2], Marcelo P. de Albuquerque [2], Marcio P. de Albuquerque [2]

1) Petróleo Brasileiro S.A. (PETROBRAS), 2)Centro Brasileiro de Pesquisas Físicas (CBPF), 3) Universidade Federal do Pará (UFPA), 4) Institute of Petroleum Geophysics (INCT-GP), 5) Centro Federal de Educação Tecnológica Celso Suckow da Fonseca (CEFET-RJ)

This paper was prepared for presentation during the 18th International Congress of the Brazilian Geophysical Society held in Rio de Janeiro, Brazil, 16-19 October 2023.

Abstract

Full-Waveform Inversion (FWI) is the current standard method to determine final and detailed model parameters to be used in the seismic imaging process. However, FWI is an ill-posed problem that easily achieves a local minimum, leading the model solution in the wrong direction. Recently, some works proposed integrating FWI with Convolutional Neural Networks (CNN). In this case, the CNN weights are updated following the FWI gradient, defining the process as a Physics-Informed Neural Network (PINN). FWI integrated with CNN has an important advantage. The CNN stabilizes the inversion, acting like a regularizer, avoiding local minima-related problems and sparing an initial velocity model in some cases. However, such a process, especially when not requiring an initial model, is computationally expensive due to the high number of iterations required until the convergence. In this work, we propose an approach that relies on combining supervised learning and physics-informed by using a previously trained CNN to start the DL-FWI inversion. Loading the pre-trained weights configures transfer learning. The pre-trained CNN is obtained using a supervised approach based on training with a reduced and simple data set to capture the main velocity trend at the initial FWI iterations. The proposed training process is different from the initial works on the area which obtained the velocity model from the shots in supervised learning tasks, and that required a large amount of labeled data to ensure reasonable model predictions. We investigated in our approach two CNN architectures, obtaining more robust results and a reduced number of parameters when using a modified U-Net. The method was probed over three benchmark models, showing consistently that the pre-training phase reduces the process's uncertainties and accelerates the model convergence using minimal prior information. Besides, the final scores of the iterative process are better than the examples without transfer learning. Thus, transfer learning solved one main limitation of the previous PINN approaches: the unfeasible number of iterations when not using an initial model. Moreover, we tested the method using data with low-frequency band limitations, since the lack of low frequencies is a common issue within real seismic data. The inversion converges to reasonable results probing the method's robustness with restricted frequency content.

Obs.: the results of this work were submitted to the Geophysical Journal International