A Physics-Driven Deep Neural Network for Inversion of Electromagnetic Logging in Subsurface Sensing and Borehole Characterization

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Solving inverse problems is fundamental to a wide variety of applications. To maximize the chances of drilling a productive well, oil and gas companies collect and study large amounts of data about the Earth's subsurface. These data are indirect measurements obtained through various sensing technologies. Through a delicate inversion process, collected information is converted into an earth model to characterize different aspects of the formation. It is still a challenging problem and current solutions can hardly keep up with the demanding requirements from the industry with regard to the accuracy and computational efficiency. In this paper, we propose to explore the deep learning techniques to solve well logging related inverse problems for azimuthal electromagnetic resistivity logging-while-drilling (LWD) service, whose applications include but not limited to well placement, reservoir mapping, geo-stopping, landing fault detection, and salt edge detection, etc. Particularly, a physics model is used to guide the training process of a deep neural network for learning an end-to-end inverse mapping function.

The relationship among the measurements, the source, and the medium is essentially governed by the physics. An analytical inversion process relies on the forward model to guide its search for solutions although the solution could be suboptimal due to noises and other unknown interferences. In a data-driven deep neural network, the convergence of the network is guided by the data misfit alone. Due to the randomness in selecting the data batch and the nonlinearity of the governing physics, the descending path will be long and fluctuating. A differentiable forward model, on the other hand, can be used to regulate the backpropagation process. In this study, we propose a novel physics-driven deep neural network to solve the inverse problem.

Experiments results show that the inversion accuracy and the training loss of the network are significantly improved by introducing a data misfit that measures the disagreement between the observed measurement and the measurement synthesized by the forward model. Our case studies conclude that the physics-driven deep learning network can deliver real-time inversion result for the azimuthal electromagnetic resistivity LWD tool with high accuracy and much-relaxed hardware restraints.