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A Novel Ai-driven Uncertainty Quantification Framework for Robust Electromagnetic Inversion in Enhanced Resistivity Geosteering

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Objectives/Scope: In geosteering applications, accurate and timely interpretation of resistivity measurements derived from electromagnetic (EM) logging tools is crucial for optimal well placement, especially in complex geological environments. However, standard deterministic EM inversion algorithms often fail to account for uncertainty, leading to overconfident or misleading subsurface models. The objective of this work is to develop a novel AI-based framework for uncertainty quantification (UQ) in EM inversion that enables real-time, probabilistic resistivity profiling. The framework aims to enhance decision-making in geosteering by providing geoscientists with both a most-likely interpretation and a quantified measure of confidence.

Methods, Procedures, Process: We introduce DeepBayesEM, a hybrid physics-informed neural network (PINN) and Bayesian deep learning architecture tailored for EM inversion under uncertainty. The algorithm combines the robustness of data-driven modeling with the constraints of Maxwell's equations to ensure physically consistent outputs. A variational inference framework is employed to approximate the posterior distribution of resistivity models given EM measurements, enabling real-time uncertainty quantification. The neural network architecture is trained on a large ensemble of synthetic and field-like geological scenarios, with a custom-designed loss function that incorporates both data misfit and physical regularization terms. Dropout is used at inference time as a Bayesian approximation to estimate predictive variance, and a mixture density network (MDN) component is incorporated to capture multimodal posterior behaviors in highly non-unique settings. To efficiently integrate with operational workflows, the method supports on-the-fly updating through online learning, using streaming EM measurements during drilling.

Results, Observations, Conclusions: The DeepBayesEM framework was tested on synthetic benchmarks and field analogs characterized by complex resistivity distributions, including thin beds, anisotropic layers, and faulted structures. Our method achieved a reduction in inversion error when evaluated against ground truth resistivity profiles, and well-calibrated uncertainty estimates, with coverage probabilities within ±5% of theoretical confidence intervals. Furthermore, we achieved sub-millisecond inference times per depth point, supporting real-time deployment. Furthermore, the model performed better capturing non-uniqueness and model ambiguity, particularly in low-signal and high-noise scenarios. Visualization of the predictive distributions allowed interpreters to identify zones of high uncertainty, enabling more conservative and informed drilling decisions. The model’s ability to learn from prior geological patterns further reduced overfitting to localized measurement anomalies.

Novel/Additive Information: This work represents the first integration of Bayesian deep learning and physics-informed modeling for real-time EM inversion under uncertainty in geosteering contexts. Unlike traditional ensemble-based or deterministic inversion methods, DeepBayesEM provides full posterior distributions over resistivity profiles without requiring repeated forward simulations. This combination of physical fidelity, statistical rigor, and operational feasibility makes DeepBayesEM a transformative tool for resistivity-based geosteering under uncertainty.