Automatic well log baseline correction for rapid characterization of potential CO2 storage sites in the Gulf of Mexico using deep learning

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Summary

We propose a deep neural network-based framework for automatic baseline correction of spontaneous potential (SP) logs. To overcome the challenge of SP log deviation and trend accumulation with depth due to salinity and temperature effects, we propose an automatic correction algorithm using deep learning. The proposed framework utilizes a deep convolutional U-Net model to estimate the baseline-corrected SP log from the raw SP log and a set of attributes. The benefit of this approach is its ability to compress and denoise the raw SP log and its attributes into a latent representation and to efficiently predict the baseline-corrected SP log without manual interpretation. We validate this approach against manually corrected SP logs, and test with unseen wells in the Gulf of Mexico. Finally, we use the trained model to estimate the volumetric concentration of shale in order to detect potential CO2 storage sites in the Gulf of Mexico.

Introduction

The spontaneous potential (SP) log is one of the earliest borehole measurements in the energy industry and has a significant role in formation evaluation for determining lithology and permeable zones (Asquith & Krygowski, 2004). SP logs, along with Gamma Ray (GR) logs, are often the only measurements available in old hydrocarbon wells. However, temperature and salinity have significant effects on the SP measurements (McConnell, 1983, 1988). These effects result in a trend accumulation along the depth of the well, and require correcting, or shifting, the log to the baseline trend for accurate interpretation of lithology and permeable zones.

Automatic baseline correction algorithms have been widely explored, and often depend on an iterative approach for data shifting based on a precomputed attribute or filter (Gan et al., 2006). McConnell (1983, 1988) is the first to apply a baseline correction method for the SP log using a linear correction term first and later a combination of potential, environmental, and salinity correction terms. Bautista-Anguiano & Torres-Verdín (2015) develop a robust mechanistic modeling framework for the interpretation of SP logs, including a physics-based correction based on reservoir topology. Peyret et al. (2019) compare deep learning methods for automatic well log interpretation from lithology-specific logs. Shan et al. (2021) develop a deep learning method for well log generation that consistent with reservoir topology. Tang et al. (2021) introduce an ensemble machine learning framework for sweet spot detection using a suite of well logs. Simoes et al. (2022) develop a deep learning-based multiwell automatic log correction workflow for imputation and generation of missing logs. However, none of these approaches combine the concepts of automatic baseline correction specifically for SP logs and the prediction of sweet spots for CO2 storage along a well and across a regional scale.

We propose a deep learning-based framework for automatic baseline correction of SP logs and sweet spot detection to identify potential CO2 storage sites in the Gulf of Mexico. The deep learning method exploits the latent representation of the raw SP log for compression and denoising and uses a combination of attributes to estimate the baseline-corrected SP log, which in turn is used to estimate the volumetric concentration of shale along the well to detect local and regional sweet spots for CO2 injection. We validate the framework on a field dataset with over 300 wells in the Gulf of Mexico.

Method

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Conclusions

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Asquith, G., and D. Krygowski, 2004, Chapter 2: Spontaneous Potential, *in* AAPG Methods in Exploration, No. 16: AAPG Special Volumes, p. 21–30.

Bautista-Anguiano, J., and C. Torres-Verdín, 2015, MECHANISTIC DESCRIPTION, SIMULATION, AND INTERPRETATION OF SPONTANEOUS POTENTIAL LOGS.

Gan, F., G. Ruan, and J. Mo, 2006, Baseline correction by improved iterative polynomial fitting with automatic threshold: Chemometrics and Intelligent Laboratory Systems, v. 82, no. 1, p. 59–65, doi:https://doi.org/10.1016/j.chemolab.2005.08.009.

McConnell, C. L., 1988, A general correction for spontaneous potential well logs in fresh water: Journal of Hydrology, v. 101, no. 1–4, p. 1–13, doi:10.1016/0022-1694(88)90024-8.

McConnell, C. L., 1983, Spontaneous potential corrections for groundwater salinity calculations — Carter County, Oklahoma, U.S.A.: Journal of Hydrology, v. 65, no. 4, p. 363–372, doi:https://doi.org/10.1016/0022-1694(83)90087-2.

Peyret, A. P., J. Ambía, C. Torres-Verdín, and J. Strobel, 2019, Automatic interpretation of well logs with lithology-specific deep-learning methods, *in* SPWLA 60th Annual Logging Symposium 2019: Society of Petrophysicists and Well-Log Analysts (SPWLA), doi:10.30632/T60ALS-2019\_SSSS.

Shan, L., Y. Liu, M. Tang, M. Yang, and X. Bai, 2021, CNN-BiLSTM hybrid neural networks with attention mechanism for well log prediction: Journal of Petroleum Science and Engineering, v. 205, doi:10.1016/j.petrol.2021.108838.

Simoes, V., H. Maniar, A. Abubakar, and T. Zhao, 2022, Deep Learning for Multiwell Automatic Log Correction, *in* Petrophysics: Society of Petroleum Engineers (SPE), p. 724–747, doi:10.30632/PJV63N6-2022a10.

Tang, J., B. Fan, L. Xiao, S. Tian, F. Zhang, L. Zhang, and D. Weitz, 2021, A new ensemble machine-learning framework for searching sweet spots in shale reservoirs, *in* SPE Journal: Society of Petroleum Engineers (SPE), p. 482–497, doi:10.2118/204224-PA.