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

We first preprocess the data by filtering a large library of well logs in the Gulf of Mexico and select the ones with the SP log. The next step is to impute any missing values with a zero mask and zero-padding the SP log for all wells to create a tabular training set. The masked and padded values flagged so that the deep learning method do not account for those values during the training. Normalization is applied to the well logs to aid the training process of the neural network model.

We compute eight attributes of the SP log to aid the prediction. The first attribute is the derivative with respect to depth. Let represent the raw SP log, then the derivative with respect to depth is given by , where is the sampling rate in depth (typically 0.25 or 0.5 ft). The autocorrelation of is given by , where  is the complex conjugate operator, , and . The linear detrend attribute is given by , where is the slope coefficient in a least-squares fit, . The fourth attribute is the Fourier transform, given by . The Hilbert transform of is given by , where is the inverse Fourier transform and is the unit step function. The symmetric infinite impulse response (IIR) filter is given by , where and are parameters of the transfer function. The Savitzky-Golay filter is given by , where are the coefficients of a polynomial fit of the raw data and is half the window size. The last attribute is the cubic spline coefficients, given by , for a cubic spline fit that ensure continuity and smoothness of the interpolant. Let represent the set of a raw SP log and its corresponding set of attributes. Figure 1 shows a raw SP log and its corresponding attributes, namely , for a randomly selected well.

Deep convolutional U-Net neural networks have been widely used for computer vision and signal processing tasks, including translation, segmentation and denoising (Chang et al., 2021). We implement a deep convolutional U-Net neural network to estimate the baseline-corrected SP log, namely , from the raw SP log and its set of attributes, . The encoder portion of the network, , compresses the inputs into a latent representation, , such that . The decoder portion, , is a mirror image of the encoder and estimates the baseline-corrected SP log, **,** from the latent representation, such that . Residual concatenations, or skip connections, connect the layers of the Encoder and Decoder to enhance data flow, retrain fine-grained details and spatial information, and reduce information loss. The Encoder is composed of three hidden layers, each with a 1D convolution, batch normalization, ReLU activation, Dropout, and MaxPooling. Similarly, the Decoder is composed of three hidden layers each ending with an UpSampling operator instead of MaxPooling. Figure 2 shows the model architecture.

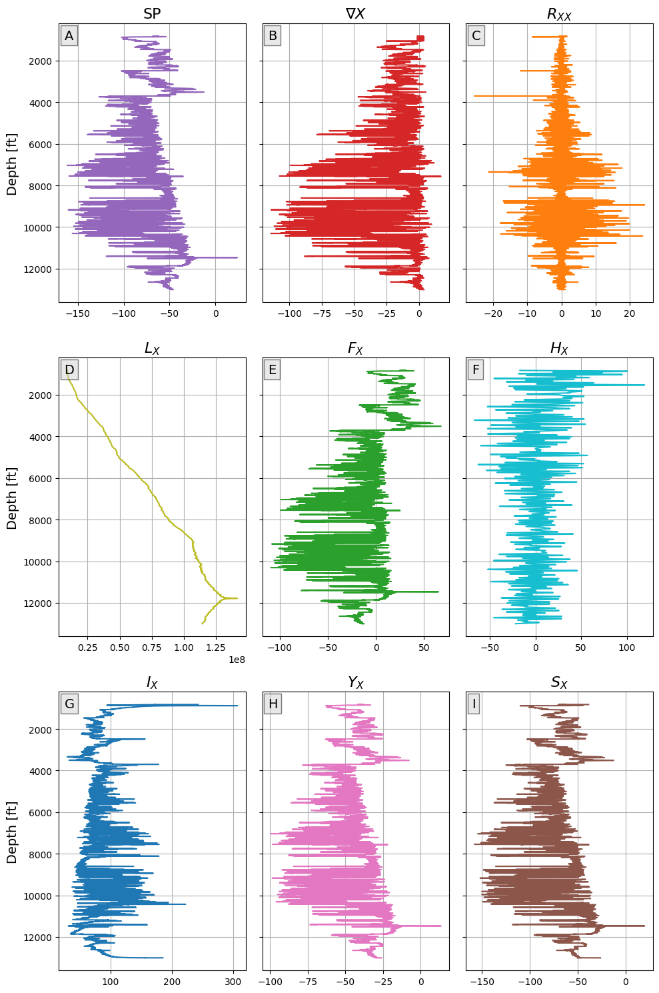


Figure 1: A randomly selected raw SP log (A) and its corresponding features – (B) derivative with respect to depth, , (C) autocorrelation, , (D) linear detrend, , (E) Fourier transform, , (F) Hilbert transform, , (G) IIR filter, , (H) Savitzky-Golay filer, , and (I) cubic spline coefficients, .

A subset of 389 is wells is selected for training. Each is preprocessed and then partitioned into a random training and testing set with 300 and 89 wells, respectively. The model is trained using the Adam optimizer with learning rate 0.01 and MSE loss with a batch size of 30 for 100 epochs using an NVIDIA RTX 3080 GPU. At each epoch, a random subset of 25% the batch size is used for validation. The model has a total of 89,681 parameters and requires approximately 1.64 hours to train. The average MSE for the training and testing sets is approximately 12.9% and 13.6%, respectively. Once trained, each test prediction takes approximately 420 miliseconds, providing a significant advantage for rapid estimation of lithology and sweet spots compared to traditional or manual techniques.

Table 1: This caption is placed outside the frame and is followed by a page break.

Conclusions

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Acknowledgements

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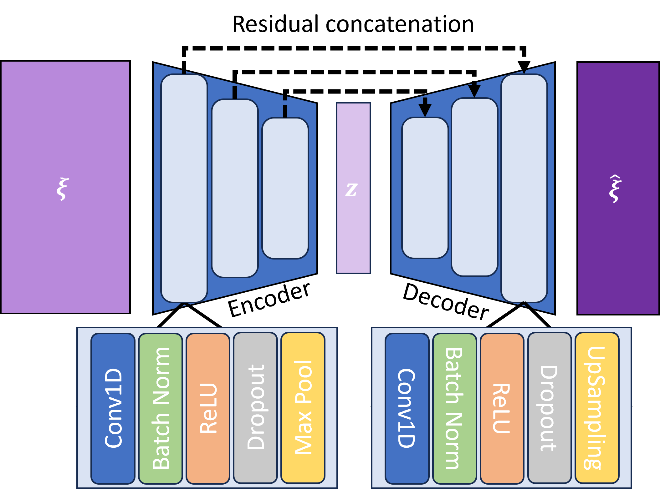
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