Lithological Identification of Carbon Dioxide Containing Formation Based on Deep Residual Network

Introduction

Since the Industrial Revolution, the combustion of fossil fuels has led to a continuous increase in CO_2 and other greenhouse gases, subsequently triggering global ecological and environmental issues. Currently, CO_2 emission reduction has become a consensus for the international community. Carbon Capture, Utilization, and Storage (CCUS) technology is widely recognized as a comprehensive countermeasure. As the final step of CCUS, CO_2 storage technology serves as the ultimate fallback solution. In the actual implementation process of CO_2 storage, it is necessary to understand the lithological information of underground formation. Based on experience, mudstone is considered a cap layer, while sandstone with high porosity is considered a CO_2 reservoir layer. The chemical properties of CO_2 are more reactive than CH_4, and it is easily soluble in water, making it easier to interact with minerals of formation. Especially for complex geological formations, which contain numerous mechanisms of action. These factors make it more difficult to identify the lithology. The traditional rock physics model can be used to identify the lithology. However, rock physics models are limited by many assumptions. Moreover, calculating lithology is an inverse problem for rock physics model, so there may exist non-uniqueness and ill-posedness problem. In addition, acoustic rock physics models can establish the relationship between elastic parameters and lithology, while electromagnetic rock physics models can establish the relationship between electromagnetic parameters and lithology, but both are equivalent to using only partial logging data information. At present, artificial intelligence and deep learning algorithms have been widely applied in the field of geophysics. For example, shear wave prediction, anisotropy parameters prediction, porosity prediction, fluid prediction, suppression of various types of noise, etc. (Zhang et al. 2021, Wu et al. 2023, Wang et al. 2023, Wang et al. 2020, Sui et al. 2022). In view of the correlation between logging data, data-driven methods can directly identify the lithology from logging data. We use deep residual network here. This network introduces residual connections to make it easier to train very deep networks. In terms of input selection for the network, we use principal component analysis and select the first four sensitive logging curves (density, resistivity, longitudinal wave velocity, gamma) to identify the lithology. Based on the requirement of CO_2 sequestration process and the geological information of the actual strata, the formation is divided into three categories: sandstone, siltstone, and mudstone. Finally, a section of formation with logging information is selected to verify the applicability and accuracy of the method.

The Relationship between Lithology and Logging Parameters

Different type logging curves at the same depth reflect the information of the formation from different aspects (physical quantities). For a certain physical quantity, there may be one or more logging curves are sensitive to it (such as gamma ray logging is often used as an important source of information to distinguish mudstone and sandstone). However, this physical quantity may not be as sensitive to other logging curves.

Principal component analysis (PCA) is a commonly used data dimensionality reduction technique (Jian et al. 2004). PCA finds the main features or most important components in the dataset by projecting the original features into a new feature space. This process simplifies the dataset, reduces feature dimensions, and preserves the most representative information in the dataset. We conduct PCA on well logging data from a work area in the South China Sea. The natural gas reservoirs in this region contain a large amount of CO_2. The lithological classification results are obtained through detailed calculations by experienced well logging interpretation engineers and geology engineers.

In *Figure 1*, the full name of horizontal axis represented are as follow (left to right): gamma ray (GR), acoustics (AC), density (DEN), resistivity (RT), compensated neutron logging (CNL), nuclear magnetic resonance logging (NML). From the figure, it can be seen that the most contribution come from GR and AC, followed by DEN and RT. CNL and NML have the smallest contribution to lithology identification. From a numerical perspective, the cumulative contribution rate of the first four principal components exceeds 98%, indicating that the first four principal components already contain most of the information from commonly used logging curves for lithology identification. So, GR, AC, DEN, and RT are used as inputs for the neural network.

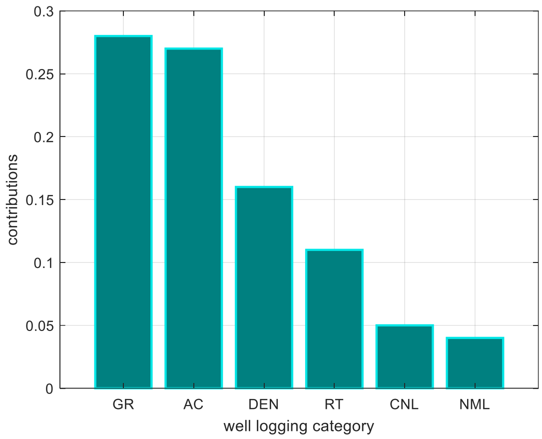

Figure 1 *The PCA outcome of different well logging parameters.*

Deep Residual Network

In deep learning, gradient vanishing and gradient descent problems are serious issues that affect model performance. The emergence of these two problems is related to the fundamental mechanism of deep learning - the backpropagation loss function gradient. For a long time, people believed that deep network is 'untrained'. However, the emergence of Deep Residual Net (DRN) changed everything (He et al. 2016). By designing a 'shortcut connection' mechanism, the residual module can better propagate gradients between layers of the network, making it possible to train 300+ layers of ultra deep neural networks. DRN does not have a fixed structure and parameters, which increases the flexibility of the network structure. Based on the complexity of the data and computational capacity, we construct the network structure of DRN (*Figure 2*). DRN is proposed to solve 2D problems such as image classification. However, DRN can also solve classification problems with one-dimensional inputs effectively. During the calculation process, the transmission of data changes from a two-dimensional matrix to a one-dimensional array. Considering the limitation of computing capability, our DRN has 16 hidden layers with ReLu activation function. The Softmax function is used to control the final output.

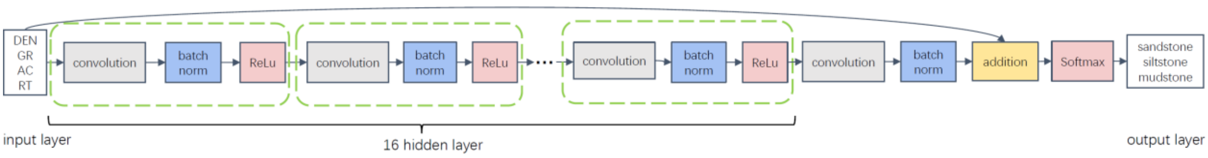

Figure 2 *Structural diagram of DRN.*

Application to the well log data

An on-going experimental CO_2 storage project is processing in the South China Sea. CO_2 is pressurized and injected in liquid form through wells into seafloor formation. This project helps accumulate experience for larger scale projects in the future.

In the process of training the network, the 185230 sets of logging data are randomly divided into training set, validation set, and testing set in a ratio of 7:2:1. The variation of the fitness value during the iteration process is shown *Figure 3*. The minimum fitness value is achieved at 63th iteration. It demonstrates that the neural network can be generalized to new data We apply the trained DRN to the actual area. The result is shown in *Figure 4*.

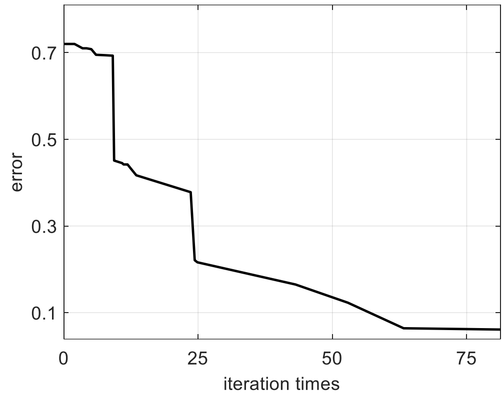

Figure 3 *The variation of optimal fitness value in DRN training process.*

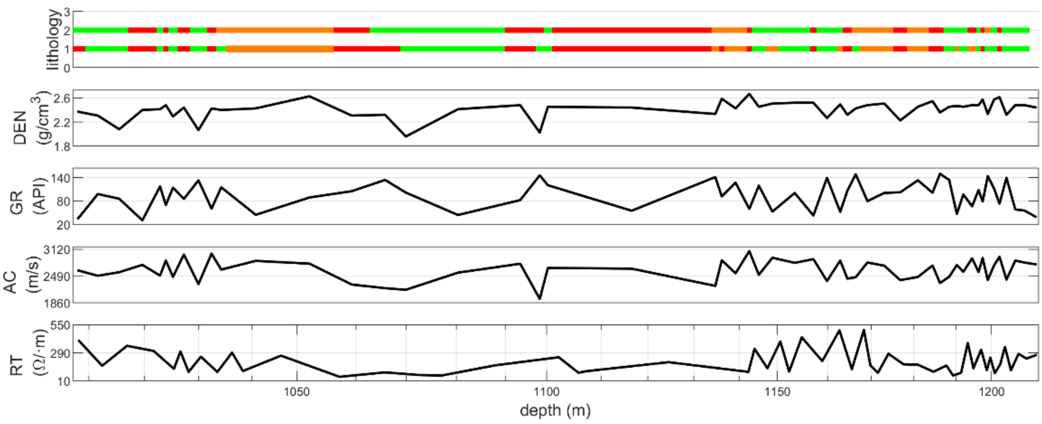

Figure 4 *The lithological identification results by DRN and corresponding well logging data. In the top subplot, green represents sandstone, orange represents siltstone, and red represents mudstone.*

In *Figure 4*, the prediction of the DRN show good consistency with the logging data. Taking each logging interval as a unit, the identification accuracy of DRN is about 93%. Overall, the recognition effect of sandstone is better, with obvious characteristics of high RT and low GR. There is a certain degree of error in siltstone identification. One possible reason for the misjudgment is that the RT and GR of three types of rock vary greatly at different depths. This may be caused by differences in the pore structure and mud content of the formation. We plan to improve the structure of DRN in the later stage to increase accuracy. For example, add the split attention theory (Zhang et al. 2022) and reinforcement learning process (Minsky 1954).

Theoretically, the more layers of DRN, the better results can be obtained. However, considering the complexity of well logging data and computational ability, a very deep network structure (such as over 1000 layers) is not used.

Conclusions

There is a correlation between the lithology and several basic logging data. However, it is difficult to describe quantitatively and accurately. This relationship can be found by neural network. Compared to traditional methods driven by rock physics theory, methods driven by actual data do not have the influence of complex geological assumptions. The impact of CO_2 makes this process more complex. Here, we use DRN to identify the different lithology. The prediction result of DRN fits well with the logging data.

After the neural network training is completed, the lithological identification at any well location in the work area can be calculated. It is very convenient to get the lithological identification in the real-time logging process. In addition, the obtained lithological identification outcome can be used in other geophysical steps. The proposed network can also be used in other similar regression problems.

Acknowledgements

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