Semi-supervised seismic data and well logs integration for reservoir lateral porosity prediction

Introduction

Reservoir porosity can reflect or evaluate the lithological, petrophysical, and hydrocarbon-bearing characteristics of the subsurface formation, and it is of significance for reservoir sweet spot area optimization, oil and gas reserves estimation, well pattern design. Traditional model-driven methods either utilize core data and well logs data to estimate porosity at the well locations, or utilize seismic inversion to invert elastic attributes (e.g., impedance) from pre-stack or post-stack seismic data, and then further convert these sensitive attributes into reservoir porosity via rock-physic models. Although these methods have some merits, seldom research investigates how to integrate seismic data and well logs to directly predict reservoir lateral porosity.

Formation porosity is theoretically associated with wave velocity and other seismic attributes (Wyllie et al., 1956, Xu and White, 1996). And machine learning algorithms can express the complex nonlinear relationship between input seismic data or attributes and output reservoir parameters. Therefore, many scholars use this universal solver for reservoir porosity estimation. For instance, Leite et al (2011) introduced a sparse-spike inversion and the neural network based sequential workflow for 3D porosity prediction. Feng et al (2020) used convolutional neural networks and a forward model to conduct unsupervised reservoir porosity prediction with a known low-frequency prior component. However, these methods depend on accurate elastic parameter results or accurate prior models.

In this abstract, different from conventional model-driven or data-driven methods, we investigate semi-supervised recurrent neural networks (SSRNNs) to integrate seismic data and (pseudo) well logs for one-step reservoir lateral porosity prediction. SSRNNs are composed of an encoder subnet and a decoder subnet, and the former simulates seismic inversion to convert the input post-stack seismic data into the predicted porosity, then the latter functions as a network-based forward model to transform the inverted porosity into generated seismic data. The predicted porosity and the generated seismic data are compared with the true porosity and the observed seismic data, respectively. The encoder subnet makes the inverted porosity result has high similarity with the reference model, and meanwhile, the decoder subnet makes the predicted porosity satisfies the forward laws and reduces non-uniqueness. In addition, the non-wellbore seismic traces are randomly selected at each iteration of SSRNNs to improve the lateral continuity of the predicted porosity result. A numerical model and a field data example are used to demonstrate the effectiveness of this method for porosity prediction.

Method

The architecture and principle of the SSRNNs for reservoir porosity prediction: In the realm of reservoir description, generalized seismic inversion usually predicts petrophysical parameters from seismic attributes inverted from the post-stack or pre-stack seismic data. To simulate this physical procedure, we adopt SSRNNs to directly predict reservoir porosity from post-stack seismic data.

As shown in Figure 1, SSRNNs include an encoder subnet $E$ and a decoder subnet $D$, and both $E$ and $D$ are shared with the same network architecture of four bi-directional gated units (Bi-GRUs) and one linear regression layer. The Bi-GRUs can consider the adjacent seismic response for predicting the porosity value at a certain time or depth point and have the ability to make the predicted results obey the sedimentary laws. The $E$ implements network-based simultaneous seismic inversion and petrophysical modelling, and transforms the input single-trace seismic data into the output single-trace porosity curve. The objective function of $E$ can be defined as:

$$L_E = \frac{1}{N} \sum_{i=1}^N \| \text{Por}_i - E(S_i; W_E) \|^2,$$

where $N$ represents the number of (pseudo) well logs or seismic traces, $\text{Por}$ and $S_i$ represents the $i$th true porosity curve and its corresponding seismic trace, respectively.
The $D$ acts as a data-driven forward model to reduce the solution space, and make the predicted porosity result via $E$ return back to seismic data. Under this situation, the estimated porosity curves (i.e., the intermediate code of SSRNNs or the output of $E$) at the well locations are not only supervised by (pseudo) well logs, but also regulated by seismic data fitting degree. In addition, to alleviate the lateral discontinuity caused by trace-to-trace porosity inversion, the seismic records at non-well locations are randomly selected at different epoch for network learning and modelling. Due to the rarity of well logs, we only use seismic data match error between non-wellbore seismic traces and their corresponding generated seismic traces via SSRNNs to indirectly control the inversion quality at the non-well locations. The objective function of $D$ can be written as:

$$L_D = \frac{1}{N} \sum_{i=1}^{N} \left( \left\| S - D(E(S; W_E); W_D) \right\|^2_2 + \left\| S - D(E(S; W_E); W_D) \right\|^2_2 \right),$$

where $S_i$ represents the $i$th non-wellbore seismic trace, $W_E$ and $W_D$ represents the network parameters in the inversion subnet $E$ and forward subnet $D$, respectively. The first and second terms of equation (2) are used to calculate seismic data misfit error at the well locations and non-well-locations, respectively. The total objective function of SSRNNs can be written as:

$$L_{total} = L_E + \lambda L_D,$$

where $\lambda$ represent the regularization parameter for balancing the contradiction between inversion accuracy and forward quality. Here, $\lambda$ is set to 1 for synthetic seismic data, and 0.2 for real seismic data. Based on the abovementioned network architecture and workflow, SSRNNs integrate rare pairs of seismic data and well logs, and abundant non-wellbore seismic traces to carry out the semi-supervised porosity prediction. The adaptive optimizer Adam (Kingma et al., 2014) is adopted to update the network parameters and to obtain the optimized reservoir porosity prediction model.

**Figure 1** The SSRNNs for reservoir porosity estimation. (a) The architecture of SSRNNs, and (b) the detailed network modules in an encoder subnet or a decoder subnet. The SSRNNs use an encoder subnet to invert the input seismic data into the predicted porosity, and then the predicted porosity result enters into the decoder subnet in SSRNNs to generate seismic data. The encoder (or decoder) subnet consists of four Bi-GRUs and one regression layer.

**Examples**

A numerical reservoir model example is first adopted to illustrate the effectiveness and advantages of SSRNNs-based reservoir porosity estimation. The porosity model (Figure 2a) is derived from the Marmousi velocity model with a rock-physic formula. The synthetic seismic data (Figure 2d) is the convolution of the reflectivity series and the source wavelet with a peak frequency of 35Hz. We extract eight pseudo well logs and their corresponding seismic traces (red lines in Figure 2a and 2d) to train SSRNNs, and six pseudo well logs and their seismic traces (blue lines in Figure 2a and 2d) for validation. In addition, we maintain other conditions and merely use the $E$ in Figure 2a to build the other porosity prediction model, which maps seismic data into porosity without a forward constraint.

Figure 2b and 2c shows the inverted porosity results via SSRNNs and the encoder $E$, respectively. The correlation coefficient (CC) between Figure 2a and 2b is 0.952, and the CC between Figure 2a and 2c is 0.960. Under the joint supervision of seismic data and well logs, SSRNNs simultaneously tackle two optimization objects to make the inverted porosity meet two different types of constraints and
reduce the search range for the optimal solution. Therefore, the prediction accuracy of SSRNNs is better than that of the encoder E. The seismic waveform information is utilized in equation (3) to control the inverted result must obey the learned forward laws of SSRNNs. While the estimated porosity at the non-well locations is close to the true value, seismic data fitting in equation (3) gradually decreases and improves the lateral continuity of the predicted porosity model. Thus, the inverted result via SSRNNs (Figure 2c) is superior to the inverted result via the E from the perspective of the lateral consecutiveness. Figure 2e shows the generated seismic data by subsequently inputting the predicted result (Figure 2c) into the decoder D of SSRNNs. The seismic residual (Figure 2f) between Figure 2d and Figure 2e indicates that the inverted result can meet seismic data fitting with few reflection energy leaks.

![Figure 2 The numerical model example. (a) The synthetic porosity model, (b-c) the predicted porosity results via the encoder E and SSRNNs, respectively, (d) the synthetic seismic data, (e) the generated seismic data via SSRNNs, and (f) the residual between (d) and (e). Both (b) and (c) are in good consistency with the reference of (a), however, the lateral continuity of (c) is better than that of (b) due to the forward modelling constraint of SSRNNs in both well locations and non-well locations.](image)
Figure 3 The field data example. (a) The observed post-stack seismic data of size 723 CDPs×119 time samples, (b) the predicted porosity result via SSRNNs, (c) the generated seismic data by inputting (b) into the decoder subnet of SSRNNs, and (d) seismic data residual between (a) and (c). The red curves in (a-d) represent the interpreted porosity logs. The predicted porosity result is in accord with the known porosity characteristics at the well locations, and it also meets seismic data matching by comparing (c) with (a). In addition, (b) indicates that the underlying formation is a favorable gas reservoir with two thin sandstone layers.

To further verify the effectiveness of the SSRNNs-based reservoir porosity estimation, we apply the proposed method to the real post-stack seismic data. The working area is a tight gas-bearing sandstone reservoir and is characterized by low porosity, low permeability, and complex pore structure. Seismic data between two interested horizons (denoted by the top and bottom white curves in Figure 3a) are low resolution. In view of the seismic and well logs difference between the numerical case and the real case, we use four interpreted porosity curves (marked by the first four red lines in Figure 3a) and their corresponding seismic traces to train a new porosity prediction model with SSRNNs. The estimated porosity result (Figure 3b) via SSRNNs shows that there are two thin and relatively high porosity (6% ~ 8%) sandstone strata in the underlying formation. The predicted porosity result has favorable lateral resolution, and its vertical resolution is higher than seismic data. In addition, the predicted result in the blind well position conforms to the true porosity (denoted by the last red vertical curve in Figure 3b). The generated seismic data (Figure 3c) and seismic data residual (Figure 3d) all demonstrate that the modeled seismic data derived from Figure 3b are comparable to the observed seismic data.

Conclusions

Traditional seismic elastic parameter inversion and rock-physic modeling based porosity prediction methods exist accumulated errors and approximate assumptions, which inevitably causes the predicted porosity is biased and even inaccurate. In this abstract, we propose semi-supervised recurrent neural networks (SSRNNs) based reservoir porosity estimation method to simplify modelling steps and directly build the complex nonlinear mapping between post-stack seismic data and porosity. Compared with the encoder \( \mathbf{E} \), SSRNNs can fully integrate (pseudo) well logs, wellbore seismic traces, and non-wellbore seismic traces to predict high-resolution reservoir porosity with favorable lateral continuity. In the future, we will attempt to explain the physical mechanism of SSRNNs for mapping the narrow seismic data into broadband porosity or other important reservoir parameters.

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References


