1D convolutional neural network with stacked bidirectional long short-term memory for seismic impedance inversion

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Summary

The seismic impedance inversion problem is ill-posed and nonlinear because of insufficient data, and is limited by wavelet estimation and frequency band-limited data. A machine learning long short-term memory algorithm (LSTM) can capture long-term dependencies so that can work with long and densely sampled well log data to eliminate these limitations and take advantage of the known rock physics trend with depth. In this work, the stacked bidirectional long short-term memory (SBDLSTM) recurrent neural network, and 1D convolutional neural network (CNN) with stacked BDLSTM have been applied to the inverse problem P-impedance and S-impedance calculation. Near, mid, far offset seismic data, migration velocity and well log data attributes are provided to generate the training set. Extreme gradient boosting (XGBoost) is used as the baseline model for comparison. Results show that SBDLSTM can predict impedance with a more accurate trend than the XGBoost method in some rapidly changing layers. 1D CNN with stacked BDLSTM can also calculate a high-frequency impedance prediction with fewer artifacts. The promising aspect is that both SBDLSTM and 1D CNN with SBDLSTM approaches can maintain a good fit when given a small number of training datasets.

Introduction

Seismic impedance inversion is used for interpreting internal rock properties. Machine learning methods have been implemented successfully to seismic inversion problems to learn the non-linear relationships, and achieve high accuracy and productivity (Calderón-Macías et al., 2000; Moya and Irikura, 2010; Alfarraj and AlRegib, 2019; Roy et al., 2020). Das et al. (2019) use a convolutional neural network to obtain seismic impedance inversion. Pham et al. (2020) apply bidirectional convolutional long short-term memory to estimate missing logs. However, because the seismic inversion problem is ill-posed due to insufficient and inaccurate data, training data collection with high quality is a difficult task. The idea is to think of a system that can handle a small group of data to predict seismic impedance based on physical meaning. The convolutional neural network has the advantage of features extraction, which can be used to analyze seismic attributes and make our inversion result close to the ground truth. Bidirectional long-term memory (BDLSTM) (Hochreiterand and Schmidhuber, 1997; Graves and Schmidhuber, 2005) can learn from both long-term forward and backward temporal dependencies from historical data, and it works with long and dense borehole traces. The deep BDLSTM architectures are networks with several stacked BDLSTM hidden layers, where the output of a BDLSTM hidden layer will be fed as the input into the subsequent BDLSTM hidden layer. These stacked layers mechanism can enhance the power of neural networks.

We propose a data-driven method to predict seismic impedance using the 1D convolutional neural network with stacked bidirectional long short-term memory (1DCNN-SBDLSTM) based on a small number of well log data. Thirty-seven attributes are applied as features or channels for the neural network to learn. For example, background velocity, stack seismic in near, mid, and far offset, instantaneous amplitude, instantaneous phase, instantaneous frequency, integrated absolute amplitude etc. 1DCNN-SBDLSTM improves prediction accuracy on different rock types. It also mitigates artifacts compared with using the extreme gradient boosting (XGBoost) method.

Theory

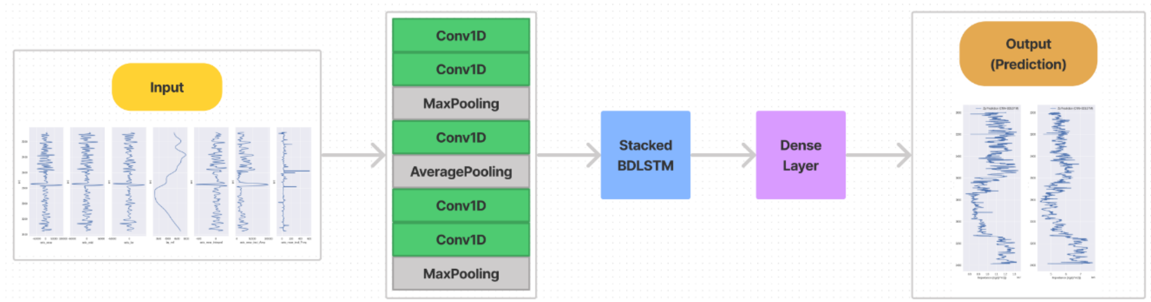

Figure 1: The proposed model has five parts. Input part includes different seismic attributes. ConvNet can extract key features from attributes and the output is fed into stacked BDLSTM. Dense layer is used for outputting the final prediction. The output of the last convolutional layer is used as the input to the stacked BDLSTM, which can keep tracking the information. P-impedance and S-impedance are predicted separately to avoid interferences.

Results and Figures

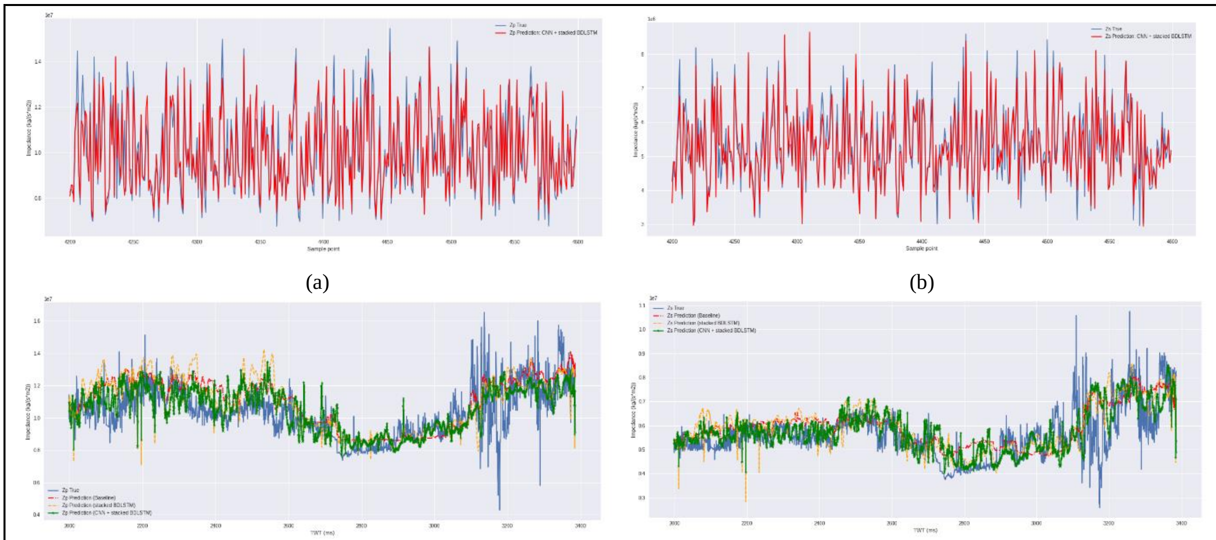

Figure 2: Part of the training well for (a) P-impedance and (b) S-impedance prediction: true value (blue) and prediction by 1DCNN-SBDLSTM (red). Testing well for (c) P-impedance and (d) S-impedance: true value (blue), XGBoost prediction (red dashed line), stacked BDLSTM prediciton (orange dashed line) and 1DCNN-SBDLSTM prediction (green solid line).

We train and test this proposed model using Poseidon 2D/3D seismic data and six well log data. XGBoost approach is considered as our baseline model. Figure 2a and 2b show a part of training well data, our proposed method can have a good alignment with the ground truth. Figure 2c and 2d show the P-impedance and S-impedance predictions separately. Compared to the XGBoost blocky result, both SBDLSTM and 1DCNN-SBDLSTM can predict a more accurate trend and indicate more precise geologic layer boundaries, for example, the two-way traveltime at around 2420, 2720 and 3140 ms. SBDLSTM will generate some incoherent spikes, whereas 1DCNN-SBDLSTM can suppress the artifacts by applying CNN feature extraction. Due to the fact of given small scale datasets, the R-squared scores of 1DCNN-BDLSTM with P-impedance and S-impedance are 0.311 and 0.315 respectively but are higher than those of the XGBoost method: 0.291 and 0.307. However, the R-squared score is not the only standard way to judge the estimation. Since even though the difference of R-squared between the baseline model and our proposed model is not large, the baseline model result is blocky and smooth, which cannot match the true well log data trend. Our proposed method can predict a better fitting of impedance when given a small number of well log data compared with XGBoost based on physical seismic attributes. In summary, results from 1DCNN-SBDLSTM on the rock boundary indication can help with further interpretation when given insufficient datasets.

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