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

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ABSTRACT

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 it 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, two models including 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 more accurately 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 and Wu (2019) 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) (Hochreiter 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' mechanisms 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

In this section, a 1D convolutional neural network with a stacked bidirectional long short-term memory algorithm will be delineated in detail, along with a basic framework shown in Figure 1.

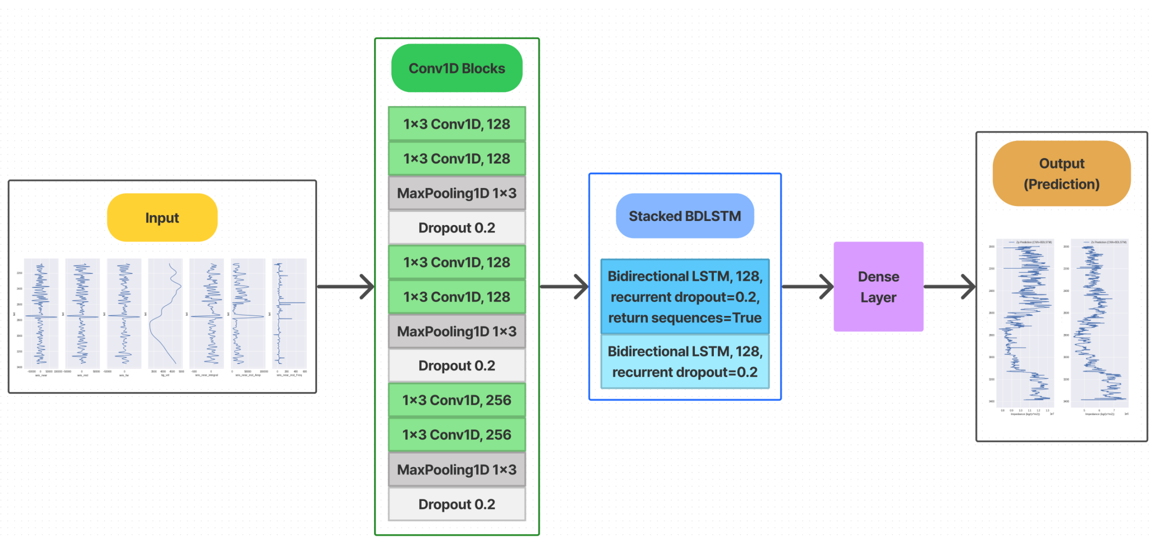


FIG. 1: Workflow for 1DCNN-SBDLSTM algorithm.

The proposed model has five parts. The input part includes different seismic attributes. ConvNet can extract key features from attributes, and the output of the last convolutional layer is used as the input to the stacked BDLSTM, which can keep tracking the information and capture long-term dependencies. A dense layer is used for outputting the final prediction. P-impedance and S-impedance are predicted separately to avoid interference. Next step, we will go over each part in detail.

Input attributes

For input traces, thirty-seven seismic attributes were chosen for the neural network to learn features. The major attributes include background velocity, stack seismic in near, mid, and far offset, instantaneous amplitude, instantaneous phase, cosine instantaneous phase, instantaneous frequency, amplitude weighted instantaneous frequency, integrated absolute amplitude, derivative amplitude and so on. They are used to characterize sequences and indicate amplitude anomalies to identify lithology variations. Additionally, the estimation of seismic attribute amplitude attenuation will help derive the potential location of oil and gas reservoirs.

1D convolutional neural network

In 1DCNN-BLSTM, 1DCNN is used to extract key features from various seismic attributes. For example, capturing rapid change through the attribute peaks or troughs. The network consists of convolutional and pooling layers. We chose the maximum pooling layer to capture variance and control some outliers or noise. In each 1D CNN-layer, the forward propagation is expressed as:

$$y_k^l = f(b_k^l + \sum_{i=1}^{N_{l-1}} conv1D(w_{ik}^{l-1}, s_i^{l-1})) \tag{1}$$

where y_k^l denotes the intermediate output, b_k^l is the bias of the k^{th} neuron at layer l, and s_i^{l-1} represents the output of the i^{th} neuron at layer $l-1$. w_{ik}^{l-1} is the kernel from the i^{th} neuron at layer $l-1$ to the k^{th} neuron at layer l. $conv1D(...)$ is used to perform 1D convolution. Then, y_k^l will be used to determine

$$s_k^l = y_k^l \downarrow ss \tag{2}$$

where s_k^l stands for the output of the k^{th} neuron at layer l, and $\downarrow ss$ means the downsampling process with a scalar factor ss.

After the $Conv$ layer blocks, the final block output will be regarded as the input of the stacked bidirectional long short-term memory block.

Long short-term memory

The output of the last convolutional layer is used as the input to the stacked BLSTM which can keep tracking the information. We can start with a simple LSTM framework, then dive into the BLSTM. Within each LSTM cell, the forget gate Γ_f is determined by

$$\Gamma_f = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

where h_{t-1} is the hidden layer vector from previous time and x_t means the current input vector. σ, W_f and b_f represent the activation function, weight matrices and bias for the forget gate.

Then, the input gate follows the similar behavior as forget gate but with different weight and bias:

$$\Gamma_u = \sigma(W_u[h_{t-1}, x_t] + b_u) \tag{4}$$

The cell input activation vector is obtained by

$$\widetilde{c_t} = g(W_c[h_{t-1}, x_t] + b_c) \tag{5}$$

Next step is to calculate next cell state by using equations 2, 3 and 4:

$$c_t = \Gamma_u \widetilde{c_t} + \Gamma_f \widetilde{c}_{t-1} \tag{6}$$

The output h_t of the LSTM cell can be determined by the output gate Γ_o:

$$\Gamma_o = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = \Gamma_o c_t \tag{8}$$

Bidirectional long short-term memory

For the bidirectional LSTM, forward LSTM and backward LSTM need to consider as two separate layers (Du et al., 2020). The final output can be obtained by

$$h_t = \alpha h_t^f + \beta h_t^b \tag{9}$$

$$y_t = \sigma(h_t) \tag{10}$$

where h_t^f is the forward LSTM layer output which takes time sequences from x_1 to x_T, h_t^b denotes the backward LSTM layer output which takes the reverse time sequences from x_T to x_1. α and β represent the importance of forward LSTM and backward LSTM, and satisfy $\alpha + \beta = 1$. h_t is the sum of two LSTM outputs, and y_t is the impedance prediction. Note that for the output dense layer, a linear activation function is chosen because seismic attributes might have negative values.

Model parameters

Three models are applied in this project. One is extreme gradient boosting (XGBoost) which is considered as the baseline model. A separate stacked bidirectional long short-term memory is implemented to see how the sequential model works on time series or the well log data in this project. Another model combines a 1D convolutional neural network and stacked bidirectional long short-term memory.

The parameters in the XGBoost approach include 50 gradient boosted trees, four-layer depth for base learners and random number seed equals to zero.

For the stacked BDLSTM model, a two-layer stacked BDLSTM block is used with 512 units and 0.2 recurrent dropouts. It will also return the hidden state for remembering and learning long dependencies. The third model uses three sets of 1D ConvNet blocks, which have 128 filters for the first two sets and 256 filters for the last set. The length of the 1D convolution window is three, and the output has the same length as the input. The size of the max-pooling layer is 3 with the same padding size. The stacked BDLSTM block in the latter method has the same parameter setting as the former approach, but has only one BDLSTM layer with returning sequences setting.

NUMERICAL EXAMPLES

In this section, training and testing sets will be shown for delineating and evaluating the approach performance.

Train and test sets

We train and test this proposed model using Poseidon 2D/3D seismic data and six well log data. For example, well log 11 information after feature engineering is shown in Figure 2. The attributes including background velocity, seismic near offset integral, instantaneous amplitude and phase will be considered as the train set.

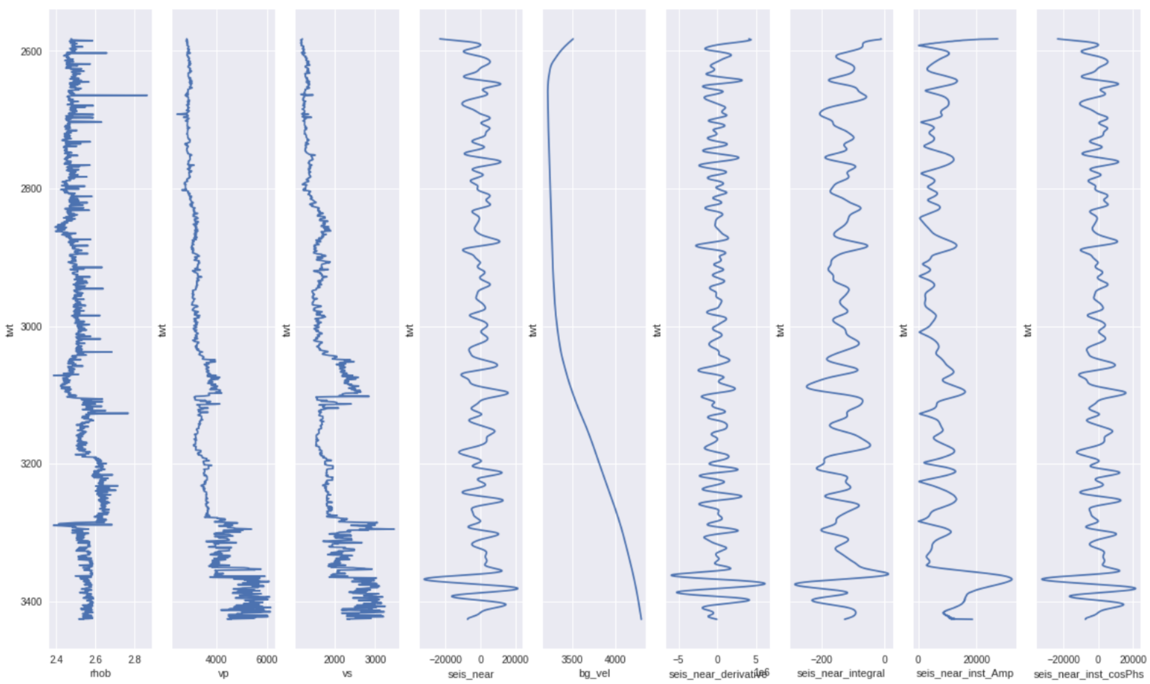


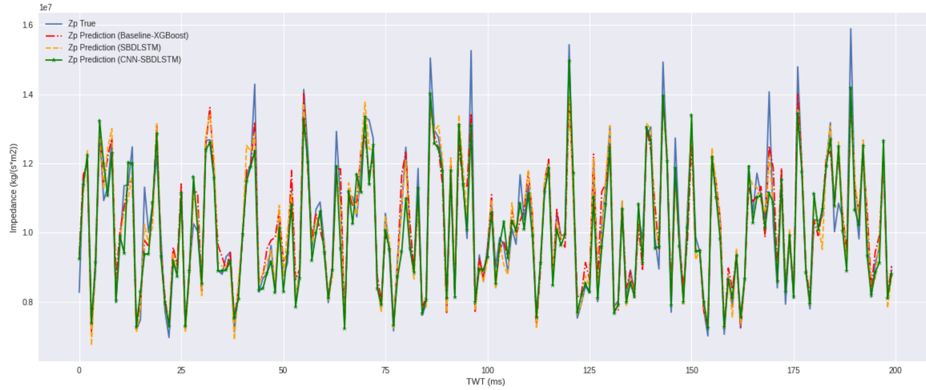
FIG. 2: Well 11 attribute information.

Train set prediction

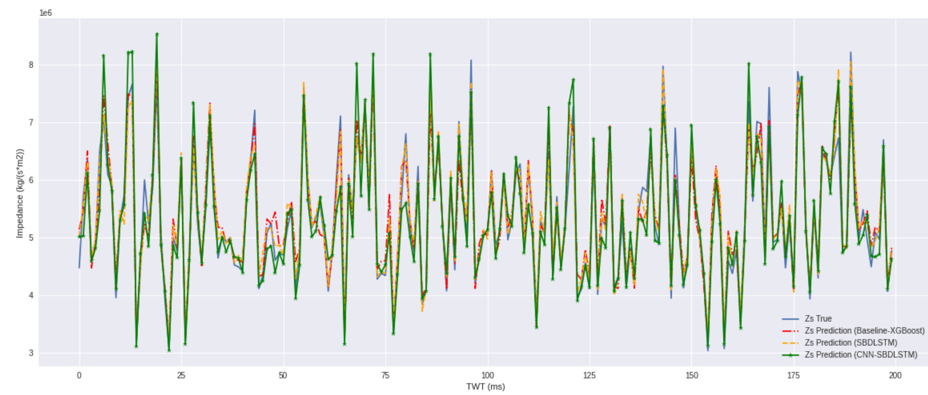
Figure 3a and 3b show a part of training well data prediction. All three models can have a good alignment with the ground truth. Some details XGBoost can perform better, but Conv layers with SBDLSTM will give more accurate amplitudes at some peaks. For example, at around point 40 and 170 in Figure 3a and point 60 and 80 in 3b, XGBoost gives higher amplitude predictions; whereas at point 120 and 150 in 3a, and point 87 and 185 in 3b, our proposed method predictions are providing a better match with the true amplitude.

Test set prediction and evaluation

Figure 4a and 4b show the P-impedance and S-impedance predictions on the test set separately. Compared to the XGBoost blocky result, both stacked BDLSTM and 1DCNN-SBDLSTM can predict a more accurate trend and indicate more precise geologic layer boundaries. For example, for the two-way traveltime at the Johnson top (2420 ms), Jameson top (2720 ms) and near Plover top (3140 ms), our proposed models can recover the lithology variance by rapid impedance amplitude change. However, the baseline model only gives small fluctuations at the boundary layers. Even though SBDLSTM will generate some incoherent spikes, 1DCNN-SBDLSTM can help suppress the artifacts by the CNN



a)



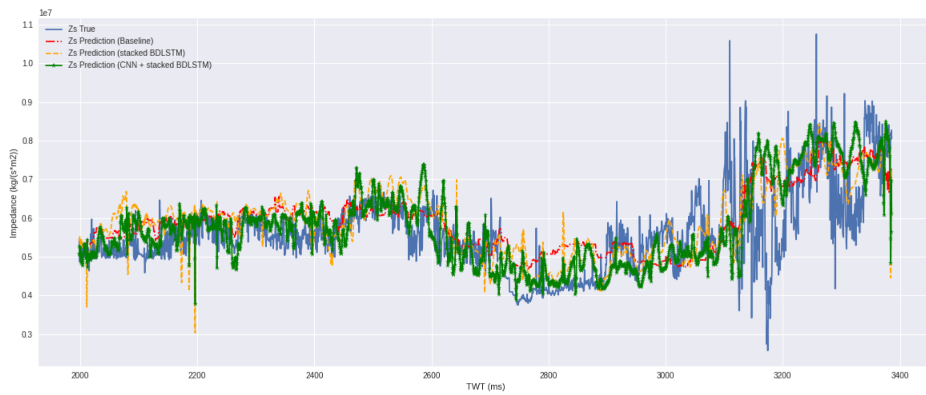
b)

FIG. 3: Part of the training well for (a) P-impedance and (b) S-impedance prediction: true value (blue) and prediction by 1DCNN-SBDLSTM (red).

feature extraction.

R-squared scores are considered as the evaluation matrix for relatively showing the regression result. Due to the fact that small-scale datasets are given, the R-squared score of 1DCNN-SBDLSTM with P-impedance is 0.314 but is higher than that of the XGBoost method: 0.291, which means P-impedance inversion by 1DCNN-SBDLSTM obeys the subsurface geologic structure and has a better alignment compared with the baseline model. On the other hand side, the score of XGBoost in S-impedance prediction is 0.308, which is higher than our proposed models. One reason could be that the baseline model result is close to the average impedance values, whereas our proposed methods give some spiking predictions. 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.

a)



b)

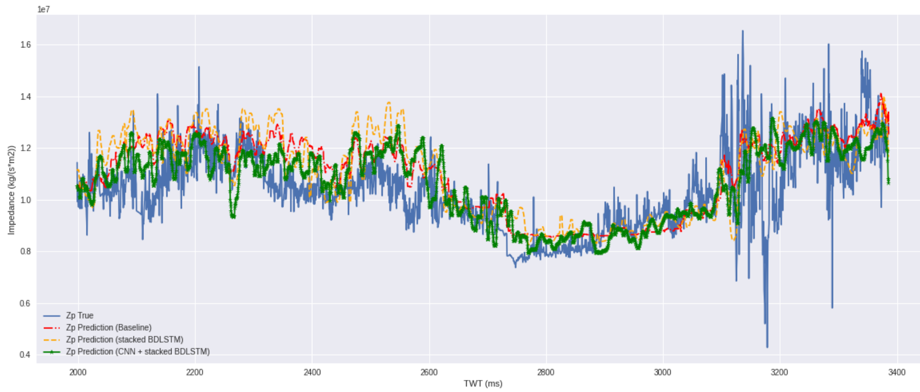
FIG. 4: Testing well for (a) P-impedance and (b) S-impedance: true value (blue), XGBoost prediction (red dashed line), stacked BDLSTM prediction (orange dashed line) and 1DCNN-SBDLSTM prediction (green solid line).

Table 1: R2 comparison in three methods.

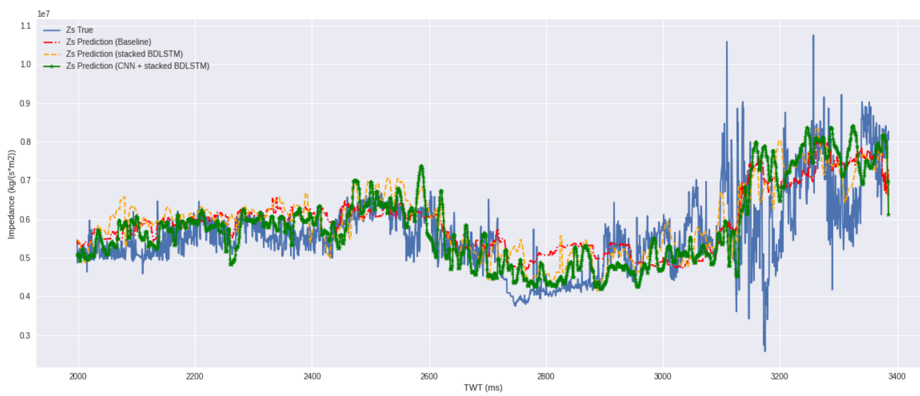
R2	Baseline: XGBoost	Model 1: BDLSTM	Model 2: 1DCNN-SBDLSTM
Zp	0.291	0.080	0.314
Zs	0.308	0.275	0.208

Applying median filter

Another option to mitigate the spiking prediction influence in our models is to apply a median filter. A 10-point median filter is chosen for fine-tuning the results of using our proposed models. The outcome in Figure 5 shows that the median filter is robust and good at preserving sharp edges and removing some outliers. Both of our proposed models can provide high resolution and good matches on P- and S-impedance prediction. For example, between time window 2200-2400 ms, and 2600-3100 ms, the variation predictions by our proposed approaches provide more accurate fitting compared with the baseline model. The R-squared scores (Table 2) in Model 2 for Z_p and Z_s after applying the median filter increase to 0.328 and 0.224 respectively.



a)



b)

FIG. 5: After using median filter, the results (a) P-impedance and (b) S-impedance: true value (blue), XGBoost prediction (red dashed line), stacked BDLSTM prediciton (orange dashed line) and 1DCNN-SBDLSTM prediction (green solid line).

Table 2: R2 comparison in three methods after median filter.

R2	Baseline: XGBoost	Model 1: BDLSTM	Model 2: 1DCNN-SBDLSTM
Zp	0.291	0.080	0.328
Zs	0.308	0.286	0.224

Our proposed method can predict a better fitting of impedance with higher resolution when given a small number of well log data compared with XGBoost based on physical seismic attributes. Again, the R-squared score does not fully count on the regression performance.

CONCLUSIONS

Stacked bidirectional long short-term memory can capture the trend of well log data, and combined with 1D convolutional neural network help to extract key features to indicate reflectors and structure boundaries. When given an insufficient dataset, 1DCNN-SBDLSTM can maintain a better fit, suppress more artifacts and recover the prediction with higher resolution and more accurate trend compared with either XGBoost or stacked BDLSTM only. In future work, we will try to train and update this approach using more well log data.

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