Seismic data shaping with transformer encoder neural networks applied to CO2 injection monitoring data

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Summary

CO2 injection monitoring data can be performed with two seismic datasets, one before injection and another after. The difference in the datasets is related to the difference in CO2. One obstacle is that CO2 is not the only cause of all the differences between the two seismic surveys. It is necessary to equalize both datasets such that the only remaining difference is the one related to CO2. We use a transformer encoder neural network to perform this equalization between both seismic datasets. This state-of-the-art neural network has been used successfully in natural language translation and computer vision. We compare their performance with respect to the usual Wiener shaping filters. We also describe how they perform the equalization using a real example.

Theory

Seismic time-lapse imaging for CO2 monitoring is usually performed by subtracting two seismic datasets acquired at different times. One dataset is the baseline, recorded before the CO2 injection and the other is the monitor, recorded after. To diminish the non-CO2 related differences while maintaining the differences caused by the CO2 injection, a procedure called cross equalization is applied to the datasets (Rickett and Lumley, 2001). Cross equalization is a general term used in the industry for shaping filtering, amplitude scaling and static corrections needed to match the monitor and baseline datasets (Ross et al., 1996). Shaping filtering is usually performed with Wiener filters that shape the monitor dataset into the baseline dataset (Robinson and Treitel, 1980) outside the CO2 injection zone.

The idea behind using transformer encoders to perform time lapse shaping filtering comes from the problem of natural language translation. It has been shown that transformer encoders perform very well translating sentences between different languages (Vaswani et al., 2017). Two traces from different seismic vintages can be seen as two sentences in different languages, if they are partitioned in segments.

One advantage of transformer encoders over recurrent neural networks is that their training can be parallelized because the attention mechanism can be calculated independently between different parts of the input, while in recurrent neural networks there is always a dependence with the previous or subsequent parts of the input, and this creates a bottleneck.

Figure 1 shows the transformer encoder shaping workflow. A portion on the monitor trace on the left is processed by the transformer encoder and the corresponding portion of the shaped monitor trace is produced. This shaped monitor trace is compared with the true baseline trace during the neural network training. We use the mean square error to compare the two traces.

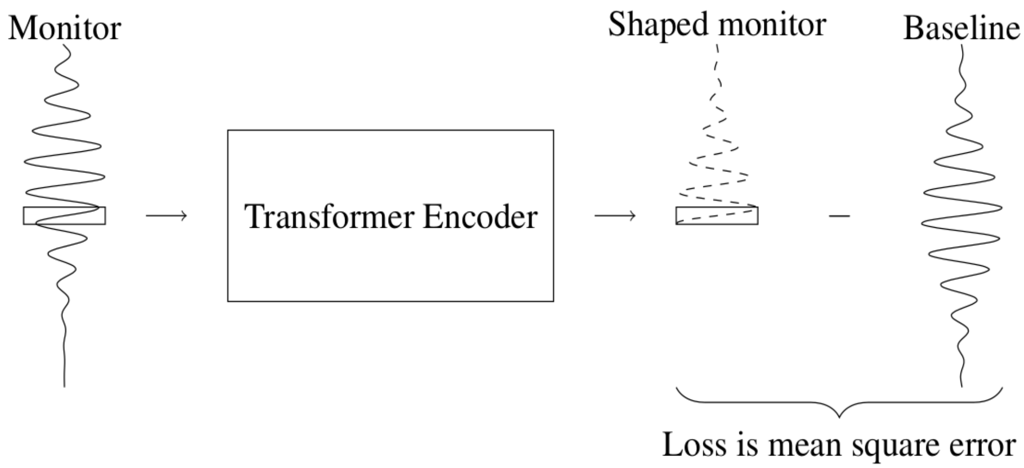

FIG. 1. Transformer encoder shaping workflow. A portion on the monitor trace on the left is processed by the transformer encoder and the corresponding portion of the shaped monitor trace is produced. This shaped monitor trace is compared with the true baseline trace during the neural network training. We use the mean square error to compare the two traces.

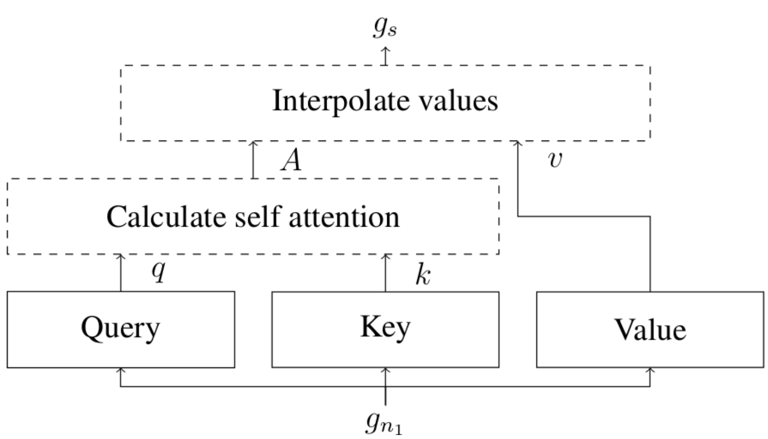

FIG. 2. Self attention head.

The heart of a transformer encoder network is the self attention head shown in Figure 2. From the input trace divided in windows g_{n1} three vectors, query q, key k and value v, are produced:

$$\begin{aligned} q &= g_{n_1} Q + b_q \\ k &= g_{n_1} K + b_k \\ v &= g_{n_1} V + b_v \end{aligned} \tag{1}$$

where Q, K and V are the weights of three dense neural networks, and b_q, b_k and b_v their corresponding bias vectors. The next layer calculates the attention scores A from q and k in the following way:

$$A = \text{softmax}\left(\frac{qk^T}{\sqrt{d_k}}\right) \tag{2}$$

where d_k is the key dimension, and the softmax function normalizes all the scores. The last step is to interpolate the value v by multiplying it with the scores A, g_s = Av. Several self attention heads can be run un parallel and stacked to increase the network results.

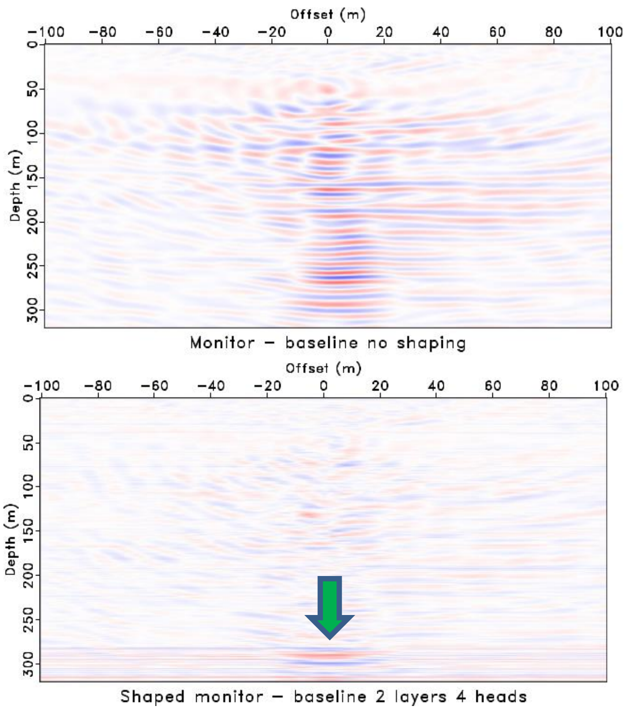

FIG. 3. CaMI 2021-2017 time-lapse difference. Top left: Original. Top right: Wiener shaped with 50m length filter. Bottom left: Transformer encoder with 2 layers and 4 heads. Bottom right: Transformer encoder with 1 layer and 4 heads. The arrows mark the CO2 anomaly.

Results

The Containment and Monitoring Institute Field Research Station is a research facility located in Newell County, Alberta, Canada, where CO2 monitoring technologies are being tested (Lawton et al., 2017). Some of the facilities include a distributed acoustic sensing (DAS) system installed in two observation wells close to where the CO2 is being injected. The CO2 is injected at around 300m depth.

In 2017 and 2021 baseline and monitor surveys were recorded using the DAS system and repeating the sources with an EnviroVibe truck to increase the survey repeatability. The datasets were processed and cross equalized with the same flow and reverse time migration (RTM) images were generated using the same velocity model.

We apply several transformer encoders with different number of layers and heads per layer obtaining satisfactory results with two of them: 2 layers with 4 self attention heads, and 1 layer with 4 self attention heads. Figure 3 shows these results along with the original difference. This figure also shows the Wiener shaped result with filter of 50m.

Regarding the transformer encoder training, the datasets were normalized with respect to the highest value of both datasets. This normalization was undone after training to recover the input amplitude levels. The training algorithm used was the adaptive moment estimation Adam with a learning rate of 0.002 and 200 iterations.

We measured the normalized root mean squared (nrms) error above the reservoir zone to measure quantitatively the performance of each filter. The original difference nrms error is 67%, the Wiener shaped difference nrms error is 54%, and the transformer encoder shaped differences nrms errors were 47% and 46%.

Figure 4 shows the trace at the centre of the rtm image and the shaped results using the transformer encoder with 1 layer and 4 heads.

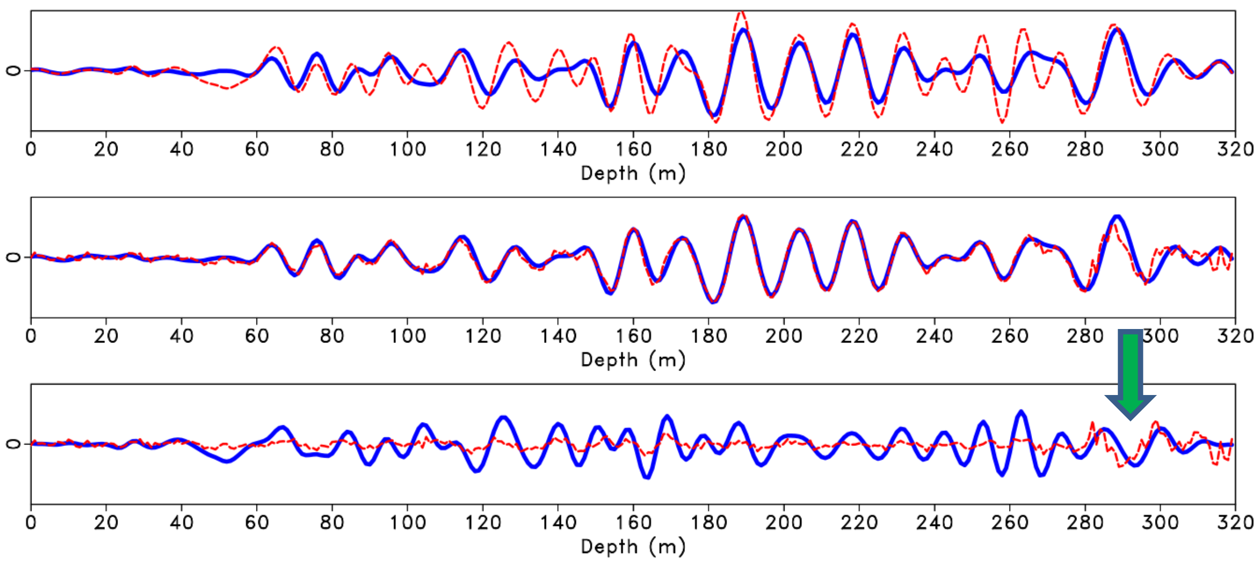

FIG. 4. CaMI 2021-2017 time-lapse difference trace at observation well position. Top: Baseline in blue and monitor in red. Middle: Baseline in blue and shaped monitor in red. Bottom: Original difference in blue and shaped difference in red. The arrow marks the CO_2 anomaly in the difference.

Conclusions

In the field data experiment the transformer encoder performed better than the usual Wiener filtered result with a significant decrease in the nrms error while revealing the CO_2 anomaly. However, some lateral bands that extend along all the RTM image and are not part of the CO_2 anomaly were created by neural networks. A low pass filter can be used to mitigate these bands.

Acknowledgements

The authors thank the CMC-CaMI Joint Industry Project members for their continuous support. The authors also acknowledge financial support from the Canada First Research Excellence Fund through the University of Calgary's Global Research Initiative in Sustainable Low-Carbon Unconventional Resources.

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