An encoder-decoder CNN for DAS-to-geophone transformation

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ABSTRACT

Distributed acoustic sensing is a technology that uses optical fibre to record seismic waves. While traditional geophones record the particle velocity created by a passing wave, optical fibre records the strain or strain rate. The conversion between the two kind of signals allows seismic time lapse imaging applications with data from these two different recording systems. Here we use convolutional neural networks to transform fibre to geophone data. Instead of using a supervised model where we provide examples of corresponding fibre and geophone traces, we utilize an encoder decoder scheme that receives fibre traces and produces fibre traces. The important distinction is that the decoder is deterministic and contains the physics of transforming a geophone trace to a fibre trace while the encoder is the convolutional neural network that does the opposite transformation. The whole encoder-decoder is trained to be the identity operator on fibre traces. At the end of the training, the application of the encoder part alone will perform the desired signal conversion from fibre to geophone.

INTRODUCTION

Time lapse seismic applications try to minimize the changes of undesired aspects like ambient noise, environment differences, near surface effects, recording equipment characteristics, acquisition parameters and processing, in order to truly detect the changes in the seismic observables like times, amplitudes, velocities, frequencies and phases (Jack, 1997).

Distributed Acoustic Sensing (DAS) is a technology that aims to solve the recording equipment part of the time lapse undesired aspects. DAS uses an optical fibre as the recording element instead of the more ubiquitous geophones (Daley et al., 2013; Mateeva et al., 2013; Parker et al., 2014). DAS optical fibre, when installed permanently, can be reused in different acquisitions to maintain the same recording equipment characteristics.

There are many cases in which transforming from fibre to geophone and vice versa is useful. For example, when one of the seismic acquisitions used in the time lapse application was recorded with geophones while the others were recorded with fibre. Another example is when we want to relate the DAS data to the corresponding geophone data. In addition, most of the imaging techniques used to create the images that time lapse seismic compares, like Reverse Time Migration (RTM) (Loewenthal and Mufti, 1983; Baysal et al., 1983) and Full Waveform Inversion (FWI) (Tarantola, 1984; Pratt et al., 1998), were developed for geophone and hydrophone signals instead of DAS.

Daley et al. (2016) proposes a method to transform DAS to geophone by integrating in time the trace and multiplying by the inverse of the local P-wave velocity. Similarly, Bóna et al. (2017) describes a frequency domain technique to perform the same transformation. This technique takes into account the DAS gauge length and the pulse length.

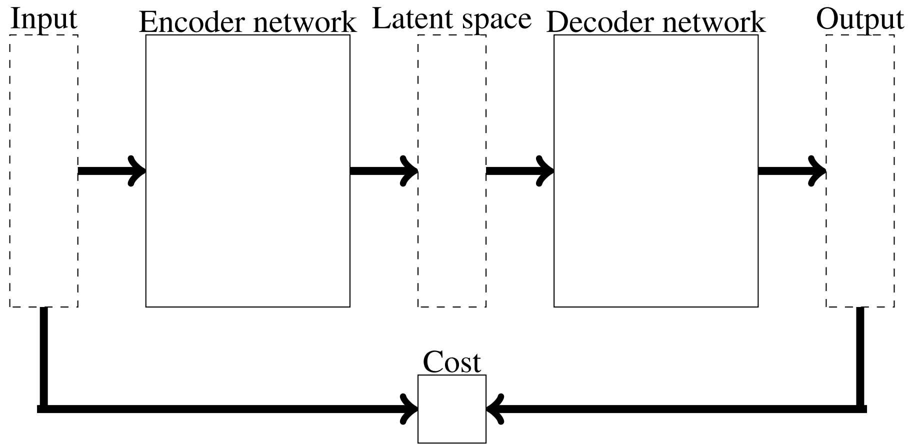

FIG. 1. Basic encoder-decoder network architecture. The network trains by optimizing the difference between input and output. The latent space is configured depending on the application.

In Monsegny et al. (2021) a least squares technique to transform DAS to geophone is presented. In this technique a linear system of equations based on DAS principles (Hartog, 2018) is assembled and solved by the conjugate gradient method. The result is close to the high frequency part of the geophone trace.

Neural networks have been used to solve inversion problems in geophysics (Murat and Rudman, 1992; Roth and Tarantola, 1994; Poulton, 2002). Convolutional neural networks (CNN) (LeCun et al., 1989) are known for solving many computer vision problems. They have several layers and in each of them they convolve small filters with the output of the previous layers. As convolution is a normal procedure in seismic processing, CNN have been used with seismic data (Shi et al., 2018; Xiong et al., 2018).

Encoder-decoders are another kind of neural network that aims to learn a different representation of the input data. Figure 1 shows the architecture of this network. The input is encoded into the latent space and then decoded back into the original space. In many networks the latent space has lower dimension than the original space so the network is compressing its input. Applying alone the encoder and the decoder allows to translate between these two spaces. They have been used, in conjunction with CNN, to invert elastic parameters from seismic traces (Biswas et al., 2019).

In this report we present an encoder-decoder neural network that transforms DAS to geophone. The encoder part is a CNN that is in charge of the DAS to geophone transformation. In contrast, the decoder part is fully deterministic and physics based, and transforms geophone to DAS. In this way we avoid the supervised training. The first section of this report presents the neural network, the second shows some synthetic and real data experiments and the last discusses the properties of the technique.

METHODS

Figure 2 displays the specific architecture of the encoder-decoder neural network. The input and output are DAS traces, and the whole network is trained to be the identity operator, that is, the input DAS trace should be equal to the output DAS one.

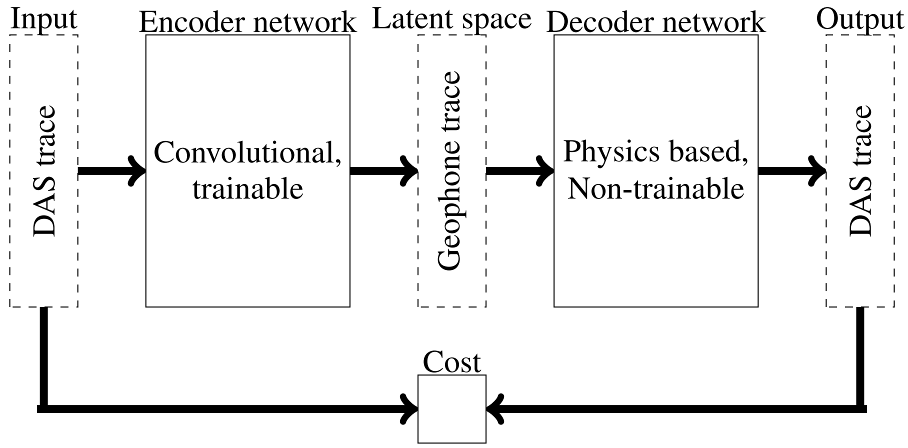

FIG. 2. DAS to geophone encoder-decoder neural network. The input and output is the DAS trace and the whole network acts like an identity operator. The encoder part is a CNN that transforms DAS to geophone, the latent space. The decoder part is non trainable and physics based that transforms geophone to DAS.

The important aspect is to make the latent space be the corresponding geophone trace. For that, the decoder network is physics based and non trainable. This decoder part transforms geophone to DAS based on a physical system described in the next section. In contrast, the encoder network is a CNN fully trainable that must perform the inverse transformation, DAS to geophone, in order to make the whole network to act as an identity operator.

This architecture permits to train the network in an unsupervised way because the physics-based decoder part forces the latent space to be the geophone trace corresponding to the DAS input trace needed during training. After training we apply only the encoder part to perform the DAS to geophone transformation.

Decoder network

Figure 3 shows a portion of optical fibre of gauge length L_G centred at s (Monsegny et al., 2021). The total elongation or contraction of this portion of fibre, $\delta l(s)$, is the difference of the displacements u at both ends:

$$\delta l(s) = u(s + L_G/2) - u(s - L_G/2). \tag{1}$$

Dividing this by the gauge length and taking the time derivative we obtain a expression for the strain rate $\dot{\epsilon}_f$ in terms of the particle velocity v:

$$\dot{\epsilon}_f(s) = \frac{1}{L_G}(v(s + L_G/2) - v(s - L_G/2)), \tag{2}$$

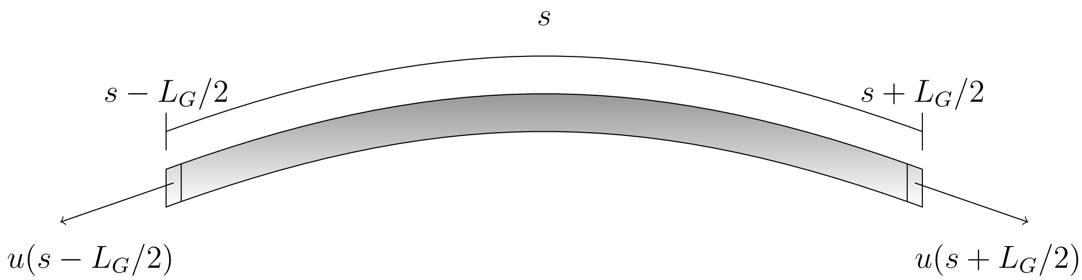

FIG. 3. A portion of optical fibre of gauge length L_G centred at s. The total elongation or contraction of this portion of fibre is the difference of the displacements at their ends (From Monsegny et al. (2021)).

We only consider the case where the fibre is straight: $v = v_z$. After discretizing this system for a series of positions s_i along the fibre we arrive at a linear system:

$$\begin{bmatrix} \dot{\epsilon}_f(s_1) \\ \vdots \\ \dot{\epsilon}_f(s_i) \\ \vdots \\ \dot{\epsilon}_f(s_M) \end{bmatrix} = \frac{1}{L_G} \begin{bmatrix} -1 & 0 & \cdots & 0 & 1 & 0 & \cdots & 0 \\ 0 & -1 & 0 & \cdots & 0 & 1 & \cdots & 0 \\ \vdots & & & \ddots & & & & \vdots \\ 0 & \cdots & 0 & -1 & 0 & \cdots & 0 & 1 \end{bmatrix} \begin{bmatrix} v_z(s_{1-N/2}) \\ \vdots \\ v_z(s_i) \\ \vdots \\ v_z(s_{M+N/2}) \end{bmatrix} \tag{3}$$

This system resembles a discrete derivative along the fibre where the operator is centred at s_i, the points are evaluated a gauge length apart and $\Delta z = L_G$. This linear system transforms vertical particle, geophone, to strain rate, DAS. To relate this decoder network to the encoder one in the next section, we name $\vec{\boldsymbol{g}}$ the vertical particle velocities vector, $\vec{\boldsymbol{d}}$ the strain rates vector, and P the matrix.

The decoder part of the encoder-decoder network applies this linear operator in a deterministic non trainable way. As mentioned before, due that the whole network must be an identity operator, this forces the encoder part to be the inverse of this linear operator, that is, to transform strain rate, DAS, to particle velocity, geophone.

Encoder network

The encoder network is a fully trainable CNN that, as mentioned before, must be the inverse of the physics guided untrainable decoder network. Its input is a DAS trace and its output, in the latent space, is a geophone one.

The encoder has two 1D convolutional layers. The first one is composed of M filters $F_1^T = (F_1^1, \ldots, F_1^M)^T$ applied to the input DAS trace $\vec{\boldsymbol{d}}$ (ignoring the activation functions):

$$\vec{\boldsymbol{d}} \xmapsto{F_1} \begin{bmatrix} F_1^1 \\ F_1^2 \\ \vdots \\ F_1^M \end{bmatrix} \vec{\boldsymbol{d}} = \begin{bmatrix} \vec{\boldsymbol{r}}^1 \\ \vec{\boldsymbol{r}}^2 \\ \vdots \\ \vec{\boldsymbol{r}}^M \end{bmatrix} \tag{4}$$

and producing M filtered traces $(\vec{\boldsymbol{r}}^1, \ldots, \vec{\boldsymbol{r}}^M)^T$. The second layer is a combining filter $F_2 = (F_2^1, \ldots, F_2^M)$ that joins all the filtered traces:

$$\begin{bmatrix} \vec{\boldsymbol{r}}^1 \\ \vec{\boldsymbol{r}}^2 \\ \vdots \\ \vec{\boldsymbol{r}}^M \end{bmatrix} \xmapsto{F_2} \begin{bmatrix} F_2^1 & F_2^2 & \cdots & F_2^M \end{bmatrix} \begin{bmatrix} \vec{\boldsymbol{r}}^1 \\ \vec{\boldsymbol{r}}^2 \\ \vdots \\ \vec{\boldsymbol{r}}^M \end{bmatrix} = \vec{\boldsymbol{g}} \tag{5}$$

and produces the geophone trace $\vec{\boldsymbol{g}}$.

Both 1D convolutional layers use the Hyperbolic Tangent activation function. Here we depart from using the Rectified Linear activation function (ReLU) because the layers must produce traces with negative and positive values and ReLU only outputs positive ones. We also tested other activation functions and obtained similar results. In addition we did not use a bias vector and the function initializer was the Xavier normal initializer (Glorot and Bengio, 2010).

Complete network

The complete network is a combination of the encoder and decoder ones. Using the notation introduced before, and ignoring the activation functions in the encoder layers, this network is:

$$\vec{\boldsymbol{d}} \xmapsto{F_1} \begin{bmatrix} F_1^1 \\ F_1^2 \\ \vdots \\ F_1^M \end{bmatrix} \vec{\boldsymbol{d}} = \begin{bmatrix} \vec{\boldsymbol{r}}^1 \\ \vec{\boldsymbol{r}}^2 \\ \vdots \\ \vec{\boldsymbol{r}}^M \end{bmatrix} \xmapsto{F_2} \begin{bmatrix} F_2^1 & F_2^2 & \cdots & F_2^M \end{bmatrix} \begin{bmatrix} \vec{\boldsymbol{r}}^1 \\ \vec{\boldsymbol{r}}^2 \\ \vdots \\ \vec{\boldsymbol{r}}^M \end{bmatrix} = \vec{\boldsymbol{g}} \xmapsto{P} P\vec{\boldsymbol{g}} = \vec{\boldsymbol{d}}^* \tag{6}$$

The operator P is physics based and deterministic. On the other hand, the filters F_1^i and F_2 are to be selected by the neural network training algorithm such that input the DAS trace $\vec{\boldsymbol{d}}$ is as close as possible to the output DAS trace $\vec{\boldsymbol{d}}^*$.

After training, the encoder network is an approximation of the inverse of the decoder operator. We apply this encoder network alone to transform DAS traces to geophone ones.

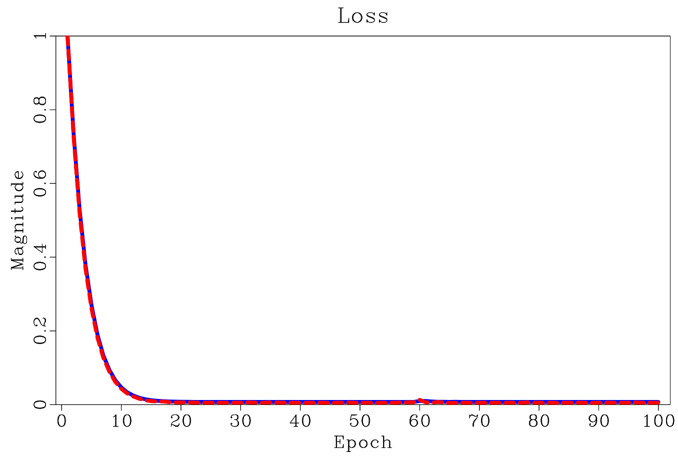

FIG. 4. Encode-decoder CNN network training loss (continuous line) and validation loss (dashed line) functions. The loss function is mean squared error.

FIELD EXPERIMENTS

We tested the neural network with DAS data from the Containment and Monitoring Field Research Station (CaMI-FRS) at Brooks, Alberta, Canada. In this research facility 5Km of optical fibre are permanently installed and used for DAS experiments. Part of this fibre is inside two 300m observation wells. The data we used is from a straight segment of fibre inside one of these wells.

We selected 17 shot gathers from a walkaway vertical seismic experiment (VSP) made in July 2017. The source were an IVI Envirovibe with a linear sweep between 10Hz and 150Hz. The separation between shot points were 20m. The DAS recorded traces every 25cm with a 10m gauge length. All the traces were normalized.

We tested different number of filters in the first CNN layer of the encoder network (M in the previous section). The smallest one with good performance was $M = 20$. We made the length of each convolutional filter an integral multiple of the gauge length, $L_G = 10$m. The smallest number that gave good results was $2L_G$.

For the neural network training we used 100 iterations, a learning rate of 0.001 and a batch size of 32 traces. The training was performed with 10% of the traces, sampled regularly, using the Adam optimizer. The validation split inside the neural network training was 0.5. We also used kernel regularization to maintain the filters coefficients small. The regularization coefficients were 0.001 for the first convolutional layer and 0.1 for the second. Figure 4 shows the training loss and validation loss functions. For both we used the mean squared error.

Figure 5 displays two sets of shot gathers. The top row is from a source located 200m from the well. The bottom row is from a gather 10m from the well. On the left column are the input DAS gathers and on the right are the DAS gathers predicted by the neural network. Remember that the neural network was trained with the objective to make these two columns as similar as possible. The central column is the geophone trace predicted

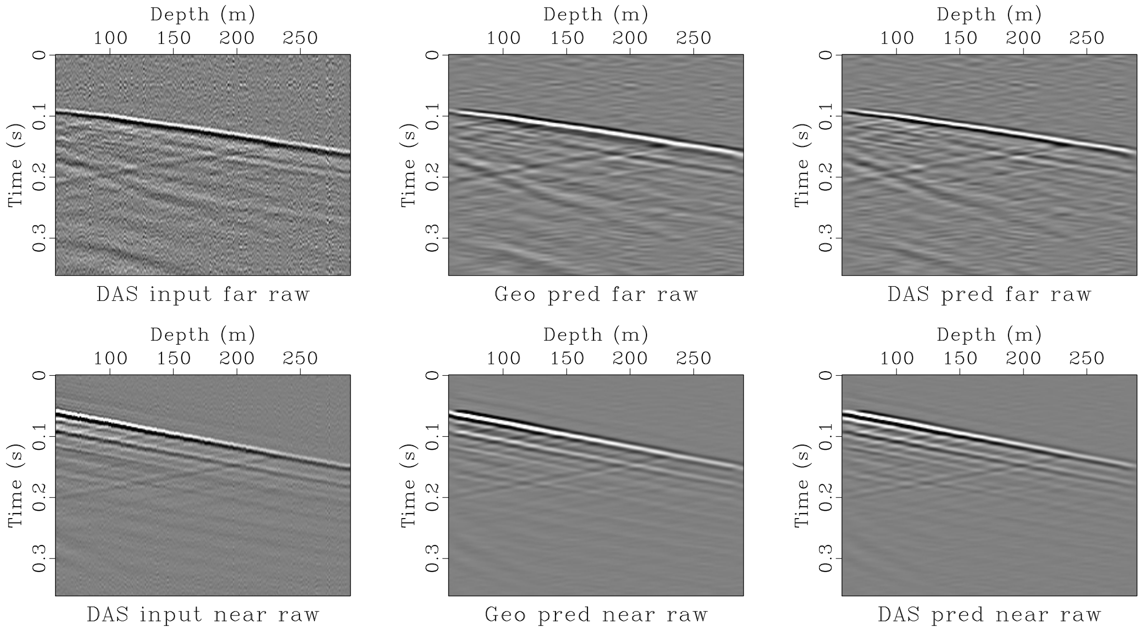

FIG. 5. Far, above, and near, below, gathers. Left column are the input DAS gathers, the middle column contains the predicted geophone gathers (in the latent space), and the right column are the predicted DAS gathers.

by the encoder part of the neural network alone. These gather are in the encoder-decoder latent space.

Figure 6 shows two sets of traces from the far and near gathers presented in Figure 5. The continuous thick black line is the input DAS trace and the continuous thin red line is the predicted output DAS trace. As mentioned before, the neural network was trained to make these two traces as equal as possible. The dashed blue line is the geophone trace predicted by the encoder alone.

DISCUSSION

The physics of the encoder layer is based on the DAS description of Hartog (2018). DAS proprietary systems can deviate from this description and as a result the neural network as it is proposed can predict inaccurate geophone traces.

The training loss function presented in Figure 4 shows a minimum error close to the 0% for the training and the validation datasets. This error is driven by the kernel regularization that keeps the convolutional filters small.

The gathers in Figure 5 show an apparent good agreement between input and output gathers. The predicted geophone gathers is noisier in the far gather. Here the encoder is predicting more anomalous values than in the near offset gather.

The traces displayed in Figure 6 show that the encoder-decoder neural network does a

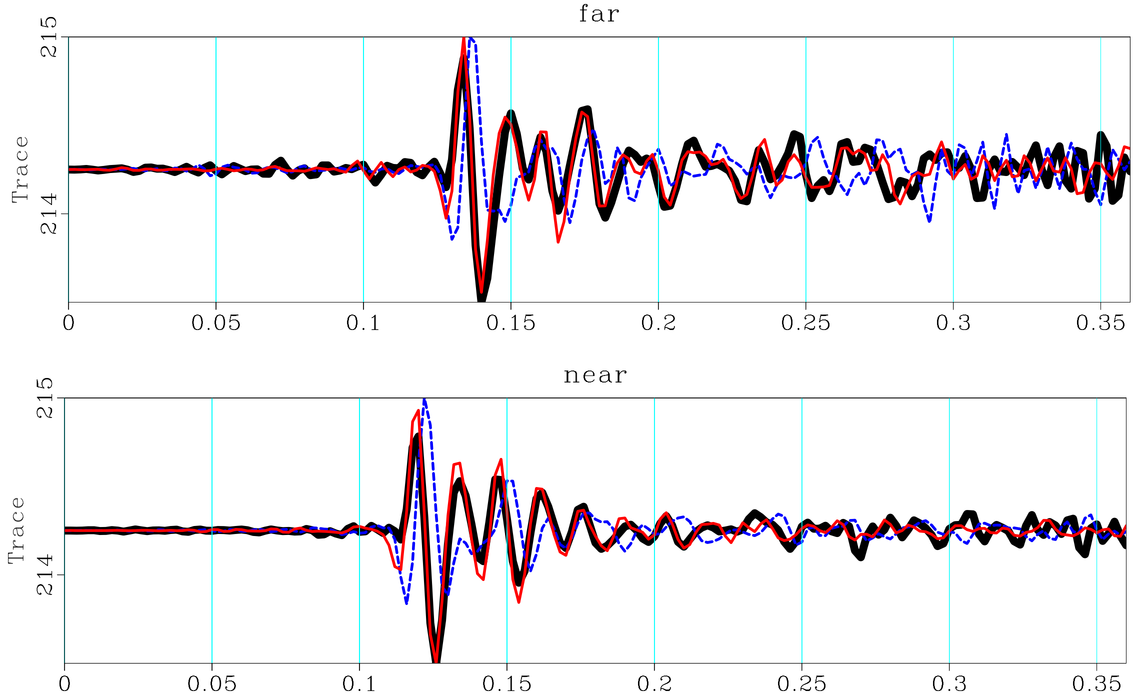

FIG. 6. Trace comparison from the original and inverted gathers of Figure 5. Above is from the far gathers and below from the near ones. Continuous thick black line is the original DAS trace, continuous thin red one is the predicted DAS trace. Dashed blue line is the predicted geophone trace in the latent space.

good job as the identity operator. The far offset trace contains more noise before the first arrivals but the neural network is not reproducing that noise due to the regularization. On the other hand, the predicted geophone trace shows a similar phase shift in both traces. However it predicts high amplitude noise in the far trace. This can be explained because the decoder is applying the DAS physical model to the noise and this is the best prediction of the encoder.

CONCLUSIONS

The DAS-to-geophone encoder decoder CNN is an example of a physics-based unsupervised neural network. The system was guided by physical principles, part of the network were in charge of inverting the physical process and we did not have to supply examples of input and output traces.

More work is needed to examine the results of the DAS-to-geophone encoder-decoder CNN with the field data. Some results in the quality of the imaging with this transformed data would be useful.

The physics part of the neural network in the decoder can be improved and the encoder will adjust itself with the neural network training. This kind of network can also be used for other purposes by making the decoder part physics based.

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