Machine Learning workflows to create pseudo-3D from 2D seismic

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Introduction

Here, we describe two Machine Learning workflows to create pseudo-3D cubes from 2D seismic grids. Pseudo-3D cubes are interesting because they enable the application of 3D seismic interpretation workflows and 3D visualization techniques to 2D seismic datasets. This work is a continuation of the Machine Learning seismic interpolation work reported by de Groot and van Hout [2021]. Our model is a 3D U-Net, a Convolutional type of Neural Network that is known as an auto-encoder [Ronneberger et.al., 2015]. It consists of a decoder part and an encoder part. The encoder decomposes the input image sequentially into smaller-size features. The decoder recombines the features sequentially into larger-size components until the target image emerges.

Data and Methodology

The seismic dataset in our experiments is called Penobscot, a free data set from offshore Nova Scotia that is downloadable from the TerraNubis cloud portal. Penobscot has both 2D and 3D seismic data but the 2D grid is too course for our purposes. Instead, we emulate a 2D seismic grid by blanking most of the 3D volume. We only pass a few in-lines and cross-lines while we blank all traces in between. The input volume with blanked traces has a bin-size of 25 x 25 m and a linespacing of 1250 x 1250 m. (Fig 1a).

To infill the missing data, we experiment with two different workflows: a direct approach and an approach that requires flattening and unflattening. In both experiments, we extract examples from a restricted training area. We apply the trained models to the entire survey. Areas not used for training thus serve as blind test areas (Fig. 1a).

In the direct experiment, we extract 9,328 cubelets of 128x128x128 samples each from the volume with blanked traces and from the corresponding original volume with complete data (Fig. 1b). Each cubelet is overlapping 90% with its neighbors in the inline, crossline and Z directions. Our 3D U-Net is a Keras model with an input shape of 128x128x128 samples that we train for 20 epochs. We use ‘mse’ as loss function, ‘mae’ as metric and ‘Adam’ as optimizer. The result is shown in Fig. 1c.

In the second experiment, we flatten both the input volume and the target volume before extracting examples. The flattening (Wheeler transformation) is done with a model-driven HorizonCube that we construct from 6 interpreted horizons. In the flattened domain the Z-axis is an index from 0 to 886 representing Relative Geologic Time. We test 3D U-Nets with input shapes 128x128x128 and 64x64x128 samples (Fig. 1a) that we train for 20 epochs on 11,440 examples. We use the same loss function, ‘metric and optimizer as before. The result after unflattening of the 64x64x128 model is shown in Fig. 1d. The output of the smaller Unet is smoother than the output of the larger model but the continuation of the main reflectors is better. Both models introduce a bias in the output amplitudes that is removed with a simple DC-removal scaling function.

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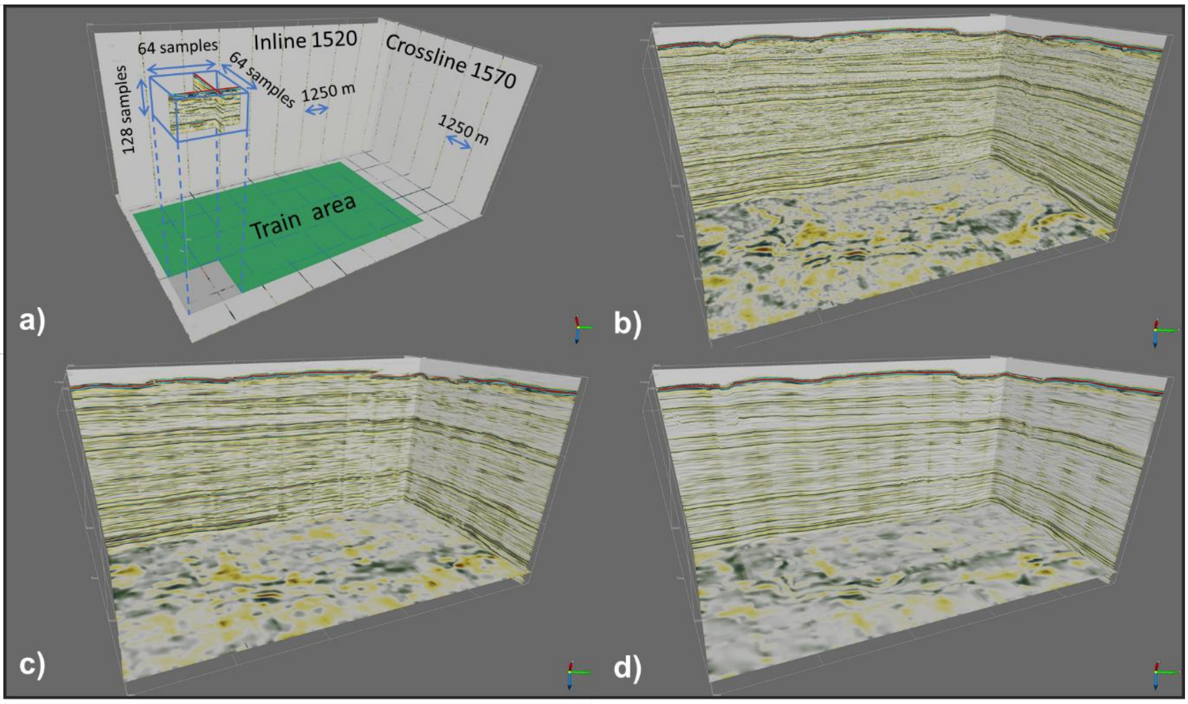

Figure 1 *a) Input data has real seismic data on in-lines and cross-lines 1250 m apart and zeros in between; training area is shown in green; example of one input cubelet of 64x64x128 samples from the flattening / unflattening experiment. b) Target data on blind test in-line 1520, blind test cross-line 1570 and z-slice 2800 ms. c) Result of the direct experiment. d) Result of the flattening / unflattening experiment.*

Conclusions

We have shown that a 3D U-Net can be trained to create pseudo-3D volumes from sparse input grids. Both interpolation results are encouraging. The direct result is a fast approach that does not require any interpretation inputs. However, the interpolated reflection patterns are less continuous than those obtained with the flattening / unflattening approach.

We expect the application of either trained model to a real 2D seismic dataset with similar grid dimensions and similar seismic character to produce a useful pseudo-3D cube. This last step in the workflow was not done because the available 2D seismic coverage in this project is too sparse.

References

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Ronneberger, O., Fischer, P. and Brox, T. [2015]. U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention (MICCAI), Springer, LNCS, Vol.9351: 234--241, 2015.