Direct estimation of local wavefront attributes using deep learning

Kirill Gadylshin, Institute of Petroleum Geology and Geophysics SB RAS, Novosibirsk State University;*
Ilya Silvestrov and Andrey Bakulin, EXPEC Advanced Research Center, Saudi Aramco

Summary

Wavefront attributes, such as local dips and curvatures of seismic events, are used in different seismic data processing methods, from prestack data enhancement to migration to tomography. The attributes' estimation for prestack data is a time-consuming and computationally expensive process. We propose a new approach based on U-Net convolutional neural network that directly map prestack seismic data to the local wavefront attributes. Using a 3D real data example, we demonstrate that this deep-learning-based approach can reduce the computational time by two orders of magnitude compared to a classical coherency-based optimization technique while preserving a reasonable quality of results.

Introduction

Kinematic wavefront attributes form the basis of many seismic data processing methods. Notably, they are used in stacking (Mann et al., 1999), reflection and diffraction imaging (Fomel, 2007; Berkovitch et al., 2009), tomography (Lambaré, 2008), data interpolation (Hoecht et al., 2009), and data enhancement (Baykulov and Gajewski, 2009; Buzlukov et al., 2013, Bakulin et al., 2018b). Different algorithms exist to estimate the wavefront attributes, including radon transform techniques, plane-wave destruction filters, and structure tensor approaches. When the data quality is low, such as in land seismic applications, the classical coherency-based search that uses semblance as a target function for optimization often shows the most robust results. Recent examples of applying such a kinematic-based approach for land prestack data enhancement can be found in Bakulin et al. (2020). For modern high-density seismic volumes, where the data size can reach hundreds and thousands of terabytes, the biggest challenge becomes a lengthy computational time required to estimate the attributes. In this work, we present a deep-learning-based approach to speed up the calculations tremendously.

Theory and Method

Our work's main idea consists of detecting the local geometrical attributes of the wavefront directly from the 3D prestack seismic data using a deep learning approach. Usually, wavefront attributes are computed on a dense regular spatial and temporal grid. The conventional estimation approaches are based on the semblance optimization procedure. In other words, at each point of the dense 3D X-Y-T grid, one needs to solve an optimization problem, which is very time-consuming. We propose using the specially trained deep neural network (DNN) to overcome this situation. This DNN directly links the prestack seismic data with estimated attributes on a regular grid.

Preprocessing

The irregular acquisition geometry is a common situation in seismic processing. It is preferable to use a regular input in deep learning, especially if we speak about estimated local wavefront attributes on a regular grid (the output of the DNN). Therefore, the substantial step in our workflow is a regularization, which makes the input seismic data grid consistent with the regular output attributes grid. To do so in an efficient way, we choose a regular grid and collect the signal to this grid using super-grouping within a small grouping aperture (Bakulin et al., 2018a). In this way, we solve two problems at once:

- We enhance the signal-to-noise ratio (SNR) of the data and simplify the problem of attributes detection; and
- we provide the regular seismic input data to be processed by a DNN.

The example of this preprocessing step is presented in Figure 1. On the left (Fig.1a), we plot a single inline section of the 3D common-receiver OBN data using wiggles. As one may observe, the original acquisition is irregular. It has a different trace density with respect to a shot X-coordinate. After supergrouping, we enhanced the SNR and obtained the inline section on a regular grid with a constant X-coordinate density (see Fig. 1b).

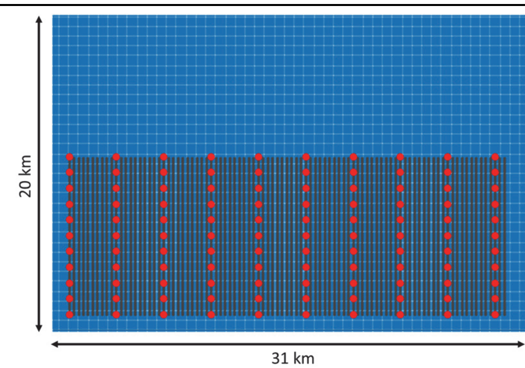

Figure 2. The acquisition geometry of the marine OBN dataset. Receiver positions are shown in black, and shots are in blue. Red points indicate common-receiver gathers used for generating the training dataset.

Local Wavefront Attributes DNN

Convolutional Neural Networks (CNN) are usually applied to analyze visual imagery. A particular case of CNN is a U-Net (Ronneberg et al., 2015), which was initially introduced for biomedical image segmentation. Nowadays, the U-Net and its modifications have broad applications in prestack seismic data processing, seismic inversion, and interpretation. In this work, we suggest to use Local Wavefront Attribute DNN (LWA DNN) to link the prestack seismic data with wavefront attributes. The architecture of the network is similar to the one used by Gadylshin et al. (2020). The only difference is using a conventional convolutional layer instead of partial convolutions. The input and output of LWA DNN are 512x512 RGB images. Its structure makes every output image point to contain all information from the input image. For simplicity, we limit our investigation to the estimation of the dip attribute only. To do so, we convert the preprocessed data and the corresponding dip attribute to grayscale RGB images, where each color component has the same value.

Real data example: signal enhancement via nonlinear beamforming

One application of the local wavefront attributes is the signal enhancement method. In this example, we train LWA DNN on a modern marine Ocean Bottom Node (OBN) dataset. We then use the AI-estimated dips in the nonlinear beamforming (NLBF) method (Bakulin et al. 2020).

The OBN dataset was acquired with a 50×50 m shot grid. Receivers have 100 m inline spacing and 300 m crossline interval. The OBN survey size is 20×31 km consisting of 95 receiver lines (Figure 2). The overall dataset contains 11,027 common-receiver gathers with a full prestack volume size of around 15 TB. For our performance test, we used the Shaheen II Cray XC40 HPC cluster from KAUST (https://www.hpc.kaust.edu.sa/content/shaheen-ii). Each CPU node of Shaheen-II is a dual-socket compute node based on 16 core Intel Haswell processors. The conventional estimation of dips based on brute-force semblance optimization took about 2500s on a single CPU node per one seismic gather. Using the 300 Shaheen-II CPU nodes, dip estimation on the entire dataset requires 25 hours. In general, signal enhancement can be applied many times at different processing steps (Bakulin et al., 2019). For example, during the early stages, one applies NLBF to achieve reliable first-break picking for tomography. Later processing stages may use NLBF to enhance refracted/reflected events for FWI (Kim et al., 2019) or imaging. Therefore, dips estimation for the whole OBN dataset requires millions of core-hours and may quickly become a computational bottleneck for large dataset. To overcome this problem, we suggest using the processing workflow based on the LWA DNN.

We presented a schematical workflow in Figure 3. The first step is performing the conventional dip estimation on 1% of prestask data (Figure 2 shows the selected common-receivers positions in red) with the subsequent conversion of estimated dips to grayscale images. The second step finalizes the creation of the representative training dataset by additionally performing regularization of the prestack data as described above. The example of the training sample is presented in Figure 4. The next step is LWA DNN training and verification. In the given OBN numerical example, we achieved ~50,000 training samples (pairs of the seismic data and the corresponding dip attributes on a 512x512 grid). We randomly split this dataset in a proportion of 80/20. We used 80% of the images directly for the DNN weights update, whereas the remaining 20% were exploited to control the generalization error (validation loss). Once the loss function on the validation subset started to grow, we interrupted the training and used the DNN weights obtained after the 20th epoch (Figure 5).

Run conventional dip estimation on 1% data and convert estimated dips to grayscale images

↓

Preprocessing of 1% of the data (regularization via supergrouping) and converting corresponding data to grayscale images

↓

Train LWA DNN on 1% of the data

↓

Predict the remaining 99% of the dips and convert them back from grayscale images to physical values

Figure 3. Flowchart of a proposed DNN-based workflow.

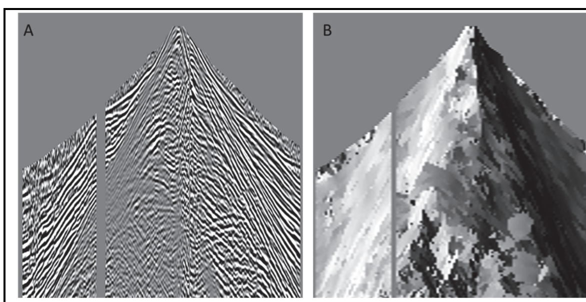

Figure 4: Random sample from the training dataset. After preprocessing, the input seismic data converted to a 512x512 grayscale image (A). The corresponding dip estimated using conventional semblance-based optimization and converted to an image (B).

The training was performed on the Ibex HPC cluster from KAUST (https://www.hpc.kaust.edu.sa/ibex) using a single GPU-node with four Nvidia Tesla P100 and took about 1,900s. We calculated the error between the dip calculated by the semblance-based optimization and by the LWA DNN method using the Frobenius norm. We found that the average accuracy of the reconstructed dips for entire OBN survey is about 78%. The example of DNN prediction is shown in Figure 6 and shows a reasonable match with the standard method. The attributes estimation is an intermediate step in signal enhancement. Therefore, it is desirable to evaluate how the predicted dips affect data after beamforming. To achieve this, we compare the original data before enhancement (Figure 7a) and two NLBF scenarios: standard (Figure 7b) and AI-assisted (Figure 7c). The difference between the two enhancement scenarios is imperceptible (Fig. 7d). It demonstrates that LWA DNN can effectively predict the wavefront attributes bypassing the expensive semblance-based conventional estimation approach.

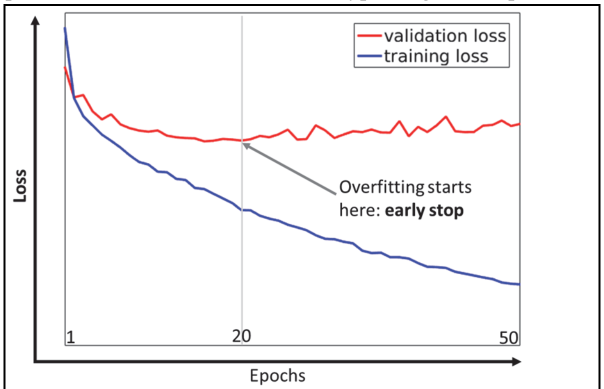

Figure 5: The training (red) and validation (blue) losses, plotted as a function of the epoch number. The arrow indicates when the early stop regularization should be applied (the generalization error starts to grow).

The LWA DNN prediction time for one common-receiver gather took about 3s instead of the 2500s using the conventional approach. Combining the training time with the prediction time of 99% of the data, one may conclude that in the end, we speed up the traditional attributes estimation by two orders of magnitude. It is worth mentioning that 99% of the data were processed on a single GPU-node, while initially, to process 15Tb of the prestack data, one has to use hundreds of CPU-nodes. With LWA DNN approach, the main bottleneck in attribute estimation becomes the I/O operations: reading seismic data, converting vast amounts of data to images, and storing them on the disk, flowing through the LWA DNN, back conversion to the physical values, and storing predicted attributes to the disk.

Discussion and conclusions

We present the workflow for automatic estimation of wavefront attributes utilizing a specially trained convolutional neural network, namely LWA DNN. This workflow is adaptive to a particular 3D prestack seismic dataset. It requires creating the training dataset consisting of only around 1% of the data. We propose using data regularization step based on supergrouping to provide DNN input on a regular grid, consistent with the regular output grids for attributes to be estimated. Preconditioning seismic data improves SNR and simplifies attribute detection making a coherent signal more "visible" to the DNN. We demonstrate a significant speed-up of the proposed workflow (two orders of magnitude) compared to the conventionally used estimation scheme based on optimization.

While we presented the numerical example comprising the dip estimation only, the other wavefront attributes, such as local curvatures, can be estimated using the same workflow. Thus one can replace the time-consuming semblance-based estimation part in signal enhancement and other algorithms with LWA DNN.

Acknowledgments

One of the authors (Kirill Gadylshin) was partially supported by RFBR and GACR, project number 20-55-26003, and by the grant from the President of the Russian Federation for young scientists – MK-3947.2021.1.5.

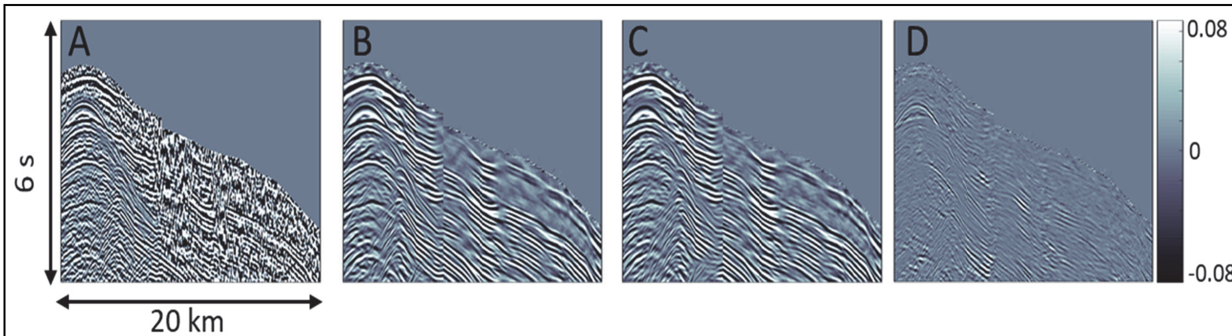

Figure 7: Evaluating the enhanced data: input data (a), conventional NLBF (b), AI-assisted NLBF (c), and the difference between two versions of NLBF data (d).

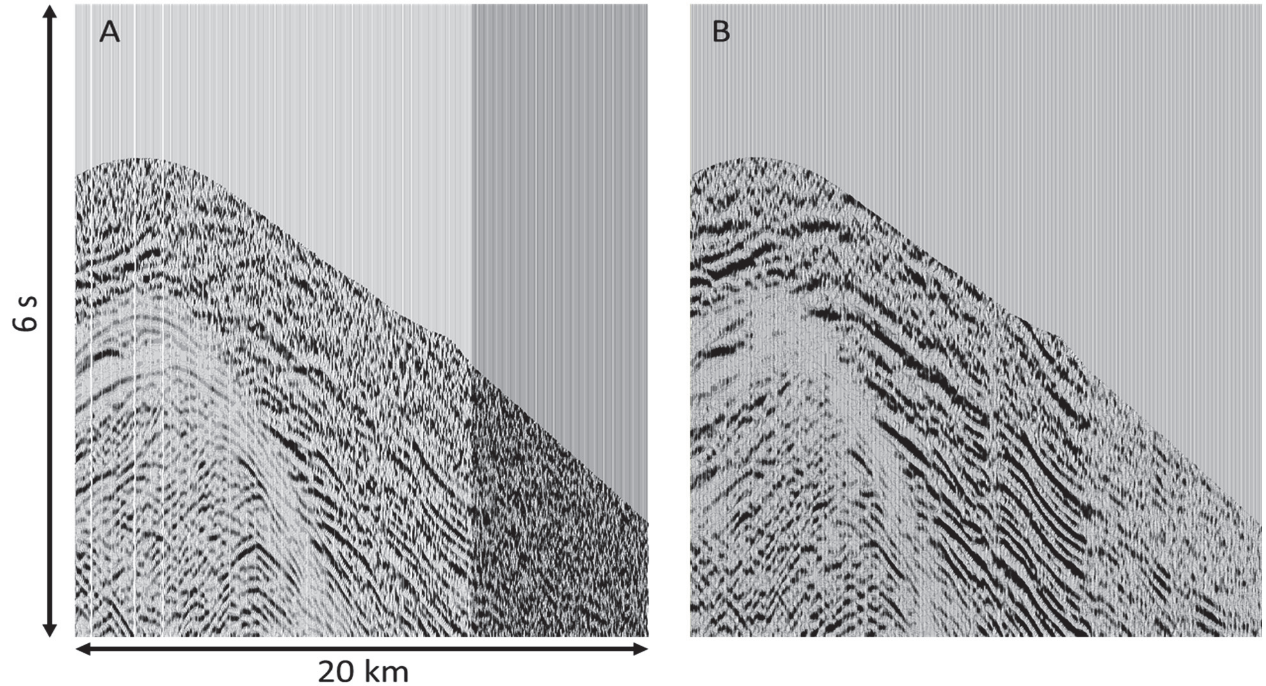

Figure 1: The 3D prestack seismic data using wiggle display before processing (A) and after regularization via supergrouping (B).

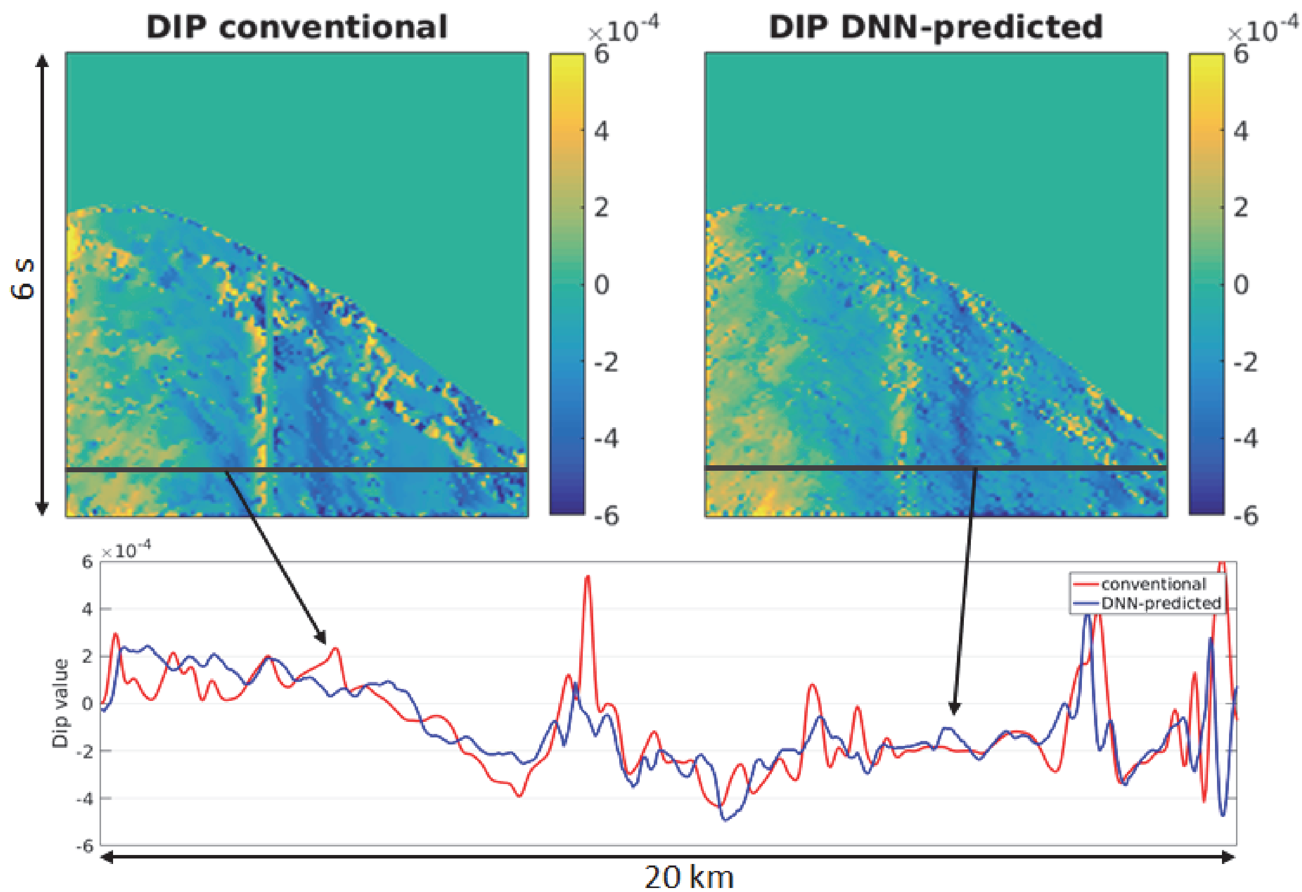

Figure 6: Example of dip prediction by LWA DNN. The conventionally estimated dips are shown on the left, whereas the DNN-predicted dips are on the right. On the bottom, we present the horizontal profile of conventional dip and DNN-predicted values.

REFERENCES

Bakulin, A., I. Silvestrov, and M. Dmitriev, 2019, Adaptive multiscale processing of challenging 3D seismic data for first-break picking, FWI and imaging: 89th Annual International Meeting, SEG, Expanded Abstracts, 3979–3984, doi: https://doi.org/10.1190/segam2019-3214616.1.

Bakulin, A., I. Silvestrov, M. Dmitriev, D. Neklyudov, M. Protasov, K. Gadylshin, V. Tcheverda, and V. Dolgov, 2018b, Nonlinear beamforming for enhancing pre-stack data with challenging near surface or overburden: First Break, **36**, 121–126, doi: https://doi.org/10.3997/1365-2397.n0143.

Bakulin, A., I. Silvestrov, M. Dmitriev, D. Neklyudov, M. Protasov, K. Gadylshin, and V. Dolgov, 2020, Nonlinear beamforming for enhancement of 3D prestack land seismic data: Geophysics, **85**, no. 3, V283–Z13, doi: https://doi.org/10.1190/geo2019-0341.1.

Bakulin, A., P. Golikov, M. Dmitriev, D. Neklyudov, P. Leger, and V. Dolgov, 2018a, Application of supergrouping to enhance 3D prestack seismic data from a desert environment: The Leading Edge, **37**, 200–207, doi: https://doi.org/10.1190/tle37030200.1.

Baykulov, M., and D. Gajewski, 2009, Prestack seismic data enhancement with partial common-reflection-surface (CRS) stack: Geophysics, **74**, no. 3, V49–V58, doi: https://doi.org/10.1190/1.3106182.

Berkovitch, A., I. Belfer, Y. Hassin, and E. Landa, 2009, Diffraction imaging by multifocusing: Geophysics, **74**, no. 6, WCA75–WCA81, doi: https://doi.org/10.1190/1.3198210.

Buzlukov, V., and E. Landa, 2013, Imaging improvement by prestack signal enhancement: Geophysical Prospecting, **61**, 1150–1158, doi: https://doi.org/10.1111/1365-2478.12047.

Fomel, S., 2007, Velocity-independent time-domain seismic imaging using local event slopes: Geophysics, **72**, no. 3, S139–S147, https://doi.org/doi:10.1190/1.2714047.

Gadylshin, K., I. Silvestrov, and A. Bakulin, 2020, Inpainting of local wavefront attributes using artificial intelligence for enhancement of massive 3-D prestack seismic data: Geophysical Journal International, **223**, 1888–1898, doi: https://doi.org/10.1093/gji/ggaa422.

Hoecht, G., P. Ricarte, S. Bergler, and E. Landa, 2009, Operator-oriented interpolation: Geophysical Prospecting, **57**, 957–979, doi: https://doi.org/10.1111/j.1365-2478.2009.00789.x.

Kim, Y. S., T. Fei, M. Dmitriev, and Y. Luo, 2019, An offshore full waveform inversion with automatic salt flooding: OBN case study: 81st Annual International Conference and Exhibition, EAGE, 1–5, doi: https://doi.org/10.3997/2214-4609.201901232.

Lambaré, G., 2008, Stereotomography: Geophysics, **73**, no. 5, VE25–VE34, doi: https://doi.org/10.1190/1.2952039.

Mann, J., R. Jäger, T. Müller, G. Höcht, and P. Hubral, 1999, Common reflection-surface stack: A real data example: Journal of Applied Geophysics, **42**, 301–318, doi: https://doi.org/doi: 10.1016/S0926-9851(99)00042-7.

Ronneberger, O., P. Fischer, and T. Brox, U-Net: Convolutional networks for biomedical image segmentation, *in* N. Navab, J. Hornegger, W. Wells, and A. Frangi, eds., Medical Image Computing and Computer-Assisted Intervention (MICCAI), Lecture Notes in Computer Science, **9351**, Springer.