EAGE ANNUAL 2021
82ND CONFERENCE & EXHIBITION
AMSTERDAM | THE NETHERLANDS

MOVING TOWARD DIRECT DNN-BASED ENHANCEMENT OF 3D PRE-STACK SEISMIC DATA

K. Gadylshin[1], A. Bakulin[2], I. Silvestrov[2]

[1] Institute of Petroleum Geology & Geophysics SB RAS; [2] Saudi Aramco, EXPEC Advanced Research Center

Summary

Pre-stack data enhancement with multidimensional stacking is indispensable part of modern data processing that very compute-intensive since multiple wavefront attributes need to be estimated on dense spatial/temporal grid. At the core of this demand are conventional local or global optimization techniques. We propose two alternative approaches based of artificial intelligence that can greatly reduce computational effort of estimation stage. First approach performs traditional computations on sparser grid and inpaints to dense grid using deep neural network (DNN) with partial convolution layers. Second approach is direct DNN-based attributes estimation from the pre-stack seismic data itself. Both methods incorporate multiparameter attributes by encoding them into RGB-images. On synthetic and real 3D data examples, we demonstrate, that application of these methods for seismic data enhancement using nonlinear beamforming can greatly speed up the computational time while maintaining similar quality of output data.

Introduction

Modern high-density seismic volumes can reach hundreds and thousands of terabytes in size. Reduced signal-to-noise ratio (SNR) of single-sensor seismic data requires new algorithms and approaches for its efficient processing and interpretation. Many novel approaches dealing with pre-stack data requires estimation of multiple attributes for each particular point in the data cube, and their efficient calculation and usage is of great importance. Examples of such techniques are multi-dimensional data-driven local stacking and data enhancement methods such as partial common-reflection surfaces stack (Baykulov et al., 2009), nonhyperbolic multi-focusing (Berkovitch et al. 2011) and nonlinear beamforming (Bakulin et al., 2018). Most compute-intensive part is estimation of multiple local wavefront attributes (dips and curvatures) that is performed on a regular dense spatial/temporal grid. Finding efficient solution for estimation scheme is of huge practical importance.

Recently, deep learning approaches succeeded at image processing tasks such as object recognition, de-noising, super-resolution (Halpert, 2018) and image inpainting (Liu et al., 2018). The latter will be explored here in the context of fast estimation of pre-stack seismic attributes required for enhancement.

Inpainting is the process of reconstructing lost or deteriorated parts of images and videos. It is also known as image interpolation with advanced algorithms to replace corrupted or missing parts of the image data. Existing approaches could be split into three main categories: structural inpainting, textural inpainting and combination of the two previous techniques. All these methods use information of the known or undestroyed image areas in order to fill the gaps. In commonly used open computer vision library OpenCV, two different algorithms were implemented. First one is based on fast marching method (Telea, 2004). Algorithm starts from the boundaries and goes inside region of interest, gradually filling the interior. Second approach is based on fluid dynamics and utilizes partial differential equations (Bertalmio et al., 2001). Recently, deep learning approaches led to significant advances in inpainting. A majority of these methods focus on inpainting inside rectangular regions located around the center of the image relying on expensive post-processing. Deep neural networks (DNNs) employ convolutional filter on images, replacing the removed content with a fixed value and as a result suffer from dependence on the initial values used to infill. To properly handle irregular masks, Liu et al. (2018) proposed using Partial Convolutional Layer, comprising of a masked and re-normalized convolutional operation followed by a mask-update step.

Method and Theory

Nonlinear beamforming

Nonlinear time-delay beamforming (NLBF) comprises of local summation of nearby traces after application of time shifts and formally can be written as follows:

$$u(x_0,y_0,t_0) = \sum_{\mathbf{x}\in B_0} w(x,y)u\big(x,y,t_0 + \Delta t(x,y;x_0,y_0)\big), \qquad (1)$$

where $u(x,y;t)$ represents a trace with coordinates x and y (Bakulin et al., 2018). The coordinates of the output trace after beamforming are given by x_0, y_0. The summation is performed over a local region B_0 (defined by summation aperture) around the output trace along a traveltime surface with some moveout $\Delta t(x,y;x_0,y_0)$. In NLBF we make an assumption that this moveout can be locally approximated by a second-order surface:

$$\Delta t = t(x,y) - t_0(x_0,y_0) = A\Delta x + B\Delta y + C\Delta x\Delta y + D\Delta x^2 + E\Delta y^2, \quad (2)$$

where A, B, C, D, E are unknown wavefront attributes that also serve as a beamforming coefficients; Δx and Δy represent spatial shifts of the summed trace with respect to the output trace. The unknown coefficients A, B (first wavefront derivatives, or dips) and C, D, E (second derivatives, or curvatures) are estimated by scanning many different beamforming trajectories and finding one with best coherency defined by the maximum value of a specified semblance function S.

Workflow 1: inpainting of local wavefront attributes inside intentionally omitted (masked) areas

The main idea of this workflow is to limit conventional and computationally-demanding estimation of wavefront attributes to a smaller subset of the data and then reconstruct or inpaint remaining attributes using a deep neural network with partial convolutional layers (Liu et al., 2018). This inpainting is based on training a deep neural network, that will provide high-resolution output for a given low-resolution input. Inpainting is much more computationally efficient, whereas it is fully capable of capturing a sufficient level of detail required for data enhancement. As a first step, we derive attributes on a sparser grid from pre-stack seismic data using conventional estimation method. We use random grid (original grid with randomly introduced masked regions) that should allow us to capture the main wavefront features present for a specific geology. Estimation of attributes on such a sparse grid provides obvious computational efficiency compared to a conventional approach where extensive computations of multiple attribute are performed everywhere. In a second step, we associate computed multiple attributes with a coloured image by a special encoding scheme that treats multi-parameter attributes as a single point of a coloured image (see Gadylshin et al., 2019). Once we obtain the encoded image, the trained partially convolutional deep neural network is used to inpaint the remaining masked regions and predict a complete high-resolution image (filling gaps or holes). The last step is decoding the predicted colored image back into multiple attribute space, that is now done on a dense inpainted grid over the entire volume.

Workflow 2: direct DNN-based attribute estimation

Second workflow is based on fully automatic attribute estimation utilizing specially trained convolutional neural network. The input for the DNN is a seismic gather and the output is the image of decoded multiple attributes described in workflow 1. The architecture of the DNN is the modification of the classical U-Net (Ronneberg et al., 2015). The goal of this AI workflow is to obtain local wavefront attributes directly from the data by replacing tedious semblance-based computations of conventional NLBF estimation procedure with DNN prediction. Since parameter estimation represents lion's share of compute time for NLBF, second workflow offers a promise of even faster enhancement compared to Workflow 1.

Field data examples (workflow 1)

We used modern marine Ocean Bottom Node (OBN) dataset acquired with 50 X 50 m shots interval, and 100 m interval along receiver lines and 300 m across them. The OBN survey size is 20 × 31 km consisting of 95 receiver lines. This results totally in 11,027 common receiver gathers with a full pre-stack volume size of around 15 TB. Data enhancement is required to achieve reliable first-break picking (tomography) and FWI (velocity model building) using offsets up to 20 km. We took 1% of the total number of common-receiver gathers and then performed calculation of kinematic wavefront attributes using NLBF. Calculated parameters were transformed into a dataset of "RGB" images. This data were randomly split onto training dataset (80% of images) and validation dataset (20%). To achieve the diversity and representability of these datasets, common-receiver gathers were extracted on a sparse sub-grid sampling all parts of original data volume.

The training was performed on modern HPC cluster Ibex from KAUST (https://www.hpc.kaust.edu.sa/ibex) using single node with 4 GPU Tesla P100. Compute time used for training is negligible compared to the calculation time required to estimate kinematic attributes for the whole dataset. To avoid overfitting we employed validation-based early stopping regularization technique. The error on the validation dataset were used as a proxy for the generalization error in determining when overfitting has begun.

The trained partial convolutional DNN was used for image inpainting of encoded wavefront attributes and delivered complete high-resolution images. Applying a decoder to these images finalized the workflow. The average accuracy of reconstructed kinematic attributes using a validation dataset is ~95%. For error calculations we use the L2 norm of the difference between original kinematic attributes determined on dense estimation grid using NLBF and inpainted attributes using the DNN. As can be seen in Figure 1, the infilled values using the neural network remain similar to the attributes calculated using conventional estimation scheme of NLBF algorithm.

A speedup factor of 2x is achieved in this specific field example whereas enhanced data are nearly identical (Figure 2). The computational time of the inpainting phase is negligible in comparison to the time required for the conventional estimation of kinematic wavefront attributes.

Synthetic examples (workflow 2)

We demonstrate promise of this ambitious approach using synthetic Marmousi dataset. For simplicity we predict only local kinematic attribute A using seismic gather as an input for DNN (see Figure 3).

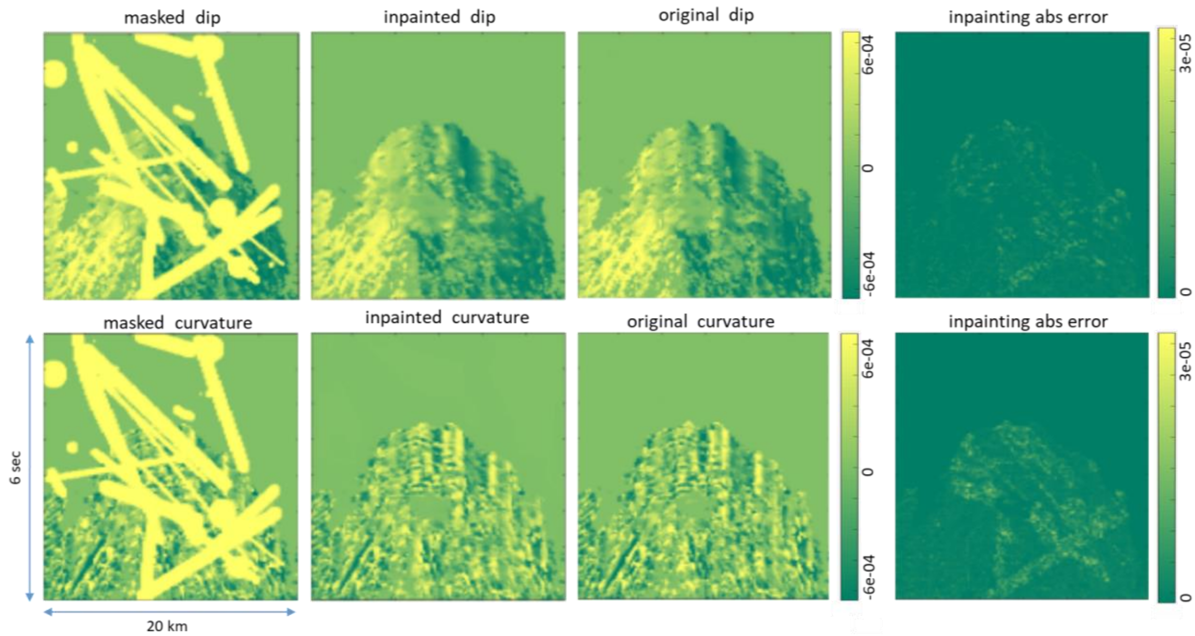

Figure 1 *Real-data example of predicting multi-parameter wavefront attributes using trained DNN. From left to right: masked, predicted, original attributes and last column - difference between predicted and original attributes - plotted in the same scale; top row – dips, bottom row - curvatures.*

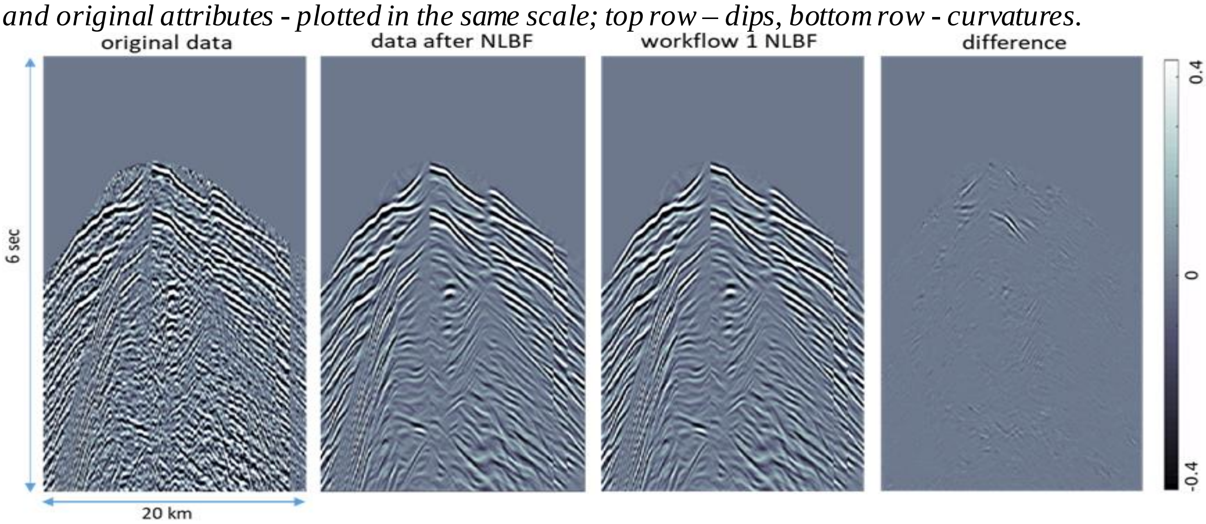

Figure 2 *From left to the right: input data, enhanced data after NLBF with conventional parameter estimation, and AI NLBF with workflow 1 using PConv DNN. Last figure shows data difference between gathers obtained from AI NLBF and conventional NLBF.*

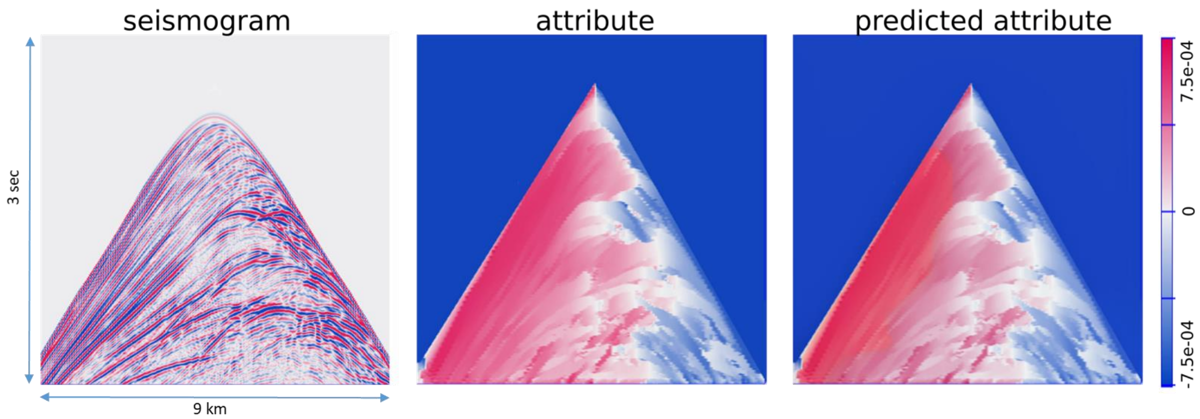

Figure 3 *Validation of second approach on Marmousi synthetics. From left to the right: seismic gather, corresponding attribute computed using traditional approach (dip) and DNN prediction by AI workflow 2 directly from the data.*

We apply NLBF to generate training and validation datasets (60% and 40% of the data correspondingly) and then perform DNN training. For this synthetic dataset with high SNR, we achieve excellent high-quality prediction of the attribute. Real-data testing is ongoing. Even if prediction is imperfect for data with low SNR, initial guess obtained with AI could be extremely valuable since we can simply supplement them with run of conventional NLBF that uses AI guess as a starting point and greatly reduce search intervals for parameters. In the current brute-force implementation, we are forced to define very broad search intervals for five desired wavefront parameters and 5D optimization routines take a lot of computing time to find best coherency in large data space.

Conclusions

We present two workflows for efficient estimation of local wavefront attributes utilizing deep neural networks and using RGB decoding scheme to convert them into coloured images. First approach requires conventional attribute estimation on a sparser grid and then intelligently inpaints them into remaining parts of the volume using DNN. A speedup factor of 2x is easily achieved for the real OBN dataset. A more ambitious second approach is demonstrated on synthetic dataset where DNN directly estimates attributes from seismic gathers. Second approach can be applied on its own or can be used as an efficient first step to obtain initial guess of required parameters with AI and then fine-tune them with quick run of conventional approach focused on narrow search intervals around initial guess. AI-based parameter estimation offers a path towards efficient seismic processing of massive noisy pre-stack seismic data using powerful multi-dimensional stacking approaches. It is worth recalling that current methods only operate in sub-volumes of data with a limited dimensions, exactly because of computational bottleneck caused by estimation phase. If breakthrough in estimation efficiency is achieved with AI, then multi-dimensional stacking with increased or full dimensions could become practical.

Acknowledgments

The authors would like to thank Maxim Dmitriev (Saudi Aramco) for support of the field study. One of the authors (Kirill Gadylshin) was partially supported by the Russian Government Grant MK-670.2019.5.

References

Bakulin, A., Silvestrov, I., Dmitriev, M., Neklyudov, D., Protasov, M., Gadylshin, K., Tcheverda, V., and V. Dolgov, Nonlinear beamforming for enhancing pre-stack data with challenging near surface or overburden. First Break, 36(12), 2018, 121-126.

Baykulov, M., Gajewski, D., Prestack seismic data enhancement with partial common-reflection-surface (CRS) stack, Geophysics, 74(3), 2009, P. V49–V58

Berkovitch A., Deev, K. and Landa, E., How non-hyperbolic MultiFocusing improves depth imaging, First Break, 2011, Vol. 29, 103-111

Bertalmio, M., Andrea, L. Bertozzi and Guillermo, S. Navier-stokes, fluid dynamics, and image and video inpainting, Computer Vision and Pattern Recognition, 2001. CVPR 2001. Proceedings of the 2001 IEEE Computer Society Conference on, vol. 1, pp. I-355. IEEE, 2001.

Gadylshin K., Silvestrov I. and Bakulin A., Inpainting of local wavefront attributes using artificial intelligence, SEG Technical Program Expanded Abstracts 2019, pp. 2212-2216

Goodfellow, I., Bengio, Y., Courville, A., Deep Learning, MIT Press, http://www.deeplearningbook.org, 2016.

Halpert, A., Deep learning-enabled seismic image enhancement, SEG annual Meeting, 2018

Liu, G., Reda, A.F., Shih, K.J., Wang, T.-C., Tao, A., Catanzaro, B., Image Inpainting for Irregular Holes Using Partial Convolutions, arXiv preprint arXiv:1804.07723, 2018

Ronneberger, O., Fischer, P., Brox, T., U-Net: Convolutional Networks for Biomedical Image Segmentation, arXiv preprint arXiv:1505.04597, 2015

Telea, A., An image inpainting technique based on the fast marching method, Journal of graphics tools 9.1 (2004): 23-34.