Volumetric estimation of local kinematic wavefront attributes from prestack seismic data through deep learning

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Summary

We introduced a new method to accelerate the estimation of local kinematic wavefront attributes, which are essential for various seismic data processing tasks, particularly for enhancing prestack data in areas with challenging near-surface conditions. Our approach utilizes a 3D Local Wavefront Attribute Deep Neural Network, a fully convolutional neural network trained explicitly for the automatic estimation of local wavefront attributes. The architecture of this DNN is a modified version of a 3D Residual U-Net. It takes a 3D subvolume of prestack seismic data as input and produces five 3D cubes representing the estimated local wavefront attributes as output. We tested this method on both realistic synthetic land datasets and real marine datasets, achieving a significant speed-up compared to conventional semblance-based optimization method while maintaining a reasonable level of quality in the results.

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Introduction

Kinematic information hidden in prestack seismic data is essential for estimating seismic wave velocities and accurately imaging the subsurface. This information can be represented as kinematic wavefront attributes, with stacking velocity being the most widely used and recognized. Other less common and more comprehensive examples include various kinematic attributes derived from multidimensional stacking techniques, such as the Common Reflection Surface and Multifocusing methods. These attributes characterize the curvatures of different wavefronts and provide a global description of wavefield kinematics across all ranges of offsets. The application of these attributes extends beyond stacking to zero-offset processing and includes techniques like tomography, diffraction imaging, and prestack data enhancement.

Another relevant approach to describe the kinematics of the seismic wavefield is to use local wavefront attributes instead of the global ones discussed above. These attributes can be associated with an arbitrary point within a full 5D prestack data volume, which includes designated shots, receivers, offsets, azimuths, or other positions. Local attributes can be derived from the directional or partial derivatives of the travel-time field. The most commonly used type of these attributes is local slopes, which can be applied across a broad range of imaging tasks, including NMO correction, Dix inversion, and prestack time migration. In depth imaging, local slopes play a fundamental role in slope or stereo-tomography methods. The first and second-order travel-time derivatives were utilized by Hoecht et al. (2009) to construct local stacking operators for seismic data interpolation, and by Buzlukov and Landa (2013) for prestack signal enhancement. Building on these works, Bakulin et al. (2020) developed the nonlinear beamforming (NLBF) technique to efficiently enhance massive 3D prestack land seismic data for purposes such as imaging, first-break picking, and full-waveform inversion.

The most commonly used methods for estimating kinematic attributes focus on maximizing the semblance coherence function through various optimization strategies. Despite the wide range of proposed solutions, significant challenges remain, particularly the high computational cost of the estimation procedures. This issue is especially pronounced in the prestack domain when applied to modern land datasets that can contain tens or even hundreds of millions of traces per square kilometer. To address this computational cost and improve the extraction of local kinematic information from prestack data, deep learning-based methods have gained interest. For instance, Gadylshin et al. (2023) introduced a workflow that accelerates the estimation of local wavefront attributes using a 2D image-based deep learning approach. In this work, we build upon these findings by presenting a specially trained convolutional neural network designed to map input 3D prestack seismic data sub-volumes onto five 3D cubes of local wavefront attributes. This novel approach allows for fast and robust volumetric estimation of local wavefront attributes, resulting in improved computational performance and significantly accelerating the solution of the 5D optimization problem.

Method

To present the approach for estimating local kinematic wavefront attributes, we consider the nonlinear beamforming method for enhancing prestack data, as described by Bakulin et al. (2020). Assuming that the travel-time wavefront can be represented locally as a second-order curve, we can use the following parabolic approximation:

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

Here, Δt represents the travel-time moveout at a specific point (x,y) within the seismic data volume, relative to the reference point (x_0, y_0). The coordinates x and y can be chosen arbitrarily; they may represent, for instance, the receiver coordinates in a common-shot gather or CDP coordinates in a common-offset plane for a given azimuth. The choice of coordinates depends on the specific case or problem of interest. The partial travel-time derivatives define the unknown kinematic local wavefront attributes: A, B, C, D, and E, which need to be estimated. As discussed in the introduction, conventional approaches typically employ a coherency-based optimization strategy to search for the coefficients that maximize a semblance-based objective function. This process results in a complex multidimensional optimization problem with a non-convex objective function, necessitating its numerous calculations on a relatively dense grid in both time and space, which leads to high computational costs.

In this work, we utilize an encoder-decoder convolutional deep neural network (DNN) to simultaneously and directly estimate all five local wavefront attributes (LWAs) from a 3D seismic volume, as illustrated in Figure 1. The proposed fully convolutional 3D LWA DNN takes the 3D prestack seismic data as an input tensor and outputs the volumes of the 3D local wavefront attributes. The DNN is based on the U-Net architecture, featuring encoder-decoder branches with convolutional layers and skip connections. To process the data, we employ a patch-based approach that divides the input volumes into overlapping patches, each measuring 64x64x64 voxels. A stride of 32x32x32 is used to determine the spacing between adjacent patches, ensuring efficient and comprehensive coverage of the entire 3D input volume.

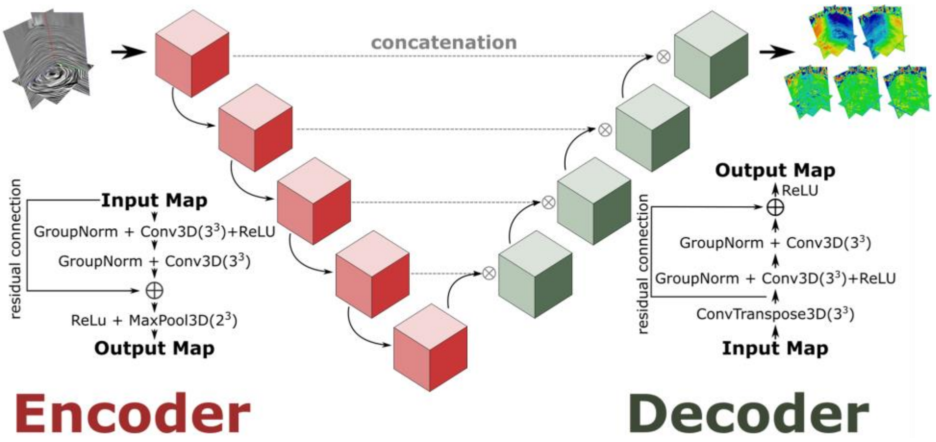

Figure 1 *The architecture of the proposed 3D LWA DNN. The regularized 3D input seismic data flows through an encoder-decoder fully convolutional neural network with skip connections and residual blocks. The output tensor combines five 3D local wavefront attribute cubes.*

LWA DNN is trained in several stages by using datasets that progressively increase in complexity. In stage 1, we utilize simplified synthetic data generated from a homogeneous model with a single reflector (Figure 2). By varying the velocity values and the reflector's depth, we create a diverse set of reflection events along with corresponding wavefront attributes that cover a wide range of dips and curvatures. These were constructed using analytical equations. To make the dataset more realistic, white Gaussian noise was added, with levels reaching down to -10 dB. This synthetic dataset enables us to obtain the initial set of neural network coefficients through the first training process. In subsequent stages, we use a transfer learning strategy that incorporates more realistic synthetic dataset, followed by real data in the final stage. During these stages, we estimate the training wavefront attributes using a conventional semblance-based optimization approach. Specifically, we employed the "dips+curvatures" optimization strategy, as described by Bakulin et al. (2021), which offers a reasonable balance between quality and performance. Alternative strategies, such as advanced global optimization techniques (e.g. Sun et al. 2022), could also be considered.

The realistic synthetic data for stage 2 were sourced from the SEAM Arid dataset, which represents the complexities of land data in arid environments (Figure 3a). These data were integrated into the training dataset, and the neural network was retrained accordingly. The resulting DNN weights served as the starting point for training the DNN in the final stage 3, where real OBN data were also included in the training ensemble (Figure 4a). Notably, only about 1% of the data from the SEAM Arid and OBN datasets were utilized in the training process.

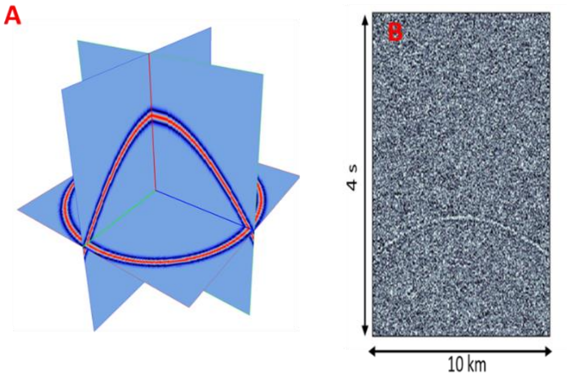

Figure 2. *Example of the generated synthetic data used for training the DNN at the initial stage: A) the original common-shot gather; B) a slice from the gather after adding white Gaussian noise with a 0 dB signal-to-noise ratio*

Examples

To assess the accuracy of the 3D LWA DNN estimation results, we compared the predictions at various stages of transfer learning using three different sets of the DNN weights, which we call weights 1, 2, and 3. This comparison utilized testing data ensembles that the DNN had not encountered during the training process. As a reference, we used the wavefront attributes calculated with the “dips+curvatures” semblance-based optimization strategy. Figure 3 presents an example of this comparison at different training stages using a cross-spread gather extracted from the SEAM Arid dataset. Notably, even at the initial stage, which relied solely on simplified analytically-based synthetics, the DNN was able to extract some meaningful kinematic information from much more complex and unseen data. This performance significantly improved after the second stage of training, which incorporated a subset of the same SEAM Arid dataset. Additionally, incorporating real OBN data into the training process did not negatively impact the results, demonstrating the effectiveness of the chosen transfer learning approach in preventing the so-called phenomena of catastrophic interference, or forgetting.

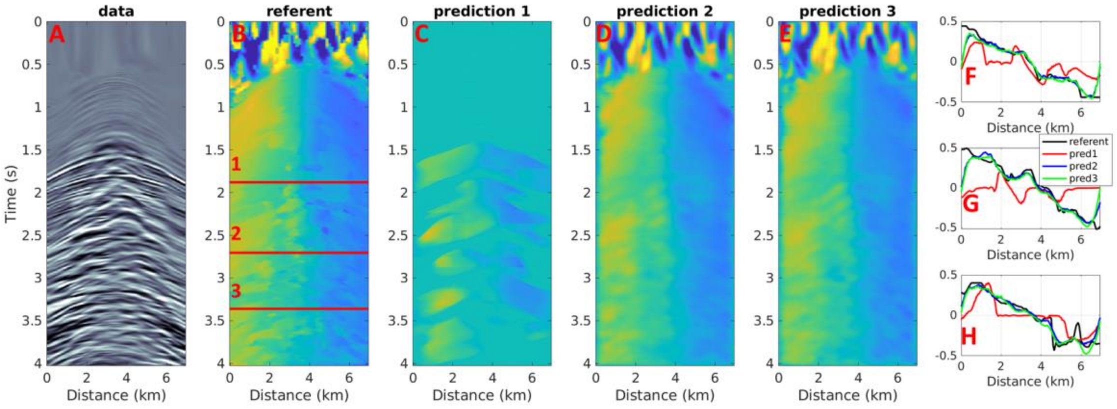

Figure 3 *An example of evaluating the DNN estimation result based on the SEAM Arid dataset: A) a slice from the cross-spread gather used for testing; B) the corresponding semblance-based estimated dip attribute. The 3D LWA DNN prediction, using (A) as input, is presented in (C) for DNN weights 1, (D) for DNN weights 2, and (E) for DNN weights 3. On the right, the cross-plots (F), (G), and (H), corresponding to horizontal sections, are schematically shown at (B) as (1), (2), and (3), respectively.*

Finally, we conducted the testing of the DNN-based attribute estimation method using a real OBN marine dataset. The dataset comprises ultra-long offsets of up to 20km for full-waveform inversion applications. The recorded wavefield is distorted due to complex bathymetry and complex near-surface velocity fluctuations, making early arrivals unclear and lacking coherence. The nonlinear beamforming is required to precondition the data for first-break picking and FWI, as discussed by Kim et al. (2020). Figure 4 shows the results of the DNN-based attributes estimation process and its comparison with more conventional semblance-based estimation approach. The obtained results are quite reasonable, allowing to achieve comparable prestack data-enhancement results by the NLBF method at the final stage (not shown here).

In terms of computational performance, a significant speedup was achieved compared to the conventional solution. The total clock training time for all three learning stages on a modern NVIDIA A100 GPU was approximately 4 hours. The estimation time for the OBN example was reduced from around 20 hours to just 2 minutes, resulting in a speedup of more than 500 times.

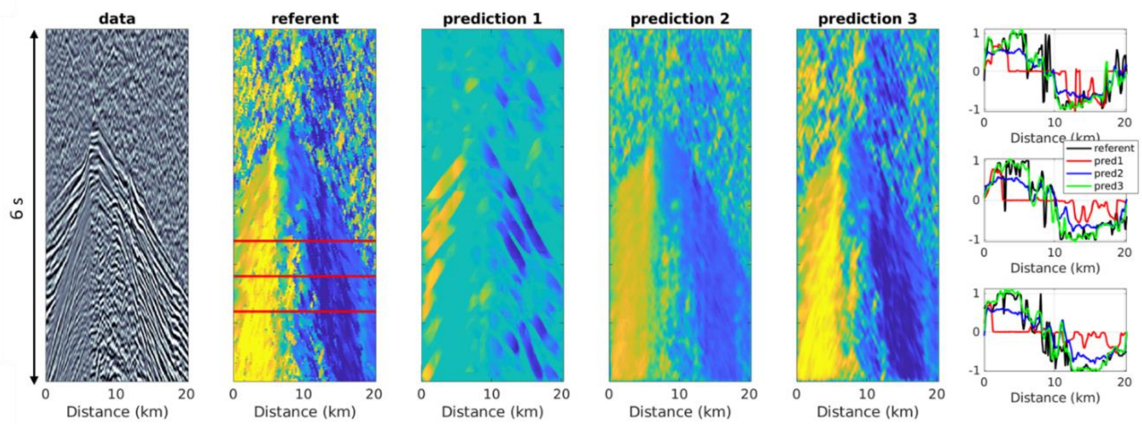

Figure 4 *A marine OBN example showing the application of DNN-based attribute estimation at different stages, compared with a semblance-based optimization approach. Please refer to Figure 3 for more details.*

Conclusions

We introduced a new method to accelerate the estimation of local kinematic wavefront attributes, which are essential for various seismic data processing tasks, particularly for enhancing prestack data in areas with challenging near-surface conditions. Our approach utilizes a 3D Local Wavefront Attribute Deep Neural Network (LWA DNN), a fully convolutional neural network specifically trained for the automatic estimation of local wavefront attributes. The architecture of this DNN is a modified version of a 3D Residual U-Net. It takes a 3D subvolume of prestack seismic data as input and produces five 3D cubes representing the estimated local wavefront attributes as output. We tested this method on both realistic synthetic land datasets and real marine datasets, achieving a significant speed-up compared to conventional semblance-based optimization method while maintaining a reasonable level of quality in the results.

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