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Impact of Data Augmentation Technique on Seismic Velocity Map Estimation using the InversionNet Neural Network

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Abstract Summary

Deep-learning-based seismic inversion approaches require a large amount of high-quality training datasets to achieve good generalization to field data. One way to enlarge the labeled dataset is to use augmentation techniques (e.g., rotation, flip, and translation) to artificially increase the amount of information extracted by the network. In this work, we analyze the effect of different data augmentation techniques on the estimation of seismic velocity maps using the improved InversionNet neural network. The results showed that the use of data augmentation techniques on the OpenFWI seismic data significantly improved the training of the InversionNet network. The best velocity map reconstructions were produced by small random rotations, low additive Gaussian noise, moderate Gaussian blur, and smooth elastic transform.

Introduction

Deep learning-based methods applied to seismic data processing often use data augmentation techniques to compensate for the small amount and variety of seismic data available in the oil and gas industry. High-quality data acquisition is limited mainly by confidentiality, the high cost of acquiring field data, high commercial value, and time-consuming labeling of synthetic and real data, which directly affects the robustness and generalization of the network. To overcome this problem, data augmentation techniques (e.g. rotation, flipping, and elastic transform) have been applied to some seismic interpretation and characterization tasks using Convolutional Neural Networks (CNN), such as salt body classification (Ağaoğlu et al., 2024; Waldeland and Solberg, 2017) and segmentation (Li et al., 2021; Liu et al., 2019), seismic facies classification (Alaudah et al., 2019) and segmentation (AlSalmi and Elsheikh, 2023), geological fault detection (Wu et al., 2019; Zu et al., 2024), and seismic velocity map reconstruction (Farris et al., 2023). These works showed that data augmentation is more efficient with good-quality seismic data, but this technique may fail to capture multiple reflections and realistic wavefield variations. Not all data augmentation strategies are efficient for seismic images, and very complex augmentations can degrade performance and hinder the network convergence process (Gu et al., 2023).

Due to the scarcity of works using the data augmentation approach in seismic inversion problems, this study analyzes the effects of data augmentation techniques on seismic velocity map estimation. This procedure is applied to the CurveVel-B synthetic seismic dataset from the OpenFWI platform using the improved InversionNet neural network (Deng et al., 2022). We applied four types of data augmentation algorithms from PyTorch's Torchvision library separately to the entire training dataset: rotation, elastic transform, Gaussian noise, and Gaussian blur.

Neural Network

The improved InversionNet network (Deng et al., 2022), a CNN with a supervised learning encoder-decoder architecture, is available on GitHub (https://github.com/lanl/OpenFWI/). This network was trained and tested using the CurveVel-B data from the OpenFWI 2D acoustic seismic reflection dataset, which was generated via numerical simulation (https://openfwi-lanl.github.io/docs/data.html). CurveVel-B seismic velocity maps are characterized by curved subsurface layers with randomly varying velocities. Network performance on the test dataset was evaluated using three regression metrics: the single-scale structural similarity index (SSIM; Wang et al. (2004a)), the multi-scale structural similarity index (MSSIM; Wang et al. (2004b)), and the peak signal-to-noise ratio (PSNR; Huynh-Thu and Ghanbari (2008)). Both SSIM and MSSIM quantify the degree of similarity between the ground truth and the generated image, capturing local structural differences by analyzing three key components: luminance, contrast, and structure. The main advantage of MSSIM over SSIM is its ability to account for different image resolutions and viewing conditions, which is crucial for evaluating the perceptual quality of images. SSIM and MSSIM values range from -1 to 1, where -1 reflects dissimilarity, 0 indicates no correlation, and 1 reflects perfect structural similarity between images. PSNR reflects pixel detail at the level of global image reconstruction. Higher PSNR values indicate higher-quality generated images.

Results

Several tests were performed by varying the parameters of the transformations applied to the training dataset. However, only the best predictions are presented (Table 1). As shown in Table 1, the results of the metrics indicate that the InversionNet network performed better with the augmented data than with the non-augmented data used in the work of Deng et al. (2022). Small random rotations, low additive Gaussian noise, moderate Gaussian blur, and smooth elastic transform produced the best velocity map reconstructions, preserving the structural features of the image and correctly estimating the velocities of the layers (Figure 1). Some artifacts are observed at the boundaries of the deeper layers and at the edges of the map (Figures 1c and 1f). The network does not clearly map the last layer interface. This is likely due to the attenuation of the seismic wavefield.

Table 1: Mean and standard deviation values of the evaluation metrics for five repetitions of training on the CurveVel-B dataset, both with and without augmentation, considering different transformations. Parameters - Kernel size: size of the Gaussian kernel; Sigma: standard deviation of the sampled normal distribution; Mean: mean of the sampled normal distribution; Alpha: size of the displacement vectors; Beta: smoothness of the displacement vectors.

DATASET	METRICS		
	SSIM	MSSIM	PSNR (dB)
No augmentation	0.7092 ± 0.0014	0.8347 ± 0.0014	17.5406 ± 0.0686
Random rotation (-3° to 3°)	0.7268 ± 0.0018	0.8528 ± 0.0008	18.0280 ± 0.0672
Gaussian blur (kernel size = 3 x 3, sigma = 0.5)	0.7217 ± 0.0030	0.8387 ± 0.0019	17.9380 ± 0.0747
Gaussian noise (mean = 0, sigma = 0.01)	0.7160 ± 0.0023	0.8405 ± 0.0026	17.7336 ± 0.0888
Elastic transform (alpha = 10, beta = 3)	0.7154 ± 0.0005	0.8311 ± 0.0008	17.5632 ± 0.0262

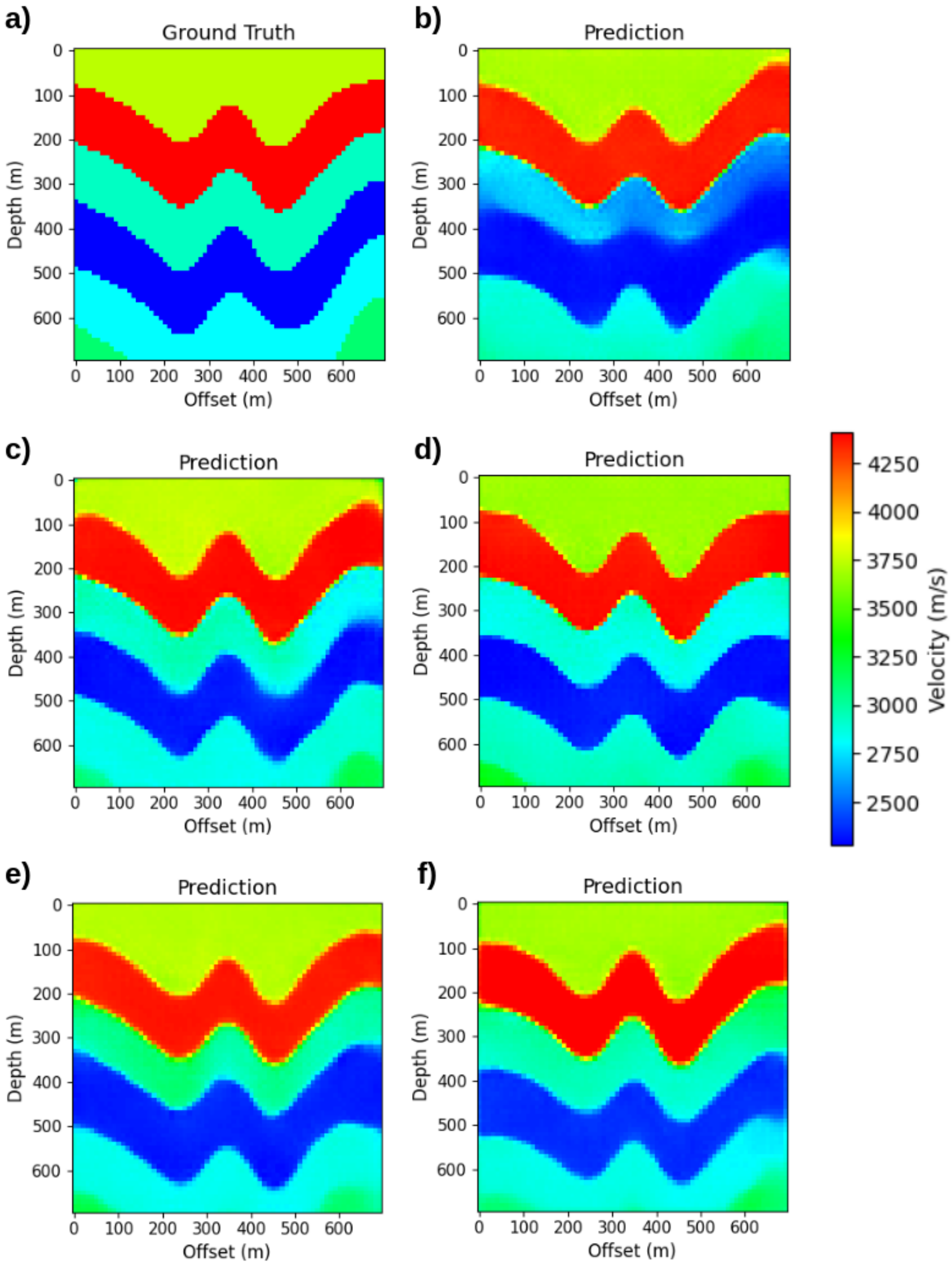

Figure 1: Velocity maps of the CurveVel-B testing dataset for the a) ground truth and predicted images for training: b) no augmentation, c) rotation ranging from -3° to 3°, d) Gaussian noise (mean = 0, sigma = 0.01), e) Gaussian blur (kernel size = 3 × 3, sigma = 0.5), and f) elastic transform (alpha = 10, beta = 3).

Conclusions

The results presented demonstrate that applying augmentation techniques to seismic data significantly improves InversionNet training. Small random rotations, low additive Gaussian noise, moderate Gaussian blur, and smooth elastic transform produced the best velocity map reconstructions. It is recommended to configure small values for the transformation parameters to avoid violating the physical properties and preserve the semantics of the seismic data.

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