

Impact of Rotation Data Augmentation on Seismic Inversion using InversionNet Network

Introduction

Several data augmentation techniques have been employed in machine-learning-based seismic interpretation approaches to overcome the limited quantity and diversity of seismic data available in the oil and gas industry. One such technique is rotation, which artificially increases training datasets by randomly rotating images, thereby improving the ability of neural networks to recognize geological structures regardless of their orientation. In this context, rotation is crucial for tasks involving significant variation in the orientation of geological structures, such as in the mapping of stratigraphic horizons (Chen et al., 2025) and the delineation of salt bodies (Li et al., 2019; Agaoglu et al., 2024). Regarding geological fault detection, most studies (Wu et al., 2019; Bi et al., 2021; Zu et al., 2024) use 90°, 180°, and 270° rotations to avoid artifacts near boundaries or interpolation processing, as well as to better map fault continuity. Other works (Alaudah et al., 2019; Zhang et al., 2021; AlSalmi and Els Sheikh, 2023) employ rotation for seismic lithofacies classification; however, Wang et al. (2025) demonstrate that this technique does not improve overall classification accuracy because it can change the seismic parameters that categorize lithofacies and worsen sample imbalance.

Although rotation data augmentation is advantageous for simulating geological variability, the literature lacks studies that apply this technique to seismic inversion. This study investigates how this on-the-fly augmentation affects the seismic velocity model reconstruction, using training datasets augmented with different rotation angles. Additionally, we analyze whether this transformation is consistent with the real-world geological scenarios and whether it preserves the physical properties of the seismic wave field. For this procedure, we use the enhanced InversionNet neural network (Deng et al., 2022) with 2D CurveVel-B synthetic acoustic seismic dataset from the OpenFWI platform.

Relationship between the Rotation Algorithm and Rotational Deformations in Rocks

Rotation is a Euclidean geometric transformation that rotates an image by various angles around a fixed point (i.e., the rotation center) in either a clockwise or counterclockwise direction. This transformation maps the intensity value from one set of pixel locations to another, while preserving the distances and angles between any two points in an image. In this process, only the position and orientation of the image within a plane change. The rotation algorithm implemented in PyTorch requires either a fixed rotation angle r or a range of random rotation values Δr in degrees. The two-dimensional rotation operation in the x - y plane involves multiplying the orthogonal matrix (Khalleefah, 2025)

$$\mathbf{R} = \begin{bmatrix} \cos(r) & -\sin(r) \\ \sin(r) & \cos(r) \end{bmatrix} \quad (1)$$

by the coordinates (x, y) of the pixels in the image. For small rotation angles r , the calculation of the matrix $\mathbf{R}$ is simplified because $\cos(r) \approx 1$ and $\sin(r) \approx r$ (Equation 1). Therefore, for small angles, the rotation matrix can be approximated by the identity matrix plus a skew-symmetric perturbation. We use bilinear interpolation (Mastyło, 2013) to estimate pixel values at new locations created during rotation, producing a smoother image with gradual pixel value variation. However, one limitation of this procedure is that it can cause blurring or loss of detail in regions of abrupt intensity variation.

The mathematical operation underlying image rotation resembles the real-world rotational deformations, which change the spatial attitude of rock volumes due to the propagation of seismic waves in the subsurface. Similar changes in orientation are observed in geological structures such as shear zones, tilted fault blocks, angular unconformities, and cross-bedded sedimentary sequences. In the context of images, the rotation algorithm alters the apparent arrival times of waves in seismograms

and changes the inclination of geological layers and structures in velocity models, thereby creating different geological scenarios.

Neural Network Architecture

The enhanced InversionNet (Deng et al., 2022) is a supervised encoder-decoder convolutional neural network. The network is implemented in PyTorch and can be found on GitHub at <https://github.com/lanl/OpenFWI>. We use 24,000 training samples from the 2D CurveVel-B acoustic reflection seismic dataset from the OpenFWI platform. CurveVel-B seismic velocity models represent relatively complex geological scenarios with curved interfaces separating layers of randomly varying velocities. During the testing stage, we evaluate the network performance in 6,000 samples from the CurveVel-B dataset using three image-quality metrics: single-scale structural similarity index (SSSIM) (Wang et al., 2004), multiscale structural similarity index (MSSIM) (Wang et al., 2003), and peak signal-to-noise ratio (PSNR) (Huynh-Thu and Ghanbari, 2008). SSSIM and MSSIM use a sliding square window scheme to measure local statistical differences between predicted and labeled velocity models, considering three main components of the image: luminance, contrast, and pixel structure. The MSSIM and SSSIM metrics are normalized and range from 0 to 1: 0 indicates no structural similarity between the labeled and predicted velocity models, while 1 represents optimal similarity between the models. PSNR measures the ratio of the maximum possible pixel intensity to the power of the reconstruction error (noise), focusing on pixel-by-pixel intensity differences at the level of global image reconstruction. In this work, PSNR values are normalized from 0 to 1 using the min-max scaling method (Borkin et al., 2019) to facilitate comparison of the results obtained using the MSSIM and SSSIM metrics.

Results and Discussions

The InversionNet model was trained using unaugmented and augmented data with the rotation algorithm, using different fixed rotation angles r and different ranges of random rotation angles Δr . Training the InversionNet model on the non-augmented CurveVel-B dataset required approximately 4 hours, whereas training on datasets augmented with the rotation algorithm required only 1-2 hours. The evaluation metrics indicate that the rotation parameters are sensitive to the 3 metrics (Panel 1 in Figure 1). Even small fixed rotation angle dramatically reduce network performance (Panel 1 in Figure 1). As shown in Panel 1 of Figure 1, only minor differences are observed in the metric values across the three ranges: $\Delta r = [-2^\circ, 2^\circ]$, $\Delta r = [-4^\circ, 4^\circ]$, and $\Delta r = [-6^\circ, 6^\circ]$. As the range of rotation angles increases, network performance decreases (Panel 1 in Figure 1). The best performance is obtained for rotation angles of $\Delta r = [-2^\circ, 2^\circ]$ (Panel 1 in Figure 1).

As observed in Figures 1a and 1b of Panel 2, the trained network with non-augmented data ($r = 0^\circ$) fails to reconstruct the deepest layer and accurately map the interface at around 500 m. Only when $\Delta r = [-2^\circ, 2^\circ]$, the velocity field and boundaries of the last layer are reconstructed and the interface at around 500 m is reasonably mapped (Figure 1c in Panel 2). Larger ranges of random rotation angles fail to reconstruct the layers at intermediate and deeper depths and generate artifacts at the upper edges of images (Figures 1d to 1f in Panel 2). These artifacts may be caused by the interpolation process employed by the rotation algorithm. In general, the reconstruction of the deeper layers is inherently difficult because the effect of the geometrical spreading becomes more pronounced with depth.

Conclusions

This study analyzes the role of the rotation augmentation technique in seismic data inversion using the InversionNet network, from both physical and geological perspectives. We evaluated several rotation angles on the CurveVel-B seismic dataset. Our results show that the rotation technique can improve InversionNet performance, reduce training time, produce more reliable predictions of elastic subsurface

properties, and enhance the the mapping of interfaces and deeper structures. Although different rotation angles produce only slight changes in the evaluation metrics, the reconstructed velocity models may exhibit significant differences in layer velocities and the geometry of geological structures. High rotation angles can generate artefacts at the edges of the image and severely distort the seismograms, resulting in a loss of physical meaning. Therefore, we recommend using small ranges of random rotation angles to reconstruct high-quality velocity models since they do not significantly alter the geometry and continuity of the geological layers and the physical signature of the seismograms, thereby preserving the geological realism of the training data.

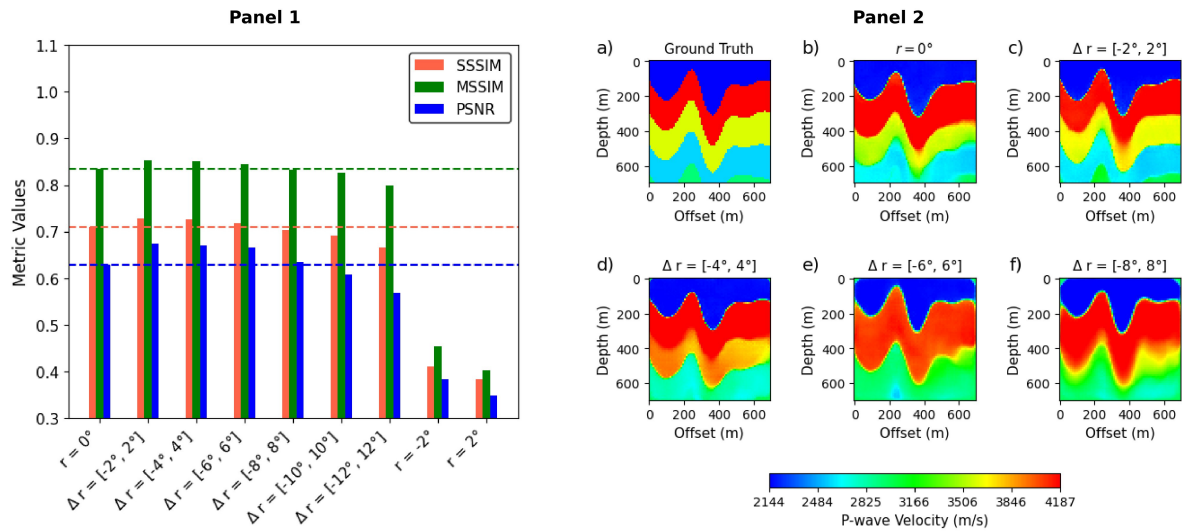


Figure 1 Panel 1 shows the mean metric values for five training repetitions of the rotation algorithm applied to the CurveVel-B dataset for different fixed rotation angles r and different ranges of random rotation angles Δr . The colored dashed lines represent the metric values of the case without augmentation ($r = 0^\circ$) for comparison. Panel 2 shows the P-wave velocity models of the CurveVel-B testing data: a) ground truth, b) predicted by InversionNet trained without augmentation ($r = 0^\circ$), and c) to f) predicted by InversionNet trained with rotation algorithm for different Δr .

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