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OBN velocity components prediction from pressure using generative neural networks

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Introduction

Deep generative learning has emerged as a significant area of research in seismic data processing. Among the various generative neural network architectures, Generative Adversarial Networks (GANs) and Denoising Diffusion Probabilistic Models (DDPMs) have seen widespread application in tasks such as denoising, interpolation, imaging, and inversion. In this study, we compare the performance of GANs and DDPMs in predicting particle velocity components from the pressure component in Ocean Bottom Node (OBN) acquisitions. High-quality predictions could enable the use of single-component receivers in certain locations, potentially reducing the overall cost of the OBN surveys by reducing the need for more expensive multi-component nodes.

Method and/or Theory

To assess the effectiveness of the networks in converting the pressure components into particle velocity components, we simulate a 2D OBN acquisition in a typical Brazilian pre-salt velocity model. To do this, we simulate a set of multi-component receiver gathers (one pressure component and vertical and horizontal components), located at 2 km depth on the sea bottom. The sources are set near the surface with a distance between sources of 50 m. In our case, we simulate three different scenarios, assuming that we measure pressure components at all receiver stations, and we measure both pressure and the two velocity components at every other station. In the first scenario, the distance between the receivers measuring all the components is 100 m, the second is 200 m, and the third is 400 m, the last being the most realistic scenario. For the three scenarios, we use the complete receivers as the training dataset and the pressure-only receivers as the testing dataset. The three scenarios allow assessing the influence of the receiver's sparsity on predicting the velocity components.

Results and Conclusions

In our current tests, we obtain that: 1. The prediction done with DDPM surpasses the GAN prediction in the three scenarios, and 2) if we increase the sparsity of the acquisition, the quality of the prediction decreases. We conclude this by comparing the predicted and the ground truth data with image metrics like RMSE and SSIM. However, we are developing strategies to assess the quality of the prediction by the use of this predicted data in other processing steps. To do this, we are testing decomposing the seismic field into up and down parts by performing the P/Vz summation with the predicted and the true data, and then migrating both parts. The assessment of the migrated image allows us to check the global effect of the predicted data with both GANs and DDPMs networks.