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Denoising 4D Seismic using Residual Pix2pix Network

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Introduction

A 4D image is the difference between baseline and monitor seismic acquisition, and the quality of the image depends on the removal of non-repeatability effects. Deep Learning (DL) may be used for 4D denoising, where it is usual to use the L1 norm as the loss function to update the weight of the convolutional layers. However, working with 4D seismic images the L1 values can be very small because of the small differences between the baseline and monitor, which don´t provide a sufficient gradient, leading to a vanishing gradient problem during backpropagation. The Pix2Pix model is a Conditional Generative Adversarial Network that uses L1 as a mean condition to generate new images, and with 4D seismic data aims to transform the monitor to baseline image reducing the non-repeatability effect. In this work, we present a novel Pix2Pix version with residual block added in a specific layer, to improve 4D denoising, solve the vanishing gradient problem, and highlight the 4D signal in the reservoir region.

Method and/or Theory

We use one Brazilian pre-salt baseline and monitor seismic dataset. The input is the monitor and the target is the baseline, using only one channel of information (Amplitude). The dataset was split into two regions: one outside the reservoir area, containing non-repeatability effects for training; and the other in reservoir area, used for the inference process. The idea is to transform the monitor to the baseline to increase the match between the traces. During the training, the corrections to the monitor amplitudes are applied. In the inference process, where reservoir changes appear, it produces a different effect than a trace match, highlighting the 4D changes. The DL model learns to identify and remove non-repeatability effects outside the reservoir. During the inference process the 4D noise is removed, while the 4D signal remains unchanged.

The main preprocessing of the dataset includes sorting the data into depth slices, normalizing the amplitudes, and splitting the data for training and validation. We train two deep learning models: the conventional Pix2Pix model and a novel residual Pix2Pix version proposed. To build this new version, we just modify the Generator, which is a U-Net with skip connection. We add two residual blocks in the intermediate layer of the down sampling layers to focus on local seismic characteristics, and two residual blocks near the bottleneck in the up-sampling layers to improve the reconstruction of the image. The residual blocks added have two convolutional layers, batch normalization, and a ReLU activation layer. During training, we use the same values for hyperparameters such as learning rate, kernel size, and the weight for the conditional L1 loss for both deep learning models. We perform several comparisons, including measurements of image quality using NdRMS maps, to assess the quality of the 4D signal by comparing the reference dataset with the predictions from the conventional Pix2Pix and our residual Pix2Pix model.

Results and Conclusions

The image generated (Monitor filtered) by our proposed network denoises the 4D image highlighting the reservoir changes. Residual Pix2Pix generates images with better quality. For example, in the NdRMS maps, we can see some artifacts introduced by the conventional Pix2Pix, while with Residual Pix2Pix, even when trained with few epochs, we do not observe these types of issues. We reduced the vanishing gradient problem and found a good setup for the Pix2Pix network with residual blocks to work with real 4D seismic data. For 4D denoising, the model generates a monitor image where changes in the amplitude distribution related to 4D noise are corrected, but these changes are not applied to the 4D signal.