Blind denoising of pre-stack seismic data using Deep Learning

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Abstract

Offshore reflection seismic data are inevitably contaminated by noise from several sources, such as sea waves, turbulence along the streamer seismic cables, wind, instruments, among others. Noise can compromise the quality of seismic data processing and further interpretation of geological features, which can have relevant consequences on exploration and reservoir management decision making. Therefore, noise attenuation and removal play a key role in the quality of processing and interpretation of seismic data.

The goal of denoising is to restore the signal as much as possible, eliminating the effect of noise, and increasing the signal-to-noise ratio. The image denoising is a classic problem in signal processing [1], but it remains a challenging inverse problem for seismic data and the solution may not be unique. In many applications, particularly in the case of seismic data, the frequency contents of signal and noise may have a significant overlap, and the more complex filtering process may be less effective and/or affect the signal, leading to a degraded final image lacking important details and features.

Recently, Deep Learning (DL) methods have had good results for image denoising. Tian et al. [2] presented a review with more than 200 articles on applications of DL models for image denoising. The article divides the problem of image denoising into four categories according to the type of noise: additive white noise, real noise, hybrid noise and blind denoising.

In practice, data is acquired in conjunction with noise, such that clean data in real offshore reflection seismic data is obtained through time consuming filtering processes. Synthetic seismic data is often used for supervised learning approach, but differences between synthetic and field data limits denoising capabilities [3]. Therefore, blind denoising plays a significant role in practical situations.

Blind denoising has been recently adopted for seismic data denoising [3][4], using additive white Gaussian noise (AWGN). In this work, AWGN and synthetic seismic datasets are used to keep a fair comparison landscape with other works. The approach applied in this work is called Noise2Noise [5], which can remove AWGN noise from seismic data without available clean data. This is possible to some reasonable extent, when multiple gaussian noise realizations are available combined with seismic signal data during training. Lehtinen et al. [5] shows that in many applications the expectation of corrupted data is the clean image, and so the neural network can learn to produce it from noisy inputs. Several deep learning models are considered in comparison to explore the potentials of the technique, like FCNNs (Fully Convolutional Neural Networks), U-Net [6] and SRGAN [7] (Super Resolution Generative Adversarial Networks), and some of their hyperparameter variations.

This work presents preliminary results of an ongoing project. The next step is to apply the method with noise extracted from real seismic data, which is much more complex than AWGN.

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