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Deep Learning for Migration Artifacts Attenuation

E. Klochikhina[1*], S. Frolov[1], N. Chemingui[1]

[1] PGS

Summary

Migrated images are often contaminated by uncompensated migration swings. While it is easy to visually distinguish the artifacts, it is often hard to remove them without damaging the image resolution. Here we propose a method for attenuation of migration artifacts that is based on a deep convolutional neural network. The network is trained on synthetic examples to predict clean seismic images from noisy migration results. Application to field data demonstrates the potential of the method to distinguish between migration swings and structural data, and successfully attenuate the artifacts.

Introduction

Generating a seismic image free of noise is desirable for robust geological interpretation. In the case of insufficient data coverage, the migrated image may be contaminated by uncancelled migration isochrones (Gardner and Canning, 1994). These migration artifacts are the result of limited illumination of the subsurface due to sparsity in data acquisition and/or poor signal penetration as a result of propagation through complex media. The noise is coherent and distorts the amplitudes of the geological structures. There are several approaches that help reduce this noise, including data regularization before migration, filtering during imaging, and post-processing after migration.

Data reconstruction can often be employed to overcome the irregularity in data coverage (Schonewille, 2000; Chemingui and Biondi, 2002). It produces cleaner results but requires a lot of effort and may affect resolution of the final image. The migration artifacts can also be reduced at the imaging stage by optimizing the migration aperture (Alerini and Ursin, 2009; Klokov and Fomel, 2012). These methods usually require knowledge of local structural dip and are highly dependent on the quality of that prior information. An alternative approach is to handle these artifacts after migration by designing filters that attenuate the noise (Hale, 2011). Unfortunately, it can be hard to devise filters that remove the noise without damaging the image resolution.

We propose a new approach based on Artificial Intelligence and Deep Learning, where instead of explicitly formulating the filters we statistically estimate them by training a convolutional neural network (CNN). The main components of CNNs are convolutional filters that are iteratively adjusted during the training step to handle the artifacts and produce clean outputs from noisy inputs. The trained models are then used to denoise the seismic images from field experiments.

Deep learning for attenuation of migration artifacts

Our goal is to remove migration swings from seismic images. In practice, it is challenging to provide a formal mathematical model of the noise or a set of rules that would eliminate it. A neural network, however, can act as a universal function approximator — given enough model capacity, it can mimic the behaviour of an arbitrarily complex function F that maps input x to an output y:

$$F(x) = y \quad (1)$$

During the training process we want to find a transform $F'(x, \theta)$ that maps a set of noisy inputs x into a set of corresponding clean outputs y. We achieve that by minimizing the $L2$ norm of a cost function J between the pairs of transformed inputs y' and desired clean outputs y with respect to trainable parameters of the network θ:

$$F'(x, \theta) = y' \quad (2)$$

$$J = \|y - y'\| \quad (3)$$

Overall, the stability and quality of predictions depend on the chosen architecture and hyperparameters of the network, and the training dataset. The training data were created using noisy images as an input to the CNN and clean images (noise free) as an output.

There are several established CNN architectures that are commonly used in Computer Vision for image classification and image denoising. We chose a U-net architecture (Ronneberger et al., 2015) because of its fast training/convergence and natural separation of scales (Figure 1). The architecture consists of three parts: the encoder (contraction; left branch), the bottleneck (bottom) and the decoder (expansion; right branch). Each convolutional layer receives an input and applies a set of 3x3 filters, followed by a nonlinear activation function. The encoder consists of four blocks: each block has two convolutional layers followed by a downsampling operation (max pooling). The number of filters in the convolutional layers doubles each time the resolution decreases, so the architecture retains the ability to explain complex features of the input. The bottom layer takes an input from the encoder and applies two convolutional layers followed by the decoder. The expansion path also consists of four blocks: each block has two convolutional layers followed by an upsampling operation. After each upsampling step, the number of filters in the convolutional layers reduces by half. The corresponding blocks of the encoder (prior to pooling) and decoder are connected by ‘skip connections’. This helps to solve the problem of vanishing gradient during the training stage and it simplifies the prediction task, as there is no need for reconstruction of the full resolution image from its compressed representation.

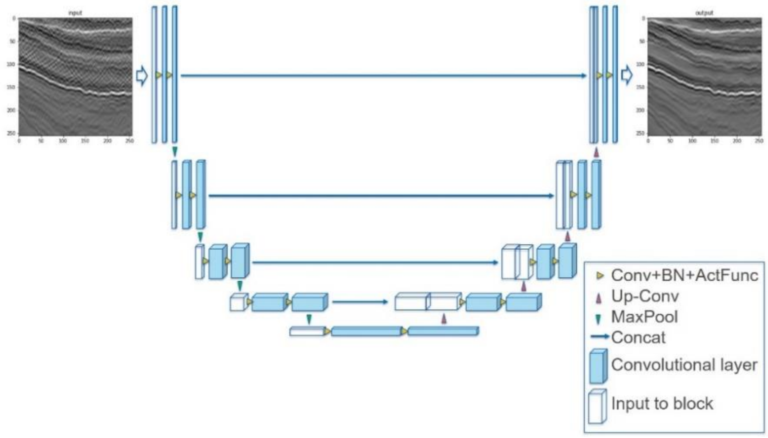

Figure 1 *Deep convolutional neural network architecture used for training and prediction.*

In order to account for the specific character of seismic data we modified the convolutional blocks of U-net and adjusted the hyperparameters of the network during the training process to minimize the cost function. An action of random layer deactivation was also applied to help with potential overfitting.

Training and validation

While the input simulated noisy images from coarsely sampled experiments, the desired output consisted of clean images from densely sampled experiments. The training used image patches of 256x256 pixels (Figure 2). The data were carefully selected to include diversity in frequency content, structural dip, amplitude, noise level and character. To increase the variability of the input, we employed data augmentation — horizontal flips, random crops and sign reversal, filtering and scaling with depth. The total number of input samples was in the order of 100,000. Hyperparameters such as learning rate schedule, dropout rate and batch size were adjusted during the training phase to minimize the prediction error. Training for 50 epochs took approximately an hour on a single Volta V100 GPU with 32Gb of memory.

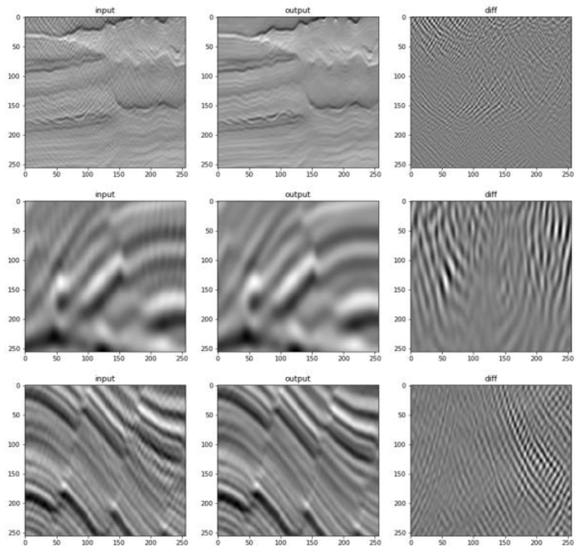

Figure 2 *Training data examples: left column – input to the neural network (noisy image); middle column – desired output from the neural network (clean image); right column – difference between desired output and input (noise).*

Depending on the training setup, a network may overfit the data - it yields good predictions on the training data but does not generalize well. To make sure the model does not overfit the data, part of the synthetic dataset was selected to validate the model performance during the training process (Figure 3). The loss function for both training and validation datasets decreases gradually during the training process, confirming good performance for both datasets.

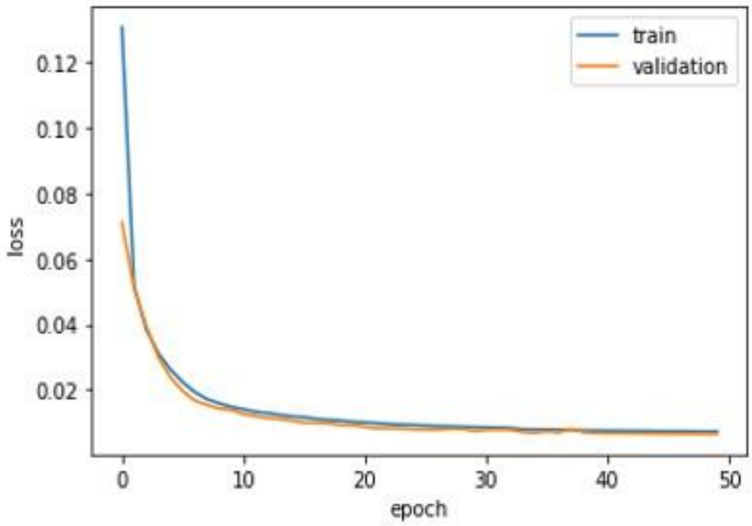

Figure 3 *Loss function for training and validation datasets.*

Application to field data

The denoising capabilities of the neural network were tested on field data. The input consisted of a migrated image contaminated by strong coherent noise (Figure 4). This is particularly visible above the water bottom (orange arrow), but present in the entire dataset (blue arrow). The neural network was able to reduce the migration artifacts without damaging the image resolution (Figure 5).

Conclusions

We propose a deep learning method for attenuating migration artifacts from seismic images. Specifically, we train a convolutional neural network to differentiate migration swings from geological structures. The application of the trained model to a field dataset demonstrates the potential of the solution to successfully attenuate migration swings without compromising the resolution or structural integrity of the seismic image — we see improvements in both structure and amplitude fidelity of the seismic image.

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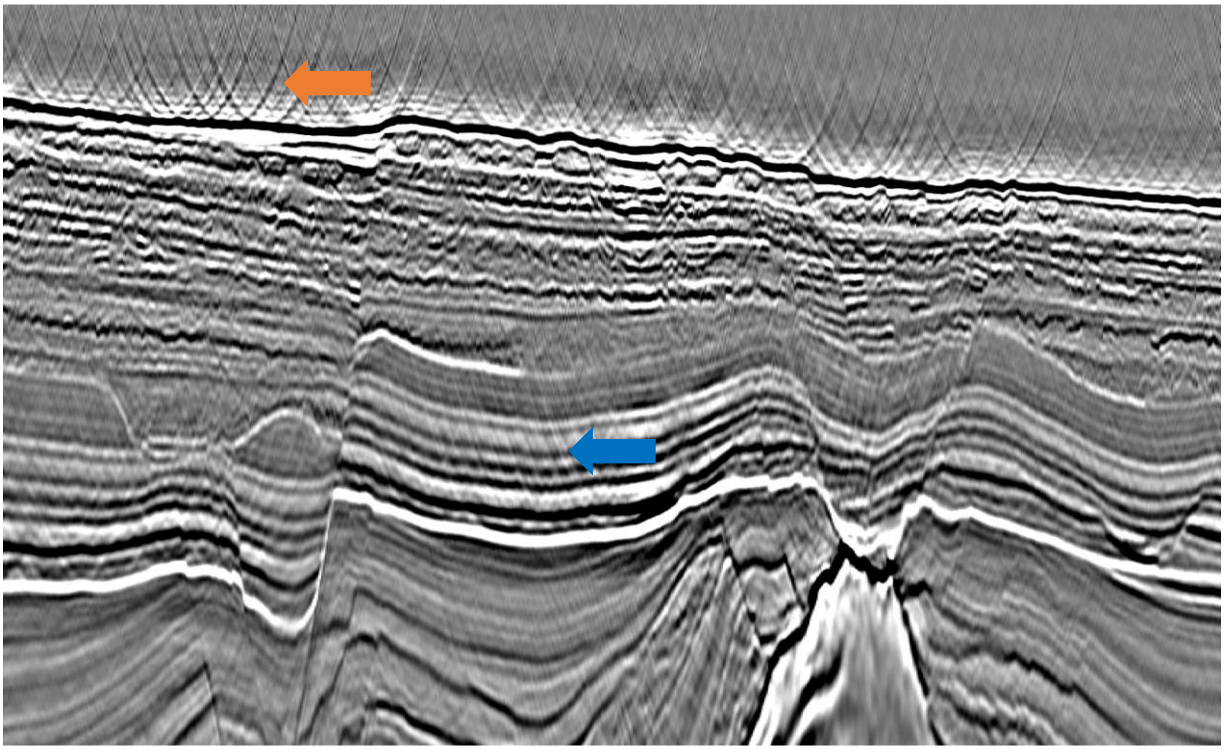

Figure 4 *Field data example: input to the neural network.*

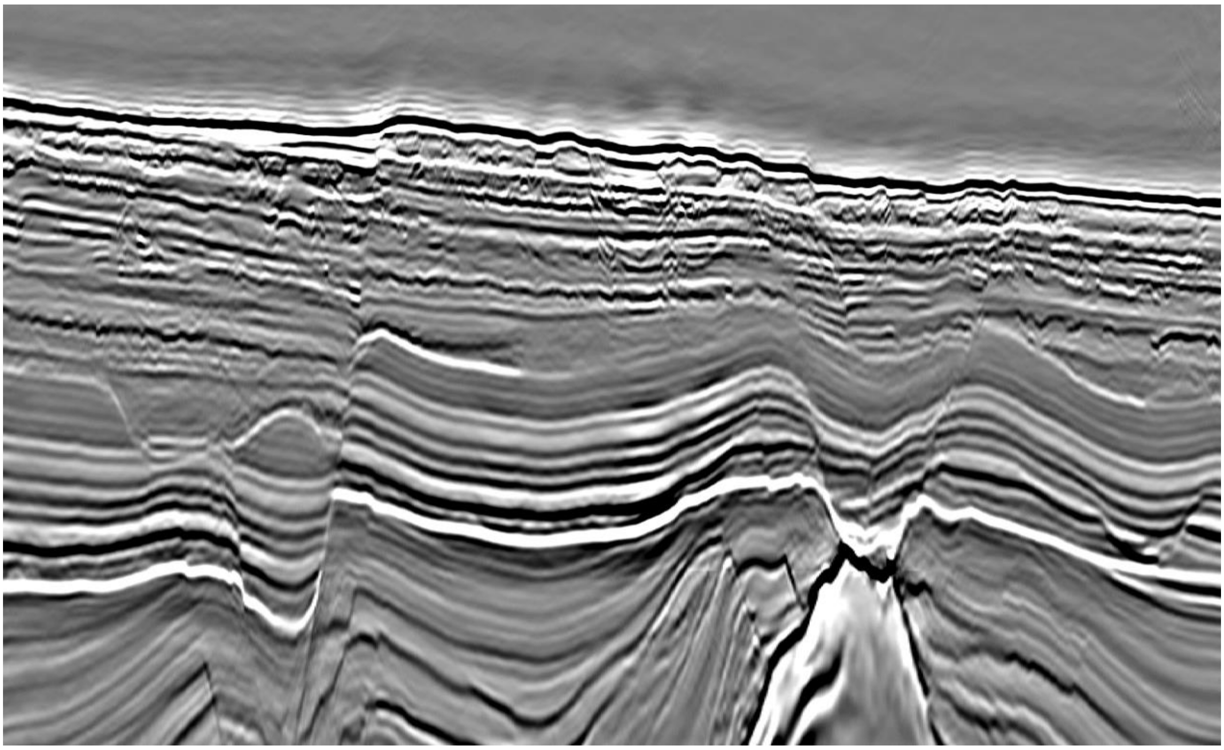

Figure 5 *Field data example: output from the neural network.*