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Seismic image de-noising with convolutional neural network

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Summary

Seismic images are often contaminated by migration noise. The noise attenuation process can take a lot of effort from the domain expert and, in many cases, it can be challenging to get the optimal result. In recent years it has been demonstrated that data-driven approaches can produce quality results with minimum effort. In digital image processing, convolutional neural networks (CNN) have gained a lot of popularity. When trained properly on carefully selected data, CNNs can potentially outperform traditional methods through task automation leading to reduced turnaround time of processing projects. In this work we propose to train a neural network, specifically a U-net architecture, to eliminate migration artifacts from seismic images. We explain the data preparation step and describe the model parameters and training process. Finally, we demonstrate the model performance on field data examples from three different geographical regions.

Introduction

Presence of noise in seismic images complicates structural and quantitative interpretation and can lead to inaccurate results. Therefore, it is crucial to eliminate any undesired energy produced by migration of seismic data. In this work we focus on coherent noise that is often present in seismic images when lacking midpoint density in the direction orthogonal to sailing in offshore settings. The level of image distortion depends on the acquisition geometry, image sampling and migration algorithm. Propagation through a complex medium further degrades the quality by reducing signal penetration. The resulting images suffer either from insufficient wavenumber content or are contaminated by migration swings (Gardner and Canning, 1994).

There are several approaches for reducing the effects of noise that is caused by limited data coverage: regularization of data in time domain before migration (Schonewille, 2000; Chemingui and Biondi, 2002), use of prior information (structural dip) during the imaging step (Alerini et al., 2009; Klokov et al., 2012), or post-migration image processing (Hale, 2011). In addition to their cost, these solutions often require significant effort from domain experts and may not lead to satisfactory results.

With machine learning methods being widely used to automate routine tasks, we seek to reduce the turnaround time of seismic image de-noising by leveraging a data-driven approach. Following the success of using convolutional neural networks (Fukushima, 1980; LeCun et al., 1989) for image enhancement in various computer vision problems, including early attempts in our industry (Wang and Nealon, 2019), we propose training a CNN architecture to attenuate coherent noise from seismic images.

Neural network for image de-noising

In this work we focus on elimination of uncanceled migration swings from seismic images. In many cases this noise is visually distinguishable from the true reflections, nevertheless its attenuation can be very challenging. Given the noise model, the removal can be done adaptively. Unfortunately, migration swing noise is quite complex, and in most cases, it is not feasible to build the noise model. Specific transformations can be key to separation of the noise and signal components, but it can time consuming to find that unique domain, and sometimes it's impossible to solve the task.

A data-driven approach like convolutional neural networks has been a popular alternative for conventional rule-based methods in many applications. Rather than dealing with various transformations and corresponding domains, one can use a more robust approach by training a neural network to perform the same task. Given enough training data, a network of reasonable capacity can approximate the behavior of the entire de-noising workflow. Instead of relying on a domain expert to develop a solution for a given dataset, we can feed a collection of data to the convolutional neural network so that it can learn to perform the image de-noising automatically. The training data has to be carefully prepared to make sure the model will generalize well on variety of field data examples. Once the training is done, there is no longer need of an expect time to de-noise images.

Among the wide variety of commonly used CNN architectures, we found a U-net architecture (Ronneberger et al., 2015) to be suitable for our de-noising objective. It shows better convergence, faster training, and it fits the problem naturally due to the presence of operations on different resolution levels (Figure 1). The architecture consists of three parts: the contraction (left branch), the bottleneck (bottom) and the expansion (right branch). Each convolutional layer receives an input and applies a set of 3x3 filters, followed by a non-linear activation function. The contracting path consists of four blocks: each block has two convolutional layers followed by a down-sampling procedure (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 present in the input. The bottom layer takes an input from the left branch and applies two convolutional layers. The expansion path receives the input from the

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bottleneck and it also consists of four blocks: each block has two convolutional layers followed by an up-sampling procedure. After each up-sampling step, the number of filters in each convolutional layer halves. The corresponding blocks of the contraction and expansion paths are linked by ‘skip connections’ as shown in Figure 1 by blue horizontal arrows. These connections help solve the problem of vanishing gradient during the training stage and simplify the prediction task as there is no need for reconstruction of the image at full resolution from its compressed representation.

We modified the original U-net architecture to account for the specific character of seismic data and achieve better output image quality while reducing the training time. We customized the activation functions, changed the number of filters in each layer and adjusted the hyperparameters of the network during the training process.

The network was trained on synthetic migration results that had been simulated with dense acquisition (desired output), and decimated data (noisy input) using existing synthetic velocity models. We created 2D image patches of 256x256

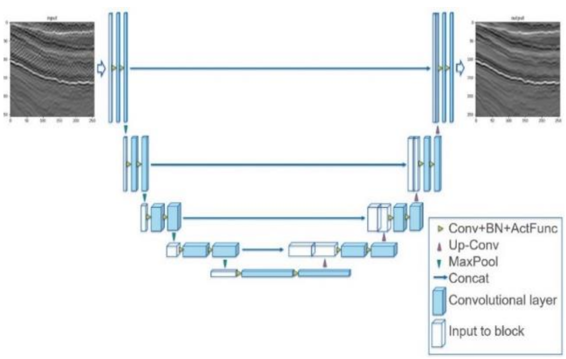

Figure 1: Deep convolutional neural network architecture used for training and prediction

pixels (Figure 2) randomly selected from the migrated results. During the training and validation steps we observed the importance of input data quality. Therefore, we carefully selected each data training set to insure they vary in frequency content, structural dips, amplitudes, noise character and intensity. We also augmented the selected pairs of data to increase the number of examples by applying horizontal flips, sign reversal, filtering and scaling with depth. The parameters of the neural network were adjusted during the training process iteratively by minimizing the difference between the predicted and the desired outputs in L_2 sense using Adam Optimizer.

The problem of noise removal can be approached in different ways. One approach is to train the network to estimate the noise from the given image, then the resulting clean image is obtained by subtracting the estimated noise. Alternatively, one can estimate the signal directly. We chose the latter approach to make predictions of the signal since we retain the majority of the structure of the input image after the de-noising.

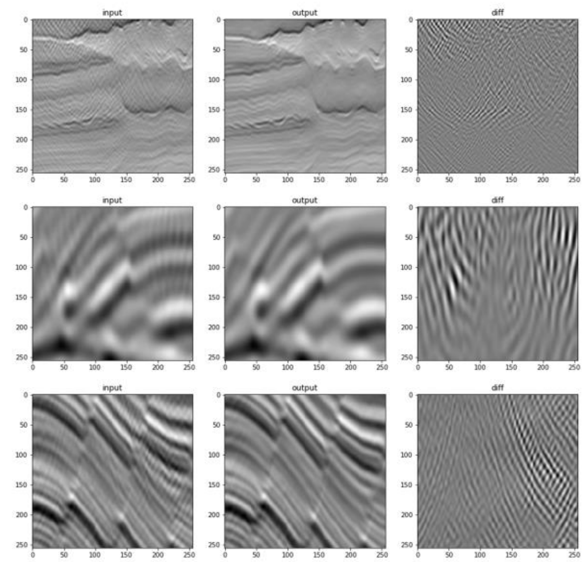

Figure 2: Training data examples: left column – input to the neural network (noisy image); middle column – desired output from the neural network (clean image); right column – difference between desired output and input (noise)

A common problem of machine learning algorithms is overfitting – the phenomenon when a model may show great accuracy and performance on the data that were used for training but produce undesirable results on unseen data. This typically happens when the capacity of the model is too large compared to the diversity of the dataset that is used for building that model. For the case of neural networks, this situation manifests itself when there are too many model parameters. The model provides a great flexibility and approximation power, but the amount and variability of the data given to it is not enough to constrain the weights without regularization. As a result, the network makes unreasonable predictions for any data that differs from the training set. As a precaution, we can split the input dataset into training and validation parts and monitor the model performance on both. A gradual decrease of the loss function for both training and validation datasets implies reasonable generalization, assuming fair selection of the validation dataset. During the training step we carefully monitored the behavior of the objective function for both training and validation datasets, assuring the proper behavior.

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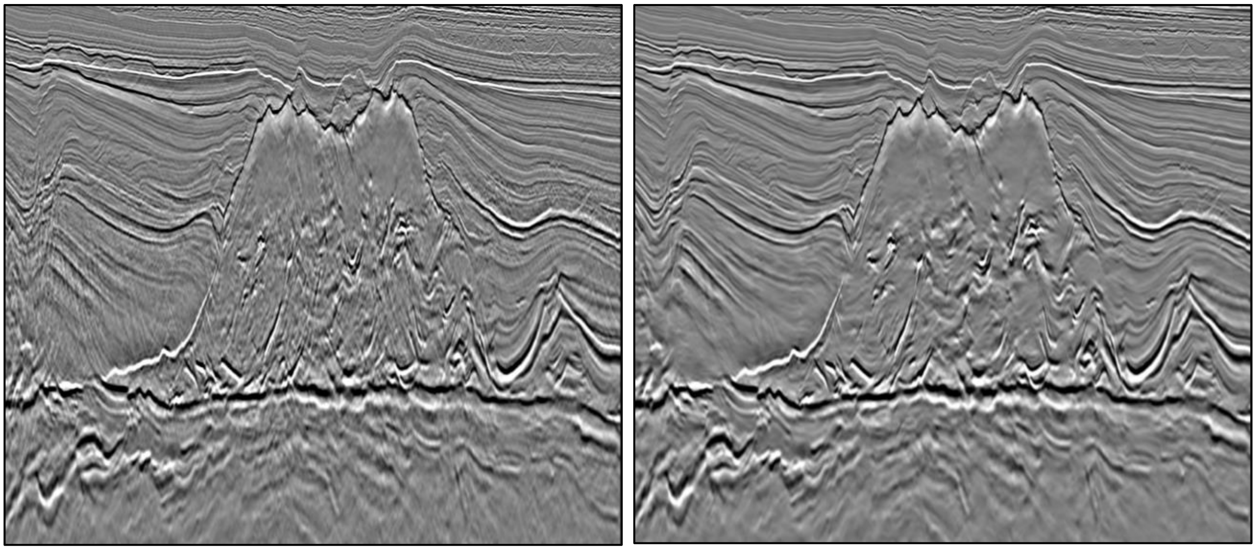

Figure 3: Field data example from offshore Brazil: migration results (left) and de-noised image (right)

Field data application

We evaluate the model performance on field data examples from three different geographical regions.

The first example from offshore Brazil (Figure 3) demonstrates the ability of the neural network to attenuate the unwanted migration isochrones without visible damage to image quality and resolution. The neural network can eliminate the migration artifacts that are seen in the shallow section and are also present in the deep part of the input image.

In other examples from the Gulf of Mexico (Figures 4 and 5), the coherent noise distorts seismic reflectors making interpretation challenging. The output from the neural network is easier to analyze since most of the unwanted energy has been eliminated from the image.

In a North Sea example shown on Figure 6, the input to the neural network is contaminated by coherent migration artifacts due to the presence of an unconformity. The neural network can reduce the noise, clearing the image above the unconformity while preserving the geological integrity of the image.

All examples demonstrate a potential of the neural network to generalize outside the training dataset.

Conclusions

We propose the use of a convolutional neural network for migration artifact attenuation. Successful applications to field data from different geological settings suggest that the model can be trained only once on properly generated synthetics and generalized for application to imaging projects from various geological regimes and different acquisition scenarios. This new approach can significantly reduce turnaround time while improving quality of the final image.

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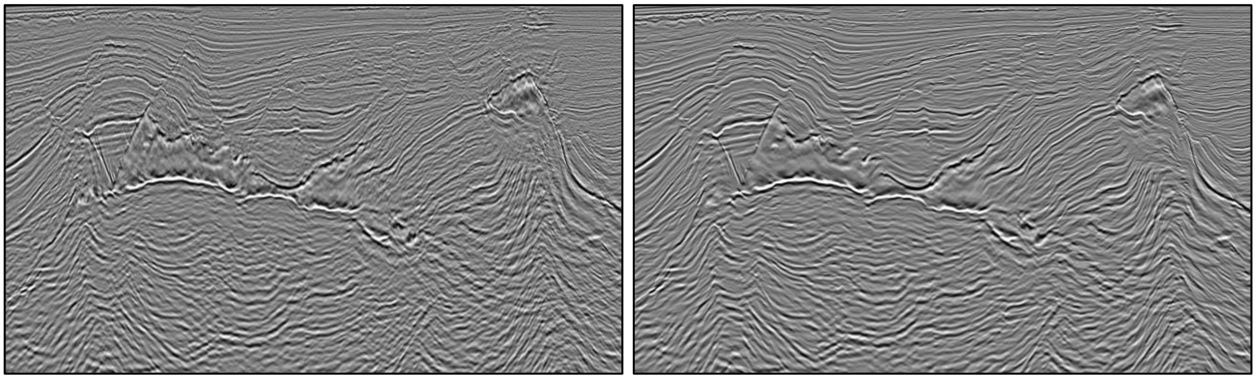

Figure 4: Field data example from the Gulf of Mexico: migration results (left) and predicted de-noised image (right)

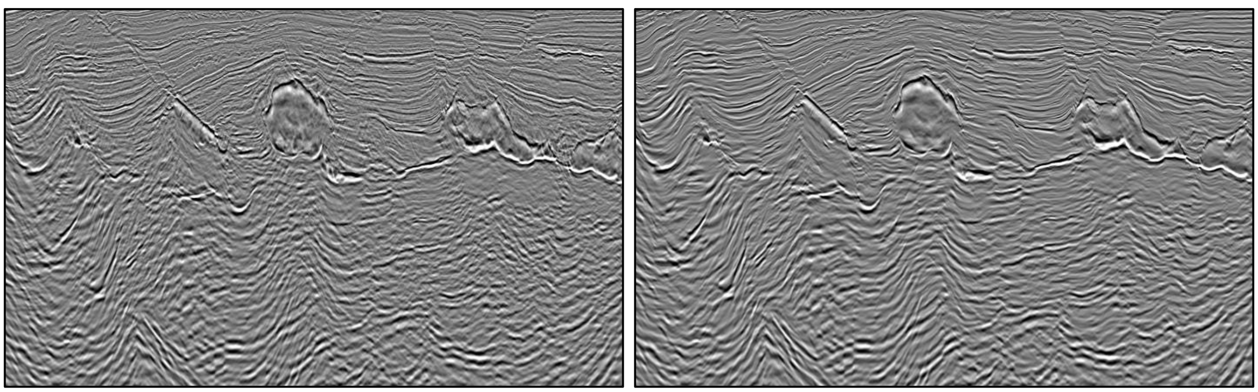

Figure 5: Field data example from the Gulf of Mexico: migration results (left) and de-noised image (right)

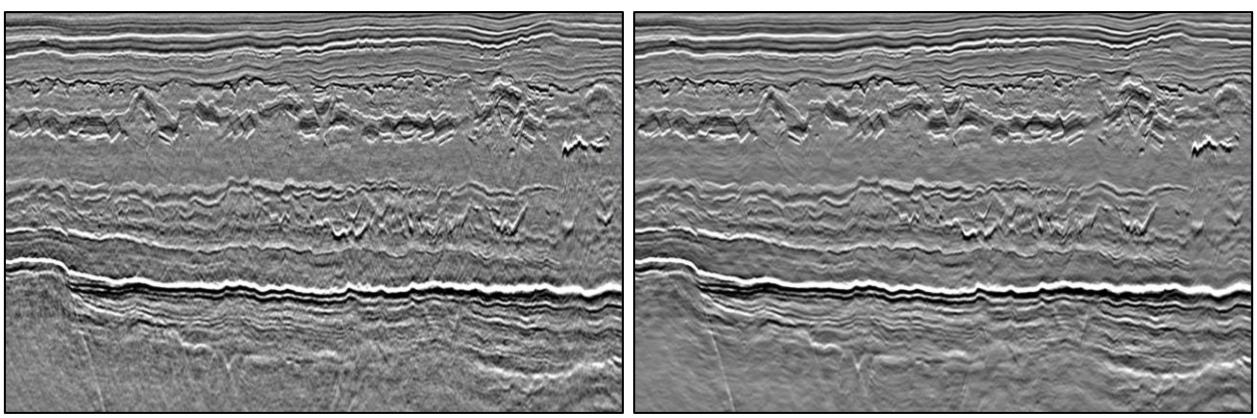

Figure 6: Field data example from North Sea: migration results (left) and predicted de-noised image (right)

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REFERENCES

Alerini, M., and B. Ursin, 2009, Adaptive focusing window for seismic angle migration: Geophysics, **74**, no. 1, S1–S10, doi: https://doi.org/10.1190/1.3002768.

Chemingui, N., and B. Biondi, 2002, Seismic data reconstruction by inversion to common offset: Geophysics, **67**, 1575–1585, doi: https://doi.org/10.1190/1.1512803.

Fukushima, K., 1980, Neocognitron: A self-organizing neural network for a mechanism of pattern recognition unaffected by shift in position: Biological Cybernetics, **36**, 193–202, doi: https://doi.org/10.1007/BF00344251.

Gardner, G. H. F., and A. Canning, 1994, Effects of irregular sampling on 3-D prestack migration: 64th Annual International Meeting, SEG, Expanded Abstracts, 1553–1556, doi: https://doi.org/10.1190/1.1822836.

Hale, D., 2011, Structure oriented bilateral filtering of seismic images: SEG Technical Program, Expanded Abstracts, 3596–3600, doi: https://doi.org/10.1190/1.3627947.

Klokov, A., and S. Fomel, 2012, Optimal migration aperture for conflicting dips: SEG Technical Program, Expanded Abstracts, 1–6, doi: https://doi.org/10.1190/segam2012-0504.1.

LeCun, Y., B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, 1989, Back- propagation applied to handwritten zip code recognition: Neural Computation, **1**, 541–551, doi: https://doi.org/10.1162/neco.1989.1.4.541.

Ronneberger, O., P. Fischer, and T. Brox, 2015, U-Net: Convolutional Networks for biomedical image segmentation, in Medical image computing and computer-assisted intervention, Springer, LNCS, **9351**, 234–241.

Schonewille, M. A., 2000, Fourier reconstruction of irregularly sampled seismic data: Ph.D. dissertation, Delft University of Technology.

Wang, E., and J. Nealon, 2019, Learning seismic image enhancement from pairs of 3D partial and full image volumes: SEG Technical Program, Expanded Abstracts, 2197–2201, doi: https://doi.org/10.1190/segam2019-3200259.1.

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