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# Abstract

Objectives/Scope: Recently there is a strong focus on developing machine learning based denoising methods. Where conventional algorithms require a priori information and user expertise to select and parameterize the algorithm, the potential benefits of machine learning methods is in the hands-off implementation and ability to learn an efficient denoising algorithm directly from the data itself. In this abstract a novel supervised machine learning algorithm for denoising is introduced. The method is illustrated using a controlled experiment where synthetic modelled data is contaminated with field data noise.

Methods, Procedures, Process: A (deep) convolutional neural network (cnn) is used to remove complex noise from seismic data. For the training phase noisy data and its reference noise-free data (label) is required. During training the various layers of the cnn, where each layer consist of a set of convolutional filters, are trained to form a set of basis functions that can be used to denoise the data. The deeper the layer the more complex these filters will become. This concept relates to conventional methods, but is not restricted to the known basis-functions (fourier, radon, curvelet ..) and the need of experienced users to select these basis functions. To create training pairs, isolated field data noise is selected and added to clean data gathers. After training the network on these data examples, the trained network can be applied to unseen data gathers.

Results, Observations, Conclusions: A controlled experiment illustrates the method. Modelled data is contaminated with field data noise gathers to form the training data pairs. Figure 1 shows the training data with noise-free data in figure 1a and the contaminated data in 1b. The training result is plotted in figure 1c. The trained network is tested on 2 data examples. Both examples use the same modelled data (to mimic real world applications, a different subsurface is used compared to the training data). The reference noise-free data are plotted in figures 2a and 3a. The examples vary in the noise gathers that are used. The first example (figure 2b) uses the same noise gather that was used in training. To test how the method generalizes, the second example (see figure 3b) uses a different noise content compared to the training data. Since the noise is from a similar distribution, the same trained network can be used. The

denoising results are plotted in figures 2c and 3c. Note how well the noise is suppressed while signal is preserved in both examples.

Novel/Additive Information: A novel denoising algorithm is introduced that utilizes a deep convolutional neural network that automatically learns its denoising algorithm directly from training data examples without specifying a priori user information. The trained algorithm show good performance when applied to unseen noisy data.

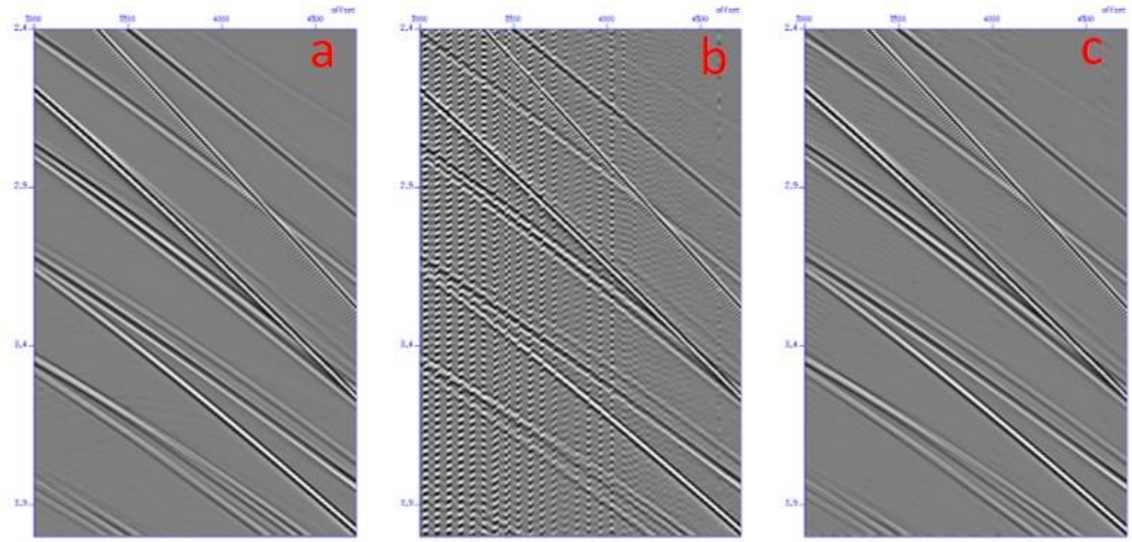


*Figure 1: a) training label, b) training input and c) training result of the convolutional neural network trained for denoising.*

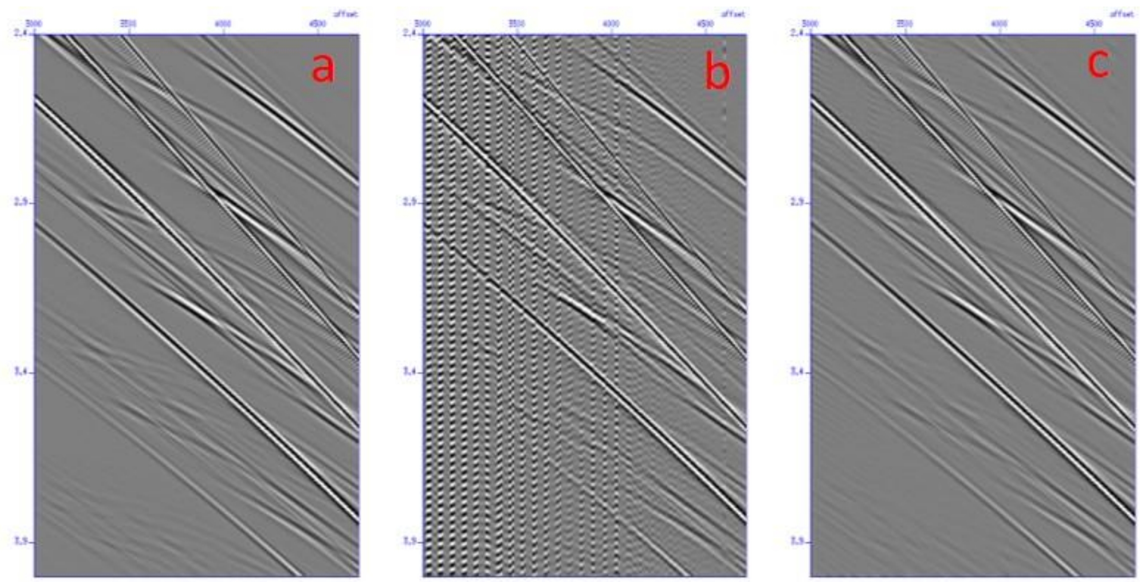


*Figure 2: data example 1 with a) reference data, b) noisy test data and c) denoising result.*

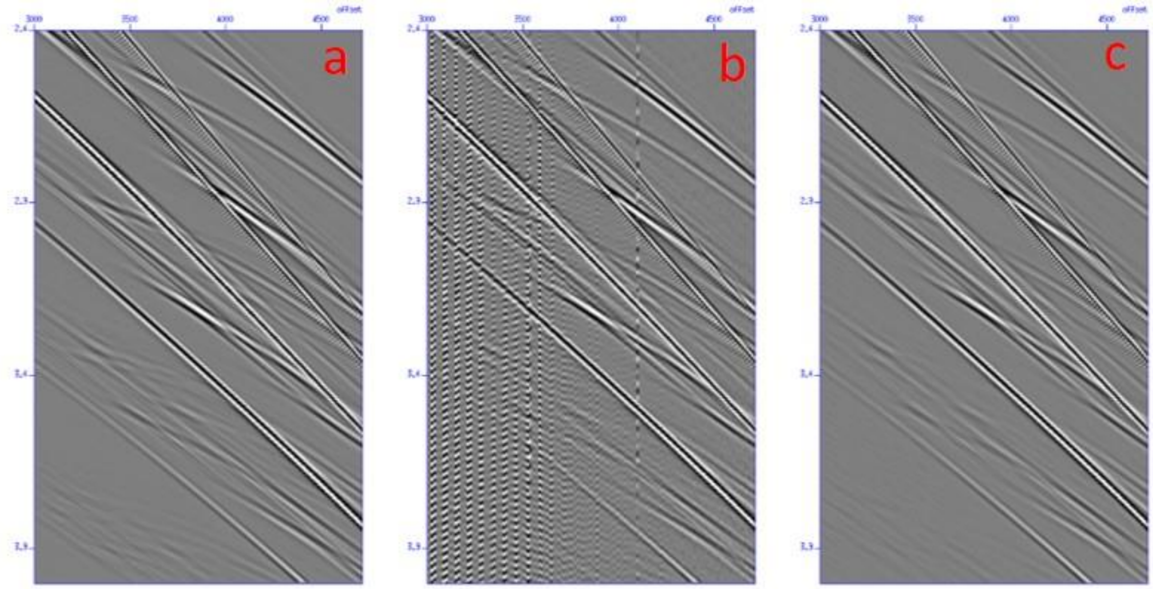


*Figure 3: data example 2 with a) reference data, b) noisy test data and c) denoising result. Compared to the training data, both the modelled data and the noise content is changed. Note that the noise is completely removed while showing very good signal preservation.*