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Please fill in your manuscript title.	A Model-Driven Deep Learning Approach to Seismic Data Deblending

Please fill in your author name(s) and company affiliation.

Given Name	Surname	Company
Wenyi	Hu	Advanced Geophysical Technology, Inc.
Shirui	Wang	University of Houston
Xuqing	Wu	University of Houston
Jiefu	Chen	University of Houston

Abstract

Objective

Simultaneous-source acquisition technology enhances the flexibility of seismic survey and reduces the survey time significantly. However, it relies on accurate deblending algorithms to separate the signals contributed from different sources. We propose a model-driven deep learning network (DNN) approach to solve realistic deblending problems by adaptively updating the training dataset to fit various geological environments without collecting massive amount of labeled data, thus substantially enhance the deblending accuracy.

Methodology and Workflow

Our methodology is based on an iterative workflow shown in Figure 1. The deblending process is initiated by training the DNN using arbitrary synthetic data. The real blended data is then input into the trained DNN to predict the preliminary deblended data, which are enlisted to obtain a velocity model through velocity model building. A new synthetic training data bearing better semblance to the real data is generated on this velocity model for the next round of learning. With the learning iteration proceeds, the deblending accuracy is enhanced and the process converges.

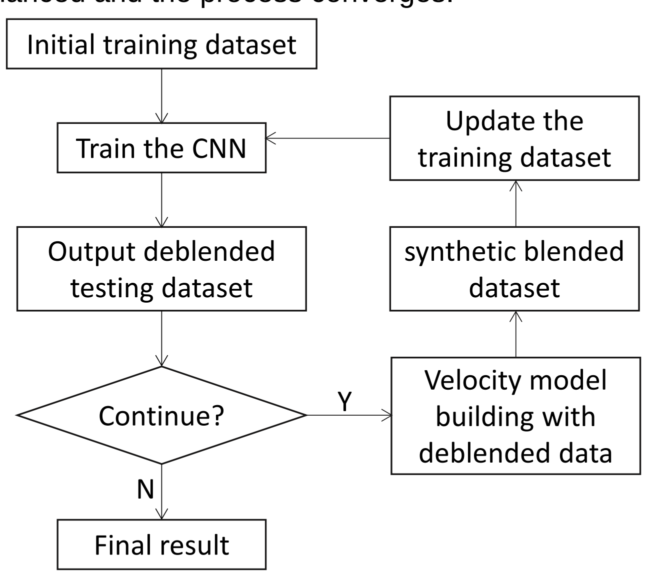

Figure 1. Deblending workflow

Numerical Results

A numerical experiment is implemented to validate the accuracy and robustness of this model-driven deep learning deblending approach. Figure 1b shows the blended data in the common-receiver domain where the signal is coherent while the blending noise is observed as incoherent energy. Figure 2c is the deblended data, which are compared against the ground truth (Figure 2b) to obtain the residual shown in Figure 2d. The first iteration deblending result (Figure 2c) are input into a velocity model building module to produce the subsurface velocity model, which is utilized to generate an updated synthetic training dataset to re-train the DNN. The newly trained DNN is expected to yield better deblending quality due to the higher-level similarity between the new training dataset and the real dataset. After three learning iterations, the deblending results are significantly improved as shown in Figure 3a and Figure 3b.

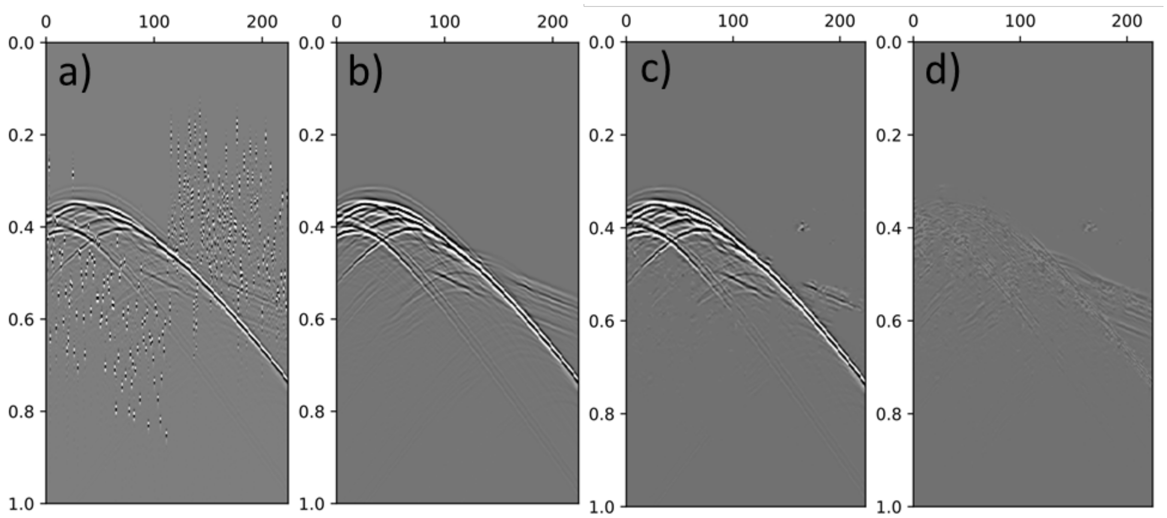

Figure 2. Deblending after one learning iteration: a) blended data; b) ground truth; c) deblended data; d) residual between ground truth and deblended data.

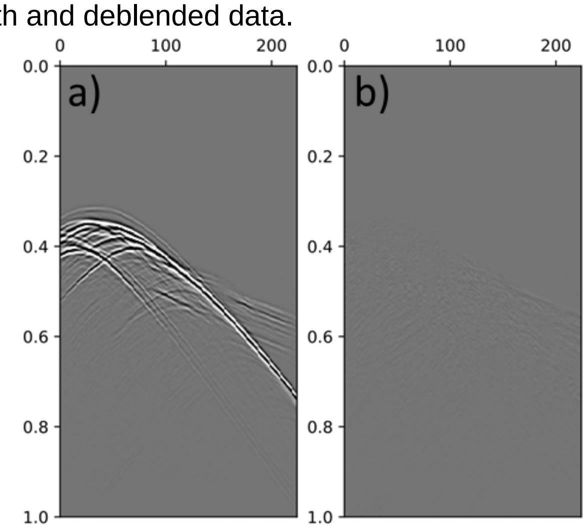

Figure 3. Deblending after three learning iterations: a) deblended data; b) residual between ground truth and deblended data.

Novel and Additive Information

In this work, we proposed an iterative deep learning approach for seismic data deblending applications. Our contribution includes the following novel features: 1) This method is built upon self-supervised learning framework and no manual labeling procedure is required; 2) the DNN model can easily adapt to various datasets and deliver accurate results without endless efforts in mining a large number of labeled training datasets.