Non-stretching NMO correction using deep learning

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SUMMARY

We propose a workflow for non-stretching NMO correction using deep neural networks. The main idea is to train the network using a few gathers to learn mapping from CMP gathers with NMO stretch to the CMP gathers with corrected stretch. The trained network can then be tested on gathers that are not a part of training. We discuss two different ways of creating the training labels. In the first method, we create the target labels by simulating synthetic data close to test data such that the network learns to correct for the NMO stretch on synthetic examples. The trained network can then be tested on different datasets that are not a part of training. In the second method, we create the training labels by correcting the NMO stretching using shaping regularization for the training datasets and test different datasets that are not a part of training. The first formulation aims to improve accuracy of the conventional NMO stretch correction algorithms, whereas the aim of the second approach is to improve the efficiency of conventional NMO stretch correction approaches by circumventing the need for iterative inversion. Such inversion is required with a conventional implementation to correct the NMO stretch using shaping regularization. The proposed approach achieves a higher-resolution stack and mitigates NMO stretch effects. We demonstrate the effectiveness of the proposed algorithm using different examples.

INTRODUCTION

Normal moveout (NMO) correction is a crucial step in seismic data processing workflow to compensate for the effect of offsets and velocity and make all seismograms resemble zero-offset seismograms. The conventional implementation of NMO correction introduces stretching of a wavelet (Buchholtz, 1972), which occurs because of the monotonic increase of velocity along with depth and the dependence of theoretical curves on zero offset (Kazemi and Siahkoohi, 2012). Stretching is severe for initial arrivals and diminishes for later arrivals. To prevent the degradation of resolution due to stretching, some traces after a certain offset need to be muted, which affects frequency content of the stack image (Dunkin and Levin, 1973; Miller, 1992). Because of the stretching limitation of conventional NMO corrections, large aperture traces are muted, eventually affecting velocity analysis and stacking process (Perroud and Tygel, 2004). Additionally, muted traces that correspond to the shallow reflectors can also affect the search for subtle traps (Noah, 1996).

Several algorithms have been developed to address the NMO stretching issue. Rupert and Chun (1975) divided traces into blocks and applied fixed NMO correction within each block to form an NMO-corrected gather. Claerbout (1992) treated NMO and stack as inverse processes and combined them into a single step by using iterative least-squares optimization to solve simultaneous equations for constant velocity cases. Sun (1997) extended Claerbout's idea to depth-variable velocity cases. Shatilo and Aminzadeh (2000) proposed a constant NMO for a finite time interval of seismic traces. Trickett (2008) combined the block NMO correction idea (Rupert and Chun, 1975) and inverse NMO stack (Claerbout, 1992) to perform NMO correction without stretch. Ma et al. (2015) implemented a stacking workflow using a sparse inversion algorithm motivated by compressive sensing. da Silva et al. (2015) proposed a recursive stacking approach using local slopes to compute a stack without stretching. Regimbal and Fomel (2015) reduced the NMO stretching effects using shaping regularization.

In this work, we propose a novel approach to automating the non-stretching NMO correction workflow using deep neural networks. We present two different formulations to create training labels. The first approach trains the network using true target labels and the second approach creates target labels using shaping regularization (Fomel, 2007; Regimbal and Fomel, 2015). Both approaches aim to extract more information from different offsets by performing NMO correction without stretch, thereby optimizing CMP stacking and enhancing resolution of the final stacked section. We test the proposed approach using different examples.

IMPLEMENTATION OF PROPOSED ALGORITHM

We implement a deep neural network architecture based on Generative Adversarial Networks (GANs) (Goodfellow et al., 2014; Zhu et al., 2017), which are a type of generative models. The GAN framework consists of a generator network (*G*), which learns to map from input distribution to target distribution, and a discriminator network (*D*), which outputs probability between 0 and 1 corresponding to a sample being real or generated by a generator. *G* and *D* are trained in a joint framework corresponding to a minimax game between *G* and *D*, where *G* maximizes the probability of *D* making a mistake (Goodfellow et al., 2014). *G* samples the input distribution consisting of NMO corrected gathers with stretch, and maps it to the target distribution consisting of NMO corrected gathers without stretch. *D* classifies the probability of a sample being real or generated by the generator. The adversarial network uses loss functions to constraint the mapping from input domain to target domain (Kaur et al., 2019).

Training labels for the target domain, which is the NMO-corrected CMP gather without stretch effects, can be generated in two different ways. In the first formulation, we simulate the data (which we call *reference gathers*) and apply inverse NMO correction to get the CMP gathers. Next, we correct for NMO using conventional implementation, which leads to NMO stretch. We train the network to learn the mapping between the NMO-corrected gather with stretch and the reference gather such that the network learns to correct for the stretch. The trained network can then be used on the test datasets that are not a part of

10.1190/segam2021-3580806.1

training to correct the stretch. In the second formulation, we create the training labels using shaping regularization, which maps the input model $\mathbf{m}$ to the space of acceptable function, where mapping is controlled by the shaping operator integrated in an interactive inversion algorithm (Fomel, 2007). In linear case, the estimated model using shaping regularization is given by:

$$\mathbf{m} = [\mathbf{I} + \mathbf{S_m}(\mathbf{BF} - \mathbf{I})]^{-1}\mathbf{S_m}\mathbf{Bd}], \tag{1}$$

where $\mathbf{F}$ and $\mathbf{B}$ are the forward operator (applies inverse moveout by spraying along hyperbolas) (Regimbal and Fomel, 2015) and the backward modeling operator (applies NMO correction and stack with stacking implemented recursively to minimize distortions) (Regimbal and Fomel, 2016), $\mathbf{d}$ is the input data, $\mathbf{S_m}$ is the shaping operator, and $\mathbf{m}$ is the desired zero-offset trace. NMO stacking using shaping regularization recovers extra bandwidth in the zero-offset trace by using signals from different offsets. The final solution is obtained by using a generalized minimum residual algorithm to perform linear inversion in Equation 1 (Regimbal and Fomel, 2015).

NUMERICAL EXAMPLES

For training and validation of the algorithm we generate 100 CMP gathers. We add amplitude variation with offset (AVO) effects to the CMP gathers where amplitude increases linearly with offset. For training and testing, we divide the CMP gathers into patches of 128×128 samples. In terms of patches, we use 480 patches for training and 4,320 patches for testing. One of the test CMP gathers with AVO effects is shown in Figure 1a. Conventional NMO correction leads to stretching of events in the shallow section and larger offsets as shown in Figure 1b. The output using the proposed method is shown in Figure 1c is close to the reference gather shown in Figure 1d. To further analyze the output using the proposed method, we plot the amplitude spectrum in Figure 1e, where red, blue, and green lines indicate the spectrum of the stacked section using the proposed method, reference gather, and conventional NMO-corrected gather. To test the robustness of the proposed algorithm with a more realistic noisy case, we add noise to the test CMP gather shown in Figure 1a to obtain the noisy gathers with one of the test gathers shown in Figure 1f. With conventional implementation, NMO corrected gather suffers from an NMO stretching issue as shown in Figure 1g. Output using the proposed method shown in Figure 1h is free from NMO stretching effects and shows that the proposed algorithm is robust in the presence of noise. Further, we plot the amplitude spectrum in Figure 1i, where red, blue, and green lines indicate the spectrum of the stacked section using the proposed method, reference gather, and the conventional NMO-corrected gather.

In the second formulation, we create training labels using shaping regularization (Regimbal and Fomel, 2015). The algorithm makes use of the linearity of the shaping operator, applies it to each trace of the CMP gather and outputs the shaping stacks, which are concatenated to extract the effective NMO gather (Regimbal and Fomel, 2015). We use five iterations with relative misfit tolerance of 10^{-5} of generalized minimum residual method (GMRES) to obtain the NMO-corrected gather without stretching. We train the network to learn the mapping between the NMO-corrected gather with stretch effects and NMO-corrected gather without stretch effects generated using shaping regularization. Similar to the previous example, we divide the CMP gathers into patches of 128×128 samples. In terms of patches, we use 480 patches for training and 4,320 patches for testing that are not a part of training. One of the test CMP gathers is shown in Figure 2a, with the conventional NMO correction with stretch shown in Figure 2b. With conventional implementation, the stretch needs to be removed by muting. The NMO-corrected gather after muting is shown in Figure 2c. The output using the proposed method is shown in Figure 2d, which is free of the NMO stretch and is close to the output using the shaping regularization Figure 2e. An advantage of using the proposed method is that, other than training labels, the proposed workflow circumvents the need for iterative inversion for each CMP gather, as required by the conventional implementation of shaping regularization. Comparison of the amplitude spectrum is shown in Figure 2f, where green, red, and blue lines indicate the spectrum of output using the conventional NMO stack, proposed method, and shaping regularization output, respectively. The conventional stack fails to recover frequencies between 110-170Hz whereas the proposed algorithm has recovered the high-frequency content and the output is close to the stacked output using shaping regularization. By creating training labels using the second formulation i.e. shaping regularization, we circumvent the need for iterative inversion for each CMP gather. The proposed framework learn weights between the NMO-stretched gather and the stretch corrected gather using shaping regularization. The learned weights can then be applied to the test gathers without the need for iterative inversion.

CONCLUSIONS

We have introduced a novel way of performing non stretching NMO correction using a deep neural network-based framework. Using different synthetic examples, we demonstrate that the proposed algorithm mitigates the NMO stretch to a great extent and restores the frequency content of the zero-offset trace. We evaluate the performance of the proposed method by comparing it to a conventional NMO correction, and stacking workflow. Using the proposed algorithm, larger offsets can be retained that, under conventional NMO correction, need to be muted to remove the NMO stretch. The proposed method avoids the undesirable NMO stretch, restores a wider frequency bandwidth, and leads to a better stack than that of conventional NMO correction workflows. It can therefore can be used for improved velocity determination. We used synthetic data to prove the concept but we plan to verify the applicability of the proposed approach on field data.

ACKNOWLEDGMENTS

We thank the sponsors of Texas Consortium of Computational Seismology for financial support.

10.1190/segam2021-3580806.1

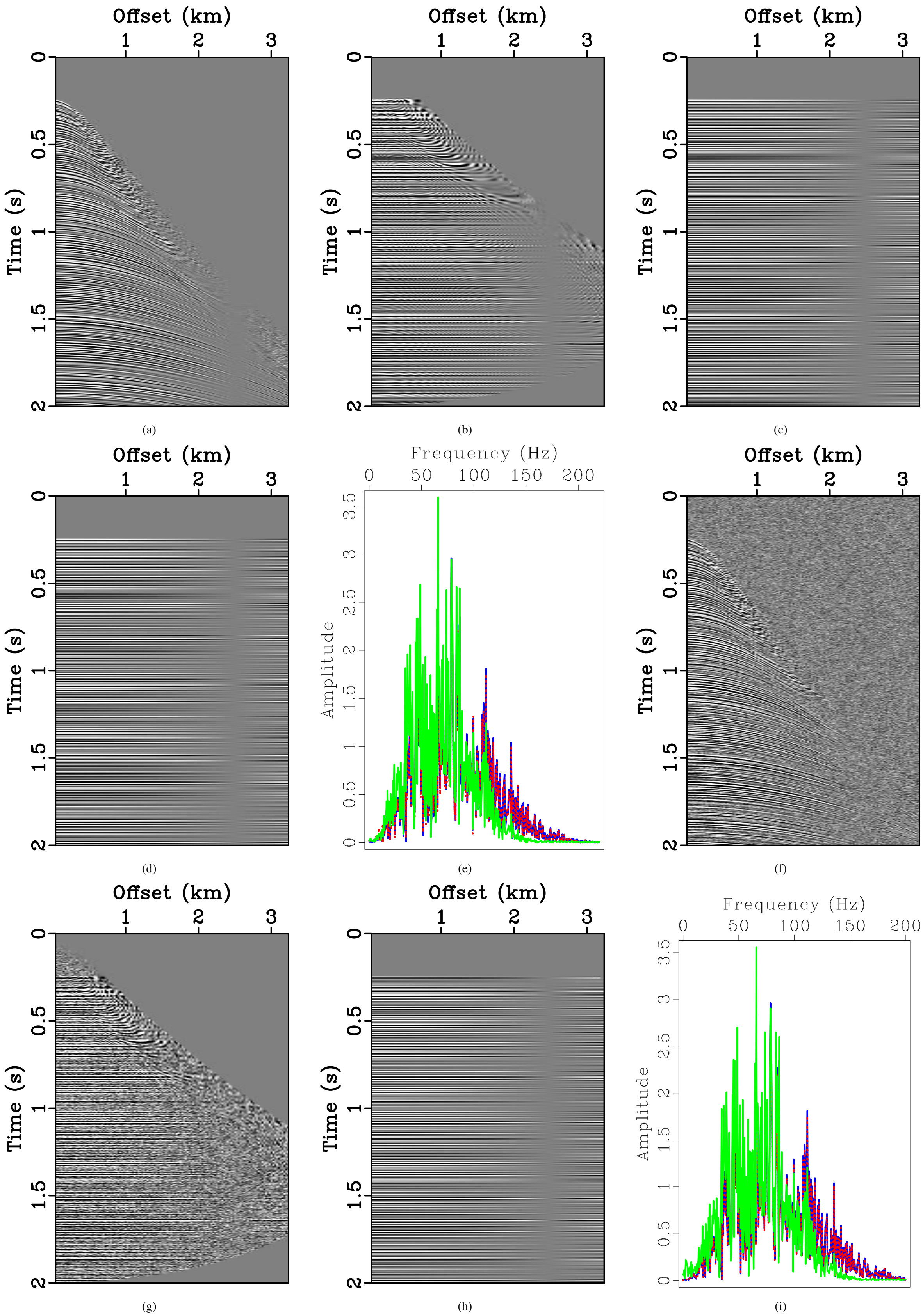

Figure 1: One of the test gathers. (a) CMP gather with AVO. (b) Conventional NMO correction with stretch. (c) NMO-corrected gather using the proposed method. (d) Reference gather. (e) Amplitude spectrum, where green, red, and blue lines indicate the spectrum of output using the conventional NMO stack, proposed method, and reference stack, respectively. (f) CMP gather with AVO and noise. (g) Conventional NMO correction with stretch. (h) NMO-corrected gather using the proposed method. (i) Amplitude spectrum for noisy gather, where green, red, and blue lines indicate the spectrum of output using the conventional NMO stack, proposed method, and reference stack, respectively.

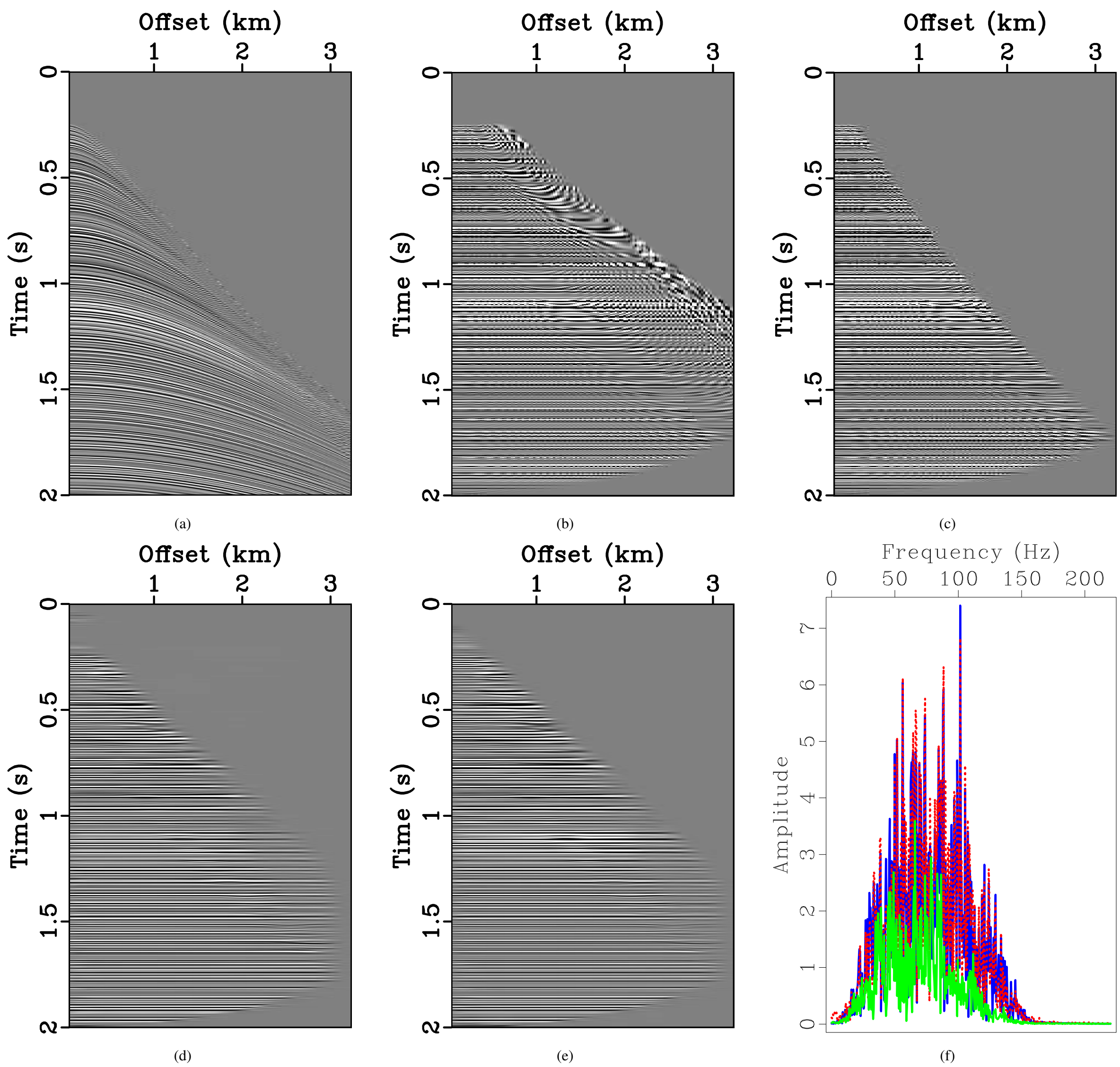

Figure 2: One of the test gathers. (a) CMP gather. (b) Conventional NMO correction with stretch. (c) Conventional NMO with stretch muting. (d) NMO-corrected gather using the proposed method. (e) NMO-corrected gather using shaping regularization. (f) Amplitude spectrum, where green, red, and blue lines indicate the spectrum of output using the conventional NMO stack, proposed method, and shaping regularization output, respectively.

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