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An AMME approach based in neural network

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Abstract

Marchenko multiple elimination (MME) is a data-driven scheme capable of attenuating internal multiples of all orders, provided that the seismic data amplitudes are correctly normalized using an optimal global scale factor (SF). MME tends to be inefficient when the optimal SF is unknown, highlighting its dependence on a SF. This work combines the MME scheme with an adaptive filter based on a U-Net neural network to reduce this dependence. The results prove that the proposed approach effectively removes internal multiples even when the optimal SF is unavailable.

Introduction

Although internal multiples generally exhibit lower energy than primary reflections, they can lead to the generation of strong artifacts in seismic images. To address these artifacts, Zhang e Staring (2018) modified the projected Marchenko equations to develop a fully data-driven multiple elimination scheme. This algorithm, known as Marchenko Multiple Elimination (MME), has been tested in various scenarios and has proven to be a robust tool for eliminating internal multiples when seismic data satisfies its requirements.

One of the requirements for using MME is the proper balance of the input data amplitudes, which can be achieved by applying an optimal global scale factor (SF). Santos et al. (2022) demonstrated the dependence of MME on data amplitudes by showing that even a slight disturbance to them tends to significantly reduce their effectiveness. Thus, the use of MME is conditioned on the ability to estimate a value sufficiently close to the optimal scale factor, which is not always possible. To overcome this limitation, Santos et al. (2023b) developed an MME scheme formulated as an adaptive filter-based sum, called AMME. This scheme was tested in a numerical example using an adaptive filter based on non-stationary regression (Fomel, 2009), and it was shown that AMME can be applied even without prior knowledge of the optimal scale factor. Although this method removes the dependence on the scale factor, it is highly sensitive to the adaptive subtraction method employed. Thus, in this work, we present a version of AMME that incorporates U-Net-based adaptive subtraction (Souza et al., 2023) and compare it with the version that uses nonstationary regression in a numerical example.

Theory

The Marchenko multiples attenuation scheme is based on evaluating the solution of the projected version of the revised Marchenko equations, as presented by (Santos et al., 2023a):

$$\overline{R}_t(\mathbf{x}_0'', \mathbf{x}_0', \ t_2) = \underbrace{\overline{R}(\mathbf{x}_0'', \mathbf{x}_0', \ t_2)}_{\text{Measured data}} + \underbrace{\overline{R}_O(\mathbf{x}_0'', \mathbf{x}_0', \ t_2, \ t_2)}_{\text{Opposing events}}, \tag{1}$$

where $\overline{R}$ represents the recorded reflection response, $\overline{R}_t$ the multiples-free reflection response, and the opposing events are calculated by $\overline{R}_O(\mathbf{x}_0'', \mathbf{x}_0', t, t_2) = (\Theta \mathbf{R} \overline{v}_m^+)(\mathbf{x}_0'', \mathbf{x}_0', t, t_2)$ with $\overline{v}_m^+$ obtained by solving the projected Marchenko equations system:

$$\begin{cases} \overline{v}^-(\mathbf{x}_0', \ \mathbf{x}_0'', \ t, \ t_2) = \left(\Theta \mathbf{R} \overline{\delta} + \Theta \mathbf{R} \overline{v}_m^+\right)(\mathbf{x}_0', \ \mathbf{x}_0'', \ t, \ t_2), \\ \overline{v}_m^+(\mathbf{x}_0', \ \mathbf{x}_0'', \ t, \ t_2) = \left(\Theta \mathbf{R}^* \overline{v}^-\right)(\mathbf{x}_0', \ \mathbf{x}_0'', \ t, \ t_2) \end{cases} \tag{2}$$

where Θ is a truncation operator to exclude values outside the window (ϵ, $t_2 - \epsilon$), being ϵ a positive value to account for the finite bandwidth. The terms $\mathbf{R}$ and $\mathbf{R}^*$ represent the multidimensional convolution and correlation operators, $\overline{v}_m^+$ and $\overline{v}^-$ are the projected focusing functions, and t_2 represents the two-way travel time from the acquisition surface $\partial\mathbf{D}_0$ to a fictitious reflector at horizon $\partial\mathbf{D}_i$. When the reflection response is regularized by an optimal global SF, the amplitude of events in $\overline{R}_O$ will agree with the multiples in $\overline{R}$, and the summation defined by Equation (1) will eliminate the internal multiples, making $\overline{R}_t$ the multiple-free primary reflections for a time t_2, thus summarizing the MME. But if the used SF is not optimal, the events in $\overline{R}$ and $\overline{R}_O$ are not in tune, and the attenuation will not be effective. Since it will not always be possible to obtain the ideal scale factor, Santos et al. (2023a) reorganized Equation (1) to present the Marchenko multiples attenuation based on an adaptive filter scheme (AMME). This approach is applied on a shot-by-shot basis in two steps: first, we predict $\overline{R}_O$; afterwards, an adaptive filter is used to sum them with $\overline{R}$, generating the multiples-free data:

$$\underbrace{\overline{R}_t(\mathbf{x}_0'', \mathbf{x}_0', t)}_{\text{Multiples-free}} = \underbrace{\underbrace{\overline{R}(\mathbf{x}_0'', \mathbf{x}_0', t)}_{\text{Measured data}} + \Big[\underbrace{\overline{R}_O(\mathbf{x}_0'',\ \mathbf{x}_0',\ t)}_{\text{Opposing events}}\Big]}_{\text{Adaptive filtering}} . \tag{3}$$

Thus, as the tuning of $\overline{R}$ and $\overline{R}_O$ is achieved through adaptive filtering, the optimum SF is no longer relevant; instead, it is the adaptive filtering strategy that matters.

Adaptive filtering based on nonstationary regression

In this alternative, AMME uses the filter ξ to tune opposing events, i.e., $\overline{R}_O = \xi\overline{R}_O$, where this filter is estimated by nonstationary regression (Fomel, 2009), given by the solution of the following problem:

$$\mathbf{F}(\xi) = \underset{\xi}{min}\Big(\underbrace{\overline{R}(\mathbf{x}_0'', \mathbf{x}_0', t)}_{\text{Measured data}} + \xi\Big[\underbrace{\overline{R}_O(\mathbf{x}_0'',\ \mathbf{x}_0',\ t)}_{\text{Opposing events}}\Big]\Big), \tag{4}$$

AMME based on adaptive subtraction using U-Net

Here, the AMME uses adaptive filtering based on U-Net architecture (Souza et al., 2023) by solving a supervised learning problem in which the input data are 2D data windows of size n extracted from the modeled multiples ($\overline{R}_O$), and the labels are 2D data windows from the seismic data containing both primary and multiple events ($\overline{R}$). The method solves a regression problem using a loss function based on the regularized L_1 norm (Li et al., 2021):

$$L(\Phi) = \sum_{i=1}^{S} \left[||\mathbf{D}_i - U(\bar{\mathbf{M}}_i; \Phi)||_1 + \mu||\Phi||_2^2 \right] . \tag{5}$$

where $\mathbf{D}_{n\times n}$ represents $\bar{R}$, $\bar{\mathbf{M}}_{n\times n}$ denotes $\bar{R}_O$ and $U(\bullet)$ represents the U-Net network with parameters Φ (kernel coefficients and bias), and μ is the regularization factor. The term S represents the batch size, or the number of windows used simultaneously in updating the network parameters.

The method trains a single U-Net network for all windows, and the learned filters are used to predict the amplitudes of the true multiples model to retrieve multiple-free data.

Results

The more distant the used SF is from the optimal one, the less effective MME becomes in attenuating the internal multiples. To support this statement, we reproduce the numerical experiment presented by Santos et al. (2023b), using the velocity and density models presented in Figures 1a and 1b, respectively, and compute the shots with a finite-differences scheme (Thorbecke e Draganov, 2011). We modeled the shot gathers presented in Figures 1c and 1h, where red arrows indicate the generated internal multiples. Then, we apply the MME and AMME schemes using both adaptive filtering approaches. Figures 1d and 1i show the results of MME, Figures 1f and 1k show the results of AMME with non-stationary filtering, and Figures 1g and 1l show the results of AMME with U-Net filtering. In this experiment, although the optimal SF is known, it is not used. For this reason, the opposite events shown in Figures 1e-1j have low amplitudes compared to the true multiples indicated in Figures 1c-1h. In Figures 1c and 1l, white arrows indicate the multiples that were correctly removed, while orange arrows indicate cases where the attenuation was not effective. The blue arrows indicate noise that was created or increased after applying the schemes. As expected, the absence of the

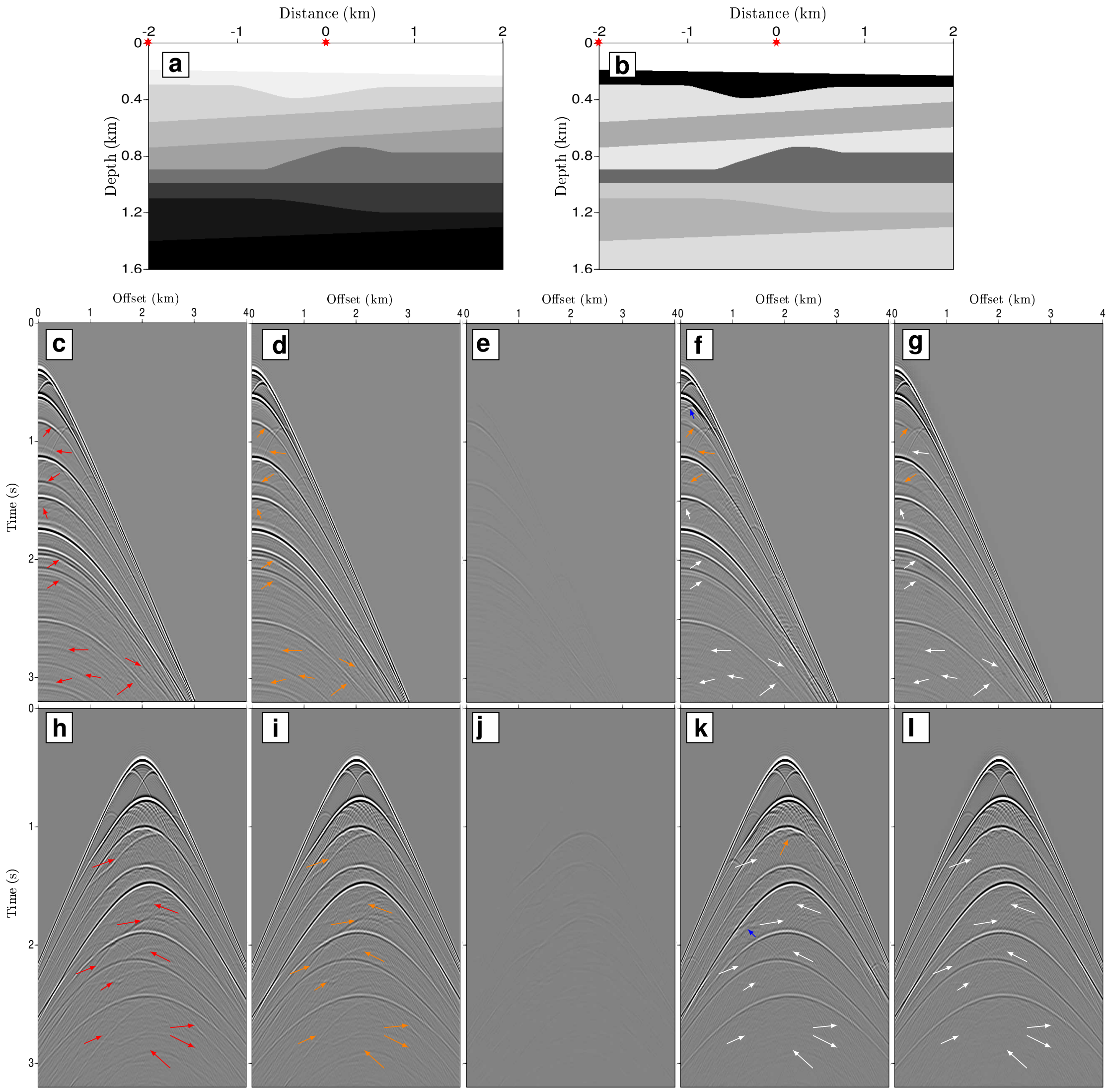

Figure 1: Velocity and density models in a) and b), respectively. c) and h) show the modeling response for the sources at the positions of the red stars of this model. d) and i) show the retrieved opposing events, and e) and j) show MME results for these shot-gathers. In f) and k), the AMME with a non-stationary filter, and g) and l), the AMME based on U-Net. Red arrows point to internal multiples, white arrows show that these events are removed after applying the schemes, and blue arrows are to indicate created noises. The orange arrows indicate noises that persist in the final output of the method.

optimal SF made MME unable to eliminate noises, as indicated by the orange arrows in Figures 1d and 1i, while AMME attenuated most of the events. When comparing the filtering schemes used in AMME, it can be noted that the U-Net approach effectively eliminates the noise, while the non-stationary approach leads to the generation of noise as indicated by the blue arrows, which persists in the final output of the method.

Conclusions

In this work, we present an AMME approach using an adaptive filter based on U-net networks and compare it with the AMME version that employs a non-stationary filter. In the numerical test presented, we showed that the MME scheme becomes ineffective without the use of the optimal SF, whereas AMME overcomes this limitation. The choice of the adaptive filtering strategy strongly influences the performance of AMME. The results indicate that U-Net filtering adapted better to the problem, producing satisfactory results without introducing any noise. Thus, the presented approach constitutes a viable alternative for internal multiple attenuation.

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