A practical approach for Multi-Dimensional Deconvolution of Seismic-While-Drilling data

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Summary

Seismic-while-drilling (SWD) provides a cost-effective solution to subsurface imaging by utilizing the drill-bit noise as a source of seismic energy. However, retrieving an accurate virtual reflection data from SWD waveforms is challenging due to the erratic and unknown nature of the source signature. We propose a novel approach for multi-dimensional deconvolution (MDD) of SWD data that generates data free of surface-related multiples, corresponding to virtual sources located on the Earth's surface. A key component of our approach is the direct arrival estimation and removal process based on the particle swarm optimization algorithm, which optimizes an initial traveltime curve by maximizing the energy of a flattened and stacked seismic recording. Moreover, to keep the computational cost of MDD to a reasonable level, the continuous SWD data is divided into smaller segments along the time axis, correlated, and stacked; in other words, we propose to form and solve the normal equations of the MDD problem. Validation on a synthetic dataset demonstrates that the proposed method can produce accurate virtual data and images of the subsurface. The proposed method is finally successfully applied to field dataset acquired in KAUST during a recent drilling campaign.

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Introduction

Seismic-while-drilling (SWD – Poletto and Miranda, 2022) has recently emerged as a cost-effective solution for imaging and monitoring the subsurface without requiring an active seismic source. SWD uses the noise produced by the drill bit during drilling as a continuous seismic source, and by placing sensors at the Earth's surface to record the resulting seismic wavefields, we can utilize such energy to image the subsurface. Although SWD data illuminate mainly the subsurface area near the wellbore (Goertz et al, 2020), they can also be used to reconstruct virtual reflection seismic data by means of seismic interferometry, which can be used to image the shallow subsurface (Asgharzadeh et al, 2019). However, cross-correlation or single-channel deconvolution-based seismic is unable to correctly handle free-surface multiples, therefore producing non-physical artifacts in the resulting imaging products. Multi-dimensional deconvolution (MDD – Wapenaar et al, 2011) can overcome these limitations and improve the overall Green's function retrieval process.

In this study, we propose a new approach for multi-dimensional processing and deconvolution of SWD data. This method relocates sources from within the well to the Earth's surface, therefore retrieving a local reflection response free of surface-related multiples and source signature effects. Some of the key challenges faced in this setting include the need to isolate and remove the direct arrivals of the recorded wavefield and to deconvolve long continuous recordings (typically lasting several minutes). We develop a data-driven approach based on a global optimizer to extract the direct arrival, whilst we construct the normal equations of the MDD problem to reduce the time length of the dataset to be processed, ultimately enabling the practical application of MDD for SWD data.

Method

Multi-Dimensional Deconvolution for SWD data

Given the acquisition geometry in Figure 1a, we consider here the source-side MDD formulation (Vidal and Wapenaar, 2014; Boiero et al, 2023), where the total wavefield (d) is convolved with the local reflection response (r) to generate the total wavefield without the direct arrival ($d - d_d$):

$$d(\mathrm{x}_R^{'}, \mathrm{x}_S, t) - d_d(\mathrm{x}_R^{'}, \mathrm{x}_S, t) = \int_{\Lambda_R} d(\mathrm{x}_R, \mathrm{x}_S, t) * r(\mathrm{x}_R^{'}, \mathrm{x}_R, t) d\mathrm{x}_R, \quad (1)$$

where $*$ refers to the convolutional operator in the time domain. By solving equation 1 for r, we can effectively relocate sources from within the well to the same position as surface receivers and retrieve a local reflection response deprived of surface-related multiples and source signature effects.

Pre-processing of SWD data for applying MDD

In order to be able to apply equation 1 to SWD data, the direct arrival must be removed from the recorded wavefield. Unlike in traditional active seismic experiments, the source signature of SWD data is random and usually unknown (unless a sensor is placed near the drill bit); this makes the identification and separation process challenging. To address this problem, we propose to use a global optimization method such as particle swarm optimization (PSO − Bonyadi and Michalewicz, 2017) to identify the travel time curve from source to receiver $\tau(x_r)$ that best aligns the data. More specifically, we start by flattening and stacking the recorded data using an initial travel time curve $\tau_0(x_r)$ computed from a constant (or smoothly varying) velocity model; this is then improved within the PSO algorithm by randomly perturbing the travel time for one of the traces with an additional time shift in order to maximize the squared L2 norm of the sum of the aligned common-shot gather (CSG). To ensure smooth variations in the travel time curve, a regularization term is used to constrain the time-shift differences between adjacent traces. The optimization process is represented by the following objective function:

$$\arg\min_{\tau(x_r)} -|| \sum_{x_r} d(t - \tau(x_r), x_r)||_2^2 + \alpha \, \|\mathrm{diff}(\tau(x_r))\|_2^2, \quad (2)$$

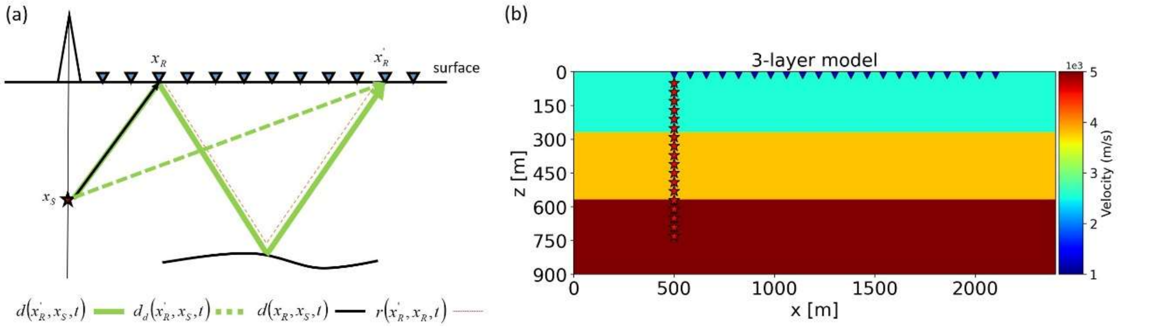

Figure 1 *(a) Schematic representation of the wavefields involved in the SWD geometry, (b) 3-layer velocity model. Red stars represent sources, blue triangles represent receivers.*

where α is a regularization parameter. After optimizing the time shifts, each CSG is first flattened and then stacked into a single trace. This process enhances the direct arrival while suppressing other events (e.g., reflections). The resulting stacked trace is then redistributed over all receivers and shifted back to obtain an estimate of the direct arrival, which is finally removed from the full data using adaptive subtraction.

MDD implementation details

A straightforward implementation of time-domain MDD (Ravasi and Vasconcelos, 2021) to SWD data would require us to repeatedly apply the multi-dimensional convolution operator to the recordings that can last up to several minutes. In order to avoid this, we instead suggest solving the normal equations. In other words, the adjoint of the modeling operator is applied to both sides of equation 1, resulting in the following equivalent MDD formulation:

$$\mathbf{D}^H(\mathbf{d}-\mathbf{d}_d)=\mathbf{D}^H\mathbf{dr}. \quad (3)$$

To create $\mathbf{D}^H(\mathbf{d}-\mathbf{d}_d)$ and $\mathbf{D}^H\mathbf{d}$, the continuous recordings are first divided into smaller segments, typically a few seconds in length, auto-correlation and cross-correlation is performed for each segment and the resulting wavefields are subsequently summed and used as input to the MDD equation. This approach is akin to a conventional processing flow in ambient noise interferometry; however, to the best of our knowledge, it has never been applied in the context of MDD.

Numerical Examples

Synthetic examples

To begin with, we verify the effectiveness of the proposed method by using a 3-layer model as shown in Figure 1b. The dataset consists of 401 surface receivers with 4 m spacing and 351 sources placed inside a vertical well with 2 m spacing. To mimic an SWD dataset, we first model the data with an impulsive source and then convolve the resulting seismic recordings with a source signature composed of 3 minutes of white Gaussian noise (Figure 2a). First, every CSG is processed using the PSO-based alignment method (the final aligned data is shown in Figure 2b). Then the aligned wavefield is stacked and spread across receivers to obtain the estimated direct arrival, which is removed from the original data by adaptive subtraction. The resulting wavefield without the direct arrival is shown in Figure 2c. Next, the 3-minute data are divided into 4-second segments. For each segment, cross-correlation is performed between the original wavefield and the original wavefield without the direct arrival, as well as autocorrelation of the original wavefield. The results of these correlations are then summed to obtain the final input wavefield for MDD, as shown in Figures 2d and 2e. For comparison, another dataset, without free-surface effects and with both sources and receivers at the surface of the Earth is modeled via finite difference (FD) (Figure 2f). We can see that the reflectivity obtained via MDD successfully recovers two reflection responses as shown in Figure 2g, whereas the cross-correlation result (Figure 2h) exhibits more artifacts as indicated by red arrows. Finally, the three reflection responses are imaged by means of pre-stack Kirchhoff depth migration. The MDD image (Figure 3b) closely matches the

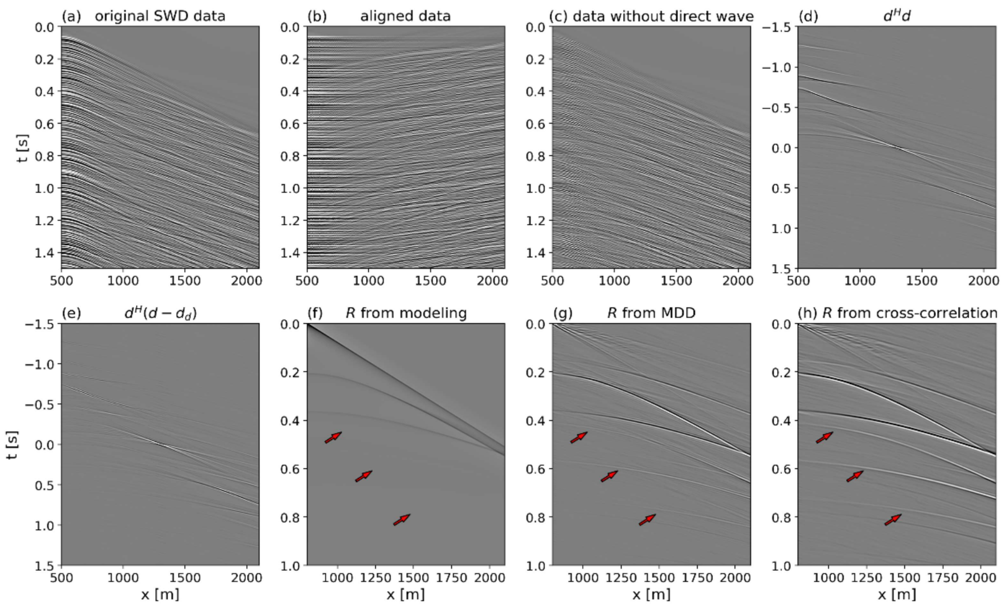

Figure 2 *(a) Original SWD data, (b) aligned wavefield, (c) wavefield without the direct arrival, (d) auto-correlation of the original wavefield, (e) cross-correlation between the original wavefield and the original wavefield without the direct arrival, (f) reflection response modeled via FD, (g) reflection response from MDD, (h) reflection response from cross-correlation.*

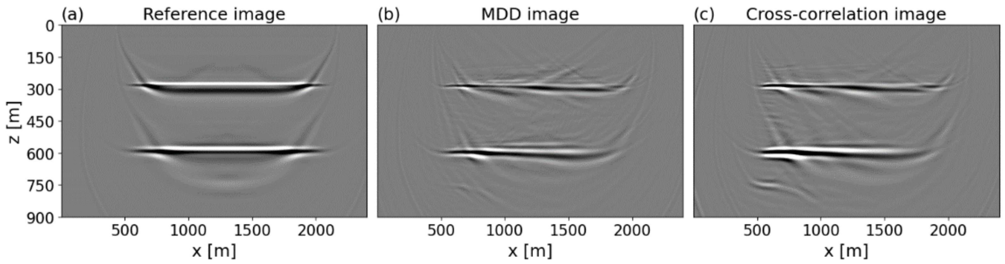

Figure 3 *Imaging results obtained from data modeled using (a) FD, (b) MDD, and (c) cross-correlation.*

reference one (Figure 3a), successfully recovering the two main reflectors and eliminating multiple-related artifacts, which are instead present in the cross-correlation image (Figure 3c).

Field data application

The proposed method is now tested on field dataset acquired within the KAUST campus from a 400 m pilot well drilled for monitoring purposes. 89 STRYDE nodes have been deployed along a 2D line with a spacing of approximately 2 m. We selected 115 source locations based on the drilling reports, as well as the acquisition schedule shown in Figure 4a, each containing 8 minutes of continuous data. The initial velocity model used for imaging is created from a previously acquired active seismic data (Figure 4b). Pre-processing steps include applying a band-pass filter to remove noise above 40 Hz and below 5 Hz, followed by transforming the filtered data into the f-k domain to eliminate coherent noise components, such as those generated by the drilling rig. Once again, the direct arrivals are estimated using the PSO method and removed through adaptive subtraction. After applying MDD, the retrieved reflection response is finally imaged using pre-stack Kirchhoff depth migration. The resulting image, shown in Figure 4c, reveals the presence of four key reflectors at depths of approximately 5, 17, 53, and 126 m. A comparison with the lithological section compiled from drill cuttings, which indicates lithological changes at approximately 5, 73, and 130 m (Figure 4d), confirms the reliability of some of the imaged reflections.

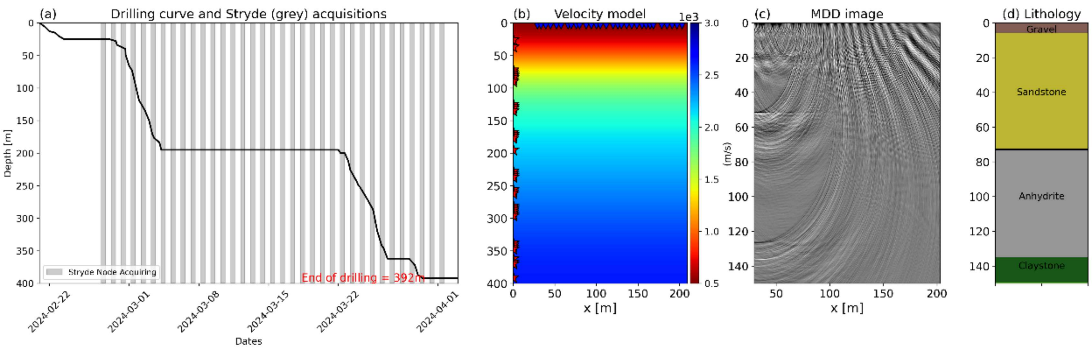

***Figure 4** (a) Drilling depth profile and seismic acquisition time windows, (b) velocity model used for migration, keys as in Figure 1, (c) MDD imaging result, and (d) lithological changes from the drilling report.*

Conclusions

We presented a practical workflow to apply MDD to SWD data, with the aim of retrieving a virtual reflection response deprived of free-surface and source effects. A key component of our method is the direct arrival estimation process, which can effectively identify and remove the complex direct arrival originating from the drill-bit noise. Moreover, to keep the computational time and memory usage of the MDD process to a reasonable level, we suggest to pre-process the continuous recordings by dividing them into smaller segments along the time axis, computing auto- and cross-correlations for each segment, and finally summing them. Our methodology has been successfully validated on both synthetic and field data, with the latter yielding results that are in line with lithological interpretations, offering valuable insights from passive seismic recordings.

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