Near-surface S-wave velocity estimation using ambient noise from fiber-optic acquisition

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SUMMARY

Distributed acoustic sensing (DAS) acquisition measures the ground motion using fiber-optic cables. Unlike conventional sensors, DAS can cost effectively provide dense seismic arrays and long-term operations, which is good for monitoring ambient noise. We propose a similarity-weighted stacking of randomly selected short-time duration noise to generate virtual common-shot-gathers (CSG). The similarity-weighted stacking only counts the primary contributions of coherent events, while a short-time correlation can suppress the crosstalk usually presents in late arrivals. Then, we use the wave-equation Rayleigh-wave dispersion-spectrum inversion, which utilizes all the dispersion modes available and avoids picking the dispersion curve, estimating the shallow S-wave velocities. We use a field DAS data set collected in Saudi Arabia to demonstrate the proposed method.

INTRODUCTION

The near-surface of the Earth plays a vital role in supporting the modern infrastructure and in imaging the deep Earth. Using an invasive method such as boreholes, we can have direct measurements of P- and S-wave velocities in the near surface at a relatively high cost and covering a limited region. Non-invasive methods, like the seismic survey, can reduce the cost and increase the lateral resolution. However, S-wave velocities in the soft soil area, such as sand dunes, tend to be extremely low, and thus, requires a dense seismic array for better sampling. Besides, seismic data in the near-source area can have low signal-to-noise ratios (SNR), which makes processing hard. To solve these problems, both acquisition systems and processing algorithms need to be improved. DAS using fiber optics as multichannel seismic arrays can have a sub-meter channel sampling at a reasonable cost. The preferred-directional strains generated by ground motions are recorded and then transferred to seismic signals. A DAS recording system with thousands of sensors can be permanently deployed in the subsurface at relatively low cost (Daley et al., 2013), which makes ambient-noise S-wave tomography practical.

Recorded ambient-noise data are often converted to virtual-shot gathers before applying currently used processing routines. One recorded trace acts as the virtual source after we crosscorrelate it with the rest channels, which is the general principle of seismic interferometry (Curtis et al., 2006). Cross-correlation cancels out the overlapped wave-path (travel time) of the signals recorded by two sensors and is thus more suitable for delineating direct arrivals such as surface waves, whose wave-paths are largely overlapped. Bensen et al. (2007) and Dou et al. (2017) have discussed the DAS data processing for

obtaining the dispersion spectra of surface waves. They promote two main processing steps, one is to remove the instrument response and another is to stack the common virtual-shot gathers. The former one is more or less a standard procedure. However, the stacking approach can vary. Cross-correlation itself can introduce coherent artifacts such as acausal signals and the crosstalk between nearby arrivals. Usually, increasing the stacking fold can suppress the random noise but also introduce coherent noise. We're introducing a randomly similarity-weighted stacking for seismic exploration purposes. A long-term recording is randomly separated into several short-term segments to allow a small time-lag cross-correlation. The crosstalk between arrivals can be suppressed in this way and the stacking fold can be increased using more random segments. The similarity-weighted stacking preserves the dominant coherent events and can increase the SNR of the stacked CSG. Acausal and causal stacking can remove coherent acausal signals, which has been discussed by Bensen et al. (2007). After obtaining high-quality common virtual-shot gathers, we use wave-equation dispersion spectrum inversion to estimate the S-wave velocities in the near-surface (Zhang et al., 2016; Zhang and Alkhalifah, 2018).

In this abstract, we first introduce the similarity-weighted random stacking method, then we review the wave-equation Rayleigh-wave dispersion spectrum inversion method. Finally, we apply the proposed method to an ambient noise DAS data collected in Saudi Arabia.

SIMILARITY-WEIGHTED RANDOM STACKING

We use the ambient noise data recorded by an iDAS system as shown in Figure 1 to demonstrate the proposed similarity-weighted random stacking. Ten 30-second records are collected at different times of the day. A full time crosscorrelation (30 s, causal part) and its $f - v$ spectrum are shown in Figures 2a and 2b, respectively. For imaging the near-surface in a limited area, we do not need large time lags common virtual-shot gathers. Besides, crosscorrelation with large time lags can introduce crosstalks between arrivals, which can be relatively strong in the late arrivals. We, thus, randomly separate the 30-second records into 100 3-second segments and apply a 3s time-lag crosscorrelation, which is larger than the desired virtual recording length (2 s). The stacking fold is increased by 10 times compared to a full-time crosscorrelation in this way, but more importantly it enhances energy of the first 1.5 seconds even further. The chosen of optimal time segments has been discussed by Alajmi et al. (2016). Figure 3a and 3b show the stacked CSG and its $f - v$ spectrum. The artifacts present in late arrivals are suppressed and the SNR is increased. To further reduce the random noise, we apply a similarity-weighted

stacking, which was used for conventional stacking (Liu et al., 2009). The stacking weights are calculated using a local cross-correlation, which is given by

$$r_w(p, s, x, t) = \frac{\int_{t-\frac{1}{2}w}^{t+\frac{1}{2}w} u(p, s, x, t) \hat{u}(s, x, t) dt'}{\sqrt{\int_{t-\frac{1}{2}w}^{t+\frac{1}{2}w} u^2(p, s, x, t) dt'} \sqrt{\int_{t-\frac{1}{2}w}^{t+\frac{1}{2}w} \hat{u}^2(s, x, t) dt'}}, \quad (1)$$

where $u(p, s, x, t)$ and $\hat{u}(s, x, t)$ are the separated and directly-stacked virtual-shot gathers, respectively, and w is the length of the window. Index p denotes the randomly separated shot gathers. In practice, the local-similarity is calculated by the solving a least-square problem with shaping regularizations (Fomel, 2007).

The similarity-weighted summation is applied to virtual-shot gathers, as shown below:

$$\bar{u}(s, x, t) = \sum_{p=1}^{n_p} r_w(p, s, x, t) u(p, s, x, t). \quad (2)$$

As a quantitative measure of improvement, we use the SNR defined below to evaluate the signal (Grion and Mazzotti, 1998):

$$SNR = 10 \log_{10} \left(\frac{\sigma_1^2 - \frac{1}{N-1} \sum_{n=2}^N \sigma_n^2}{\frac{1}{N-1} \sum_{n=2}^N \sigma_n^2} \right), \quad (3)$$

where σ denotes the singular values of stacked common shot gathers (after singular value decomposition). N is the number of singular values.

The similarity-weighted CSG and its $f-v$ spectrum are shown in Figures 4a and 4b, respectively. The CSG has the highest SNR (27.02) compared to the full-time stacking (18.35) and the random short-time stacking (20.05). However, we also notice some acausal events appearing in Figure 4a. These are caused by noise from the opposite direction and can be suppressed by causal (positive time lag) and acausal (negative time lag) stacking as shown in Figure 5a (Bensen et al., 2007). The coherent acausal events are suppressed after the causal and acausal stacking, which will reduce the SNR. However, the data quality is improved since the suppressed coherent acausal events are noise to our inversion objective. Also, the dispersion spectrum as shown in Figure 5b is improved: the strong fundamental mode and a weak higher mode events are more continuous. We use the calculated $f-v$ spectrum (Figure 5b) as our observed data and conduct the wave-equation dispersion spectrum inversion.

WAVE-EQUATION DISPERSION SPECTRUM INVERSION

We first use an example processed data to illustrate the basic concept of the wave-equation dispersion spectrum inversion. Figure 6a shows the virtual-shot gathers after processing. The Rayleigh waves, which have two main cycles with different slopes, are dominant in the data. These trapped waves are often considered as strong coherent noise and removed in

Figure 1: Example ambient noise recorded by an iDAS system. The total recording time is 30 s and there are ten records. Notice that the recorded noise has a direction preference: noise near the main source ($X < 200$ m) is stronger than the rest ($X > 200$ m).

Figure 2: Full time (30 s) stacked virtual-shot gathers (a) and its $f-v$ spectrum (b).

Figure 3: Random short-time (3 s) stacked virtual-shot gathers (a) and its $f-v$ spectrum (b). Notice that the crosstalk artifacts in the late arrivals are attenuated.

Figure 4: Random short-time (3 s) similarity-weighted stacked virtual-shot gathers (a) and its $f-v$ spectrum (b).

regular data processing. In our proposed method, we utilize such events in estimating the S-wave velocities in the near

Figure 5: Random short-time (3 s) causal/acausal similarity-weighted stacked virtual-shot gathers (a) and its $f-v$ spectrum (b). Notice that the coherent acausal events are suppressed.

surface. Figure 6b is the corresponding dispersion spectrum after applying the multiple channel analysis of surface waves (MASW). Two main dispersion modes including a strong fundamental mode and a weak higher mode are observable in the spectrum. The existing surface wave dispersion inversion methods often utilize the picked dispersion curve (the green dashed curve) to estimate the S-wave velocities in the near-surface. However, picking such a dispersion curve includes more uncertainties in the inversion and often ignores the weak higher modes. Under the framework of full waveform inversion, we propose to use the dispersion spectra (Figures 6b) as observed data to estimate S-wave velocities in the near surface. The main benefits of the proposed methods are 1) avoiding picking the dispersion curves, 2) utilizing all the existing dispersion modes and 3) easy-implementation by modifying the objective function and the adjoint source used in conventional elastic FWI codes.

Figure 6: The observed data. a) Common shot gathers and b) its dispersion spectrum. The dashed lines mark the dominant modes.

We use a local-similarity based objective function, which is given by

$$\phi(m) = \frac{1}{2} \int_s \int_r \int_f \int_{f'} W(f') C_w^2(f, v, f') df' df dr ds, \quad (4)$$

$$\text{where } C_w(f, v, f') = \frac{\int_{f-\frac{1}{2}w}^{f+\frac{1}{2}w} |C^p(f, v)| |C^o(f, v, f')| df}{\sqrt{\int_{f-\frac{1}{2}w}^{f+\frac{1}{2}w} |C^p(f, v)|^2 df} \sqrt{\int_{f-\frac{1}{2}w}^{f+\frac{1}{2}w} |C^o(f, v, f')|^2 df}}$$

denotes the local-crosscorrelation of predicted and observed $f-v$ spectra. f' denotes frequency extensions. $W(f')$ is a polynomial-type weighting function, which satisfies the following boundary conditions: $W|_{\pm f'} = 0$; $W'|_{\pm f'} = 0$; $W|_0 =$

1 ; $W'|_0 = 0$. The dispersion spectrum ($f-v$) is calculated using a linear Radon transform. After a temporal Fourier transform of the shot gather, the linear Radon transform can be calculated for each temporal frequency component f as $C(f, v) = \int_{x_{\min}}^{x_{\max}} D(f, x) e^{-\frac{i2\pi fx}{v}} dx$ and its adjoint form is given by $D(f, x) = \int_{v_{\min}}^{v_{\max}} C(f, v) e^{\frac{i2\pi fx}{v}} dv$. The gradient for the S-wave velocity updating with respect to the objective function can be calculated by cross-correlating the forward-propagated source wavefield with the backward-propagated adjoint-source (Plessix, 2006; Zhang and Alkhalifah, 2018).

NUMERICAL EXAMPLE

The data were acquired 100 km east of Riyadh at Se'ed area (a picture of the data acquisition is shown in Figure 7). The fiber cable was buried along a 500 m long line into 15 cm trench. We apply the wave-equation dispersion spectrum inversion to the virtual-shot gathers. The ambient noise attenuates fast and thus only 20 shots (expected to be near the main noise source) with a spread length of 180 m are used for the inversion due to their comparably higher quality. 951 horizontal sensors with a spatial separation of 0.5 m are used. We apply the phase correction by convolve the observed data with $t^{-\frac{1}{2}}$ (Pica et al., 1990). An example observed data and its $f-v$ spectrum are shown in Figures 8a and 8b, respectively. The two dashed lines in Figure 8a indicate two main cycles of Rayleigh waves with different phase velocities. They most probably correspond to the two dispersion modes as shown in Figure 8b. As expected, the fundamental mode is stronger than the higher-order mode. The initial S-wave velocity (Figure 9a) is a linear-gradient one, whose gradient can be roughly decided by the $f-v$ spectrum (e.g., Figure 8b). The P-wave velocity and density model used in the inversion are homogeneous models ($v_p = 2.0 \text{ km/s}$ and $\rho = 1.6 \text{ g/cm}^3$), which have ignorable influences on the S-wave velocity estimation (Zhang and Alkhalifah, 2018). The inverted S-wave velocity is shown in Figure 9b. The inverted velocity near the surface is around 150 m/s and the thickness of the sand might be up to 40 m as we compare the inverted results with those analyzed by Al-Shuhail et al. (2018). It seems that this area does not have strong heterogeneity, which is also in agreement with the observed data (Figure 8a). To further validate the inverted S-wave velocity, we compare the predicted data and the corresponding spectra with the observed ones. Figures 10a and 10b are the predicted data and its spectrum using the initial S-wave velocity. Both the predicted data and the dispersion spectrum are far from the observed ones. Figures 11a and 11b are the predicted data and its spectrum using the estimated S-wave velocity. The slopes of arrivals in the predicted data are close to those in the observed data and so is the dispersion spectrum. The dashed lines mark the region of the observed dispersion spectrum. However, there are some body waves remain in the predicted data (Figure 11a), which can prevent the data matching since they are not existing in the observed data (Figure 8a).

Figure 7: The geology map showing the target area marked by the red rectangular. The area is surrounded by sand dunes and there is a village nearby, which could be the main source of the noise.

Figure 8: The observed data. a) Common shot gathers and b) its dispersion spectrum. The dashed lines mark the dominant modes.

Figure 9: The S-wave velocity models. a) The initial model and b) the inverted model. The velocities at the surface are around 150 m/s, which is expected in sand.

CONCLUSIONS

We utilized a random selection of short time windows in the interferometric crosscorrelation that allows us to add more en-

Figure 10: The predicted data using the initial model. a) Common shot gathers and b) its dispersion spectrum. The dashed lines mark the observed dominant modes.

Figure 11: The predicted data using the inverted model. a) Common shot gathers and b) its dispersion spectrum. The dashed lines mark the observed dominant modes. The predicted data is close to the observed one.

ergy to the correlation process by using more random windows than the length of the desired data. The random selection, which is a kind of data augmentation, can increase the stacking fold and thus the stacking SNR. We combined that with a similarity-weighted stacking to reduce the random noise after stacking, as well as, impose an acausal/causal stacking to suppress the acausal events. The wave-equation spectrum inversion adapts finely to such ambient noise data. It does not require the picking of dispersion curves from the $f - v$ spectrum and considers all the available dispersion modes. This full waveform inversion can be easily implemented by modifying the conventional elastic full waveform inversion code. One potential limitation of the proposed method on ambient noise based virtual sources data is that the simulated seismic data can produce body waves (such as P-waves), which is attenuated in the interferometric process. However, considering that body waves decay and travel faster than surface waves, the proposed inversion algorithm is still valid without much special data treatments.

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