Supporting Information for

Urban Basin Structure Imaging based on Dense Arrays and Bayesian Array-based Coherent Receiver Functions

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This supporting material provides additional information on data analysis and results. The organization of the supplementary material is provided below.

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Section S1: Teleseismic waveforms and their spectrograms

Figure S1. Examples of vertical and radial components seismograms (filtered to 0.1 – 2.0 Hz) of three teleseismic events recorded by node stations in the SG3 line. As the station spacing (~250
m) smaller than the dominant wavelength of teleseismic P-waveforms (Figure S2), the recorded waveforms at nearby stations are coherent.

Figure S2. Time-frequency analysis. Upper plot: The bandpass filtered (0.05 – 5.0 Hz) vertical and radial component waveforms from node station S15 in the SG3 line. Lower plot: spectrogram. In general, the dominant frequency of the teleseismic waveforms recorded by the node stations is less than 1 Hz. Although we only show two representative waveforms, the results still provide a basis for the dominant frequency of the teleseismic waveforms recorded by node stations.

Section S2: 2-D synthetic test
We apply our array-based Coherent Receiver Function (CRF) method to 2-D synthetic data. The input 2D model consists of three major tectonic structures: a subducting oceanic crust with various dipping angles, a curved Moho interface, and a flatten mid-crust discontinuity (Figure S3a). Three teleseismic earthquakes with different source time functions were simulated to generate synthetic waveforms using the GPU-based 2-D finite different method (Li et al., 2014). We also added random noise that has a similar frequency spectrum to that of the synthetic data, with the resulting waveforms shown in Figure S3b.

For CRF inversion, we divided the entire array into overlapping sub-arrays, with each sub-array contains five stations. For each sub-array, we filtered the vertical and radial components to 0.02–1.0 Hz to estimate the CRF using our proposed method. Figure S4a shows the obtained ensemble solutions for a representative sub-array, where the left panel indicates the probability of the model space given the observations and the right panel shows the corresponding amplitude information. We can immediately see a few spots with brighter colors representing that there is a high
probability to have conversions at ~5 sec, ~6 secs, and ~9.0 sec. To present the CRF in a similar manner as the conventional RF, we conducted the following post-processing steps. We first found all the peaks with the probability over a certain threshold (e.g., larger than one or two standard deviations of the mean) in the 2-D probability map, to construct the 1-D trace that contains discrete delta functions with different timings, amplitudes, and slownesses. We then convolved the 1-D trace with a Gaussian low-pass filter of \( G(w) = e^{-w^2/4a^2} \) to generate the 1-D CRF time series. It is worthwhile to note that different threshold values result in different 1-D CRF time series, providing a quantitative way for deciding which features are well resolved by data. Figure S4b shows the 95% confidence level (threshold is two standard deviations of the mean) CRF results, where the purple lines show the slowness that was used to link the phases at nearby stations. Even though we have imposed a maximum of 15 phases in trans-dimensional inversion, there are only four phases pop up in the final results. In comparison to the Neighborhood Algorithm (NA) inversion which needs to manually tune the number of phases, our approach avoids the subjective choice of the number of phases and produces reproducible results (compare to Figure 5 in Zhong & Zhan (2020)’s study). More details about the discussion of the effect of the number of phases and the computation efficiency are given in Section S3.

Once we have the CRF for each sub-array, we can combine all the CRFs to produce a complete CRF profile for the entire array. Figure S5 shows the pseudo 2-D cross-section by simply juxtaposition of individual CRFs obtained in this study. The upper and lower boundaries of the thin oceanic crust, the Moho discontinuity, and the mid-crust discontinuity are well resolved. We then use the slowness-based Common Conversion Point (CCP) stacking method mentioned in the main text to generate the 2D stacking image. Figure S5 shows the comparison of the slowness stacked CRF image and the direct stacked RF CCP image estimated from the single-station time-domain iterative deconvolution (Ligorria & Ammon, 1999). Though the main structures are trackable on the conventional CCP stacking image, a lot of spurious phases are shown, mainly due to the existence of noise in single-station deconvolution and the insufficient stacking (Figure S6). The traditional CCP stacking image also shows stair-step artifacts when imaging the dipping structures, due to the out-of-phase stacking from the sparsely spaced stations (Figure S5). The smearing effect of direct stacking results in a bias to underestimate the actual amplitude of the dipping structures. In comparison, our slowness stacked CRF image can better image the dipping structures and greatly reduces the artifacts that might be mistakenly interpreted as geological structures (Figure S5), demonstrating that our method is capable of producing reliable, robust, and easy-to-interpret RFs.
Figure S3. (a) The synthetic subduction zone model, comparing a 7 km oceanic crust with various dipping angles, a curved Moho interface, and a flatten mid-crust discontinuity. The squares at the surface denote the evenly distributed receivers with a station-spacing of 5 km. (b) The synthetic seismograms used in synthetic tests. Three teleseismic earthquakes with different source time functions were simulated. We added random noise that has a similar frequency spectrum to that of the synthetic data to mimic the real observations.
Figure S4. Trans-dimensional CRF inversion of synthetic data for a representative sub-array. (a) The left panel shows the density plot that represents the probability of model space, with a brighter color indicating a higher probability. The right panel shows the corresponding amplitude information. (b) The extracted 1-D CRF time series with the phases have a probability larger than 95% (two standard deviations of the mean). The purple lines show the slowness that used to link the phases at nearby stations. (c) The waveform fits between the radial component and the convolution of CRF and vertical component.
Figure S5. (a-c) Array-based CRF results for the synthetic test. From the top to the bottom shows the pseudo 2-D cross-section by simply juxtaposition of individual CRFs obtained in each sub-array, the slowness information obtained in each sub-array, the slowness stacked CRFs. (d) Conventional CCP stacking of RFs estimated from single-station time-domain iterative deconvolution. The conventional CCP stacking image contains a lot of spurious phases due to the existence of noise in single-station deconvolution and the insufficient stacking, while our slowness
stacked CRF image greatly reduces the artifact that might be mistakenly interpreted as geological structures.

Figure S6. Single station deconvolution results. Due to the presence of noise (Figure S3) and the non-uniqueness of deconvolution, a lot of spurious phases are shown in the single-station deconvolution results. Stacking RFs from three events can suppress the noise to some extent, while the stacking image still contains many artifacts that might be mistakenly interpreted as geological structures (Figure S5d).

Section S3: Compare with the Neighborhood Algorithm based CRF inversion

In this section, we compare our trans-dimensional McMC based CRF inversion method to the Neighborhood Algorithm (NA) based CRF inversion method (Zhong & Zhan, 2020). In CRF inversion, the number of phases controls the complexity of the inverse problem. As mentioned in Zhong and Zhan (2020), the NA-based CRF inversion requires the user to manually tune the number of phases to find an “optimal” value through the misfit trade-off curve (Figure S7a). Hence, the resulting CRF is inevitably influenced by subjectively chosen tuning parameters. In addition,
the efficiency of NA-based CRF drops quickly as the number of phases increases. For example, as the number of phases reaches 8 which corresponds to 24 unknown parameters, it takes about one hour to finish a single sub-array inversion on a modern desktop workstation (Figure S7b). Due to the high computation cost, it is therefore impractical to apply the NA-based CRF method to large datasets. In comparison, the trans-dimensional McMC inversion algorithm used in this study naturally adapts the model complexity to the data complexity, thus avoids the need to manually tune the number of phases. The inversion algorithm used in this study produces reproducible or even better results (in terms of the misfit of the “best” model) than the NA-based CRF inversion (Figure S7a). In addition, the high-efficiency sampling of model space in McMC inversion allows us to look at the ensemble solutions instead of a single “best” model, providing a quantitative way to determining which features are well resolved and warranted geological interpretation (Figure S7c). In terms of computation efficiency, the trans-dimensional McMC inversion is an iterative stochastic search approach, where the computation efficiency is mainly controlled by the computation cost for solving a forward problem and the number of McMC iterations. As simulating the forward problem is fast, the amount of computing time is largely controlled by the number of iterations in McMC inversion. For inversion of 20,000 McMC steps, it only takes ~300 sec to finish the calculation. Compared to the NA inversion, the McMC algorithm substantially reduced the computation cost by as much as 90%. Thus, our method is capable of processing large datasets efficiently. To conclude, compared to the NA CRF method, our trans-dimensional McMC CRF method produces reproducible or even better results, with affordable computation cost and minimal user interaction.
**Figure S7.** (a) The misfit of “best” fitting model as a function of the number of phases. The McMC inversion algorithm used in this study produces reproducible or even better results than the Neighborhood Algorithm (NA) based CRF method. (b) The computation cost as a function of the number of phases. The computation efficiency of NA-based CRF drops quickly as the number of phases increases, while the computation cost of the McMC algorithm remains low and is not significantly affected by the number of phases. (c) Comparison of the obtained CRFs from the NA-based CRF inversion and the trans-dimensional McMC inversion.

**Text S4: The effect of sub-array size and frequency bands on array-based coherent receiver function inversion**

In array-based CRF inversion, we divide the full array into overlapping sub-arrays. The deconvolution at a single station involves constraints from the neighboring stations within the sub-array to suppress the incoherent noise and local scatters to better image the subsurface structure. Optimal choices of the size of the sub-array will surely vary with station-spacing and the target sub-surface structures. We tested three-, five- and seven-station sub-array configurations, but these did not alter the basic results (Figures S8-S10). We also tested effect of different high frequency cut-offs (1Hz, 2Hz, 3Hz) on array-based CRF inversion (Figures S9, S11, and S12). As the
dominant frequency of the teleseismic waveforms recorded by node stations is around 1Hz (Figure S2), slightly changing the high-frequency (1Hz, 2Hz, 3Hz) cut-off did not change the basic results (Figures S11-S12).

Figure S8. Array-based Coherent Receiver Function (CRF) results using a three-station sub-array configuration (filtered to 0.1-2.0 Hz). From the top to the bottom shows the pseudo 2-D cross-section by simply juxtaposition of individual CRFs obtained in each subarray, the slowness information obtained in each sub-array, and the slowness stacked CRF images.
Figure S9. Similar as the Figure S8, but for CRFs results obtained using a five-station sub-array configuration (filtered to 0.1 – 2.0 Hz).

Figure S10. Similar as the Figure S8, but for CRFs results obtained using a seven-station sub-array configuration (filtered to 0.1 – 2.0 Hz).
Figure S11. Similar as the Figure S8, but for CRFs results obtained using a five-station sub-array configuration (filtered to 0.1 – 1.0 Hz).

Figure S12. Similar as the Figure S8, but for CRFs results obtained using a five-station sub-array configuration (filtered to 0.1 – 3.0 Hz).
Figure S13: Comparison of single-station receiver function deconvolution results. From the left to the right shows the results obtained using water-level deconvolution (Ammon, 1991), multi-taper deconvolution (Park & Levin, 2000), and time-domain iterative deconvolution (Ligorría & Ammon, 1999). Though the major features are reasonably consistent for all three methods, the distribution, the continuity, and the amplitude of these features are different from each other in detail, indicating the non-uniqueness of single-station deconvolution.
Figure S14. Profiles of 1-D $S$- and $P$-wave velocity structure within the basin (at distance around 2-5 km along the profile shown in Figure 9c in the main text) extracted from the Southern California Earthquake Center Community Velocity Model (Lee et al., 2014).

Reference:


