Using deep learning for direct velocity model and source wavelet inversion from near-surface seismic data

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ABSTRACT

Detection of near surface (NS) voids is a challenging problem. Targets for this application could be related to natural (karsts) or man-related activities (mining). Accurate void mapping is important for safety, environment, security, and mineral exploration studies. Within the suite of geophysical approaches, seismic methods have been demonstrated to be effective in a range of settings and depths. Recent advances have allowed intensive usage of deep learning (DL) at different stages of seismic data processing and inversion workflows, e.g. for full-waveform inversion - FWI (Tarantola, 1984), which has become widely used for accurate void delineation.

For typical NS application, the source time function (STF) is unknown and estimated with a filtering (Song and Williamson., 1995) or adjoint (Zhou et al., 1997) method. These approaches require accurate initial properties to perform well, and could be implemented in an alternating manner (Borisov et al., 2020). However, given the same velocity model, the estimated STF could significantly differ, depending on the portion of data selected in the estimation process. This is especially true for NS applications where interference between surface and body waves occurs across sizeable portions of the recorded offsets.

In this study we demonstrate the application of supervised DL for NS imaging. To accomplish this, we design two convolutional networks taking recorded data as input while outputting S-wave velocities (Vs) and STF. More than 100,000 realistic, randomly generated models along with random wavelets were used in the training process. For brevity, we only demonstrate the field data results from the Yuma Proving Ground dataset (Smith et al., 2019) with a known 1.8 m high, 1.5 m wide and >20 m long void. A subset of 24 weight-drop source locations is recorded by 10 lines separated by 2 m. Each line consisting of 72 vertical geophones separated by 1-m. Individual and averaged wavelets estimated with a filtering approach using early arrivals between 36 m and-71 m offset from the source and surface-body waves within 5-10 m offset from the source compared with DL derived wavelets shows significant variations (Figure 1). Commonly, early-arrivals-based estimation (STF-1) is a preferred approach since it excludes dispersive Rayleigh waves from the process. It is worth noting that the averaged wavelet estimated from the near-offset wavefield (STF-2) is closer to the DL-based one (STF-3). The degraded consistency between individual STF in the last approach might be related to a source repeatability issue. We then carried out 3D elastic FWI with the corresponding averaged wavelets. 1D initial models were used in FWI-1 and FWI-2, while a DL derived Vs model was used in FWI-3. Interestingly, FWI-1 fails to map the void and overestimates velocities due to the phase delayed wavelet. FWI-2 shows a good cavity reconstruction, but not well matched with the FWI-3 results using the DL derived Vs and STF, which better delineates the known void.

We demonstrate the importance of using an appropriate source wavelet and velocity model for accurate NS characterization. We designed DL-based estimation of the desired properties. The result could serve as input for conventional or DL physics-guided FWI, preferably with both properties updated in an alternating manner.

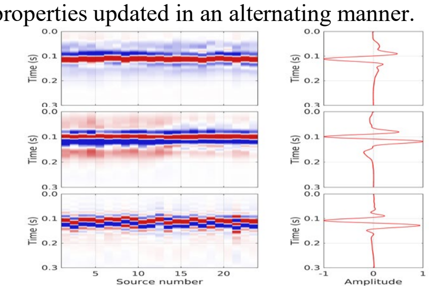

Figure 1: Individual source wavelets along with corresponding averaged ones estimated from: (top) early arrivals 36-71 m offset, (mid) full wavefield within 5-10 m offset, and (bot) DL approach.

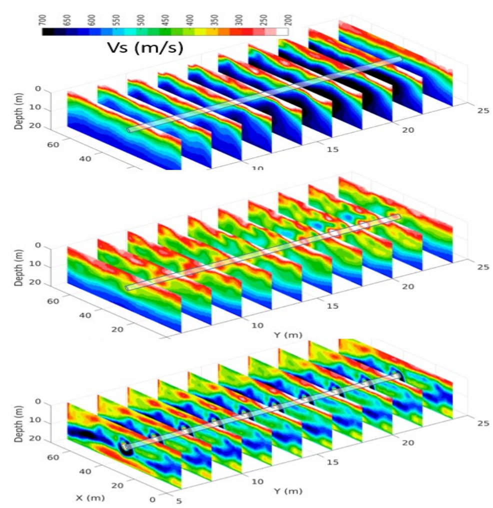

Figure 2: FWI Vs models with STF estimated from: filtering approaches using (top) early arrivals within 36-71 m offset, (mid) 5-10 m offset full recordings, (bot) DL network.