

Urban Near-surface Seismic Monitoring using Distributed Acoustic Sensing

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Key Points:

- Using the Stanford DAS array, we demonstrate the reliability of urban DAS recordings when deployed in existing infrastructures.
- Short DAS recordings of far-field quarry blasts show sensitivity to the changes in near-surface velocity within the boundaries of the array.
- DAS can play an important role in real time, high resolution, and long term urban monitoring applications.

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Abstract

Urban subsurface monitoring requires high temporal-spatial resolution, low maintenance cost, and minimal intrusion to nearby life. Distributed acoustic sensing (DAS), in contrast to conventional station-based sensing technology, has the potential to provide a passive seismic solution to urban monitoring requirements. Based on data recorded by the Stanford Fiber Optic Seismic Observatory, we demonstrate that near-surface velocity changes induced by the excavation of a basement construction can be monitored using existing fiber optic infrastructure in a noisy urban environment. To achieve the satisfactory results, careful signal processing comprising of noise removal and source signature normalization are applied to raw DAS recordings. Repeated blast signals from quarry sites provide free, unidirectional, and near-impulsive sources for periodic urban seismic monitoring, which are essential for increasing the temporal resolution of passive seismic methods. Our study suggests that DAS will likely play an important role in urban subsurface monitoring.

1 Plain Language Summary

Seismic monitoring can provide crucial information about near-surface changes due to natural or manmade activities. However, the high cost and the “after-effect” nature of conventional station-based monitoring methods limit their application in urban environments where near real-time and meter-scale resolution are required. Distributed acoustic sensing (DAS) has the potential to achieve all requirements utilizing existing communication infrastructure. Using Stanford Fiber Optic Seismic Observatory, we demonstrate that its recordings of quarry blasts 13.3 km away carry important subsurface velocity information within the footprint of the array. These short bursts of quarry blast signals provide us free, unidirectional, and repetitive sources that sample the urban subsurface at an interval frequent enough for monitoring. We observe large velocity decrease from the recordings close to the excavation site. Our study suggests that telecommunications fiber repurposed for DAS will potentially play an important role in many urban subsurface monitoring applications.

2 Introduction

Characterizing and monitoring changes in the top tens of meters of the Earth’s subsurface will play a significant role in satisfying the increasing need for urban sustainability and resilience (Díaz et al., 2017). Near-surface changes due to natural or man-made events may lead to hazards including ground subsidence (Tran & Sperry, 2018), sinkholes (Dahm et al., 2011; Gutiérrez et al., 2014), and landslides (Renalier et al., 2010; Schenato et al., 2017), which may result in direct casualties and damages to existing infrastructure (Douglas, 2004). Many such subsurface changes manifest themselves as temporal variations in geophysical properties (such as velocity, attenuation, electric conductivity, gravity, etc.) before catastrophic hazards occur, which can be monitored and predicted by geophysical prospecting.

Compared to conventional geophysical exploration for resources, near-surface monitoring in urban environments has unique acquisition requirements including high spatial resolution towards meter-scale, high temporal resolution towards real-time data collection and daily warning, low maintenance cost for long term monitoring and minimal intrusion to urban life. These requirements are met by a passive system enabled by DAS that we present in this paper. DAS arrays can measure strain along kilometers of optical fiber, producing large datasets with kilohertz time sampling and at sub-meter channel spacing (Parker et al., 2014). Over the past decade, DAS has been a rapidly evolving technology for downhole recording in oil and gas reservoirs (Willis et al., 2016). Recent success of DAS applications using existing telecommunication infrastructures (Jousset et al., 2018; Yu et al., 2019; Ajo-Franklin et al., 2019) demonstrates its cost-effectiveness

66 in deployment and maintenance. However, these experiments are conducted for appli-
 67 cations in earthquake seismology in remote areas where anthropogenic noise is rare and
 68 desired signals are clearly visible above the random noise in DAS measurements.

69 Studies using DAS arrays deployed in urban environments have reported that near-
 70 surface velocities can be estimated with ambient noise recorded by DAS over month-long
 71 periods (Dou et al., 2017; Martin et al., 2018; Spica et al., 2019). Averaging over long
 72 observation times is needed to suppress strong near-field anthropogenic noise, but severely
 73 limits the temporal resolution of passive seismic monitoring with DAS. Here we present
 74 a case study from the Stanford Fiber Optic Seismic Observatory where we take advan-
 75 tage of far-field anthropogenic activities - quarry blasts - to monitor the near-field an-
 76 thropogenic activity - excavation. Weekly quarry blasts can be used to sample the sub-
 77 surface with sufficient energy at intervals relevant to urban monitoring. We perform care-
 78 ful signal processing to reduce the effect of strong nearby noise and the variability in the
 79 blast sources. We demonstrate that with 100 seconds of DAS recordings after quarry blasts,
 80 near-surface velocity changes caused by construction of a basement within the array can
 81 be observed.

82 **3 Data and Signal Processing**

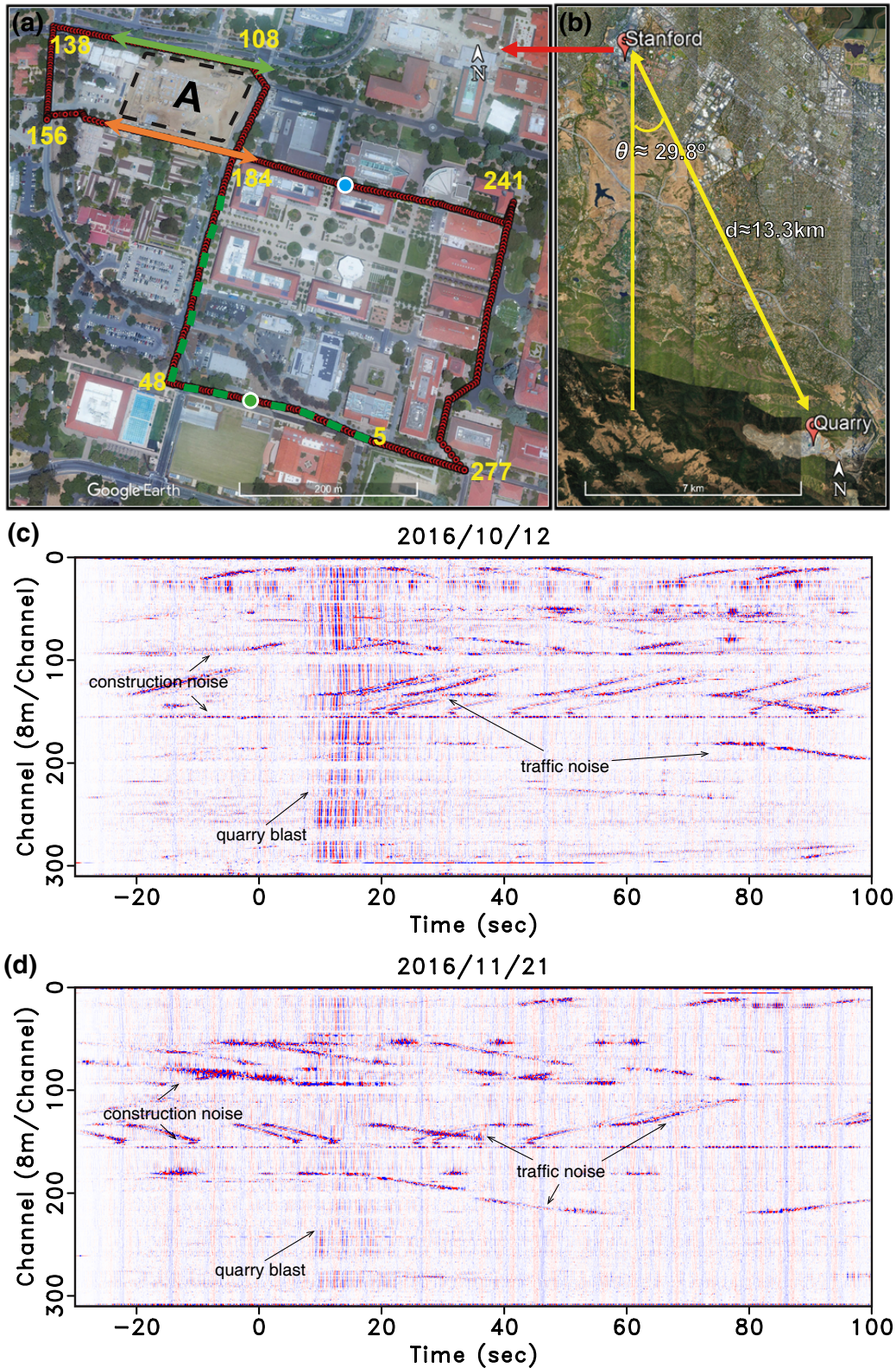
83 **3.1 Stanford Fiber Optic Seismic Observatory data acquisition**

84 The Stanford Fiber Optic Seismic Observatory (also called Stanford DAS Array) (Biondi
 85 et al., 2017) is one of the first DAS arrays to use existing telecommunication infrastruc-
 86 ture, and is the longest-running ultra-dense urban seismic study in the world. In this ex-
 87 periment, 2.5 kilometers of fiber-optic cable are deployed loosely in existing underground
 88 telecommunication conduits (typically 10–15 cm wide PVC pipes) under the Stanford
 89 University campus. Coupling between the fiber cable and the surrounding conduit re-
 90 lies only on gravity and friction. This experiment simulates DAS acquisition using dark
 91 fibers (the unused backup fiber-optic cables) that are commonly available in existing telecom-
 92 munication systems. Figure 1a shows the layout of the DAS array, which records data
 93 at a 25 Hz Nyquist frequency with 8.16 m channel spacing and 7.14m gauge length (Dean
 94 et al., 2017; Lindsey et al., 2017). Construction of a basement (labeled with "A" in Fig-
 95 ure 1a) began by its excavation on 7 November 2016.

103 **3.2 Quarry blasts data**

104 Lehigh Permanente Quarry is located 13.3 km away 29.9° southeast of the DAS ar-
 105 ray (Figure 1b). Figures 1c and 1d show the DAS recordings on 12 October 2016 18 :
 106 30 : 16.9 UTC and on 21 November 18 : 56 : 12.5 UTC, after applying a bandpass fil-
 107 ter from 0.25 to 2.5 Hz. The origin of the time axis denotes the blasting time provided
 108 by analysis of the data recorded by a USGS seismometer at the Jasper Ridge seismic sta-
 109 tion (JRSC) that is managed by the Berkeley Digital Seismic Network. The near ver-
 110 tical events originate from the quarry blasts, whereas strong dipping events are the di-
 111 rect impact of traffic on the fiber and the horizontal events are construction noise. We
 112 observe polarity flips around the corners of each pair of orthogonal segments of the DAS
 113 array (Figures 1c, 1d and Movie S1 in supporting information), which are caused by the
 114 angular sensitivity of DAS strain measurements (Lindsey et al., 2017). Table S1 in sup-
 115 porting information lists the time and the magnitude of 10 quarry blast events used for
 116 further analysis.

117 In the subsequent signal processing section, we aim to extract subsurface information
 118 based on far-field quarry blasts while minimizing the influence of near-field anthro-
 119 pogenic noise. Figures 2a and 2b zoom in on two blast signals after geometric polarity
 120 sign-correction (Biondi et al., 2017). Because of the strong surface wave energy originat-
 121 ing from the quarry blast and anthropogenic noise (mainly traffic and construction noise)



96 **Figure 1.** (a) Layout of the DAS array with the corner points labeled by the corresponding
 97 channel numbers. The green dashed line represents the segment of DAS recording used for beam-
 98 forming calculation in Figure 2. The green and orange arrows represent the segment of DAS
 99 recording used in Figure 4. The green and blue dots are virtual sources used for seismic inter-
 100 ferometry in Figures 4 and 5, respectively. Box A denotes the basement construction site. (b)
 101 Location of the quarry relative to the DAS array. (c) and (d) Bandpassed DAS recordings on 12
 102 October 2016 and 21 November 2016, respectively.

122 during the daytime, it is hard to identify any body wave in the records. Based on the
 123 facts that the quarry blasts events propagate through the DAS array in a non-perpendicular
 124 uniform direction and the arrival times of Rayleigh and Love waves are close, a combi-
 125 nation of Rayleigh and Love waves are expected to be observed by the DAS array. The
 126 blast vibration events reach the south portion of the array (channel 5) almost 0.7s ear-
 127 lier than they reach the north portion (channel 138). This time lag matches the relative
 128 distance and the average velocity between these two portions of the array, which is es-
 129 timated in the next section. The blue lines overlaid on the profiles of Figures 2a and 2b
 130 are the single-channel responses of channel 120 on two different days. Figures 2c and 2d
 131 show their time-frequency spectrograms, respectively. Note that the main energy of the
 132 two quarry blasts events arrives at the DAS array around 14s after the explosion. Their
 133 dominant frequencies are approximately 1.2 Hz.

134 Beamforming based on multiple signal classification (MUSIC) (Zhang et al., 2019)
 135 is applied on the southwest corner of the DAS array (indicated by green dashed line in
 136 Figure 1a) within a small time window of 10-15s (labeled with the red dashed box in Fig-
 137 ures 2a and 2b). Figures 2e, 2f and movie S2 in supporting information show the beam-
 138 forming results for different days' data. Their peaks roughly indicate the wavefield propa-
 139 gation direction and velocity, which support the assumption that the quarry blasts can
 140 be seen as unidirectional plane wave sources. Although the quarry blasts signals recorded
 141 at different times show certain similarity, their waveforms are complex and quite differ-
 142 ent as shown by the blue lines in Figures 2a and 2b. The reasons for this difference may
 143 lie in the randomness of explosive energy, excitation environment and the rugged earth
 144 surface where the source is excited. Urban noise further contaminates the signals.

153 3.3 Signal processing

154 We propose a data processing workflow to reduce the impact of urban noise and
 155 waveform differences. It starts with raw DAS records and results in cross-correlograms
 156 between virtual sources and other channels, which are used for velocity estimation. The
 157 workflow is the same for all quarry blasts.

158 **Bandpass, FK and median filter:** A Butterworth bandpass filter with cut-off
 159 frequencies from 0.25 Hz to 2.5 Hz is applied to all quarry blast data. A narrowband
 160 frequency-wavenumber(FK) filter is applied to remove the high frequency, large move-
 161 out events, which are primarily generated by direct traffic impact or the equipment on
 162 the construction site. Therefore, the parameters to control the FK filter are tuned daily
 163 according to noise on that day. A sliding 2-D median filter is used to remove spike noise
 164 for all the data.

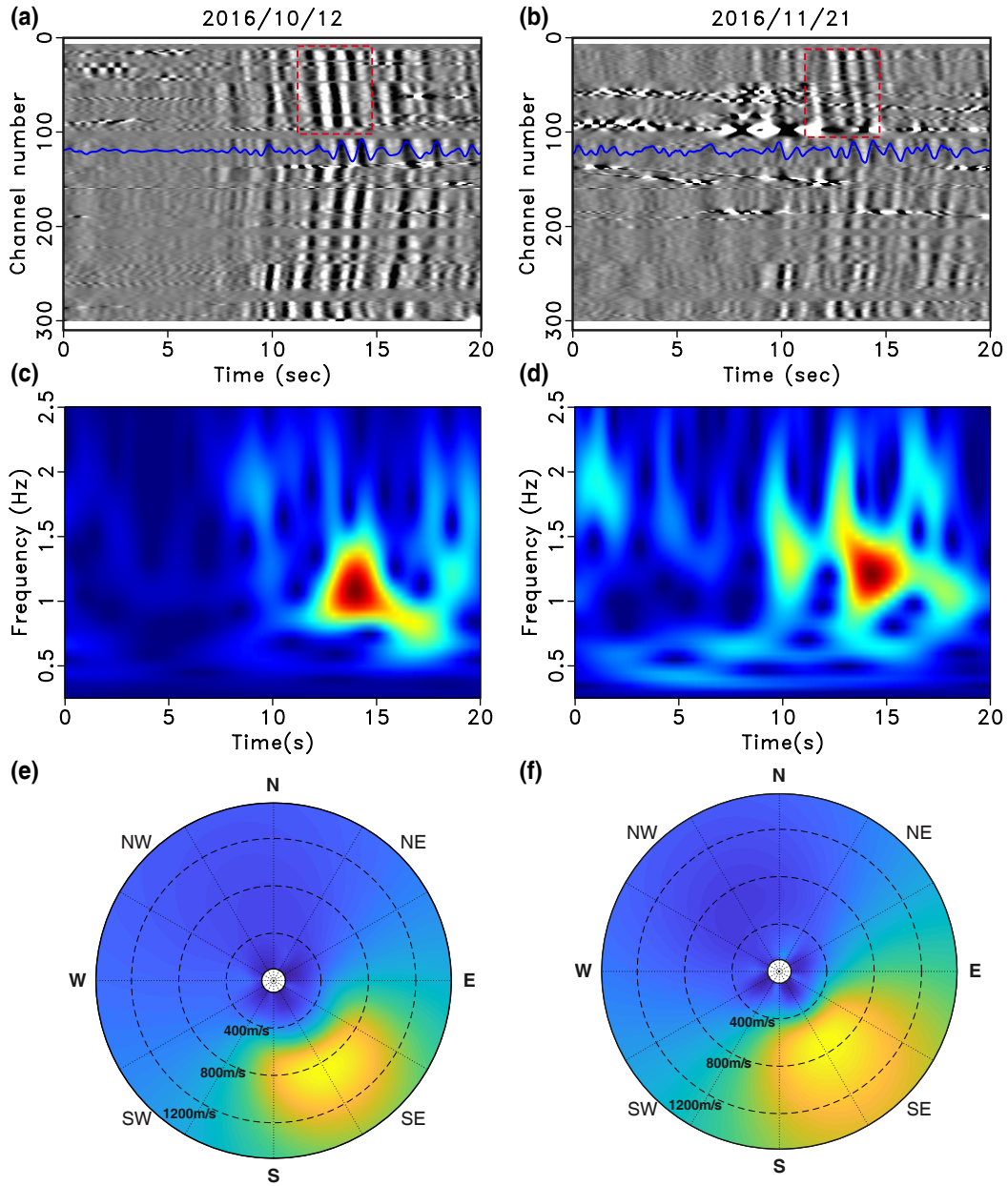
165 **Normalized cross-correlation:** The quarry sets off each blast with a different
 166 source signature. We use normalized cross-correlation to eliminate the imprint of the source
 167 signature. Under the assumption of far-field plane-wave propagation and uniform receiver
 168 response, the signals U recorded at receivers A and B in the frequency domain can be
 169 approximated by 1-D wave propagation as follows

$$170 \quad U(R_A, \omega) = S(R_S, \omega)e^{ikDis(R_A, R_S)}, \quad (1)$$

$$U(R_B, \omega) = S(R_S, \omega)e^{ikDis(R_B, R_S)}, \quad (2)$$

171 where $S(R_S, \omega)$ is the source spectrum, k is the wavenumber, R_A and R_B are locations
 172 of A and B, $Dis(R_A, R_S)$ are the distance between R_A and R_S , respectively. The nor-
 173 malized cross-correlation operator is defined as

$$C_N(R_A, R_B, \omega) = \frac{U(R_A, \omega)U^*(R_B, \omega)}{\langle\langle U(R_B, \omega)U^*(R_B, \omega) \rangle\rangle} \approx e^{ikDis(R_A, R_B)}, \quad (3)$$



145 **Figure 2.** Quarry blasts DAS data on (a) 12 October 2016 and (b) 21 November 2016. Both
 146 plots (a) and (b) are after noise attenuation and polarity correction. Blue lines denote the signals
 147 at channel 120. Plots (c) and (d) compare the time frequency spectrograms of these two days
 148 data, which are calculated with the single channel shown with blue lines in plot (a) and (b), re-
 149 spective. Plot (e) and (f) compare with the beamforming spectrum calculated with the data in
 150 the red dashed box in (a) and (b), whose peaks indicate the wavefield direction of propagation
 151 and its velocity. The channels used for beamforming are from 12-77, indicated by green dashed
 152 line in Figure 1a.

174 where $\ll \cdot \gg$ is a Gaussian smoothing operator. Equation 3 is an implementation
 175 of deconvolution in the frequency domain, which can both remove the influence of the
 176 source wavelet and improve the data resolution. More details of data processing results
 177 can be found in supporting information Figures S1-S2.

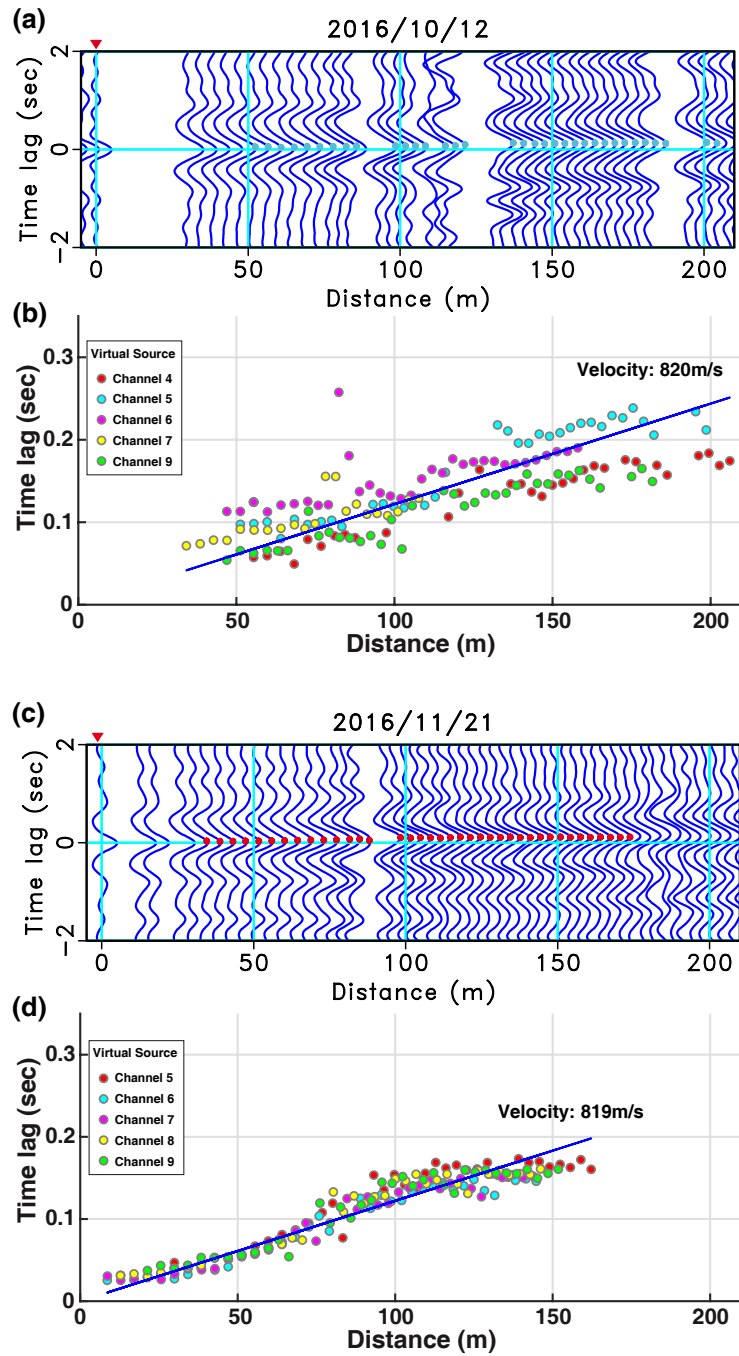
178 4 Results

179 Using data recorded at channels away from the construction site, we first estab-
 180 lish the baseline velocity of the site and demonstrate that DAS recordings, after urban
 181 noise removal, can provide reliable velocity estimates. We select channels 5-48, use 5 chan-
 182 nels near channel 5 as virtual sources, and calculate the normalized cross-correlograms.
 183 Figure 3a shows one of these normalized cross-correlograms on 12 October 2016, whose
 184 vertical axis represents the seismic time lag from virtual source to channels. The chan-
 185 nels that are still contaminated by near-field noise after signal processing are omitted.
 186 Figure 3b shows the picked travel-time lag along the distance between virtual source and
 187 receiver, where the different colored dots denote the picks from different virtual sources.
 188 Figures 3c and 3d are similar to Figures 3a and 3b but computed on 21 November 2016.
 189 The surface seismic velocities are estimated by a least-squares linear regression of the
 190 picked travel times on each day. After correction for the propagation angles obtained
 191 from beamforming spectrums (as shown in Figures 2e and 2f), the measured velocities
 192 on 10 different days show small variations over 3 months (Table S1 in supporting infor-
 193 mation). The average velocity over 3 months is measured at 816 m/s and their coeffi-
 194 cient of variation is 3.2%, with which the measurements at the construction site are bench-
 195 marked.

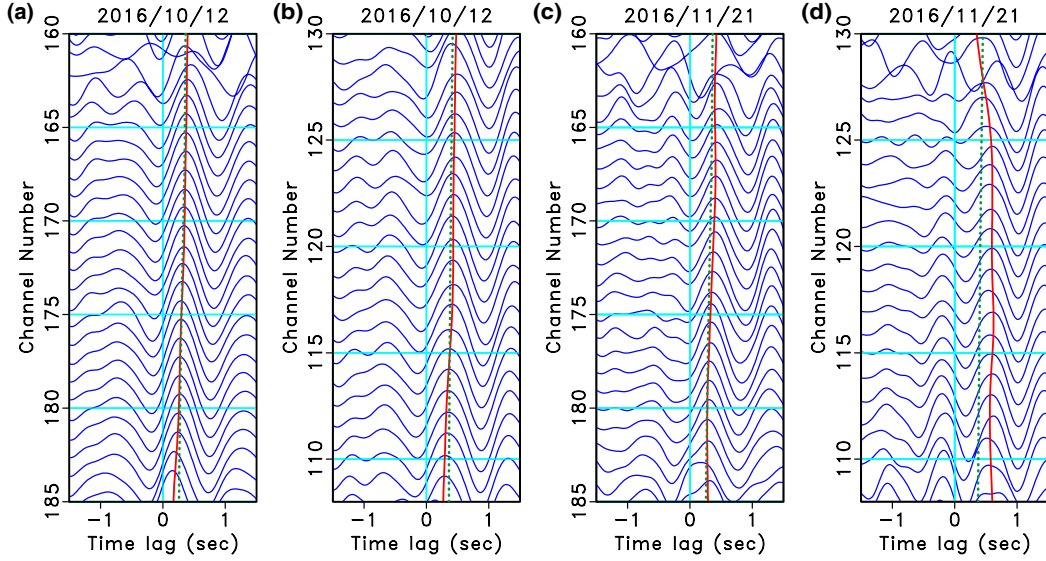
205 When we focus on the segment of the array closer to the construction site, the ef-
 206 fects of excavation on velocity are observed. We select two segments of the DAS record-
 207 ings surrounding the construction site, one on the south edge (channels 170-184), and
 208 the other on the north edge (channels 108-128). Figure 4 shows the normalized cross-
 209 correlograms between channel 36 (the green dot in Figure 1a) and the two segments be-
 210 fore and after the excavation. The measured arrival time shift in Figure 4 only depends
 211 on the velocity within the boundaries of the DAS array. In Figures 4a and 4b, we ob-
 212 serve that before construction started the surface wave arrivals show high spatial coherency
 213 in both segments. Their picked arrival times (red solid line) with slight moveout across
 214 the channels agree well with the computed arrival times (green dashed line) according
 215 to the average velocity of 816 m/s. Figures 4c and 4d show the cross-correlograms two
 216 weeks after excavation on both segments. In Figure 4c, the south channels maintain the
 217 consistent arrival times at the reference velocity, indicating a stable subsurface environ-
 218 ment between the two investigations (as expected because no excavation was performed
 219 along this ray path). In Figure 4d, systematic time delays are observed on the north seg-
 220 ment, which suggests that the subsurface velocity between the two segments was reduced
 221 due to excavation of the basement.

229 To investigate the spatial sensitivity of the passive DAS monitoring system, we ex-
 230 tract surface wave velocities from channels 162-205, where the construction site is be-
 231 tween channel 172 and 184. We use 3 channels near channel 205 as virtual sources to cal-
 232 culate normalized cross-correlations. Figure 5a and 5b show one of the cross-correlograms
 233 (channel 205 as virtual source) before and after the excavation, respectively. The black
 234 lines denotes the picked travel time. Figure 5c displays the picked travel time versus dis-
 235 tance (green dots: before excavation, red triangles: after excavation). The picked travel
 236 times stay within the same clusters with similar linear trends at channels east and west
 237 of the basement. At the basement, however, the cluster of red triangles deviates from
 238 that of the green circles, indicating significant changes in velocity.

239 The yellow dashed and blue solid lines are the least-squares piecewise linear fit of
 240 the red triangles and green dots of the three parts. As expected, at both the west (chan-



196 **Figure 3.** Five channels close to the channel 5 are used as virtual sources to calculate nor-
 197 malized cross-correlograms with channels 5-48. Plot (a) shows the normalized cross-correlograms
 198 on 12 October 2016. The channel used as virtual source (channel 5) is labeled with red triangle.
 199 The x axis denote the distance between virtual source and each receiver. Cyan dots denote the
 200 picked travel time lag. Plot (b) shows the picked time lag along the actual spatial distances from
 201 all the normalized cross-correlograms. The dots with different color denote the time delay picked
 202 with different virtual sources. Plot (c) and (d) are similar to (a) and (b), but computed on 21
 203 November 2016. The marked surface seismic velocities are calculated by the slopes of the blue
 204 lines.



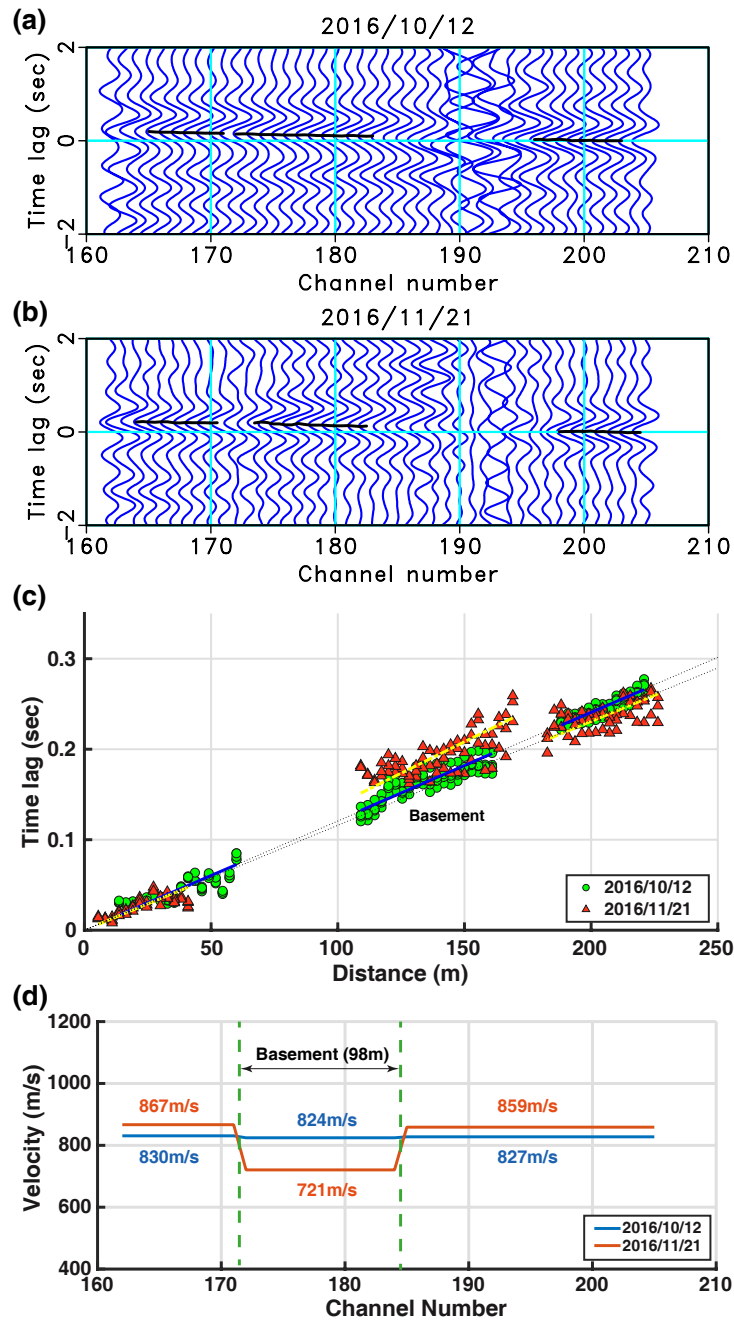
222 **Figure 4.** Plot (a) and (b) compare the normalized cross-correlograms between the virtual
 223 source (channel 36) and the front channels 165-183 and the back channels 108-136 on 12 October
 224 2016, respectively. The virtual source location is denoted by the green dot in Figure 1a. The
 225 front and back channels are denoted by the orange and green lines in Figure 1a. Plot (c) and
 226 (d) are similar to plots (a) and (b), but on 21 November 2016. The green dashed lines show the
 227 calculated time lag according to the reference velocity, 816 m/s . The red solid lines show the
 228 picked time lag of the normalized cross-correlation.

241 nels 162-172) and east (channels 184-205) of the basement, the yellow and the blue lines
 242 have very similar slopes. However, across the basement (channels 172-184) the yellow
 243 line has a larger slope compared to the blue line, which indicates a lower subsurface ve-
 244 locity. Figure 5d displays the estimated average velocities along the three segments. Com-
 245 paring the velocities before and after excavation, it is obvious that the velocities to the
 246 west and east of the basement are not significantly changed, whereas an apparent ve-
 247 locity drop from 824 m/s to 721 m/s is observed at the basement. The relative veloc-
 248 ity drop is 12.5%, nearly 4 times larger than the coefficient of variation 3.2% observed
 249 at stable sections of the array. Therefore, we believe the velocity drop is statistically sig-
 250 nificant, and caused by the excavation. This demonstrates the ability to detect changes
 251 due to the excavation of a single building basement with unprecedented resolution for
 252 a DAS-based urban seismic monitoring system.

260 5 Discussion

261 5.1 Observed velocity variations by DAS

262 Any monitoring system must strike an important balance between its sensitivity
 263 in detecting changes and its accuracy in issuing an alarm. In this study, we show that
 264 the velocity measured using a DAS array does vary in time and space. Factors leading
 265 to the velocity variations are three-fold: random DAS measurement error, changes in noise
 266 fields and source wavelet, and changes in subsurface geological conditions. Through care-
 267 ful signal processing, we have reduced the effect of DAS measurement noise, changes in
 268 noise fields and source wavelet, so as to improve our ability to isolate changes due to sub-
 269 surface geological conditions.



253 **Figure 5.** (a) and (b): Normalized cross-correlograms on 12 October 2016 and 21 November
 254 2016, respectively. The black lines denote the picked travel time for three segments along the
 255 fiber cable. (c) Picked time lags on 12 October 2016 (Green circles) and 21 November 2016 (red
 256 triangles) plotted against distance. The gap from 60-100 meters distance are caused by removing
 257 the poor quality data around channel 193. The yellow dashed lines and the blue solid lines are
 258 least-squares linear fits to the red triangles and the green circles respectively. (d) Average veloci-
 259 ties measured in three segments before and after excavation with a channel interval of 8.16m.

270 Individual DAS channels have a lower signal-to-noise ratio (SNR) compared to con-
271 ventional geophones in an ideal coupling condition (Lindsey et al., 2017; Yu et al., 2019).
272 In this experiment, the fiber cable is loosely lying in an existing conduit, which further
273 reduces the SNR. Moreover, DAS recordings in urban areas are severely contaminated
274 by nearby construction and traffic noise. We observe a significant decrease in SNR af-
275 ter construction began, which reduces the sensitivity of velocity anomaly monitoring. The
276 variations in measured velocity are quantified using data recorded in a geologically sta-
277 ble zone, and later used as baseline statistics to identify abnormal velocity variations caused
278 by changes in subsurface geology.

279 With the Stanford DAS array, the measured velocity variation (12.5%) after ex-
280 cavation provides strong statistical confidence of detection of an anomaly. On the other
281 hand, the 3.2% baseline variance suggests that small changes in subsurface velocity may
282 not be identified by the Stanford DAS system, which may limit its applicability to iden-
283 tify the development of small cavities in urban environments. With newer DAS inter-
284 rogators with smaller channel spacing and gauge length and higher frequency noise sources,
285 there is in principle a chance to detect smaller velocity changes, such as sinkhole devel-
286 opment. These baseline statistics and sensitivities vary with site conditions, acquisition
287 parameters, and signal characteristics. Establishing baseline velocity measurements and
288 uncertainty bounds is very important for quantitative urban monitoring.

289 5.2 Temporal resolution of DAS urban monitoring

290 Many of the passive seismic methods assume far-field and full azimuthal random
291 sources with equipartitioning in energy (Roberts & Asten, 2008; Shapiro et al., 2005).
292 However, urban ambient noise usually comes from fixed-location human activities that
293 are often not perfectly random and isotropic (Bonnefoy-Claudet et al., 2006). When the
294 sources are in close proximity to the array, longer recordings are used to increase the ran-
295 domness and azimuthal coverage and reduce their susceptibility to near-field effects, par-
296 ticularly for the low SNR DAS recordings.

297 In this experiment, we make use of the repetitive quarry blasts as far-field, unidi-
298 rectional sources to extract subsurface velocity based on much shorter recordings than
299 would be required for an ambient noise approach. The temporal resolution of our exper-
300 iment depends on the interval of the blasts, a few days in this case, which is sufficient
301 for urban subsurface monitoring and alert. When an array is placed closer to a blast site
302 that emits strong impulsive noises, abundant high-frequency signals may be recorded by
303 DAS for higher spatial resolution subsurface monitoring.

304 6 Conclusions

305 Analysis of quarry blasts recorded by the Stanford Fiber Optic Seismic Observa-
306 tory suggests that a surface DAS array in an existing communication infrastructure can
307 be used for time-lapse monitoring of near-surface velocity changes. Compared to a 3.2%
308 baseline velocity variation, a strong velocity decrease (12.5%) is observed after two weeks
309 of a basement excavation. The high temporal resolution is achieved by making use of
310 repetitive quarry blast signals and a careful data processing workflow to remove the near-
311 field noise and to normalize the variations in the blasting conditions. Our study suggests
312 that a DAS array deployed in existing communication infrastructure has a strong po-
313 tential for high-resolution urban near-surface monitoring and urban geohazard risk man-
314 agement.

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 319 able at GitHub (<https://github.com/GeoGANGFANG/StanfordDASQuarryBlast>).
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