Urban Monitoring Using Pre-Existing Telecommunication Fiber-Optic Networks as Distributed Acoustic Sensing Systems: A Review

Jingxiao Liu[a,*], Haipeng Li[b], Jiaxuan Li[c], Doyun Hwang[d], Jatin Aggarwal[d],
Biondo Biondi[b], Hae Young Noh[d]

[a] *Senseable City Laboratory, Massachusetts Institute of Technology, Cambridge, 02139, MA, USA*
[b] *Department of Geophysics, Stanford University, Stanford, 94305, CA, USA*
[c] *Department of Earth and Atmospheric Sciences, University of Houston, Houston, 77204, TX, USA*
[d] *Department of Civil and Environmental Engineering, Stanford University, Stanford, 94305, CA, USA*

Abstract

Urban monitoring is important for maintaining safe and sustainable urban life through infrastructure assessment, resource optimization, and public safety enhancement. Vibration and seismic signals offer rich insights into urban environments, reflecting both physical and environmental conditions and societal activities. Recent advancements in Distributed Acoustic Sensing (DAS) have leveraged pre-existing telecommunication (telecom) fiber-optic networks as dense arrays of seismic and vibration sensors, providing a scalable, cost-effective, and continuous urban monitoring solution. DAS technology uses internal imperfections in fiber-optic cables to measure dynamic strain (rate), enabling fibers to capture seismic waves and structural vibrations at meter-scale intervals over tens of kilometers. By utilizing pre-existing telecom fiber networks as urban-scale sensing platforms, DAS has demonstrated broad applications ranging from seismic monitoring and subsurface imaging to urban activity detection and structural health assessment. As research and technological advancements continue, DAS is positioned to become prominent in next-generation urban sensing, supporting smarter, more resilient, and more sustainable urban planning and development. Building on these devel-

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[*] Corresponding author, email: jingxiao@mit.edu

opments, this paper reviews the latest progress in urban monitoring using pre-existing telecom fiber networks as DAS systems.

Keywords: urban sensing, distributed acoustic sensing, fiber optics, seismic monitoring, seismic imaging, smart city, intelligent transportation systems, structural health monitoring.

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1. Introduction

As centers of human activity and major contributors to global emissions, cities have become focal points for research aimed at improving governance, enhancing the quality of life, and promoting sustainability [1, 2]. Rapid urbanization, population growth, natural hazards, and aging infrastructure present challenges that threaten urban resilience, efficiency, and sustainability. Addressing these challenges requires continuous and accurate urban monitoring, which enables the assessment of infrastructure health, optimization of resource management, and enhancement of public safety [3, 4]. A key enabler of urban monitoring is the availability of large-scale datasets that capture diverse urban “signals” with high spatial and temporal resolution [5, 6]. Among the various signals generated by urban environments, vibration and seismic data are particularly valuable, offering rich insights into urban environments, such as infrastructure conditions [7, 8, 9, 10], subsurface properties [11, 12], and human activities [13, 14].

Among vibration and seismic sensing technologies, Distributed Acoustic Sensing (DAS) [15, 16, 17] has recently emerged as a powerful tool for urban monitoring due to its advantages, including low weight, immunity to electromagnetic interference, and high spatio-temporal resolution. By measuring Rayleigh backscattered signals, DAS captures continuous dynamic strain (rate) data along fiber-optic cables with meter-level spatial resolution over a hundred of kilometers. Notably, DAS can leverage pre-existing telecommunication (telecom) fibers – originally installed for data transmission – transforming them into dense arrays of virtual strain (rate) sensors. These telecom fibers are commonly buried along roadways, suspended on utility poles, or integrated into civil infrastructure such as bridges, making them well-suited to capture vibration and seismic responses across the urban environment. This enables large-scale, cost-effective urban sensing without additional onsite sensor deployment or maintenance. Recognizing these advantages and DAS’s growing prominence, this paper provides a review of recent advancements in urban monitoring using pre-existing telecom fiber-optic networks as DAS systems (referred to as 'telecom DAS' throughout this paper).

A growing body of research has explored the diverse applications of telecom DAS technology in urban settings. In natural seismic monitoring, telecom DAS has been extensively used to capture and characterize seismic phenomena such as earthquakes, thunder-induced ground motions (thunderquakes), avalanches, and other seismic events. Studies (e.g., [18, 19]) have demonstrated that telecom DAS can effectively record earthquake wavefields, enabling accurate seismic event detection, source localization, and characterization of wave propagation across urban areas. In urban geophysics, DAS recordings from telecom cables have been leveraged for subsurface imaging, aiding in the estimation of near-surface velocity structures and the monitoring of subsurface changes (e.g., [20, 21, 22]). Telecom DAS has also proven valuable in detecting environmental changes by capturing continuous seismic noise, facilitating the monitoring of groundwater dynamics and soil moisture variations (e.g., [23, 24]). Additionally, advances in signal processing and machine learning (e.g., [25, 26]) have enhanced telecom DAS's ability to navigate complex urban seismic environments effectively.

Beyond natural seismic monitoring, telecom DAS has demonstrated strong potential for urban activity monitoring, particularly in transportation-related applications such as traffic flow analysis, vehicle tracking, and pedestrian activity detection. Telecom DAS-based sensing has been effectively used to monitor vehicle movements, estimate traffic volumes and speeds, and classify vehicle types (e.g., [27, 28, 29]). Advancements in machine learning have further enhanced the accuracy and efficiency of these systems, enabling real-time traffic analysis (e.g., [30, 31, 32]). In addition to human mobility, telecom DAS has been applied to structural health monitoring, particularly for bridges, where dynamic strain measurements help estimate structural properties and assess integrity using urban fiber networks [33, 34, 35].

Despite these advancements, several challenges remain in realizing the full potential of telecom DAS for urban applications. One major limitation is the heterogeneous coupling and unknown physical properties of pre-existing telecom fiber-optic cables, which were not originally designed for sensing. Variations in fiber type, cable installation methods, coupling conditions, and external environmental influences introduce inconsistencies in sensitivity and accuracy across virtual sensor arrays [36, 37]. Additionally, the urban environment presents complex and spatially heterogeneous noise conditions, complicating the extraction of meaningful signals [38]. Overcoming these challenges requires advancements in fiber characterization techniques and data processing algorithms to ensure reliable and accurate sensing.

Looking ahead, continued research efforts are needed to enhance telecom DAS capabilities and address its limitations. Innovations in interrogator technologies, advanced machine learning algorithms, and hybrid sensor integration could significantly improve performance. Expanding telecom DAS applications beyond traditional monitoring – such as public health surveillance, archaeological studies, and environmental sustainability – could unlock new research frontiers. Additionally, leveraging cloud computing and large-scale data analytics has the potential to enhance real-time processing and interpretation, paving the way for scalable and automated urban monitoring platforms.

This paper is structured as follows: Section 2 covers fiber-optic sensing technologies, while Section 3 focuses on telecom DAS systems. Section 4 reviews key scientific studies and applications of telecom DAS in urban settings, and Section 5 discusses remaining challenges and highlights future research directions.

2. Background: Fiber-Optic Sensing Methods for Vibration-Based Urban Monitoring

Fiber optic sensing works by injecting light into the fiber optic cables and detecting the changes in optical properties such as wavelength and phase. It offers several advantages over conventional sensors, such as accelerometers, geophones, and strain gauges. Fiber-optic sensing systems are lightweight, immune to electromagnetic interference, resistant to corrosion, and well-suited for long-term deployment in harsh environments [39, 40, 41]. Moreover, these systems support multiplexing and distributed configurations, enabling dense measurements at multiple locations along each fiber. These attributes make fiber-optic sensing especially attractive for large-scale vibration and seismic monitoring.

Fiber-optic sensors can be broadly classified into three types, depending on the sensing architecture: point sensors, quasi-distributed sensors, and fully distributed sensors. This review paper focuses on DAS, a specific class of fully distributed fiber-optic sensing uniquely capable of scalable, city-wide deployment due to its long sensing range. Before delving into DAS specifically, we briefly review point and quasi-distributed sensing approaches for comparison.

2.0.1. Point and Quasi-Distributed Fiber-Optic Sensing

Point fiber-optic sensors measure physical and environmental parameters at discrete, predefined locations along the fiber. A common example is the Fiber Bragg Grating (FBG) sensor [42], which reflects specific wavelengths of light depending on the local strain or temperature. Fiber gratings are etched onto the fiber by varying the refractive index of the fiber so that specific wavelengths of light are either reflected or filtered. Changes in strain can be detected by measuring the change in the specific wavelength. Although highly sensitive, point sensors are limited by their spatial coverage and scalability, as each measurement point requires an individual fiber optic cable.

To overcome these limitations, quasi-distributed sensing extends point sensing by combining multiple sensors along a single fiber. In multiplexed FBG systems [43], each grating is assigned a unique wavelength, allowing for simultaneous interrogation of multiple points. Multiplexing techniques such as wavelength, frequency, and time division are commonly used [44]. However, the practical sensing range of quasi-distributed systems typically remains within a few hundred meters, making them more suitable for monitoring individual structures or specific components within a broader urban system.

2.0.2. Distributed Fiber-Optic Sensing

Distributed fiber-optic sensing enables continuous measurement of physical or environmental parameters along the entire length of an optical fiber. Unlike point or quasi-distributed sensing systems, distributed fiber-optic sensing does not rely on discrete sensing locations but instead turns the entire fiber into a sensor. The principle underlying distributed fiber-optic sensing is optical backscattering. As laser light propagates through the fiber, it encounters microscopic fluctuations in the fiber's material properties or refractive index, causing a small fraction of the light to scatter in the reverse direction. This backscattered signal carries localized information about temperature, strain, or dynamic events occurring along the fiber.

Distributed fiber-optic sensing relies on three main types of optical backscattering (Figure 1): Raman, Brillouin, and Rayleigh scattering. Raman and Brillouin scattering are inelastic processes, meaning that the scattered light undergoes a frequency shift as a result of energy exchange between photons and the fiber medium [45, 46]. Rayleigh scattering differs in that it is an elastic process; the scattered light retains the same frequency as the incident light. Depending on the direction of energy transfer, the scattered photons may either gain energy, resulting in an anti-Stokes shift, or lose energy, resulting in a Stokes shift. Raman scattering is primarily influenced by temperature, making it ideal for distributed temperature sensing without interference from strain variations [47]. Brillouin scattering is sensitive to both strain and temperature, allowing for simultaneous monitoring of these parameters [48]. Rayleigh backscattering is highly responsive to axial strain while exhibiting only weak temperature sensitivity. Compared to Rayleigh backscattering, Brillouin is a weaker backscattering mechanism, and the temporal averaging reduces its tracking speed. Therefore, Brillouin-based fiber-optic sensing is typically used to measure strain and temperature changes that are nearly static, while Rayleigh-based fiber-optic sensing is used for sensing fast-changing dynamic strain.

These optical backscattering mechanisms are the foundation for two widely used reflectometry methods: optical frequency-domain reflectometry (OFDR) and optical time-domain reflectometry (OTDR). OFDR involves injecting a frequency-swept laser into the fiber and analyzing the resulting interference pattern to reconstruct the reflectivity profile along the fiber [49]. It offers high spatial resolution, down to the centimeter or even millimeter scale, but its effective sensing range is limited to a few hundred meters, restricting its applicability in large-scale urban monitoring. OTDR, on the other hand, relies on injecting short laser pulses and measuring the intensity and time delay of the returning backscatter. This method can cover distances of tens to over a hundred kilometers [50], with spatial resolutions typically on the order of meters. Its extended sensing range makes OTDR highly suitable for monitoring long-span infrastructure and urban environments.

A key application of OTDR is in DAS, specifically using phase-sensitive OTDR (ϕ-OTDR). An optoelectronic interrogator repeatedly sends laser pulses into the fiber, and an optical interferometry system measures the Rayleigh-backscattered light. The backscatter is caused by intrinsic inhomogeneities in the refractive index of the fiber, which act as scattering centers. Because the speed of light in the fiber is known, the arrival time of the backscattered signal can be mapped to a specific location along the fiber using the time-of-flight. Strain perturbations cause phase shifts in the scattering centers, which are quasi-linearly proportional to the accumulated strain along the fiber [51]. The phase unwrapping algorithm is used to identify the phase change, which can be converted to strain. By sending the laser pulses at a high frequency, the dynamic strain profile along the fiber can be determined [52]. Two key parameters are gauge length, the length over which

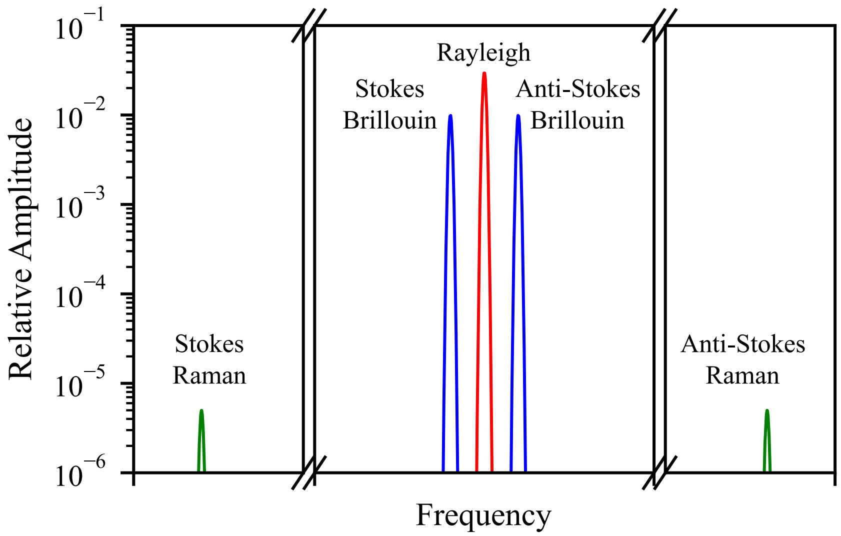

Figure 1: Types of optical scattering used in distributed fiber-optic sensing.

strain is averaged, and channel spacing, the distance between adjacent virtual sensors. These parameters involve trade-offs: longer gauge lengths offer higher signal-to-noise ratios but lower spatial resolution, while finer channel spacing improves spatial resolution but increases data redundancy and storage demands. Typically, the channel spacing is set smaller than the gauge length, creating overlapping measurement segments. This overlap enhances robustness: if some channels suffer from fading or noise, neighboring channels can still reliably capture the signal in that region.

3. Distributed Acoustic Sensing Through Pre-Existing Telecom Fiber-Optic Cables

Modern cities are interconnected with extensive networks of telecom optical fiber cables – totaling approximately 57.1 million miles across the U.S. as of 2022 [53] – typically buried underground or attached to infrastructure such as bridges and poles. Bundled typically in standardized counts (288, 432, or 864 fibers), these cables form the backbone for internet and telecom services both within and between cities. However, a significant portion (over 50%) remains unused, installed proactively to meet future demands. Known as “dark fiber," these unused fibers can be repurposed as virtual strain sensors using DAS, enabling vibration and seismic sensing without disrupting existing telecom operations. Recent research indicates that incorporating pre-existing telecom fiber-optic cables as seismic sensors can significantly expand the monitoring coverage of low-amplitude ground-motion events (moment magnitude > 0.5) in U.S. metropolitan statistical areas from an average of 1% to approximately 12% [54].

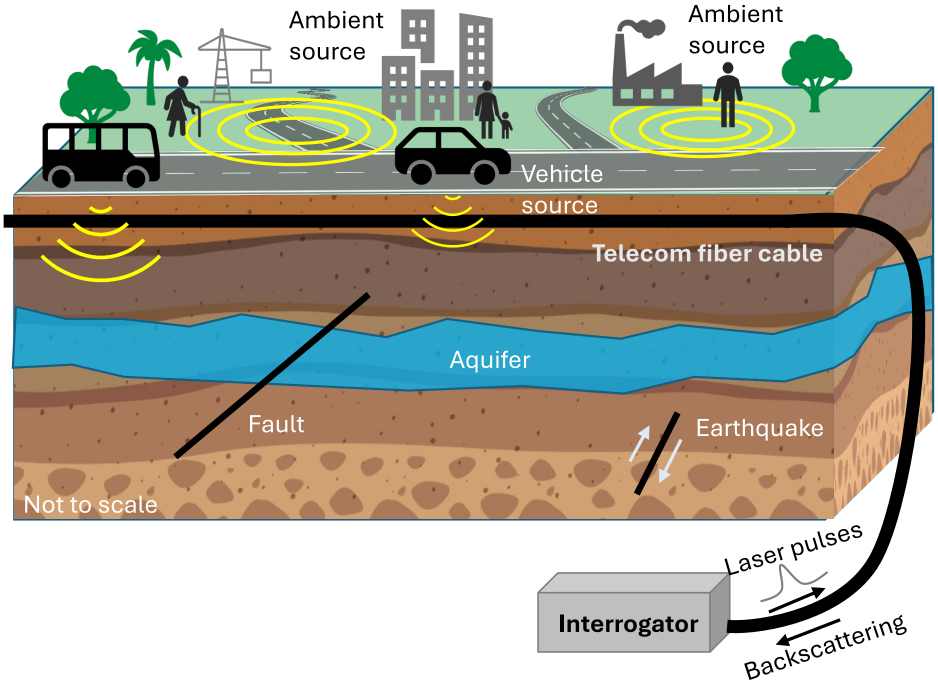

Figure 2: Schematic illustration of a DAS system utilizing existing telecommunication fiber to capture seismic signals in an urban environment. Seismic sources include earthquakes, transportation movements, and ambient seismic noise generated by human activities.

Transforming urban-scale dark fiber into DAS systems offers scalable urban monitoring solutions without additional sensor installations or on-site maintenance. As illustrated in Figure 2, a single optoelectronic instrument (interrogator) connects to one end of the fiber, and the natural scattering points within the fiber, up to 160 km in sensing range, act as dynamic strain sensors spaced every few meters to measure vibration and seismic responses across the urban environment. Laser pulses sent by the interrogator interact with natural scattering points within the fiber, effectively creating ultra-dense seismic arrays with sensor spacing every few meters at minimal cost [15]. DAS technology ensures privacy by avoiding the collection of identifiable information and facilitates continuous, real-time sensing integrated seamlessly into existing telecom networks [55]. Due to its dense array properties, DAS is highly effective in capturing a wide range of urban vibrations and seismic signals, particularly high-frequency (e.g., > 1 Hz) seismic sources that are challenging for traditional seismic networks due to scattering and rapid attenuation [56].

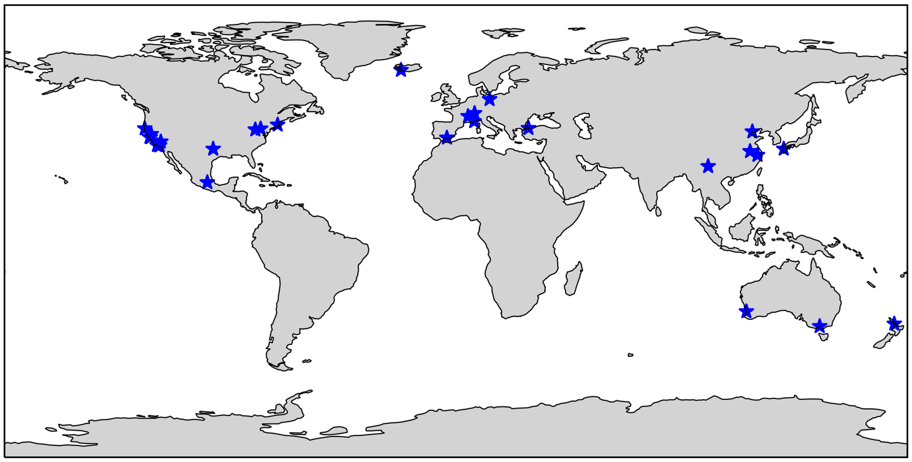

Figure 3: DAS deployments utilizing pre-existing telecom cables in urban areas, as reported in various publications. These deployments span locations including Arcata, CA [57], Athens, Greece [58], Auckland, New Zealand [59], Berlin, Germany [60], Bern, Switzerland [61], Binchuan, China [62], Cambridge, MA [63], Dallas, TX [64], Granada, Spain [65], Grindavík, Iceland [66, 67, 68], Hangzhou, China [69], Hefei, China [70], Istanbul, Turkey [71], Kumamoto, Japan [72], Los Angeles, CA [73], Lyon, France [35], Melbourne, Australia [74], Mexico City, Mexico [75], Nice, France [76], Oxnard, CA [77], Pasadena, CA [27], Perth, Australia [78], Pittsburgh, PA [79], Ridgecrest, CA [23], San Jose, CA [55], Sacramento, CA [80], Stanford, CA [25], State College, PA [81], Tangshan, China [82].

Researchers have actively explored applications of pre-existing telecom fiber-optic cables for urban monitoring, including traffic analysis, bridge health assessment, earthquake detection, and subsurface imaging, as discussed further in the subsequent sections. Figure 3 illustrates urban DAS deployments leveraging pre-existing telecom optical fiber infrastructure across multiple continents, including North America, Europe, Asia, Australia, and Central America, as documented in recent studies. As a specific example, Figure 4 illustrates telecom fiber cables used in Stanford DAS experiments, with

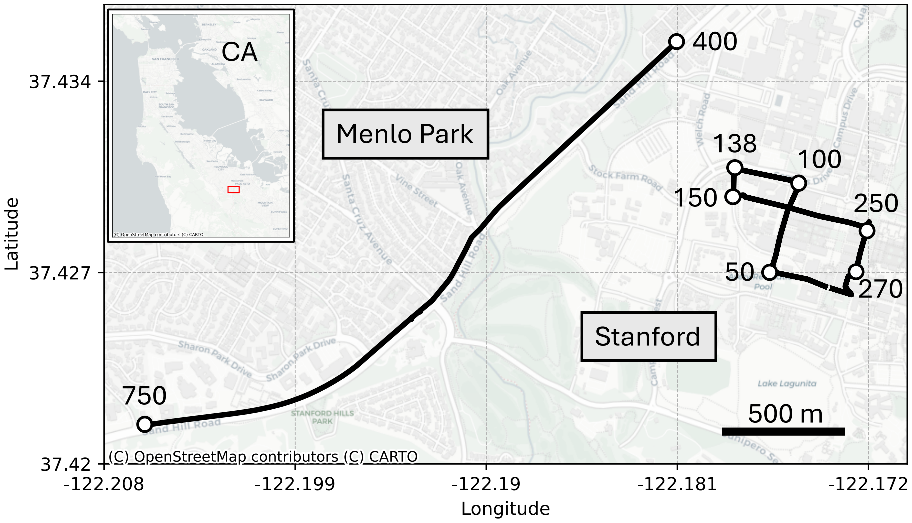

Figure 4: Map of the pre-existing telecom optical fiber cables (black lines) used for DAS in the Stanford DAS experiment. Numbers indicate DAS channel positions, with a channel spacing of 8.16 meters. DAS recordings from channels 400 to 750 along Sandhill Road are presented in Figure 5, where channel 400 is set as the origin (0 m).

DAS channel positions uniformly spaced at 8.16 meters. This deployment includes a figure-eight loop within the Stanford campus and an extended route along Sand Hill Road next to the campus.

In urban environments, DAS signals exhibit distinct spectral and temporal characteristics. Figure 5 presents DAS recordings from channels 400 to 750 along Sand Hill Road after preprocessing steps such as linear and median trend removal, with channel 400 defined as the origin (0 meters). The data captured within a 15-second window demonstrates diverse signal types. Specifically, Figure 5a shows DAS signals bandpass-filtered between 0.1 Hz and 1 Hz, highlighting low-frequency quasi-static vibrations primarily induced by the weight of each vehicle driving by. These signals provide real-time traffic information, such as vehicle speed, direction, and classification based on amplitude variations related to vehicle size or weight [29]. Figure 5b, filtered between 1 Hz and 20 Hz, emphasizes intermediate and higher-frequency signals. This frequency range includes surface waves, notably Rayleigh waves generated by traveling vehicles, valuable for continuous, high-resolution subsurface imaging [25]. The imaging results help the detection of subsurface anomalies like sinkholes, ground subsidence, and potential seismic hazards. Telecom DAS also captures the structural vibrations of any attached civil infrastructure, along with seismic signals from earthquakes and ambient seismic noise. Earthquake-induced signals typically manifest as planar wavefronts due to their near-vertical incidence. Horizontally oriented DAS fibers are more sensitive to S-waves than P-waves [20]. Additionally, ambient vibrations from anthropogenic sources (e.g., distant trains, traffic, construction) and natural phenomena (e.g., ocean microseismicity, atmospheric disturbances) further contribute to the rich spectrum of signals recorded by DAS [83].

4. Scientific Studies and Applications of Telecom DAS Systems

The broadband frequency capabilities of telecom DAS systems have been successfully demonstrated in various urban monitoring studies and applications. Figure 6 provides an overview of these studies, presenting the corresponding DAS frequency ranges of interest. The corresponding references are summarized in Table 1. The static & quasi-static ($<$1 Hz) and intermediate-frequency (1$\sim$20 Hz) DAS responses have proven highly effective in monitoring natural seismic activities, including earthquake detection, near-surface imaging, and avalanche monitoring (e.g., [84, 20]). Moreover, they have found utility in city activity monitoring and civil infrastructure monitoring tasks, such as characterizing roadway traffic, detecting footsteps, identifying man-made blasts, and monitoring underground telecom infrastructure (e.g., [55, 29]). Additionally, high-frequency DAS responses ($>$20 Hz) have been used for thunderquake detection and localization, audible event detection, and bridge health monitoring (e.g., [85, 33]). These diverse applications underscore the versatility and capability of telecom DAS systems in effectively monitoring complex urban environments. In the following sub-sections, scientific studies and applications of telecom DAS systems for urban monitoring are summarized.

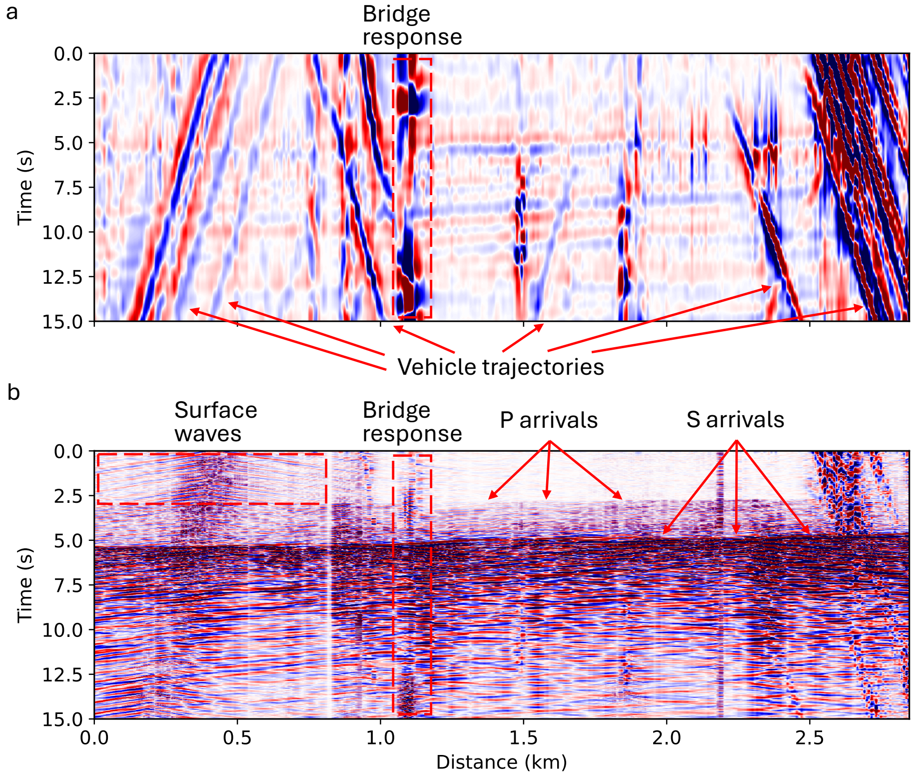

Figure 5: The continuous DAS recording from channels 400 to 750 of the Stanford DAS experiment (Figure 4) after preprocessing (removal of linear and median trends). (a) displays the quasi-static DAS signal band-passed between 0.1 and 1 Hz, capturing vehicle-induced quasi-static signals and bridge response at low frequency. (b) shows the DAS signal band passed between 1 and 20 Hz, highlighting surface waves generated by a vehicle moving at approximately 35 mph, seismic wavefields from an earthquake event near Portola Valley, and bridge dynamic response. Key features such as vehicle trajectories, bridge response, surface waves, P-wave, and S-wave arrivals are annotated.

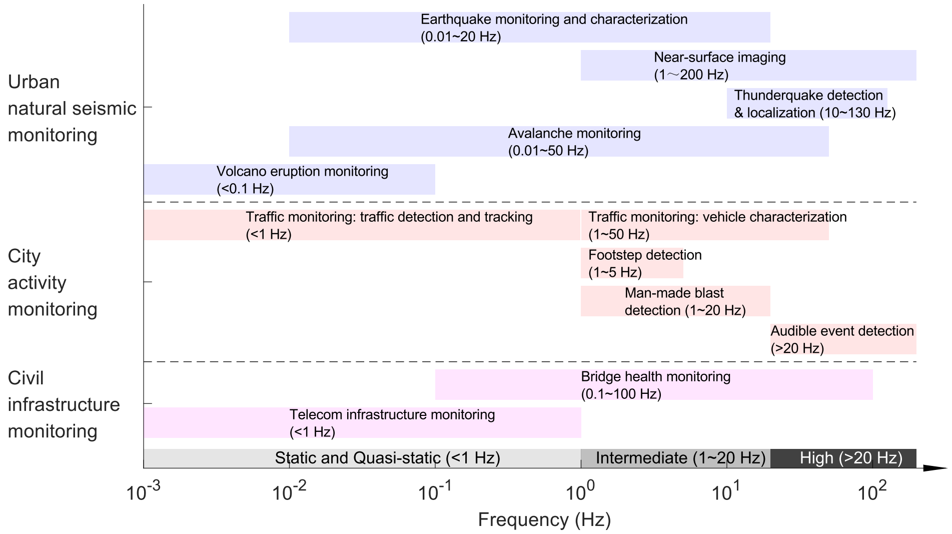

Figure 6: Scientific studies and applications of telecom DAS for urban monitoring, along with their corresponding frequency ranges of interest, are summarized based on current literature. For earthquake monitoring and characterization in urban settings, induced seismic events (such as those from mining or reservoirs), which typically exhibit higher frequencies, are excluded from consideration.

Table 1: Urban monitoring applications using telecom DAS systems.

Applications		**References**
Natural seismic monitoring	Earthquake monitoring and characterization	[66, 28, 86, 87, 19, 88, 18, 89, 90, 91, 80, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 26, 102, 103, 104, 105, 106, 107, 72, 108, 109, 110, 111, 112, 84]
	Near-surface imaging	[113, 20, 93, 21, 114, 115, 65, 17, 77, 18, 116, 117, 118, 119, 120, 23, 25, 121, 122, 29, 24, 22]
	Thunderquake detection and characterization	[123, 85, 91]
	Avalanche characterization	[124]
	Volcano eruption monitoring	[67, 68]
City activity monitoring	Traffic monitoring and vehicle characterization	[27, 28, 125, 126, 127, 128, 129, 130, 131, 29, 132, 133, 134, 31, 32, 135, 136, 137, 30, 55]
	Footstep detection	[138, 91, 139]
	Man-made Blast detection	[19, 113, 91, 140]
	Audible event detection	[91, 141, 129, 55]
Civil infrastructure monitoring	Bridge health monitoring	[33, 35, 34]
	Telecom infrastructure monitoring	[142, 143, 144, 145, 126, 146]

4.1. Urban Natural Seismic Monitoring

This section focuses on studies about using telecom DAS systems to monitor natural seismic events in or near urban areas. These include studies related to earthquake monitoring and characterization, near-surface imaging, thunderquake identification, avalanche characterization, and volcano eruption monitoring.

4.1.1. Earthquake Monitoring and Characterization

DAS uses pre-existing telecom fiber-optic cables to achieve dense spatial sampling of seismic wavefield across long distances (up to 160 kilometers [50]) and at meter-scale resolution. DAS accurately records ground motion across a broadband spectrum. By converting strain or strain rate measurements to ground velocity or acceleration, empirical calibrations have shown that DAS exhibits a nearly flat instrumental response from 0.01 to 10 Hz compared to collocated broadband seismometers or accelerometers, with negligible phase distortion [66, 28, 86, 87]. Although the noise floor of DAS is higher than that of expensive broadband seismometers, it is comparable to that of accelerometers [87], making DAS a cost-effective and scalable solution for earthquake monitoring and characterization.

Numerous studies have demonstrated telecom DAS's ability to capture distinct seismic wavefields from local earthquakes, including clear recordings of P-wave, S-wave, surface waves, and crustal phases [19, 88, 18, 89, 90, 91, 80, 92, 93, 94]. These recordings enable earthquake location through inverting traveltime picks or beamforming [95, 96] and can be used for structural imaging of the near-surface and crust [97, 94]. Beyond local events, telecom DAS has also been shown to detect teleseismic events [89, 98, 99], highlighting its potential for deep Earth imaging.

DAS's ability to operate on the extensive pre-existing telecom infrastructure marks its unique potential for earthquake rapid response and earthquake early warning (EEW). For example, four days after the 2019 Mw7.1 Ridgecrest earthquake, a 10-km DAS array was established to monitor aftershocks and detected six times more earthquakes than the SCSN catalog using template matching [100]. Operational EEW with DAS requires real-time processing and accurate determination of strain amplitudes [101]. A recently developed machine-learning-based phase-picker, PhaseNet-DAS, enables real-time earthquake detection and phase picking from raw DAS data streams [26]. Furthermore, the earthquake magnitude can be estimated in real-time using either converted ground motions from local slant-stacking [102] or a transferable empirical relationship directly from strain-rate recordings [103]. Together, these tools form the foundation for integrating telecom DAS into operational EEW systems [104, 105].

However, telecom DAS-based EEW still faces several challenges, including suboptimal fiber geometry, channel-specific parameter optimization, and amplitude saturation/cycle skipping [105]. Among them, the most fundamental challenge is the cycle skipping during strong ground motions, which occurs when strain-rate-induced phase change between laser pulses exceeds the range of $[-\pi, \pi]$, leading to incorrect strain amplitudes [106, 107, 87]. The maximum strain rate scales proportionally to f_R/G, where f_R is the laser pulse rate and G is the gauge length [87]. Thus, this limitation can be mitigated by decreasing the gauge length or increasing the pulse rate, both of which improve the dynamic range but come at the cost of decreased signal-to-noise ratios and reduced interrogating length [87]. Alternative strategies, such as correcting clipped channels using the nearby unclipped channels, have also been proposed [72]. Nevertheless, signal saturation on DAS remains an open challenge and an ongoing research direction.

Beyond EEW applications, telecom DAS has also enabled detailed characterization of earthquake source properties, including source parameters, source mechanisms, and rupture process. Earthquake source parameters such as the seismic moment, corner frequency, and stress drop can be determined either by converting strain or strain rate recordings to ground motion recordings [108] or through the empirical Green's function (EGF) approach [109, 110]. In addition, S-wave coda envelopes on telecom DAS have been used to estimate earthquake moment magnitude and spectra [111].

Determining the earthquake source mechanism with DAS on telecom fibers is challenging since the strain or strain rate recording is insensitive to the near-vertical incident P-waves and the dominance of surface scatterings due to low shallow structure velocities. This characteristic hinders both waveform-based and polarity-based source mechanism inversions. Nevertheless, a recent study overcomes this limitation by using waveform cross-correlations between earthquake pairs to infer relative P-wave polarities, which are then inverted for absolute P-wave polarities [112]. This method enables high-resolution source mechanism inversion with lower uncertainties. Finally, an ultra-dense DAS array also enables high-resolution rupture imaging. Li et al. [84] performed the first telecom DAS-based back-projection rupture imaging of a moderate-sized Mw6 earthquake, resolving the break of four earthquake asperities that cannot be resolved by the local seismic network. This demonstrates telecom DAS's unique ability to understand earthquake rupture dynamics with high spatiotemporal resolution.

4.1.2. Near-surface Imaging

Continuous, high-resolution monitoring of the near-surface structure is essential for detecting sinkholes, subsidence, and seismic hazards in urban environments. Traditional active-source seismic methods rely on geomechanical sources, such as hydraulic vibrators, to generate seismic waves (e.g., surface waves, refractions), which are then recorded by deployed seismometers and geophone arrays [147]. However, these surveys are costly, logistically challenging, and often impractical in densely populated urban areas due to the need for specialized equipment, permitting constraints, and deployment difficulties.

DAS offers a viable sensing solution by converting pre-existing telecom fiber-optic cables into ultra-dense seismic arrays. For instance, Fang et al. [113] demonstrated that a DAS seismic array using a pre-existing fiber cable on the Stanford campus recorded seismic signals from weekly quarry blasts (13.3 km away from the DAS array), further supporting the detection of velocity changes associated with nearby anthropogenic excavation activities. Ambient noise interferometry with DAS has recently become a useful workflow for extracting surface wave energy for near-surface characterization and monitoring [20, 93, 21, 114, 115, 65]. This technique utilizes continuously recorded seismic wavefields from ambient noise sources, whether anthropogenic or ocean microseismicity, to retrieve coherent seismic signals [148, 149, 150]. By cross-correlating these wavefields between sensor pairs, it reconstructs the empirical Green's function, where surface wave energy often dominates [151, 152]. The dense spatial sampling of DAS makes it particularly useful, with the retrieved surface waves applied in geophysical inversion for geotechnical and civil infrastructure applications [17].

Despite these advantages, DAS in telecom cables is limited to measuring axial (i.e., along the cable orientation) strain or strain rate, restricting the retrieved wavefields primarily to Rayleigh-type surface waves in colinear fiber geometries [114, 77]. Martin et al. [18, 116] explored cross-correlations across 2-dimensional DAS arrays, revealing that colinear virtual sources predominantly yield Rayleigh waves, while parallel-line configurations enhance Love-wave detection. Ji et al. [117] successfully observed and analyzed both Rayleigh and Love waves derived from ambient noise interferometry by utilizing orthogonal segments of fiber-optic cables. The joint inversion of Rayleigh and Love wave dispersion curves provides better constraints on the depth-dependent subsurface velocity structures. Researchers have investigated the complex geometry of fiber cables, which is often the case for pre-existing fiber networks in urban settings, to assess the directional sensitivity of DAS for retrieving a mixture of surface wave modes, thereby improving 2-dimensional ambient noise tomography [118, 77].

Telecom DAS seismic arrays have also been instrumental in time-lapse monitoring of near-surface changes [93, 119, 120, 23]. Yang et al. [119] analyzed a 10-month dataset from a telecom cable in central Perth, Australia, uncovering correlations between surface wave velocities and rainfall patterns. Shen et al. [23] utilized telecom DAS to monitor vadose zone soil moisture fluctuations in Ridgecrest, California, revealing sub-seasonal precipitation dynamics and prolonged drought effects, suggesting an annual evapotranspiration-driven water loss of 0.25 m. Tribaldos and Ajo-Franklin [120] demonstrated the use of pre-existing fiber-optic cables in the Sacramento Valley, CA, for monitoring aquifers using ambient noise interferometry. They found that near the Sacramento River, shear-wave velocity variations of 2%–3% aligned with precipitation events and approximately 1.5 m fluctuations in river stage, whereas areas 2.5 km away from the river showed minimal subsurface velocity changes.

Although ambient noise interferometry has been effectively used to retrieve coherent surface waves with DAS arrays, it requires long cross-correlation periods for convergence and tends to be less sensitive to high-frequency signals, which are often attenuated in urban noise environments [25]. For monitoring purposes, the retrieved ambient noise is influenced by the spatiotemporal distribution of noise sources, introducing uncertainty in structural monitoring results. To accurately interpret structural changes, one must account for and exclude potential impacts from variations in noise sources [121]. This challenge is particularly pronounced in heterogeneous urban settings.

To overcome these limitations, Yuan et al. [122, 25] introduced an alternative approach utilizing passing vehicles as cost-effective and repeatable seismic sources for near-surface characterization. Their method employs a Kalman filter and smoothing-based algorithm [29] to isolate high-quality surface waves from individual vehicles, enabling daily or even hourly monitoring of subsurface structure without requiring long-term ambient noise accumulation. By constructing virtual shot gathers with minimal computational cost, they demonstrated applications in time-lapse monitoring of soil moisture and groundwater levels. Building on this work, Li et al. [24] conducted time-lapse elastic full waveform inversion using vehicle-induced surface waves to track groundwater table fluctuations. Their observations revealed a 2.9% reduction in S-wave velocity, corresponding to a 9.0 m rise in the water table following atmospheric river storms in the Water Year 2022–2023. Further refining this approach, Liu et al.[22] examined how vehicle characteristics, including traveling speed and car weight, influence surface wave generation and near-surface imaging results. By classifying vehicles based on weight and speed, they extracted dispersion curves and inverted subsurface structures for different vehicle types. Their results show that heavier vehicles generate higher signal-to-noise ratio surface waves, with a sevenfold increase in vehicle weight reducing dispersion measurement uncertainties by up to a factor of three.

4.1.3. Other Natural Seismic Signal Characterization

In addition to earthquakes, there exist numerous natural sources that generate seismic waves. These seismic waves can be captured through telecom DAS systems. Zhu et al. [85] were the first to identify ground motions caused by thunder, referred to as thunderquakes, using a telecom DAS system. The researchers employed Geiger's method [153] to estimate the thunderquakes' origin time, location, and seismic wave velocity. Furthermore, the study demonstrated a correlation between the stacked DAS seismic energy and the lightning current energy, as reported by the National Lightning Detection Network. Building upon their initial findings, the same research group successfully detected and characterized thunderquakes in four distinct thunderstorms [123]. This evidence highlights the efficacy of employing telecom DAS responses for thunder event detection and localization.

Moreover, Paitz et al. [124] proposed to use DAS responses to measure strain rate along a fiber-optic cable to characterize ground deformation induced by avalanches. The researchers captured and analyzed 12 snow avalanches of varying dimensions at Switzerland's Vallée de la Sionne during the winter season of 2020-2021. By examining the DAS responses induced by the avalanches in both the time-distance and frequency-wavenumber domains, the authors utilized Bayesian Gaussian Mixture Models [154] to extract key avalanche characteristics, such as the frequency content and phase velocities, while monitoring their spatial and temporal evolution. The study successfully demonstrates the potential of employing telecom DAS responses for avalanche monitoring and early warning systems.

Recently, Li et al. [67, 68] used a telecom DAS array crossing Grindavik, a small town on the Reykjanes Peninsula in southwest Iceland, to monitor the quasi-static ground deformation caused by magma intrusions and to issue early warning alerts for volcanic eruptions. Their real-time monitoring system provided a 26-minute early warning prior to the eruption on 22 August 2024. Since 15 January 2025, the Icelandic Met Office has continued efforts towards operational DAS-based eruption alert systems [155].

4.2. City Activity Monitoring

Urban environments exhibit dynamic interactions between human activities and the built environment, generating seismic and vibration signals that can be captured by DAS using telecom fiber-optic cables. These signals encode valuable information about urban persistent and dynamic features, including traffic patterns, social activities, and demographic information [55]. Leveraging pre-existing telecom fiber networks as large-scale seismic arrays presents a scalable and cost-effective approach to continuous city-wide activity monitoring.

4.2.1. Traffic Monitoring and Vehicle Characterization

Telecom fiber-optic cables, often installed along roads and highways, serve as a unique sensing infrastructure when repurposed as a DAS array. By capturing ground vibrations induced by vehicular motion, these systems enable real-time traffic monitoring, offering advantages over conventional methods such as inductive loop detectors [156, 157], vision-based systems [158, 159], and crowd-sensing approaches [160, 161]. The extensive deployment of telecom fibers along urban roadways enhances the scalability and efficiency of DAS-based traffic monitoring compared to standalone sensor networks.

Existing research has demonstrated the feasibility of using pre-existing telecom fiber-optic cables for monitoring various traffic parameters, including traffic volume and speed estimation [27, 28, 125, 126, 127], congestion detection [128, 129], and detection, tracking, and characterization of individual vehicles [130, 131, 29]. Studies have reported a strong correlation between DAS signal responses and roadway traffic volume. For instance, reduced traffic during the COVID-19 pandemic and school holidays led to a measurable decrease in DAS signal amplitudes [132]. Lindsey et al.[28] and Wang et al.[27] further observed a decline in traffic volume and an increase in average speed during lockdown periods. Beyond road traffic monitoring, DAS technology has been applied to railway transportation. Telecom fibers deployed along the railways have been successfully used for train localization, bogie cluster detection, and speed estimation [133, 134]. This capability underscores the versatility of DAS in multi-modal transportation monitoring.

Furthermore, recent studies have increasingly incorporated machine learning and deep learning techniques to enhance the accuracy and robustness of DAS-based traffic monitoring frameworks [31, 32, 135, 136]. These methods enable advanced feature extraction and pattern recognition, facilitating automated traffic monitoring with higher precision. For example, deep deconvolution models have been introduced to extract vehicle impulse responses from low-frequency (< 1 Hz) quasi-static DAS recordings, significantly enhancing resolution and suppressing noise [131, 137, 30].

Recent studies have also utilized telecom DAS responses for tracking and characterizing individual vehicles. Corera et al.[130] proposed a trajectory detection framework using the Hough Transform[162] to extract vehicle movement patterns from DAS signals. Subsequently, a support vector machine classifier was applied to differentiate vehicle sizes (e.g., passenger cars vs. trucks) and travel directions. Liu et al. [29] introduced a spatial-domain Bayesian filtering and smoothing algorithm that effectively incorporates the spatial dependencies of distributed DAS sensors. This approach enables precise vehicle tracking while also providing weight estimations. Moreover, high-frequency DAS responses (> 3 Hz) have been leveraged to estimate vehicle wheelbases by analyzing the time lag between consecutive wheel-induced vibrations relative to vehicle speed [29].

4.2.2. Footstep Detection

Pedestrian movement induces ground vibrations that can be detected using vibration sensors such as geophones [163, 164, 165, 166, 167] and DAS systems [138, 91, 139]. These footstep-induced seismic signals provide valuable insights into individual walking patterns and pedestrian mobility within urban environments. Zhu et al. [91] demonstrated the feasibility of detecting footstep-induced vibrations in the 1–5 Hz frequency range using DAS responses from telecom fiber-optic cables deployed in a pedestrian-only area. The study successfully leveraged these signals to estimate walking speeds and infer pedestrian activities such as boarding and disembarking from public transportation. Additionally, footstep activity reductions during COVID-19 lockdowns were identified, illustrating the potential of telecom DAS for monitoring large-scale changes in pedestrian mobility[139]. Despite these advancements, accurately detecting footstep signals in outdoor environments remains a challenge due to the relatively low signal energy of footstep-induced vibrations. To enhance detection performance, Jakkampudi et al. [138] developed a convolutional neural network model capable of automatically extracting deep features from telecom DAS responses, which improved footstep detection accuracy.

4.2.3. Other Anthropogenic Seismic Signal Detection

Beyond traffic and pedestrian monitoring, telecom DAS systems capture a wide range of anthropogenic seismic signals, offering valuable insights into various urban activities. Notably, explosive blasts generate seismic waves detectable over long distances via DAS-equipped telecom cables [19, 113, 91, 140]. Researchers have exploited these signals as unidirectional and repetitive seismic sources for subsurface imaging [113]. In addition, DAS responses have been used to identify vibrations generated by construction activities [113, 168, 55]. DAS technology has also proven effective in detecting crowd activities and large-scale public events. Wang et al.[129] utilized a telecom DAS array to monitor the 2020 Rose Parade in Pasadena, California, successfully tracking the movement of parade participants, including marching bands, floats, and motorcycle squads. Similarly, DAS arrays have recorded vibrations from live concerts, revealing clear distinctions between different musical sections and interludes [91, 141].

In a recent study, Liu et al. [55] demonstrated the capability of DAS-equipped telecom fiber-optic networks for locating urban seismic sources and estimating how their intensity varies over time. By repurposing a 50-kilometer telecom fiber as an ultra-dense seismic array, they generated high-resolution spatiotemporal maps of Seismic Source Power (SSP) across San Jose, California. Their analysis revealed strong correlations between SSP values and environmental noise levels, as well as persistent urban features such as land use patterns and demographic distributions. These findings underscore the potential of DAS-equipped telecom networks as a scalable, non-intrusive platform for large-scale monitoring of urban dynamics and seismic activity.

4.3. Civil Infrastructure Monitoring

Telecom fiber-optic cables are frequently integrated with civil infrastructure, such as bridges and pipelines, providing a unique opportunity for DAS-based structural health monitoring. By leveraging these pre-existing networks, DAS enables continuous, large-scale monitoring without requiring dedicated sensors, significantly reducing installation and maintenance costs.

4.3.1. Bridge Health Monitoring

Telecom DAS-based bridge monitoring leverages existing fiber-optic cables coupled to bridge structures to record dynamic strain responses in real-time. These strain measurements provide crucial insights into bridge dynamics, facilitating bridge health assessments, early damage detection, and data-driven maintenance planning.

Liu et al. [33] introduced a bridge health monitoring system utilizing telecom fiber-optic cables for DAS-based sensing. The system captures dynamic strain responses to estimate bridge modal properties, including natural frequencies, strain mode shapes, and displacement mode shapes. The authors developed a physics-guided system identification method, incorporating parametric mode shape functions derived from bridge dynamics [169]. By analytically double-integrating the strain mode shape, they obtained the displacement mode shape while minimizing error propagation. The system was validated on a concrete three-span bridge, demonstrating the ability to accurately estimate the natural frequencies (99% accuracy), strain mode shapes, and displacement mode shapes (up to 96% accuracy). Comparisons with conventional accelerometer-based measurements further confirmed the accuracy of the DAS-based method.

Recently, Rodet et al. [35] conducted a study assessing the feasibility of using dark fiber for monitoring multiple bridges over an extended fiber network. Their study spanned five bridges across a 24-km-long urban optical fiber network in Lyon, France, allowing for large-scale, long-term monitoring. Their estimation of bridge modal parameters aligned well with conventional velocimetric measurements, validating DAS as a viable option for bridge health assessment. Additionally, their study explored the daily variations in bridge natural frequencies, revealing a cyclic fluctuation between day and night – a phenomenon likely linked to temperature-induced stiffness changes in the bridges. This finding underscores the importance of accounting for environmental and operational conditions when interpreting DAS data for long-term monitoring.

Beyond modal analysis, propagating waves also offer insights into bridge structural properties. Liu et al. [34] demonstrated that DAS using pre-existing telecom fibers can capture the wavefields of both standing and propagating low-frequency (1–70 Hz) Lamb waves in box girder bridges. These propagating Lamb waves had not been previously observed, as conventional methods struggle to capture their wavefields due to the prohibitive cost of deploying dense sensor networks. Using ambient noise interferometry [83], they reconstructed virtual shot gathers from traffic-induced vibrations, enabling wavefield analysis without active seismic sources. By modeling the box girder bridge as an elastic isotropic plate, they found strong agreement between measured and numerically modeled Lamb wave dispersion curves. Their work highlights the potential of DAS for scalable, real-time bridge monitoring, with future research focusing on damage-sensitive features in Lamb wave propagation to enhance structural health diagnostics.

4.3.2. Telecom Infrastructure Monitoring

Accurately estimating the geographic location of telecom fiber-optic cables is essential not only for the aforementioned urban monitoring applications but also for infrastructure maintenance tasks such as pinpointing fiber faults. However, as-designed and as-built maps of underground fiber networks are often inaccurate, failing to account for slack loops that accumulate underground, such as spools in cabinets and manholes. This discrepancy poses a challenge for telecom operators and researchers aiming to precisely geolocate fiber networks.

A common approach for geo-localizing underground fiber cables involves matching seismic sources with known locations to corresponding DAS responses. Traditionally, tap tests (e.g., weight drops and hammer strikes) are conducted near the interrogated fiber, with the strongest DAS amplitude indicating the nearest virtual sensor location [143, 144]. However, for large-scale DAS networks, where hundreds of sources are needed to map entire fiber networks, this method becomes costly and time-consuming.

To address this, Huot et al. [146] applied machine learning with Markov Decision Processes to map DAS array geometry based on spatial variations in recorded wavefields. Yuan et al. [126] developed a cost-effective alternative by leveraging telecom DAS responses generated by a vehicle equipped with an onboard global positioning system (GPS). Since telecom cables are often installed alongside roadways, the authors conducted tests by driving a vehicle along city roads under regular traffic conditions. A strong quasi-static DAS signal was observed when the vehicle was close to a virtual DAS sensor. By recording the peak signal times and synchronizing them with GPS data, they estimated the geographic positions of roadside virtual sensors. To minimize GPS errors, the authors repeated the tests multiple times and averaged the estimated locations. This approach is non-intrusive, cost-efficient, and scalable, as it can be implemented using city maintenance vehicles, public transit, mail delivery trucks, or any regularly operating vehicles. Building on this idea, Biondi et al. [145] expanded the method to a 100-km-long telecom fiber network, demonstrating its effectiveness on a larger scale.

5. Remaining Challenges and Future Directions

Despite significant progress in using pre-existing fiber-optic networks as DAS systems, several challenges remain for more reliable urban monitoring applications. This section highlights the key limitations and outlines future research directions to enhance the utility and efficiency of telecom DAS systems. Addressing their challenges will require interdisciplinary collaboration among engineering, computer science, and geophysics, along with the development of innovative computational and experimental methods.

5.1. Unknown and Heterogeneous Virtual Sensor Properties

A central challenge in leveraging pre-existing fiber-optic cables for DAS applications lies in the limited understanding of the telecom cables' physical and mechanical properties. Unlike dedicated, calibrated sensing systems [170], telecom cables were not originally intended for seismic or vibration sensing. As a result, variations in fiber composition, cladding, coupling conditions, and installation geometry introduce spatial heterogeneity in both directional sensitivity and amplitude response. These factors can significantly affect data quality and complicate interpretation across DAS arrays [36]. To address these challenges, several efforts have been made to infer the geometry and location of buried fiber-optic cables, which have been discussed in Section IV C. However, developing a systematic and automated framework to assess the quality of virtual sensor properties remains an open challenge. Such a framework should ideally evaluate parameters including signal-to-noise ratio, polarization sensitivity, and coupling conditions along the fiber. Benchmarking sensor behavior across deployments and validating consistency over time and across source types are critical for improving the robustness of DAS-based urban monitoring.

Another key limitation is the poorly characterized instrument response of DAS systems. The lack of calibration hinders the use of traditional seismological techniques that depend on accurate amplitude and spectral measurements [28]. To address this, some studies have compared DAS recordings to those from co-located broadband seismometers as a means of calibration [171]. Numerical modeling has also been used to assess the influence of heterogeneous coupling on the amplitude response of DAS systems [37]. Advancing our understanding of sensor heterogeneity and instrument response is essential for enhancing the reliability of DAS, particularly for amplitude-based analyses in seismology, infrastructure monitoring, and environmental sensing.

5.2. One-Component Measurement

DAS systems are inherently limited to measuring axial strain or strain rate along the orientation of the fiber cable, with sensitivity influenced by the applied gauge length. Unlike conventional three-component seismic sensors that record three orthogonal components of ground motion, DAS captures only the projection of the seismic wavefield along the fiber axis. As a result, analyses that require full wavefield information – such as Horizontal-to-Vertical Spectral Ratio analysis, source moment tensor inversion, and elastic waveform tomography – are not directly feasible using single-component DAS data.

To overcome this limitation, researchers have explored deployment strategies that enhance the directional sensitivity of DAS arrays. For example, fiber layouts incorporating loops or orthogonal segments have demonstrated improved sensitivity to multiple wavefield components, thereby enabling more comprehensive subsurface characterization [172, 173]. Even when constrained to pre-existing fiber infrastructure, careful consideration of cable geometry and orientation, coupled with advanced processing techniques, can improve surface wave analysis and near-surface imaging outcomes [174, 117].

In addition, integrating DAS with conventional multi-component seismic sensors, such as geophones or broadband seismometers, provides complementary measurements that mitigate the inherent limitations of DAS [175]. For instance, Yu et al. [176] utilized co-located seismometers to perform receiver function analysis for imaging, while Spica et al. [177] employed a hybrid DAS–seismometer array for site characterization in urban environments. More recently, earthquake detection algorithms have been developed for hybrid fiber-optic–seismometer networks, combining data from both fiber-optic cables and traditional seismometers to enhance detection capabilities and improve source localization [178].

Innovative DAS deployment configurations and hybrid sensing strategies represent promising avenues to expand the range of DAS applications. These efforts offer the potential for improved directional sensitivity and more comprehensive urban seismic monitoring, particularly in environments where multi-component measurements are essential.

5.3. Complex Noise Conditions

Urban environments present significant challenges for DAS-based seismic monitoring due to the complex and often non-stationary nature of ambient noise. Seismic noise generated by vehicle traffic, construction activity, industrial operations, and human movement frequently obscures signals of interest, complicating the extraction of other meaningful information for various applications. For instance, while ambient noise interferometry has been widely adopted to extract subsurface properties by exploiting naturally occurring seismic energy, it relies on the assumption of uniformly distributed and temporally stable noise sources – an assumption that is rarely satisfied in urban settings, where noise is highly heterogeneous and variable across both space and time.

Recent advances in ambient noise processing have sought to address the non-uniformity of urban noise sources. For instance, Yuan et al. (2024) introduced a targeted interferometry approach that leverages vehicle-induced signals as controlled, repeatable sources for time-lapse subsurface monitoring [25]. By exploiting the regularity of anthropogenic activity, especially recurring traffic patterns, this method improves the stability of empirical Green's function estimates in noisy, real-world environments.

Other studies have demonstrated the value of customized processing strategies to enhance DAS data quality under complex urban noise conditions. Lai et al. [179], for example, observed that excluding midnight recordings helped reduce interference from acoustic energy generated within subsurface infrastructure such as tunnels and pipelines. Similarly, Smolinski et al. [38] applied meticulous processing to DAS data acquired in dense urban environments, enabling the successful imaging of shallow subsurface structures despite challenging noise conditions. Together, these efforts highlight the importance of adapting noise processing strategies to the urban context.

Beyond signal extraction, complex urban noise also poses challenges for localizing noise sources, which are often distributed irregularly in space and vary in frequency content. In this context, the geometry of the fiber-optic array plays a crucial role. Accurate estimation of the direction of incoming wavefields requires the DAS array to span a sufficiently large azimuthal aperture. Inadequate array geometry may lead to biased or ambiguous localization results, limiting the effectiveness of DAS in complex urban environments.

5.4. New Directions

Below, we outline several promising directions for future research and development.

5.4.1. Advancements in Interrogator Technology

The interrogator unit is a core component of DAS systems, responsible for converting optical signals into dynamic strain data. Future advancements in interrogator design – such as improved resolution and reduced power consumption – have the potential to significantly lower deployment costs and broaden accessibility. The development of portable, cost-effective interrogators could democratize DAS usage, especially in resource-limited settings or for small-scale deployments.

5.4.2. Automated and Efficient Data Analysis

Large-scale urban DAS deployments often utilize hundreds of kilometers of fiber-optic cable to record data on dense two-dimensional grids aligned with city streets. For such extensive systems, scalability is essential across the entire workflow, from data acquisition and storage to processing, analysis, and, ultimately, the delivery of actionable results to decision-makers.

Innovative archival systems (e.g., [98]) and standardized data formats have been proposed to manage the DAS data [180, 181, 182]. Cloud-based infrastructures (e.g., [183, 184]) offer viable and cost-effective solutions for storing and transferring massive datasets. In addition, recent efforts have focused on developing open-source tools for DAS data processing, such as DASCore [185] and DASPy [186], which facilitate reproducible workflows. However, an open-access, integrated, and industry-grade framework for scalable and automated DAS processing of large-volume data has yet to emerge.

Deep learning has emerged as a useful tool in automating DAS data processing. Applications include data compression for efficient storage and transmission [187, 188, 189], denoising [190, 191, 192, 193], real-time event detection [194], automated phase picking [26], and traffic signal analysis [131, 30]. Integrating these algorithms with low-cost, high-performance processing hardware is critical to enabling real-time analysis and rapid response capabilities.

The advent of large language models offers exciting new opportunities in DAS data interpretation. Foundation models such as SeisLM [195] have the potential to be trained directly on large volumes of DAS data representative of urban environments. Once trained, such models can be fine-tuned for a wide range of downstream tasks, including denoising, phase picking, and seismic data interpretation, within a single, unified framework. However, a key challenge that remains is the development of high-quality, labeled training datasets, which are essential for effective fine-tuning and validation.

5.4.3. Hybrid Sensing Systems

The integration of DAS with conventional sensing technologies has been widely recognized as a promising approach to overcoming current limitations and expanding the scope of DAS applications. Numerous studies have demonstrated the benefits of hybrid systems that combine DAS data with complementary datasets. For example, integrating DAS with co-located geophones or broadband seismometers enhances waveform fidelity and directional sensitivity [196, 175, 178]. Additionally, novel approaches incorporating visual data from roadside cameras have shown potential for improving traffic detection and source localization in urban DAS applications [136]. These multi-modal sensing systems provide a richer and more comprehensive view of urban dynamics and subsurface processes, enabling more robust interpretations and applications across seismology, infrastructure monitoring, and smart-city development.

6. Conclusion

This paper presents a review of recent advancements in urban monitoring using pre-existing telecom fiber-optic networks as DAS systems. By repurposing existing telecom fiber-optic infrastructure, DAS offers a scalable, cost-effective sensing solution that enables continuous, real-time data acquisition without the need for additional sensor deployment. The use of DAS in urban monitoring has demonstrated remarkable potential across multiple domains, from seismic hazard monitoring and subsurface imaging to transportation analysis and structural health monitoring. Despite these advantages, several challenges remain, including the heterogeneous coupling of fiber-optic cables, complex urban noise environments, and the limitations of one-component strain measurements. Overcoming these challenges requires advancements in fiber characterization, signal processing, and machine learning-driven analytics. Additionally, integrating DAS with conventional sensing systems and cloud-based computational frameworks will further enhance its effectiveness for large-scale urban monitoring. Looking ahead, telecom DAS presents exciting opportunities for cross-disciplinary applications, including environmental monitoring, public health surveillance, and smart city innovations. As research and technological advancements continue, telecom DAS is poised to become a cornerstone of next-generation urban sensing, driving the development of more resilient and intelligent urban environments.

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