Spatial Deep Deconvolution U-Net for Traffic Analyses with DAS

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Abstract—Distributed Acoustic Sensing (DAS) that transforms city-wide fiber-optic cables into a large-scale strain sensing array has shown the potential to revolutionize urban traffic monitoring by providing a fine-grained, scalable, and low-maintenance monitoring solution. However, there are challenges that limit DAS’s real-world usage: noise contamination and interference among closely traveling cars. To address the issues, we introduce a self-supervised U-Net model that can suppress background noise and compress car-induced DAS signals into high-resolution pulses through spatial deconvolution. To guide the design of the approach, we investigate the fiber response to vehicles through numerical simulation and field experiments. We show that the localized and narrow outputs from our model lead to accurate and highly resolved car position and speed tracking. We evaluate the effectiveness and robustness of our method through field recordings under different traffic conditions and various driving speeds. Our results show that our method can enhance the spatial-temporal resolution and better resolve closely traveling cars. The spatial deconvolution U-Net model also enables the characterization of large-size vehicles to identify axle numbers and estimate the vehicle length. Monitoring large-size vehicles also benefits imaging deep earth by leveraging the surface waves induced by the dynamic vehicle-road interaction.

Index Terms—Traffic monitoring, intelligent transportation, Distributed Acoustic Sensing, deconvolution, U-Net.

I. INTRODUCTION

Traffic monitoring systems, which automatically and continuously detect, track, and characterize vehicles in moving traffic, provide valuable information for urban management, maintenance, and planning. Conventional monitoring systems include vision-based [1]–[3] and pavement sensing technologies (e.g., inductive loops [4]–[6] and piezoelectric sensors [4], [7], [8]). These approaches are well-developed but have several drawbacks. For example, camera systems bring individual-privacy concerns and are sensitive to weather conditions; point pavement sensing systems provide spatially sparse sampling and are challenging to maintain. Recent mobile sensing methods overcome the on-site installation and maintenance challenge, but such systems require users to optimize location tracking and rely on cellular connectivity.

An emerging fiber-optic sensing technology, Distributed Acoustic Sensing (DAS), which turns optical fibers into dense-sampling seismic recording arrays, has the potential to revolutionize urban traffic monitoring by providing fine-grained and ubiquitous traffic flow and accident information. DAS-based monitoring is performed by connecting an optoelectronic DAS instrument called the interrogator to one end of a standard telecommunications-grade optical fiber. The interrogator sends short laser pulses into the optical fiber and measures the subtle phase shifts of Rayleigh scattered light returning to the detector at a predicted two-way travel time [9], [10]. In this way, the strain field induced by natural processes (e.g., earthquakes) and urban activities (e.g., moving vehicles, construction, pumps) acting on the fiber coupled to the Earth can be sampled at a meter-scale spatial resolution over tens of linear fiber kilometers. More recently, DAS has been proven effective even on pre-existing telecommunication fiber infrastructure (“dark fiber”) to record broadband signals for earthquake monitoring and near-surface imaging [11]–[13]. As fibers installed near roads capture deformation induced by moving cars, DAS technology has provided a geophysical solution for real-time traffic monitoring including average speed monitoring, congestion time estimation, and queue detection [14]. However, due to the hardware constraints, their system only has intensity measurements without the phase information limiting its practical value. With the DAS technology advancement, new interrogators (e.g., OptaSense QuantX [15]) capable of recording full waveform information for up to 50 km with 1 m channel spacing have become practical for traffic monitoring applications. Thanks to their broadband nature, QuantX-like DAS recordings comprise rich traffic information, including high-frequency (> 2 Hz) surface waves due to vehicle-road dynamic interaction and the low-frequency quasi-static deformation caused by vehicle loading [16]–[18]. The surface wave components have been used to image the subsurface velocity structure down to hundreds of meters beneath the road [16]. The quasi-static components reflecting the vehicle trajectories are much more compact and have a simpler waveform than the surface waves. [17], [19], [20] demonstrate the feasibility of using the quasi-static signals to estimate vehicle count and speeds, and illustrate several advantages for a DAS traffic monitoring system: first, DAS records absolute signals of human-induced deformation that cannot be easily tied to any individual; second, DAS monitoring can be cost-efficient for city-scale monitoring with pre-existing “dark fiber”; last, DAS has low day-to-day operation and maintenance costs with only a single interrogator being deployed in a secure and easily accessible location, as opposed to having numerous individually powered instruments deployed across a city (exposed to meteorological conditions and detrimental interactions with humans, plants, and animals).

Despite the aforementioned advantages, analyzing data from a DAS array located in an urban environment is challenging because it records a complex mixture of inherently unla-
beled signals [21]. A robust and accurate car-signal detection algorithm is essential to enable the real-world usage of a DAS-based traffic monitoring system. To detect car-induced quasi-static signals, [17] applied a common seismological method, the short-time-average through long-time-average trigger (STA/LTA). To exploit the array geometry of DAS, beamforming algorithms have been applied to detect cars and measure their speed [19], [20]. These simple methods performed well on roads with relatively light traffic and without complicated traffic patterns. But they are likely to become inaccurate if many vehicles transit simultaneously close to the same segment of the fiber cable, as signals from different cars start overlapping leading to complex patterns.

To reduce the interference among closely traveling cars, [22] proposed a self-supervised time-domain deconvolution Auto-Encoder (time-domain DAE) with the vehicles’ impulse response from the quasi-static recordings. Compared to a conventional channel-wise deconvolution algorithm, the time-domain DAE model has the benefit of incorporating the spatial-temporal characteristics of car signals, leading to much sharper and localized outputs. Applying a beamforming algorithm to the localized outputs rather than the original inputs shows significant improvements in terms of the resolution in car-speed estimation and detection accuracy. Furthermore, as shown in [22], the time-domain DAE model, once trained, can deconvolve 24-hour recordings in less than 30 seconds, achieving > 400 times speedup compared to a conventional iterative approach, which makes the method promising for real-time processing. However, the time-domain DAE model assumes a stationary Ricker wavelet in the time domain as the vehicle’s impulse response. As the following sections of the paper will show, vehicle’s temporal wavelet is non-stationary to speed variation. Due to the wavelet mismatch, a time-domain DAE model that works well with fast-speed traffic produces low-resolution results for low-speed vehicles causing inaccurate speed tracking.

To address the challenge, we first characterize the vehicle impulse response. Based on our observation that the vehicle’s spatial wavelet is robust to speed change, we propose a new deconvolution U-Net model (space-domain DAE model) using a space-domain vehicle wavelet. The U-Net model takes quasi-static signals as inputs and outputs sharp deconvolution results reflecting the vehicle trajectory. It is a weak-supervised approach not requiring any groundtruth labels: The data-fitting term in the loss function only involves network input and a reconstructed input resulted from a spatial convolution between the network output and the assumed wavelet. The benefits of our method over the time-domain DAE model is that it is effective and robust to compress signals of speed-varying cars into compact pulses leading to more accurate vehicle tracking and better resolving complicated patterns in heavy traffic condition.

The rest of the paper is organized as follows: Section II demonstrates the resolution reduction of traffic-induced DAS signals due to a combination effect of physics and the limitation of the sensor. Through the numerical characterization of vehicle impulse response and observations from field experiments, we design a spatial DAE model aiming to improve the signal resolution for speed-varying vehicles. Section III describes the method of our spatial DAE model in detail. Section IV describes the training procedure and baseline approaches. Section V benchmarks the proposed DAE model with baselines for car motion and speed tracking, and resolving closely traveling vehicles in heavy traffic. Furthermore, we demonstrate the use of the space-domain DAE model for bus axle number counting and length estimation. Besides, we discuss a potential limitation of the spatial DAE model for a case with a spatially non-stationary vehicle response. Section VI concludes our work.

II. VEHICLE-INDUCED DAS RESPONSE

This section aims to better understand the vehicle-induced DAS response to guide the design of the proposed DAE model. We discuss two types of vehicle-induced DAS responses as background. We then conduct theoretical study and numerical simulation to demonstrate a resolution reduction of the quasi-static signals due to physics and sensor limitation, which motivates resolution improvement through deconvolution. Lastly, we observe the speed-invariant nature of the spatial wavelet leading to the design of the space-domain DAE model.

A. Quasi-static and dynamic response

Permanently deployed fibre-optic cables are often buried (trenched) or placed within underground conduits. We assume here that the DAS fiber is deployed alongside a road at some depth below the surface. When a vehicle passes nearby the virtual sensors of the roadside telecom fiber cable, the interaction between the vehicle and the road structure induces the deformation of the telecom fiber cable. The signal pattern of vehicle-induced telecom fiber deformation is a function of the vehicle characteristics, fiber conduit properties, ambient conditions, etc. There are mainly two components of signals produced by moving vehicles: quasi-static signals (< 1 Hz) resulting from the ground deformation due to the vehicle’s weight, and surface waves (2 to 20 Hz) caused by the dynamic vehicle-road interaction resulting from the roughness of the road (e.g., bumps). Previous studies [16], [17] have found that the quasi-static component dominates the energy of vehicle-induced telecom fiber vibration and is theoretically described by the Flamant-Boussinesq approximation [23], [24]. As a vehicle approaches the virtual sensor, ground deformation above the sensor increases, and the fiber coupled to the earth is stretched, resulting in increased tension in the fiber. As the vehicle moves away, ground deformation near the virtual sensor and the fiber tension decreases. Due to the relatively strong energy, simplicity and compactness compared to the surface-wave component, quasi-static signals have been used for car tracking and detection tasks [22]. For the same reason, our car tracking method is also based on the quasi-static response.

B. Sensing resolution limited by physics and sensor limitation

We conduct synthetic experiments to demonstrate the resolution degradation of quasi-static signals due to physics and
sensor limitations. We model vehicular seismic sources using a collection of vertical point forces located at the vehicle’s wheel-road contacts [16], [17], [24], [25]. Define $x$ as the horizontal distance along the fiber. The quasi-static or geodetic strain ($E_x$) DAS signal from a vehicle centered at $x = 0$ is equal to the change in displacement over the DAS gauge length ($L$). Displacement in the direction of the fiber ($U_x$) can be modeled using the Flamant-Boussinesq equation for a point load applied to a half space with basic knowledge of the fiber and vehicle locations, the vehicle load ($F_x$), the soil shear modulus ($\mu$), and Poisson’s ratio ($\nu$):

$$U_x(x) = \frac{z x}{4 \pi \mu r^3} \left(1 - \frac{2\nu}{r + z} \left(\frac{x}{r}\right)\right), \quad (1)$$

$$E_x(x) = \frac{U(x + \frac{L}{2}) - U(x - \frac{L}{2})}{L}, \quad (2)$$

where $z$ is fiber depth, $r = \sqrt{x^2 + y^2 + z^2}$ is the 3-D distance from the fiber position to the car, $y$ is the lateral fiber-road offset. From the equation, we can see that for fixed soil properties, the shape of spatial strain response depends on the gauge length and the relative position between the load and the fiber. To compute the modeled synthetic horizontal strain signal, we assumed a fiber depth of 2 m, appropriate values for sandy/clayey soils, such as a Poisson’s ratio of 0.4. Fig. 1 shows the simulated strain along the fiber for a point load at $x = 0$ m and $y = 0, 15, 25$ m. We investigate the gauge length effect by simulating wavelets with $L$ of 0 (equivalent to point sensor), 8, and 16 m in Fig. 1 (a), (b), and (c), respectively. From the point sensor wavelets shown in Fig. 1(a), we can see that the wavelet is compact and sharp when the fiber is right beneath the load. As $y$ increases, we can observe an increasing smoothing effect leading to wider wavelets and lower resolution. By comparing Fig. 1 (a) with (b) and (c), we can see that increasing gauge length leads to a wider wavelet for 0 offset, but has a limited impact on larger $y$ (15 and 25 m). Fig. 2(a) and (b) show the simulation of a two-axle car with 2.8 m axle spacing and a three-axle vehicle with 9 m axle spacing, respectively. We compare the point sensor recording to that obtained with $L = 16$ m and the fiber-road offset of 15 m and 25 m. We can see that the axles are resolved from the point sensor recordings with zero lateral offset, but become indistinguishable in recording with a larger offset due to the smoothing effect.

C. Wavelet dependency on vehicle speed

This subsection studies the effect of vehicle speed on the DAS response in the temporal and spatial domain, which is important to guide the design of the DAE model. For a vehicle traveling from an initial position, $x_0$, with a constant speed of $c$, the measured strain response at fiber location $x$ is,

$$\varepsilon_x(x, t) = E_x(x - ct - x_0). \quad (3)$$

The temporal wavelet at a constant time $x_0$ and the spatial wavelet at a constant location $t_0$ can be written as $\phi(t) = \varepsilon_x(x = x_0, t)$ and $\psi(x) = \varepsilon_x(x, t = t_0)$, respectively. From equations (1) to (3), we can see that the car speed, $c$, acts as a scaling factor of $\phi(t)$, determining the compactness of the temporal wavelet. This can be confirmed through numerical experiments. Fig. 3 shows the simulation of the temporal wavelet of a two-axle car traveling at 10, 20, 30, and 40 mph. We can see that faster car speed leads to sharper temporal wavelet. On the other hand, we can see from the equations that the shape of the spatial wavelet is speed-independent. The speed term only introduces a space shift accounting for the different vehicle positions at time $t_0$ for different speeds.

Our observation that the shape of the space-domain rather than the time-domain wavelet is speed-invariant is confirmed using field experiments at Sand Hill road monitoring by the Stanford DAS2 array [16]. Fig. 4 shows the map of a subsection of the roadside fiber labeled with distances along the fiber. The horizontal distances from the centers of the south- and north-bound traffic lanes to the fiber are around 15 m and 25 m, respectively. We drove a test car southward to understand the car impulse responses for various driving speeds, including 10, 20, 30, and 40 mph. Fig. 5 shows the quasi-static signals of our car indicated from DAS recordings using orange arrows. The bottom panels show the corresponding Frequency-Wavenumber spectra. It can be seen that the frequency components vary with speeds, i.e., a higher car speed leads to a broader bandwidth (narrower temporal wavelet). We can also observe that the wavenumber...
Fig. 2. Simulation of quasi-static signals of a DAS array with zero and 16 m gauge length, L, loaded with (a) a two-axle car with an axle spacing of 2.8 m; (b) a three-axle vehicle with an axle spacing of 9 m with various lateral offsets, \( y \), to the fiber.

Fig. 3. Numerical simulation of the time-domain quasi-static signals of a two-axle car with constant speeds of 10, 20, 30, and 40 mph.

components remain relatively invariant to car speeds, implying that the spatial wavelet for different speeds is stationary.

III. METHOD

As discussed in Section II B., the resolution of the quasi-static signals of vehicles is degraded due to the smoothing effect of large fiber-road offset and gauge length. In order to improve the resolution, we introduce a space-domain DAE model to perform deconvolution along the spatial axis with a space-domain wavelet taking the offset and gauge length effect into account.

The space-domain DAE model is based on the idea of the original time-domain DAE model that performs deconvolution along the time axis with a stationary wavelet in time. The time-domain model is effective when car speed is approximately constant in time. However, as was shown in the previous section, the car’s time-domain impulse response changes with speed, indicating the method could be suboptimal when the speed varies (e.g. stopping or accelerating). In contrast, the impulse response in the space domain is speed-invariant and can be tied to wheelbase and axle numbers.

A. Network Architecture

Our space-domain DAE model shown in Fig. 6 is a 2-D fully convolutional U-Net adapted from [22]. The inputs are quasi-static traffic recordings, a set of \( N_x = 256 \) (256 meters) consecutive waveforms of \( N_t = 1024 \) time samples (20.48 s) in duration, organized in an \( N_x \times N_t \) matrix. The outputs are
sharp deconvolution results with the same shape as the inputs. The U-Net model comprises 3 convolutional layers, followed by 3 encoder blocks containing a downsampling (max pooling) layer and 3 convolutional layers. The kernel sizes for the convolution layers are $3 \times 5$. The number of convolutional filters is initialized at 8 and gets doubled after each downsampling operation. The maxpooling operation downsamples the data by a factor of 2 along the DAS sensor axis and by a factor of 4 along the time axis (i.e., the maxpooling kernel and strides are of size $2 \times 4$). The decoder reverses the encoding operations with 3 blocks of bilinear upsampling. The U-Net contains skip-connections, which directly connect the output of one encoder block with the corresponding decoder block. Lastly, the output layer is a single convolutional layer with 1 output channel and ReLU activation, which enforces positivity in the model output.

Our model is a semi-supervised algorithm, in the sense that no ground truth deconvolution is required as labels to train the model. Weak supervision comes from the spatial car impulse response kernel shown as the red bell-shaped curve in Fig. 6. The key difference between our DAE model and the original time-domain DAE model is that we obtain the impulse response kernel shown as the red bell-shaped curve in Fig. 6. The choice of $y$ and $y$ length match the real settings of the Sand Hill road DAS experiments. The training dataset we used is 2-hours’ worth of traffic recordings of the Sand Hill DAS fiber. We split the 2-hour recordings into a training and evaluation set with a ratio of 80% to 20%.

B. Evaluation baselines

As a baseline, we trained a time-domain DAE model with the same dataset. The temporal wavelet used for training is simulated with a car speed of 30 mph (shown in Fig. 3) matching the speed limit of the Sand Hill road.

We also benchmark our spatial DAE model using a conventional spatial deconvolution algorithm with an objective function:

$$\hat{x}_q = \arg\min_{x_q} \left\{ \frac{1}{2} \|k \ast x_q - y_q\|_2^2 + \rho \|x_q\|_1 \right\} \tag{5}$$

Notations have the same meaning as in equation (4). Note that $|k \ast x|_d$ stands for convolution in space between a known spatial impulse response kernel and the underlying impulse model, $x$. One commonly used algorithm to solve this optimization problem is the Iterative Shrinkage Thresholding Algorithm (ISTA; [27], [28]). For this study, we adopt an accelerated version of ISTA (Fast-ISTA or FISTA) due to the reason described in [29], which exhibits faster convergence guarantees. With FISTA performing spatial deconvolution, signals at each time index are processed independently.

IV. RESULTS

We show the evaluation results of the proposed DAE model for car tracking, resolving closely traveling vehicles, large-vehicle axle counting, and a potential limitation of the approach with our solution.

A. Car tracking

To test the performance of the proposed spatial DAE model, we conducted controlled driving experiments where we drove a test car equipped with a speed sensor and a GPS receiver southward along the subsection of the Sand Hill road shown in Fig. 4. In Fig. 7 we focus on a case where our car is first speeding up and then slowing down. Fig. 7(a) shows the quasi-static signal of our car. The car speed is inversely proportional to the slope in the time-space coordinate. We can see in (a) that when the car speed is low (< 10 s and > 30 s), the wavelet is “stretched” in time. When the car speed is relatively higher, the time-domain wavelet is “compressed”, agreeing with our observation in Section II. Fig. 7(b), (c), and (d) show the deconvolution results from the proposed space-domain DAE model, the original time-domain DAE model and the space-domain FISTA algorithm. Both the space- and time-domain
Fig. 6. Conceptual overview of the spatial DAE model. The input is the quasi-static response of DAS to cars, which can be viewed as a matrix, 256 channels (256 meters) x 1024 time steps (20.48 seconds). The output is the deconvolution results. The loss is computed with the input and the reconstructed input is obtained through a spatial convolution of the output with a known car impulse response in the spatial domain.

DAE models are trained with L-1 norm regularization loss to promote sparsity in the outputs. We can see that the proposed space-domain DAE model yields the sharpest and the most localized results regardless of car-speed variation. Meanwhile, we can see that the background noise is suppressed by the DAE model. In contrast, the time-domain DAE model yields results that are dependent on the speed, e.g. the output is more compact in space with a higher speed but becomes stretched out when the speed is lower. The spatial deconvolution via the FISTA algorithm yields result that is speed-invariant but is not as compact as the spatial-DAE results. Signals < 5 seconds are oversuppressed by the L-1 norm term in the equation 5. We can also observe artifacts shown in black in the FISTA outputs.

Using the signals in Fig. 7 (a) to (d), we can track the car movement by picking the amplitude at each time step. The estimated trajectory for each panel is shown as a thin blue curve in Fig. 7. Car speed estimates can be obtained efficiently through a local beamforming algorithm applied to either the quasi-static signals or the deconvolution results (Fig. 8). The beamforming spectrum at each time step is computed using a local 2-D window (3 s x 30 m) following the estimated trajectories. In Fig. 8, a brighter color indicates higher stack energy in each panel. The red curves represent speed measurements from an onboard speed sensor. Our speed estimates, indicated with the black curves, are obtained by picking the maximum amplitude of the beamforming spectrum at each time step. We can see that our beamforming estimates using the space-domain DAE output match the red curve the best. Using the Controller Area Network (CAN) bus reading from the vehicle as the ground truth, the root-mean-squared errors (RMSE) for the original recording, space-domain DAE, time-domain DAE, and FISTA are 2.56, 2.14, 4.55, and 2.48 mph, respectively. Our space-domain DAE model achieves the lowest RMSE thanks to the sharp deconvolution outputs and its highest noise suppression performance. The large error of the time-domain DAE model is mainly due to the falsely high-speed event around 33 s as shown in Fig. 7 (c) and the wiggled
lane wavelet (red light and restarting). Fig. 9 (d) shows the results of the DAE model yields sharp results with fast car speed. However, evident sidelobe artifacts shown in black. The time-domain DAE model under dense traffic conditions. Fig. 9 (a) shows a 200-second quasi-static recording in heavy traffic. Vehicles transiting southward are closer to the fiber and thus generate stronger quasi-static signals than the northbound traffic. In the plot, we label several interesting events. We can see that when multiple cars trailing closely, their quasi-static signals interfere with each other causing complicated patterns that pose ambiguity for individual car identification. Fig. 9 (b) and (c) show the FISTA and time-domain DAE (L-1 norm regularization) results, respectively. We can see that FISTA generates poorly resolved results and contains evident sidelobe artifacts shown in black. The time-domain DAE model yields sharp results with fast car speed. However, as can be seen from the boxes in Fig. 9 (c), the results get blurred when the car speed is low, e.g. cars stopping for a red light and restarting. Fig. 9 (d) shows the results of the proposed space-domain DAE model trained with the near-lane wavelet (y = 15 m) and L-1 norm regularization loss. We can see that the model yields sharp results regardless of speed changes. However, signals of the northbound traffic in a further lane are oversuppressed. To recover the further lane traffic, we experiment with a spatial DAE model trained with the wider far-lane wavelet (simulated with y = 25 m matching the fiber-northbound lane offset). Fig. 9 (e) shows the far-lane DAE results. We observe less oversuppression issues for the northbound traffic and sharper signals for both near and far lanes. Nonetheless, artifacts that could be misinterpreted as vehicles appear as circled out in the plot. In Fig. 9 (f), we experiment with space-domain DAE models trained with L-2 norm regularization loss using the near-lane wavelet. We can see that with L-2 norm regularization, weak signals of the far-lane traffic are better preserved, which benefits the tracking of the northbound vehicles. Fig. 9 (g) shows the results of the L-2 norm space-domain DAE model trained with the far-lane wavelet. Although the signals are slightly sharper than that shown in (f), the background noise level gets increased.

C. Large-size vehicle monitoring

Heavier and longer vehicles, e.g. buses, trucks, and trains, generate quasi-static signals with much larger amplitudes and wider spatial wavelets than cars, e.g., sedans and SUVs. The wider spatial wavelet can be viewed as the superposition of quasi-static signals of wheels at axles that are farther apart. Fig. 10 (a) shows a quasi-static recording of an 18-meter three-axle bus transiting southward (video captured by our camera). Due to the smoothing effect of the road-fiber offset and gauge length, the axles are indistinguishable from the quasi-static signals. Fig. 10 (b) shows the deconvolution results of the space-domain DAE model trained with L-1 norm regularization loss using the simulated near-lane impulse response wavelet. We can see the three axles are recovered as three strong-energy trajectories corresponding to the three axles. The amplitude difference between the three trajectories could imply a non-uniform weight distribution on different wheel groups. The distance between the two most substantial peaks is about 17 m agreeing with the bus length, indicating the usage of our L-1 norm model for counting long-size vehicle axles and length characterization. Fig. 10 (b) shows the results of the space-domain DAE model trained with L-2 norm regularization. We can see that axles are smoothed out by the L-2 norm regularization. The L-2 norm model could be used to track the bus motion.

Monitoring large-size vehicles benefits not only traffic management but also non-intrusive shear-wave velocity imaging, which can support city sustainability on applications including sinkhole detection, excavation monitoring, and earthquake hazard analysis. A shear-wave profile can be estimated through an optimization algorithm using traffic-induced surface waves as inputs. Fig. 11 (a) and (b) show the dynamic surface wave components (> 1 Hz) excited by a moving bus and a car, respectively. We can see that the bus excites much stronger surface waves than the car. With the surface waves within the two dashed lines, we compute the dispersion spectrum reflecting the relationship between the phase velocity and frequency as shown in Fig. 11 (c) and (d) for the bus and car, respectively. We can see that large-size vehicles, such as a bus, generates surface waves with frequency as low as 2.5 Hz, which is absent from the car-induced surface waves. Low frequencies at 2.5 Hz have a wavelength of ~ 200 m. The maximum investigation depth of the shear-wave velocity structure using surface waves is about half of the longest wavelength [30]. Therefore, with buses, we can retrieve depths...
Fig. 9. (a) Quasi-static signals of passing vehicles in heavy traffic. (b) spatial deconvolution via FISTA. (c) temporal deconvolution via the time-domain DAE model. Boxes indicate signals in lower resolution due to slower car speeds. (d) and (e) show the results from the proposed space-domain DAE model with L-1 norm regularization using near and far lane wavelets, respectively. Artifacts that could be misinterpreted as transiting cars are circled out. (f) and (g) show the results of the space-domain DAE model with L2 regularization using the near and far wavelets, respectively.
D. Spatial non-stationarity

Our spatial model assumes that the car impulse response is stationary in space. However, the impulse response is a function of the recording system and the near-surface conditions surrounding the fiber optic cable. Thus, the deconvolution of a DAS array covering heterogeneous near-surface conditions using a single stationary spatial impulse response could be suboptimal. Fig. 12 (a) shows DAS recordings of traffic in downtown San Jose City (SJC). (b) shows deconvolution results of the proposed space-domain DAE model with a simulated car impulse response kernel. The deconvolution results look encouraging for most of the fiber, which can be contributed to the consistency of the assumed wavelet to the real wavelet. However, we can see that the results in the red box are relatively poorly resolved. The low resolution is more noticeable from the zoomed-in view of data and deconvolution results in the red box in Fig. 13 (a) and (b). The under-performance could be explained as the wavelet inconsistency due to the non-stationarity of the near-surface properties. Assuming that the near-surface properties, and in turn the car response, at each channel location is stationary in time. A possible solution would be to estimate the spatial car response at different parts of the fiber by averaging responses of multiple passing cars around each location. To verify this, we employ a local maximum finding algorithm as a simple car detector for the quasi-static signals. We average the responses of six identified cars passing the area in the red box of Fig. 12 as the impulse response input to the U-net model. We retrain the U-net using this estimated kernel, which produces a sharper result in Fig. 13, indicating the effectiveness of our approach.

VI. DISCUSSION AND CONCLUSIONS

This paper focuses on the application of traffic monitoring with car-induced quasi-static signals recorded by an urban DAS array. To denoise the data and to reduce the interference among closely traveling cars, we propose a self-supervised convolutional U-Net model (space-domain DAE model) that can compress the quasi-static signals into sharp pulses and remove the background noises. The goal is achieved through spatial deconvolution with an assumed spatial wavelet of the quasi-static signals, which is a major difference from the previously proposed time-domain DAE model.

This paper shows that using the spatial instead of the temporal kernel is advantageous because it is invariant to car speed variation. This leads to an improved precision robustness of tracking cars with varying speeds, which is essential for driving behavior identification and accident detection. The benefits of our DAE model are more obvious for heavy-traffic conditions where car signals interfere. With our space-domain
Fig. 12. Deconvolution of traffic recording in downtown SJC via a space-domain DAE model with a simulated impulse response stationary in space. (a) Input data; (b) deconvolution results. The red box indicates results that are poorly resolved due to the spatial non-stationarity of the car wavelets.

DAE model, compressing signals of individual cars to sharp pulses, traffic patterns are much better revealed. Furthermore, we show that our space-domain DAE model is robust to deconvolve signals of large-size and heavy vehicles, such as a bus. Being able to identify large vehicles can be helpful in extracting low-frequency surface waves to image the velocity structure down to hundreds of meters beneath the fiber. Lastly, we point out that a limitation of our spatial-domain DAE model arises when car impulse responses at different locations along the fiber vary due to coupling heterogeneity and/or fiber properties. We address the issue by extracting car wavelets using statistical averaging, and train separated networks. Future work would be adapting the DAE model to different parts of the fiber using location-dependent spatial wavelets.

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REFERENCES

[1] K. Robert, “Video-based traffic monitoring at day and night vehicle features detection tracking,” in 2009 12th International IEEE Conference on Intelligent Transportation Systems, 2009, pp. 1–6.
[2] S. R. E. Datondji, Y. Dupuis, P. Subirats, and P. Vasseur, “A survey of vision-based traffic monitoring of road intersections,” IEEE Transactions on Intelligent Transportation Systems, vol. 17, no. 10, pp. 2681–2698, 2016.
[3] P. Reinartz, M. Lachaise, E. Schmeer, T. Krauss, and H. Runge, “Traffic monitoring with serial images from airborne cameras,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 61, no. 3, pp. 149–158, 2006, theme Issue: Airborne and Spaceborne Traffic Monitoring. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0924271606001146
[4] N. K. Jain, R. Saini, and P. Mittal, “A review on traffic monitoring system techniques,” Soft Computing: Theories and Applications, pp. 569–577, 2019.
[5] S.-T. Jeng and L. Chu, “A high-definition traffic performance monitoring system with the inductive loop detector signature technology,” in 17th International IEEE Conference on Intelligent Transportation Systems (ITSC), 2014, pp. 1820–1825.
[6] T. Cherrett, H. Bell, and M. McDonald, “Traffic management parameters from single inductive loop detectors,” Transportation Research Record, vol. 1719, no. 1, pp. 112–120, 2000. [Online]. Available: https://doi.org/10.3141/1719-14
[7] J. Zhang, Y. Lu, Z. Lu, C. Liu, G. Sun, and Z. Li, “A new smart traffic monitoring method using embedded cement-based piezoelectric sensors,” Smart Materials and Structures, vol. 24, no. 2, p. 025023, 2015.
[8] Z.-X. Li, X.-M. Yang, and Z. Li, “Application of cement-based piezoelectric sensors for monitoring traffic flows,” Journal of Applied Engineering, vol. 132, no. 7, pp. 565–573, 2006.
[9] R. Posey, “Rayleigh scattering based distributed sensing system for structural monitoring,” in Fourteenth International Conference on Optical Fiber Sensors, A. G. Mignani and H. C. LeFevre, Eds., vol. 4185, International Society for Optics and Photonics. SPIE, 2000, p. 41850E. [Online]. Available: https://doi.org/10.1117/12.2302157
[10] A. Masoudi and T. P. Newson, “Contributed review: Distributed optical fibre dynamic strain sensing,” Review of Scientific Instruments, vol. 87, no. 1, p. 011501, 2016. [Online]. Available: https://doi.org/10.1063/1.4939482
