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Deep Deconvolution Applied to Distributed Acoustic Sensing for Traffic Analysis

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Abstract—Distributed Acoustic Sensing (DAS) is a nascent technology that facilitates the measurement of vibrations along fibre-optic telecommunication cables, which has numerous novel applications in many domains of science and engineering. In the present study, we use DAS to analyse traffic along a fibre-optic cable deployed along a major road in Nice, France. For the objective of estimating the speed of individual vehicles, we propose a MUSIC beamforming algorithm, which exhibits superior performance when applied to data that has been deconvolved with a Deep Learning model. The accuracy of the speed estimation is in the range of 0.14-0.25 km h⁻¹, which is at least one order of magnitude better than conventional methods. DAS therefore has great potential in urban traffic analysis applications.

I. INTRODUCTION

Distributed Acoustic Sensing (DAS [1]) is a laser-pulsing technology that converts fibre-optic telecommunication cables into arrays of thousands of vibration sensors, positioned every few metres along the fibre-optic cable. An interrogator unit systematically sends short pulses of laser light into one end of an optical glass fibre, and measures the phase and/or amplitude of the back-scattered photons that have interacted with nanometric-scale defects along its path through the fibre. Through interferometric techniques, the (rate of) stretching of the fibre can be inferred from the back-scattered measurement at equidistant points along the fibre, at temporal sampling rates up to several kHz. This has enabled numerous applications in science and engineering, including (but not limited to) geophysics and seismology [2]–[4], structural integrity monitoring [5], and hydrology [6].

One particular application of interest of the present study, is that of vehicular traffic monitoring. As many commercial telecommunication cables are being deployed immediately adjacent to public roads, DAS has the ability to record the passage of vehicles over these roads [7], [8]. When a vehicle drives past a given location along the cable, its weight pressing down on the road causes small deflections in the subsurface, which is transferred to the fibre and subsequently measured by the interrogator (see Fig. 1). By estimating the timing at which a vehicle passes by a given sensing point, and knowing the (fixed) spacing between sensing points, one can precisely obtain the location and velocity of the vehicle. Roadside DAS therefore holds enormous potential for high-resolution traffic monitoring, and can be complementary to conventional instrumentation like traffic cameras and inductive loops embedded in the road.

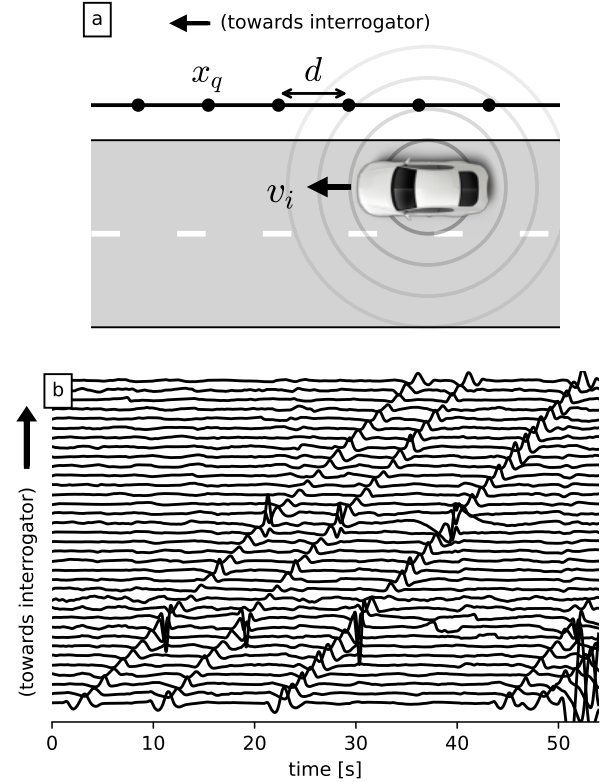


Fig. 1. a) Schematic illustration of the layout. A vehicle with velocity v_i travels along the DAS cable that was deployed parallel to the road. The spacing between the sensors is d , with the q -th sensor being located at x_q ; b) Example of DAS data containing three cars. Each black line represents a time-series measurement at a given sensor. Each car traces out a diagonal line in the data, the slope of which equals its velocity.

To enable “smart city” applications facilitated by DAS, such as advanced traffic control, robust and accurate DAS analysis algorithms are needed. In this paper, we propose a frequency-domain MUSIC beamforming algorithm to estimate the speed of vehicles in an urban setting. To massively improve upon the accuracy and precision of the speed estimation, we leverage a self-supervised, non-blind Deep Learning deconvolution model that deconvolves the characteristic signal of cars and other vehicles from the DAS data.

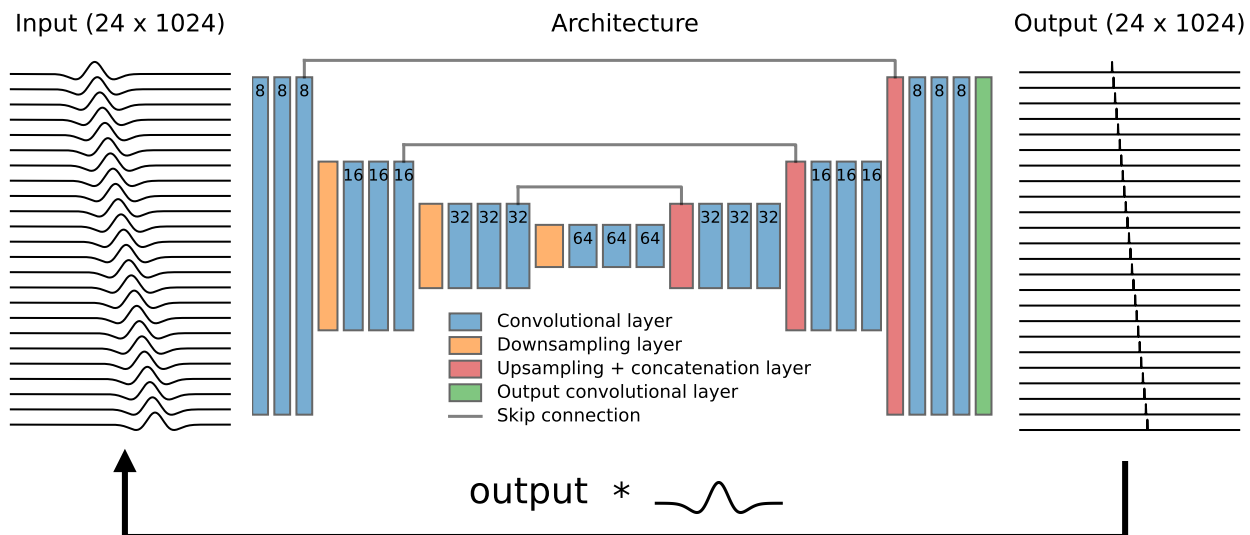


Fig. 2. Architecture of the Deconvolution Auto Encoder. We take a set time-series of size 1024 samples, recorded by 24 consecutive DAS sensor. This input is passed to a U-Net Auto-Encoder and produces an output X of the same size as the input. This output is subsequently convolved with the known impulse response of a car, and the learning objective is to minimise the difference between the convolved output and the original input (subject to a sparsity constraint on X).

II. APPROACH

A. Signal model

The problem as illustrated in Fig. 1a consists of estimating the velocity (v) of a vehicle, using the vibrations recorded along the DAS cable. In this study we focus on the analysis of isolated vehicles. For a linear equidistant array of sensors with spacing d positioned tangent to the road, the characteristic signal y of a vehicle observed at time index $n = 0 \dots N - 1$ and sensor $q = 0 \dots M - 1$ can be modelled as:

$$y_q(n) = \alpha s(n - \tau - q\Delta_t) + n_q(n)$$

in which s is the vehicle's characteristic signal with amplitude α , τ is a constant time offset, $\Delta_t \propto d/v$, and n is assumed to be Gaussian-distributed noise.

Then, let $Y_q(k)$ be the Discrete Fourier Transform (DFT) of signal $n \rightarrow y_q(n)$ at frequency k/N and $\mathbf{y}(k)$ the vector collecting $Y_q(k)$ at all sensors q . We can write:

$$\mathbf{y}(k) = \alpha S(k) \exp\left(\frac{-j2\pi k\tau}{N}\right) \mathbf{e}_{k,N}(\Delta_t) + \mathbf{n}(k) \quad (1)$$

where $S(k)$ is the DFT of $s(n)$ and $\mathbf{e}_{k,N}(\Delta_t)$ is the steering vector defined as:

$$\mathbf{e}_{k,N}(\Delta_t) = \left(1, \exp\left(-j\Delta_t \frac{2\pi k}{N}\right), \exp\left(-j\Delta_t \frac{4\pi k}{N}\right), \dots\right)^\top$$

We then estimate the interspectral covariance matrix by averaging $\mathbf{y}(k)\mathbf{y}(k)^\dagger$ w.r.t. k over a narrow frequency band centred at frequency \bar{k} , and subsequently apply the MUSIC beamforming algorithm using $\mathbf{e}_{\bar{k},N}(\Delta_t)$ as the steering vector. This yields an estimation of the distribution of beam pseudo-power over v .

B. Deconvolution Auto-Encoder

As is apparent from Fig. 1b and from theoretical considerations [2], the characteristic signature of a car as recorded by DAS is the same for each car (up to a proportionality constant). We can therefore achieve higher resolution traffic measurements by deconvolving this characteristic impulse response from the DAS data. To this end we employ a Deep Learning model, which takes as an input a subset of the DAS data and produces some output (X) of the same size as the input. We then convolve this model output by the (known) impulse response of a car (R), i.e. $\hat{y}_q = [R * X_q]_t$, where $[a * b]_t$ denotes the convolution between a and b along the temporal axis. We then define the learning objective as:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^N \|y_q^i - \hat{y}_q^i\|_2^2 + \lambda \|X_q^i\|_1 \quad (2)$$

in which the average is taken over N samples in a training batch, and λ is the strength of the ℓ_1 regularisation on X (promoting sparsity). Following the completion of the training phase, the output of the model X is such that upon convolution with the car's impulse response, the original input y is approximated; the Deep Learning algorithm therefore represents a deconvolution operation. Note that this learning approach is entirely self-supervised.

III. EXPERIMENTAL SETUP

The data analysed for this study were acquired during a measurement campaign performed in the city of Nice, in the south of France. The fibre was nested within a bundle of cables firmly attached to the side of a multi-lane suspended road crossing the city, and was sensed with an hDAS interrogator

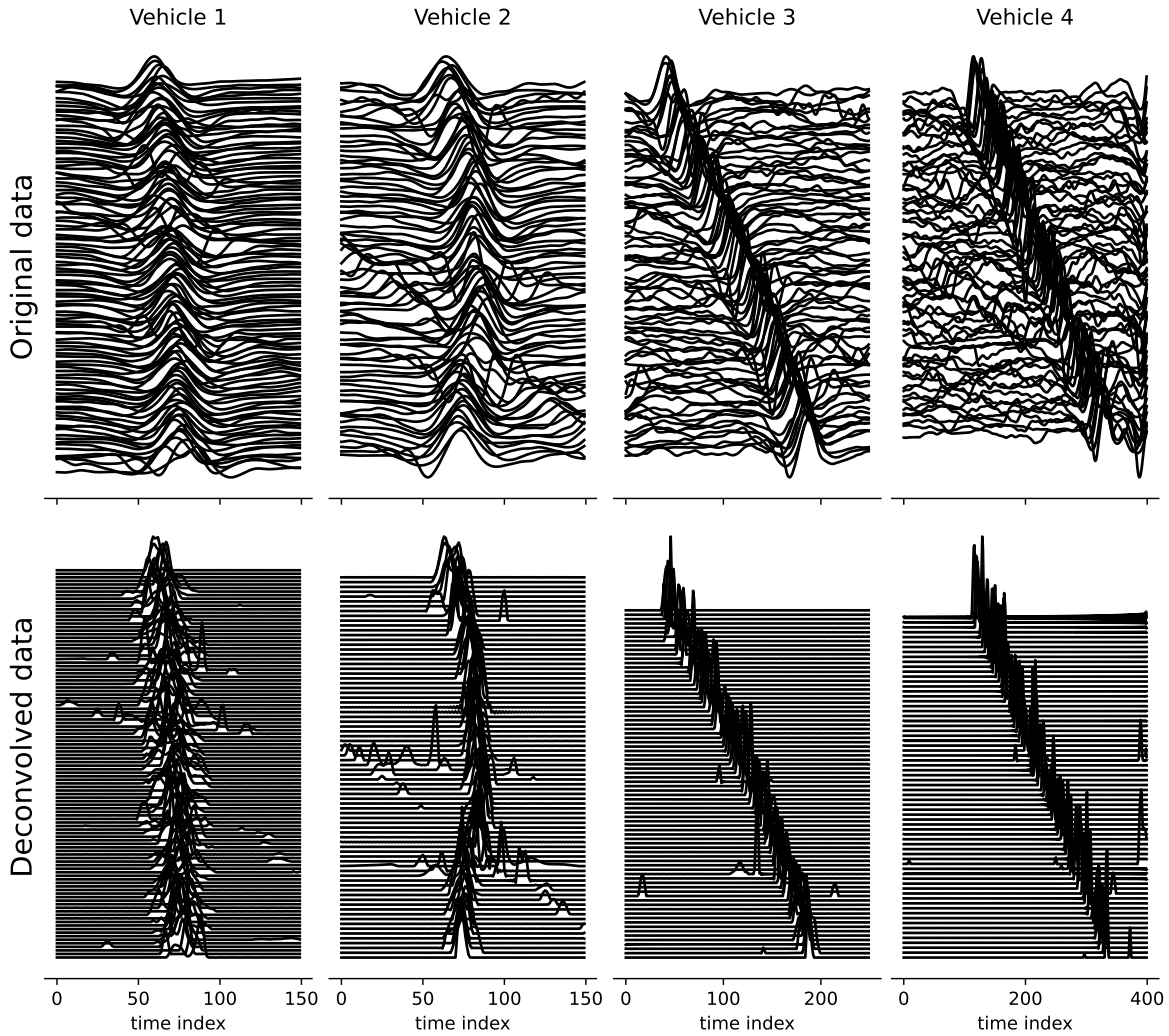


Fig. 3. Top row: four selected examples of recordings of cars, characterised by a large-amplitude wiggle near the centre of each panel. The waveforms are shifted according to a reference velocity of 70 km h^{-1} (see text); Bottom row: results of the Deconvolution Auto-Encoder algorithm, taking the waveforms from the top row as an input.

(Aragon Photonics) with a channel spacing equal to the gauge length of $d = 10 \text{ m}$, at a temporal sampling frequency of 250 Hz . To preprocess the data, we applied a bandpass filter with a $0.1\text{-}2 \text{ Hz}$ pass band, and downsampled the data to 25 Hz . We assess the performance of the proposed workflow based on four typical examples of DAS recordings of cars travelling towards the interrogator (see top row of panels in Fig. 3). These example recordings were deconvolved with the Deconvolution Auto-Encoder (bottom row in Fig. 3). Both the original and the deconvolved data were subsequently analysed with MUSIC beamforming.

For the beamforming analysis, we computed the beampower over a grid of slowness (reciprocal velocity) values $\{\sigma_j\}$, for which we defined $\sigma_j = \sigma_0 + \delta\sigma_j$. The constant reference slowness σ_0 was factored out of Eq. (1), performing the computation over slowness perturbations $\delta\sigma_j$. As a reference slowness, we took $\sigma_0^{-1} = v_{ref} = 70 \text{ km h}^{-1}$, being the speed limit of the road under study. For visualisation purposes, all

of the waveforms in Fig. 3 are shifted in accordance with this reference slowness. Under this transformation, a vehicle with a speed of exactly v_{ref} would trace out a vertical line, with faster vehicles tracing out a diagonal line from top left to bottom right (and v.v. for slower vehicles). We apply the MUSIC algorithm to a sliding window of 15 consecutive DAS sensor recordings, equivalent to 140 m distance. This sliding window traverses the data along the spatial axis, estimating the distribution of beampower as a function of distance along the cable.

For reference, we also estimate the velocity of each selected vehicle by estimating the timing of passage at a given DAS sensor as the timing of the peak strain for that sensor (i.e. by taking the peaks seen in e.g. Fig. 1b). The average velocity between consecutive DAS channels is consequently $v = d / (t_{i+1} - t_i)$. Owing to the presence of noise in the data (with spatially non-uniform signal-to-noise ratio), this method is sensitive to outliers, and manual fine-tuning with a

median filter and a Savitzky-Golay filter was needed to obtain stable estimates of the vehicle's velocity $v = d\Delta q / \Delta t_{peak}$ over a distance interval $d\Delta q$. We suppose that the extensive fine-tuning renders this approach based on peaks in the DAS recordings infeasible for automated traffic analysis.

IV. RESULTS

Corresponding with the four selected vehicles shown in Fig. 3, we plot the distribution of beampower for each vehicle as a function of distance along the cable in Fig. 4. By comparing the top row (original data) with the bottom row (deconvolved data), it becomes immediately apparent that the distribution of beampower is much more narrowly distributed for the deconvolved data than for the original data. Especially for vehicles 3 and 4 (Fig. 4c and d), the beampower distribution for the original data is very broad and multi-modal, which inhibits a precise estimation of the vehicles' velocities. By contrast, the beampower distribution for the deconvolved data of these vehicles (Fig. 4g and h) has only a single and sharp peak in beampower for each DAS channel, which could be easily detected and characterised with a basic automatic peak detector.

In comparison to the baseline estimation of the velocity (based on peaks in the strain, as described in the previous section), both data sets seem to be very accurate. We can quantify this accuracy by taking the location of the peak in beampower for each channel, and computing the absolute difference with the corresponding baseline estimation at the same channel. The mean absolute difference, averaged over all the channels, is indicated in each panel in Fig. 4. Likewise, the precision of the method is estimated as the *full width at half maximum* (i.e. the width of the peak at 50 % of its maximum) of the beampower peak for each channel. This measure is not entirely meaningful for a multi-modal distribution like seen in Fig. 4d, in which case the estimated precision is merely indicative.

Considering these quantitative performance metrics, we find that the beamforming results on the deconvolved data systematically outperform those for the original data. In the most extreme example, the accuracy and precision for the deconvolved data (0.17 and 1.32 km h⁻¹, respectively) are almost one order of magnitude better than for the original data (3.55 and 7.14 km h⁻¹, resp.). Moreover, the performance on the deconvolved data is much more consistent across samples, which is an important aspect to consider for real-world implementations.

V. CONCLUSIONS & FUTURE PERSPECTIVES

In this paper we demonstrate the accuracy of MUSIC beamforming algorithms in estimating the velocity of isolated cars in Distributed Acoustic Sensing (DAS) data. Particularly when the characteristic signal of a vehicle is deconvolved from the data do the estimated velocities achieve extremely good accuracy and precision. With an accuracy in the range of 0.14-0.25 km h⁻¹ and a precision in the range range of 0.82-1.54 km h⁻¹, DAS-based vehicle speed estimations are

very competitive compared to established traffic analysis techniques. To give an example, the winning contender of the 2018 NVIDIA AI City Challenge [?] achieved an RMS accuracy of 6.6 km h⁻¹ based on traffic camera data, using state-of-the-art computer vision techniques. Handheld radar guns could in principle achieve an accuracy of less than 1 km h⁻¹, but have a tendency to produce outlier results [?]. Since the performance of DAS does not depend on environmental factors (weather conditions, lighting situation, etc.), we expect DAS to deliver accurate and consistent performance at all times.

Another major advantage of using DAS for traffic analysis, is that the fibre-optic infrastructure it relies on is already in place in many urban locations. While dedicated deployments could achieve better signal-to-noise ratios as a result of specific deployment protocols (e.g. improving coupling between the fibre and the road [?]), existing telecom cable deployments could be sufficient (as we demonstrate in this study). Upscaling DAS technologies can therefore be logistically more feasible than discrete sensor networks (inductive loops, cameras, roadside laser guns, etc.).

Lastly, we stress the notion that "smart city" applications facilitated by DAS are still in their infancy, and that advances in laser pulsing, fibre manufacturing, and cable deployment technologies may yield massive improvements in the signal quality that may bolster signal analysis algorithms in the near future.

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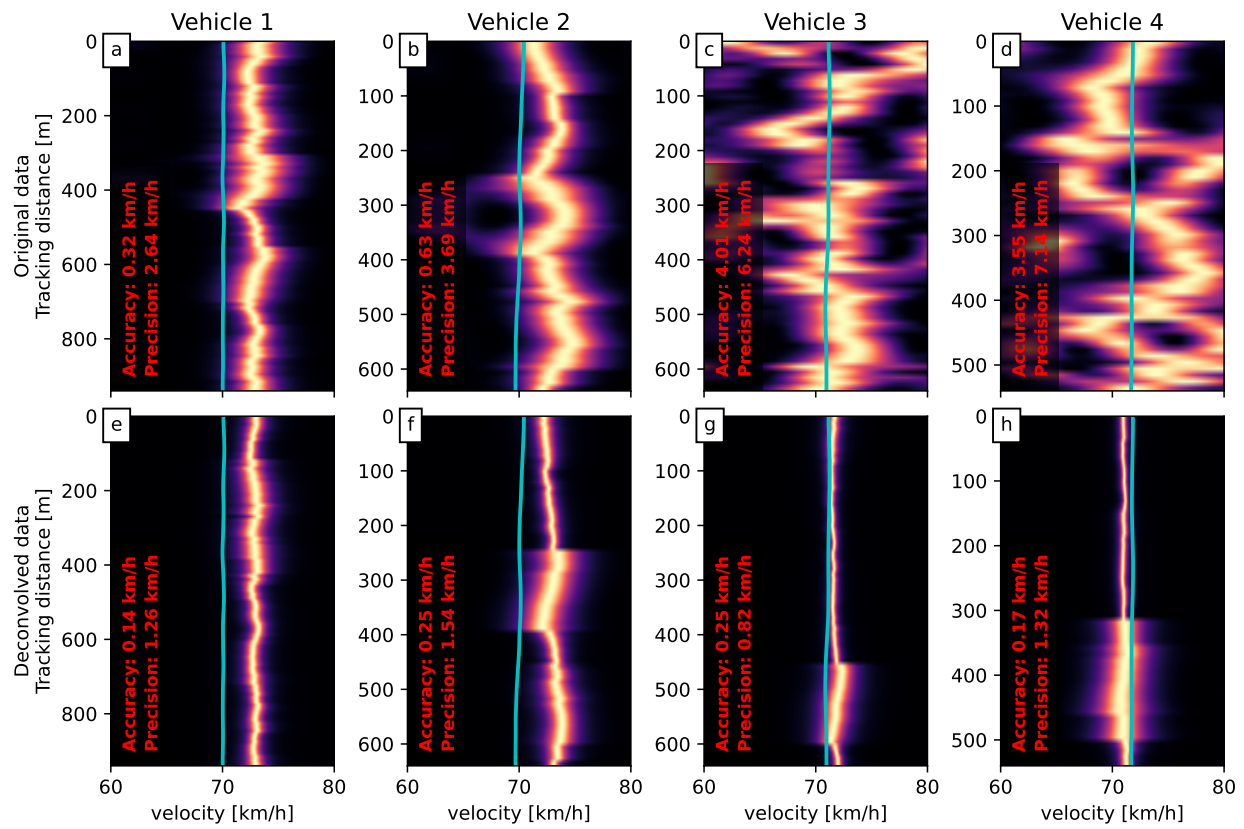


Fig. 4. Overview of beamforming performance. Top row: the beampower distributions for the four selected vehicles estimated from the original data (corresponding with the top row in Fig. 3). Bottom row: the beampower distributions estimated from the deconvolved data (corresponding with the bottom row in Fig. 3). In each panel, we indicate the velocity estimated from the peak strain as cyan lines, and the estimated accuracy and precision as red text.

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