A Distributed Acoustic Sensor System for Intelligent Transportation using Deep Learning

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Abstract

Intelligent transport systems (ITS) are pivotal in the development of sustainable and green urban living. ITS is data-driven and enabled by the profusion of sensors ranging from pneumatic tubes to smart cameras. This work explores a novel data source based on optical fibre-based distributed acoustic sensors (DAS) for traffic analysis. Detecting the type of vehicle and estimating the occupancy of vehicles are prime concerns in ITS. The first is motivated by the need for tracking, controlling, and forecasting traffic flow. The second targets the regulation of high occupancy vehicle lanes in an attempt to reduce emissions and congestion. These tasks are often conducted by individuals inspecting vehicles or through the use of emerging computer vision technologies. The former is not scale-able nor efficient whereas the latter is intrusive to passengers’ privacy. To this end, we propose a deep learning technique to analyse DAS signals, which are correlated to the weight and other physical features of vehicles, achieving 86% vehicle classification accuracy and 94.98% in occupancy detection based on DAS data collected under controlled conditions.

Introduction

Intelligent transportation systems (ITS) analyse traffic data to automate traffic management decisions that would result in environmental-friendly and efficient traffic-flow [1]. One ITS interest is to encourage vehicles with multiple occupants by allowing these to reduce their journey times relative to single-occupant vehicles, particularly when the general purpose lanes are congested. To this end, High Occupancy Vehicle (HOV) lanes are designed to prioritise HOVs and buses. The expected outcome is the reduction of vehicles on the road network which would positively impact the overall congestion, CO2 emissions, and fuel consumption. Various trials in Europe and the USA resulted in time reduction of trips on HOV corridors by 4% to 30% [2]. It has also been reported that willingness to share cars and to use buses increases after the opening of an HOV lane. Automatically calculating passenger numbers has other uses in ITS applications such as adapting the reach and operation of public transportation facilities with new infrastructure and optimising traffic waiting time by developing adaptive traffic light systems.

Current methods used to enforce HOV lanes and occupancy detection require the physical presence of police officers to visually monitor the number of passengers in cars. It is usually dangerous, highly-repetitive, time-consuming, and expensive. The lack of cost-effective methods to detect vehicle occupancy limits these applications and the potential of ITS to enable sustainable commuting as an optimised mix of public and private transport means.

Hopefully, sensors connected by the Internet of Things (IoT) network become a potential approach for monitoring traffic conditions. Sensors incorporated into the Internet of Things enable secure and uninterrupted monitoring of vehicles and their operating status. Recently, camera-based technologies have been proposed for automating the passenger or vehicle counting task [3]. It is, however, extremely challenging and costly to cover and analyse kilometers of road networks with video cameras and the limitation due to blind areas would be inevitable. In addition, continuously transmitting high-definition images or videos leads to a huge burden on communication networks. Therefore, to achieve low-cost vehicle detection, it is necessary to develop a sensor specific to the ITS.

In this work, we examine how Distributed Acoustic Sensor (DAS) systems could be used as an alternative source for classifying vehicle types and occupancy. DAS reuses underground fiber optic cables as a distributed strain sensing system where the strain is caused by moving objects above ground. Research on DAS was initially targeted toward the monitoring of oil and gas pipelines, peripheral safety, structural health, and submarine power cables. By employing the DAS systems in smart transportation, it can detect the vehicles by monitoring the strain caused by the vehicles. The DAS system empowered by machine learning techniques has broad functions, such as vehicle positioning, vehicle type detection, vehicle load evaluation, and traffic load monitoring. On the one hand, DAS can detect the

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The lack of cost-effective methods to detect vehicle occupancy with new infrastructure and optimising traffic waiting time by numbers has other uses in ITS applications such as adapting willingness to share cars and to use buses increases after the and the USA resulted in time reduction of trips on HOV lanes are designed to prioritise HOVs and buses. The expected are congested. To this end, High Occupancy Vehicle (HOV) occupant vehicles, particularly when the general purpose lanes which would positively impact the overall congestion, CO2 and forecasting traffic flow. The second targets the regulation of ITS. The first is motivated by the need for tracking, controlling, and estimating the occupancy of vehicles are prime concerns in data source based on optical fibre-based distributed acoustic pневmatic tubes to smart cameras. This work explores a novel driven and enabled by the profusion of sensors ranging from

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We present the first work that leverages DAS systems as a vehicle occupancy and type detection solution for ITS. Due to the complexity and massive size of the DAS data, machine learning and deep learning in particular are suggested to model the key features that help answer ITS-related questions. To this end, we propose to employ convolutional neural networks (CNN) trained with both one-dimensional (1D) DAS time series and two-dimensional (2D) spacio-temporal DAS segments. The results for both occupancy (94–98% accuracy) and vehicle size (86% accuracy) classification reinforce our thesis that the DAS signal contains key information for ITS applications that can be mined using CNN. In order to motivate more research in this area, we have set up a github repository for this project that will become available under the publication of the article (https://github.com/DT4SDG-QMUL/Distributed-Acoustic-Sensor-Systems-for-Intelligent-Transportation-using-Deep-Learning).

**RELATED RESEARCH**

To estimate a vehicle’s occupancy rate, the actual passenger number and the nominal capacity of the vehicle are needed. There are a few kinds of IoT devices used in passenger flow estimation:

1. Closed-circuit television (CCTV)/Thermal images;
2. Infrared sensor;
3. Impulse Radio Ultra-104 Wideband (IR-UWB) radar sensors.

CCTV is commonly used in monitoring real-time visual information in a given area. In [1], two CCTV cameras were deployed on board of a bus to capture the full picture of total passenger heads. However, the CAE model wasn’t sophisticated enough to deal with light exposure in blurred and obstructed areas. It is one of the common issues of computer vision that model prediction performance is heavily influenced by extreme lightness, wide-angle distortion, and blind spots. In addition, compared to the infrared sensor and radar sensors, CCTV may cause privacy breach concerns. According to the General Data Protection Regulation (GDPR), the public should be informed of what data is being recorded, its use, and how long the footage is stored. Therefore, it is difficult to widely implement such technology for monitoring occupancy rates in private vehicles.

Infrared light based methods count the passenger number by fitting a Radial Basis Function neural network (RBF) [6] on pulse data collected by the infrared light sensor [7]. Alternative methods, such as [8], use K-nearest neighbours to classify motion direction based on the distances measured by three infrared sensors. The former method suffers from a decrease in detection accuracy when more passengers pass simultaneously. The latter method only works when a single person passes through the sensors. The limitations in [7] and [6] can be circumvented by using IR-UWB radar sensors. In [9], for instance, the model error rate for detecting multiple people passing simultaneously through the subway entrance is 10%. The number of detected passengers could be up to 9000 or more or as small as a single digit in a day. The deployed module for human detection contains two sensors that receive two signals respectively. The signals were then calculated for their maximum correlation which served as an indicator of human detection and direction detection. The application was cost-effective and easily set up but with the same location limitation as camera sensors.

As mentioned in the previous section, DAS has been used for the detection and classification of acoustic events, but not for the ITS purposes covered in this work. In line with acoustic signals classification, manual feature extraction techniques were first adopted in DAS event classification. Such techniques include wavelet packet transform [10], spectral substitution [11], and empirical mode decomposition [12]. The classification task is then conducted using conventional classifiers such as support vector machines (SVM such as [10]). In order to improve the classification results, authors in [12] use XGBoost, an ensemble algo-

![FIGURE 1. The overview of the importance of the DAS system.](https://github.com/DT4SDG-QMUL/Distributed-Acoustic-Sensor-Systems-for-Intelligent-Transportation-using-Deep-Learning)
This phenomena creates a continuous time series of back-scatter intensity which is commonly called “fibre shot,” where a shot corresponds to a time unit that is proportional to the time that a pulse takes to travel along fibre.

**FIGURE 2.** Raw DAS data (top) vs DAS signals (down): a) raw DAS data with (left) occupancy labels or (right) car type labels. For each map of a raw DAS data, the x-axis is fibre shot and the y-axis is bin. The color intensity of each pixel is the strength of displacement in radians; b) DAS signals with (top) HOV/LOV labels or (down) car size labels. For each graph of a 1D DAS signal, the x-axis is time in second while the y-axis is the strength of displacement in radians.

DAS: System and Data

In this section we present a brief overview of DAS systems and of the real DAS data used in this research.

**DAS System**

DAS system is an opto-electronic device sensitive to strain distribution that measures the variation of force in different parts of fibre (up to a total fibre length of 40–50km). The hardware of the DAS system consists of two main parts, the DAS integrator, and the optical fiber. The DAS integrator needs to be deployed in a protected environment (e.g., an indoor station or in a chassis), while the optical fiber needs to be buried underground along the serving road section. The principle of DAS detection is based on Optical Time Domain Reflectometry (OTDR) where a pulse of coherent light is periodically injected into the fibre. A fraction of this pulse gets reflected through a back-scattering mechanism and is captured by a photodetector. This phenomena creates a continuous time series of back-scatter intensity which is commonly called “fibre shot,” where a shot corresponds to a time unit that is proportional to the time that a pulse takes to travel along fibre. In a DAS system without any variety of external strain, the intensity is modelled as a random function of fibre position and the cumulative phase of the interference of back-scattered signal and interrogating pulse. Although interference phase is inherently random because of the random molecular structure of the fibre glass, it remains constant if the state of fibre is unchanged. On the other hand, if the dynamic strain varies, the back-scatter phase and its intensity will vary accordingly. Therefore, many different measurements are used to evaluate the variation of back-scatter at a given fibre distance to draw insights into how the strain evolves dynamically in a given fibre position.

The width of the probing pulse determines the accuracy and spatial resolution of DAS. A pulse with 100 ns corresponds to 10 m spatial resolution. Because the number of sensing units is decided by spatial sample period, the smaller the period the more likely a pulse with the same type of light can be captured by multiple sensing units at once. On the other hand, temporal sampling resolution (TSR) is given by interrogating pulse repetition frequency which is limited by fibre length because it becomes harder to complete a cycle of the pulse when the pulse’s travelling length is increased. TSR refers to how often data of the same fibre position is collected and has a trade-off relation with the spatial resolution. Hence, the output of DAS is a collection of digitised fibre shots retrieved by a given TSR.

Since the DAS system needs to process an enormous number of fibre shots, it raises challenges to the computing and storage capabilities of the DAS interrogators. The DAS interrogator used in the experiment has a professional hardware configuration, which also leads to higher costs. In practice, since the optical fibre of the DAS system is connected to the network, the DAS interrogators can hand...
over a part of computing and caching tasks to edge servers and other IoT devices for processing, thus reducing the hardware cost of the DAS system.

**DAS Data**

In a controlled field trial, DAS data was collected on a 4.8km road stretch equipped with a DAS system as described earlier. The fibre was buried 20cm in a micro-trench and Fotech’s Helios was used to capture the DAS signals. Two use cases were considered: driving the same car with different occupancy (Fig. 2a left, Fig. 2b right), driving five different vehicles in a predefined queue with controlled speed. Figure 2b represents the raw data, i.e., the entirety of the data measured at the DAS interrogator during the experiments. The total raw DAS data has 8.41 GB. In both figures, the x-axis indicates the time in fibre shots, where one shot is equivalent to 1/1000.04 seconds. The y-axis shows the position along the fibre in bins where one bin is equivalent to 0.68 metres. The color intensity of each pixel, at certain bin and shot, shows the strength of displacement in radians.

There are ten dominant lines composed of clear white-black pixels across multiple-bins. These are car signals that have generated a linear disturbance as a result of fixed speed and are highlighted in red in Fig. 2a. The data collected for each use case is detailed in the following sections.

**Car 2 (Renault Clio) at 60km/h With All Occupancy Cases (Car2-[1-5p]-60km):** In the experiment, a Renault Clio (maximum capacity is five passengers) was driven at a fixed speed of 60 km/h in both directions of the road stretch. Each trip was repeated in a predefined order with different number of passengers: from five to one, as highlighted in blue in Fig. 1a. Three other tracks/lines can be seen; these represent the movement of other objects outside the controlled experiment. The red lines between 0th to 200th bin indicate an approximate speed of 5km/h, hence may be the speed of a person speed walking in both directions. The yellow line between 0th to 500th bin on the right side of Fig. 1a indicates the motion of a fast object at an approximate speed of 60 km/h, which may be a vehicle outside the controlled experiment. The amplitude strengths from different numbers of passengers are shown in Fig. 1b. The same-shape DAS signals indicate that the same car (Car 2) was driven. However, the number of passengers is distinguished by the amplitudes of the peaks and troughs in each shown DAS signal.

**Car 2 at 60km/h with Five Passengers (Car2-[5p]-60km):** Similar to the experiment described earlier and shown in Fig. 1a, the Car 2 is driven in both directions at the same speed of 60km/h with five passengers at all times. This dataset is used later as a part of training data for the CNN model.

**Five Vehicles at Different Speeds (ALL-Cars-[1p]-AllSpeed):** In this case, five different vehicles were driven (no other passengers or the driver) at different fixed speeds (30 km/h, 40 km/h, 50 km/h, 60 km/h, 70 km/h). Figure 2a left shows a section of the collected data for the 50 km/h speed dataset. The dominant five lines highlighted in the figure represent the track of the five vehicles moving in a queue at the same speed and respecting the same inter-distance. Two other lines can be seen in Fig. 2a left. The first represents another vehicle outside the controlled experiment that is moving in the same direction and is positioned between Car 2 and Car 5. Since this work is concerned with detecting the size of a vehicle and its corresponding occupancy, we group the five vehicles into two groups. The first group, Large, is created by combining data from Car 1 (Sports utility vehicle) and Car 5 (Light commercial vehicle). The second group, Small, includes Car 2 (RC), Car 3 (compact), and Car 4 (multi-purpose vehicle). Figure 2a right shows distinct signal shapes from Car 1 to Car 5.

### Problem Formulation

In this section, we formulate the problem of estimating the selected car’s occupancy and size, based on the imprinted DAS signature. Consider a raw DAS dataset collected from continuous fibre bins over a duration of fibre shots (time unit in DAS systems). Each fibre bin represents a virtual acoustic sensor that measures the displacement of the optical signal in Radian at any fibre shot during the measuring time. We collected a complete raw dataset over the entire length of the fibre and over the full recording period.

#### Occupancy Detection (5-Way)

For a user-defined time window collected from bin/sensor b, there are five states of the vehicle load, depending on the number of passengers, which are integers in the range one to five. We can then group the set of all into different datasets according to passenger number. A data sequence for a single test includes the collected by every sensor in the test duration. The timing (starting shot and end shot) of each data sample differs, and each data sample spans a different duration. It follows that, we can express a complete dataset as a union of all such sequences collected under the case of five different load labels.

The problem can thus be formulated as a regression predictive modelling; a process of predicting passenger number that is categorised into five labels (5-way) that correspond to the number of passengers by approximating a mapping function from input sensor detected into discrete load labels. To this end, we reorganise the set of input into a training set and a testing set. The sum of training and testing dataset for this problem contains 2,947 DAS signals and sizes 128 MB in total.

#### HOV or LOV (2-Way)

As discussed in the introduction, ITS applications such as HOV lane control are concerned with knowing whether a vehicle has low or high occupancy and less concerned with the actual number of passengers formulated earlier. As such, in this section, we propose a simplification to the original problem of detecting the exact number of passengers. Instead, we formulate an alternative classification problem that aims to distinguish between low occupancy (LOV-one or two passengers) or high occupancy (HOV-three or more passengers). It follows that the binary classification problem is the one of detecting whether a vehicle is of high occupancy or not.
We show proposed 1D-CNN architecture (top) for both 5-way occupancy detection and vehicle size classification. For the former, the softmax function is replaced with an SVM classifier. Moreover, the 2D-CNN architecture (bottom) is used for vehicle occupancy detection. Similar to 1D, we used SVM classifier to find occupancy and HOV/LOV predictions: a) 1D CNN structure; b) 2D CNN structure.

**Vehicle Size Classification**

The data that relates to vehicle types is similar to that of occupancy detection with some differences. Firstly, there are five different vehicle types numbered between 1 to 5 which are regrouped into two classes: Large and Small. The Large group contains Car 1 and Car 5 while the Small group contains Car 2, Car 3 and Car 4 as mentioned earlier. The difference between data from vehicle size classification and the one in occupancy detection, as seen in Fig. 2a, the former has five different types of control vehicles drive in a queue in a single direction dataset whereas the latter with only Car 2 drive in both directions with different loads (Fig. 2a left). In addition to this difference, these five different types of vehicles were driven at five different speeds whereby the data from each experiment is collected in a separate dataset. Thus, there are five different datasets for each type of vehicle at the speed of 30km/h, 40km/h, 50km/h, 60km/h, and 70km/h, respectively. The vehicle detection problem can thus be formulated as a classification predictive modelling: a process of predicting vehicle sizes that are categorised into large car or small car, by approximating a mapping function from input DAS data samples into discrete output labels representing the vehicle size. The sum of training and testing dataset for this problem contains 11,267 DAS signals and sizes 563 MB in total.

**Deep Learning Methods**

For each of the intelligent transportation problems: Vehicle Type and Vehicle Occupancy detection, we investigate two CNN methods. The first is the 1D-CNN which is based on a DAS signal from a single bin over a time window, we refer to this as a 1D DAS signal. The second is the 2D-CNN which is based on concatenated DAS signals from a number of consecutive bins over a time window, we refer to this as a 2D DAS signal. It is expected that the 2D DAS signal may be more descriptive of the vehicle weight distribution and therefore might carry better representation of the occupancy information. On the other hand, a 2D-CNN is generally more computationally expensive than a 1D-CNN. In this work, we conduct a study to evaluate the suitability of each method on each of the use cases, vehicle type and occupancy detection. For each method, we propose the following workflow:

- Extract vehicle signals (2D for occupancy and 1D for type) from the raw DAS data.
- Extract representative features from the 1D/2D DAS signals using a tailored CNN.
- Predict the class based on the obtained feature vector using a classifier, SoftMax or SVM depending on the problem.

We will elaborate on two CNN models in detail in the following paragraphs.

**Pre-Processing of DAS Signals**

In order to train the CNNs, the first step is to excerpt the DAS signal with a limited time domain length that records the phase shift caused by vehicles. The reason for this is to ensure feasibility complexity and avoid entering empty signals. To extract 1D DAS signals from raw DAS data, we locate the start shot and the end shot of the DAS signals by drawing two linear regressions for each track (see highlighted in blue in Fig. 2a). The DAS signals then are cut out from the raw data by finding their time windows defined inside the two regressions. The final results are shown in Fig. 2b.

**1D-CNN**

We first adopt a 1D-CNN (Fig. 3) to extract the features from DAS signals. The feature extraction is conducted by using CNN kernels to scan over DAS signals. The CNN then updates weights in the kernel such that the total loss of a given classifier is decreased after each batch of 32 input 1D DAS signals is processed. A total loss can be seen as a penalty of bad prediction of all signals. The goal of model training is therefore to minimise the total loss from the training set and the testing set.

After passing input to convolution layer, the extracted features are compressed by a maxpooling layer to exclude most feature information but retain the max pixel value in each pre-defined region. A maxpooling layer not only preserve important features but minimizes computation costs. A Dropout layer is then added after the maxpooling layer. The dropout layer randomly sets the number of input values to 0 so the neurons in the current layer are not activated. By doing so, CNN is forced to train itself with limited feature information and is less likely to be overfitting; a known risk in occupancy detection due to the limited number of data samples.

In occupancy detection or HOV/LOV detection, for each input 1D DAS signal, the SVM classifier produces an output. The output of SVM geometrically represents the distance between given a 1D DAS signal and the hyperplane that decides whether is classified as one of the defined labels in occupancy or HOV/LOV detection.

As for vehicle size classification, SVM is replaced by softmax classifier, for softmax the loss
function is based on the cross-entropy or negative log likelihood. The softmax output layer is responsible for selecting the most matching class for each input signal from the total number of classes.

2D-CNN

The 1D DAS signal used earlier does not include spatial information about moving objects. We assume that such spatial information contains features that would indicate the vehicle occupancy, since this is related to weight distribution over the area of a vehicle. To this end, we posit here that a 2D CNN can capture spatial features, hence, provide better performance than a 1D CNN for this given problem.

To generate 2D spatial-temporal DAS signals, we used the sliding window method with a window size of six bins (each bin covers 0.68 meters), which is $6 \times 0.68 = 4.08$ metres (the Renault Clio is 4.05 metres in length), and stride was one bin. Effectively, a 2D DAS signal is a result of concatenating 6 1D DAS signals over 6 consecutive bins. As shown in Fig. 3, we add dropout layers to mitigate the overfitting problem, as mentioned earlier.

**Experimental Results and Analysis**

In this section, we present the results and interpretation for the three defined problems from earlier.

**Vehicle Occupancy Detection (5-Way and 2-Way)**

Both 1D-CNN and 2D-CNN models were trained to solve both occupancy detection problems (5-way and 2-way) on all of the data samples with training/testing ratio as indicated in Table 1. For each set of results, the accuracy of occupancy detection is presented, based on the merged dataset: Car2-[1-5p]-60km + Car2-[5p]-60km + ALLCars-[1p]-AllSpeed (Car2 60km). For further model validation and testing, we randomly sampled 20% and 10% of the merged dataset. To obtain test accuracy for 5-way models, samples from 1-passenger and 5-passenger classes were extracted from the test set. Whereas in test 2-way models, we re-used the same samples from the two classes, 1-passenger and 5-passenger classes, and relabelled them to LOV and HOV, respectively.

There are a few insights that can be drawn by examining these results, related to model validity, 1D versus 2D representation, computational cost and data size comparing 1D with 2D models, and the impact of data distribution among the pre-merged three datasets. The overarching insight is that the hypothesis that the DAS signal contains information about the number of passengers in a known car is confirmed. It is indeed possible to detect the exact number of passengers with 94% and that of the binary occupancy by 98% with the 2D-CNN model. In multiple test experiments using different data sets, 2D-CNN has shown a classification accuracy of more than 90%. These test results indicate that with the assistance of deep learning algorithms, the proposed DAS system can make reliable and stable classifications of vehicle occupancy.

As suspected and discussed earlier, the information concerning the car occupancy is better captured through 2D DAS samples as opposed to 1D samples. This is due to the fact that the information relates to the weight distribution over the area of the car as opposed to its absolute weight. This is confirmed by examining the results in Table 1 in which the 2D-CNN results outperform the 1D-CNN in both 5-way and 2-way scenarios.

Moreover, we can draw on the computational complexity of the model training by examining the number of training epochs required for each model to converge. The 2D-CNN systematically requires more time to converge in comparison with the 1D-CNN.

**Vehicle Size Detection**

The results of the second problem, vehicle size classification, are summarised in Table 2. In this case, the 1D-CNN model was trained based on 70% of the data samples which includes all of the five experiments described earlier. Since each of these experiments relates to the same five vehicles driven with a single passenger but at different speeds, the aim of mixing samples is to discern features that represent the size of the vehicle despite the often dominant speed characteristics. The results of the model are first tested based on 10% of the ALLCars-[1p]-AllSpeed, as shown in Table 2. Next, we validate the model further by testing it on the Car2-[1-5p]-60km samples to examine if the number of passengers affects the vehicle size classification (since both vehicle occupancy and size affect its weight). In this case, the aim is to separate vehicle size features from the absolute weight affected by the number of passengers. The average difference in weight between heaviest small vehicle and the heaviest lightest large vehicle is 350 kg and the average weight of one passenger is 80 Kg; thus, four additional passengers weigh 320 Kg which renders the total weight of Car 2 comparable to that of large vehicles.

The test accuracy result from (ALLCars-[1p]-AllSpeed) clearly confirms that the features delin-
are still a number of remaining open research challenges.

We see these approaches useful for monitoring the occupancy of road public transport vehicles, as can be deduced from the promising accuracy results both in large car: 70% and small car: 96% (Table 2). It is worth noting that these results are significantly better than the prior art [11] which achieves 71% accuracy in differentiating cars, SUVs and trucks. The proposed 1D-CNN approach in [13] achieves more than 82% in differentiating five different vehicles under the category car, which is a more difficult task than [11]. In this work, the 1D-CNN approach is used to successfully differentiate the group size of a car with 86% accuracy with an interdependent test set, thus outperforming prior art.

In order to validate the findings further, we use DAS signals from Car 2-[1-5p]-60km as an independent test dataset. In this case, the same Car 2 is driven along the same stretch of the road carrying a different number of passengers between one and five. As shown in Table 2, the model is able to correctly classify the size of Car 2 (Small car) 89% for any occupancy. This finding suggests that the large and small vehicle class inherits distinct information that is not overshadowed by the speed or the occupancy of the vehicle. However, it is clear that higher occupancy cause higher error in detecting the size of the vehicle which suggests that a 2D-CNN, in this case, would yield better data representation.

**Performance from Other Models than CNNs**

In comparing CNNs with other AI models, we conducted experiments fitting DAS data to SVM and Long Short-Term Memory (LSTM) models. However, the results indicated that neither of these models surpassed the performance of CNNs, which achieved a classification accuracy of over 90%.

SVM, while recognized for its effectiveness in certain contexts, is not well-suited for handling high-dimensional data efficiently. Given the complex nature of our DAS signals, which may not be easily separable by linear or nonlinear functions/planes, SVM proves to be inadequate for DAS classification tasks.

Regarding LSTM, originally designed for predicting the next word in natural language processing, it has been applied in various studies to classify DAS data. However, [14] found that LSTM’s performance in analyzing temporal data was inferior to feature recognition in the frequency domain. Furthermore, [15] did not utilize LSTM as a standalone classification model; instead, they employed CNN to extract features before LSTM’s temporal analysis.

**Application Scenarios and Open Challenges**

**Application Scenarios of DAS**

The DAS system empowered by machine learning techniques has broad application scenarios, which can be summarized into the following categories.

**Smart Transportation Management:** Besides the loads and vehicle types detection mentioned in this article, DAS systems are also capable of detecting the number, speeds, and locations of vehicles. This information can assist governments and traffic managers in implementing better law enforcement, such as overweight and overspeed monitoring. The implementation of this system can achieve seamless coverage on long road sections of several kilometers or even dozens of kilometers, detecting and preventing these dangerous behaviors, thereby improving traffic safety. This automated solution also reduces the labor costs of traffic enforcement and protects the health and safety of traffic enforcement officers.

**Active Travel Detection:** The DAS system has the potential to detect other targets that use active travel, such as bicycles and pedestrians, in addition to motor vehicles. As people who use active travel are less effectively protected in the transport system, it is even more important to monitor their safety. The DAS system can be applied to monitor the occurrence of dangers such as abnormal movements, falls, car accidents, etc., thereby ensuring the safety of traffic participants in the city.

**Smart City and Data Science:** Data collected by DAS, including but not limited to the traffic throughput, accident locations, and mean velocities can be used to support data science in smart cities and data science in transportation systems. Thanks to the broad coverage and privacy protection features of the DAS systems, it is a promising solution for data collection. The collected data can be invoked to train artificial intelligence for smart cities and direct traffic, such as intelligent traffic guidance, autonomous driving, and etc.

**The Potential Setup for Future DAS Experiments**

**Extend Current DNN Methods to Detect Large Vehicles:** DNN methods are flexible and have the ability to be extended to identify the load of large vehicles (e.g., bus). Due to the following reasons:

- First, in a physical view, large vehicles having more passengers generally have significant weight, and the DAS signals caused by the large vehicles are more pronounced and easier to identify.
- Secondly, as long as large vehicles are included in the training data, the DNN model has the ability to identify them in practice.

During the training of DNN models, the vehicle type and maximum capacity are a priori information for the proposed occupancy detection model. We see these approaches useful for monitoring the occupancy of road public transport vehicles, such as buses, for optimised routing and efficiency.

To be more specific, the work demonstrates the potential of DAS in detecting the occupancy of vehicles with a priori knowledge of the vehicle...
type. Two approaches are presented for detecting a vehicle occupancy: the first aims to get the exact number of passengers in a known vehicle and the second aims at distinguishing two categories of occupancy defined by a threshold. The vehicle used for investigating this problem is a Renault Clio with a maximum capacity of 5 passengers (including the driver). The occupancy threshold is defined based on its maximum capacity and the regulations of the HOV lane usage; low = 1 or 2 and high = 3, 4, or 5. These values would differ if the passenger detection was used for a different problem, e.g., bus occupancy which may have a maximum capacity of 50 passengers. In this case the objective of monitoring the bus occupancy is to plan the bus routes and time table efficiently to maximise the occurrence of full loads and that of passengers comfortable and waiting time and the threshold would be defined accordingly.

**Combine DAS with Other IoT Sensors to Fortify Vehicle Detection:** The potential of DAS for intelligent transportation systems is best harnessed in conjunction with other IoT data streams, e.g., cameras. For instance, cameras may be used at road intersections to identify the vehicle type and match it to the database of registered vehicles. This would then be used as an uninterrupted continuous sensing system to track this vehicle and its occupancy. In this case, the CNN models need to be updated to represent new added vehicle types.

**Open Challenges**

Although there have been several successful experiments of applying DAS systems for intelligent transportation, there are still a number of remaining open research challenges to prevent the DAS system from achieving higher accurate recognition results, which are summarized below.

**Directional Sensitivity:** Since the fibre extends in a certain direction, DAS systems have different directional sensitivities in different directions. In existing research, the experiment is often set to a certain road section, and the directional sensitivity of DAS is not considered sufficiently. In more complicated road sections, such as intersections, roundabouts, etc., vehicle signals are likely to come from any direction of the optical fiber. Then, how the DAS system can simultaneously maintain high sensitivity to signals from multiple directions in such a complicated situation is still an open question.

**Environmental Impact:** In practice, variable environmental factors can have a more or less adverse effect on the detection accuracy of the DAS system. Optical fiber relies on strain to identify vehicles, and this strain applied on the fibre is affected by factors such as the road surface material, the hardness of the soil, and even the roots of street trees. In addition to the road environment in different regions, weather and climate are also variable factors that affect the performance of DAS. Changes in precipitation and varying temperatures will lead to changes in the hardness of the roadbed, thereby affecting the perception effect of the optical fiber.

It thus remains an open challenge to investigate if a model trained on DAS signals collected during a dry day would represent accurately a DAS signal generated by the same vehicle on a rainy day or in a system using different optical fibres. A feasible solution to deal with the above challenges is to conduct extensive experiments and data collection in different regions and different seasons, and to use these data to train generalized artificial intelligence models. However, the experimental cost of this solution will be very high. Low-cost solutions against the practical environment are still highly awaited.

**Fibre Access Scheduling:** A significant cost advantage of DAS comes from the reuse of existing optical fibres. However, the original mission of optical fibres is to serve the city’s backbone network, and they may be busy or idle at a specific time, depending on the transmission demand of the communication system. Therefore, how to jointly schedule communication tasks and optical fibre sensing tasks has become a practical issue that must be considered. Some resource allocation and scheduling algorithms, such as matching theory, reinforcement learning, etc., can be considered for this challenge.

**Conclusion**

In this manuscript, we present pioneering research that uses signals generated by a DAS system for intelligent transportation. We formulate two dominant problems in this domain: occupancy estimation of moving vehicles and vehicle size classification. Based on a real DAS dataset collected in a controlled experiment, we demonstrate that the DAS signal generated by a moving car is indicative of its size and occupancy level. We propose two different CNN to extract the spatio-temporal features of the DAS signal which successfully classifies the level of occupancy (HOV/LOV) with 98% accuracy and estimates the number of passengers with 94% accuracy. In the case of vehicle size classification, the 1D model succeeds in determining the size of a car irrelevant to the speed of movement with 86% accuracy. The results of this article indicate that DAS is a potential privacy-preserving vehicle sensing scheme.

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Biographies

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Peter Hayward (peter.hayward@t2sensing.com) studied at the University of Sussex, gaining a D.Phil. in the field of Nonlinear Dynamics. Thereafter, continuing at Sussex continuing Post-Doctorate research. In 2004 Pete joined the commercial sector, working in the field of distributed optical fibre sensing, ultimately leading development of many commercial & research solutions, in the Oil & Gas sector. Over time he pioneered the development of numerous commercial distributed sensing solutions, leading to the delivery of many strain, temperature, pressure, vibration, and acoustic sensing solutions. Notably, in 2006 delivering the world first commercially commissioned distributed pressure sensing system, on a 9km subsea pipeline. In 2008 he joined with Dr. Handerek as founding technologists at Fotech Solutions, where the pair were instrumental in the development of the first generation of Distributed Acoustic Sensing solutions. Remaining for 15 years, developing the technology for applications in the Oil & Gas, security, and utilities sectors, whilst additionally returning to support academic research students in the field, through industrial supervision. He, with Dr. Handerek, has now founded T2 Sensing, an organisation that continues research in distributed fibre sensing, currently developing the next generation of distributed vibration, acoustic, and multimelectric sensors.